A Latent Variable Investigation of Emergency Room Use

by

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A Thesis submitted to the Faculty of Graduate Studies of

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in partial fulfilment of the requirements of the degree of

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Abstract

Previous research has identified a number of factors associated with emergency room (ER) use. However, many studies have focussed on describing ER users based only on frequency (i.e., frequent versus non-frequent users). This unidimensional characterization ignores the complex and heterogeneous factors underpinning ER use. This study sought to identify homogeneous subgroups of ER users in an empirical and multidimensional manner.

A retrospective cohort design was employed using linked administrative data housed at the Manitoba Centre for Health Policy. The study sample (n=143,584) comprised all adults who used Winnipeg Regional Health Authority ERs from fiscal year 2003/04 to 2004/05. Latent class analysis (LCA) was used to define subgroups, with grouping variables based on the Andersen-Newman framework of healthcare utilization. ER users were stratified into younger (19-64) and older cohorts (65+) prior to the application of LCA to the data.

Seven classes were used to define both older and younger cohorts based on an assessment of model fit. Classes could be distinguished by sex, area-level wealth, amount of resources used (i.e., physician, hospital and ER), and physical and mental health diagnoses. High resource utilization was seen in classes that resided in both poorer and wealthier areas of Winnipeg and coincided with prevalent mental health diagnoses, while low utilization was most often observed in classes where males predominated.

The identification of distinct user classes within the population of ER users is an important first step in the development of strategic and targeted interventions and programs.

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1. Chapter 1: Introduction

1.1. Background

The overcrowding of emergency rooms (ER), and concerns about potentially inappropriate use has garnered much recent interest[1,2]; as a result, this issue has gained a high profile on medico-political agendas[3]. A small minority of the population are responsible for a disproportionate amount of ER use[4]. Sun et al. estimate that three to four percent of ER users are responsible for approximately 12 to 20 percent of total ER use[5]. Users of ER often have chronic illnesses, multiple co-morbid conditions, and psychological illnesses[6-15]. Although research conducted with ER users has identified a number of key characteristics, important questions remain. For example, some studies have shown that ER users tend to not be engaged in the health care system, and thus their only avenue for health care is through the ER[16]. However, other studies have suggested those that have a regular source of care may be more prone to ER use[17]. Irrespective of individual findings, a consistent theme that emerges from the literature is that ER users have complex characteristics, and no single characteristic defines, nor drives use.

1.2. Limitations of Previous Research

The lack of a framework within which to organize and understand characteristics of ER users[18], the limitations in analytical approaches[19-21], and the datasets frequently adopted to examine ER use[19,22] have been acknowledged in the literature. This section briefly outlines the limitations of previous research, and then explains how the objectives of the present study attempt to address these limitations.

1.2.1. Organizing and understanding characteristics of ER users

A variety of frameworks have been proposed to study health care use, of which some have been applied to ER use. Mechanic[7] separates these various frameworks into two types: *psychosocial and organizational*, and *multivariate* frameworks. A well-used example of the former type is the Health Belief Model, as proposed originally by Hochbaum[23], and further elaborated by such researchers as Becker[24]. In its original incarnation, the framework posited that health care use is driven by three factors (relating to some specific, hypothesised illness): perceived susceptibility, perceived severity and perceived benefits of seeking care. Major strengths of this framework include assessment of subtler aspects of health care use[7], as well as the inherent communicability of findings and recommendations; interventions (and measures) can be neatly compartmentalized into the three factors.

However, by definition, this psychosocial framework is limited by its subjective assessment of user characteristics. The Health Belief Model in particular has been criticized for its low explanatory power[25,26], and the belief that it may be better suited to explaining the use of preventive health care, and for specific diseases, as opposed to utilization of a broad range of health services[27]. Nonetheless, this framework has influenced the development of many other types of frameworks[7], such as illness behaviour, reasoned action and planned behaviour theories[25].

The second type of framework, which Mechanic refers to as the *multivariate* type, has been dominated by the use of the Andersen-Newman behavioural framework of health care utilization[28,29]. Although a more detailed discussion is included in Section 2.1, briefly, this framework overcomes some of the limitations of the psychosocial-type frameworks by including variables that can be measured objectively, as well as being appropriate for describing and predicting more general health care use. Finally, in its most general form, this framework can incorporate aspects of psychosocial characteristics[27].

1.2.2. Analytical approaches

With respect to analytical approaches, most of the ER literature concentrates on characterizations of users on a unidimensional axis, primarily frequent versus non-frequent ER use. From a policy context, distinguishing frequent and non-frequent use has produced useful results[4,5,30]. For example, in addition to discovering that a small proportion of users are responsible for a disproportionate amount of visits[4,5], studies have shown that frequent users are more likely to be burdened by co-occurring psychiatric and substance abuse issues[30], as well as being more likely to be admitted for a hospitalization after an ER visit[30]. However, the importance of a multidimensional examination of ER users has been noted by many researchers[19,27]. The unidimensional approach, by its very nature, only captures a single aspect of ER use. For example, focussing solely on frequency of use may hinder exploration of other significant variables that may distinguish different types of ER users, and hence, the understanding of inter-variable relationships governing unique user groups may be limited[31]. Huang et al.[31] suggest that some of the inconsistent results observed regarding the amount of overall non-ER medical services use by frequent, compared to non-frequent users may be attributable to narrowly-defined groups that do not account for heterogeneity in the frequent user groups, however they are defined. Moreover, studies of frequent vs. non-frequent use are often limited by the lack of a standard definition of frequent use[8,9,30].

1.2.3. Datasets

Because the bulk of data from ER studies have originated either from a single clinical setting, or from a limited number of sites, the generalizability of research findings to the population remains in question. Relatively few ER studies are population-based[31-38], with those that are generally relying on the use of population-based administrative data[31-34,37-39] or nationally-representative samples[35,40]. As well, the applicability of findings to the Canadian context is uncertain, since the majority of studies are based on data from the United States, where issues of insurance coverage may significantly affect aspects of ER use[41,42]. Thus, studies to inform policy within the Canadian context are warranted[38,43-48].

1.3. Objectives

The purpose of this study was to characterise Winnipeg ER users focussing on a multidimensional set of characteristics, using available linked population-based databases. The specific objectives were:

i. To apply the Andersen-Newman health care utilization framework to select variables to identify ER users from administrative data;

ii. To use latent class analysis to develop typologies of ER users.

1.4. Justification

The study utilized the technique of latent class analysis (LCA)[49,50] to construct typologies of ER users based on an empirical, and multidimensional characterisation of users, using linked population-based databases. This study used a well-established framework, the Andersen-Newman health utilization framework[28], to guide and organize variables of interest, with the goal of facilitating understanding of different types of ER users.

LCA has not been used widely with the behavioural framework, although some authors suggest that the incorporation of *latent variables*, or those variables that are *unobserved*, is ideal for the study of the utilization of health services, as many of the processes and determinants underlying health services utilization are only observed directly with great difficulty, or indirectly, through proxy measures[14,19,51]. Aside from one study which examined the validity of different sources of information for ER visits (and which concluded that administrative data were the most valid source of data)[44], to the best of our knowledge, no studies have employed LCA to characterize ER users.

By focussing the investigation on a multidimensional approach, this study will contribute to evidence-informed and targeted health policy planning, by using a data-driven method to distinguish different types of ER users, creating insight into the various subpopulations that constitute the universe of ER users.

2. Chapter 2: Review of Literature

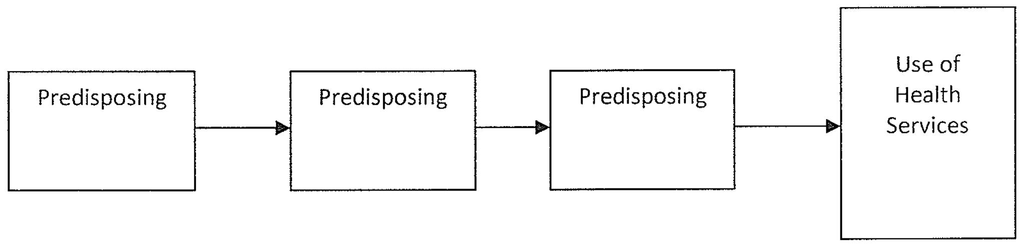
This chapter reviews the literature on the following topics: (a) the behavioural framework of health services use and its application in research, (b) types of ER users, (c) determinants of ER utilization, (d) data sources to study ER use and (d) use of latent variable models in health services research.

2.1. Behavioural Framework of Health Care Utilization

Andersen and his colleagues' behavioural framework of heath care utilization is a well-known framework to describe and predict an individual's use of health care services[8,19,22,27-29,52-56]. This framework identifies a number of types of determinants of health care use, and the relationships among them.

The behavioural framework focuses on utilization as a function of three types of characteristics: 1) Predisposing characteristics; 2) Enabling characteristics; and 3) Need. Predisposing characteristics are those characteristics that are present prior to an individual's illness, and which predispose an individual to use health services[22,27,28,54]. Enabling characteristics are those characteristics that permit (or block) access to the health care system, given an individual's predisposition for use[22,27,28,54]. Need is defined as the amount of illness or disability present in an individual[54], and is typically the most immediate cause of health service use[27,28]. In his original conceptualization of the framework, Andersen proposed two types of need: perceived (i.e., subjective) , and evaluated (i.e., objective) need[22,27,28].

Figure 1: The Andersen-Newman Behavioural Framework of Health Care Utilization



As seen in Figure 1, the framework provides a means by which to organize and conceptualize the direct effects of variables on health care use, which is useful in comparing, and communicating the results of different models.

2.1.1. Application of the behavioural framework

The behavioural framework has typically been used in multivariable regression models, to assess the relative contribution of different determinants to explain ER use. The design of the behavioural framework, which categorizes theorized determinants, has made the hierarchical subsets approach to model-building useful[33]. As well, empirically derived model-building approaches (e.g., stepwise regressions) have been used to determine the most important determinants of use[17].

Although widely used, the behavioural framework has also been criticized. Padgett and Brodsky[57] discuss some of the limitations of the behavioural framework as it has been applied to the investigation of health care utilization. The narrow focus on direct effects of the three hypothesized sets of characteristics; and 3) the overly broad examination of health care utilization.

With respect to the first point, although the Andersen framework has been shown to have low explanatory power, it explains a larger proportion of total variance than other frameworks (e.g., the Health Belief Model)[7]. Padgett and Brodsky[57]and Andersen[22], have commented that narrowing the focus to a specific type of health care use (e.g., use of ER services) tends to make the behavioural framework more useful, with respect to understanding the contributions of each type of factor. Inconsistency of definitions of the characteristics[57], and the reliability and validity of self-reports of health utilization (i.e., recall bias), and of the indicators of the three characteristics[54,58-60] have also been noted as criticisms in the use of the behavioural framework. As an example of inconsistency, income, typically defined as an enabling factor[27,28], has been defined by some researchers as a predisposing factor[61].

2.2. Types of ER users

In addition to defining ER users based on frequency, users have been defined based on the presence or presence of one or more physical diseases, including asthma[39,62-64], migraines[65-67], respiratory conditions[63,64,68], and other chronic conditions. Similarly, users have been classified on the basis of substance use/abuse[69,70], the presence of various mental health issues[71-74], injuries (self-inflicted, drug-related or otherwise)[37,75-77], and urgent vs. non-urgent (e.g., potentially inappropriate) use of ERs[38,78]. The effects of therapeutic interventions[63], as well as economic costs[64] have been assessed for different types of users. For example, in one study of the costs of ER care, users who presented with cardiac-related issues utilized the most resources compared to those that presented with asthma, chronic obstructive pulmonary disorder or other respiratory infections[64].

2.3. Characteristics of ER Users

This section discusses the characteristics of ER users, categorized into the predisposing, enabling, and need characteristics of the Andersen-Newman framework. It is important to note that studies typically have assessed the *independent* contributions of multiple characteristics of users, and save for some exceptions[31,79], the interrelationships between various characteristics (i.e., their interaction) have not been widely studied[80].

2.3.1. Predisposing Characteristics

Predisposing characteristics are present prior to an individual's illness and include such characteristics as age and sex. Advanced age is associated with increased ER use[46,81]. However, the relationship between ER use and age may be mediated by other characteristics. For example, one American study showed that among diabetics, younger age (i.e., less than 50 years) was associated with increased ER use[18]. As well, among females, psychological distress and substance abuse were shown to have differential effects on ER use, dependant on age[82]; older females (60+ years) with these issues were more likely to be frequent users of ER services, compared to their younger counterparts. A review by McCusker et al. suggests that need plays a greater role in ER use in the elderly relative to younger populations[46]. Finally, recent research conducted in Winnipeg suggests that in general, older age was significantly associated with multiple ER visits; however, among those that had multiple ER visits, younger age was inversely associated with the number of visits[34]. Ethnicity has also been cited as a predisposing factor associated with ER use in the US[83] and other countries[84]; however, since most studies that include ethnicity have been conducted in countries without universal health care coverage, the effect of ethnicity, independent of other socioeconomic characteristics such as wealth, and presence of health insurance has been difficult to assess.

2.3.2. Enabling Characteristics

Enabling characteristics are those that permit (or block) access to the health care system given an individual's predisposition for use. They include income, presence of health insurance, and availability of physician care. A consistent predictor of ER use is socioeconomic disadvantage, as well as poverty[5,85-87]. Although many studies of ER use have been conducted within the American context (where factors such as medical insurance may play a role)[5,86,88], studies from Canadian settings[33,53] suggest that socioeconomic status is still associated with ER use. Geography[33] (i.e., where someone lives), and mobility[53] (i.e., the degree of stability in one residence location) are other enabling characteristics associated with ER use. ER use was positively associated with living in a disadvantaged geographic area and with residents that were prone to instability in housing. Prior utilization of physician and hospital services has been shown to be predictive of overall health care use [54,58], including ER use[89-91]. However, there has been some inconsistency observed in the positive relationship between prior (and concomitant) health care utilization and ER use. Some studies have observed that those individuals who received the majority of their care from ERs used physician services less frequently[83,84,92].

Having a regular source of care has been associated with increased use of preventive care[53,93-96], and decreased use of ER services[43,53]. However this relationship has not been consistently demonstrated in the literature[5,53,86,89,91,96,97].

Olsson and Hansagi, in their qualitative study of Swedish ER users, observed that frequent users tended to lack social supports[98]. Finally, a few European studies have demonstrated that foreign-born individuals were more likely to regularly receive care from ERs[84,92].

2.3.3. Need Characteristics

Need has been defined as the amount of illness or disability present in an individual. Measures of need include the presence of chronic illnesses[17], number of comorbid conditions[18,53,99], or amount of prior utilization[89-91]. Need is positively associated with ER use; research has shown that it may be useful to separate psychosocial need from other need conditions[57,80,100]. A strong, and independent relationship exists between ER utilization and psychosocial health[57,80,89], although the direction of this relationship is not necessarily straightforward[101-103]. Most studies have found positive associations between psychosocial health and utilization[6,8,17,57,89], although negative associations have also been observed[60].

2.4. Sources of Data to Study ER Use

Most studies have examined ER use in clinical samples; that is, in samples obtained by enrolling patients from single or multiple hospital sites[17,43,48,79,80,86,104,105]. ER use and its determinants have been assessed either through self-reported quantitative surveys[3,89], or a combination of survey and clinical (administrative or otherwise) data[17,68,69,80]. In the United States data from insurance/Health Maintenance Organization administrative databases[106,107] have been used to study ER users. Although in some instances the sample sizes may be extremely large, such as studies employing HEDIS (Health Plan and Employer Data and Information Set) data[107], the generalizability of these studies to the entire population may be limited because of selection bias.

ER studies have employed population-representative data[35,40 70-74,80]; for example, several US-based studies utilize data from the US National Hospital Ambulatory Medical Care Survey[35,40,71-74]. However, surveys are generally costly and time consuming to conduct.

ER research utilizing routinely collected, population-based administrative data overcome some of the above limitations in cost and population coverage[108-110]. Canadian researchers[39,90,111,112] as well as some Taiwan-based researchers[31], have used administrative data to study ER use. However, only a few have applied the behavioural framework to ER use[33,53].

2.5. Use of Latent Class Analysis in Health Services Research

Latent class analysis, a type of latent variable modelling[113], is a technique of discovering unobserved heterogeneity (i.e., qualitatively distinct *latent classes*) from multivariate categorical data[50]. The latent classes, by definition, are thought to be unobserved, and are inferred from a combination of categorical indicators[50,114] [50]. The assumption in LCA is that a heterogeneous population can be grouped, or clustered, into a finite number of homogenous classes. LCA is used when a researcher cannot assume that observed (i.e., indicator) variables are discrete manifestations of an underlying *continuous* latent variable, as is the case in factor analysis (FA)[115]. Unlike regression methods, indicator variables for LCA are not considered to be either dependent or independent; rather, underlying qualitatively distinct subgroups are thought to be represented by the various patterns of endorsed indicator variables. Maximum likelihood methods are used to estimate the conditional probabilities of each case belonging to a certain class, based on their endorsement of indicator variables specified[50].

LCA has been used in the psychological and psychiatric literatures to discover underlying patterns of pathology and disease[116-120]. For example, using data from the National Comorbidity Survey, Shevlin et al.[117] hypothesised the existence of four qualitatively distinct classes of schizophrenia: a psychosis class, a hallucinatory class, an intermediate class and a normative class. These classes were based on the endorsement of thirteen questions on a standard psychosis screen, the International Diagnostic Interview. The authors found that individuals in the psychosis class, relative to the other classes were more likely to have experienced traumatic events. The authors used the results of the analysis to recommend targeted intervention/treatment programs for each class.

Mitchell and Plunkett used LCA to develop classes of substance users among American Indian youth in Mississippi[120], based on responses to questions about lifetime substance use. The authors concluded that four classes fit the data best: abstainer, predominantly alcohol, predominantly alcohol and marijuana, and plural (i.e., multiple) substance classes. The authors argued for using LCA over techniques like cluster analysis due to the availability of measures to facilitate decisions regarding the number of optimal classes. Although the authors argue that LCA has potential value in providing insight into substantive subpopulations that may not be discovered using traditional statistical techniques (e.g., regression models), they caution that theory should guide the selection of indicator variables. Additionally, Mitchell and Plunkett view the use of LCA as being complementary to (as opposed to being a replacement for), other traditional techniques.

Prosser et al. used LCA to identify asthma cases from administrative data in British Columbia[32]. The authors developed subtypes of asthmatics from administrative data, and compared asthmatics identified using LCA to those identified *a priori* using conventional administrative data definitions. The Prosser et al. study contributed to existing knowledge around developing case definitions from administrative data when no gold standard for disease diagnosis exists. Dendukuri et al. used LCA to examine administrative data from four hospitals in Quebec linked to clinical and client survey data to compare the validity of each data source[44]. In LCA, multiple indicators are used to measure an underlying construct, therefore, this approach is useful to control for measurement error[50,113,115].

In summary, previous research has consistently shown that factors associated with ER use are multifactorial, and driven by complex interactions between objectively measured factors (e.g., presence of multiple chronic conditions) and systemic features such as availability of health care services.

3. Chapter 3: Methods

3.1. Study Design and Description of Data Sources

This study used a retrospective cohort design to identify a cohort of ER users and characterize them in terms of a number of measures of predisposing, enabling, and need characteristics. Study data were from the Research Data Repository housed at Manitoba Centre for Health Policy (MCHP). The Repository contains linkable administrative health records for all eligible Manitoba residents. Although the databases contain utilization data at the individual level, the Repository does not maintain identifying information of the individual, such as name and street address. Linkages among databases are made through an individual's anonymized personal health information number (PHIN).

Administrative data in Manitoba have been validated[109], and used extensively in health services research[10,52-54,108,109,121-128]. In addition to ER data, this study used data from the research registry, physician claims, physician resource and hospital abstracts databases from the Repository. Data from the 2001 Statistics Canada census was also used.

ER data are collected as part of the Winnipeg Regional Health Authority's (WRHA) Admission/Discharge/Transfer (ADT) system. The system contains data from all adult, as well as some children's visits to ERs in Winnipeg since April 1, 1999, with the exception of the Health Sciences Centre, which started contributing data on May 1, 2000. Data are presently available up to Fiscal Year (FY) 2005/06.

The research registry contains demographic, place of residence and health insurance coverage information for every individual in Manitoba registered with the Manitoba Health Services Insurance Plan (MHSIP). These data are linkable to other databases through the use of the anonymized PHIN.

The physician claims database captures billing information from all fee-for-service physicians and the majority of salaried physicians in Manitoba; this database contains information on tariff codes for services provided, as well as diagnosis information using the ICD-9-CM classification system. The physician resource database contains demographic data about each physician eligible to practice in Manitoba as well as information on practice patterns such as specialty and years of practice.

The hospital abstracts database records all separations from acute care facilities in Manitoba. Within each record, multiple diagnosis codes (up to 16 ICD-9-CM codes prior to FY 2004/05, and up to 25 ICD-10-CA codes after this date) are recorded for each individual. Data on median household income at the Dissemination Area (DA) level from the 2001 Statistics Canada Census were used to construct income quintiles for the Manitoba population.

3.2. Study Sample and Inclusion/Exclusion Criteria

Two samples were drawn for analysis in this study: one study sample and one validation sample. This section will describe the study sample while sections 3.7 and 4.4 will describe the validation sample.

The study sample included all ER users who visited any of the six adult ERs in the Winnipeg Regional Health Authority (WRHA) between April 1, 2003 and March 31, 2005 (i.e., FY 2003/04 to 2004/05), who resided in Winnipeg, and who were 18 years and over at the time of their first visit during this two-year time period. Users who were less than 18 years of age at their first visit during the study period were excluded because data from Children's Emergency were not available at the time the study was initiated. All individuals for whom databases in the Repository could not be linked via the scrambled PHIN were excluded from the study. Two subgroups, or cohorts were defined: those aged 18 to 64 years were included in the Younger Cohort and those 65 years and over were included in the Older Cohort; previous studies have shown that the burden of disease, as well as utilization patterns differ by age[33,45,46].

All eligible subjects' most recent visit in FY 2004/05 was used as the endpoint of ER visits. From this most recent (i.e., 'most proximal') visit, all ER visits in the one-year period prior to this endpoint was counted (i.e., the 'most distal' visit). For example, if subject A's most recent ER visit in 2004/05 was on February 22, 2005, all of their visits in the period between February 22, 2004 and February 22, 2005 would be included and counted in the study.

3.3. Measures

Measures of predisposing, enabling, and need for ER services, as described within the Andersen-Newman framework, were defined using administrative data.

3.3.1. Predisposing Characteristics

Consistent with previous research, the predisposing variables included in this study were age and sex. These variables were defined using registry data. Age was calculated based on an individual's birth date and the date of their first ER visit (i.e., their most distal visit) in the period between FY 2003/04 and FY 2004/05.

3.3.2. Enabling Characteristics

Enabling variables that were investigated included area of residence and income group.

Area of residence: This was determined by an individual's six-digit postal code, as identified from 2003/04 registry data using a previously defined methodology[129]. Each postal code was assigned to one of three urban areas: Inner Core, Outer Core and Suburban. According to Lix et al., "…this categorization was generated from 2001 Census data on neighborhood density (persons per hectare), housing age (proportion of housing stock built before 1946), and income (median household income). Core neighborhoods had density and housing age values above the Winnipeg RHA median; the remaining neighborhoods were suburban. Neighborhoods in the inner core were poorer, with household income values below the median, while those in the outer core were substantially more affluent"[129]. For both Younger and Older Cohorts, outer core and suburban residency was collapsed into one group, while inner core residency remained separate.

Income Group: Income group is a measure of socioeconomic status. Individuals were assigned to income quintiles based on their six-digit postal code, which is linked to a Census DA, the smallest geographic unit for which Census data are released. Income ranges were determined such that the entire Manitoba population was divided into five approximately equal groups. Residents were assigned an income quintile according to their dissemination area median household income. Some residents could not be assigned to an income group; for example postal codes in which more than 90 percent of the residents are in long-term care facilities are excluded from the quintile assignment because the census does not collect income for institutionalized persons. Postal codes associated with institutions, such as prisons and mental health institutions are excluded for this same reason. Overall, less than two percent of the study population in any given year can not be assigned to an income quintile using this methodology. Only urban income quintiles were defined in this study. Moreover, a binary variable was constructed for income quintiles; the top two income quintiles were collapsed into one category, while the remaining three, as well as those with missing values, formed the second category.

3.3.3. Need Characteristics

Evaluated need was operationalized using morbidity and utilization measures. The former included measures of physical and mental health. A series of measures about the presence/absence of physical and mental health conditions (i.e., case definitions) were defined[34,130,131]; these case definitions are based on diagnoses in hospital and physician data.

3.3.3.1. Morbidity Measures

Physical

The following measures were selected to assess physical morbidity as they have previously been used in research on ER use in Manitoba[34], and thus their definitions are thought to be valid and reliable.

Arthritis: The following ICD-9-CM codes were used to define arthritis: 274, 446, 710-721, 725-729, 739. An individual was considered to have arthritis if any of the above ICD-9-CM codes appeared 1 or more times in hospital data (1+H) or 2 or more times in physician claims data (2+P) in 3 years of data (FY 2001/02 – FY 2003/04).

Ischemic Heart Disease (IHD): The following ICD-9-CM codes were used to define IHD: 410-414. An individual was considered to have IHD if any of the above ICD-9-CM codes appeared 1 or more times in hospital data (1+H) or 1 or more times in physician claims data (1+P) in 3 years of data (FY 2001/02 – FY 2003/04).

Diabetes: An individual was considered to have diabetes if ICD-9-CM code 250 appeared 1 or more times in hospital data (1+H) or 2or more times in physician claims data (2+P) in 2 years of data (FY 2002/03 – FY 2003/04).

Ambulatory Diagnostic Groups (ADGs): For physical health, in addition to specific diseases (such as diabetes) comorbidity was defined using Ambulatory Diagnostic Groups (ADGs)[132]. ADG groupings labelled 'psychosocial' were not included in the physical health latent variable. Individuals were assigned into different ADGs based on one year of utilization (FY 2003/04). For the Younger Cohort, the number of ADG groups was categorized as follows: 0 to 1, 2 to 4 and 5 or more ADGs, while for the Older Cohort, individuals were assigned to the following ADG categories: 0 to 3, 4 to 7 and 8 or more.

Mental

Anxiety Disorders: An individual was considered to have an anxiety disorder if ICD-9-CM code 300 appeared one or more times in hospital data (1+H) or three or more times in physician claims data (3+ P) in three years of data (FY 2001/02 – FY 2003/04).

Dementia: The following ICD-9-CM codes were used to define dementia: 290, 294, 331, 797. An individual was considered to have dementia if any of the above ICD-9-CM codes appeared one or more times in hospital data (1+ H) or one or more times in physician claims data (1+P) in three years of data (FY 2001/02 – FY 2003/04).

Depression: The following ICD-9-CM codes were used to define depression: 396, 309, 311. An individual was considered to have depression if any of the above ICD-9-CM codes appeared 1 or more times in hospital data (1+ H) or 1 or more times in physician claims data (1+P) in three years of data (FY 2001/02 – FY 2003/04).

Personality Disorders: An individual was considered to have a personality disorder if ICD-9-CM code 301 appeared one or more times in hospital data (1+ H) or one or more times in physician claims data (1+P) in three years of data (FY 2001/02 – FY 2003/04).

Schizophrenia: An individual was considered to have schizophrenia if ICD-9-CM code 295 appeared one or more times in hospital data (1+H) or one or more times in physician claims data (1+ P) in three years of data (FY 2001/02 – FY 2003/04).

Substance Abuse: The following ICD-9-CM codes were used to define a substance abuse diagnosis: 291, 292, 303-305. An individual was considered to have a substance abuse diagnosis if any of the above ICD-9-CM codes appeared one or more times in hospital data (1+H) or one or more times in physician claims data (1+ P) in three years of data (FY 2001/02 – FY 2003/04).

Presence of any mental health disorder: A binary variable was created to indicate the presence of any of the above mental health disorders.

3.3.3.2. Utilization Measures

Utilization measures included ER visits, hospital separations, physician office visits, and continuity of care.

Number of ER visits: The number of ER visits was defined as the number of visits in the 365 days prior to the person's proximal ER visit. Thus, one year's worth of visits was captured for two fiscal years' worth of individual ER users. For the Younger Cohort, ER visits were grouped into the following categories: 1, 2 to 4, and 5 or more. For the Older Cohort, a binary variable was created, with those only having 1 visit as one group, and those with 2 or more visits in the other group.

Physician visits: The number of physician visits in FY 2004/05 was tabulated for each individual if the following inclusion criteria were met: if the visit was considered an ambulatory physician visit (according to MCHP criteria), and if there was no indication that the visit was to an emergency room on an outpatient basis[54]. An ambulatory visit was defined as any contact with a physician that was billable by the physician to Manitoba Health, and if it occurs while the individual was not in the hospital. For the Younger Cohort, the number of physician visits in FY 2004/05 was grouped into the following categories: 0 to 2, 3 to 6, 7 to 11 and 12 or more visits. For the Older Cohort, physician visits were grouped into the following categories: 0 to 5, 6 to 11 and 12 or more visits.

Hospitalizations: The number of in-patient hospitalizations in FY 2004/05 was tabulated for each individual based on the date of discharge[54]. For both the Younger and Older Cohorts, the number of hospital separations in FY 2004/05 was grouped into 0, 1, and 2 or more visits.

Continuity of care: A binary variable was created for continuity of care, based on the 'majority of care' definition[53]. An individual was considered to have continuous care if 75% of their physician visits (based on the earlier definition of physician visit) in FY 2004/05 were to the same provider. Those with only one physician visit in the prior year were classified as having continuous care by default.

3.4. Conducting Analyses in a High Security Environment

Typically, all analyses at MCHP are conducted on a secure Unix platform called HealthSys using SAS 9.1. Since LCA was the *de facto* statistical methodology used in this study, specialized software (i.e., Mplus[133]) was required. LCA can be performed using the CATMOD procedure (i.e., PROC CATMOD) in SAS, but the use of this procedure for LCA is severely hampered by the inability of PROC CATMOD to create more than two latent classes, the lack of model diagnostics, the limiting of classifiers to binary variables, as well as the overly complex programming involved. A procedure for LCA, PROC LCA, is available in Windows-based versions of SAS 9.1. Although there have been published studies using PROC LCA, the Mplus software has become the gold standard for LCA, due to the simplicity in programming language, expansive literature on its various algorithms, extensive features for model-building not available in other software packages and its flexibility through implementation of the features of Muthen's well-developed generalized latent variable modelling framework[134,135]. Currently, no Unix-based version of Mplus exists. This required data, in the form of aggregated output tables, to be transferred from HealthSys to another (equally secure) protected MCHP server, where Mplus was installed. In accordance with

MCHP policy, all cells in the outputted tables containing fewer than six observations were suppressed.

An illustration of cross-classification is illustrated in Tables 1 and 2. Table 1 displays a line-listing of a fictional dataset which includes the variables ID, sex and diabetes (DM) status. Table 2 shows the fictional dataset cross-classified by sex and DM status. As can be seen, when data are categorical, it is possible to preserve information from an entire dataset in this manner, when frequency weights are applied to each cross-classification pattern.

Table 1: Example of original subject-specific dataset

ID	Sex	DM
1	Male	No
2	Male	No
3	Male	No
4	Male	No
5	Male	No
6	Male	No
7	Male	Yes
8	Male	Yes
9	Male	Yes
10	Female	No
11	Female	No
12	Female	No
13	Female	No
14	Female	Yes
15	Female	Yes

Table 2: Example of data cross-classified by sex and diabetes (DM) status

Sex	DM	Frequency Weights
Male	No	6
Male	Yes	3
Female	No	4
Female	Yes	2

Because of MCHP's policy regarding confidentiality of personal health information, rows of cross-classified data where the count (i.e., frequency weights) in a given cell was less than six were suppressed. To use the above illustration, only the first row of Table 2 (i.e., where the frequency weight was greater than five) could be used for analysis, once the data were transferred from the HealthSys server to a personal computer.

Therefore, *analytical cohorts* (which were a subset of the study sample) were created from cross-classified data. Cell counts are also generally referred to as "weights". To retain the maximum number of subjects in each cohort, the variables chosen to cross-classify the data had to be limited; as well, the categories of each variable had to be broad rather than narrow. As an example of the latter point, income quintiles were collapsed into two categories (the two wealthiest quintiles were combined and all remaining quintiles were collapsed). An iterative series of analyses were conducted to determine the number of variables to use, and the categories of each variable. The goal was to balance the goals of maximizing the number of subjects retained in the analysis and maintaining sufficient information to differentiate the classes in a substantive manner. One of the consequences of this manipulation was that a number of variables were grouped in different ways for Older or Younger Cohorts. The distribution of variables, stratified by age cohorts is reported in Table 3.

3.5. Statistical Analysis

Initially, the data were described using frequencies and percentages for both the Younger and Older Cohorts. To ensure models converged for both the Younger and Older Cohorts and to ensure that maximum likelihood estimation did not converge to a local minimum[133], 100 random starts, with 40 final stage optimizations were requested for each LCA model. Descriptive statistics for each class for separate model solutions, as well as probabilities of class membership are reported. LCA was performed using Mplus version 4.2[133].

3.5.1. Determination of Number of Classes

Two to eight classes were requested for each cohort. Similar to other authors, the maximum number of classes was capped at 8, because it was felt that any more than that would be would be hard to interpret[136]. Penalized log-likelihood criteria were used to enumerate the optimal number of classes in LCA. The Bayesian-Schwarz Information Criterion (BIC)[137], and the related adjusted BIC, in particular, have been shown to perform the best out of available information criterion[115,138-141]. Like other information criterion, a smaller value for BIC across models suggests better model fit.

A likelihood ratio test (LRT), a common procedure for testing fit for nested models, is not asymptotically distributed as a χ^2 statistic when comparing nested models with different numbers of classes in LCA[138]. The Lo-Mendell-Rubin (LMR) test[142,143] is an approximation to the LRT to assess whether there is a statistically significant improvement in fit when one more class is considered. Although the LMR test has shown good properties with respect to guiding the enumeration of classes in LCA[144], other researchers have questioned its validity[145]. Research by Nylund et al.[138] suggest that the bootstrap likelihood ratio test (BLRT), where bootstrap samples are used to empirically derive the distribution of the LRT test[146], shows great potential in the enumeration of classes in LCA. Although the BLRT is available in Mplus software, it was unavailable for this study due to the weights applied in the analyses.

Thus, because of the consistency in the literature regarding the superiority of the BIC, and due to the BLRT not being available for weighted analyses, BIC, in combination with the LMR test was the main index used to enumerate classes.

3.5.2. Other Grouping Methods

Although other grouping or clustering methods, such as cluster analysis, discriminant function analysis (DFA) or factor analysis (FA) can be used to develop typologies, LCA was chosen over these methods for several reasons. There is no evidence that suggests users of ERs can be distinguished from each other on a quantitative basis; in fact, most of the available evidence points to qualitative, or discrete differences (e.g., high psycho-social morbidity) between users. Thus, a technique like FA is not an appropriate choice. Second, manifest indicators are categorical in nature, precluding the use of FA and DFA. Third, an advantage LCA has over cluster analysis is that the available criteria for testing hypotheses about, and determining the optimum number of classes (e.g., BIC) make model selection more precise [32,50,115,120,133,135]. Moreover, results from cluster analysis are known to be highly dependent on the linkage specified, choice of similarity measure, and clustering method [147-149], thus introducing a degree of arbitrariness when conducting analyses. Fourth, methods such as DFA require *a priori* defined groups, while LCA does not require groups to be defined prior to analysis. Finally, LCA allows the predicted probability of membership in classes to be calculated, based on endorsement of clustering variables.

3.6. Validation of Latent Classes

The decision about the number of classes in LCA is of critical importance. The goal of LCA is to uncover heterogeneity in a sample, which is inferred empirically through available data. The number of classes is not known *a priori* because there is no "gold standard". Therefore, internal and/or external validation has been recommended to increase confidence in the researcher's ability to generalize the results to the population from which the sample was drawn[147]. The concept of validation has been strongly advocated as an important step in the use of other statistical techniques, such as regression modelling, by authors such as Harrell[150].

For internal validation, re-sampling techniques are used to draw observations from the original sample. The three primary techniques for sub-sample creation are split-sample, cross-validation, the jack-knife and bootstrapping[150]. Split-sample validation involves randomly splitting the sample into two separate subgroups, while cross-validation requires splitting the original sample into any number of subgroups (i.e., *folds*). The jack-knife and bootstrapping requires the generation of a large number of datasets (i.e., greater than 1000) from the original dataset, whereby datasets created by the jack-knife method randomly leave out an individual, while bootstrapping involves creating datasets by sampling *with replacement* (i.e., an individual can be sampled more than once) from the original dataset.

Conversely, external validation involves the use of a sample drawn from a different population[151,152]. The key issue for external validation is generalizability, or the ability to generalize the results from one population to another[151,152]. Justice et al. suggest that generalizability can be thought of comprising two components: reproducibility and transportability[151]. Transportability can be further broken down into: historical (i.e., comparison of cohorts from different historical periods), geographic (i.e., cohorts from different geographical areas), methodological (i.e., cohorts collected through different sampling methods) and spectrum (i.e., cohorts with different underlying conditions or health status)[151].

Once internal or external validation (or both) has been decided, the parameters (e.g., coefficients from regression modelling) or outcomes (e.g., probabilities) from the original "training" sample are compared to those from a validation sample. The fit of the model developed on the training sample is evaluated for the validation sample[153]. Quantitative measures of performance include calibration, discrimination and accuracy[151,152,154]. Most of the literature on validation has involved the use of regression models[150,154]. With respect to LCA, results from an analysis can be validated by a group of techniques that fall under the umbrella of what has been called *confirmatory LCA*, which is analogous to confirmatory factor analysis[50]. McCutcheon notes that in confirmatory LCA, either conditional, or latent class probabilities from one sample can be confirmed in another sample[50], using similar methodology to that of structural equation modelling[113].

In this study, a historical validation was conducted, using the approach suggested by Aldenderfer[147] and others[136]. Specifically, the model results obtained for the study sample were validated by repeating the LCA using data from a validation sample, which was defined using the same inclusion and exclusion criteria but applied to data from FY 2001/02 and 2002/03. Three-year definitions for physical and mental health conditions were defined using data from FYs 1999/00 to 2001/02. Geography, income quintiles, ADG groupings, hospital and physician visits and continuity of care measures were defined using data from FY 2002/03.

4. Chapter 4: Results

4.1. Study Sample Characteristics

In total, 143,584 ER users were included in the study sample. Predisposing, enabling and need characteristics are described in Table 3. These data are also presented separately for the Younger (n=108,714) and Older (n=34,870) Cohorts.

4.1.1. Predisposing and Enabling Characteristics

Study sample: The average age of ER users in the entire study sample was 48.0 years (SD: 20.7; median: 45.0), with almost half (49%) under the age of 45 years. The study sample included slightly more females (53%) than males. Approximately two-thirds (61%) resided in the suburbs of Winnipeg. One-third (33%) of ER users were in the two wealthiest urban quintiles.

Younger Cohort: The average age of ER users in the Younger Cohort was 38.5 years (SD: 13.3; median: 38.0), there was equal representation of females (50%) and males (50%). Approximately two-thirds (60%) resided in Winnipeg's suburbs.

Older Cohort: The average age of the Older Cohort was 77.6 years (SD: 7.7; median: 77.0). A higher proportion of the Older Cohort (60%) than of the Younger Cohort was female. Fewer than one-third (31%) of Older Cohort members resided in the Inner Core, while 28% were in the two wealthiest income quintiles.

4.1.2. Need Characteristics

Study Sample: Arthritis was the most prevalent of the physical conditions that was investigated (29%). IHD (11%) and diabetes (9%) were less common. Approximately one third of the study sample had at least one diagnosed mental disorder, with depression (21%) being the most common. Dementia (4%), personality disorders (2%), and schizophrenia (2%) were less prevalent. Comorbid conditions were common; the mean number of ADGs was 4.3 (SD: 2.9; median: 4.0).

The mean number of ER visits in the 365 days prior to the last ER visit in FY 2003/04 to FY 2004/05 was 1.8 (SD: 2.0; median: 1.0). Almost two-thirds of the study sample (64%) had only one visit and 4.1% had five or more visits. The mean number of physician visits in FY 2004/05 was 8.0 (SD: 7.8; median: 6.0) and about half (53%) of the study sample had six or fewer visits. Hospitalizations in FY 2004/05 were less common; over 80% had no hospitalizations. More than one-half (57%) of the study sample had continuous physician care.

Younger Cohort: Arthritis was the most prevalent diagnosed physical condition (24%). Diabetes (6%) and IHD (4%) were the least prevalent conditions. Approximately one third (30%) of the Younger Cohort had at least one diagnosed mental disorder, with depression (22%) being the most common. Anxiety (9%), substance abuse (8%), personality disorders (2%) and schizophrenia (2%) were less prevalent; diagnosed dementia was rare (1%). The mean number of ADGs was 3.8 (SD: 2.7; median: 3.0).

The mean number of ER visits in the one-year period prior to the last ER visit was 1.7 (SD: 2.1; median: 1.0). Two thirds of this Cohort (66%) had only one visit and 4% had five or more visits. The average number of physician visits was 6.9 (SD: 7.4; median: 5.0). Over 90% of the Younger Cohort had no hospitalizations in a one-year period. Over half (53%) of the Younger Cohort had continuous physician care.

Older Cohort: Close to half (47%) of the Older Cohort had diagnosed arthritis. The prevalence of other physical conditions was high: 33% had IHD and 17% had diabetes. The proportion of Older Cohort members with at least one diagnosed mental disorder was similar to that of the Younger Cohort (31%). Depression (18%), dementia (14%) and anxiety (7%) were the three most commonly diagnosed disorders, while substance abuse (3%), schizophrenia (1%) and personality disorders (1%) were less common. The mean number of ADGs was 5.8 (SD: 3.0; median: 5.0).

The mean number of ER visits in the one-year period prior to the last ER visit was 1.9 (SD: 1.7; median: 1.0). Approximately 55.9% had only one visit to the ER in a one-year period. The average number of physician visits was 11.4 (SD: 8.0; median: 10.0), with almost 90% of the Cohort having three or more visits in a year. Approximately two thirds (65%) of the Older Cohort had no hospitalizations in FY 2004/05. Almost three quarters (70%) of the Cohort had continuous physician care.

4.2. Censored Cohorts

4.2.1. Younger Cohort

Table 4 includes a comparison of predisposing, enabling and need characteristics of three censored Analytical Younger Cohorts cross-classified from the original Younger Cohort. To avoid confusion, *uncensored Younger Cohort* will be used to refer to the original Younger Cohort from this point on. The three Analytical Cohorts were developed to illustrate the effect that aggregation of different variables has on sample size when importing data from MCHP's Unix-based HealthSys system to a Windows-based platform. As more variables are aggregated, sample size increases from Analytical Cohort #1 (75%; n = 80,795) to Analytical Cohort #3 (86%; n = 92,511). As explained in Section 3.5., increasing the sample size of the Analytical Cohorts comes at the cost of broader characterisations of the study sample. Specifically, instead of characterising the sample by individual mental disorders (i.e., the presence/absence of anxiety, dementia, depression and substance abuse), as in Analytical Cohort #1, Analytical Cohort #2 aggregates this information into one variable: the presence/absence of any mental disorder. This has the effect of increasing sample size from 80,795 (74.7% of the uncensored Younger Cohort) to 89,860 (83%). Similarly, by not including IHD as a cross-classifying variable, the sample size in Analytical Cohort #3 was 92,511 (86%). Analytical Cohort #3 was used in subsequent latent class analyses as it offered the largest sample size (i.e., compared to Cohorts 2 & 3), without significant loss of precision.

Table 4 reports the unadjusted ORs for univariate comparisons between each censored Analytical Cohort and the uncensored Younger Cohort. The focus of the rest of this section will be on describing the results for the third Analytical Cohort, as this was the Cohort used in LCA. Compared to the uncensored Younger Cohort, Analytical Cohort #3 differed significantly on all variables, with the exception of sex (p=.30) and income group (p=.58). Specifically, the Analytical Cohort had significantly more individuals 25-44 years of age (OR:1.06, 95% CI:1.03, 1.08), fewer people residing in the outer core areas of Winnipeg (OR:0.52, 95% CI:0.49, 0.55) and more individuals residing in the suburbs (OR: 1.04, 95% CI:1.02, 1.06). Individuals in the Analytical Cohort were significantly less likely to have arthritis (OR: 0.86, 95% CI:0.84, 0.88), diabetes (OR: 0.51, 95% CI:0.49,0.54), any mental health condition (OR: 0.65, 95% CI:0.63, 0.66) and 5 or more comorbid conditions (OR: 0.91, 95%CI:0.88, 0.93). Finally, individuals in Analytical Cohort #3 tended to have fewer individuals with 5+ ER visits (OR: 0.31, 95% CI:0.29, 0.33), 12+ physician visits (OR: 0.88, 95% CI:0.86, 0.90) and 2+

hospitalizations (OR: 0.29, 95% CI:0.27, 0.31), and were more likely to have a regular source of care (OR: 1.04, 95% CI:1.02, 1.05).

Similar significant differences were observed in Analytical Cohorts #1 and #2; given the large sample size of this study, significant differences were not unexpected. Practically speaking, as sample size increased (from Analytical Cohort #1 to Analytical Cohort #3), the difference in magnitude (as measured by ORs) between the Analytical Cohort and the uncensored Younger Cohort diminished for all variables (with the exception of two) that were statistically significant. For example, the odds of having arthritis in Analytical Cohort #1 were 0.76 times that of the odds for the uncensored Younger Cohort members; this figure increased to 0.86 in Analytical Cohort #3. The exceptions were continuity of care (ORs increased from 1.03 to 1.04) and age, where the odds of inclusion of the 25-44 age group increased from Analytical Cohort #1 to Analytical Cohort #3. However at the same time, increasing sample size had the effect of decreasing differences in the 45-64 age group, so that the odds of inclusion of this age group into Analytical Cohort #3 was statistically indistinguishable from the odds for the uncensored Younger Cohort.

4.2.2. Older Cohort

Table 5 contains the unadjusted ORs for two Analytical Cohorts drawn from the uncensored Older Cohort. Analytical Cohort #2 (77% of uncensored Older Cohort) was used in LCA because this Cohort offered the optimal sample size, although it did not reach the target of 80%. Sample size could not be increased without substantially reducing the number of variables used to cross-classify the Cohort. With the exception of the presence of arthritis, Analytical Cohort #2 significantly differed from the uncensored Older Cohort on all variables used for cross-classification. Analytical Cohort #2 contained fewer individuals that were 85 years or older (OR: 0.76, 95%CI:0.73, 0.80), and contained more females (OR: 1.14, 95%CI:1.10,1.17). Individuals included in Analytical Cohort #2 were more likely to reside in suburban Winnipeg (OR: 1.10, 95%CI:1.07,1.14), and belong to the lowest three quintiles (OR: 1.10, 95%CI:1.06,1.14). Analytical Cohort members were less likely to have any mental disorders (OR: 0.80, 95%CI:0.78,0.83), and were less likely to have any individuals with 8 or more comorbid conditions (OR: 0.91, 95%CI:0.87,0.95). In terms of utilization, Analytical Cohort #2 was less likely to have individuals with 2+ ER visits (OR: 0.87, 95%CI:0.84,0.90), one (OR: 0.69, 95%CI:0.67,0.72) and 2+ (OR: 0.57, 95%CI:0.54,0.60) hospitalizations, while having more individuals that had 6-11 physician visits (OR: 1.12, 95%CI:1.08,1.17) and 12+ physician visits (OR: 1.20, 95%CI:1.15,1.25). Finally, individuals in Analytical Cohort #2 were more likely to have a regular source of care (OR: 1.33, 95%CI:1.28,1.37).

4.3. Latent Class Analysis

LCA results are reported in terms of estimated posterior probabilities. Figure 2 reports the BIC for both Cohorts as the number of classes requested in the LCA is increased from 2 to 7. The BIC decreased as the number of classes was increased, although the rate of decrease levelled off as the number of classes got larger. For the Younger Cohort, moving from two to three classes decreased the BIC from 1,459,631 to 1,421,542, or by 2.6%. Increasing the number of classes from six to seven decreased the BIC by only 0.4%. Similarly, moving from two to three classes in the Older Cohort resulted in a 1.9% decrease (from 420,435 to 412,590), while BIC decreased by 0.4% when the number of classes was increased from 6 to 7 classes. Both naïve and adjusted LMR tests were statistically significant (p <.001) as the number of classes were increased for the Younger and Older Cohorts, suggesting an improvement in model fit. Although the BIC continued to decrease as the number of classes requested was increased (up to 8), the decrease in BIC was minimal after 7 classes (i.e., less than 0.4%). As suggested by Monga et al.[136] who invoked the principle of parsimony in choosing the number of classes in LCA, the remainder of this section will describe the classes derived from the LCA for the 7-class solution (as opposed to the 8-class solution) to ease the interpretation of classes. Younger Cohort results will be first discussed, followed by results for the Older Cohort. For convenience, classes were arranged by frequency of ER use, with class 1 comprised of those that had the most ER use, and class 7, the least (see Table 6).

4.3.1. Younger Cohort

Members of class 1 (11%, n=10,236) were most likely to be the oldest of all 7 classes, with a 65% probability of being between 45-64 years of age. Members of this class had a 60% probability of being female. There was a 72% probability of members residing in inner core areas, and a 100% probability of residing in the least wealthy neighbourhoods. The probability of an arthritis diagnosis was highest in this class (57%), as was the probability of diagnosis of diabetes (12%) and any mental disorder (60%); members had a 91% probability of having 5 or more ADGs, which was the second highest among the classes. ER use, as well as physician use was the highest among the classes, with members having a 49% probability of having 2 or more visits, and a 70% probability of visiting physicians 12 or more times in a year. Similarly, there was a 17% probability that members had 1 or more hospitalizations, which was the highest among the classes. The probability of a regular source of care was among the highest of the classes, at 62%. For these reasons above, this class was labelled *High frequency ER users with very poor health, who were old and less wealthy.*

In contrast to class 1, members of class 2 (7%, n=6,925) included some of the youngest members of the Younger Cohort. There was a 31% probability of members being 17-24 years, and an 81% of being female. Both probabilities were highest among all classes. There was a 63% probability of members residing in the inner core; similar to class 1, all members resided in the least wealthy neighbourhoods. The probability of an arthritis diagnosis was relatively low (10%), and diabetes was non-existent; members had a 42% probability of having a diagnosed mental disorder. Comorbidity was highest in this class, with members having a 100% probability of having 5 or more ADGs. Like class 1, ER use was highest in this class, with a 50% probability of 2 or more ER visits in a year's time. Physician use and hospitalizations was high; there was a 30% probability of members having 12 or more visits in a year, and a 23% probability of 1 or more hospitalizations. Probability of having a regular source of care was lowest in this class, at 38%. This class was labelled *High frequency ER users with many comorbidities, who were younger and female without a regular source of care.*

Class 3 members (15%, n=14,263) were the second oldest of all classes, with a 57% probability of being 45-64 years. There was a 68% probability of members being female; almost all members (98%) lived in the suburbs, with a 71% probability of residing in the wealthiest neighbourhoods. Health seemed to be poor in this class, although not to the extent of class 1. The probability of an arthritis diagnosis was 34%, diabetes 5%, and a diagnosed mental disorder, 35%. Members had a 69% probability of having 5 or more ADGs. ER use was moderate in this class, with a 34% probability of 2 or more ER visits in a year's time. Physician use and hospitalizations were high: there was a 42% probability of members having 12 or more visits in a year, and a 14% probability of 1 or more hospitalizations. Probability of having a regular source of care was, along with class 1, the highest among the classes, at 62%. Members of this class were similar to class 1, with the main exception being that they were more likely to reside in more affluent areas. This class was labelled *Moderate ER users with poor health, who were older, female and more affluent.*

Similar to class 3, class 4 members (20%, n=18,487) had multiple chronic diseases; however, members of this group tended to be more middle-aged, with a 53% probability of being 25 to 44 years. There was an equal probability of being male or female, with a 66% probability of members residing in the inner core, and no members living in Winnipeg's wealthiest areas. There was a 16% probability of members being diagnosed with arthritis, and a 5% probability of diabetes. The probability of having a diagnosed mental disorder in this class was 27%; comorbidity was moderately high, with a 97% probability of membership having two to four ADGs. Use of ERs was moderate as well, with a 31% probability of two or more visits in a year's time. Use of physicians and hospitalizations was moderate, with a 64% probability of 3 to 6 physician visits, and a 6% probability of having one hospitalization in a year's time. There was a 59% probability of members having a regular source of care. This class was labelled *Moderate ER users with poorer health, who were middle-aged and less wealthy.*

The characteristics of Class 5 (14%, n=13,066) were substantially different from previous classes discussed. Members tended to be younger, with a 58% probability of being 25-44 years. There was a very high likelihood of male membership in this class (i.e., 74% probability), a 63% probability of residing in the inner core, and a 100% probability of not living in the wealthiest neighbourhoods. The probability of arthritis (7%), having a mental disorder (15%) was low, and of having diabetes, non-existent. The likelihood of having a diagnosed comorbidity was the lowest among the identified classes, with a 90% probability of having 0-1 ADGs. ER use was low: the probability of having only 1 visit to the ER was 77% in this class. Likewise, physician use was low (i.e., 95% probability of 0-2 visits), while no hospitalizations were recorded in this class. There was a 40% probability of members having a regular source of care. This class was labelled *Healthy younger males living in the inner core who were low ER users.*

Members of class 6 (21%, n=19,138) were very similar to class 4, with the most obvious exception being that class 6 members were far more likely to reside in the suburbs (i.e., 95% probability), and more likely to live in the wealthiest areas of Winnipeg (i.e., a 70% probability). As well, ER use in this class was much lower. Thus, this class was labelled *Low frequency ER users with poorer health, who were middle-aged and affluent.*

Echoing the similarities between class 6 and class 4, the characteristics of class 7 (11%, n=10,396) were very similar to class 5. The main differences being that members from class 7 were more likely to be from the suburbs (i.e., 96% probability) and to be low frequency users of ER, with an 85% probability of visiting an ER only once in a year's time. This class was labelled *Healthy suburban younger males who were low ER users*

Table 7 summarizes the key predisposing, enabling and need characteristics of each class for the Younger Cohort.

4.3.2. Older Cohort

Table 8 shows the characteristics of the various classes derived from LCA for the Older Cohort. In the same way as was reported in Table 6, classes will be described individually in decreasing order of ER visit frequency.

Class 1 comprised 10% (n=2,584) of the censored Older Cohort. Members of this group had a 72% probability of being 75 years or older, and a 58% probability of being female. Members were most likely to reside in the suburbs, although they only had a 19% probability of living in the wealthiest neighbourhoods of Winnipeg. Need characteristics were high in this class: members of this group were at the second highest probability of being diagnosed with arthritis (56%) or any mental health condition (35%). Moreover, they had a 90% probability of having 8 or more ADGs, second highest among the 7 classes. Practically all members of this grouping had two or more visits to an ER, which was highest among all classes. Physician utilization was the second highest as well (e.g.., 84% probability of 8 or more visits in a year), while the probability of having 2 or more hospitalizations (68%) was highest. The probability of having a regular source of care (81%) was highest among all classes. This class was labelled *Older, intense resource users.*

Class 2 members (15%, n=4,079) had a 39% probability of being 65 to 74 years of age, 67% probability of being female, and a 74% chance of residing in the suburbs (74%). Of all classes, members in class 2 had the highest probability of having arthritis (68%), a mental health condition (43%) and eight or more ADGs (100%). There was a 47% probability of having two or more ER visits in a year's time; physician utilization was extremely high in this class (i.e., 100% had 12 or more visits in a year), although hospitalizations were on the low side (i.e., 28%

probability of having only one hospitalization). It was this low use of hospitalizations that distinguished class 2 from class 1; thus, this class was labelled *Older, intense physician users, with a high burden of need.*

Members of class 3 (6%, n=1,654) had the highest probability of being over 85 years (38%) and female (72%). There was a 63% probability of members residing in the suburbs, although with only a 6% probability of being located in the wealthiest Winnipeg neighbourhoods. There was a moderate probability of having arthritis (33%), and a mental health condition (21%); while members had an 89% probability of having four to seven ADGs. ER use was moderate, with a 43% probability of two or more visits in a year's time. Physician visits were low in this class, with a 53% probability of having more than six annual visits; paradoxically, hospitalizations were high in this class, with a 12% probability of two or more hospitalizations, which was the second highest among all classes. The probability of continuity of care was 80%. This class was labelled *Older, high hospital users who were female.*

Class 4 (24%, n=6,574) exhibited similar characteristics to Class 2, with notable differences including a higher probability of including members from the inner city (48%), substantially fewer comorbidities, and decreased physician visits and hospitalizations. Members of this class were at a 38% probability of having two or more ER visits in a year. This class was labelled *Older, moderate physician users from the inner core, with a high burden of need.*

The characteristics of class 5 (18%, n=4,912) were somewhat distinct from previous classes discussed. Relatively speaking, members of this class were younger, with a 54% probability of being under 75 years and the highest probability (51%) of being male. All members were from the suburbs, and there was a 67%

probability of being from Winnipeg's wealthiest areas. The probability of having arthritis was moderate (46%), while diagnosed mental disorders were low (18%). Members had a 32% probability of having two or more ER visits, while compared with the rest of the classes, physician visits was moderate, with a 43% probability of having 12 or more annual visits. The likelihood of hospitalizations was also low, as members had an 84% probability of having no hospitalizations. This class was labelled *Younger affluent males, with moderate resource use.*

Members of class 6 (17%, n=4,578) had a 40% probability of being under 75 years of age, a 66% chance of being female, and a relatively high likelihood of residence in the inner core (47%). The probability of diagnosed arthritis (29%) and mental disorders (20%) were low, as were comorbidities. Members had a 23% probability of having two or more ER visits. Physician visits and hospitalizations were substantially lower in this class, with a 67% probability of 5 or fewer physician visits and a 99% probability of no hospitalizations. This class was labelled *Younger and poorer, with lower resource use.*

The characteristics of class 7 (10%, n=2,621) were similar to class 5, with the most substantial differences including fewer comorbidities (i.e., 91% probability of 0-3 ADGs), fewer physician visits (i.e., 68% probability of 0-5 visits) and practically no hospitalizations (i.e., 98% probability of 0 hospitalizations). This class was labelled *Younger affluent males, with low resource use.*

4.4. Validation Sample

The validation sample was comprised of 126,843 individuals who visited a WRHA ER between FY 2001/02 and FY 2002/03. The validation sample was stratified by age into two cohorts, with Younger Cohort members comprising 77.5% of the total validation sample.

Table 10 displays the characteristics of the validation sample, and the Younger and Older Cohorts derived from this sample. Generally speaking, the validation sample characteristics were similar to the study sample characteristics. One notable difference was that the number of diagnosed diabetes cases was lower in the validation sample than in the study sample; this was true for both Younger and Older Cohorts. For example, diabetes was present in 9% of study sample members, compared to 6% of the members of the validation sample. Another difference was that there was slightly less frequent use of ERs in the validation sample, independent of stratification into Younger and Older Cohorts. Approximately 66% of the validation sample had only one visit to the ER, compared to 64% of the study sample. However, the average number of ER visits in the validation sample (1.7; SD: 1.6) was similar to the study sample's overall average (1.8; SD: 2.0). Similarly, the validation sample had slightly fewer hospitalizations than study sample members, independent of stratification.

4.5. Comparison of LCA Results of Validation Sample

Figure 3 shows the BIC values associated with the LCA models for both Younger and Older Cohorts of the validation sample.

4.5.1. Younger Cohort

Table 11 displays the 7 class solution from LCA undertaken on the censored Younger Cohort, compared to the 7 class LCA solution from the study sample. Similar to previous sections, classes are ordered in descending order of ER visit frequency.

Class 1, whose members comprised the highest ER users accounted for 5% of the validation sample (compared to 11% in the study sample). Members of class 1 in the validation sample tended to be older (51% probability of belonging to the

45-64 year age group), although unlike the study sample, this class was not the oldest of the 7 classes enumerated from the validation sample. Like the study sample, members of class 1 of the validation sample were mostly female (69% probability), had the highest probabilities out of all 7 classes of living in the inner core (79% probability); and having a diagnosis of arthritis (61% probability), diabetes (7% probability) and a mental health condition (80% probability). As well, mirroring the study sample, this class had the highest probability of members having fiveor more ADGs (98% probability), five or more ER visits (13% probability), 12 or more physician visits (90% probability) and two or more hospitalizations (5% probability). Unlike the study sample, however, members of this class had a relatively low probability of having a regular source of care (46%).

Characteristics of the members of classes 2, 3, 5, 6 and 7 in the validation sample were remarkably similar to those of the study sample. Class 2 members were the youngest out of all classes, had the highest probability of being female, were more likely to be residing in the inner core, had low probability of having arthritis or diabetes, and had moderate levels of mental health and resource utilizations. Class 3 was almost exclusively older, affluent females that had poor health and moderate ER use. One difference between validation and study samples was that class 3 was the oldest class in the validation sample, whereas in the study sample class 1 was the oldest. The main difference in class 5 between the validation and study samples was that class 5 members in the validation sample had higher levels of comorbidity and higher physician utilization. The higher levels of comorbidity and physician utilization in the validation sample, compared to the study sample was also observed in classes 6 and 7.

The one class where there were some discrepancies was class 4. Although similar with respect to male to female ratio (50:50), area of residence and income quintile, the validation sample was much older, had greater levels of arthritis, mental health and overall comorbidity. Physician utilization was substantially higher, but hospitalizations somewhat lower. Members of class 4 in the validation sample had higher levels of continuity of care.

4.5.2. Older Cohort

Table 12 compares 7-class solutions for both the validation and study samples in the Older Cohort. Overall, there was less consistency in the enumerated classes in the Older Cohort, compared to the Younger Cohort. Classes which showed the most consistency will be discussed first, followed by a brief discussion of those classes which differed between the two samples.

Classes 6 and 7 showed the most consistency between samples; both these classes were characterized by younger age, lower resource use and relatively better health. The main differences in both classes include less mental health and more comorbidity in the validation sample. As well, physician utilization was lower in class 6 and higher in class 7 for the validation sample.

The characteristics of class 1 (the highest users of ERs) were similar with respect to age, area of residence and area-level income, as well as ER, physician and hospital utilizations. However, the validation sample of this class contained more females, had higher levels of arthritis and mental health, while at the same time having lower levels of comorbidity than the study sample. The increased levels of arthritis and mental health, and lower comorbidity in the validation sample, compared to the study sample was also observed in classes 2 and 3. Members of class 2 from the validation sample were also more likely to have resided in the inner core of Winnipeg, while members of class 3 from the validation sample were more likely to have been older and female. Moreover, members of class 3 from the validation cohort used more physician resources, while having substantially fewer hospitalizations. Classes 4 and 5 differed substantially on almost all variables, with the exception of the ER and hospital utilization variables.

5. Chapter 5: Discussion

Given the high political and economic costs of delivering health care in Canada[11,155-159] and the high visibility of ER use, it comes as no surprise that ER use, in the words of Guttman et al., "...present(s) policy challenges to legislators...medical staff, and patient advocates" (p.1090)[88]. The populations that are frequent users of ER are typically the ones that are hardest to reach. That is, the highest-risk, and most marginalized populations tend to receive their care regularly from ERs[16,160-162].

This study reasoned that further understanding of ER use can be achieved by examining use within the context of predisposing, enabling and need characteristics[57,163]. From this very broad perspective, this study was designed to uncover how these forces interact in the real world, using an empirically-driven method to segment the ER user population. Clarification of the heterogeneous ways predisposing, enabling and need characteristics interact in various situations may reveal some mutable aspects of these relationships that can lead to over- (and under-) utilization of some resources. This knowledge ultimately can help to inform gaps in service delivery in different sectors of the health care system.

This concluding section will discuss the various classes identified from LCA, within the context of the known literature. In order to summarize the abundance of data, the discussion will be separated into predisposing, enabling and need sections. Except where indicated, proportions and probabilities reported are from the study sample. This section will conclude with discussions on the usefulness of LCA as an analytical tool in this sample, as well as policy implications of the study findings.

5.1. Summary of Results

5.1.1. Predisposing Characteristics

Increasing age has been shown to be positively associated with ER use in both younger and older populations[43]. The results of this study suggest that although frequent ER use was often associated with older age, older age was not a sufficient explanation for ER use. The results also suggest that male sex was associated with fewer ER visits. In the Younger Cohort, both classes 5 and 7 were low resource users, and were the classes that had the highest probability of including males. This finding runs somewhat counter to what has been found in the literature, that the most frequent ER users are males living in poor socioeconomic conditions with high morbidity and psychosocial needs[89]. Since censoring of the Analytical Cohorts filtered out the most extreme ER users (both in frequency of use and need), this study may not have included the group of ER users that were the most extreme users. As well, some ER researchers have separated out those individuals that are very low users of health care services (typically less than three physician visits in a year), with the logic being these individuals are qualitatively distinct from the rest of the population[43].

5.1.2. Enabling Characteristics

Residence in the inner core of Winnipeg, and living in less wealthy neighbourhoods were both associated with a high burden of illness and resource utilization in classes 1 and 2 of the Younger Cohort. The relationship between low socioeconomic status and poorer health is well-documented in both the general health services and the ER literatures[34,121,122,130,164]. However, as suggested by the characteristics of classes 3 and 5 the association between less wealth and poorer health is not necessarily a straightforward one. This was true for both Older and Younger Cohorts. To illustrate, almost all members of class 3 of the Younger Cohort lived in the suburbs, with a 71% probability of living in the wealthiest neighbourhoods. Yet the members of this class had the second highest probability of having arthritis and diabetes, while also having a high probability of being diagnosed with a mental disorder. Not surprisingly, given their diagnosed conditions, and level of comorbidity (as measured by ADGs), the members of this class were high resource users, particularly with respect to physician visits. In contrast, class 5, who had a 63% probability of living in the inner core, and a 100% probability of living in Winnipeg's least wealthy neighbourhoods, had the lowest levels of arthritis, low levels of mental health and comorbidities, and no diabetes. Consequently, their utilization of resources (including ERs) was extremely low.

5.1.3. Need

The finding that high levels of comorbidity, mental health and specific chronic disorders, such as arthritis and diabetes are associated with more frequent ER use is consistent with many studies[5,16,18,34,82,84,86,92,160-162]. Classes with high resource users were also more likely to include members with diagnosed mental health conditions. An intriguing finding from the censored Younger Cohort was in those classes that included more males (i.e., classes 5 & 7), area-level wealth and residence in the inner core were neither necessary nor sufficient to explain ER use. Both class 5 and 7 displayed similar characteristics (including low ER use), but one class (i.e., class 5) was predominantly from the inner core, while all members of the class 7 resided in the suburbs, most likely in some of Winnipeg's wealthiest neighbourhoods.

5.2. Policy Implications

The results of this study can help inform policy with respect to services offered within, and outside of ERs, as well as informing the intersection between the two. Researchers such as Rockett et al. are proponents of expansion of ER services to include screening, and delivering brief interventions for addressing mental health issues such as substance abuse[70,80]. Although this approach may be paradoxical to the intended purpose of ERs (i.e., a facility solely for acute care) for some, Rockett et al. argue that not addressing broader issues within the ER environment is tantamount to a lost opportunity for intervention, which ultimately fuels the "revolving-door" realities of ERs and the rest of the health care system. The authors point to the success of programs which screen for signs of domestic violence in ERs, as possible models to emulate[70]. That mental health diagnoses coincide with classes defined by high resource utilization in this study seems to lend weight to the argument of broader service provision within ERs.

With respect to services offered outside of ERs, some authors have suggested that a lack of access to physician resources contributes to more frequent ER use[16]. An obvious policy implication would be to then make services more accessible (however "access" is defined). However, the results of this study suggest that lack of access (as measured by healthcare utilization) is neither a sufficient nor necessary characteristic of frequent ER use. This finding aligns with previous studies of Winnipeg's ER user population[34,165], as well as of ER users in other countries[89,91,166]. It is important to note that this observation may be less pertinent to settings that lack universal health care coverage[84,92].

Some authors have suggested that fragmentation of services (and not lack of access) can explain why so many resources are being consumed by particular segments of the population[33,53]. The "disorganization" of primary care has been criticized within Canada, highlighting the need for studies to inform the reformation of health policy[167]. The results of this study can neither refute, nor confirm the question of service fragmentation. However, since members of some classes appear, in both the Younger and Older Cohorts, to be reliant on ERs for their health care, on top of already pronounced resource use suggests that some significant needs are not being met. For example, at multiple points in their health care trajectory, members of class 1 and class 2 of the Younger Cohort were assessed, evaluated and diagnosed with a multitude of health issues. Each of these points represents an opportunity for a response to health care needs. Further studies using clustering techniques such as LCA may help better define the types of services certain groups are more likely to utilize.

A frequent policy recommendation from the ER literature is to target high-resource use groups and develop interventions for these groups at the primary care, or (less commonly) secondary- and tertiary-care levels[30,84,166]. Although this is an intuitive recommendation, Dent et al., in their study of users of an inner city ER in Australia, caution that the high demands of heavy ER users may be overwhelming to primary health care services as they are presently delivered[168]. Dent et al. further advise that the majority of the heaviest ER users in their study were at some point, receivers of more focussed and intensive forms of health care services, such as those found in case-management[168].

That continuity of care was associated with both frequent and low ER users in this study, and that ER use was associated with healthcare utilization in general, suggests no simple policy recommendations. Understanding the role that mental health plays in ER use, however, may lend insight to where needs are most unfulfilled, and where gaps remain the widest. Doupe et al.[34] comment that presence of a mental health condition was the strongest predictor of regular use of ERs in this population. Researchers have proposed that investments in mental health may be an efficacious and efficient avenue to decrease health care use[9,12,59,80]. Bergh et al. theorize that frequent users have different coping mechanisms, and not necessarily more stressful life events than non-frequent users of health care[15]; this in turn suggests that poor mental health is not entirely a stochastic process, and that interventions aimed at enhancing coping skills may be effective in reducing severity of mental health complaints. A greater role played by general practitioners with respect to the diagnosis, treatment, and referral (to specialized psychiatric services) of cases with mental health disorders has been demonstrated in recent years[169,170], although this may not necessarily be the case for substance abuse. Understanding the direct and indirect effects of mental health and substance abuse on ER utilization, and its relation to physical need, as well as how having a regular source of care can mediate, or be mediated by these psychosocial issues can further inform policies of integration, and mental health training for general practitioners. Ultimately, this may lead to better detection and treatment of physical disease.

The paradoxical examples of the effects of area-level wealth and area of residence on health serve to illustrate the importance of accounting for context, as well as the complexity in measuring and specifying area-level effects[171,172].

Ecological effects (like area-level wealth) can not be assumed to be the same across different subpopulations. Ethnicity, marital status and occupation may also be plausible explanations independent of, or in conjunction with, area-level wealth[171-174]. Alternatively, area-level wealth (or any omitted variable) may be a proxy for other, unobserved processes[171-174]. Further research to clarify the reasons for this observed heterogeneity is warranted. Diez Roux in particular, with respect to the investigation of area-level effects on health, has commented on the need for assigning specificity, consideration of spatial scale, and clarifying the effects of cumulative exposure[171].

5.3. Future Research Directions

One useful feature of LCA is the characterization of *normative classes*; that is, classes that do not seem to be burdened with poor health nor consume significant resources. The normative class serves as a useful reminder that although a substantial body of literature has developed regarding the use of ERs as a substitute for insufficient primary care, and in characterizing the overburdened populations that frequently utilize this resource [34,43,97,99,175], oftentimes, the use of ERs is motivated by no more complex a construct than simply having an ailment (real or perceived), and the ER being a convenient resource for health care. The results of this study suggest that in the Younger Cohort, these normative groups are characterized by younger age, low levels of comorbidity and especially in those groups more likely to include males, low physician utilization. An interesting avenue for exploration would be to clarify the degree membership in these normative classes is due to immutable characteristics such as sex or genetics, and how much is due to factors that can be influenced through more systemic means.

What is clear is that ER use, in some situations, is driven by more complex reasons than mere availability (or unavailability) of other health resources. More research is needed to clarify the relationship between overall health care and ER use, particularly in clearly delineating the context in which this relationship is seen to be either negative or positive.

Similarly, although the bulk of the ER literature has consistently found a strong relationship between low socio-economic status and high ER use[34,165], this study's results suggest that high ER and health services use is also observed in those that live in wealthier neighbourhoods. Although understanding the socioeconomic gradient between health outcomes and socioeconomic position has been of vital importance in the formation of policy to reduce inequalities in health care delivery[10,121,124,176], a potentially useful direction for research would be to characterize those exceptional individuals that are at poorer health in relatively wealthy areas, and to examine reasons how and why individuals remain healthy despite living in areas of low socioeconomic standing. The inherent assumption here is that low utilization is a proxy for better health; it may be that low utilizers have poor health but cannot, or are unwilling to seek formal health care, or their health care use is somehow systematically unaccounted for in the provincial administrative datasets. As well, it is important to reiterate that for the most part, the most extreme users of ER are unaccounted for in this analysis.

5.4. Strengths and Limitations

The issue of non-standard definitions of frequent use has been well-discussed[30,89,177], although there have been attempts to derive a more objective basis for this classification. For example, Locker et al. suggest that the basis for categorization into either group should be made by assessing whether the number of ER visits can be considered random (or not), through the use of statistical means, such as comparing number of visits to the Poisson distribution[30]. However, this is still a narrow view of ER users. This study extends the scientific literature on ER users by expanding the available analytical tools used for empirically deriving and describing different subgroups of ER users.

Consistent with observations by Huang et al.[31], as the data in this study show, heterogeneity exists not only in these more moderate user groups, but in those groups that would be classically defined as frequent users as well. Clearly defining and articulating heterogeneous groups may help inform policies designed to optimize existing health care delivery, as well as in the design of alternative delivery systems. The multifactorial nature of the determinants of ER use has been written widely [89,91,98,177]; thus, it makes intuitive sense that users should be described (and categorized) in a multidimensional manner. The usefulness, to the analyst, of a focus on normative classes has been discussed; similarly, the usefulness of a more nuanced description of ER users is a major strength this study. Complexity of needs is not just confined to those living in less wealthy neighbourhoods, and neither is more frequent ER utilization.

One of the more vexing issues in the use of LCA is whether or not enumerated classes reflect genuine subgroups that may be generalizable to other locales or are statistical artefacts, driven by characteristics of a particular dataset. The use of a separate validation sample to validate the study sample is another strength of this study. For the most part, this study demonstrated that classes were robust between the two samples, although this was truer for the Younger (vs. Older) Cohort.

This study had several limitations. The most obvious limitation is in the potential bias introduced by censoring of data. Comparisons of censored to uncensored data suggest that the censored Analytical Cohort did not include the more afflicted members of the population of ER users, as measured by need characteristics such as presence of illnesses and health care utilizations. By definition, individuals in this extreme population were a rarity, and thus were censored from the Analytical Cohort when data were outputted from HealthSys. Increasing the sample size by broadening categories used for cross-classification alleviated the differences somewhat, and was more successful in the Younger Cohort. However, the fact remains that the results of this study may not be generalizable to the entire population of ER users in Winnipeg, but perhaps only to those types of ER users that were less rare. Further analyses which include this censored group should be conducted. However, as ER research tends to narrowly focus on the most extreme users, and thus obfuscating some equally important groups of ER users, the results from this study are still useful in characterizing the full spectrum of ER use.

A second limitation of this study is that WRHA ERs were grouped as though they were a homogeneous entity, with the assumption that the populations visiting separate ERs were indistinct from each other. Although similar in terms of morbidity characteristics, Doupe et al. have shown some clear differences in demographic and utilization characteristics by ER location in this population[34]. Future analyses should take the heterogeneity in populations between ERs into account. A third limitation lies in the use of the behavioural model as a theoretical framework for this research. A longstanding criticism of this model is that it overemphasizes the extent to which individual determinants (i.e., need) are associated with utilization; that is, contextual/structural characteristics (e.g., physician availability, satisfaction with care, community characteristics, etc.) are usually not fully incorporated into the model[7,11,19,27,59]. This study did not explicitly model contextual/structural characteristics, other than geography. The fourth, and related limitation is that even with a framework to guide variable selection, ultimately, our choice of variables influenced which groups emerged from the LCA. However, many authors have commented on the valuable role that LCA and other grouping techniques (e.g., cluster analysis) have as exploratory, and thus, hypothesis-generating tools[178]. Thus, the ultimate test of usefulness of this technique is confirmation of classes derived from this study in other samples.

For the fifth limitation, the use of administrative data has been criticized on the grounds of high rates of misclassification and measurement error[179,180]. Although case definitions used in the study have been validated, this criticism is still warranted. However, other methods of data capture, such as chart review or population-based surveys, also have their limitations[131]. For the purposes of this study, administrative data provided a population-based perspective of ER users that was both very efficient and extremely economical. On a related note, the sixth limitation relates to subjective processes that underlie the assessment that: a) an illness is important enough to warrant medical attention; and b) to actually seek medical attention through the ER. Padgett and Brodsky[57] hypothesise a three-stage model in which the characteristics in the behavioural model play a specific and varied role in each stage of the model; the key issue is the concept of perceived need. Since only administrative data were used in this study, all measures were based on evaluated need, as perceived need (or in their words, 'subjectively determined need') cannot be captured by these data. Subjective factors such as timely access to care have been shown to be of considerable importance in determining ER use [181]. As well, the seventh limitation lies in the suggestion by Menec et al. that reasons for lack of continuity of care are probably related to both systemic and patient traits[126]. This study examined only one side of the relationship (i.e., patient behaviour). The concept of supplier-induced demand may be of some salience[182-185]; this study did not evaluate what aspects of ER use are patient-initiated vs. practitioner-initiated. The eighth limitation is that reasons for ER visits were not explicitly assessed in this study, as this variable was not captured across all WRHA ERs in a uniform manner. The ninth limitation lies in the validation method used. Some members of the study sample were likely included in the validation sample, introducing a measure of dependency between these two samples. However, the historical method used to choose study and validation samples has been used in other published studies[186], and has been noted by other authors as a valid technique for assessing generalizability of results[151,152]. Finally, although one of the advantages of using LCA over other grouping techniques is that theoretically speaking, there are better methods for enumeration of classes[50,115], the study results suggest that these techniques may not be as well-defined for very large population-based datasets. Further work using LCA should explore the use of other avenues to guide class enumeration.

5.5. Conclusion

Using LCA, this study identified heterogeneous groups of ER users from administrative data collected at all ERs located in Winnipeg. Validation through a separate sample suggests that some groups may be more robust than others. Older age and highly complex needs, such as significant physical morbidity was strongly interwoven with mental health conditions, while both, in turn, were associated with high utilization patterns. However, this pattern of complex needs and high resource utilization was not only confined to those living in the inner city, nor was low utilization and being relatively diagnoses-free exclusive to wealthier areas of Winnipeg. LCA was a useful tool in exploring the ER administrative data, although it had its limitations. Consistent with other authors, LCA should be viewed within the context of hypotheses-generation, suggesting future avenues of research by illuminating how complex factors can interact to drive utilization in the real world.

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Table 3: Predisposing, Enabling and Need Characteristics of Younger and Older Cohorts Derived from Study Sample

		Study Sample N=143,584		Younger Cohort N=108,714		Older Cohort N=34,870	
		n	%	*n*	%	*n*	%
Age Group	85+ years	6,895	4.8	--	--	6,895	19.8
	75-84 years	14,612	10.2	--	--	14,612	41.9
	65-74 years	13,363	9.3	--	--	13,363	38.3
	45-64 years	38,492	26.8	38,492	35.4	--	--
	25-44 years	49,120	34.2	49,120	45.2	--	--
	17-24 years	21,102	14.7	21,102	19.4	--	--
	Median	45.0		38.0		77.0	
	Mean (SD)	48.0(20.7)		38.5(13.3)		77.6(7.7)	
Sex	Female	75,455	52.6	54,636	50.3	20,819	59.7
	Male	68,129	47.5	54,078	49.7	14,051	40.3
Area of Residence	Suburb	86,941	60.6	65,422	60.2	21,519	61.7
	Core	7,418	5.2	4,878	4.5	2,540	7.3
	Inner core	48,641	33.9	37,914	34.9	10,727	30.8
	Missing	584	0.4	500	0.5	84	0.2
	Q1 (Lowest)	36,293	25.3	27,183	25.0	9,110	26.1
Income Quintile	Q2	30,296	21.1	22,919	21.1	7,377	21.2
	Q3	27,775	19.3	21,037	19.4	6,738	19.3
	Q4	25,738	17.9	20,593	18.9	5,145	14.8
	Q5 (Highest)	20,940	14.6	16,427	15.1	4,513	12.9
	Missing	2,542	1.8	555	0.5	1,987	5.7
Arthritis	Present	42,050	29.3	25,813	23.7	16,237	46.6
	Absent	101,534	70.7	82,901	76.3	18,633	53.4
IHD	Present	15,856	11.0	4,401	4.1	11,455	32.9
	Absent	127,728	89.0	102,524	94.3	23,415	67.2

Diabetes	Preset	12,242	8.5	6,190	5.7	6,052	17.4
	Absent	131,342	91.5	98,686	94.3	28,818	82.6
Anxiety	Present	12,535	8.7	10,028	9.2	2,507	7.2
	Absent	131.049	91.3	98,217	90.8	32,363	92.8
Dementia	Present	5,424	3.8	734	0.7	4,690	13.5
	Absent	138,160	96.2	107,980	99.3	30,180	86.6
Depression	Present	29,694	20.7	23,596	21.7	6,098	17.5
	Absent	113,890	79.3	85,118	78.3	28,772	82.5
Personality	Present	2,368	1.7	2,150	2.0	218	0.6
Disorders	Absent	141,216	98.4	106,564	98.0	34,652	99.4
Schizophrenia	Present	2,459	1.7	2,004	2.0	455	1.3
	Absent	141,125	98.3	106,710	98.2	34,415	98.7
Substance Abuse	Present	9,677	6.7	8,619	7.9	1,058	3.0
	Absent	133,907	93.3	100,095	92.1	33,812	97.0
Any Mental Health	Present	43,736	30.5	32,844	30.2	10,892	31.2
	Absent	99,848	69.5	75,870	69.8	23,978	68.8
Number of Mental	6	14	0.0	14	0.0	--	--
Health	5	136	0.1	121	0.1	15	0.0
Disorders	4	702	0.5	602	0.6	100	0.3
	3	2,802	2.0	2,234	2.1	568	1.6
	2	10,097	7.0	7,459	6.9	2,638	7.6
	1	29,985	20.9	22,414	20.6	7,571	21.7
	0	99,848	69.5	75,870	69.8	23,978	68.8
	Median	0.0		0.0		0.0	
	Mean (SD)	0.4(0.8)		0.4(0.8)		0.4(0.7)	
Number of ADGs	9+	13180	9.2	6,783	6.3	6,397	18.4
	5-8	46114	32.3	30,606	28.4	15,508	44.6
	2-4	58057	40.7	47,020	43.6	11,037	31.7
	0-1	25262	17.7	23,416	21.7	1,846	5.3

	Median	4.0		3.0		5.0	
	Mean (SD)	4.3(2.9)		3.8(2.7)		5.8(3.0)	
Number of ER Visits	5+ visits	6,317	4.4	4,213	3.9	2,104	6.0
	2-4 visits	45,723	31.8	32,444	29.8	13,279	38.1
	1 visit	91,544	63.8	72,057	66.3	19,487	55.9
	Median	1.0		1.0		1.0	
	Mean (SD)	1.8(2.0)		1.7(2.1)		1.9(1.7)	
Number of Physician Visits	12+	34,101	23.8	19,724	18.1	14,377	41.2
	7-11	32,948	23.0	22,872	21.0	10,076	28.9
	3-6	40,798	28.4	33,484	30.8	7,314	21.0
	0-2	35,737	24.9	32,634	30.0	3,103	8.9
	Median	6.0		5.0		10.0	
	Mean (SD)	8.0(7.8)		6.9(7.4)		11.4 (8.0)	
Number of Hospitalizations	2+	7,473	5.2	3,493	3.2	3,980	11.4
	1	19,246	13.4	10,955	10.1	8,291	23.8
	0	116,865	81.4	94,266	86.7	22,599	64.8
	Median	0.0		0.0		0.0	
	Mean (SD)	0.3(0.7)		0.2(0.6)		0.5 (0.9)	
	Yes	82,287	57.3	50,955	53.1	10,342	70.3
Continuity of Care	No	61,297	42.7	57,759	46.9	24,528	29.7

NOTE: Q: Quintile

IHD: Ischemic heart disease

ADG: Adjusted Diagnostic Groupings

ER: Emergency Room

Table 4: Comparison of Characteristics of Three Censored Younger Cohorts to Uncensored Younger Cohort, Derived from Study Sample: Unadjusted Odds Ratios (ORs) and 95% Confidence Intervals (95%CI)[a]

	n (%)	Analytical Cohort #1 80,795 (74.7%) OR	95% CI	Analytical Cohort #2 89,860 (83.0%) OR	95% CI	Analytical Cohort #3 92,511 (85.5%) OR	95% CI
Age Group	45-64	0.89[‡]	(0.86,0.91)	0.92[‡]	(0.90,0.95)	**0.99**	**(0.97,1.02)**
	25-44	1.03[†]	(1.00,1.05)	1.05[‡]	(1.02,1.07)	**1.06[†]**	**(1.03,1.08)**
	17-24	Ref	--	Ref	--	**Ref**	--
Sex	Female	1.00	(0.98,1.02)	1.02[†]	(1.00,1.04)	**1.01**	**(0.99,1.03)**
	Male	Ref	--	Ref	--	**Ref**	--
Area of Residence	Suburb	1.11[‡]	(1.09,1.13)	1.04[‡]	(1.02,1.06)	**1.04[‡]**	**(1.02,1.06)**
	Core	0.51[‡]	(0.48,0.54)	0.50[‡]	(0.47,0.53)	**0.52[‡]**	**(0.49,0.55)**
	Inner core	Ref	--	Ref	--	**Ref**	--
Income Quintile	Other	0.95[‡]	(0.93,0.97)	1.00	(0.98,1.02)	**1.01**	**(0.99,1.02)**
	Top 2	Ref	--	Ref	--	**Ref**	--
Arthritis	Present	0.76[‡]	(0.74,0.77)	0.83[‡]	(0.82,0.85)	**0.86[‡]**	**(0.84,0.88)**
	Absent	Ref	--	Ref	--	**Ref**	--
IHD	Present	0.28[‡]	(0.26,0.30)	0.32[‡]	(0.30,0.34)	--	--
	Absent	Ref	--	Ref	--	--	--
Diabetes	Present	0.34[‡]	(0.32,0.36)	0.38[‡]	(0.37,0.40)	**0.51[‡]**	**(0.49,0.54)**
	Absent	Ref	--	Ref	--	**Ref**	--
Anxiety	Present	0.40[‡]	(0.39,0.42)	--	--	--	--
	Absent	Ref	--	--	--	--	--
Depression	Present	0.63[‡]	(0.62,0.65)	--	--	--	--
	Absent	Ref	--	--	--	--	--
Substance Abuse	Present	0.30[‡]	(0.29,0.32)	--	--	--	--

	Absent	Ref	--	--	--	**--**	**--**
Any Mental Health	Present	--	--	0.63‡	(0.62,0.65)	**0.65‡**	**(0.63,0.66)**
	Absent	--	--	Ref	--	**Ref**	**--**
ADG	5+	0.76‡	(0.74,0.78)	0.87‡	(0.85,0.89)	**0.91‡**	**(0.88,0.93)**
	2-4	0.97‡	(0.94,0.99)	0.99	(0.97,1.01)	**1.00**	**(0.98,1.03)**
	0-1	Ref	--	Ref	--	**Ref**	**--**
ER Visits	5+	0.09‡	(0.08,0.10)	0.29‡	(0.27,0.31)	**0.31‡**	**(0.29,0.33)**
	2-4	0.80‡	(0.78,0.81)	0.87‡	(0.85,0.88)	**0.89‡**	**(0.87,0.91)**
	1	Ref	--	Ref	--	**Ref**	**--**
Number of Physician Visits	12+	0.67‡	(0.65,0.69)	0.82‡	(0.80,0.85)	**0.88‡**	**(0.86,0.90)**
	7-11	0.84‡	(0.82,0.86)	0.91‡	(0.88,0.93)	**0.93‡**	**(0.91,0.96)**
	3-6	0.98	(0.96,1.00)	0.99	(0.96,1.01)	**0.99**	**(0.97,1.02)**
	0-2	Ref	--	Ref	--	**Ref**	**--**
Number of Hospitalizations	2+	0.16‡	(0.14,0.17)	0.24‡	(0.22,0.26)	**0.29‡**	**(0.27,0.31)**
	1	0.53‡	(0.51,0.55)	0.61‡	(0.59,0.63)	**0.64‡**	**(0.62,0.66)**
	0	Ref	--	Ref	--	**Ref**	**--**
Continuity of Care	Yes	1.03	(1.01,1.05)	1.02†	(1.00,1.04)	**1.04‡**	**(1.02,1.05)**
	No	Ref	--	Ref	--	**Ref**	**--**

[a] Calculated from univariate logistic regression

†p<.05, ‡p<.001

See Table 3 note

Table 5: Comparison of Characteristics of Two Censored Cohorts to Uncensored Older Cohort, Derived from Study Sample: Unadjusted Odds Ratios (ORs) and 95% Confidence Intervals (95%CI)[a]

	n (%)	Analytical Cohort #1 22,978 (65.9%)		Analytical Cohort #2 27,002 (77.4%)	
		OR	95% CI	OR	95% CI
Age Group	85+	0.67[‡]	(0.64,0.70)	**0.76[‡]**	**(0.73,0.80)**
	75-84	0.94[‡]	(0.91,0.98)	**0.99**	**(0.96,1.03)**
	65-74	Ref	--	**Ref**	--
Sex	Female	1.07[‡]	(1.03,1.10)	**1.14[‡]**	**(1.10,1.17)**
	Male	Ref	--	**Ref**	--
Area of Residence	Suburb	1.16[‡]	(1.12,1.21)	**1.10[‡]**	**(1.07,1.14)**
	Inner Core	Ref	--	**Ref**	--
Income Quintile	Q1 (lowest), Q2 & Q3	1.07[‡]	(1.03,1.12)	**1.10[‡]**	**(1.06,1.14)**
	Q4 and Q5 (highest)	Ref	--	**Ref**	--
Arthritis	Present	0.93[‡]	(0.90,0.96)	**0.99**	**(0.96,1.03)**
	Absent	Ref	--	**Ref**	--
Anxiety	Present	0.13[‡]	(0.12,0.15)	--	--
	Absent	Ref	--	--	--
Dementia	Present	0.31[‡]	(0.29,0.34)	--	--
	Absent	Ref	--	--	--
Depression	Present	0.35[‡]	(0.33,0.37)	--	--
	Absent	Ref	--	--	--
Any Mental Health	Present	--	--	**0.80[‡]**	**(0.78,0.83)**
	Absent	--	--	**Ref**	--
ADG	8+	0.78[‡]	(0.74,0.81)	**0.91[‡]**	**(0.87,0.95)**
	4-7	1.00	(0.96,1.04)	**1.04**	**(1.00,1.08)**

	0-3	Ref	--	**Ref**	--
ER Visit	2+	0.79‡	(0.76,0.82)	**0.87‡**	**(0.84,0.90)**
	1	Ref	--	**Ref**	--
Number of	12+	1.07‡	(1.02,1.11)	**1.20‡**	**(1.15,1.25)**
Physician Visits	6-11	1.09‡	(1.04,1.14)	**1.12‡**	**(1.08,1.17)**
	0-5	Ref	--	**Ref**	--
Number of	2+	0.54‡	(0.51,0.58)	**0.57†**	**(0.54,0.60)**
Hospitalizations	1	0.67‡	(0.65,0.70)	**0.69‡**	**(0.67,0.72)**
	0	Ref	--	**Ref**	--
Continuity of Care	Yes	1.30‡	(1.25,1.35)	**1.33‡**	**(1.28,1.37)**
	No	Ref	--	**Ref**	--

[a] Calculated from univariate logistic regression
†p<.05, ‡p<.001
See Table 3 note.

Table 6: Probability of Class Membership for 7- Latent Class Solution, Censored Younger Cohort of ER Users (Study Sample), N=92,511

		7-Class Solution													
		Class 1		Class 2		Class 3		Class 4		Class 5		Class 6		Class 7	
		%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*
Variable		*11.1*	*10,236*	*7.49*	*6,925*	*15.42*	*14,263*	*19.98*	*18,487*	*14.12*	*13,066*	*20.69*	*19,138*	*11.24*	*10,396*
Age Group	45-64	0.65	6,653	0.04	277	0.57	8,130	0.28	5,176	0.16	2,091	0.37	7,081	0.23	2,391
	25-44	0.35	3,583	0.65	4,501	0.34	4,849	0.53	9,798	0.58	7,578	0.42	8,038	0.47	4,886
	17-24	0.00	0	0.31	2,147	0.09	1,284	0.19	3,513	0.26	3,397	0.21	4,019	0.30	3,119
Sex	Female	0.60	6,142	0.81	5,609	0.68	9,699	0.50	9,244	0.26	3,397	0.51	9,760	0.28	2,911
	Male	0.40	4,094	0.19	1,316	0.32	4,564	0.50	9,244	0.74	9,669	0.49	9,378	0.72	7,485
Area of Residence	Suburb	0.28	2,866	0.36	2,493	0.98	13,978	0.32	5,916	0.36	4,704	0.95	18,181	0.96	9,980
	Outer Core	0.01	102	0.01	69	0.02	285	0.02	370	0.02	261	0.04	766	0.03	312
	Inner Core	0.72	7,370	0.63	4,363	0.00	0	0.66	12,201	0.63	8,232	0.01	191	0.01	104
Income Quintile	Q1 (lowest), Q2 & Q3	1.00	10,236	1.00	6,925	0.29	4,136	1.00	18,487	1.00	13,066	0.31	5,933	0.26	2,703
	Q4 and Q5 (highest)	0.00	0	0.00	0	0.71	10,127	0.00	0	0.00	0	0.70	13,397	0.74	7,693
Arthritis	Present	0.57	5,835	0.10	693	0.34	4,849	0.16	2,958	0.07	915	0.17	3,253	0.08	832
	Absent	0.43	4,401	0.90	6,233	0.66	9,414	0.84	15,529	0.93	12,151	0.83	15,885	0.92	9,564

Diabetes	Present	0.12	1,228	0.00	0	0.05	713	0.02	370	0.00	0	0.03	574	0.00	0
	Absent	0.88	9,008	1.00	6,925	0.96	13,692	0.98	18,117	1.00	13,066	0.98	18,755	1.00	10,396
Any Mental Health	Present	0.60	6,142	0.42	2,909	0.35	4,992	0.27	4,991	0.15	1,960	0.19	3,636	0.08	832
	Absent	0.40	4,094	0.58	4,017	0.65	9,271	0.73	13,496	0.85	11,106	0.82	15,693	0.92	9,564
ADG	5+	0.91	9,315	1.00	6,925	0.69	9,841	0.03	555	0.00	0	0.03	574	0.00	0
	2-4	0.09	921	0.00	0	0.13	1,854	0.97	17,932	0.10	1,307	0.96	18,372	0.11	1,144
	0-1	0.00	0	0.00	0	0.00	0	0.00	0	0.90	11,759	0.02	383	0.89	9,252
ER visits	5+	0.07	717	0.05	346	0.01	143	0.01	185	0.00	0	0.00	0	0.00	0
	2-4	0.42	4,299	0.45	3,116	0.33	4,707	0.30	5,546	0.23	3,005	0.20	3,828	0.15	1,559
	1	0.51	5,220	0.50	3,463	0.67	9,556	0.70	12,941	0.77	10,061	0.80	15,310	0.85	8,837
Number of Physician Visits	12+	0.70	7,165	0.29	2,008	0.42	5,990	0.01	185	0.00	0	0.00	0	0.00	0
	7-11	0.28	2,866	0.50	3,463	0.47	6,704	0.17	3,143	0.00	0	0.15	2,871	0.00	0
	3-6	0.02	205	0.22	1,524	0.11	1,569	0.64	11,832	0.05	653	0.70	13,397	0.04	416
	0-2	0.00	0	0.00	0	0.00	0	0.19	3,513	0.95	12,413	0.16	3,062	0.96	9,980
Number of Hospitalizations	2+	0.04	409	0.03	208	0.02	285	0.00	0	0.00	0	0.00	0	0.00	0
	1	0.13	1,331	0.19	1,316	0.12	1,712	0.06	1,109	0.00	0	0.04	766	0.00	0
	0	0.83	8,496	0.78	5,402	0.86	12,266	0.94	17,378	1.00	13,066	0.96	18,372	1.00	10,396
Continuity of Care	Yes	0.62	6,346	0.32	2,216	0.62	8,843	0.59	10,907	0.40	5,226	0.62	11,866	0.46	4,782
	No	0.38	3,890	0.68	4,709	0.39	5,563	0.42	7,765	0.60	7,840	0.38	7,272	0.54	5,614

Table 7: Summary of Differences: Results from LCA of ER Users, Censored Younger Cohort (Study Sample)

Class	Predisposing	Enabling	Need
1	Older, 60% Females	Mixed area of residence, 72% Inner core	High diabetes & arthritis High mental health High comorbidity High utilizations High continuity of care
2	Younger, 81% Females	Mixed area of residence, 63% Inner core	No diabetes, low arthritis High mental health High comorbidity High utilizations Low continuity of care
3	Older, 68% Females	Suburban 71% top 2 Quintiles	Moderate diabetes, high arthritis High mental health High comorbidity High utilizations High continuity of care
4	Middle-aged, 50% Females	Mixed area of residence, 66% Inner core	Moderate diabetes, moderate arthritis Moderate mental health Moderate comorbidity Moderate utilizations Low continuity of care
5	Middle-aged, 26% Females	Mixed area of residence, 63% Inner core	No diabetes, Low arthritis Low mental health Low comorbidity Low utilizations Low continuity of care

6	Middle-aged, 51% Females	Mostly Suburban 70% Top 2 Quintiles	Low presence of diabetes & moderate arthritis High mental health High comorbidity High utilizations High continuity of care
7	Middle-aged, 28% Females	Mostly Suburban 74% Top 2 Quintiles	No diabetes, low arthritis Low mental health Moderate comorbidity Moderate utilizations High continuity of care

Table 8: Probability of Class Membership for7- Latent Class Solution, Censored Older Cohort of ER Users (Study Sample), N=27,002

		7-Class Solution													
		Class 1		**Class 2**		**Class 3**		**Class 4**		**Class 5**		**Class 6**		**Class 7**	
		%	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*
Variable		*9.57*	*2,584*	*15.11*	*4,079*	*6.12*	*1,654*	*24.35*	*6,574*	*18.19*	*4,912*	*16.95*	*4,578*	*9.71*	*2,621*
Age Group	85+	0.20	517	0.14	571	0.38	629	0.20	1,315	0.05	246	0.18	824	0.08	210
	75-84	0.52	1,344	0.47	1,917	0.53	877	0.45	2,958	0.41	2,014	0.42	1,923	0.33	865
	65-74	0.28	724	0.39	1,591	0.09	149	0.36	2,367	0.54	2,652	0.40	1,831	0.59	1,546
Sex	Female	0.58	1,499	0.67	2,733	0.72	1,191	0.70	4,602	0.51	2,505	0.66	3,021	0.54	1,415
	Male	0.42	1,085	0.33	1,346	0.28	463	0.30	1,972	0.50	2,456	0.34	1,557	0.46	1,206
Area of Residence	Suburb	0.69	1,783	0.74	3,018	0.63	1,042	0.52	3,418	1.00	4,912	0.53	2,426	1.00	2,621
	Inner Core	0.31	801	0.26	1,061	0.37	612	0.48	3,156	0.00	0	0.47	2,152	0.00	0
Income Quintile	Other	0.81	2,093	0.74	3,018	0.93	1,538	1.00	6,574	0.33	1,621	1.00	4,578	0.24	629
	Top 2	0.19	491	0.26	1,061	0.07	116	0.00	0	0.67	3,291	0.00	0	0.74	1,940
Arthritis	Present	0.56	1,447	0.68	2,774	0.33	546	0.43	2,827	0.46	2,260	0.29	1,328	0.28	734
	Absent	0.44	1,137	0.32	1,305	0.67	1,108	0.47	3,090	0.54	2,652	0.71	3,250	0.73	1,913
Any Mental Health	Present	0.35	904	0.43	1,754	0.21	347	0.33	2,169	0.18	884	0.20	916	0.13	341
	Absent	0.65	1,680	0.58	2,366	0.79	1,307	0.68	4,470	0.83	4,077	0.80	3,662	0.87	2,280
ADG	8+	0.90	2,326	1.00	4,079	0.12	198	0.01	66	0.00	0	0.00	0	0.00	0
	4-7	0.10	258	0.00	0	0.89	1,472	0.96	6,311	1.00	4,912	0.12	549	0.09	236
	0-3	0.00	0	0.00	0	0.00	0	0.03	197	0.00	0	0.88	4,029	0.91	2,385
ER visits	2+	0.99	2,558	0.47	1,917	0.43	711	0.38	2,498	0.32	1,572	0.23	1,053	0.20	524
	1	0.01	26	0.53	2,162	0.57	943	0.62	4,076	0.68	3,340	0.77	3,525	0.81	2,123

Number of	12+	0.84	2,171	1.00	4,079	0.10	165	0.49	3,221	0.43	2,112	0.02	92	0.02	52
Physician Visits	6-11	0.16	413	0.00	0	0.43	711	0.52	3,418	0.55	2,702	0.31	1,419	0.30	786
	0-5	0.01	26	0.00	0	0.47	777	0.00	0	0.02	98	0.67	3,067	0.68	1,782
Number of	2+	0.68	1,757	0.00	0	0.12	198	0.00	0	0.01	49	0.00	0	0.00	0
Hospitalizations	1	0.32	827	0.28	1,142	0.88	1,456	0.12	789	0.15	737	0.01	46	0.02	52
	0	0.00	0	0.72	2,937	0.00	0	0.88	5,785	0.84	4,126	0.99	4,532	0.98	2,569
Continuity of Care	Yes	0.81	2,093	0.70	2,855	0.80	1,323	0.78	5,128	0.75	3,684	0.75	3,434	0.76	1,992
	No	0.20	517	0.30	1,224	0.20	331	0.22	1,446	0.25	1,228	0.26	1,190	0.24	629

Table 9: Summary of Differences: Results from LCA of ER Users, Censored Older Cohort (Study Sample)

Class	Predisposing	Enabling	Need
1	Older, 58% Females	Mixed area of residence, 31% Inner core	High presence of arthritis High mental health High comorbidity High ER visits High utilizations High continuity of care
2	Older, 67% Females	Mixed area of residence, 26% Inner core	High arthritis High mental health High comorbidity Moderate ER visits High physician utilizations, Moderate hospitalizations Lowest continuity of care
3	Oldest, 72% Females	Mixed area of residence, 37% Inner core	Low arthritis Moderate mental health Moderate comorbidity Moderate ER visits Moderate utilizations High continuity of care
4	Middle-aged, 70% Females	Mixed area of residence, 48% Inner core	Moderate arthritis Moderate mental health Moderate comorbidity Moderate ER visits High physician utilizations, low hospitalizations High continuity of care

5	Middle-aged, 51% Females	0% Inner core	Moderate arthritis Low mental health Moderate comorbidity Low ER visits Moderate physician utilizations, low hospitalizations Moderate continuity of care
6	Younger, 66% Females	Mixed area of residence, 47% Inner core	Low arthritis Low mental health Lowest comorbidity Low ER visits Low utilizations Lowest continuity of care
7	Younger, 59% Females	100% Suburban, 74% Top 2 quintiles	Low arthritis Low mental health Low comorbidity Lowest ER visits Moderate physician utilizations, low hospitalizations Moderate continuity of care

Figure 2: Adjusted BIC for Younger and Older Cohorts, Study Sample, by Number of Classes

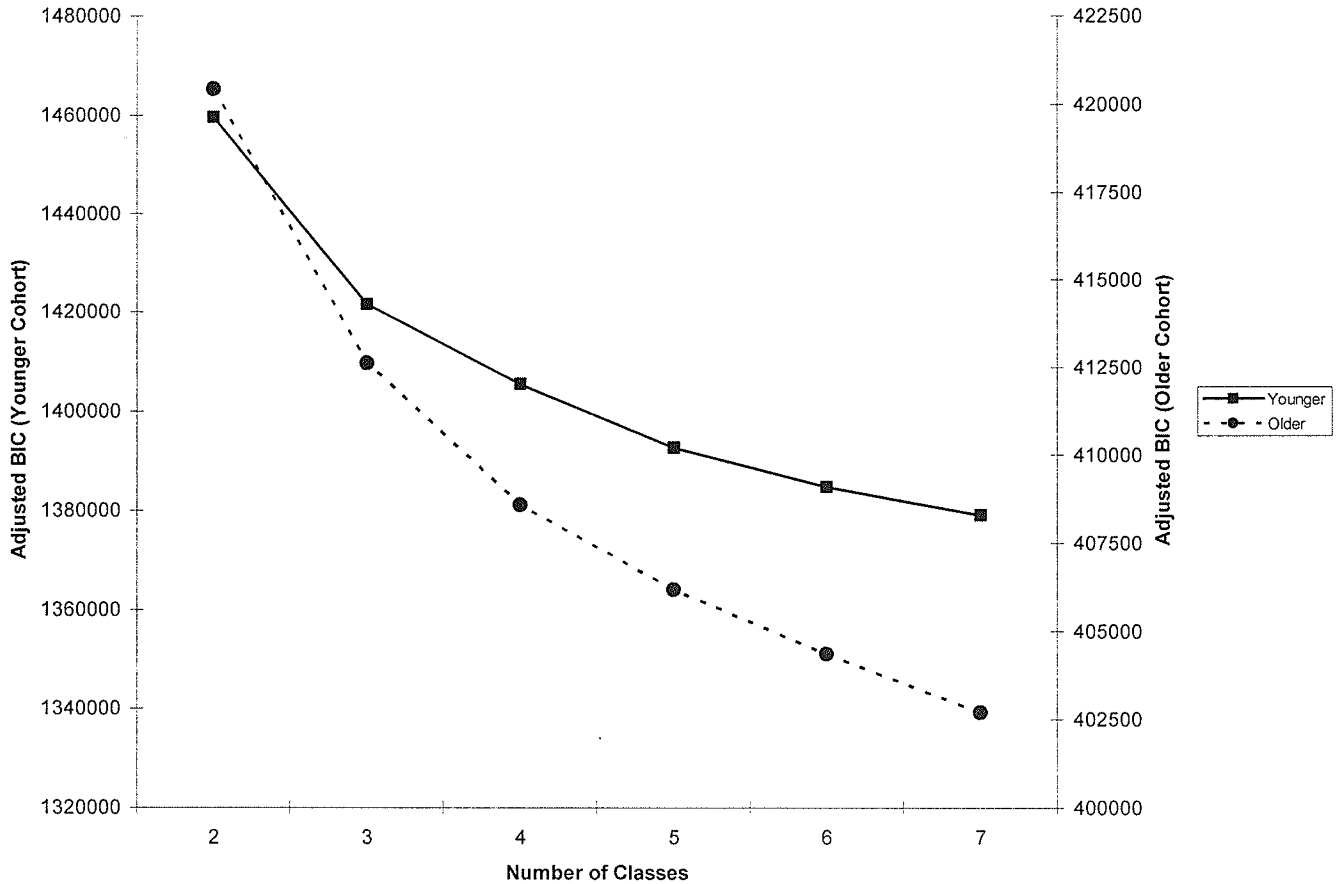

Table 10: Predisposing, Enabling and Need Characteristics of Younger and Older Cohorts Derived from Validation Sample

		Validation Sample N=126,843		Younger Cohort N=98,292		Older Cohort N=28,551	
		n	%	*n*	%	*n*	%
Age Group	85+ years	5,643	4.2	--	--	5,643	19.8
	75-84 years	11,662	9.2	--	--	11,662	40.9
	65-74 years	11,246	8.9	--	--	11,246	39.4
	45-64 years	34,548	27.2	34,548	35.2	--	--
	25-44 years	45,465	35.8	45,465	46.3	--	--
	17-24 years	18,279	14.4	18,279	18.6	--	--
	Median	44.0		38.0		77.0	
	Mean (SD)	47.3(20.2)		38.6(13.0)		77.4(7.8)	
Sex	Female	66,325	52.3	49,169	50.0	17,156	60.1
	Male	60,518	47.7	49,123	50.0	11,395	39.9
Area of Residence	Suburb	78,135	61.6	60,399	61.4	17,736	62.1
	Core	6,407	5.1	4,441	4.5	1,966	6.9
	Inner core	41,749	32.9	32,988	33.6	8,761	30.7
	Missing	552	0.4	464	0.5	88	0.3
Income Quintile	Q1 (Lowest)	30,721	24.2	23,467	23.9	7,254	25.4
	Q2	26,578	21.0	20,615	21.0	5,963	20.9
	Q3	24,420	19.3	18,941	19.3	5,479	19.2
	Q4	23,527	18.6	19,291	19.6	4,236	14.8
	Q5 (Highest)	19,042	15.0	15,440	15.7	3,602	12.6
	Missing	2,555	2.0	538	0.6	2,017	7.1
Arthritis	Present	37,620	29.7	23,789	24.2	13,831	48.4
	Absent	89,223	70.3	74,503	75.8	14,720	51.6
IHD	Present	12,606	9.9	3,564	4.1	9,042	31.7
	Absent	114,237	90.1	94,728	96.4	19,509	68.3

Diabetes	Present	8,140	6.4	3,986	3.6	4,154	14.6
	Absent	118,703	93.6	94,306	95.9	24,397	85.5
Anxiety	Present	11,187	8.8	8,996	9.2	2,191	7.7
	Absent	115,656	91.2	89,296	90.9	26,360	92.3
Dementia	Present	4,214	3.3	647	0.7	3,567	12.5
	Absent	122,629	96.7	97,645	99.3	24,984	87.5
Depression	Present	26,115	20.6	20,999	21.4	5,116	17.9
	Absent	100,728	79.4	77,293	78.6	23,435	82.1
Personality	Present	2,188	1.7	1,972	2.0	216	0.8
Disorders	Absent	124,655	98.3	96,320	98.2	28,335	99.3
Schizophrenia	Present	2,189	1.7	1,789	1.8	400	1.4
	Absent	124,654	98.3	96,503	98.2	28,151	98.6
Substance Abuse	Present	9,132	7.2	8,084	8.2	1,048	3.7
	Absent	117,711	92.8	90,208	91.8	27,503	96.3
Any Mental Health	Present	38,883	30.7	29,867	30.4	9,016	31.6
	Absent	87,960	69.4	68,425	69.6	19,535	68.4
Number of MH	6	12	0.0	10	0.0	--	--
Conditions	5	128	0.1	114	0.1	14	0.1
	4	619	0.5	524	0.5	95	0.3
	3	2,436	1.9	1,916	2.0	520	1.8
	2	8,841	7.0	6,710	6.8	2,131	7.5
	1	26,847	21.2	20,593	21.0	6,254	21.9
	0	87,960	69.4	68,425	69.6	19,535	68.4
	Median	0.0		0.0		0.0	
	Mean (SD)	0.4(0.8)		0.4(0.8)		0.4(0.7)	
ADGs	9+	9,123	7.3	4,850	5.0	4,273	15.0
	5-8	34,712	27.7	23,177	23.9	11,535	40.5
	2-4	52,570	41.9	42,245	43.5	10,325	36.3
	0-1	29,124	23.2	26,790	27.6	2,334	8.2

	Median	3.0		3.0		5.0	
	Mean (SD)	3.8(2.9)		3.4(2.7)		5.3(3.0)	
ER visits	5+ visits	4,599	3.6	3,237	3.3	1,362	4.8
	2-4 visits	39,188	30.9	28,851	29.4	10,337	36.2
	1 visit	83,056	65.5	66,204	67.4	16,852	59.0
	Median	1.0		1.0		1.0	
	Mean (SD)	1.7(1.6)		1.6(1.7)		1.8(1.6)	
Number of Physician Visits	12+	28,095	22.2	16,142	16.4	11,953	41.9
	7-11	27,635	21.8	19,076	19.4	8,559	30.0
	3-6	36,523	28.8	30,579	31.1	5,944	20.8
	0-2	34,590	27.3	32,495	33.1	2,095	7.3
	Median	6.0		4.0		10.0	
	Mean (SD)	7.7(8.0)		6.5(7.5)		11.6(8.2)	
Number of Hospitalizations	2+	5,367	4.2	2,813	2.9	2,554	9.0
	1	15,828	12.5	9,813	10.0	6,015	21.1
	0	105,362	83.3	85,396	87.1	19,966	70.0
	Median	0.0		0.0		0.0	
	Mean (SD)	0.2(0.6)		0.2(0.5)		0.4 (0.8)	
Continuity of care	Yes	71,912	56.7	51,630	52.5	8,269	29.0
	No	54,931	43.3	46,662	47.5	20,282	71.0

Figure 3: Adjusted BIC for Younger and Older Cohorts, Validation Sample, by Number of Classes

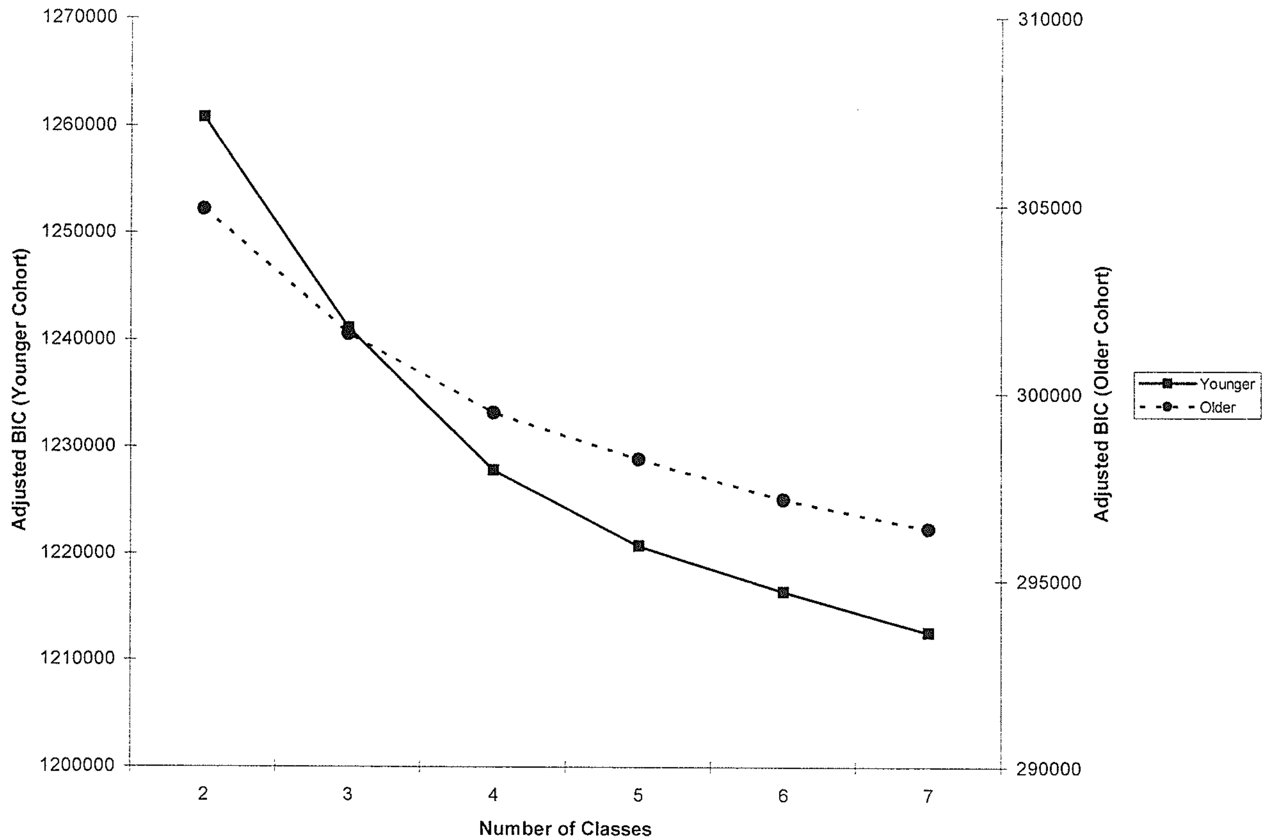

Table 11: Probability of Class Membership for 7 Class Solution, Censored Younger Cohort of ER Users – Comparison between Validation Sample and Study Sample[a]

		Class 1		Class 2		Class 3		Class 4		Class 5		Class 6		Class 7	
Variable	%	*5.24*	*11.10*	*9.59*	*7.49*	*10.08*	*15.42*	*11.73*	*19.98*	*25.43*	*14.12*	*25.42*	*20.69*	*12.51*	*11.24*
Age Group	45-64	0.51	0.65	0.00	0.04	0.64	0.57	0.58	0.28	0.18	0.16	0.39	0.37	0.20	0.23
	25-44	0.47	0.35	0.64	0.65	0.32	0.34	0.42	0.53	0.60	0.58	0.44	0.42	0.48	0.47
	17-24	0.03	0.00	0.36	0.31	0.05	0.09	0.00	0.19	0.23	0.26	0.18	0.21	0.32	0.30
Sex	Female	0.69	0.60	0.91	0.81	0.74	0.68	0.50	0.50	0.28	0.26	0.59	0.51	0.21	0.28
	Male	0.31	0.40	0.10	0.19	0.26	0.32	0.50	0.50	0.72	0.74	0.41	0.49	0.79	0.72
Area of Residence	Suburb	0.20	0.28	0.41	0.36	0.99	0.98	0.30	0.32	0.32	0.36	0.98	0.95	0.96	0.96
	Outer Core	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.04	0.03	0.03
	Inner Core	0.79	0.72	0.58	0.63	0.00	0.00	0.69	0.66	0.65	0.63	0.00	0.01	0.01	0.01
Income Quintile	Q1 (lowest), Q2 & Q3	1.00	1.00	1.00	1.00	0.35	0.29	1.00	1.00	1.00	1.00	0.28	0.31	0.30	0.26
	Q4 and Q5 (highest)	0.00	0.00	0.00	0.00	0.65	0.71	0.00	0.00	0.00	0.00	0.72	0.70	0.70	0.74
Arthritis	Present	0.61	0.57	0.02	0.10	0.47	0.34	0.40	0.16	0.09	0.07	0.17	0.17	0.09	0.08
	Absent	0.39	0.43	0.98	0.90	0.53	0.66	0.60	0.84	0.92	0.93	0.83	0.83	0.91	0.92
Diabetes	Present	0.07	0.12	0.00	0.00	0.03	0.05	0.02	0.02	0.00	0.00	0.01	0.03	0.00	0.00
	Absent	0.93	0.88	1.00	1.00	0.97	0.96	0.98	0.98	1.00	1.00	0.99	0.98	1.00	1.00
Any Mental Health	Present	0.80	0.60	0.38	0.42	0.48	0.35	0.39	0.27	0.15	0.15	0.19	0.19	0.06	0.08
	Absent	0.20	0.40	0.62	0.58	0.52	0.65	0.61	0.73	0.85	0.85	0.81	0.82	0.94	0.92

ADG	5+	0.98	0.91	0.44	1.00	0.76	0.69	0.35	0.03	0.03	0.00	0.17	0.03	0.01	0.00
	2-4	0.02	0.09	0.53	0.00	0.24	0.13	0.62	0.97	0.36	0.10	0.69	0.96	0.26	0.11
	0-1	0.00	0.00	0.03	0.00	0.00	0.00	0.03	0.00	0.61	0.90	0.15	0.02	0.73	0.89
ER visits	5+	0.13	0.07	0.00	0.05	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	2-4	0.49	0.42	0.38	0.45	0.33	0.33	0.29	0.30	0.25	0.23	0.21	0.20	0.19	0.15
	1	0.38	0.51	0.62	0.50	0.67	0.67	0.71	0.70	0.75	0.77	0.79	0.80	0.81	0.85
Number of	12+	0.90	0.70	0.13	0.29	0.55	0.42	0.18	0.01	0.00	0.00	0.02	0.00	0.00	0.00
Physician Visits	7-11	0.09	0.28	0.34	0.50	0.36	0.47	0.38	0.17	0.03	0.00	0.22	0.15	0.01	0.00
	3-6	0.00	0.02	0.47	0.22	0.10	0.11	0.39	0.64	0.26	0.05	0.56	0.70	0.17	0.04
	0-2	0.00	0.00	0.07	0.00	0.00	0.00	0.05	0.19	0.71	0.95	0.21	0.16	0.82	0.96
Number of	2+	0.05	0.04	0.00	0.03	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hospitalizations	1	0.15	0.13	0.14	0.19	0.07	0.12	0.03	0.06	0.03	0.00	0.06	0.04	0.01	0.00
	0	0.80	0.83	0.86	0.78	0.92	0.86	0.97	0.94	0.97	1.00	0.94	0.96	0.99	1.00
Continuity of Care	Yes	0.46	0.62	0.37	0.32	0.63	0.62	0.70	0.59	0.46	0.40	0.62	0.62	0.59	0.46
	No	0.54	0.38	0.63	0.68	0.37	0.39	0.30	0.42	0.54	0.60	0.38	0.38	0.41	0.54

[a]Shaded cells correspond to Validation Sample

Table 12: Probability of Class Membership for 7 Class Solution, Censored Older Cohort of ER Users – Comparison between Validation Sample and Study Sample[a]

		Class 1		Class 2		Class 3		Class 4		Class 5		Class 6		Class 7	
Variable	%	*5.96*	*9.57*	*14.67*	*15.11*	*9.18*	*6.12*	*14.12*	*24.35*	*24.09*	*18.19*	*16.47*	*16.95*	*15.52*	*9.71*
Age Group	85+	0.19	0.20	0.22	0.14	0.47	0.38	0.07	0.20	0.10	0.05	0.14	0.18	0.04	0.08
	74-84	0.56	0.52	0.45	0.47	0.44	0.53	0.46	0.45	0.50	0.41	0.38	0.42	0.32	0.33
	65-74	0.25	0.28	0.33	0.39	0.10	0.09	0.46	0.36	0.40	0.54	0.49	0.40	0.63	0.59
Sex	Female	0.69	0.58	0.75	0.67	1.00	0.72	0.54	0.70	0.40	0.51	0.60	0.66	0.50	0.54
	Male	0.31	0.42	0.25	0.33	0.00	0.28	0.46	0.30	0.60	0.50	0.40	0.34	0.50	0.46
Area of Residence	Suburb	0.77	0.69	0.54	0.74	0.66	0.63	1.00	0.52	0.56	1.00	0.50	0.53	1.00	1.00
	Inner Core	0.23	0.31	0.46	0.26	0.34	0.37	0.00	0.48	0.44	0.00	0.50	0.47	0.00	0.00
Income Quintile	Q1 (lowest), Q2 & Q3	0.87	0.81	1.00	0.74	1.00	0.93	0.31	1.00	1.00	0.33	1.00	1.00	0.29	0.24
	Q4 and Q5 (highest)	0.13	0.19	0.00	0.26	0.00	0.07	0.69	0.00	0.00	0.67	0.00	0.00	0.71	0.74
Arthritis	Present	0.79	0.56	0.76	0.68	0.62	0.33	0.60	0.43	0.41	0.46	0.24	0.29	0.30	0.28
	Absent	0.21	0.44	0.24	0.32	0.38	0.67	0.40	0.47	0.59	0.54	0.76	0.71	0.71	0.73
Any Mental Health	Present	0.53	0.35	0.50	0.43	0.57	0.21	0.24	0.33	0.16	0.18	0.08	0.20	0.07	0.13
	Absent	0.47	0.65	0.50	0.58	0.43	0.79	0.76	0.68	0.85	0.83	0.92	0.80	0.93	0.87

ADG	8+	0.46	0.90	0.58	1.00	0.11	0.12	0.34	0.01	0.10	0.00	0.01	0.00	0.00	0.00
	4-7	0.50	0.10	0.42	0.00	0.51	0.89	0.66	0.96	0.75	1.00	0.27	0.12	0.40	0.09
	0-3	0.03	0.00	0.00	0.00	0.39	0.00	0.00	0.03	0.16	0.00	0.73	0.88	0.60	0.91
ER visits	2+	1.00	0.99	0.52	0.47	0.41	0.43	0.37	0.38	0.28	0.32	0.19	0.23	0.18	0.20
	1	0.00	0.01	0.48	0.53	0.59	057	0.63	0.62	0.73	0.68	0.81	0.77	0.82	0.81
Number of	12+	0.88	0.84	1.00	1.00	0.33	0.10	0.75	0.49	0.38	0.43	0.00	0.02	0.09	0.02
Physician Visits	6-11	0.12	0.16	0.00	0.00	0.54	0.43	0.26	0.52	0.62	0.55	0.27	0.31	0.49	0.30
	0-5	0.00	0.01	0.00	0.00	0.14	0.47	0.00	0.00	0.00	0.02	0.73	0.67	0.42	0.68
Number of	2+	0.61	0.68	0.00	0.00	0.01	0.12	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Hospitalizations	1	0.39	0.32	0.15	0.28	0.23	0.88	0.16	0.12	0.13	0.15	0.05	0.01	0.05	0.02
	0	0.00	0.00	0.85	0.72	0.76	0.00	0.83	0.88	0.87	0.84	0.95	0.99	0.95	0.98
Continuity of Care	Yes	0.92	0.81	0.71	0.70	1.00	0.80	1.00	0.78	0.78	0.75	0.67	0.75	0.75	0.76
	No	0.08	0.20	0.30	0.30	0.00	0.20	0.00	0.22	0.22	0.25	0.33	0.26	0.25	0.24

[a]Shaded cell indicates Validation Sample