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An Examination of Predictors of Multiple Hospital Admissions among the Non-Institutionalized Elderly

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AN EXAMINATION OF PREDICTORS OF MULTIPLE HOSPITAL ADMISSIONS AMONG THE NON-INSTITUTIONALIZED ELDERLY

By

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VITA

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Doctor Suhayda's professional career has involved nursing education, clinical practice and clinical research. She has published scholarly and research based articles and has presented professional papers and consulted on local, regional, national, and international levels. She is a member of Sigma Theta Tau, the International Honor Society for Nursing, and a recipient of a Post Baccalaureate Faculty Fellowship Award from the Department of Health and Human Services, Division of Nursing. She is currently a practitioner teacher at Rush University College of Nursing.

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CHAPTER ONE

INTRODUCTION

The demography of aging and the morbidity and mortality patterns of the elderly and the oldest old have received considerable attention in recent years due to their profound and widespread impact on this nation's economic, social, and the added services provided by health care institutions. One in every eight Americans is 65 years of age or older (Feinleib, 1988). Demographics predict that the population aged 65 and over will double between 2010 and 2019, and nearly double again between 2020 and 2029 (Butler, 1983). By the year 2040, the population aged 65 and older will have increased to 67.3 million, expanding from approximately 11% of the population to 21% (Manton & Soldo, 1985). The fastest growing of this population segment is the 'oldest old', those aged 85 years and over. Projected to increase 117% by the year 2000, this age cohort will advance from 2.3 million in 1980 to 4.9 million by 2000, to 7.1 million by 2020, and to over thirteen million by 2040 (Rosenwaike, 1985). Even these estimates may be conservative depending on the forecasting models chosen (Olshansky, 1988).

This demographic shift is unprecedented in our history. The aging of the population and the acceleration of the aging process caused by declining mortality will result in a substantial burden on this nation's health care system (Olshansky, 1988). Projected changes in the size and age distribution alone would have a significant impact on utilization and expenditures regardless of other changes associated with morbidity, therapies and technologies, availability and cost of care, and social and economic conditions (Rice & Feldman, 1983). Methods of providing and reimbursing health care, determination of which professionals define, prescribe and implement care, and identification of mechanisms for monitoring individuals' entrance and progression through the health care system will need to be carefully examined. The graying of America will challenge not only the structure but also the philosophy of the entire health care system.

We can expect major differences in the health status of older persons, in their use of health care, and in its costs (Feinleib, 1988). Since older people tend to have more health problems than younger people, the implications of the aging of the population on the demand for medical care and on public policy are significant. There are now more persons suffering from conditions that are managed or controlled rather than cured. These conditions cause afflictions for decades, impairing ability to function and requiring much medical care (Rice & Feldman 1983). Whereas the life expectancy in 1900 was 47 years, today it is 75 years, that is, an additional 28 years on the average have been added to life expectancy. Of great concern is the possibility that a reduction in the risk of death from some of the major degenerative diseases, such as heart disease and stroke, could expose the survivors to an increase in the numbers of years spent in a state of frail health, thereby increasing both the duration of individual frailty and aggregate morbidity for the population (Denson, 1987; Butler, 1983). If present trends in mortality continue, it is possible that the needs for increased health care for our older population will be enormous and could truly overwhelm future health care resources (Guralanick, Yanagashita, & Schneider, 1988).

Medical care utilization patterns among the elderly reflect their poor health status. Several reports indicate that those 65 years and older disproportionately consume national health care expenditures and most types of health care services (Garfinkel & Riley, 1988; Zook & Moore,1980; Rice & Feldman, 1983; Vladeck & Firman, 1983). They visit physicians and use hospital and nursing homes more frequently than younger persons, and the use rates rise significantly for the very old (Rice & Feldman, 1983). Reports of the National Health Survey reveal that in the course of a year, about 80,000 out of every 100,000 elderly in the population see a doctor, 22,000 make use of community agencies, and 31,000 are hospitalized (Densen, 1987). In 1981, those over 65 years of age accounted for 25% of prescription drug utilization, 40% of acute hospital days, 30% of the total personal health budget and 50% of the federal health care budget (Katz, 1981).

A careful examination of utilization data has revealed that not all elderly persons are high consumers of health care resources and that a relatively small proportion uses a high percentage of both inpatient and outpatient services (Garfinkel & Riley, 1988; Zook & Moore, 1980; Anderson & Knickman, 1984a; Anderson & Steinberg, 1984; Roos & Shapiro, 1981). Riley (1986) reported that the top 1% of the aged Medicare beneficiaries accounted for 21% of expenditures in 1975 and 20% in 1982. Gornick, Beebe, and Prihoda (1983) found that 14% of Medicare beneficiaries accounted for 84% of Medicare reimbursements nationally, in 1980, and McCall and Wai (1983) reported that 19% of Medicare beneficiaries in Colorado incurred 88% of Medicare allowed charges in 1978. The burden of high cost care has affected the elderly consumer, as well. Garfinkel and Riley (1988) reported that elderly high cost users devote a substantial portion of their income to out-of-pocket health care expenses, exclusive of insurance premiums.

A recent focus of concern has been on the high cost of inpatient hospitalizations. Health care expenditures for people aged 65 or more are substantial, and highly concentrated on the 22% of enrolles who enter the hospital each year (Christensen, Long, & Rodger, 1987). Nearly 75% of the government's total 1984 outlay of $80.5 billion was associated with the costs of reimbursable inpatient care for the elderly (Soldo and Manton, 1985). Hospital revenues in 1986 amounted to $180 billion, 7.4% more than in 1985. By the year 2000, expenditures for hospital services are projected to be $621 billion. Because the Medicare population is projected to increase faster than the total population, the Federal Government share of costs is expected to increase as well.

High cost hospitalizations can be characterized as either single cost intensive episodes or multiple admission patterns. Growing evidence indicates that it is the multiple admission patterns which represent a significant proportion of high cost illness (Fleming,1985). Anderson and Steinberg (1984), in a longitudinal investigation, examined the proportion of medicare expenditures attributable to repeated admissions. Their results indicated that medicare inpatient expenditures are highly concentrated on a small percentage of beneficiaries who are repeatedly admitted to the hospital. Twenty-three percent of medicare's beneficiaries who were discharged more than once accounted for 80% of medicare's inpatient hospital expenditures. Almost 60% of medicare's inpatient expenditures were attributable to the 12.5% of its beneficiaries who were discharged three or more times. Over 20% of inpatient expenditures were attributable to the 2.6% of beneficiaries who were discharged more than five times. The expensive patients tended to be those who were hospitalized repeatedly often in the same disease category, rather than those with single, cost intensive hospital days; furthermore, the increased rate of hospitalization remained constant throughout a three year period (i.e., high users in a given year continue to be high users in the following years). Previous studies have reported similar findings (Anderson & Knickman, 1984a; McCall & Wai, 1983; Zook & Moore, 1980). However, Graham and Livesley (1982) in a study examining readmissions to a medical geriatric unit, reported that nearly 50% of their readmissions could have been prevented through enhanced patient education, rehabilitation, or provision of support services. Hendricksen, Lund, and Stromgard (1989), in a three year controlled trial involving hospitalized elderly, reported a significant reduction in hospital readmissions following preventive home visits to the elderly post-discharge.

The fact that a small fraction of consumers utilizes a major portion of medical resources raises a number of important issues with respect to cost distribution, predictability, preventability, equity in treatment, and ultimate health status of the high-cost user. Despite a plethora of research on health services utilization, and despite the volume of health services used by the elderly, little is known about the characteristics of the high cost user (Densen, 1987; Garfinkel & Riley, 1988). In particular, research focusing on characteristics of the elderly with multiple hospital admissions is extremely limited.

In an attempt to identify high-risk patient groups for whom outpatient supports might be cost-effective, developers of high-utilization profiles need to relate patient characteristics with a hospital readmission data set (Anderson & Steinberg 1984). Even a small decrease in hospital readmission rates could result in substantial savings for the Medicare program (Anderson & Steinberg, 1984; Garfinkel & Riley, 1988).

The overall research question addressed in the study described below relates to the identification of predisposing, enabling, and need characteristics predictive of multiple hospital admission patterns in the non-institutionalized elderly. It was anticipated that a systematic analysis of data set obtained from the Supplement on Aging to the 1984 National Health Interview Survey would yield a risk profile that could assist us in our prediction of hospital readmissions in this population.

Examining the characteristics of those individuals who make the greatest demands on the health care system would contribute to the body of knowledge associated with health services research, would provide impetus for public policy cost control programs to include provisions based on the special characteristics of high-cost users, would offer a re-examination of the organizational arrangement for the delivery of health services, and would assist the health care professional in identifying high risk individuals and in developing strategies for effective intervention.

CHAPTER TWO

LITERATURE REVIEW

Introduction

The reported rising costs of social and health care services draws attention to the importance of understanding the factors which influence their utilization. Utilization of health care services among the elderly is of particular concern because the projected changes in the size, age distribution, and level of morbidity in the aging population will substantially impact the delivery and economics of health care. Studies focusing specifically on the use of health services by the elderly, however, suggest that a small proportion account for a disproportionate share of service utilization. Included in this high-cost group are those elderly characterized by multiple hospital episodes as opposed to single cost-intensive stays.

While numerous studies have examined predictors associated with the use of health services by the elderly, relatively little is known about the characteristics of this high cost user group. Results of studies are difficult to summarize because of diversity in patient populations, the types of research methods employed, and the numerous operational definitions of the predictive and outcome measures. Nonetheless, common conclusions have emerged about multiple hospital episodes: they are common and usually occur within 30 days post discharge; they account for a major component of health care cost; they are usually for health problems associated with the original hospitalization; and they are frequently preventable.

The major thrust of health services research today is cost containment, hopefully without negatively affecting health status. To contain health care expenditures, utilization must be reduced or reallocated to less costly care and services. Predictive models provide an important means of identifying those patients at high risk for multiple hospital episodes so that these patients can be targeted for intensive intervention.

The literature review reported below incorporated investigations which described patterns of health services utilization in non-institutionalized elderly populations. In order to identify all possible variables, both general utilization patterns and those associated with hospital readmissions were systematically reviewed. Discussion of investigations focusing specifically on hospital readmissions follows the introduction to general utilization patterns. The Andersen Behavioral Model for Health Services Utilization served as an overall framework for this investigation. In this chapter The Andersen Behavioral Model for Health Services Utilization is described after which sections are presented describing the selection of studies, measures and predictors of health care utilization, and a summary of findings associated with health service utilization. A final section of the chapter provides a summary of findings associated with hospital readmissions.

The Andersen Model for health services utilization

Conceptual approaches to the study of health care utilization furnish a useful framework within which to integrate gerontological research and utilization data. The use of such approaches help make discussions of future research needs regarding both the aged and health care utilization more coherent, and policy implications more apparent.

The health services utilization model cited most widely in the literature is that developed by Andersen and his colleagues (Andersen & Newman, 1973). The Andersen Model incorporates both contextual and system properties. Aspects of the access to medical care concept are integrated into a framework that views health policy as affecting both the characteristics of the health care delivery system and of the population at risk in order to improve services and health care outcomes. Andersen has suggested indicators for the measurement of the various relevant aspects of access, with the delivery system and population descriptors as process indicators and utilization and satisfaction as outcome indicators. The delivery system is characterized by the volume and distribution of its resources and by the coordination and control of resources in providing medical services. Frequently, location of the delivery system has served as proxy for determining volume and distribution of services. The descriptors of the population at risk are characterized by predisposing, enabling, and need variables. Predisposing variables describe characteristics which existed prior to onset of the illness episode. Such characteristics include age, sex, race, religion, and values concerning health and illness. Enabling variables provide the means for individuals to use health care services. They include resources specific to the individual and his family and attributes of the community in which he lives. Need variables include health related factors associated with the most immediate cause of health services use. The need for care may be either that perceived by the individual or that evaluated by the delivery system.

Selection of studies

A systematic online bibliographic search of the National Library of Medicine's Medline files as well as a hand search of the Index Medicus was performed to locate investigations of patient factors associated with health services utilization published from 1975 through 1989. Articles were obtained, also, through examination of indexes in relevant journals and citations in the literature. An additional Medline search was performed to locate investigations associated with high utilization of health services and hospital readmissions. Only those investigations reporting statistical analyses pertaining to utilization of services by non-institutionalized elderly were included. Forty-one relevant studies were identified for this review. Ten of these studies pertain to hospital readmissions in the elderly.

Measures and predictors of health services utilization

Sources of utilization data varied across studies. Of the 44 data sets used in the 41 studies, 66% were obtained from patient interview; 34% were obtained from Medicare files or records from third-party payers. The sampling periods spanned the years 1968-1986. Five percent of the studies examined data sets obtained before 1970; 69% examined data sets from the 1970's; and 26% examined data sets from the 1980's. Four of the studies used a longitudinal design. The remaining 37 studies examined cross-sectional data.

Process and outcome indicators associated with health care delivery were characterized by descriptors of the population at risk, resource distribution and utilization patterns.

For purposes of this review, population descriptors were grouped according to the Andersen Behavioral Model Framework and included predisposing characteristics (age, sex, race); enabling characteristics (education, income, possession of medicaid or supplemental insurance, retirement status, marital status, living arrangements, family and social support, regular source of care) and need characteristics (physical and emotional health status, activity capabilities, clinical descriptors, and prior use).

Utilization variables generally fell into four categories: total medical care expenditures; hospital services; physician services; and support services. Total expenditures were measured, in most studies, as total dollars reimbursed by the Medicare program during a particular day. Hospital services were measured by the number of hospital episodes, the number of hospital days, or total dollar reimbursements under Medicare. Physician services, the most frequently investigated, were measured as the annual number of physician visits. Health support services were measured by the number or types of services used: skilled nursing facilities; home health care; home care assistance; ambulatory care; and social services such as recreational and rehabilitation services.

Distribution of health care resources was characterized by types of areas in which populations resided. The patient population, data source, utilization measures, and predictor measures for each of the studies reviewed are outlined in Table 1.

TABLE 1 STUDIES EXAMINING PREDICTORS OF HEALTH SERVICES UTILIZATION

STUDY	SAMPLE SIZE	PATIENT POPULATION AND DATA SOURCE	UTILIZATION MEASURE(S)	PREDICTOR MEASURE(S)
(1) Anderson & Knickman (1984a)	236,964	20% random sample from 1974-1977 Medicare History File	Medicare expenditures Medicaid	Prior total expenditures;
(2) Anderson & Knickman (1984b)	204,917	1% random sample 1974-1977 Medicare History File	Hospital admission; total expenditures	Prior use; medicare expenditures
(3) Anderson & Steinberg (1984)	270,266	1% random sample of medicare beneficiaries enrolled from 1974-1977; American Hospital Association Annual Survey of Hospitals	Hospital admission	Sex; prior use; medicaid eligibility; georgraphic location
(4) Anderson & Steinberg (1985)	21,043	same as (2) using every 20th data record	Hospital readmission	Age; sex; race; prior use; number and acuity of conditions; urban/rural; surgery
(5) Anderson et al (1986)	189,088	1% national random sample of Medicare benficiaries alive from 1974-1978	Medicare expenditures	Age; sex; region; prior expenditures
(6) Beebe, Lubitz & Egger (1985)	20,733	0.1% sample of Health Insurance Master Accretion File: Oct. 1974-Sept. 1975; 1976 Medicare Person Summary File	Medicare reimbursement	Age; sex; prior use; supplemental insurance
(7) Branch et al (1981)	1,625	1974 Massachusetts Department of Health Survey; statewide random sample of non-institutionalizedelders	Annual physician visits; hospital days; use of ambulatory and home care	Age; sex; race; education; marital status; income; regular source of care; living arrangements; impaired activity

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STUDY	SAMPLE SIZE	PATIENT POPULATION AND DATA SOURCE	UTILIZATION MEASURE(S)	PREDICTOR MEASURE(S)
(8) Buczko (1986)	7,643	State Medicaid Household Survey Portion of the 1980 National Medical Care Utilization and Expenditure Survey	Physician visits; total expenditures	Age; sex; race; marital status; education; living children; employment; region; insurance; regular source of care; health status; limiting conditions; beddays
(9) Cafferata (1987)	4,560	1977 National Medical Care Expenditure Survey; randomly selected households	Disability days; physician visits; hospital episodes	Age; sex; race; education; employment; marital status; living arrangements; activity limitations; chronic conditions; perceived health; health worry; usual source of care; ratio of physicians
(10) Coulton & Frost (1982)	1,519	Cluster sample of Cleveland residents eligible for Medicare and supplemental security income, 1975-1976	Physician visits; use of mental health, personal, and support services	Sex; race; education; income; insurance; perceived health; disability days; activity limitations
(11) Davis & Reynolds (1975)	11,790	National Center for Health Statistics 1969 Health Interview Survey	Physician visits	Age; sex; education; retirement; activity limitations; chronic conditions
(12) Evashwick et al (1984)	1,317	Massachusetts Health Care Panel Study 1974-1976; statewide probability sample	Physician visits; hospital services; support services	Age; sex; race; education; marital status; living arrangements; income; employment; regular source of care; activity limitations; conditions; perceived health

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STUDY	SAMPLE SIZE	PATIENT POPULATION AND DATA SOURCE	UTILIZATION MEASURE(S)	PREDICTOR MEASURE(S)
(13) Eve (1988)	1,894	Social Security Administrations's Longitudinal Retirement History Survey, 1968	Physician visits; hospital epsodes; hospital nights	Age; race; marital status; education; income; employment; insurance; regular source of care; living children; prior health; activity limitations; prior use; region
(14) Fethke et al (1986)	101	Subjects drawn from daily census of University Teaching Hospital, 1983	Hospital readmission	Age; sex; education; marital status; living arrangements; prior use; number of diagnoses; conditions; life satisfaction
(15) Freeborn et al (1977)	708	5% subsample of Oregon Region Kaiser Permanante Medical Care Program; Jan. 1969-Dec. 1970	Outpatient contacts	Education; income; perceived health; index of physical symptoms
(16) Garfinkel et al (1988)	1,934	National Medical Care Utilization Survey 1980	Total charges	Sex; marital status; income; insurance; conditions; restricted bed days; activity limitations
(17) German et al (1976)	352	Random sample of households in East Baltimore, 1974	Physician visits	Age; sex; living arrangements; conditions
(18) Gooding & Jette (1985)	444	Hospital data of all elderly patients admitted to a lartge metropolitan teaching hospital from Jan. through June 1982	Hospital readmissions	Age; sex; length of hospital stay; primary diagnosis
(19) Graham & Livesely (1983)	153	Retrospective analysis of hospital discharges from a geriatric medical unit, 1982	Hospital readmissions	Age; sex; conditions

TABLE 1 STUDIES EXAMINING PREDICTORS OF HEALTH SERVICES UTILIZATION

STUDY	SAMPLE SIZE	PATIENT POPULATION AND DATA SOURCE	UTILIZATION MEASURE(S)	PREDICTOR MEASURE(S)
(20) Haug (1981)	625	Random sample, National Opinion Research Center, 1978	Physician visits	Sex; race; marital status; health status; activity limitations
(21) Holloway et al (1988)	665	Medicare beneficiaries hospitalized in Michigan during Jan. 1982-June 1983	Hospital readmission	Age; sex; living arrangements; education; perceived health; conditions
(22) Kelman & Thomas (1988)	1,855	July-1984-March 1985 Norwood-Montefore Aging Study. New York	Hospital services; ambulatory care	Age; sex; race; income; insurance; living arrangements; perceived health; depression; activity limitations
(23) Krause (1988)	351	Random community survey in Galveston, Texas, 1984	Physician visits	Social support; stressful life events
(24) Link et al (1980)	8,239	1976 National Health Interview Survey	Hospital days; physician visits	Supplemental health insurance; health status
(25) Link et al (1982)	30,000	1969, 1974, 1976 National Health Interview Survey	Hospital days; physician visits	Income; race; region; chronic condition
(26) Markides et al (1985)	327	Household interview data from 1981-1982 of Mexican Americans living in San Antonio	Physician visits	Age; sex; marital status; education; income; insurance; conditions; perceived health; health worry
(27) Narain et al (1988)	396	Retrospective analysis of records for all patients 70 years and older admitt to a Veterans Association Medical Center, July 1985-June 1986	Hospital readmissions	Age; race; marital status; living arrangements; activity limitations; medical problems
(28) McAll & Wai (1983)	4,368	Random sample of Colorado Medicare beneficiaries enrolled from Oct. 1974-Dec. 1978	Hospital days; physician visits; medicare reimbursement	Age; sex; race; region; prior use; medicaid

TABLE 1 STUDIES EXAMINING PREDICTORS OF HEALTH SERVICES UTILIZATION

STUDY	SAMPLE SIZE	PATIENT POPULATION AND DATA SOURCE	UTILIZATION MEASURE(S)	PREDICTOR MEASURE(S)
(29) Mutran & Ferraro (1988)	3,150	Subsample of 1973 survey of low income aged and disabled	Recency of physician visits; hospital days	Age; sex; race; marital status; education; income; insurance; region; proximity to children; conditions; activity limitations
(30) Rich & Freeland (1988)	410	Retrospective analysis of records for patients with congestive heart failure admitted to Washington University Medical Center, Jan. 1983-June 1986	Hospital readmission	Age; sex; secondary diagnosis; region; length of original stay
(31) Riley & Lubitz (1986)	---	2% probability sample from the 1979-1981 Medicare Provider Analysis and Review Files	Hospital readmission	Age; type of surgery; region; length of original stay
(32) Roos & Shapiro (1981)	2,526	1971 Manitoba Longitudinal Study on Aging; government data files on service utilization	Physician visits; hospital days	Age; sex; type of residence; prior use; conditions; income
(33) Rosner et al (1988)	189	Selected by random digit dialing from residents in three mid-western communities	Physician visits	Age; sex; race; education; living arrangements income; regular source of care; perceived health; symptoms
(34) Smith et al (1988)	499	Patients admitted to and discharged from the internal medicine service in a midwestern city between Oct. 1979-July 1980	Hospital readmission	Age; sex; race; emergency room visits; physiologic measures
(35) Steel et al (1982)	150	Review of Medical records of enrollees in Home Medical Service Boston: March-May 1980	Number of home medical service contacts	Age; race; living arrangements; conditions

TABLE 1 STUDIES EXAMINING PREDICTORS OF HEALTH SERVICES UTILIZATION

STUDY	SAMPLE SIZE	PATIENT POPULATION AND DATA SOURCE	UTILIZATION MEASURE(S)	PREDICTOR MEASURE(S)
(36) Wan (1982)	1,987	Interview data from 1975 National Health Services Research Community Survey	Physician visits; hospital days	Sex; race; education; regular source of care; insurance; conditions; activity limitations
(37) Weinberger et al (1986)	155	Elderly public housing tenants	Hospital admissions	Perceived health; activity limitations
(38) Wolinsky et al (1983)	401	Interview data from a 2 stage sample of elderly in south-central metropolitan St. Louis, 1983	Hospital readmission; physician visits; beddays	Age; sex; race; marital status; family size; nutritional risk; income; insurance; regular source of care; perceived health; activity limitations
(39) Wolinsky et al (1984)	15,899	1978 National Health Interview Survey	Physician visits; hospital days	Age; sex; race; marital status; education; living arrangements; employment; regular source of care; income; insurance; region; perceived health; activity limitations; body mass ratio
(40) Wolinsky et al (1988)	99,445	Pooled National Health Interview Survey: 1972-1973; 1976-1977; 1980-1981	Physician visits	Sex; race; education; marital status; living arrangements; income; region; perceived health; activity limitations
(41) Young et al (1983)	---	20% sample of all aged and disabled medicare beneficiaries receiving services in 1976	Total charges; hospital admission; support services	Sex; race; condition

Findings associated with health services utilization

Both univariate and multivariate models were used in examining predictors of health care utilization. Eleven of the forty-one studies, used t-test and chi-square to examine the strength of association between predictors and utilization measures. Twenty-eight of the studies used regression analysis, including stepwise, standard, hierarchial, logistic regression, and path analysis. Two studies used Automatic Interaction Detector (AID) analysis, a computer program which splits the sample into binary groups in an iterative fashion, always splitting the data into two categories that explain the maximum variance between groups. One study used discriminant function analysis to divide subjects into overutilizers and underutilizers of health care services.

Predictors of service utilization. Predisposing and enabling characteristics, examined in all but three of the forty-one studies, achieved significance as predictors of health care utilization in 53% of the instances examined. Predisposing characteristics achieved statistical significance 52% of the time with sex achieving significance more often then either race or age. Enabling characteristics achieved significance 56% of the time, with regular source of care and retirement status achieving significance more often than other characteristics. Need related characteristics achieved significance in 90% of the instances examined, with prior use achieving significance more often than health status, activity limitations, or clinical descriptors.

Examination of predisposing and enabling characteristics revealed noteworthy effects on health services utilization. For example, utilization of all health services, particularly hospital services, increased with age (Davis & Reynolds, 1975; Wolinsky & Coe, 1984). Mutran (1988), in an examination of medical need and use of services among older men and women, found, however, that aging acted as an equalizer of physician contacts among men and women. Poor health by itself was no more likely to cause an older woman to see a physician than it was to cause an older man to see a physician. Other investigators reported sex differences in health services utilization once medical need was considered. Garfinkel and Riley (1988) reported that men were more likely to incur high costs while Young (1980) reported higher costs for women. Several studies reported that women used more physician and support services; whereas males were hospitalized more frequently (Coulton & Frost, 1982; Davis & Reynolds, 1975; Riley & Lubitz, 1986; Wolinsky, Arnold, & Nallapati, 1988; Young, 1980). Cafferata (1987) reported that elderly women in poor health had a higher rate of institutionalization; consequently, the majority of elderly women living in society were in better health than the elderly male population, accounting for the higher rate of hospitalization amongst men. Speculation has existed as to whether the increased use of physician services by women is due to increased morbidity or differences in medical care behavior related to sex roles (Mutran & Ferrano, 1988). Wolinsky, Coe, Miller, Prendergast, Creel, and Chàvez (1983) suggested that more women, particularly those who have been recently widowed, sought emergency room and physician contact as a substitution for social interaction. Coulton and Frost (1982), on the other hand, reported that socially isolated individuals had a lower utilization of support services and suggested that they may have had weak ties to other parts of the community and health service network, as well.

Examination of race, education and income variables revealed both direct and indirect effects on health services utilization. Freeborn, Pope, Davis, and Mullooly (1977) reported that, in general, those with lower income and education levels were in poorer health. Rosner, Namazi, and Wykle (1988) reported that race and education had significant indirect effects through income and severity of symptoms. Blacks and subjects with lower educational levels reported more symptoms as severe (Link, Long, and Settle, 1982). Blacks with less education and lower income were more likely to use neighborhood health centers and less likely to use hospital and physician services (Wan, 1982). Several investigators reported that elders with lower levels of formal education were more likely to report a greater number of hospital days and use more home care services (Branch, Jette, Evanshwick, Polansky, Rowe, and Diehr, 1981; Wan, 1982). Women with higher education had higher use of preventive services (Freeborn et al, 1977). Whites used more of all services than did non-whites (Coulton & Frost, 1982; Cafferata, 1987). Those who could afford supplemental health care insurance and had a regular source of care used more of all services (Branch et al 1981; Buczko, 1986). Higher income was associated with increased education which resulted in better health assessment and greater physician use.

Several investigators examined the effects of employment status, marital status, and living arrangements on health services utilization. Hospitalizations and use of physician services were decreased in the employed elderly population. Markides, Levin, and Ray (1985) reported that employed elderly were more likely to define their health as good, leading to fewer physician visits. Those elderly who continued to work were hospitalized less often and for shorter periods of time. Examination of the relationship between use of health services and marital status revealed that the use of health services was higher among divorced, separated, widowed, and never-married persons than among those who were married (Evanshwick, Rowe, Diehr, & Branch, 1984). The literature suggested that married persons used fewer health services because marriage may have contributed to one's mental and physical health. In contrast widowhood was associated with an immediate decrease in perceived health status (Fenwick & Barresi, 1981).

Cafferata (1987) suggested that the relationship between marital status and the use of health services may have had more to do with living arrangements than with marriage itself. She found that while marital status was not directly related to hospital use or the number of physician visits, living arrangements did have a significant effect. Both married and unmarried persons who lived with others had a significantly higher average number of bed-disability days. Bed disability days was considered informal use of and the first entry level into the health care system by Wolinsky and Coe (1984). Cafferata (1987) found, also, that elderly persons who lived with others, married persons who lived with a spouse only, and married persons who lived with others had a lower likelihood of physician use. Elderly with living children had a higher rate of health services utilization.

Examination of need related variables revealed that impaired activity was the most frequently investigated, achieving significance in 85% of the instances examined. Those individuals in poor health with dependence in activities of daily living, functional limitations, and activity limitations used more health services. Level of activity was measured in global terms (presence or absence of a disability or activity limitation); as specific measures of functional limitations and dependence in activities of daily living (ability to climb stairs, walk 1/2 mile, performance on an activity of daily living and instrumental activities of daily living scale); and as numbers of restricted activity or bed disability days. Garfinkel and Riley (1988) reported that total charges increased with the number of restricted activity days, and number of functional limitations. Wolinsky et al (1983) reported that those individuals with limited activities and dependence in activities of daily living were more likely to have restricted activity or bed disability days.

Perceived health was examined in fifteen studies and achieved significance in 89% of the cases. Perceived health generally was measured with a single item: "compared to other people would you say that your health is excellent, good, fair, or poor?" Kaplan, Barrell, and Lusky (1988) suggested that self-rated health might be a more accurate indicator of actual physical health than are other more objective measures. Several investigations have revealed a substantial correlation between subjective health status and objective measures of health (Kaplan et al, 1988; Linn & Linn, 1980). Epstein and Cumella (1988) reported little difference among questions of perceived health status relative to the number of response categories. Frequencies of achieved significance were similar whether two, three, or four response choices were given. Perceptions of previous health was generally determined with the question: "compared with two years ago, would you say that your health is now better, worse, or about the same as it was then?" Previous health achieved significance as a predictor in each of the instances examined.

Psychological health was measured in terms of health worry, depression, and life satisfaction. Weinberger, Darnell, Tierney, Martz, Hiner, Barker, and Neill (1986) and Fethke, Smith, and Johnson (1985) reported that depression and reduced life satisfaction were associated with poor perceived health and hospital admissions.

Prior utilization was examined in eleven studies and achieved significance in 95% of the instances examined. Based on available data, prior use appears to be consistent for hospital utilization (100%), physician utilization (100%), and total costs (80%). Several investigations revealed that adding prior use improved the predictive power of their utilization models (Anderson & Knickman, 1984a; Anderson & Knickman, 1984b; Anderson, Steinberg, Holloway, & Cantor, 1986). Coulton and Frost (1982) reported that an additional 18% variance of current use was explained when past use was added to their predictive model.

Clinical and diagnostic information were considered in 19 investigations of medical utilization. Predictive information included: direct measures on the existence of acute or chronic health problems; physiologic measures; nutritional risk; and whether or not surgery had been performed. Of the 39 instances examined, clinical descriptors achieved significance in 87% of the cases. Wolinsky et al (1983) found that nutritional risk was the single best predictor of physician visits, emergency room visits, and hospitalized episodes, the three most expensive aspects of medicare reimbursement. Smith, Norton, and McDonald (1985) found that anemia and low albumin levels, indicators of nutritional risk, were significant predictors of hospital use. Young and Fisher (1980) and Holloway, Thomas, and Shapiro (1988) reported specific conditions associated with higher incidence of health care utilization: cardiovascular disorders; neurological disorders; Diabetes Mellitus; cancer; and fractures.

Geographic region and service location served as proxy measures for physician and service distribution in several of the studies reported and achieved significance in 60% of the instances examined. Standard Metropolitan Sampling Area achieved significance more often than did either geographic region or urban/rural setting.

Examination of individual outcome measures revealed that predisposing characteristics were most predictive of total costs. Enabling characteristics were most predictive of health support services. And need characteristics were most predictive of physician services. Predisposing and enabling characteristics achieved significance in 51% of the cases examining hospital utilization and in 59% of the cases examining physician utilization. Need variables predicted hospital utilization in 89% of the cases, physician utilization in 94% of the cases, total costs in 83% of the cases, and use of support services in 87% of the cases. The proportion of explained variability associated with the effects of predisposing and enabling factors on health services utilization ranged from only 1% to 7%, indicating weak predictive power. Need accounted for 11% to 24% of the variability associated with health services utilization. Frequencies with which variables achieved significance relative to utilization measures are summarized in Table 2.

<u>Findings associated with hospital readmissions</u>

Of the forty-one studies reviewed, ten examined characteristics associated with hospital readmissions. Sample sizes across studies ranged from 191 to 1,894. National and state medicare files served as data sources for four of the studies. The remaining six used hospital based records. Most of the studies had recent publication dates indicating the immediate interest in this area of service utilization.

Six of the studies used multivariate models to explain hospital readmission risk. Anderson and Steinberg (1985), Fethke et al (1986), Holloway et al (1988), and Narain et al (1988) used logistic regression. The dependent variable was dichotomized as readmitted and not-readmitted. Since none of these investigators, however, reported data relative to specificity, sensitivity and predictive success of their models, one can only speculate on the practical significance and applicability of their findings. Smith et al (1985) used discriminant function analysis with relatively low predictive success. He reported 67.43% overall correct classification

TABLE 2 FREQUENCIES OF ACHIEVED SIGNIFICANCE FOR PREDICTOR VARIABLES IN HEALTH SERVICES UTILIZATION LITERATURE

Predictor variables	Hospital services	Physician services	Support services	Total costs	Summary of studies
<u>Predisposing characteristics</u>					
Age	9/18	5/12	1/3	3/3	4-9;11-14;17-20;26-29; 30-34;36;38-40
Race	6/13	7/15	1/3	2/2	7;10;12;13;20-22;25;28;29; 33-36;38-40
Sex	9/18	11/17	2/5	3/4	1;3-12;14;16-22;26-30;32; 34;36-40
<u>Enabling characteristics</u>					
Income	3/9	7/14	3/4	1/1	7;10;12;13;15;16;22;26; 29;32;38-40
Education	3/8	8/10	3/4	---	7-15;26;29;33;36;39;40
Marital status	4/7	3/8	1/2	---	7;9;12-14;16;20;27;29;38-40
SMSA	3/4	3/5	---	---	8;13;28;30;39;40
Geographic region	4/6	2/4	---	1/2	3;4;8;25;30;39;40
Living arrangements	2/6	3/7	---	---	7;9;12;14;17;19;21;32;34;40
Living children	2/4	2/4	---	0/1	8;13;29;38;27
Retirement	2/3	3/4	---	---	9;11;13;39;40
Medigap coverage	6/9	6/10	1/4	2/3	4;7-10;12;13;16;22; 24;28;29;38;39
Regular source of care	3/4	5/6	---	---	7;12;34;36;38;39
<u>Need characteristics</u>					
Nutritional risk	3/3	2/2	---	---	32;38;39
Perceived health	10/11	11/12	2/2	---	7;8;11;15;20;21;27;29;36;40
Beddays	1/2	3/3	---	1/1	8;9;11;16
Health compared to others	1/1	3/3	1/1	---	9;10;13
Perceived life satisfaction	2/4	1/2	---	1/1	6;9;10;14
Disability status	7/7	6/6	3/4	0/1	4;78;12;13;28;32;36
ADL dependence	2/3	2/3	---	2/2	1;6;12;21;38
Activity limitations	5/6	6/7	2/3	---	7;9-12;37;39;40
Prior use	11/11	3/3	---	4/5	1;2;4;5;13;14;22;28;30;31;33
Chronic conditions	7/8	5/7	1/1	---	9;11;16;17;21;22;24;25;29;36;40
Physical symptoms	3/3	2/2	---	---	26;32-34;36
Doctor visits	1/1	---	---	---	29
Serious conditions	5/6	2/2	---	---	4;14;29;33;34;40
Surgery performed	1/2	---	---	---	3;4

and 59% correct classification of those readmitted. Positive predictive value was calculated at 29%. Eve (1988) was the only investigator using multiple regression analysis. The truncated number of hospital episodes served as the dependent variable. Riley and Lubitz (1986), Rich and Freeland (1988), Gooding and Jette (1985), and Graham and Livesly (1983) used univariate analysis to examine the association between predictor and outcome variables.

Inferences about the generalizability of these studies was limited by the fact that 7 of the 10 studies focused on specific patient populations. Two of the studies incorporated patients with only circulatory disorders (Gooding & Jette, 1985; Rich & Freeland, 1988). Two selected either exclusively medical or exclusively surgical patients (Smith, et al (1988); Riley et al (1986). Two selected patients according to sex (Eve, 1988; Narain et al 1988). One study examined hospital readmissions in another country (Graham & Livesly, 1983).

Predictors of hospital readmissions. Examination of studies focusing exclusively on hospital readmissions revealed that indicators associated with general service utilization were associated with readmission risk, as well. The selection of indicators and the frequency with which they were included across studies, however, was disappointingly limited.

Age was the most frequently examined predisposing variable; but contrary to the general utilization literature, no consistent pattern between age and readmission risk emerged. Several studies associated readmission risk with older age, while others associated the risk with younger age. In the multivariate model reported by Smith et al (1985), older age was significantly associated with hospital readmission; however, since neither diagnostic category nor acuity of the disease process were included, it is not known whether age would have remained in their final prediction model had these variables been entered. Riley and Lubitz (1986) reported higher rates in older beneficiaries but limited their patient population to surgical patients, exclusively. Older patients, generally, are poor surgical risks. Gooding and Jette (1985) reported that age was a significant predictor for subjects 85 years and older with impaired cerebral perfusion exclusive of stroke. This age group, however, consisted of only two subjects, severely limiting conclusions. Anderson and Steinberg (1985) and Eve (1988) reported rehospitalization risk associated with slightly younger patients. The odds-ratio reported by Anderson and Steinberg, while statistically significant, was only 0.95, indicating little difference between older and younger subjects. Eve's patient population consisted exclusively of women with a relatively narrow age range. The beta weight associated with age, while significant was the weakest of the predictors in her final regression model. The remaining five studies concluded that age was not significantly associated with readmission risk.

Findings associated with readmission risk and the sex and race of the patient reinforced reports in the general utilization literature. Gooding and Jette (1985) observed a trend toward increased hospital readmissions in men suffering from impaired cerebral circulation. Graham and Livesly (1983) attributed the increased readmissions in men to a higher incidence of physical deterioration and severity of illness. Anderson and Steinberg (1985) reported that the relative risk of men being readmitted was slightly higher than that of women with an odds ratio of 1.12. Fethke (1986) reported that being male significantly increased the probability of readmission, but only at six weeks and six months post discharge.

Race was examined in only two studies and remained a significant predictor of readmissions in the final model reported by Anderson and Steinberg (1985). Their relative odds-ratio indicated a higher probability of readmissions in the white population. Narain et al (1988), examining hospital readmissions of male patients in a Veterans Administration Hospital, did not find a significant association between race and readmission rate. Only 3% of his subjects were non-white.

Five of the ten studies examined enabling characteristics, despite their prevalence in the general utilization literature. The characteristics included marital status, living arrangements, income, living children and education. Three of the studies examined marital status and living arrangements (Fethke et al, 1986; Eve 1988; Holloway et al 1988). General conclusions indicated that marital status did not influence hospital readmission risk, contrary to general utilization findings. Of the three, Fethke was the only investigator to report significant predictive risk associated with being widowed, particularly when income was included in the model. Subjects with higher incomes were readmitted at a six week period post discharge; whereas, subjects with lower incomes had an increased readmission rate one year post discharge. Fethke (1986), the only investigator examining income, suggested that early readmission might be more likely if the patient were not bound by an income constraint. She also observed that living alone was a significant predictor of hospital readmissions. General utilization literature indicated that subjects with higher incomes who lived alone had increased service utilization patterns, due possibly to increased resources. On the other hand, several investigators reported higher readmission rates for subjects living with others (Graham & Livesly 1983; Narain et al 1988). In several of the cases, relatives could not cope with the added strain of home care. This explanation might have accounted for the significant association between having living children and hospital readmissions reported by Eve (1988) and Narain et al (1988).

Education was examined in only one study and was found to be a nonsignificant predictor of readmission risk, despite its relevance to general utilization patterns (Holloway et al, 1988).

Consistent with findings reported in the general utilization literature, need characteristics dominated the prediction of readmission risk. Surprisingly, however, the examination of need variables was limited across and within studies; furthermore, not all studies specified need indicators in their prediction model. Graham and Livesly (1983) examined inadequacies in health care management which resulted in hospital readmission. Riley and Lubitz (1986) associated rehospitalization rates with particular types of surgical procedures. Rich and Freeland (1988) examined only length of hospital stay prior to discharge. Fethke (1986) focused primarily on non-disease specific indicators but did construct a single index of health problem severity based on the number of diagnoses, number of chronic conditions, and number of medications at discharge. Her severity factor achieved significance as a predictor at each of the three discharge time periods. She also included a life satisfaction indicator and found that emotional distress was a significant predictor of hospital readmissions. The primary need related characteristics examined in the six remaining studies included type of diagnosis, activity limitations, and health perception.

Two studies controlled for disease categories (Smith et al, 1985; Narain et al, 1988). Smith examined nonelective readmissions in medical patients, and revealed a higher incidence of rehospitalization associated with neoplastic disease, followed by cardiovascular disorders and diabetes mellitus. He further reported significant prediction associated with specific physiologic indicators: elevated Blood Urea Nitrogen levels; hypoxemia, leukocytosis, anemia, and hypoalbuminemia. These indicators are associated with a variety of conditions including cardiac, renal, pulmonary, and neoplastic diseases, as well nutritional risk. Narain reported that cardiac and neurologic diseases significantly predicted readmission of patients discharged from a Veteran's Administration Medical Center. Unlike Smith, Narain did not find diabetes mellitus and neoplastic disease to be significant. Since Smith did not include patients with neurologic deficits, it is difficult to know whether this variable would have remained in the final prediction model.

Several investigators examined type and chronicity of condition associated with readmission risk. Gooding and Jette (1985) examined readmission rates associated with circulatory disorders. While not controlling for specific diagnoses, they found that patients with a primary diagnosis of cardiac disease leading to congestive heart failure were at high risk for short term hospital readmission, particularly if they had been discharged directly to the home. Successful control of congestive heart failure demands considerable active cooperation and involvement of the patient in controlling diet, medications, etc. Anderson and Steinberg (1985) classified patients according to disease chronicity. In their final prediction model, self-limited, non-chronic disease showed a negative association with readmission. Holloway et al (1988) similarly reported that patients with chronic conditions were nearly three times as likely to be rehospitalized. Since neither investigators controlled for type of diagnoses, it is impossible to speculate which specific condition contributed to increased risk.

Three studies examined activity levels in association with hospital readmission risk (Eve, 1988; Holloway et al, 1988; Narain et al, 1988). General conclusions paralleled those reported in the general utilization literature. Subjects who had limited functional ability and dependence in activities of daily living were rehospitalized more often than were those subjects without impaired activity levels. Narain suggested that functional status may be a crucial parameter to assess in all hospitalized patients because of its relationship to outcomes and service needs and that it may make an important modifier to the existing diagnosis based prospective hospital payment system.

Despite the predictive significance associated with perceived health status only two studies examined the influence of this variable (Eve, 1988; Holloway et al, 1988). Holloway reported that those with poor perceived health status and presence of chronic illness were twice as likely to be rehospitalized. He reported four risk factors most highly associated with readmission: poor self-perceived health status, affliction with seven or more chronic medical conditions, limited functional ability, and dependence in activities of daily living. Eve reported that poor health compared to others significantly increased readmission risk.

The effect of hospital location on readmission was examined by Anderson and Steinberg (1985) and Riley and Lubitz (1986). In both instances, persons living or hospitalized in standard metropolitan areas were less likely to have repeated hospitalizations. It is likely that standard metropolitan areas have community resources which reduce the need for hospitalization. Use of community services, however, was not addressed in either of these studies.

Recapitulation

This literature review was directed at examining characteristics associated with general health services utilization patterns and hospital readmissions. The overall purpose was to identify those characteristics predictive of service use, particularly readmission risk. Evidence has suggested that the cost-effectiveness of interventions may be enhanced by targeting them to patients at high risk thereby reducing the financial impact of hospital readmissions (Weinberger and Odone, 1989). Development of a risk profile would permit providers to increase the intensity of strategies to reduce readmission and to establish policy related to haven of educational policy studies may provide a false sense of security, one by which philosophers may become entangled in political ideology; a situation which he sees as untenable. Thus, he advocates caution and the preservation of a critical philosophical perspective as educational philosophers delve into the educational policy studies area. It seems he would prefer to see the philosophy of education remain independent of educational policy studies.

Another philosopher, Thomas Green, tells about the emerging educational policy studies movement as a defense against claims that departments of educational foundations were not relevant to the preparation of teachers. In his article, "Philosophy and Policy Studies: Personal Reflections" (1979), he notes the reciprocal benefits of philosophy and educational policy studies. His scholarly work emphasizes the practical application of philosophy in the understanding and solution of education related dilemmas. As a philosopher, he relates the study of public policy to the study of public virtue; however, he seems to be telling philosophers that their work will remain irrelevant unless they become actively engaged in policy formation. Noting that there may be some doubt as to whether philosophy will improve policy, he sees the trend toward the study of educational policies as likely to benefit and improve educational philosophy.

CHAPTER THREE

METHODS

Introduction

In this chapter, the univariate and multivariate methodologies used to determine predictors of multiple hospital admissions in the non-institutionalized elderly are described. The Supplement on Aging to the 1984 National Health Interview Survey data set is introduced and application of the Andersen Health Services Utilization Model is discussed. Finally, two statistical techniques used for development of the prediction model are presented.

Statement of the Problem

The primary purpose of this study was to identify the predisposing, enabling, and need characteristics predictive of multiple hospital admission patterns in the non-institutionalized elderly.

Four research questions were addressed:

1. Which combination of predisposing, enabling, and need characteristics best predict multiple hospital admissions in the non-institutionalized elderly?

2. Which of the variables are most important in predicting readmission risk?

3. What are the probable odds of multiple hospital admissions associated with the risk profile?

4. How accurately does the proposed model predict multiple hospital admission patterns?

A description of The Supplement on Aging to the 1984 National Health Interview Survey Data Set

Background. The National Health Survey Act of 1956 provided for a continuing survey to secure, on a voluntary basis, accurate and current statistics on the amount, distribution, and effects of illness and disability in the United States and the services rendered because of such conditions. Mandated by this legislation, the National Health Interview Survey (NHIS) was a principal source of information on the health of the civilian noninstitutionalized population and a reflection of the social and economic dimensions of health issues. The purpose of the survey was to provide national data on the incidence of illness and accidental injuries, the prevalence of chronic conditions and impairments, the extent of disability, and the utilization of health care services.

Concerns among a number of public health agencies and individuals about the increasing proportion of older people in the United States population led to recommendations that the NHIS address this special subgroup. It was postulated that information about the prevalent health conditions, living arrangements, family and social support availability, retirement income and financial obligations, functional status and limitations, and attitudes and opinions about their own health and abilities would help in assessing the future needs of the elderly. As a result, the Supplement on Aging (SOA) to the National Health Interview Survey was developed. A major strength of this survey, unlike general population surveys, is that its data on the extent and impact of illness and disability and the resulting uses of health services are obtained during household interviews from more than 90% of the people actually experiencing such problems, not their proxies.

Validity. Topic suggestions were received from a variety of sources including the National Institute on Aging, the Administration on Aging, the U.S. Senate Select Committee on Aging, The U.S. House of Representatives Special Committee on Aging, the Social Security Administration, voluntary and nonprofit organizations, and experts in the field of aging. The evaluation of suggestions and development of the first version of the questionnaire involved systematic literature reviews, reviews of previous or existing surveys, extensive consultation with both agencies and individuals knowledgeable in the suggested topic areas, and active participation in both privately and federally sponsored conferences and meetings on issues related to aging. These efforts yielded twenty-two suggested topics and the development of a questionnaire covering seven areas (family structure, relationships, support and living arrangements; community and social support; occupation and retirement; conditions and impairments; structural characteristics of housing, activities of daily living and instrumental activities of daily living, regular medical care and nursing home stay; and health opinions and behavior).

The questionnaire underwent two pretest trials: the first on a sample of 256 subjects aged 65 years and older (43% male; 56% female); the second on a sample of 234 subjects. Results of the pretest trials led to revisions which eliminated redundant and ambiguous questions and shortened the time of interview from more than 40 minutes to 25 minutes. The final questionnaire was reviewed and approved by a panel of experts who were members from all survey programs involved in the National Center for Health.

Reliability. To establish reliability and accuracy of the Supplement on Aging, approximately 5% of all interviewees were reinterviewed within two weeks. Responses were entered on a form specially designed for reinterviewing. In the analysis of reinterview data, the degree of inconsistency was determined by a computer run on the processed reinterview questionnaires. Although actual reliability coefficients are not available in the public literature, reports developed by the National Center for Health Statistics revealed high test-retest (interview-reinterview) reliability (J. E. Fitti, personal communication, November 8, 1989).

Interviewer training. Interviewing for the 1984 Supplement on Aging was conducted in a standard face-to-face interviewing procedure by a highly trained permanent staff supervised by the U.S. Bureau of the Census under detailed specifications provided by the Division of Health Interview Statistics, National Center for Health Statistics. Initial training of interviewers consisted of: preclassroom training (a home self-study program), classroom training (4-5 days of instruction covering the questionnaire and interviewing techniques), post-classroom training (self-study programs reviewing classroom topics), on the job training (in-field observation for of all interviewers), and editing of questionnaires by interview supervisors. Bureau of the Census interviewers trained on the NHIS, some of whom had worked on this survey for over 10 years, generally work on this survey only and remain as its field staff for their full careers as Census interviewers (Fitti, 1987).

<u>Quality control: data processing and editing</u>. Quality control of coding questionnaire information consisted of recoding 10% of all questionnaires by two independent coders. Comparison of results were analyzed to determine if any coder exceeded the acceptable error level of no more than 5% of the coded items. Additional computer checks were introduced to avoid inconsistencies and invalid responses. Quality of machine keying was maintained by a 100% independent key verification of all items in the questionnaires.

<u>Sample design and selection</u>

The NHIS sample design was a multistage probability design which produced, in effect, a sample distribution for people ages 65 years and over, approximating the civilian non-institutionalized population. The interview period spanned January 9, 1984 through January 6, 1985. Because continuous sampling of the population was carried out throughout the year, seasonal bias was eliminated. The design involved dividing the United States into geographically defined sampling units covering all states. These sampling units were classified into strata from which small clusters of housing units were selected. Cluster sampling associated with complex survey designs usually results in variances that are larger than those obtained through simple random sampling procedures. In general, however, older people tend not to cluster; they tend, instead, to be distributed throughout communities, living alone or with only one other person. Moreover, they tend to have disabilities associated with chronic conditions for which there is relatively less geographic or household clustering (Fitti, 1987). As a consequence, the design effects for the data of the SOA are relatively small (Fitti, 1987).

A total of 16,697 sample persons in the 39,996 households responding to the 1984 NHIS were selected for the SOA interview. The microcomputer extract for this sample was composed of all 855 blacks in the age cohort, and a random sample of 3,000 of the 10,642 nonblacks aged 65 years and over. Subjects whose data were supplied by proxy members were not included in the study sample for this analysis. The final sample consisted of 3,536 subjects.

Description of variables

Dependent variable. The dependent measure, multiple hospital admissions, was represented by a dichotomous grouping variable: presence or absence of multiple hospital admissions during the prior year.

Independent variables. The health care services utilization framework developed by Andersen and his colleagues served as basis for identifying and organizing the independent variables (Aday & Andersen, 1974). The framework organized predictor variables according to predisposing, enabling, and need characteristics. Predisposing characteristics existed prior to the onset of illness. Enabling characteristics provided the means for individuals to use services. Need characteristics referred to illness level, the most immediate cause of health service use.

Variables for this analysis were selected based on review of the utilization literature which focused on hospital readmissions. Predisposing variables included age, race, and sex. Enabling variables included: education, income, retirement status, marital status, SMSA resident as proxy for distribution of services, living arrangements, living children, difficulty getting outside, and level of social activity. Need variables included: health status; number of conditions; presence of cardiovascular disease, diabetes mellitus, cancer, or stroke; dependence with activities of daily living; body mass index; number of beddays; number of doctor visits; change in health and activity; perceived control of health; health worry; and level of exercise.

Nine of these twenty-nine variables had not been reported in prior utilization studies: perceived control of health; level of social activity; difficulty getting outside; community services used; change in health; change in activity level; worry over health; and level of exercise. It was believed that inclusion of these variables would strengthen the prediction model since many had been discussed in the nursing and health related literature. Hershey and Luft (1975) advised against analyzing utilization data with a restricted set of independent variables. Rather, they advised that a full complement of relevant variables should be included to stabilize the relationship represented by the model. Information on two significant predictors of health services use, prior use and medigap coverage, was not included in the SOA data; consequently, these variables were not available for this analysis. Nominal and categorical variables were included as dummy variables. Continuous variables retained their original units of measure. A description of the coding procedures for all of the variables used in the study is summarized in Table 3.

Procedure

Descriptive statistics were used to present total sample characteristics and characteristics associated with each subgroup. Univariate F-ratios were examined to determine

TABLE 3 SUMMARY DESCRIPTION OF VARIABLES

SERVICE UTILIZATION:	
Hospital episodes	0 = not recurrent 1 = recurrent
PREDISPOSING VARIABLES:	
Age	Total years
Race	0 = white 1 = black
Sex	0 = Male 1 = Female
ENABLING VARIABLES:	
Income	Total dollars
Education	Total years
Married	0 = Yes 1 = No
Widowed	0 = Yes 1 = No
SMSA	0 = Non-SMSA 1 = SMSA
Living arrangements	0 = Lives with others 1 = Lives alone
Living children	0 = No 1 = Yes
Social activity	0 = Enough 1 = Would like more
Retirement	0 = Not retired 1 = Fully retired
Difficulty getting outside	0 = No 1 = Yes
NEED VARIABLES:	
Body mass index	Kg. in weight/ (mtrs. in height)^2
Perceived health	0 = Good/excellent 1 = Fair/poor
Bed days	Total days
Doctor visits	Total visits
Number of community services	0 = < 2 1 = > 2
Stroke	0 = No 1 = Yes
Diabetes Mellitus	0 = No 1 = Yes
Cancer	0 = No 1 = Yes
Cardiac disease	0 = No 1 = Yes
ADL dependence	Total number
Change in health	0 = No change 1 = Worse than last year
Health worry	0 = No worry/some 1 = Great deal
Perceived control of health	0 = Great deal 1 = Some/very little
Change in activity	0 = No change 1 = Less than last year
Exercise	0 = Enough 1 = Not enough
Number of conditions	Total number

equality of group means. A correlation matrix was calculated to determine the relationship between hospital admissions and the predictor variables and to identify intercorrelations between variables.

A two group stepwise discriminant function analysis procedure was performed with SPSS-X to determine which predictor variables discriminated between groups reporting presence or absence of multiple hospital admissions. Stepwise logistic linear regression was performed with the SAS logit procedure in an attempt to obtain a more parsimonious prediction model and to calculate probable odds of readmission risk. Both models addressed prediction to the dichotomous dependent variable on the basis of the twenty-nine predisposing, enabling, and need characteristics.

<u>Discussion of discriminant function analysis and logistic linear regression</u>. Discriminant function analysis, introduced by Fisher, is a method for determining linear combinations of predictor variables which optimally classify individuals into two or more distinct multivariate normally distributed groups with a common covariance matrix. It is analagous to multiple linear regression in which the dependent variable is either 0 or 1. Fisher's discriminate function can be written as:

$$Z = \beta_1 X_1 + \beta_2 X_2 + . . . + \beta_k X_k$$

where X's represent predictor variables and ß's are coefficients estimated from the data. The discriminant criterion is based on Mahalanobis' Distance, $\underline{D}^2$, which is a function of the group means and the pooled variances and covariances of the variables. The term $\underline{D}^2$ is interpreted as the squared distance between the means of the standardized value of Z and is analagous to $\underline{R}^2$. For each pair of groups, the unexplained variation from the regression is $1-\underline{R}^2_{ab}$ where $\underline{R}^2_{ab}$ is the square of the multiple correlation coefficient when the dependent variable is coded 0 or 1. Fisher selected coefficients which maximized $\underline{D}^2$. The optimality criterion was developed by Fisher to equate the probability of misclassification between groups. The significance probability that the two sets of population means are equal is determined by the $\underline{F}$-transformation:

$$\underline{F} = \frac{(n-1-p)n_1n_2}{p(n-2)(n_1 + n_2)} = \underline{D}^2$$

The stepwise algorithm combined both forward selection and backward elimination. Criteria for variable selection was based on Rao's V, a generalized distance measure which attains its largest value when greatest overall separation is achieved. The sampling distribution of Rao's V is approximately a chi-square with $\underline{p(q-1)}$ degrees of freedom.

Standardized discriminant coefficients were examined to determine the relative effect of each variable on the discriminant function. Each subject's score on the discriminant function was found by multiplying the standardized score on each predictor variable by its associated standardized discriminant function coefficient and adding the products over all of the predictor variables. The standardized coefficients were obtained by multiplying the betas by the corresponding pooled standard deviations.

Relative contributions of each variable to the discriminant function was determined by the absolute magnitude of its standardized discriminant function coefficient and by the loadings of predictor variables on the loading matrices. Variables with large coefficients were identified as contributing more to the overall discriminant function as were variables with correlations in excess of .30 (Tabachnick and Fidell, 1983).

Significance of the discriminant function was determined by the chi-square transformation of the observed Wilk's lambda and its associated Eigenvalue. The Eigenvalue is the ratio of between-groups to within-groups sums of squares. Large Eigenvalues were associated with good discrimination. Rejection of the null hypothesis that the mean vectors of both criterion groups in the population were equal was determined by a p-value of $<.05$.

The strength of association between group membership and the set of predictor variables was determined by the canonical correlation. In the two group situation, the canonical correlation is the Pearson correlation coefficient between the discriminant score and the group variable. When squared, the canonical correlation represents the shared variance between the grouping variable and the predictor variables. Wilk's lambda represents the total unexplained variance.

Stepwise logistic linear regression was performed to determine whether a better fitting and more parsimonious prediction model could be determined than was obtained with the discriminant function analysis. The logistic regression model has become the standard method, particularly in the health sciences field, for modeling the relationship between a dichotomous outcome variable and a set of covariates (Hosmer and Lemeshow, 1989). While linear discriminant analysis allows direct prediction of group membership, the assumptions of multivariate normality of the independent variables and equal variance-covariance matrices in the two groups are required for the prediction rule to be optimal. This is particularly true when the model contains a mixture of continuous and discrete independent variables.

The logistic regression model is relatively robust, has fewer assumptions than does the linear discriminant model, and is as efficient as discriminant analysis even when all of the assumptions are met (Press and Wilson, 1978). It differs from linear regression and discriminant analysis in its assumptions and in the choice of parametric model (Hosmer & Lemeshow, 1989; Afifi & Clark, 1984).

The first assumption associated with the general linear model is that the conditional mean $E(Y|x)$, where Y denotes any outcome and x denotes a value of the independent variable, can be expressed as an equation linear in $\underline{x}$.

$$E(Y|x) = \beta_0 + \beta_1 X$$

The expression implies that $E(Y|x)$ can take on any value as x ranges between $-\infty$ and $+\infty$. With dichotomous outcome variables, however, the conditional mean of the regression equation must be formulated to be bounded between zero and 1 $[0 \leq E(Y|x) \geq 1]$. The change in the $E(Y|x)$ per unit change in x becomes progressively smaller as the conditional mean approaches zero, producing an S-shaped curve which resembles the plot of a cumulative distribution of a random variable. The distribution is known as a logistic distribution.

A second assumption associated with the general linear model is that error terms are normally distributed. In the case of a dichotomous dependent variable, the binomial, not the normal distribution describes the distribution of errors.

The model which satisfies both of these constraints can be written as the logistic function:

$$\pi(x) = \frac{e^z}{1 + e^z}$$

where $\pi(x)$ represents the conditional mean of Y given X when the logistic distribution is used; e is the base of the natural logarithm, approximately 2.178; and Z is the linear combination:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + . . . + \beta_k X_k$$

β_0 and β_k are coefficients estimated from the data, X is the independent variable.

The transformation of $\pi(x)$ central to the study of logistic regression is the logit transformation, defined in terms of $\pi(x)$:

$$\underset{\text{(odds)}}{\ln} \left[\frac{\pi(x)}{1 - \pi(x)} \right] = Z$$

The log of the odds (logit) satisfies the assumptions that the logit is linear in its parameters, may be continuous, and may range from $-\infty$ to $+\infty$. No assumptions are made regarding the distributions of the independent variables.

The equation relating ln(odds) to the discriminant function is:

$$\ln(\text{odds}) = a + b_1X_1 + b_2X_2 + \ldots b_kX_k$$

Since the equation is in the same form as the multiple linear regression equation it has been called the multiple logistic regression equation and the coefficients can be interpreted as the change in the log odds associated with a one-unit change in the independent variable.

The model assumed is:

$$\ln(\text{odds}) = \alpha + \beta_1X_1 + \beta_2X_2 + \ldots \beta_kX_k$$

Since the logistic regression model is nonlinear, an iterative algorithm was necessary for parameter estimation. Parameter estimates were based on the method of maximum likelihood. Application of this method requires the construction of the likelihood function which expresses the probability of the observed data as a function of the unknown parameters. The maximum likelihood estimators yield values for the unknown parameters which maximize the probability of obtaining the observed set of data. The Wald statistic (the maximum likelihood estimated chi-square) tested the hypothesis that a parameter was zero and was calculated by computing the parameter estimate divided by its standard error and squaring the results.

The first iteration estimated parameters for variables forced into the model. The adjusted chi-square statistic for variables not in the model was computed based on Rao's efficient score statistic for variable selection. The residual chi-square statistic was examined to test the hypothesis that the coefficients for all variables not in the model were 0.

Coefficients were examined for level of significance and overall contribution to the prediction model. The $\underline{R}$ statistic associated with each of the variables determined the contribution of individual variables in the logistic regression. The $\underline{R}$ statistic, similar to the partial correlation between dependent and independent variable, ranges in value from -1 to +1. $\underline{R}$ has a value of 0 if the variable is of no value and one for perfect correlations. The $\underline{R}$ statistic is defined by:

$$\underline{R} = ((\text{MLE chi-square} - 2)/(-2L(0))^{1/2}$$

Small values for $\underline{R}$ indicated that the variable had a small partial contribution to the model. In instances of a Wald statistic less than 2, $\underline{R}$ was set to 0. Significance of coefficients was established at a level of $p<.05$.
In the overall model, $\underline{R}$ was the value such that:

$$R^2 = (\text{model chi-square} - 2p)/(-2L(0))$$

where p is the number of variables in the model excluding intercepts, L(0) is the maximum log-likelihood with only intercepts in the model, and R^2 is the proportion of loglikelihood explained by the model.

To obtain insight into the magnitude of impact each statistically significant variable had on the probability of hospital readmission, the relative risk (odds ratio) of readmission and its 95% confidence interval were calculated for each variable. The equation associated with the probability of readmission was represented by:

$$\text{Prob.(readmission)} = \frac{1}{1 + e^{-z}}$$

Goodness of fit of the logistic regression model and accuracy in prediction were determined by the -2 log likelihood ratio chi-square statistic which tested the joint association of all variables in the model with the dependent variable. The model chi-square statistic, similar to the overall F test for regression, tested the null hypothesis that the coefficients for all of the terms in the regression model, except the constant, were 0.

Accuracy of the prediction model was determined by the two probabilities of misclassification, probability (II given

I) and probability (I given II). The classification tables obtained with both discriminant function analysis and logistic regression were examined to determine the proportion of subjects correctly classified according to the criterion grouping variable. Sensitivity represented the proportion of true positives that were predicted to be positive. Specificity represented the proportion of true negatives that were predicted to be negative. The false positive rate indicated the proportion of predicted positives that actually were negative. The false negative rate indicated the proportion of predicted negatives that were actually positive. Estimation of these probabilities was derived from the empirical method, that is, the proportion of incorrectly classified subjects was computed by applying the discriminant function and logistic regression to the same sample from which they were calculated. Because the same sample was used for deriving and validating both the discriminant function and logistic regression, true probabilities of classification may have been underestimated. The models were not subjected to split sample validation as the resultant sample sizes would have been too small.

Summary of methods

Data were obtained from the 1984 National Health Interview Survey, Supplement on Aging from a random sample of non-institutionalized elderly for the purpose of developing a risk profile that could predict multiple hospital admission patterns. The health care services utilization framework developed by Andersen and his colleagues served as a context in which to organize and examine the relationships between the independent and dependent variables. Independent variables were selected based on a review of the literature and reflected the predisposing, enabling, and need characteristics associated with use of health services. The dependent grouping variable classified subjects into those reporting and those not reporting multiple hospital admissions. Univariate and multivariate analyses were used to describe the data, formulate the prediction model, and calculate probable odds of readmission risk.

CHAPTER 4

RESULTS OF STUDY

In this chapter, the results of the data analysis are organized to address each research question. In organizing the data set, primary considerations were given to identifying which combination of variables best predict multiple hospital admissions, determining which variables were most important in determining readmission risk, calculating probable odds of readmission associated with the risk profile, and establishing accuracy of the prediction model.

As noted earlier, predictor variables were organized according to Andersen's Health Care Utilization Model. Predisposing variables described characteristics which existed prior to the onset of illness and included: age, race, sex. Enabling variables identified means available to individuals for use of services and included: education, income, marital status, living arrangements and residence, living children, social activity, retirement status, and difficulty getting outside. Need variables represented the most immediate cause of health service use and included: body mass index; beddays; doctor visits; number of conditions; use of community services; dependence in activities of daily living; perceived health; presence of cardiovascular disease, diabetes mellitus, or cancer; change in health and activity, health worry, perceived control of health and level of exercise. The dichotomous grouping variable was based on presence or absence of multiple hospital admissions during the prior year.

Sample demographics, the intercorrelation matrix, and univariate differences between groups are discussed below.

Demographic characteristics of sample

As described in Table 4, demographic characteristics were consistent with descriptions of the elderly population reported in the literature. Sixty percent of the subjects were female with an average age of 73 years. The average educational level attained was tenth grade. Subjects reported an average annual income of $14,400, and, as expected, 78% were completely retired. Fifty-three percent of all subjects were married; 36% were widowed. Seventy-nine percent reported living children. Sixty-four percent lived in a standard metropolitan sampling area and 36% lived alone. Only 23% reported inadequate social activity levels, and 8% indicated difficulty in getting outside. Twenty-two percent of the subjects were black, greater than that reported in the general population of elderly.

Subjects reported an average of 1.7 conditions with low incidence of stroke, Diabetes Mellitus, cancer, and acute heart disease. The average calculated body mass index was 25.36, well within the normal standard. Thirty nine-percent reported a need for more exercise, indicating that the

TABLE 4 MEANS, STANDARD DEVIATIONS, AND INTERCORRELATIONS OF VARIABLES

	Mean (S.D.)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Age	72.82 (6.17)		-.02	.08	-.10	-.08	-.22	.26	.01	.18	-.13	-.04	.15	.18	-.16	.00
2 Black	.22 (0.42)			.03	-.21	-.29	-.10	.05	.08	.03	-.11	.05	.00	.09	.17	.16
3 Female	.60 (0.49)				-.09	.01	-.41	.40	.02	.30	-.07	.04	.00	.10	.01	.03
4 Income	14.39 (9.27)					.30	.22	-.17	.14	-.33	.07	-.10	-.10	-.09	-.07	-.16
5 Education	10.11 (3.73)						.05	-.04	.07	-.02	.03	-.02	-.07	-.08	-.13	-.22
6 Married	.53 (0.49)							-.80	-.04	-.73	.16	-.04	-.05	-.10	.00	-.01
7 Widowed	.36 (0.48)								.01	.59	.02	.02	.05	.10	-.01	.01
8 SMSA	.64 (0.47)									.01	-.04	.01	.03	.02	.01	-.06
9 Lives alone	.36 (0.48)										.20	.02	.04	-.04	.03	.00
10 Children	.79 (0.40)											.03	-.04	-.03	.03	.03
11 Soc. actv. inadeq.	.23 (0.42)												.01	.11	.03	.14
12 Retired	.78 (0.42)													.08	-.01	.10
13 Diff. get out	.08 (0.27)														.05	.22
14 BMI	25.36 (4.5)															.07

TABLE 4 MEANS, STANDARD DEVIATIONS, AND INTERCORRELATIONS OF VARIABLES

	Mean (S.D.)	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
15 Poor health	.33 (0.47)	.24	.09	.07	.13	.19	.07	.16	.25	.34	.24	.25	.20	.18	.40	.17
16 Beddays	14.57 (54.86)		.23	.05	.14	.11	.01	.09	.29	.19	.22	.21	.16	.10	.27	.18
17 Dr. vsts.	8.51 (54.78)			.03	.05	.05	.01	.03	.10	.08	.09	.08	.07	.07	.12	.10
18 Com. serv. (>2)	.10 (0.30)				.05	.05	.01	.03	.15	.09	.05	.04	.07	.02	.13	.09
19 Stroke	.05 (0.23)					.06	-.02	.11	.16	.10	.11	.10	.08	.08	.21	.08
20 Diabetes	.11 (0.31)						.02	.10	.10	.08	.10	.07	.02	.06	.19	.09
21 Cancer	.11 (0.31)							.02	.01	.07	.05	.04	.02	.01	.13	.09
22 Heart disease	.12 (0.32)								.05	.11	.11	.09	.06	.06	.26	.10
23 ADL's	.53 (1.34)									.22	.24	.23	.13	.15	.34	.09
24 Health change	.16 (0.36)										.29	.44	.21	.16	.31	.18
25 Health worry	.08 (0.27)											.29	.19	.14	.32	.15
26 Activity change	.08 (0.27)												.17	.15	.27	.19
27 Health control	.15 (0.35)													.08	.18	.05
28 Exercise inadeq.	.39 (0.48)														.23	.09
29 Num. of conditions	1.7 (1.8)															.19
30 Readmitted	.05 (.22)															

TABLE 4 MEANS, STANDARD DEVIATIONS, AND INTERCORRELATION OF VARIABLES

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1 Age	.02	.01	.13	.05	-.03	.03	.03	.14	.08	.02	.06	.03	.01	.06	.04
2 Black	.10	.04	.03	.05	.11	-.12	-.07	.07	.05	.02	.02	.06	.03	.04	-.01
3 Female	.03	.04	.12	-.02	.03	-.03	-.03	.09	.03	.02	.02	-.01	.09	.05	.01
4 Income	-.08	.02	-.08	.-04	-04	.03	.09	-.08	-.08	-.09	-.07	-.07	-.05	-.14	-.03
5 Education	-.07	-.03	-.00	.06	.10	.10	.03	-.08	.10	-.08	.08	-.10	.00	-.09	.01
6 Married	-.06	-.04	-.15	-.01	-.03	.01	.00	-.01	-.05	-.05	-.02	-.05	-.05	-.08	-.03
7 Widowed	.06	.05	.15	.02	.03	.02	.01	.09	.03	.05	.03	.03	.03	.08	.03
8 SMSA	-.01	.01	.01	.01	.01	-.01	-.01	.00	-.02	-.03	.01	-.01	-.01	-.02	.02
9 Lives alone	.05	.04	.18	-.03	-.01	.00	.01	.02	.06	.03	.03	.03	.03	.08	.01
10 Children	-.01	-.02	-.04	.02	.01	.03	-.05	-.03	-.03	.00	.00	-.03	-.01	-.01	.02
11 Soc. actv. inadeq.	.12	.04	.02	.05	.07	.01	.05	.12	.13	.14	.13	.09	.18	.20	.05
12 Retired	.05	.02	.06	.07	.03	.04	.05	.06	.07	.08	.07	.05	.08	.11	.06
13 Diff. get out	.27	.09	.09	.17	.12	.03	.02	.65	.23	.22	.23	.14	.19	.29	.09
14 BMI	.00	-.01	-.01	.00	.15	-.06	.01	.01	.01	.10	.01	.01	.14	.07	.03

majority of elderly were satisfied with their exercise levels. Only 8% reported change in their activity levels during the prior year and the majority assumed independence in their daily activities, requiring assistance with an average of only .53 daily activities.

Surprisingly, despite generally healthy indicators, 33% of the subjects rated their health as fair or poor. Only 8%, however, expressed worry over health; and 15% indicated having little or no control over their health.

Use of health services reported by subjects in this survey reflected general population trends and indicated that only a small segment of the elderly population account for high cost use. Five percent of the subjects reported multiple hospital admissions during the prior year. Subjects reported an average of 8.5 physician visits and 14.6 beddays. Only 10% indicated use of two or more community services.

Univariate correlations between variables

Examination of the pooled within groups correlation matrix (See Table 4) indicated moderate to high correlations between several of the variables, supporting general population trends. Although interdependencies among variables affect most multivariate analyses, the computer program for discriminant function analysis and logistic regression protect against this possibility by specifying a tolerance value. Variables not meeting tolerance are not allowed to participate in the prediction. Multicollinearity and singularity, therefore, were not a threat in this analysis.

Correlation coefficients between predisposing, enabling, and outcome variables ranged from -.01 to .09, indicating poor independent predictive power. None of these variables, independently, explained variability associated with hospital episodes. These findings support health service distribution is equitable and unrelated to specific demographic traits. Significant but small associations were found between hospital admissions and inadequate activity levels, being fully retired, and having difficulty in getting outside. These findings were consistent with trends reported in the literature.

Intercorrelations between the predisposing, enabling, and need characteristics ranged from .01 to .80. The largest coefficients were associated with marital status. A correlation of -.80 between being married and being widowed indicated that some individuals, although married, had been widowed at some time. Widowed subjects were more likely to be women and to live alone. This was consistent with the correlation between being female and living alone, since most females were unmarried. Married subjects reported living with others.

Income, as expected, had a positive correlation with education. A negative correlation between income and living arrangements indicated that the majority of subjects, despite level of income lived with others. Blacks reported lower incomes, educational levels, and health status. Income generally was higher for married individuals and lower for those who were widowed. Those with higher levels of education also reported better health status.

Difficulty getting outside showed a strong relationship with dependence in activities of daily living and a moderate relationship with total number of conditions and total number of beddays. Significant but weaker relationships were found between difficulty getting outside and poor health, change in health, change in activity, worry over health, and age. These findings were not surprising and supported the notion that individuals who were environmentally dependent were likely to have had compromised health. Inadequate social activity, although indirectly related, also showed positive correlations with total number of conditions, need for more exercise, and poor health.

Coefficients between the need indicators and the outcome variable ranged from .05 to .19. While direct relationships were significant, they generally were very weak. The largest correlations existed between hospital admissions and change in activity, total number of conditions, change in health, poor health status and worry over health.

Intercorrelations between need indicators ranged from .01 to .44. None of the findings were unexpected since decline in health status is associated with change in health and reduced activity tolerance. The highest correlation existed between change in health and change in activity. Health change also showed a moderate correlation with poor health status as did total number of conditions. Weaker correlations existed between poor health status and total number of beddays, dependence in activities of daily living, health worry, and change in activity. Individuals who perceived little or no control over health reported poor health status, decline in health over the prior year, and increased dependence in activities of daily living. Increased dependence in activities of daily living also was associated with change in health, and increased health worry.

Total number of conditions showed moderate correlations with several of the need indicators: dependence in activities of daily living; change in health; and worry over health. Weaker correlations existed between total number of conditions and total beddays, stroke, heart disease, change in activity, and inadequate levels of exercise.

As expected, individuals who reported more beddays, experienced more doctor's visits, increased dependence in activities of daily living, change in their activity level, and increased health worry. Health worry, also, was associated with change in activity over the prior year.

Univariate differences between groups

Group means, standard deviations and *F*-ratios based on the grouping factor presence or absence of multiple hospital episodes are represented in Table 5.

Examination of predisposing and enabling characteristics revealed that, on the average, subjects reporting multiple admissions were older, white, female, widowed, and fully retired. They reported a slightly lower income, a higher incidence of living alone, living in a non-SMSA, and having living children. A greater proportion had difficulty getting outside and inadequate levels of social activity. *F*-ratios associated with predisposing and enabling characteristics indicated, however, significant differences between groups for only four of the thirteen variables ($p<.05$): age, level of social activity, retirement status, and difficulty getting outside.

Examination of variables related to health perception revealed that subjects with multiple hospital admissions expressed, generally, poor health status, increased worry over health, and little perceived health control. Sixty-eight percent rated their health status as fair or poor and 26 percent worried a great deal about their health. Twenty-three percent perceived that they had little control over their health.

Examination of the more direct indicators of health status revealed that subjects with multiple hospital

TABLE 5 UNIVARIATE DIFFERENCES BETWEEN GROUPS

Variable	Group without readmits (N=3295)	Group with readmits (N=182)	Wilk's Lambda	F-ratio (1,3475)	Sig.
Age	72.76 (6.14)	73.76 (6.63)	0.99854	5.077	0.02*
Black	.22 (0.41)	.20 (0.40)	0.99988	0.410	0.52
Female	.60 (0.49)	.62 (0.49)	0.99932	0.198	0.66
Income	14,000 (8.27)	13,500 (8.10)	0.99932	2.359	0.12
Education	10.09 (3.74)	10.34 (3.74)	0.99994	0.727	0.40
Married	.53 (0.50)	.50 (0.50)	0.99961	2.359	0.24
Widowed	.36 (0.50)	.42 (0.50)	0.99923	2.672	0.10
SMSA	.65 (0.48)	.62 (0.49)	0.99979	0.740	0.39
Lives alone	.36 (0.48)	.38 (0.39)	0.99993	0.232	0.63
Children	.80 (0.40)	.83 (0.38)	0.99968	1.127	0.29
Soc. actv. inadeq.	.22 (0.42)	.31 (0.47)	0.99764	8.224	0.00*
Retired	.77 (0.42)	.88 (0.33)	0.99764	11.350	0.00*
Diff. get. out	.07 (0.26)	.18 (0.39)	0.99222	27.260	0.00*
BMI	25.39 (4.59)	24.81 (4.53)	0.99922	2.715	0.10
Poor health status	.31 (0.46)	.68 (0.47)	0.96984	108.100	0.00*
Beddays	12.25 (52.28)	56.69 (78.54)	0.96744	116.900	0.00*

TABLE 5 UNIVARIATE DIFFERENCES BETWEEN GROUPS

Variable	Group without readmits (N=3295)	Group with readmits (N=182)	Wilk's Lambda	F-ratio (1,3475)	Sig.
Dr. vsts.	7.26 (47.43)	31.12 (97.05)	0.99059	33.020	0.00*
Com. serv. (>2)	.10 (0.30)	.18 (0.39)	0.99191	28.330	0.00*
Stroke	.05 (0.22)	.13 (0.34)	0.99437	19.689	0.00*
Diabetes	.10 (0.31)	.23 (0.41)	0.99285	25.020	0.00*
Cancer	.10 (0.30)	.23 (0.42)	0.99248	26.340	0.00*
Heart disease	.11 (0.31)	.26 (0.44)	0.98950	36.780	0.00*
ADL's	.50 (1.31)	1.00 (1.70)	0.99187	28.500	0.00*
Health change	.14 (0.35)	.44 (0.50)	0.96733	115.900	0.00*
Health worry	.07 (0.26)	.26 (0.44)	0.97689	82.190	0.00*
Activity change	.07 (0.25)	.30 (0.46	0.96377	130.600	0.00*
Little health control	.15 (0.35)	.23 (0.41)	0.99758	8.437	0.00*
Exercise inadeq.	.38 (0.46)	.58 (0.48)	0.99191	28.330	0.00*
Num. cond.	1.63 (1.75)	3.17 (2.22)	0.96410	129.400	0.00*

admissions had a greater number of conditions, a lower body mass index, and a higher incidence of stroke, diabetes, cancer, and heart disease. They experienced a greater number of bed days and doctor visits, used more community services, required more assistance with activities of daily living, and expressed a greater need for more exercise. There was also a greater proportion who reported a decline in health status and level of activity over the prior year.

On the average, subjects with multiple hospital admissions had 1.5 more conditions, experienced 45 more beddays and reported 24 more doctor visits. Eighteen percent used more than two community services. Forty-four percent reported a decline in health status and 30% indicated a decline in level of activity. The incidence of stroke, diabetes, cancer, and heart disease was more than double in this group of subjects.

$\underline{F}$-ratios revealed significant differences between groups for all but one of the need indicators ($\underline{p}<.01$). Body mass index, although slightly less in the group with multiple hospital admissions, did not differ significantly between groups.

In summary, univariate analysis revealed that subjects with multiple hospital admissions were slightly older and more likely to be retired. They expressed less physical and social activity levels and had a higher incidence of environmental dependence. They reported a decline in health and activity levels, were more worried about health, perceived less control over their health, and consumed more health care services. More than twice as many, proportionately, rated their health as poor. Race, sex, education, living arrangements, family and economic supports, and marital status did not significantly differentiate between the groups.

Results of discriminant function analysis and logistic linear regression

While univariate F's represent the ability of each predictor variable to predict group membership, univariate F's, by themselves, can be misleading. They neither take into account correlations among predictor variables nor compensate for increased Type I errors with multiple testing (Tabachnick and Fidell, 1983). Multivariate procedures were required to analyze variables simultaneously and to identify which combination of variables best predicted multiple hospital admissions.

Step-wise discriminant function. Step-wise discriminant function analysis was performed to identify the combination of characteristics which best discriminated between the study groups. Of the original 3,536 cases processed, 59 had at least one missing discriminating variable and were excluded from the analysis. Final analysis was performed on 3,477 cases. Of those, 182 subjects reported multiple hospital episodes during the prior year.

All twenty-nine variables were entered into the prediction model. The standardized canonical discriminant function coefficients as well as the correlations between discriminating variables and the canonical discriminating function are contained in Table 6.

The factor loading matrix was examined to determine the correlation between predictor variables and the discriminant function. Factor loadings are analogous to raw correlations between the canonical variate and the predictor variables rather than semipartial correlations as seen in multiple regression. By convention, correlations in excess of .30 are usually considered eligible while lower ones are not (Tabachnick and Fidell, 1983).

Since factor loadings do not necessarily indicate which variables contribute most heavily to discrimination among groups after adjustment for remaining variables, relative importance of variables was determined by the absolute magnitude of the standardized canonical discriminant function coefficient (Tabachnick and Fidell, 1983). Variables with large coefficients were identified as contributing more to overall discrimination.

Correlations between predictor variables and the discriminant function indicated moderate to strong associations between hospital episodes and eight of the need variables: activity change; number of conditions; beddays; health change; poor health; health worry; heart disease; and

TABLE 6 CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS AND WITHIN GROUPS CORRELATIONS

Variable	Pooled within-group Correlation	Variable	Standardized Coefficients
Activity change	0.58	Beddays	0.33543
Number of conditions	0.58	Activity change	0.31648
Beddays	0.55	Poor health	0.22245
Health change	0.55	Community services	0.20536
Poor health	0.53	Health change	0.19194
Health worry	0.46	Cancer	0.18624
Heart disease	0.31	Number of conditions	0.17182
Doctor visits	0.30	Education	0.15949
Difficulty getting out	0.29	Health worry	0.15378
ADL's	0.27	Doctor visits	0.14307
Community services	0.27	Heart disease	0.12605
Inadequate exercise	0.27	ADL's	-0.12137
Cancer	0.26	BMI	-0.11184
Diabetes	0.26	Diabetes	0.11165
Stroke	0.23	Health control	-0.11034
Inadequate soc. activ.	0.20	Inadequate exercise	0.08244
Retired	0.17	Retired	0.06325
Health control	0.15	Stroke	0.06302
Widowed	0.09	Living children	0.06194
Income	-0.09		
BMI	-0.08		
Age	0.07		
Lives alone	0.07	Canonical correlation	0.31462
Married	-0.06	Eigenvalue	0.10986
Living children	0.05	Chi-square	$361.24_{(19)}$, $p<.01$
Sex	0.05		
Education	0.04		
SMSA	-0.01		
Race	0.01		

number of doctor visits. Weaker correlations existed between hospital episodes and seven additional characteristics: difficulty getting outside, dependence in activities of daily living, community services, inadequate exercise levels, cancer, diabetes, stroke, and inadequate social activity.

Examination of the standardized canonical discriminant function coefficients revealed that nineteen variables remained in the final prediction model. All of the sixteen need variables were retained, seven of these variables had moderate to strong correlations with the canonical discriminant function: beddays, activity change, poor health, health change, number of conditions, health worry, and doctor visits. Number of community services used and presence of cancer, while showing weak correlations with the discriminant function, contributed significantly to discrimination between groups.

Need variables with lower coefficients in descending order were: presence of heart disease, dependence in activities of daily living, presence of diabetes, health control, body mass index, level of exercise, and presence of stroke.

Three of the enabling characteristics contributed significantly but with less importance to the prediction model: level of education, retirement status, and living children. Of the three variables, only retirement status distinguished significantly between groups on the univariate

F-test. Level of education and living children did not significantly differentiate between groups based on the univariate F-tests; both, however, have been cited in the literature as contributing to hospital utilization. Difficulty getting outside, while showing a moderate association with the discriminant function, was not retained in the final model.

None of the predisposing characteristics remained in the final model, further indicating that age, race, and sex did not contribute to discrimination between groups.

The final prediction model based on discriminant function analysis was as follows:

Z = 0.33543 (beddays) + 0.3164 (activity change)+ 0.22245 (health status) + 0.20536 (com. srv.)+ 0.19194 (health change) + 0.18624 (cancer)+ 0.17182 (num. conds.) + 0.15949 (education)+ 0.15378 (health worry) + 0.14306 (dr. vsts.)+ 0.12605 (heart disease) - 0.12137 (ADL's) + 0.11165 (diabetes) - 0.11184 (BMI) - 0.11034 (health control) + 0.8244 (exercise) + 0.06325 (retired) + 0.6302 (stroke) + 0.06194 (living children)

A calculated Chi-square ($X^2_{(19)}$ = 361.24, $p<.01$) indicated, statistically, that the obtained function significantly discriminated between groups, i.e., it is unlikely that subjects with multiple hospital admissions and those without multiple hospital admissions had the same means on the discriminant function. A canonical correlation of 0.315 and an Eigenvalue of 0.10 indicated, however, only a moderate degree of association between the discriminant function score and group membership. Only 10% of the variability was accounted for by this prediction model. Prediction models reported in the literature, in general, have accounted for less than 10% of the variance associated with health services utilization. None of the reports associated specifically with hospital readmissions identified percent of variability explained by the prediction model.

Stepwise logistic regression. While linear discriminant function analysis allowed direct prediction of group membership, it required the assumptions of multivariate normality and equal variance-covariance matrices for the prediction rule to be optimal. Since, in this analysis, both assumptions were violated, the obtained prediction model may have included the erroneous retention of meaningless variables (Press & Wilson, 1978).

Stepwise logistic regression analysis was performed to determine whether a better fitting and more parsimonious prediction model could be determined than was obtained with discriminant function analysis. The logistic regression model has become the standard method for modeling the relationship between a dichotomous outcome variable and a set of covariates (Hosmer and Lemeshow, 1989). It is relatively robust and has fewer assumptions than does the linear discriminant model.

The logistic regression model was based on 2,879 observations; 657 of the original 3,536 cases were deleted due to missing values. Of those cases included in the final analysis, 2,727 had not experienced multiple hospital admissions, whereas, 152 had experienced multiple hospital admissions.

All twenty-nine predictor variables were entered into the logistic regression equation as had been entered into the discriminant function analysis. Eight of the need variables were retained in the final logistic regression model. Seven of these variables had been selected as most important in discriminant function analysis as well: beddays, community services, number of conditions, cancer, poor health, activity change, and health change. Number of doctor visits, the eighth variable retained in logistic regression was preceded in importance by level of education and health worry in the discriminant function analysis. Both education and health worry would have entered the logistic regression had the entry criterion been raised to 0.1. None of the predisposing or enabling characteristics were retained in the final logistic regression model.

Regression coefficient, chi-square, R-statistic, and level of significance for each of the eight remaining variables are represented in Table 7. Since the logistic linear regression coefficients and R-statistic values are based on logarithmic calculations, they are not subject to the same interpretation as in multiple linear regression. The R-statistic is the partial correlation between the dependent

TABLE 7 LOGISTIC REGRESSION OF PREDICTOR VARIABLES ON INCIDENCE OF HOSPITAL EPISODES

Variable name	Coefficient	Std. Error	Chi-square	P	R
Constant	-4.81061429	0.31579517	232.05		
Beddays	0.00715074	0.00120541	35.19	0.0000	0.167
Community services	0.28084512	0.08119831	11.06	0.0005	0.092
Poor health	0.73944174	0.09524564	10.87	0.0050	0.091
Number of conditions	0.13531320	0.04499837	9.04	0.0026	0.077
Cancer	0.65869145	0.22241390	8.77	0.0031	0.075
Activity change	0.64885047	0.24855194	6.81	0.0090	0.064
Health change	0.59265620	0.22937837	6.68	0.0098	0.063
Doctor visits	0.00301952	0.00122597	6.07	0.0138	0.058

variable and each of the independent variables. Its value ranges from -1 to +1 and indicates relative contribution of each variable to the prediction model. R^2 refers to the proportion of loglikelihood explained by the model. The regression coefficients are interpreted as the change in the log odds associated with a one-unit change in the independent variable. The chi-square tests the hypothesis that a coefficient is 0. R-values indicated that beddays provided the greatest contribution to the logistic regression model. Beddays was most important in the discriminant function analysis, as well. Additional variables remaining in the logistic regression model were: number of community services; number of conditions; cancer; poor health; health change; activity change; and doctor visits.

Significance of the prediction model was determined by the model chi-square. The model chi-square is similar to an overall $\underline{F}$ test for regression and tests the null hypothesis that the coefficients for all terms, except the constant, equal zero. The obtained chi-square ($X^2_{(8)}=216.83$, $p<.01$) supported overall significance of the logistic regression model.

The final logistic linear regression model was as follows:

$$\pi(x) = \frac{1}{1 + \underline{e}^{-z}}$$

Where $\pi(x)$ represents the probability of hospital admissions, $\underline{e}$ is the base of the natural logarithm (2.718) and

$$Z = .0072(\text{beddays}) + .2808(\text{com.srv.}) + .1353(\text{num.cond.}) + .6587(\text{cancer}) + .7394(\text{health stat.}) + .6489(\text{activ.chng.}) + .5927(\text{health change}) + .0030(\text{dr.vsts.}) - 4.8106.$$

In general, $\pi(x)$ greater than 0.5 predicts that the event will occur. Based on this regression model, a subject reporting 100 beddays, three or more community services, four or more conditions, presence of cancer, poor health status, decline in activity, decline in health, and 20 or more doctor visits would be at risk for multiple hospital admissions.

The relative importance of variables to both the discriminant function and logistic regression models are compared in Table 8. Remarkable similarities existed. Both models ranked number of beddays, health status, and community services as most importance and number of doctor visits as least important. A very slight discrepancy existed in the rankings of number of conditions, presence of cancer, and change in health. The largest discrepancy existed in the importance of activity change, ranked second most important in discriminant function and sixth most important in logistic regression analysis.

TABLE 8 RANKED IMPORTANCE OF SIGNIFICANT VARIABLES FOR DISCRIMINANT FUNCTION AND LOGISTIC REGRESSION

DISCRIMINANT FUNCTION ANALYSIS	LOGISTIC REGRESSION ANALYSIS
Beddays	Beddays
Activity change	Community services
Poor health	Poor health
Community services	Number of conditions
Health change	Cancer
Cancer	Activity change
Number of conditions	Health change
Education	Doctor visits
Health worry	
Doctor visits	
Heart disease	
ADL dependence	
Body mass index	
Inadequate exercise	
Retired	
Stroke	
Living children	

Odds ratios and impact of variables on readmission risk

To determine the relative risk of hospital readmission associated with predictor variables, odds-ratios were calculated for the eight predictor variables common to both discriminant function and logistic regression analyses. Odds ratios and confidence intervals associated with each of the eight variables are presented in Table 9. The values of 1.75 and 2.32 listed for community services indicated that, after adjustments are made for all other variables in the analysis, subjects who used two and three community services were 1.75 and 2.32 times more likely, respectively, to be readmitted than subjects who used only one service.

As seen in Table 9 subjects who reported poor health, decline in health, and decline in activity levels were nearly twice as likely to experience multiple hospital admissions as were subjects in good or stable health and no change in activity tolerance. Likewise, cancer patients were nearly twice as likely as non-cancer patients to be rehospitalized. As the number of conditions increased, so did the likelikhood of rehospitalizations. Subjects who reported two conditions were 1.31 times as likely to be rehospitalized as subjects not reporting any conditions; and subjects reporting three conditions had an odds ratio of 1.58.

The odds ratio associated with number of beddays, despite its importance in the overall logistic regression equation, indicated very little difference in the likelihood of multiple

TABLE 9 ODDS RATIOS AND CONFIDENCE INTERVALS FOR PREDICTOR VARIABLES IN LOGISTIC REGRESSION

Variable name	Variable value	Odds ratio	95% CI
Health status	Poor	2.09	1.37-3.19
Cancer	Currently have cancer	1.93	1.60-2.99
Activity change	Worse than prior year	1.91	1.44-3.11
Health change	Worse than prior year	1.80	1.22-2.68
Community services	2	1.75	1.49-1.05
	3	2.32	1.98-2.72
Num. of conditions	2 conditions	1.31	1.20-1.43
	3 conditions	1.58	1.37-1.63
Beddays	25 days	1.19	1.19-1.20
	55 days	1.48	1.47-1.50
Doctor visits	10 visits	1.03	1.02-1.03
	20 visits	1.06	1.05-1.06

admissions for as many as 25 beddays. Subjects reporting 55 beddays were 1.5 times as likely to be rehospitalized as someone reporting only one bedday. Total number of doctor visits were not associated with increased hospital readmission risk. A subject with 20 visits was just as likely to be rehospitalized as someone with only one visit.

Odds ratios were calculated for both education (.95 for four years) and health worry (1.0). Both variables were retained in the discriminant function analysis but eliminated in the logistic regression. Based on the odds ratios, neither of these variables was associated with increased risk of hospital readmission.

Accuracy of prediction models

Accuracy of the prediction models obtained with discriminant function analysis and logistic regression was determined by examination of the final classification tables associated with each analysis, and calculation of sensitivity (correct classification of those readmitted), specificity (correct classification of those not readmitted), and overall correct classification.

Accuracy of classification of the models is presented in Table 10. Of the two specified prediction models, logistic regression achieved a higher overall correct classification rate (99%) than did the discriminant function model (83%). Logistic regression also achieved better specificity (99%) than did discriminant function analysis (84%). Sensitivity

TABLE 10 ACCURACY OF CLASSIFICATION FOR DISCRIMINANT FUNCTION AND LOGISTIC REGRESSION MODELS

DISCRIMINANT FUNCTION ANALYSIS

	Negative	Positive	Total
Negative	2753	542	3295
Positive	68	114	182
Total	3721	656	3477

Sensitivity--62.6% Specificity--83.6%
Overall Correct Classification--82.5%

LOGISTIC REGRESSION ANALYSIS

	Negative	Positive	Total
Negative	2748	13	2761
Positive	132	19	151
Total	2870	32	2912

Sensitivity--13% Specificity--99%
Overall Correct Classification--95%

of both models, however, was very low. Of the 152 subjects reporting multiple hospital episodes, only nineteen (13%) were classified correctly with the logistic regression model: 132 (87%) were classified incorrectly. The discriminant function model resulted in slightly better sensitivity (63%); however, overall classification was less accurate and the obtained sensitivity was only slightly better than that achieved through chance alone.

<u>Summary</u>

Univariate and multivariate procedures were performed to develop a risk profile of a multiple hospital admission pattern in non-institutionalized elderly.

Univariate <u>F</u>-ratios indicated differences between groups for nineteen of the twenty-nine variables: age, inadequate social activity, fully retired, difficulty getting outside, poor health, beddays, doctor visits, community services, stroke, diabetes, cancer, heart disease, ADL dependence, health decline, health worry, activity decline, little health control, inadequate exercise, and number of conditions.

Linear discriminant function analysis and logistic linear regression were used to identify the combination of variables which best predict multiple hospital admissions. Nineteen variables were retained in the discriminant function model; eight were retained in the logistic regression model.

Eight variables emerged as most important to each of the prediction models: beddays, community services, number of conditions, cancer, poor health, activity and health decline, and number of doctor visits. Calculated odds ratios for each of the eight variables indicated that subjects with poor self-reported health status, decline in health and activity, and cancer were nearly twice as likely to experience multiple hospital admissions as subjects who did not report the presence of these indicators. Hospital admissions increased as number of conditions and use of community services increased. Total number of beddays and number of doctor visits did not greatly impact the risk of hospital admissions, despite importance of these variables to the overall prediction models. A subject would have had to report over 100 beddays and 20 doctor visits to increase his risk for hospital readmission.

Despite the statistical significance established for the prediction models and the identification of significant predictors of multiple hospital admissions, sensitivity of the final prediction models was weak. Only 13% of the subjects with multiple hospital admissions were classified correctly according to the logistic regression model. The discriminant function model, while achieving higher sensitivity, had a lower overall correct classification rate. Furthermore, the proportion of explained variability associated with the models was small. Discriminant function analysis explained only 10% variability associated with multiple admissions. R-values obtained with logistic linear regression indicated weak prediction, as well.

CHAPTER V

SUMMARY AND CONCLUSIONS

Summary of findings

Two multivariate statistical procedures were applied to determine predictors of multiple hospital admissions in a population of non-institutionalized elderly. Data were obtained from the 1984 National Health Interview Survey, Supplement on Aging. Analyses were performed on 3,477 cases; 5% reported multiple hospital admissions.

Predictors were organized according to Andersen's Model for Health Services Utilization for purposes of establishing a profile which could be used to target high risk individuals. Twenty-nine variables obtained from reports on health service utilization trends were examined. Thirteen of these variables reflected socio-demographic data and were defined as predisposing and enabling characteristics: age, race, sex, education, income, residence, married, widowed, living arrangements, living children, social activity, retirement, difficulty getting outside. Sixteen variables reflected health related data and were defined as need characteristics: body mass index, beddays, doctor visits, number of conditions, number of community services, dependence in activities of daily living, perceived health, cardiac disease, cancer, stroke, or Diabetes Mellitus, change in health, perceived control of health, health worry, change in activity, and level of exercise.

The dependent grouping variable classified subjects according to the presence or absence of multiple hospital admissions during the prior year. Survey data did not include the length of each hospitalization, time span between hospital episodes, nature of each hospital episode, or specific needs during and following the hospitalization.

Four research questions were addressed in this study.

1. Which combination of predisposing, enabling, and need characteristics best predict multiple hospital admissions in the non-institutionalized elderly?

Results of discriminant function and logistic linear regression analyses identified eight variables which in combination predicted multiple hospital admissions (number of beddays, number of community services used, health status, number of conditions, cancer, change in activity and health, and number of doctor visits). It is interesting to note that number of community services used and change in activity and health had not been reported in prior investigations.

None of the predisposing and enabling variables were found to contribute significantly to the prediction model. These findings support reports of equity in distribution of hospital services and indicate that hospital readmissions are based on physician discretion and associated with need.

Although dependence in activities of daily living, body mass index, and the presence of stroke, diabetes, or heart disease had been reported as predictors of service use, these variables did not contribute significantly to the prediction of multiple hospital admissions. Inadequate exercise levels, perceived control of health, and health worry, while significantly associated with multiple admissions in univariate analysis, did not contribute significantly to the prediction model when all other variables were controlled.

2. Which of the significant variables are most important in predicting readmission risk?

Importance of variables was determined by the magnitude of the descriminant function coefficients and the R values associated with logistic regression coefficients. Although slight disparity existed between the prediction models in the ranking of importance, general patterns emerged. Both prediction models identified number of beddays, health status, and use of community services as most important to prediction and number of doctor visits as least important; furthermore, both models attributed nearly equal importance to the presence of cancer. Cancer was ranked as fifth most important to prediction along with number of conditions in the logistic regression model and sixth most important in the discriminant function model. Number of conditions followed cancer in the discriminant function model. The greatest discrepancies existed between models in the rankings of activity and health change. Activity change was ranked as second most important to prediction in the discriminant function model and sixth most important in the logistic regression model. Activity change and health change were of nearly equal importance in the logistic regression model. Health change was ranked as fifth most important in the discriminant function model. Level of education and health worry were ranked as more important than doctor visits in the discriminant function model but were eliminated in the final model obtained with logistic regression.

Of the two analyses, logistic regression produced a more parsimonious prediction model; furthermore, violations of assumptions associated with normality and equality of the variance covariance matrix in discriminant function analysis may have caused erroneous retention of unimportant variables. The final decision regarding importance of predictors was based, therefore, on logistic regression. The ranked importance of variables was as follows: beddays, health status, community services, number of conditions, cancer, activity change, change in health, and doctor visits.

3. What are the probable odds of multiple hospital admissions associated with the risk profile?

Calculated odds ratios indicated that the relative risk of rehospitalization was nearly doubled in subjects who reported cancer, poor health, or a decline in health or activity over the prior year. Odds were nearly doubled, as well, for subjects reporting three conditions or the use of two community services and tripled for those using four community services.

Subjects confined to bed for fifty-five days were 1.5 times as likely to be rehospitalized, and those confined for 100 days had twice the risk. The total number of doctor visits, while significant as a predictor, did not greatly increase the risk of rehospitalization. Subjects with twenty doctor visits were equally as likely to be hospitalized as subjects with only one doctor visit. These results supported conclusions that number of doctor visits was the weakest predictor remaining in the model.

The composite high-risk profile obtained with application of the logistic regression equation described an elderly individual with cancer, poor health status, and a decline in both health and activity over the prior year. In addition, this individual had at least four conditions, used three or more community services, spent 100 days in bed, and made at least 20 doctor visits.

4. How accurately does the proposed model predict multiple hospital admissions?

The prediction model containing the eight variables obtained with logistic linear regression was statistically significant; furthermore, calculated odds ratios and associated confidence intervals indicated accuracy of the individual predictors. Overall correct classification was achieved at a 95% level, and correct classification of subjects not reporting multiple admissions was achieved at a 99% level. Accuracy in classifying subjects who had reported multiple admissions, however, was low; only 13% were correctly classified. Eighty-seven percent were not distinguished from those who had not reported multiple admissions. The low Eigenvalue obtained with discriminant function analysis and R value obtained in logistic regression further indicated a weak association between the risk profile and multiple hospital admissions.

Since investigators of multiple hospital admissions have not reported accuracy associated with obtained prediction models, it is impossible to determine whether this model is more or less accurate than those identified in the utilization literature. Based on the classification table, however, it is safe to conclude that this risk profile does not accurately predict multiple hospital admissions in non-institutionalized elderly. In general, prediction models have explained only a small proportion of the variability associated with service use. Further research is needed to clearly identify and target high-risk populations.

Conclusions

Today, more than ever before in the history of our country, a higher number and percentage of our population are living to the age of 65 and beyond. This is largely a result of the fact that medical science has been successful in eliminating the acute diseases of the very young, thus allowing more people to live through the entire life cycle. A consequence of the extended life expectancy, however, is that the older population are more likely to suffer from chronic conditions and debilities which can impose years spent in frail health. Furthermore, elderly confront social stresses thought to influence adaptation and health. Such stresses include loss of income, loss of role and status, loss of spouse, social isolation, and loss of cognitive function (Palmore, 1970).

As a group the elderly report their health to be poorer, they experience more days of restricted activity, and they spend more days in bed than does any other age group. Of major concern to the health care industry is the cost attributed to overutilization of services. As a consequence, a major focus of health services research has been on the identification of risk profiles which identify high-cost users of health care services.

Results of this analysis support reports which have described high-cost users of hospital services as individuals with increased health care needs, exclusive of sociodemographic characteristics. Poor predictive ability of the profile, however, and weak association with multiple hospital admissions have made its clinical relevance questionable. Nonetheless, odds ratios obtained with individual variables indicated trends which might be useful to health care professionals in their assessment of elderly clients and the health care services available to them.

That cancer emerged as a significant predictor of hospital readmissions was not surprising. It is a debilitating condition associated with high morbidity and ranked second, only to heart disease, as the leading cause of death in the United States. Older people are more vulnerable to cancer than are younger persons making the incidence of cancer, now, higher than when people died at a younger age.

Generally speaking, cancer is expensive and its treatment is technical and lengthy. Advances in cancer therapeutics have increased life expectancy without necessarily improving health. Radiation and chemotherapy affect activity tolerance and general well-being, possibly accounting for increased beddays and decline in health and activity. Treatments administered in either physicians offices or hospitals by specially trained personnel, account for increased use of physician services, short term hospital admissions, and cost. Furthermore, treatments must be repeated at regular intervals to be effective. As technology advances and life expectancy increases, so to will the bill associated with cancer treatment.

Hospital admissions can be attributed to complications of both the disease process and its treatment. While not all cancer-related admissions are avoidable, early detection and treatment of cancer-related problems might, in some instances, reduce the frequency of hospital readmissions. These survey data, unfortunately, did not identify the nature and extent of each hospital episode, nor did they identify whether or not the readmission was cancer-related. Such information is crucial in the anticipation of health care needs and the distribution of costs and services. Unless cancer-related problems are delineated and alternative care options explored and made available to the patients and their families, it is unlikely, in the long run, that a substantial reduction in hospital readmissions will occur.

Health care professionals and policy makers who examine the financing and distribution of health care must focus on the source of services, the source of payment, and the financing mechanisms. For example, hospital administrators might consider, as an alternative to acute care hospitalization, the cost benefits of establishing minimal care or twenty-four hour observation units for cancer patients requiring short courses of treatment or uncomplicated intervention. Hospitals, also, might explore the benefits of out patient or home health services which target, specifically, the cancer population. Such services would include specially educated professionals able to perform risk assessments, carry out family education, implement treatment plans, and determine the need for hospital referrals. It is probable that some complications could be recognized and treated without requiring hospitalization. Financing and reimbursement organizations could provide impetus for the development of programs through cost incentives.

Some have advocated shifting the care of long term patients away from acute care facilities to lower-cost settings such as nursing homes or hospice. Hospice care is a relatively new concept. Unfortunately, there are few hospice beds available in acute care settings and even fewer free standing hospice agencies. Further exploration is required to determine both the cost and health care benefits associated with hospice as well as factors influencing the effectiveness of hospice care.

Suggestions have been made, also, to shift the cost of medicare and medicaid to different groups including families. As long as families are willing to provide care and assume the costs of many community services, such care is less expensive (Montgomery, R. and Borgatta, E., 1987). Results of this study, contrary to some reports, indicated that subjects with children and those living with others, including spouses, were not at risk for multiple admissions. Others had reported that family members unable to cope with increased health care needs admitted patients as a form of respite. Nonetheless, if the burden of health care shifts more to the family, it is likely that family members will require support services, including respite care and special education, to assist them. Issues surrounding the types, amount, and financing of services made available to the elderly and their families will need to be addressed.

While individual investigators have associated stroke, diabetes, and heart disease with multiple admissions, general findings have been inconclusive. Results of this study indicated, that when all variables were controlled, these conditions, by themselves, did not increase the risk of multiple hospital admissions. Heart disease and stroke, however, are frequently linked with diabetes. Since results of this study indicated that readmission risk increased as the number of conditions increased, it would be of interest to examine whether the combination of these conditions is specifically associated with hospital readmissions. If so, strategies could be developed to target this population in particular.

Surprisingly, the use of community services did not reduce the risk of hospital readmissions. To the contrary, as the use of community services increased, so did the risk of readmission. These findings might be attributed to an increased hospital referral network provided by the community services. On the other hand, the types of services available might not have been appropriate to the needs of these individuals, resulting in readmission. It is likely, also, that these elderly exhausted their health care resources and, as such, had no alternative but to be rehospitalized. The relationship between community services and hospitalization had not been examined prior to this investigation. Results of this study indicate a need for further exploration of the types and effectiveness of community services and their association with hospital readmissions in the elderly.

Total number of beddays and poor health status have been consistent predictors of health services use. In this study, health status was a strong predictor of multiple admissions. Two additional health indicators, decline in activity and health when compared to the previous year, emerged as strong predictors and were associated with twice the likelihood of multiple hospital admissions. These variables had not been included in prior investigations. All health care professionals establish patient data bases from which they determine health care needs and develop treatment plans. It might be of value to include questions on total number of beddays, perceived health status, and change in health and activity. Although it is premature to relate these variables, conclusively, to multiple admissions, it would be of interest to examine their association with hospital admission patterns. In particular, since these patients reported multiple doctor visits, physicians and their associates could obtain information on beddays and change in health and activity relative to health status, seasonal patterns, recency and need for doctor visits and hospitalization, and types of health conditions.

Several variables thought to influence multiple admissions were not included in the final prediction model nor did they increase the relative risk of hospital readmission as indicated by odds ratios. Age, race, sex, and income, consistently, have not been strong predictors of service use. General conclusions have indicated that there is equity in the distribution of health care services amongst the elderly, particularly with the introduction of medicare. It may be premature, however, to eliminate these variables from future investigations, particularly since policies governing medicare reimbursement plans are changing. Furthermore, the issue of medigap insurance coverage and income may need further exploration.

Marital status and living arrangements did not increase the risk of multiple hospital admissions. Based on reports in the utilization literature, it was anticipated that subjects who were widowed and those living with others would experience increased hospitalizations. The inference to be made is that hospitalizations are discretionary and based on patient, not family, needs.

Difficulty getting outside had not been included in prior prediction models. It was anticipated that subjects with environmental dependence would have greater need for health services. While subjects who experienced difficulty getting outside, generally experessed greater dependence in activities of daily living and increased beddays this variable did not increase the risk of multiple hospital admissions. Perhaps, because of the environmental dependence, these individuals did not have adequate access to health care services. It might be of interest to further explore environmental dependence and its association with health care needs and service use.

The fact that body mass index did not emerge as a significant predictor of multiple admissions was of interest, particularly since cancer increased readmission risk, and in many cases, patients with cancer have a reduced body mass index. Furthermore, many health complications are associated with an increased body mass, obesity. The average body mass index across groups, however, was equal. It might be of interest to specifically examine body mass index as it relates, for example, to cancer, cardiovascular disease, and service use.

Dependence in activities of daily living has been a consistent predictor of service use. Results of this study, however, did not confirm previous reports. While dependence in ADL's discriminated between groups, it did not increase the risk of multiple hospital admissions.

Limitations of the study

Several limitations emerged. First of all, a secondary analysis of an existing data set was used here. As such, it was not possible to gather specific types of data relative to the nature of each hospital episode and the types of problems that precipitated hospitalization. It was not clear, for example, whether patients required emergency services, whether they were admitted for short-term outpatient services, or whether repeated admissions were associated with the same condition or problems related to the same diagnosis. Also, it was not possible to determine the type of health care intervention or followup between admissions. Furthermore, it was not possible to determine the general status of the disease process. For example, survey data indicated only the presence or absence of a condition, not its management or physiologic affects. Specific clinical descriptors were not available. The predictiveness of the model for hospital admissions might be improved with the inclusion of more comprehensive medical information.

A limitation was that the number of subjects in the smaller group was limited (N=152). While it was expected that the proportion of subjects with multiple admissions was far less than that without multiple admissions, the small number might have resulted in the underestimation of correlations and influenced accuracy of the prediction model.

Perhaps one of the most serious limitations of the data set was that the data were collected in 1984. Generally, these types of survey data are not released for several years following collection. As a result, an approximate ten year lag exists between data collection, data analysis, and publication of results. Because medicare has been in existance throughout this time period and because medicare policies and medigap coverages have changed, it is likely that admission practices have changed as well. Possibly, sociodemographic characteristics that did not emerge as significant in this study may influence service use as policies governing health care change.

Recommendations for future research

The results of this study have added to the body of knowledge associated with health services utilization by identifying variables not associated with multiple hospital admission patterns. It is clear from the classification table, however, that the variables remaining in the prediction model are very weak in their association with multiple hospital admissions. To strengthen the prediction model, data needs to be obtained retrospectively from hospital records of patients with multiple admissions and then applied prospectively, within the context of an on-going longitudinal research designs.

Specifically, it is the recommended that:

1. Hospital records of patients with more than one hospital admission be examined to determine: reasons for each admission, seasonal patterns of admission, time-span between admissions, types of medical diagnoses, patterns of abnormal physiological clinical descriptors, problems encountered during the hospitalization, length of hospitalization, condition at the time of discharge, discharge instructions and followup, and types of community services used.

2. Patients with cancer be followed longitudinally in a prospective study to determine the types of problems leading

to multiple admissions.

3. The association between use of community services and hospital admissions be more closely examined to determine specific linkages.

4. Patient history data base records include questions directed at health status and change in activity and health and that these variables be examined retrospectively relative to types of medical diagnoses, physiological indicators, and support services and prospectively relative to hospital admissions.

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APPENDIX A

APPENDIX A

1984 NATIONAL HEALTH INTERVIEW SURVEY SUPPLEMENT ON AGING (MODIFIED)

1. Person #

2. Sex
   1. Male
   2. Female

3. Name
   Last First Middle

4. Date of birth

5. Race
   1. White
   2. Black
   3. Other

6. Annual income
   ________dollars

7. Education (completed years)

8. Marital status
   1. Married
   2. Widowed
   3. Divorced
   4. Separated
   5. Never married

9. How long married
   1. Less than one year
   2. _____years

10. How long (widowed, divorced, separated)
    1. Less than one year
    2. ______years

11. Living children, including step and adopted
    1. None
    2. _____Number

12. Living arrangements
    1. Lives alone
    2. Lives with spouse only
    3. All other

13. 1. SMSA
    2. Non-SMSA

14. In the past twelve months did you

1. Use a senior center	1. Yes	2. No
2. Use special transportation	1. Yes	2. No
3. Have meals delivered to your home	1. Yes	2. No
4. Use a homemaker service	1. Yes	2. No
5. Use a service which makes routine telephone calls to check on you	1. Yes	2. No
6. Use a visiting nurse service	1. Yes	2. No
7. Use a health aide	1. Yes	2. No
8. Use adult day care	1. Yes	2. No

15. Regarding your present social activities, do you feel you are doing about enough, too much, or would like to be doing more
    1. About enough
    2. Too much
    3. Would like more

16. At this time do you consider yourself completely retired, partly retired, or not retired all
    1. Completely retired
    2. Partly retired
    3. Not retired at all
    4. Never worked

17. Do you now have

1. Coronary heart disease	1. Yes	2. No	3. DK
2. Rheumatic heart disease	1. Yes	2. No	3. DK
3. Angina pectoris	1. Yes	2. No	3. DK
4. A myocardial infarction	1. Yes	2. No	3. DK
5. Any other heart attack	1. Yes	2. No	3. DK
6. A stroke	1. Yes	2. No	3. DK
7. Cancer of any kind	1. Yes	2. No	3. DK
8. Diabetes	1. Yes	2. No	3. DK

18. Because of health or physical problems, do you have any difficulty?

1. Bathing or showering	1. Yes	2. No	3. Doesn't do
2. Dressing	1. Yes	2. No	3. Doesn't do
3. Eating	1. Yes	2. No	3. Doesn't do
4. Getting in an out of bed	1. Yes	2. No	3. Doesn't do
5. Walking	1. Yes	2. No	3. Doesn't do
6. Getting outside	1. Yes	2. No	3. Doesn't do
7. Using the toilet	1. Yes	2. No	3. Doesn't do

19. Compared with one year ago, would you say that your health is now better, worse, or about the same
   1. Better
   2. Worse
   3. Same

20. During the past year, has your overall health caused you a great deal of worry, some worry, hardly any worry, or no worry at all
   1. A great deal of worry
   2. Some worry
   3. Hardly any worry
   4. No worry at all

21. Compared to your own level of physical activity one year ago, would you say you are now more active, less active, or about the same as you were then
   1. More active
   2. Less active
   3. About as active

22. How much control do you think you have over your future health? Would you say you have a great deal of control, some, very little, or none at all
   1. A great deal of control
   2. Some control
   3. Very little control
   4. None at all

23. Do you feel that you get as much exercise as you need or less than you need
   1. As much as needed
   2. Less than needed

24. How many times during the past year have you seen your doctor
   1. Dr. never seen
   2. ______visits

25. How many times during the past year have you been admitted to the hospital
   1. Never admitted
   2. ______times

26. Because of health or physical problems, do you usually stay in bed all or most of the time
   1. Yes
   2. No

27. During the past year, how frequently have you had to stay in bed

28. Would you rate your health as excellent, bery tood, good, fair, or poor

1. Excellent
2. Very good
3. Good
4. Fair
5. Poor

29. Height without shoes_________ Weight without shoes__________

DISSERTATION APPROVAL SHEET

The dissertation submitted by Rosemarie Suhayda has been read and approved by the following committee:

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The final copies have been examined by the director of the dissertation committee and the signature which appears below verifies the fact that any necessary changes have been incorporated and that the dissertation is now given final approval by the Committee with reference to content and form.

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