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ABSTRACT

Innovations in technology and subsequent changes in clinical practice have often led to increases in healthcare costs. The objective of this paper is to assess the role of health technology intensity and adoption in the evolution of average health expenditures on physician services as well as on the changes in the distribution of expenditures by age and sex. We used patient-level administrative data on physician service expenditures in the Canadian Province of Ontario for the years 1994 to 2004. The data set provides information about diagnoses, treatments, and payments to physicians with corresponding service dates, according to patient age and sex. We developed an algorithm to classify services into three levels (High, Medium, and Low) of technology and decompose changes in expenditures into these three categories of services. We found that those over the age of 65 received more high technology treatments than the younger population. Moreover, females of all ages were more likely to have medium and high technology treatment than males. Overall, the increases from applying high technology accounted for almost 60% of the growth of Ontario government health expenditures on physician services during the period investigated.

Keywords: Healthcare Technology, Technology Adoption, Health Costs, Population Aging

INTRODUCTION

Population aging and more especially changes in patterns of care are often cited as the main drivers of increases in health care spending (Colombier and Weber, 2010; Westerhout, 2006; Barros, 1998; Oliveira et.al., 2006; Bodenheimer, 2005; Fuchs, 2009; Sheiner, 2004; Denton et al., 2002; Narayan, 2007; Alcalde-Unzu et al., 2009; Costa-Font and Pons-Novell, 2007). Changes in patterns of care are comprised of technological innovation (doing more and possibly spending more) and pure cost increases (doing the same but paying more) (Fogel, 2008; Baumol, 1993; Hartwig, 2008). Most economists agree that changes in patterns of care are much more important than aging per se (Denton et al., 2002; Bodenheimer, 2005; Fuchs, 2009; Sheiner, 2004; PCA, 2005; Hsiao and Heller, 2007; Glenn et al., 2009).

Understanding the impact of technological innovations on healthcare services and expenditures and how they vary across age groups is an important aspect of assessing the burden of population aging on healthcare systems and government budgets (Sheiner, 2004; Denton et al., 2002). Our objective in this research is to investigate the relationship between these two drivers: the role of changing patterns of care on one hand, and on the other hand the relative impact on different age groups.

Changing patterns of care involves two things: fee inflation (physicians get paid more for performing the same services or procedures) and technical change (they provide different and hopefully better and more effective procedures and treatment). We control for fee inflation and are therefore in a position to study changes in what physicians do. This is called technical change. Even though technical change can generate savings on a particular procedure (e.g., cataract excision) it is well known that it increases average spending, due to the expansion effect (new technologies allow more patients to be treated) (Cutler and Meara, 1997; 2001). We are also interested in understanding how it can affect the elderly/non elderly ratio in average spending (Sheiner, 2004).

In assessing the effects of technology innovations on healthcare expenditures, we have taken advantage of a detailed set of anonymized data accumulated by the Canadian province of Ontario's *Ontario Health Insurance Program* (**OHIP**) claims. The dataset we have used relates to the fiscal years 1994–1995, 1999-2000, 2000-2001, 2001-2002 and 2004-2005; the files were accessed in the Statistics Canada Research Data Centre at McMaster University. The database includes information about all services provided on a fee-for-service basis by physicians, the treatments and diagnoses they provided, as well as service dates, patient age, and sex. These records provide a unique opportunity for understanding the time dependent effects of medical technology on age-specific health services provided, and on physician service expenditures.

We have developed a comprehensive age specific framework to assess the healthcare adoption of technological innovations in Ontario to examine the relative importance of technological innovations affecting healthcare expenditures in the province. Our approach involves the use of fuzzy modeling methodology to match medical technology adoption patterns between the older (age 65+) and younger (age< 65) population groups, separately for males and females. A new method was developed to calculate a Health Technology Intensity (HTI) to explain age-specific patterns of adoption of different technologies, based on fuzzy linguistic modeling.

The remainder of the paper is organized as follows. We proceed by discussing previous research concerning the impact of adoption of technological innovations on health expenditures. Next we describe the data files on which our calculations were based. We then explain and demonstrate the methodology for calculating the Health Technology Intensity (HTI) and discuss the three technological intervention levels and how data records were distributed among these levels (represented by fee billing code categories) and among physician specialties. Next, we develop a framework for calculating the "pure" effects of age-specific technological innovation adoption on aggregate physician service expenditures and on the number of services received. We separate the overall effects into those attributable to the three different levels of technology adoption. The framework is then used to study the age/technology/expenditure profiles of the Ontario population. Lastly, we project future age specific healthcare expenditures per person over the ten year period 2004 - 2014, based on historical rates of technology adoption.

LITERATURE REVIEW

As far as we are aware, there have been no other studies of age-specific medical technology adoption or its impact on healthcare expenditures. There have been a few studies of the differential growth of healthcare spending by age (Meara et al., 2004; Cutler and Meara, 1997, 2001; Denton et al., 2002; Dormont et al., 2006), and age-specific medical progress and its impact on the age profile of future health expenditures (Goldman, et al., 2004). But most studies on the adoption of technology innovations in healthcare have focused on a very few technological innovations and they have not been age-specific. Cutler and Meara (1997; 2001) measured the impact of technological adoption on medical spending and concluded that "a substantial amount of high cost medical use is associated with the increasing technological capability of medicine". However, they were not able to analyze the impact of all changes in technological adoption on the age profile of patients because their conclusions were based only on diagnoses for high-cost uses: substantial respiratory or other acute conditions (for infants) and circulatory diseases and cancer (for the elderly). Fuchs (1999) studied the age and sex specific healthcare utilization for seven common technological procedures (angioplasty, coronary artery bypass graft, cardiac cauterization, carotid endarterectomy, hip and knee replacement, and laminectomy), without regard to the effect of these technologies on expenditures. Sheiner (2004) found that the most technologically intensive health sectors spend relatively less on the oldest old age as compared to the younger old age. However, her research was based on only three available measures: the number of computerized axial tomography (CAT) scanners, the number of magnetic resonance imaging machines (MRIs), and the number of coronary angioplasties (heart bypasses) performed per million population respectively. Specific interventions, such as cardiac catheterizations, angioplasty and bypass grafts have also been considered; Tu et al. (2002) found that the rates of procedure utilization have increased three times faster among the over 65 age segment than among the younger population of Ontario between 1981 and 1995, and Pilote et al. (2002) found similar results for Québec between 1988 and 1994. The difference is even greater in the U.S., where the rate increased 15 times faster among the 65-74 and 30 times faster among the 75+ age groups between 1985 and 1997 (McClellan et al., 1999).

DATA AND METHODS

All analyses were based on data from the Canadian Community Health Survey, Cycle 1.1 (**CCHS 1.1**) (2000/2001) linked with Medical Services File claims from the Ontario Health Insurance Program (**OHIP)** for 1994/1995, 1999/2000, 2000/2001, 2001/2002, 2004/2005. The database was made available by the Ontario Ministry of Health and Long –Term Care (MOHLTC) to Statistics Canada, who prepared the necessary linkages using deterministic matching on encrypted health numbers. The linked data which contains information about costs, treatments, and diagnoses as well as specific service dates, provides an opportunity for research on major determinants of healthcare expenditures.

OHIP linked files have cross-sectional components to the individual over the course of 10 years; respondents entered the sample at different ages. No dataset elsewhere matches the quality and breadth of this linkage. For example, the National Long Term Care Survey in the United States is linked to expenditure data but is longitudinal in that sample persons join the survey once they reach 65 years of age and stay in the survey until they either die or are lost to follow-up.

During the study period, services provided by physicians outside the fee-for-service (FFS) payment scheme were not included: approximately 6% (1996-1997) and 16 % (2004-2005) of physician payments were not FFS in Ontario (CIHI, 2001, 2007). The fees to physicians that were reimbursed by OHIP on the FFS basis with a fixed fee schedule set by the Ontario Ministry of Health and Long Term Care (MOHLTC, 2008) were included and are referred to throughout this research.

Data Limitations

The total OHIP sample from CCHS1.1 for Ontario contains 39,278 respondents and covers the population aged 12 or older, except members of the regular Armed Forces and residents of institutions, Indians on reserves, and other Aboriginal settlements. CCHS respondents were asked for permission to link information collected during the compilation of the database with their provincial health information, including past and continuing use of services such as hospitals, clinics, doctor's offices or other services provided by the province; 83.5% (32,848) gave their permission. The sample used for this study consists of 32,769 (49.1% male and 50.9 female) respondents aged 12 or older (in 2000-2001), who agreed to allow the link information and who survived to 2004-2005.[1]

We have excluded records with payments made to out-of-province or out-of-territory physicians. We also excluded records of services provided by allied health professionals

[1] We have excluded the respondents who died before 2004-2005 year for results comparison.

(non medical specialists), laboratory specialists, and dental professionals in order to focus only on physicians[2] (Table I).

Table 1 Number of Records for Analysis

Description	Records N	Records %
Total Records	3,878,720	100.0
Excluding HP,DP and LAB	1,407,631	36.3
Shadow Billing	66,071	1.7
Adjustment to Previous Billing	185,008	4.8
Total Records for Analysis	2,220,010	57.2

Shadow billing tracks services delivered without the fee for service cost of providing that service. These services were globally funded or were not paid by OHIP. Our data files included 66,071 such services submitted to OHIP during 1994-2004 (Table I). They accounted for 1.7% of total services during the ten year period for the linked data. To avoid skewing the cost per person results by including service counts without the payments associated with them, we excluded these records from the analysis, as proposed by CIHI (2007).

Our data contained 92,504 negative payments numbers as a result of data adjustments to previous billing. These negative payments reflect retroactive claims, payment clawbacks, or other accounting practices used within administrative payment systems (CIHI, 2007). The resulting adjustments accounted for 4.8% of total services billed during 1994-2004 (Table 1), and were also excluded.

The estimates projected from the OHIP data to the Ontario population in general may be biased by the sample design. To have estimates representative of the entire Ontario population, sample design effects were represented using bootstrap weights, provided by Statistics Canada in their CCHS 1.1 linked file.

Methods

We used a three-stage approach to examine the relative importance of technological innovations affecting healthcare expenditures on physician services. First, we developed a health technology intensity measure (HTI) in which three levels (high, medium and low) of health technology were identified (see next section). Then both the per capita number of services and expenditures were decomposed at each level of technology, year, age group and gender.

[2] Health professional specialties include: physiotherapy, chiropractics, and optometry. Although dental services are not covered by OHIP, few people received emergency dental services. We have excluded these records as they were not representative of the population.

The starting point of the decomposition formula is the sum of technology adoption levels for number of services (Eq.1) and healthcare expenditures (Eq.2):

$$N_{all}(t_n) = N_L(t_n) + N_M(t_n) + N_H(t_n); \quad (1)$$
$$E_{all}(t_n) = E_L(t_n) + E_M(t_n) + E_H(t_n), \quad (2)$$

where t_n= year, n =1994, 1999,....2004; $N_{all}(t_n)$= average number of services per capita; $E_{all}(t_n)$= average expenditures on physician services; $N_L(t_n), N_M(t_n), N_H(t_n)$= average number of services per capita for low (L), medium (M) and high (H) technology intensities respectively; $E_L(t_n), E_M(t_n), E_H(t_n)$=average health care expenditures per capita for low (L), medium (M) and high (H) technology intensity. Equations 1 and 2 can be also decomposed for gender $i = 1,2$ (males and females) and for $j = 1,2$ age groups (non-elderly, elderly) as follows.

$$N_{all}(t_n) = \alpha_{ij}(N_{Lij}(t_n) + N_{M\,ij}(t_n) + N_{H\,ij}(t_n)) \quad (3)$$
$$E_{all}(t_n) = \alpha_{ij}(E_{Lij}(t_n) + E_{Mij}(t_n) + E_{H\,ij}(t_n)), \quad (4)$$

where α_{ij} - is proportion of persons in gender and age groups.

For every group and technological intensity level, annual growth rates were calculated for number of services $a_{i,j,k}(t_n, t_0)$ and expenditure $r_{i,j,k}(t_n, t_0)$:

$$a_{i,j,k}(t_n, t_0) = \left(\frac{N_{i,j,k}(t_n)}{N_{i,j,k}(t_o} \right)^{\frac{1}{t_n - t_0}} - 1; \quad (5)$$

$$r_{i,j,k}(t_n, t_0) = \left(\frac{E_{i,j,k}(t_n)}{E_{i,j,k}(t_o} \right)^{\frac{1}{t_n - t_0}} - 1, \quad (6)$$

where $k = 1,2,3$ – service technology level (low, medium and high); $j = 1,2$ - age groups (non-elderly, elderly), $i = 1,2$ - gender (males, females), t_n= final year, t_0= first year.

To project the impact of health technology on physician service expenditure we used annual rate of change of technology intensity from 1994 to 2004, assuming that annual growth would remain the same during the period 1994-2004.

4. HTI CALCULATION ALGORITHM

Health technology (HT) is any intervention that may be used to promote health, or to prevent, diagnose or treat disease, or to provide rehabilitation or long-term care

(EUnetHTA, 2008) for the maintenance, restoration and promotion of health. Usually HT is divided into two categories:

1. Devices, equipment, procedures, organizational systems and instruments used in the clinical and administrative delivery of health services, for the maintenance, restoration and promotion of health (EUnetHTA, 2008; OHTAC, 2009); and
2. Information and knowledge, which form the basis of the skills and expertise of clinical healthcare givers (Geisler, 1999).

The Health Technology Intensity (HTI) that we developed is based on the idea that each intervention (or procedure) can be characterized along three dimensions: technical complexity of the procedure, level of expertise (*knowledge of person using the technology)* of the provider performing it, and *cost of technology used*. The idea is that a more complex procedure performed by a specialist physician at higher cost should be classified as involving a high level technology than a less complex procedure provided by a less specialized physician at lower cost.

The classification algorithm aggregates these three dimensions, the first two of which are qualitative. When there are qualitative components or a mixture of quantitative and qualitative components involving imprecise and qualitative knowledge, to handle the resulting uncertainty, a fuzzy logic approach is convenient since knowledge can be represented in a manner that is similar to language used in daily life (Zadeh, 1965; Steiman, 2001; Phuong and Kreinovich, 2001).

An algorithm for constructing fuzzy HTI calculations was adapted from Roham (Roham et al, 2009). It contains **six** steps, as represented in Appendix A, Figure A1. The HTI algorithm is discussed in Appendix B.

Here we describe how we assigned the three HTI components.

1) Technical complexity. The allocation of three technological intervention classifications (LOW (L), MEDIUM (M) and HIGH (H))[3] is based on the fee schedule code (FSC) for physician services. *MOHLTC* (MOHLTC 2008) classifies all services insured by *OHIP* (about 6000 in total) into 28 main categories, based on expert opinion, Canadian and International clinical guidelines, medical standards of technology usage, and systemic reviews (Appendix A, Table A, Table C)

High Technology Treatments: We define *high technology* treatments as those with high fixed costs to implement and/or high variable costs per use (McClellan and Kessler, 1999). For example, diagnostic imaging procedures, such as magnetic resonance imaging (MRI), computed tomography (CT), and technological treatments such as cardiac catheterization, angioplasty and bypass surgery, involve "substantial setup costs in hiring

[3] 3647 billing codes were used during 1994-2004. All codes, except diagnostic and therapeutic codes, can be defined at one technological level (low, medium, high). Diagnostic and therapeutic procedures were classified into one of the three technology levels using expert opinion, Canadian and International clinical guidelines and medical standards of technology usage, and systemic reviews (Table III and Appendix C).

specialized personnel (for example, interventional cardiologists, cardiac surgeons, and specialized nurses) and the purchase of specialized equipment (such as catheterization tables and fluoroscopes)" (McClellan and Kessler, 1999).

Low Technology Treatments: Have low fixed and incremental costs to use, and do not need highly specialized training to use the technology; thus they can be provided by healthcare personnel with little additional input of labor, capital equipment, or materials (McClellan and Kessler, 1999).

Medium Technology Treatments: All treatments which are not included in high and low technology categories were assigned to this category.

The main criteria for grouping treatment interventions, including examples, are in Table 2, and the included medical intervention classifications are presented in Table 3. In our research, FSC is defined as:

$$FSC = \{LOW, MEDIUM, HIGH\}.$$

Table 2 HTI Components and Their Descriptions

Key Attributes of Component	**Identification of Technology**		
	Low	**Medium**	**High**
1) Technology Used Description: Technological Intervention			
a) complexity; b) cost of device, equipment.	a) Simple; b) Low cost. ***Example:*** Consultation, Simple Injection.	a) Medium complexity; b) Relative medium cost. ***Example:*** Nerve Block;	a) High complexity b) High cost. ***Example:*** Computed Tomography (CT); Coronary Artery Repair
2) Technology Knowledge Description: Physician Specialization			
Additional a) specialization, b) skills, c) training needed	No	Yes- short term	Yes- long term
3) Cost of Technology Description: Fee for Technological Intervention			
Clustering Fee for service	Appendix A, Step 1.b.2.	Appendix A, Step 1.b.2.	Appendix A, Step 1.b.2.

Table 3 shows the number of billing codes and records in each intervention category during 1994-2004. High technology intervention codes accounted for 26 percent of all codes and 17 percent of all records. (Table 3)

Table 3 Technical Complexity of Procedures Classification

LOW			MEDIUM			HIGH		
Description	**Number of**		**Description**	**Number of**		**Description**	**Number of**	
	Codes	**Records**		**Codes**	**Records**		**Codes**	**Records**
CONSULATATIONS AND VISITS	599	1,064,156	PULMONARY FUNCTION STUDIES	28	27,384	NUCLEAR MEDICINE	127	21,801
Which also include:			INTEGUMENTARY SYSTEM SURGICAL PROCEDURES	204	27,677	RADIATION ONCOLOGY	19	239
a) CONSULTATIONS AND VISITS (EMERG. DEPT. PHYS.ON DUTY)	14	14,998	MUSCULOSKELETAL SYSTEM SURGICAL PROCEDURES	494	11,217	DIAGNOSTIC RADIOLOGY	183	202,315
b) COMPREHENSIVE GERIATRIC CONSULTATION	2	1,081	RESPIRATORY SURGICAL PROCEDURES	121	4,536	CLINICAL PROCEDURES ASSOCIATED WITH DIAGNOSTIC RADIOLOGICAL EXAMINATIONS	45	1,813
ASSISTANCE	5	3,669	HAEMATIC AND LYMPHATIC SURGICAL PROCEDURES	18	463	MAGNETIC RESONANCE IMAGING (MRI)	26	4,756
PREVENTIVE CARE MANAGEMENT	3	215	DIGESTIVE SYSTEM SURGICAL PROCEDURES	308	28,500	DIAGNOSTIC ULTRASOUND	77	87,513
HOME CARE	1	17	UROGENITAL AND URINARY SURGICAL PROCEDURES	117	5,121	CARDIOVASCULAR SURGICAL PROCEDURES	106	2,157
			MALE GENITAL SURGICAL PROCEDURES	47	1,697	NEUROLOGICAL SURGICAL PROCEDURES	67	603
			FEMALE GENITAL SURGICAL PROCEDURES	101	7,501	OCULAR AND AURAL SURGICAL PROCEDURES	134	8,423
			ENDOCRINE SURGICAL PROCEDURES	15	292	SPINAL SURGICAL PROCEDURES	52	577
			OBSTETRICS	*39*	*29,718*			
*DIAGNOSTIC AND THERAPEUTIC PROCEDURES**	*165*	*241,523*	*DIAGNOSTIC AND THERAPEUTIC PROCEDURES**	*429*	*378,156*	*DIAGNOSTIC AND THERAPEUTIC PROCEDURES**	*101*	*41,891*
TOTAL	789	1,325,658		1921	522,262		937	372,089

*Notes: *DIAGNOSTIC AND THERAPEUTIC PROCEDURES coded as different categories*

2) Knowledge of persons using the technology (or level of expertise). For this component, the specialty claimed by the physician (SP) who provided the health service is based on the Ontario Statistical Reporting System (OSRS). For our purposes, 30 physician specialties were combined into three classes (Low, Medium, High) depending on to what degree the technological intervention requires a combination of specialization, skills, and specific training (see Table 4). The main criteria used for grouping the specialized knowledge required for these specialties can be found in Table 2, and the specialties grouped into the three classifications are shown in Table 4.

$$SP = \{LOW, MEDIUM, HIGH\}$$

Table 4 also provides information about the number of records in the database for each physician specialty during 1994-2004.

3) Cost of technology used. Fee payments by the OHIP medical care insurance plan to physicians are made in accordance with payment schedules (also known as benefit schedules), in which the amounts payable for particular services are specified (MOHLTC, 2008). As this is a quantitative component in the model, we can use data mining techniques (fuzzy clustering analysis) to group the technology costs into three classes.

Clustering is a technique for classifying data, i.e., to divide a given dataset into a set of classes or clusters (Bezdek, 1981; Balasko et al., 2007). The objective of fuzzy clustering methods is to divide a given dataset into a set of clusters based on similarity. In classical cluster analysis each datum must be assigned to exactly one cluster. Fuzzy cluster analysis relaxes this requirement by allowing gradual memberships (membership degrees), thus offering the opportunity to deal with data that belong to more than one cluster at the same time. The proposed method integrates the fuzzy clustering method as a partitioning and fuzzifying procedure. Thus the fitness between data and the fuzzy clustering method will influence the classification performance. The most widely used, adapted, and generalized (Bezdek, 1981; Bezdek et.al., 1999; Hathaway and Bezdek, 2000) clustering algorithm is the Fuzzy C- Means algorithm (FCM), proposed by Bezdek (Bezdek, 1981). In this research the extended FCM – Gustafson-Kessel (GK) is used, first described by Gustafson and Kessel (Gustafson and Kessel,1979), modified by Babuška et al.(Babuška et al.,2002) and implemented in the Fuzzy Clustering and Data Analysis Toolbox (Balasko et al., 2007).

The clustering algorithm (GK, FSM) requires the user to predefine the number of clusters, denoted as c in this research. However, the determination of an optimal cluster number is still an unsettled and subjective issue. The literature suggests various cluster validity indexes for each partition, when the number of clusters is unknown a priori. The optimal partition can be determined by the extrema of the validation indexes, depending on the number of clusters (Ozer, 2005; Balasko et al., 2007).

To determine the appropriate number of clusters, validity measures are used to assess the goodness of the obtained partitions (Bezdek et.al., 1999; Dunn, 1976; Xie and Beni, 1991; Ozer, 2005; Balasko et al., 2007). Explanations of validity measures can be found in Appendix D. Fig. D1 summarizes validity indices and indicates that a three-cluster solution was appropriate for our data, based on recommendation of previous studies to pay attention to interpretability of the results (Balakrishnan et al, 1996; Ozer, 2005).

Table 4 Technical Knowledge of Physician Medical Specialities

SPF* LOW		SPF MEDIUM		SPF HIGH	
Description	**Number of Records**	**Description**	**Number of Records**	**Description**	**Number of Records**
GENERAL AND FAMILY PRACTICE, COMMUNITY MEDICINE	1,122,030	ANAESTHESIA	32,768	NEUROSURGERY	2,567
GERIATRICS	1,064	DERMATOLOGY	33,013	ORTHOPAEDIC SURGERY	26,768
PSYCHIATRY	45,593	GENERAL SURGERY	48,089	PLASTIC SURGERY	10,492
		EMERGENCY MEDICINE	3,595	CARDIOVASCULAR & THORACIC SURGERY	4,607
		INTERNAL MEDICINE	264,830	NEUROLOGY	13,649
		OBSTETRICS & GYNAECOLOGY	84,114	OPHTHALMOLOGY	54,474
		OTOLARYNGOLOGY	38,734	DIAGNOSTIC RADIOLOGY	285,817
		PAEDIATRICS	16,385	THERAPEUTIC RADIOLOGY	3,910
		PHYSICAL MEDICINE	10,685	CARDIOLOGY	48,149
		UROLOGY	22,957	HAEMATOLOGY	4,699
		GASTROENTEROLOGY	11,018	NUCLEAR MEDICINE	8,656
		RESPIRATORY DISEASE	9,668	GENERAL THORACIC SURGERY	1,700
		RHEUMATOLOGY	3,065		
		OSTEOPATHY	110		
		CHIROPODY (PODIATRY)	6,802		
TOTAL	1,168,687		585,835		465,488

*Note: * SPF - SPECIALTY FISCAL/OSRS; OSRS- Ontario Statistical Reporting System.*

RESULTS AND DISCUSSION

Table 5 provides percentage estimates of five years healthcare technology users and services by HTI level, Table 4 provides estimates of the average number of health services of the three HIT levels separately for each year, and Table 7 provides estimates for average physician expenditures, in each case by age and sex. The HealthCare Deflator was used to express expenditures in 2002 dollars (Statistics Canada, online resource).

Health Care Users and Services by Technology Level

Table 5 shows some interesting differences among user groups in the level of health technology embodied in services received. By the end of the ten year period nearly 82 % of population had been provided with at least one health service provided by FFS physicians. Of these, more than 98.5 % had received at least one low technology service, 42% medium and 51% high. Trends in the use of medium and high technology were positive, rising over the period from 36% to 42% and from 42% to 52%, respectively, with females more likely than males to receive services involving medium and high technology. From 1994 to 2004 the use of high technology grew significantly from 36 to 45 % for men and from 47 to 57 % for women.

Table 5 Number of Health Care Users by Health Technology Intensity, Age and Sex 1994-2004

Year	Number of Observations, * N	%	Health Care Users, %	At Least One Health Service, by HTI,% L	M	H	Number of Observations, * N	%	Health Care Users, %	At Least One Health Service, by HTI,% L	M	H	Number of Observations, * N	%	Health Care Users, %	At Least One Health Service, by HTI,% L	M	H
	MALE						**FEMALE**						**M & F****					
	AGE GROUP < 65																	
1994-1995	15004	93.3	72.4	99.3	29.5	34.1	15128	90.6	82.8	99.6	37.1	45.2	30132	92.0	77.7	99.4	33.6	40.0
1999-2000	14331	89.1	75.2	99.0	29.2	37.6	14415	86.4	87.4	99.4	37.2	48.2	28746	87.7	81.3	99.2	33.5	43.3
2000-2001	14196	88.3	76.3	98.8	31.7	38.5	14252	85.4	89.6	99.2	36.3	50.1	28448	86.8	83.0	99.0	34.2	44.8
2001-2002	14048	87.4	76.0	98.5	31.1	39.5	14094	84.4	90.1	99.1	37.6	51.7	28142	85.9	83.1	98.8	34.7	46.1
2004-2005	13606	84.6	73.6	98.1	32.8	40.2	13611	81.5	87.6	98.4	40.7	53.1	27218	83.1	80.6	98.3	37.1	47.2
	AGE GROUP > 65																	
1994-1995	1072	6.7	92.4	99.4	63.4	56.6	1565	9.4	93.9	99.7	58.0	66.1	2637	8.0	93.3	99.6	60.2	62.3
1999-2000	1745	10.9	94.6	99.3	66.2	59.2	2278	13.6	95.8	99.6	60.4	69.2	4023	12.3	95.3	99.5	62.9	64.9
2000-2001	1881	11.7	94.3	99.5	67.2	62.2	2440	14.6	97.1	99.5	59.6	69.7	4321	13.2	95.9	99.5	62.9	66.5
2001-2002	2028	12.6	95.2	99.2	67.4	61.5	2599	15.6	96.4	99.5	65.6	72.5	4627	14.1	95.9	99.3	66.4	67.8
2004-2005	2470	15.4	85.2	99.5	67.5	65.2	3081	18.5	88.6	99.3	65.2	71.3	5551	16.9	87.1	99.4	66.2	68.7
	ALL AGES																	
1994-1995	16076	100	73.8	99.3	32.3	36.0	16693	100	83.9	99.6	39.3	47.4	32769	100	78.9	99.5	36.1	42.1
1999-2000	16076	100	77.3	99.1	34.1	40.4	16693	100	88.6	99.4	40.6	51.3	32769	100	83.1	99.3	37.7	46.4
2000-2001	16076	100	78.4	98.9	36.7	41.8	16693	100	90.7	99.2	40.0	53.2	32769	100	84.7	99.1	38.5	48.0
2001-2002	16076	100	78.5	98.6	36.7	42.9	16693	100	91.1	99.2	42.3	55.1	32769	100	84.9	98.9	39.7	49.6
2004-2005	16076	100	75.4	98.3	38.8	44.6	16693	100	87.8	98.6	45.2	56.5	32769	100	81.7	98.5	42.3	51.1

*Note:*Number of observations adjusted by weight, ** M & F- Male and Female*

Table 5a shows the estimated average number of health services per capita (procedures or interventions) by technology level. The average, for both sexes combined, increased from 11.3 to 14.2 over the period, with most of the increase in medium and high technology services. From 1994 to 2004 the average number of low technology services grew slightly from 8.5 to nearly 9.4 per person, although the share of low technology services declined 8.5% (from 75 % to 66.5%). The opposite trend occurred for medium and high technology services: from 1994 to 2004 the share of medium technology services increased noticeably from 14.4 to 16.1% (for medium HTI) and from 10.7 to 17.4% (for high HTI). Table 6a also demonstrates that there are differences in health services provided for males and females, for both elderly (Age >65 years) and non-elderly (Age <65). Females received more health services in the low, medium and high technologies than males, although the number of technology services received grew significantly with patient age.

Figure 1 demonstrates the ratio for females to males of per capita health services at medium and high HTI levels during the period 1994-2004. It also shows the ratio of the differences among the elderly (age 65+ years) and non-elderly (age <65). The ratio of per capita health services using high technologies for non-elderly increased slightly over time, although the ratio for non-elderly was larger than for elderly. The ratio of per capita health services using high technologies for females compared to males was 1.9 times for non-elderly and 1.1 times for elderly. The picture is different for medium technologies: the ratio per capita of health services using medium technologies for females was 1.6 times and 0.9 times more than males, respectively for non-elderly and elderly (Figure 1).

Table 5a Number of Health Services by Health Technology Intensity, Age and Sex, 1994-2004

Year	Average Number of Health Services*	Share of Health Services, by HTI, %			Average Number of Health Services	Share of Health Services, by HTI, %			Average Number of Health Services	Share of Health Services, by HTI, %		
		L	M	H		L	M	H		L	M	H
	MALE				**FEMALE**				**M & F****			
AGE GROUP < 65												
1994-1995	8.0	76.6	13.2	10.2	12.6	75.0	14.1	10.8	10.3	75.6	13.8	10.6
1999-2000	8.0	74.7	12.5	12.8	12.4	73.4	12.8	13.8	10.3	73.9	12.7	13.4
2000-2001	8.6	73.2	13.6	13.3	13.0	72.4	12.9	14.7	10.8	72.7	13.2	14.1
2001-2002	8.8	68.4	15.2	16.4	13.8	68.4	13.5	18.1	11.3	68.4	14.1	17.5
2004-2005	8.7	68.2	15.4	16.4	14.3	66.5	14.6	19.0	11.5	67.1	14.9	18.0
AGE GROUP > 65												
1994-1995	22.3	69.6	20.2	10.2	23.4	72.8	15.6	11.5	23.0	71.6	17.4	11.0
1999-2000	26.2	69.5	19.2	11.3	25.3	70.7	15.3	14.0	25.7	70.1	17.0	12.8
2000-2001	27.2	68.9	19.8	11.2	25.8	69.8	16.0	14.2	26.4	69.4	17.7	12.9
2001-2002	30.4	65.6	20.1	14.3	28.8	66.0	16.3	17.7	29.5	65.8	18.0	16.2
2004-2005	27.0	64.0	20.6	15.4	27.6	66.3	17.1	16.6	27.3	65.3	18.6	16.1
ALL AGES												
1994-1995	9.0	75.4	14.3	10.2	13.6	74.7	14.4	10.9	11.3	75.0	14.4	10.7
1999-2000	10.0	73.2	14.4	12.4	14.2	72.7	13.4	13.8	12.1	72.9	13.8	13.2
2000-2001	10.7	71.9	15.4	12.7	14.9	71.8	13.7	14.5	12.8	71.8	14.4	13.8
2001-2002	11.5	67.5	16.8	15.7	16.2	67.8	14.2	18.0	13.9	67.6	15.3	17.1
2004-2005	11.5	66.7	17.3	16.0	16.8	66.4	15.3	18.2	14.2	66.5	16.1	17.4

*Note: *Number of observations adjusted by weight,** M & F- Male and Female*

Table 5b Annual Percentage Change of Share Health Services for All Ages by Health Technology Intensity and Sex, 1994-2004

Year	Annual Percentage Change of Share of Health Services, by HTI, %								
	L	M	H	L	M	H	L	M	H
	MALE			**FEMALE**			**M & F**		
1994-1999	-0.6	0.1	3.9	-0.5	-1.4	4.8	-0.5	-0.8	4.4
1999-2000	-1.8	7.2	2.3	-1.4	2.2	5.0	-1.5	4.4	3.9
2000-2001	-6.2	9.0	24.4	-5.6	3.9	23.7	-5.8	6.1	24.0
2001-2004	-0.4	0.9	0.6	-0.7	2.5	0.5	-0.5	1.7	0.6
1994-2004	-1.2	1.9	4.6	-1.2	0.6	5.2	-1.2	1.1	5.0

*Note: * M & F- Male and Female*

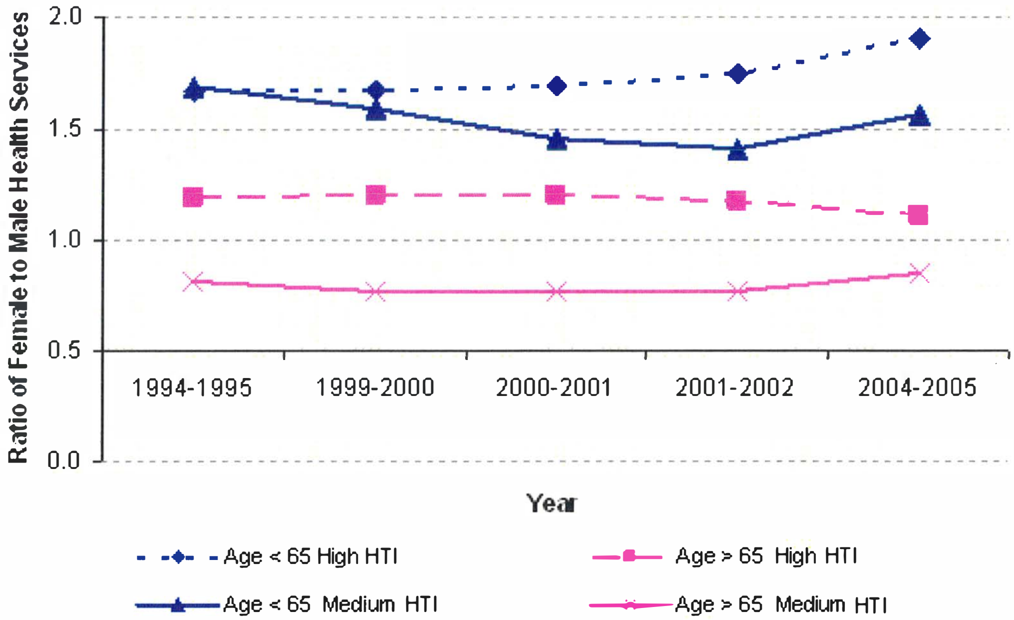


Figure 1 Ratio of Female to Male Number of Health Services by HTI (High and Medium) by Year and Age Group.

The annual percentage change of the share of the number of high technology health services over all age groups was 4.4% for both sexes in the 1994-1999 period, though the growth for females was bigger than for males. The growth was the most rapid in 2000-2001, probably when diagnostic imaging technologies were becoming widely adopted in Ontario. In the next 3 years the growth slowed to 1.1 and 5 percent per year for medium and high HTI respectively (Table 5b).

Figure 2 shows that the growth in the number of health services for both sexes of medium and high HTI averaged respectively 3.4 and 7.4 percent annually between 1994 and 2004. The rates for low HTI grew slowly, near 1.1 percent annually. The growth of services at the high technology level was the highest for non-elderly females, probably reflecting that in this group the females are of childbearing age.

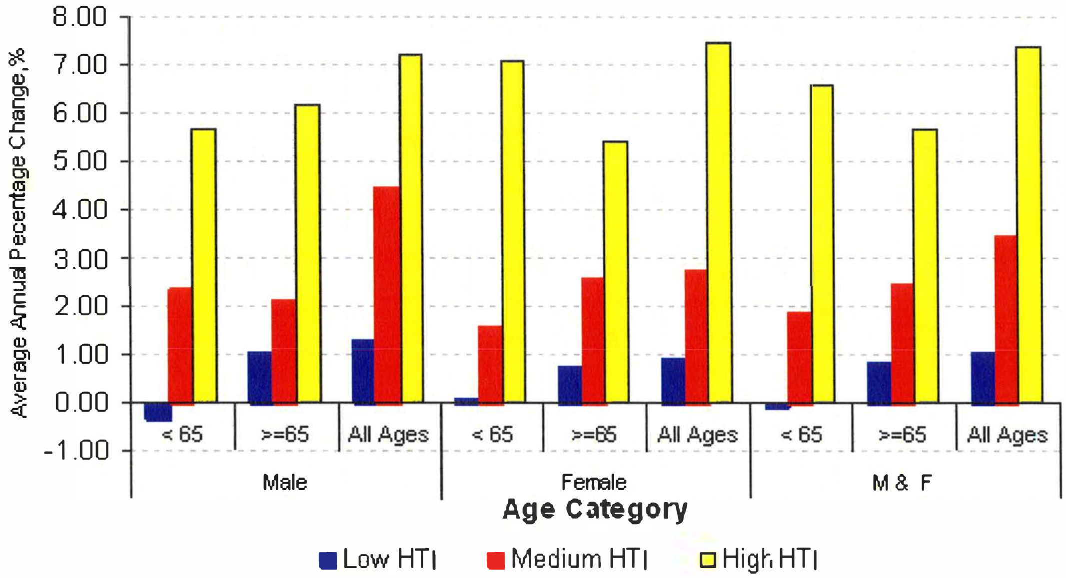
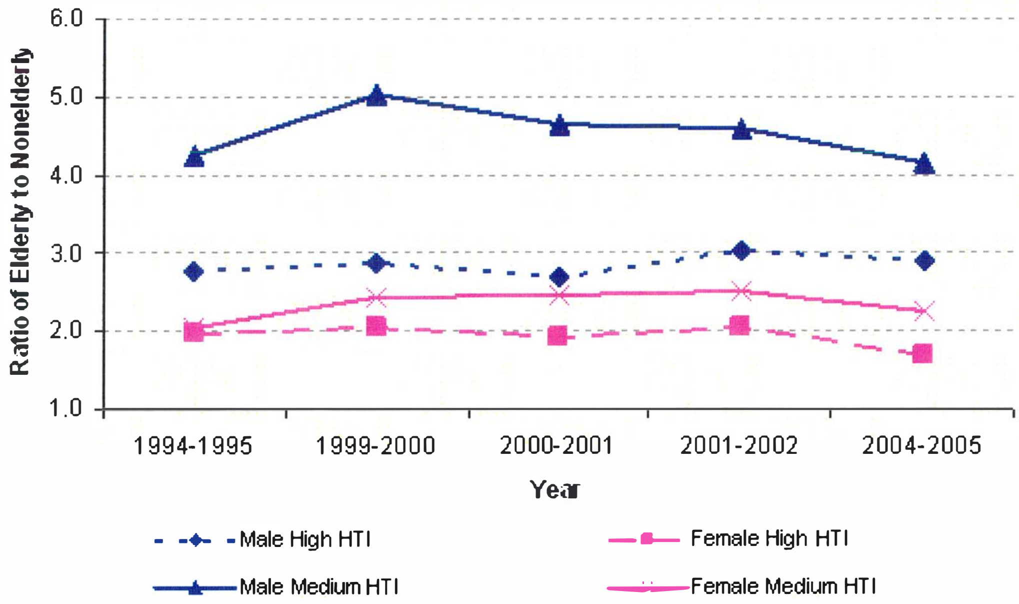
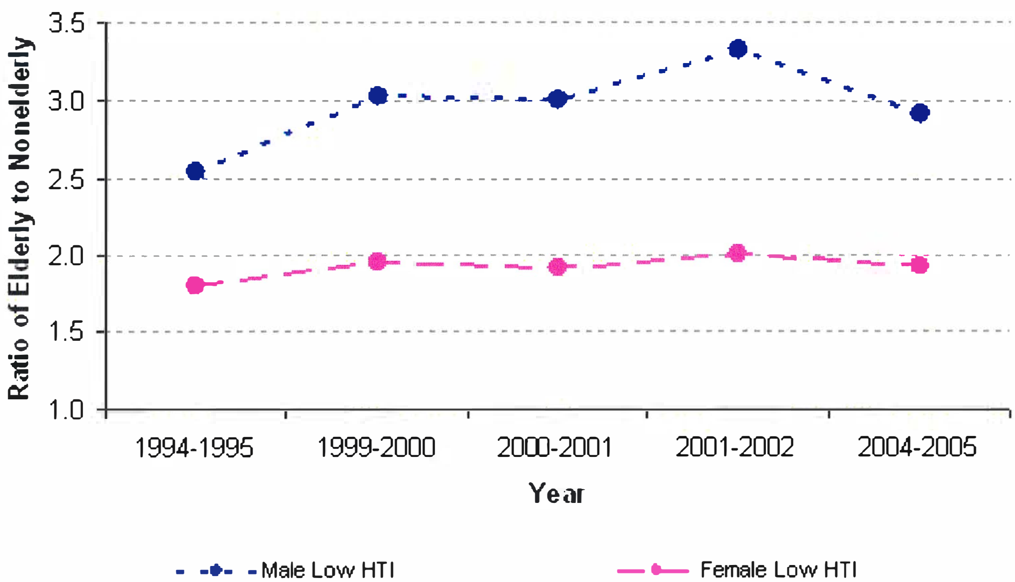


Figure 2 Average Annual Percentage Change in the Per Capita Number of Health Services for Non-Elderly (Age < 65) and Elderly (Age >65) Patients by Sex and HTI, 1994-2004.

Figure 3a demonstrates the ratio of per capita health services at medium and high levels HTI for the elderly (age 65+) to the non-elderly (age <65) during the period 1994-2004. It also shows the ratio of the differences among males and females. The ratio of per capita health services using medium and high technologies for males and females increased slightly over time, although the ratio for males was larger than for females. The ratio of per capita health services using high technologies for the elderly compared to the non-elderly is 3 times for males and 1.7 times for females. This is also true for low technologies: the ratio per capita of health services using low technologies for the elderly was 2.9 times and 1.9 times more than the non-elderly, respectively for males and females (Figure 3b).



a)



b)

Figure 3 Ratio of Elderly to Non-Elderly Number of Health Services by HTI, Year and Sex: a) High and Medium HTI; b) Low HTI.

Physician Service Expenditures by Technology Levels

Estimated average health payments per patient capita to physicians by HTI categories are presented in Table 7a. From 1994 to 2004 the growth in the average physician payments increased from $384.2 to $445.3 per capita (Table 7a, column 10). Total per capita physician spending for females was consistently higher than for males for all years. For example in 2004 the average physician expenditures for females were about 37% higher than that for males (513.8 vs. 374.2), probably replicating the differences in health status, because the usage of health services is also higher for women (Table 7a, columns 2 and 6).

Table 7a reveals that in 1994, 68 percent of average expenditure was on low technology services, and in 2004 this spending declined to 59 % (column 11). About 70% of expenditures for the non-elderly population and nearly 59% for elderly patients in 1994 were for low technology; its share in total expenditure decreased for both groups in all years (column 11). The greatest decline in share of expenditure for low technology services during 1994-2004 was for male patients – nearly 1.6% (from 67.1 to 57.3) annually for both age groups, or 1.1% (from 69.2 to 61.8) and 1.3% (from 56.5 to 49.4) respectively, for elderly and non-elderly males (Table 7a and 7b). The age group over 65 was mostly responsible for increases in real 2002 dollars spending for medium and high technologies. The share of average expenditures for medium and high technology for elderly were significantly higher than for non-elderly, though the share of average expenditures for medium technology services increased more for non-elderly patients than for the elderly near 1.7% annually (from 14.8 to 17.5) and 1.4% (from 19.6 to 22.5) respectively during the 1994-2004 period (Table 7a, column 12).

Table 7a Physician Service Expenditure by Health Technology Intensity, Age and Sex 1994-2004

Year	Average Physician Service Expenditure*	Share of Physician Service Expenditure, by HTI			Average Physician Service Expenditure	Share of Physician Service Expenditure, by HTI*			Average Physician Service Expenditure	Share of Physician Service Expenditure, by HTI*		
		L	M	H		L	M	H		L	M	H
	MALE				FEMALE				M & F**			
	AGE GROUP < 65											
1994-1995	276.0	69.2	16.1	14.7	430.8	70.1	14.0	16.0	353.7	69.7	14.8	15.5
1999-2000	283.8	64.7	17.2	18.1	433.7	68.3	14.2	17.5	359.0	66.9	15.4	17.8
2000-2001	312.8	63.7	18.1	18.2	447.6	66.5	14.6	18.9	380.3	65.4	16.0	18.6
2001-2002	312.7	61.6	20.8	17.6	452.3	65.8	14.3	19.9	382.6	64.1	17.0	19.0
2004-2005	283.9	61.8	19.0	19.2	444.7	62.3	16.5	21.2	364.3	62.1	17.5	20.4
	AGE GROUP > 65											
1994-1995	742.6	56.5	22.1	21.4	727.0	60.9	17.8	21.3	733.3	59.1	19.6	21.3
1999-2000	900.2	52.8	21.8	25.5	857.8	53.3	19.6	27.1	876.2	53.1	20.6	26.4
2000-2001	905.9	53.3	23.4	23.4	825.4	55.9	18.6	25.5	860.4	54.7	20.8	24.5
2001-2002	1003.1	51.8	24.4	23.8	907.1	54.5	20.7	24.7	949.2	53.3	22.4	24.3
2004-2005	871.5	49.4	24.3	26.3	819.1	54.6	20.9	24.4	842.4	52.2	22.5	25.3
	ALL AGES											
1994-1995	307.1	67.1	17.1	15.8	458.5	68.7	14.5	16.8	384.2	68.1	15.5	16.4
1999-2000	350.7	61.4	18.5	20.2	491.5	64.7	15.5	19.8	422.5	63.3	16.7	20.0
2000-2001	382.2	60.8	19.6	19.6	502.8	64.0	15.5	20.5	443.6	62.6	17.2	20.1
2001-2002	399.8	58.5	21.9	19.6	523.1	62.7	16.1	21.2	462.6	60.9	18.5	20.5
2004-2005	374.2	57.3	20.9	21.8	513.8	60.0	17.8	22.2	445.3	58.9	19.1	22.0

*Note: *Average Expenditure is in real 2002 dollars adjusted using HealthCare Deflator, ** M & F- Male and Female*

Table 7b Annual Percentage Change of Share of Physician's Service Expenditure for All Ages by HTI and Sex, 1994-2004

Year	Annual Percentage Change of Share of Physician Service Expenditure, by HTI, %								
	L	M	H	L	M	H	L	M	H
	MALE			FEMALE			M & F*		
1994-1999	-1.8	1.6	5.0	-1.2	1.3	3.4	-1.4	1.5	4.0
1999-2000	-0.9	6.0	-2.8	-1.2	0.3	3.6	-1.1	3.2	0.9
2000-2001	-3.8	11.9	-0.2	-1.9	3.4	3.4	-2.7	7.6	1.9
2001-2004	-0.7	-1.5	3.6	-1.5	3.5	1.5	-1.1	1.0	2.4
1994-2004	-1.6	2.0	3.3	-1.3	2.1	2.8	-1.4	2.1	3.0

*Note: * M & F- Male and Female*

The share of average health expenditures for high technology grew noticeably over the same time. The annual real per capita growth rate of share of average expenditures for high technology services was more substantial for males than for females: 3.3% (from 15.8 to 21.8) and 2.8% (from 16.8 to 22.8) respectively (Table 7a and 7b). These results confirm the main role of technology innovation in health expenditures (Sheiner, 2004; Fuchs, 1999).

The main growth in average expenditure of medium and high technology services affected the growth of total expenditures. Figure 4 demonstrates the average annual percentage change of physician patient service expenditure by sex, age groups and technology service used.

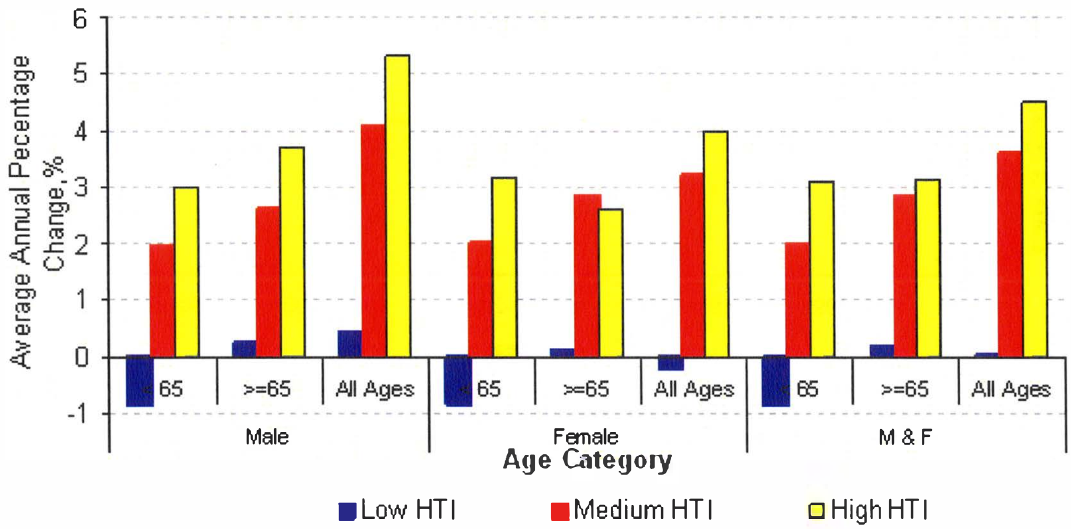


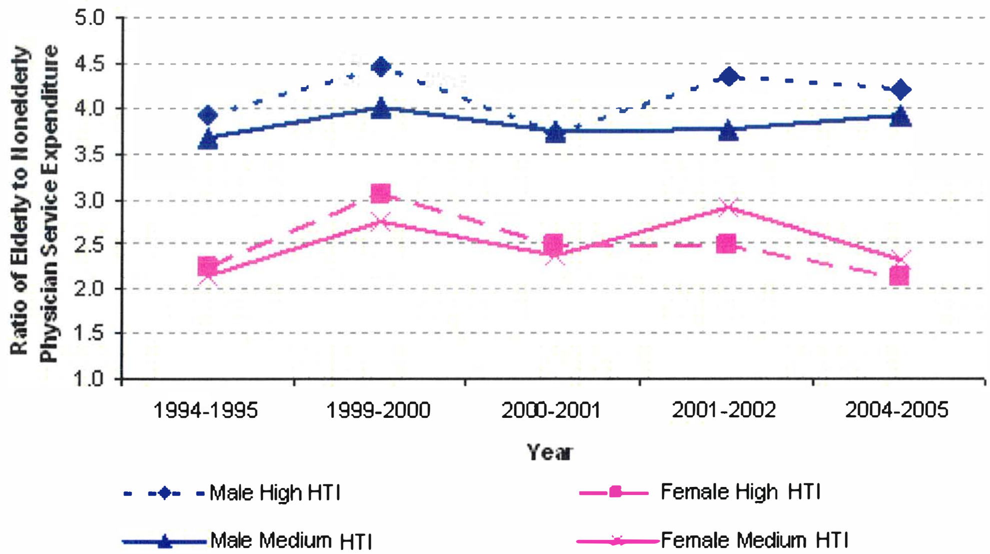
Figure 4 Average Annual Percentage Change of Physician Service Expenditure by Sex and Technology Service Used 1994-2004.

It shows that the annual expenditure rates for low HTI and non-elderly patients declined for males and females between 1994 and 2004. The annual growth of expenditures for both sexes for medium and high HTI averaged respectively 3.6 and 4.5 percent annually between 1994 and 2004[4].

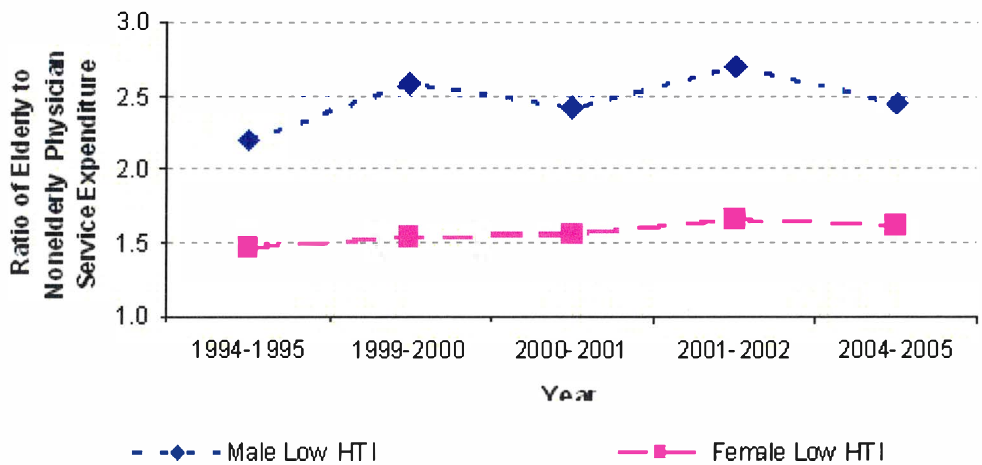
The ratio of per capita health expenditures for medium and high technology services for the elderly (over 65) to the non-elderly during the research period is plotted in Figure 5a. This also shows the ratio differences between males and females. The ratio of per capita health expenditure on high technology services for elderly relative to non-elderly is 4.2 for males and 2.1 for females. The ratio for elderly to non-elderly of per capita health expenditure on low HTI for males and females increased slightly over time, although the ratio for males is bigger than it is for females, as shown in Figure 5b.

[4] We estimated the annual growth of physician expenditures by technology levels used for persons which had at least one health service, both in 1994 and 2004, to resolve the effects of migration on the Ontario population. The annual growth for this population was not significantly different from the overall population.

Figures 5a and 5b show noticeable differences between the ratios of elderly to non-elderly expenditures as a function of technology service levels: the ratio of expenditures for high technology services for men and women was bigger than the ratio of expenditures for low technologies. It is evident that expenditures for high and medium technologies tends to be more substantial for the elderly than for the non-elderly; this tends to confirm the hypothesis of an increased concentration of health spending among the elderly, especially for medium and high technology services.



a)



b)

Figure 5. Ratio of Elderly to Non-Elderly Physician Service Expenditure by HTI, Year and Sex: a) High and Medium HTI; b) Low HTI.

TECHNOLOGY IMPACTS ON FUTURE PHYSICIAN EXPENDITURES

Predictions of future healthcare expenditures often take into account two long-term trends: a decrease in age-specific mortality rates and a significant increase in the over-65 population. Goldman et al. (2004) point out that, as individual healthcare expenditures depend on various factors: age, sex, health status, diseases and medical technology to treat them, etc., the estimates of future expenditures are very uncertain. Per capita estimates of spending are uncertain because they depend on hard-to-predict changes in all these factors. The impacts of health technology on physician service expenditures for Ontario's population were projected at one year intervals from 2004-2014. These projections were generated for each category of technological adoption, assuming that the annual rate of change of technology intensity (low, medium, high and all technology) would remain the same as during 1994-2004. To our knowledge there is no such prediction in the literature. Projected expenditures are presented in 2002 dollars. Figure 6 shows the projections for health expenditure for physician services per person by technology level for 1994-2014.

Based on our projections, the average physician expenditure per person for all technologies can be expected to increase from \$445 in 2004 to \$537 (in constant 2002 Canadian dollars) as a result of advances in technological adoption in healthcare. Expenditures for low level technologies are projected to increase very slightly from \$262 in 2004 to \$263 (annual growth 0.03%); expenditures for medium technology can be expected to increase from \$85 to \$121 (annual growth 3.6%); expenditures for high technology are estimated to rise from \$98 to \$152 (annual growth 4.5%) in constant 2002 dollars. This projection suggests that high technology adoption can explain about 59% of the growth in health expenditures for physician services.

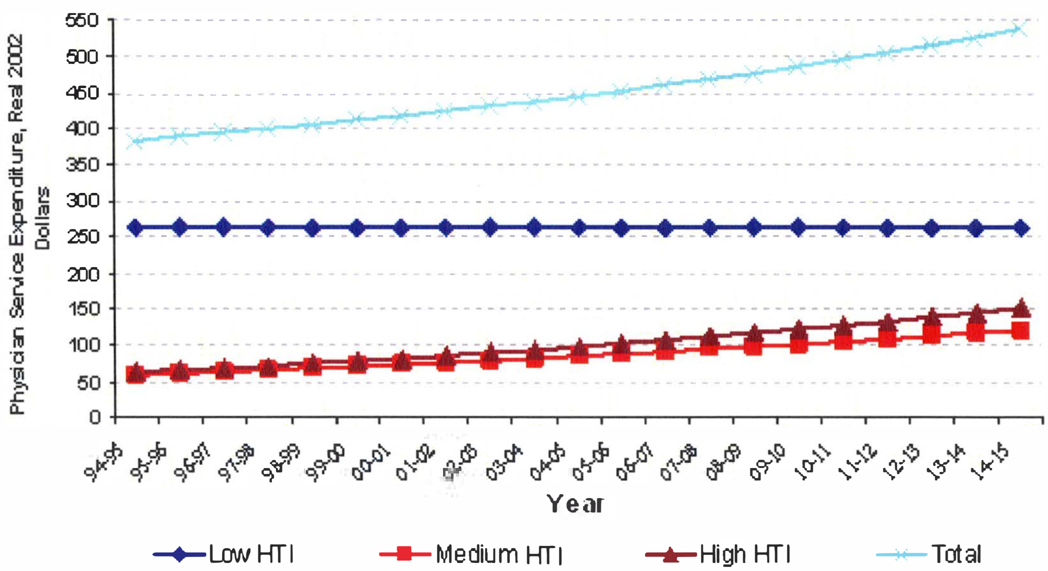


Figure 6 Projected Physician Service Expenditure by HTI, 1994-2014

CONCLUSIONS

Health costs continue to grow more rapidly than most other components of public budgets. Most experts believe that technological changes and innovations in healthcare are being used more widely now than in the past and they are the primary reasons for rapidly rising healthcare expenditures. How much healthcare expenditure growth is caused by technological innovations is hard to answer because of our lack of knowledge of economic effects of technology in healthcare. The result is that uncertainty in our understanding of medical technology innovation reduces the healthcare system's ability to manage efficiently the introduction of technology in a way that ensures the best benefits for patients, healthcare providers, governments, and insurers.

This research has sought to extend and deepen our understanding of technological innovation adoption and implementation for healthcare providers (physicians) and recognize its impact on healthcare expenditure growth. Based on data on expenditures in Ontario during the ten year period from 1994 to 2004, our analysis has demonstrated the impact of the growth in technology adoption on physician service expenditures.

We found that, during 1994 to 2004, the adoption of high technology in healthcare grew a total of nearly 9 %, or 1.9% annually, but it was adopted at different rates for patients in different age groups. In 2004 nearly 51 % of all patients received at least one high technology treatment. The elderly were more likely to receive high technology treatment than the non-elderly - the ratio of the number of high technology services for elderly was 3 times and 1.7 times more than the non-elderly, respectively, for males and females. The results also indicate that females are more likely to have medium and high technology treatment than males.

Physician expenditures per capita for all levels of technology, as well as for low, medium and high technologies separately, were generally more concentrated among the elderly group of patients. Physician expenditures per capita on medium and high technologies for males in the non-elderly age group were consistently lower than that of females in the same age groups, probably reflecting that in this group females are of childbearing age. Throughout the senior ages, expenditures per capita on medium and high technologies for males are slightly higher, which could be due to more severe conditions among males, necessitating more high and medium technology treatments and diagnostics.

Finally, our projection suggests that high technology effects will add about 59% annually to the total growth of 1.6% for provincial government health expenditures on physician fees between 2004 and 2014.

The results of this research will help health policy analysts and researchers to understand the relationships between aging populations and the relative distribution of spending on healthcare for different categories of technology adoption. The observed changes in the use of technology by patient age will also help to produce better predictions of future healthcare expenditures under various scenarios of technology adoption.

More accessibility of age-specific data on determinants of health, drug expenditures, hospital expenses, etc. among all provincial health agencies would allow more sophisticated projections in the future, using multi-variable models and different scenarios of changes in the level of medical diagnostic and treatment technologies.

ACKNOWLEDGEMENTS
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REFERENCES

Alcalde-Unzu J., Ezcurra R and Pascual P. 2009. Cross-country disparity in health-care expenditure: a factor decomposition. *Health Economics* 18: 479–485.

Babuška, R, van der Veen, P. J., Kaymak,U, 2002. Improved Covariance Estimation for Gustafson-Kessel clustering. *IEEE International Conference on Fuzzy Systems*: 1081-1085.

Balakrishnan P.V., M.C. Cooper, V.S. Jacob, P.A. Lewis, 1996. Comparative performance of the FSCL neural net and Kmeans algorithm for market segmentation, *European Journal of Operational Research* 93 : 346–357.

Balasko,B, Abonyi,J. and B. Feil, B, 2007. The Fuzzy Clustering and Data Analysis Toolbox.

Barros PP. 1998. The black box of health care expenditure growth determinants. *Health Economics* 7: 538–544.

Baumol W.J. 1993. Health Care, education and the cost disease: a looming crisis for public choice. Public Choice 77: 17–28.

Bensaid A.M., L.O. Hall, J.C. Bezdek, L.P. Clarke, M.L. Silbiger, J.A. Arrington, and R.F. Murtagh, 1996. Validity-guided (Re) Clustering with applications to image segmentation. *IEEE Transactions on Fuzzy Systems*, 4:112-123.

Bezdek J. C..1981. *Pattern Recognition with Fuzzy Objective Function Algorithms.* Plenum Press, 1981.

Bezdek J.C., J. Keller, R. Krisnapuram, N.R. Pal, 1999. Fuzzy Models and Algorithms for Pattern Recognition and Image Processing, Kluwer Academic Publishers, Boston, MA.

Bodenheimer T. 2005. High and rising healthcare costs. Ann Intern Med142: 932-937.

Bojadziev G. and Bojadziev M, 1997. *Fuzzy Logic for Business, Finance and Management,* World Scientific Publishing Co.Pte.Ltd., Singapore.

Canadian Institute for Health Information. 2001. National Physician Database: National Grouping System Categories Report, Canada, 1996/97 to 1998/99. Canadian Institute for Health Information (CIHI), Ottawa.

Canadian Institute for Health Information 2007. *National Grouping System Categories Report, Canada, 2004–2005, Revised August 2007,* Canadian Institute for Health Information (CIHI), Ottawa.

Costa-Font J, Pons-Novell J. 2007. Public health expenditure and spatial interactions in a decentralized national health system. *Health Economics* 16: 291–306.

Cutler, D. and E. Meara, 1997. *The Medical Costs of the Young and Old: A forty year Perspective.* NBER Working paper 6114.

Cutler D. M. and E. Meara, 2001. The Concentration of Medical Spending: An Update. In *The Economics of Aging,* ed. D. Wise, Chicago: University of Chicago Press: 217–240.

Denton, F.T, Gafni, A and Spencer B.G., 2002. Exploring the effects of population change on the costs of physician services", Journal of Health Economics 21: 781–803.

Dormont, B., M. Grignon, and H. Huber, 2006. Health expenditure growth: reassessing the threat of aging. *Health Economics* 15: 947-963.

Dunn J.C., 1976. Indices of partition fuzzyness and the detection of clusters in large data sets, in: M.M. Gupta (Ed.), Fuzzy Automata and Decision Processes, Elsevier, New York.

EUnetHTA, 2008. HTA Core Model for Diagnostic Technologies v 1.0r, Available at: www.eunethta.net

Geisler, E., 1999. Multiple-Perspectives Model of Medical Technology. *Healthcare Management Review.* 24(3):55-63.

Glenn,R., Greenhalgh, T., MacFarlane, F. and Peacock, R. 2009. Organisational factors influencing technology adoption and assimilation in the NHS: a systematic literature review. Report for the National Institute for Health Research Service Delivery and Organisation Programme, UK.

Goldman D.P. et al., 2004. *Health Status and Medical Treatment of the Future Elderly:* Final Report, Pub. no. TR-169-CMS, Santa Monica, Calif.: RAND.

Gustafson, D.E. and. Kessel, W.C., 1979. Fuzzy clustering with fuzzy covariance matrix. In *Proceedings of the IEEE CDC, San Diego*: 761-766.

Hartwig J. 2008. What drives health care expenditure? Baumol's model of unbalanced growth revisited. J Health Econ 27: 603–623.

Hsiao W, Heller PS. 2007. What should macroeconomists know about health care policy? International Monetary Fund, Washington DC.

Herrera F, .Martínez L. and Sánchez P.J., 2005. Managing Non-Homogeneous Information in Group Decision Making. *European Journal of Operational Research* 166: 115-132.

Fogel, R. W. 2008. Forecasting the Costs of U.S Healthcare in 2040. NBER Working Paper 14361.

Fuchs, V. 1999. Healthcare for the Elderly: How Much? Who Will pay for it? Health Affairs, 18(1): 11-23.

McClellan, M and Kessler, D. A, 1999. Global Analysis of Technological Change in Healthcare: The Case Of Heart Attacks. Health Affairs 18(3): 250-255.

Meara, E., C. White, and D. Cutler 2004. Trends in medical spending by age: 1963-2000. *Health Affairs*, 23(4): 176-183.

MOHLTC 2008. The Schedule of Benefits: Physician Services is a schedule under Regulation 552 of the *Health Insurance Act* with the exception of the Table of Contents, Appendices A, B, C, F, G, H, and both the Alphabetic and Numeric Indices., Ministry of Health and Long Term Care, Ontario , Canada.

Narayan PK. 2007. Do health expenditures ''catch-up''? Evidence from OECD countries. *Health Economics* 16: 993–1008.

Nedosekin, O., 2003. *Financial management in fuzzy environment,* Sezam, Saint-Petersburg, Russia, (in russian)

Oliveira Martins, J, De la Maisonneuve Ch Bjørnerud S. 2006. Projecting OECD health and long-term care expenditures: what are the main drivers? Economics Department WorkingPaper No. 477, OECD, Paris.

OHTAC 2009. Decision Determinants Guidance Document. The Ontario Health Technology Advisory Committee (OHTAC) Decision-Making Process for the Development of Evidence-Based Recommendations. Available at: <http://www.health.gov.on.ca/ohtas>.

Ozer, M., 2005. Fuzzy c-means clustering and Internet portals: A case study. *European Journal of Operational Research* 164: 696–714.

Pedrycz W. 2005 Knowledge Based Clustering. From Data to Information Granules, John Wiley & Sons.

Phuong N. H. and Kreinovich V. 2001. Fuzzy logic and its applications in medicine. *Int. J. Med. Inf.* 62(2):165–173.

Pilote, Louise, Frédéric Lavoie, Vivian Ho, and Mark J. Eisenberg, 2002. Technological Change in Heart Attack in Québec, Canada, in McClellan Mark B. and Daniel P. Kessler, (eds.), *Technological Change in Healthcare – A Global Analysis of Heart Attack*, Ann Arbor, The University of Michigan Press, 72-87.

Productivity Commission Australia (PCA). 2005. Modelling the aggregate impact of medical technology on expenditure—Technical Paper 1. Impacts of Advances in Medical Technology in Australia. Research Report, PCA, Melbourne. Available at: http://www.pc.gov.au/__data/assets/pdf_file/0019/17182/technicalpapers.pdf

Roham, M, Gabrielyan A. R and Archer, N.P., 2009. Fuzzy Linguistic Modeling of Ease of Doing Business Indicators, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems Vol. 17, No. 4: 531−557.

Roubens M., 1982. Fuzzy clustering algorithms and their cluster validity, European Journal of Operational Research 10: 294–301.

Sheiner, L. 2004 The Effects of Technology on the Age Distribution of Health Spending: A Cross-Country Perspective. Federal Reserve Board of Governors, Washington DC.

Statistics Canada. Table 326-00211 - Consumer price index (CPI), 2005 basket, annual (2002=100 unless otherwise noted), CANSIM (database). http://cansim2.statcan.gc.ca/cgi-win/cnsmcgi.exe?Lang=E&CNSM-Fi=CII/CII_1-eng.htm, (Accessed: June 25, 2009).

Steimann F. 2001. On the use and usefulness of fuzzy sets in medical AI. *Artificial Intelligence in Medicine* 21:131-137.

Tu, Jack V., Peter C. Austin, and C. David Naylor, 2002. Technological Change in Heart Attack in Ontario, Canada, 1981-1995, in McClellan Mark B. and Daniel P. Kessler, (eds.), *Technological Change in Healthcare – A Global Analysis of Heart Attack*, Ann Arbor, The University of Michigan Press, 58-71.

Westerhout W.M.T. 2006. Does ageing call for a reform of the health care sector? *CESifo Econ Stud* 52: 1–31.

Xie X.L. and Beni G.A, 1991. Validity measure for fuzzy clustering. *IEEE Trans. PAMI*, 3(8):841-846.

Xu, Z.S., 2008. Linguistic Aggregation Operators: An Overview, in *Fuzzy Sets and Their Extensions: Representation, Aggregation and Models,* eds. H.Humberto Bustince, F. Herrera and J.Montero, Springer Berlin / Heidelberg, 163–181.

Xu Z. S.and Da Q.L., 2003. An overview of operators for aggregating information, *International Journal of Intelligent Systems* 18:9**:** 953–969.

Yager, R.R., 1993. Families of OWA Operators, *Fuzzy Sets and Systems* 59: 125- 148.

Yager, R.R., 1996. Quantifier Guided Aggregation Using OWA Operators, *International Journal of Intelligent Systems* 11: 49–73.

Yager, R.R., 1998. Including Importance in OWA Aggregation Using Fuzzy Systems Method, *IEEE Transactions on Fuzzy Systems* 6(2): 286–294.

Yager R.R. and Kleinovich, V., 2002. Main Ideas Behind OWA Lead to a Universal and Optimal Approximation Scheme, *Fuzzy Information Processing Society, Proceedings NAFIPS:* 428 – 433.

Zadeh L. A. 1965. Fuzzy sets. *Information and Control* 8: 338–353.

APPENDIX A
HTI ALGORITHM

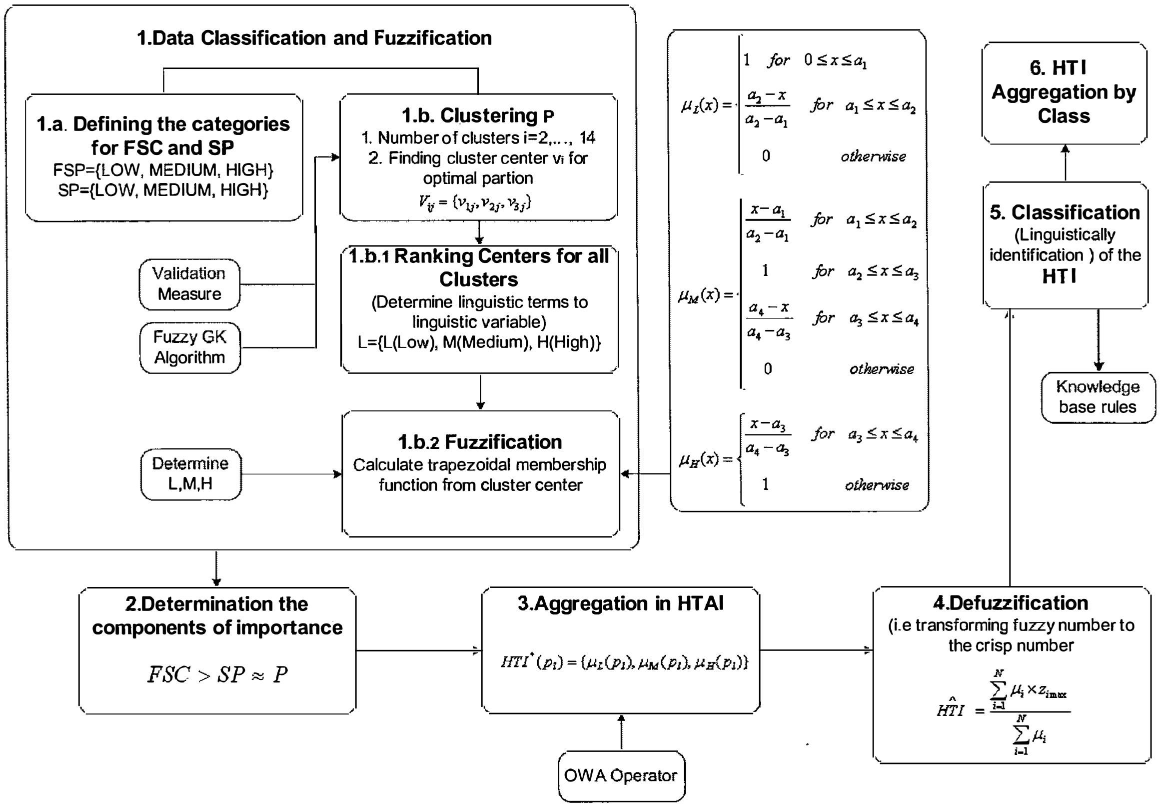

Figure A1. Algorithm Steps for HTI Calculation

APPENDIX B
ALGORITHM STEP DESCRIPTION

Step 1: *Data classification and fuzzification*

Step1.a: Defining the categories for HTI component "*Technological complexity*" (FSC) and "*Knowledge of person using the technology*" (SP):

$$FSC = \{LOW, MEDIUM, HIGH\} \quad (1.1)$$
$$SP = \{LOW, MEDIUM, HIGH\} \quad (1.2)$$

Step 1.b: Clustering of "*Cost of technology used*" (P).
Fuzzy cluster analysis divides a given dataset into a set of clusters with degrees of membership, thus offering the opportunity to deal with data that belong to more than one cluster at the same time. Suppose we have X_j indicators to aggregate in the *HTI*. An appropriate fuzzy clustering procedure is selected to cluster the quantitative X_j component into $c \geq 2$ clusters in this step. The proposed method integrates the fuzzy clustering method as a partitioning and fuzzifying procedure. Thus the fitness between data and the fuzzy clustering method will influence the classification performance. The most widely used clustering algorithm is the *Fuzzy C-Means* algorithm (FCM), proposed by Bezdek (1981). In this research the extended FCM – Gustafson-Kessel (GK) is used, as it detects clusters of different geometrical shapes in one data set. The algorithm was first described by Gustafson and Kessel (1979), modified by Babuška et al. (2002) and implemented in the *Fuzzy Clustering and Data Analysis Toolbox* (Balasko et al., 2007).
After applying GK, the cluster centres for the X_j indicator are denoted as v_{ij} (i= 1,2,…,c and j=1,2,….m). The indicator X_j has its own clusters centre (weighted mean) $V_{ij} = \{v_{1j},...,v_{cj}\}$. The cluster centres after application of the GK clustering algorithm for component x_3 - "*Cost of technology used"* in real 2002 dollars is $V_3 = \{70;1078;398\}$.

Step 1.b.1*:* In this sub-step we rank each cluster to define the clusters as ordered linguistic terms in the linguistic variables L_{ij} (i = 1, 2,. . . , c). For example, suppose we have three clusters whose centres are 70, 1078 and 398. Respectively, their centres are utilized as C_1, C_3 and C_2 and we define them as L_1, L_3 and L_2, respectively. We define for all individual indicators the following linguistic terms:

L_i= {L (Low), **M** (Medium), **H** (High)}. (1.3)

After ranking component x_3 "*Cost of technology used*"

$$V_3 = \{v_{1\,3}, v_{2\,3}, v_{3\,3}\} = \{v_{L\,3}, v_{M\,3}, v_{H\,3}\} = \{70;398;1078\} \quad (1.4)$$

Step 1.b.2*:* Indicator X_j is fuzzified by using a trapezoidal fuzzy membership function. The trapezoidal fuzzy membership function was chosen for several purposes. First, it is very simple to interpret and understand, and second, for classifying indicators we need ranges that include zones of absolute confidence, where a simple indicator or aggregated index can be classified with 100% confidence for each linguistic term (**Low**, **Medium**, **High**). A trapezoidal membership function with three linguistic terms is presented in Figure B1.

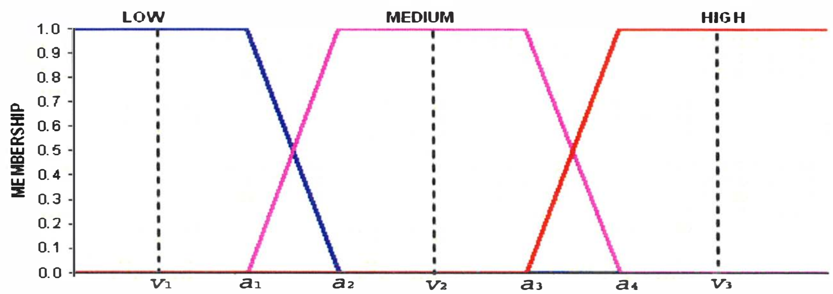

Figure B1. Trapezoidal Membership Function

Each point in the fuzzy set is calculated according to:

$$a_1 = v_1 + \frac{v_2 - v_1}{3};\ a_2 = v_2 - \frac{v_2 - v_1}{3};\ a_3 = v_2 + \frac{v_3 - v_2}{3};\ a_4 = v_3 - \frac{v_3 - v_2}{3}. \qquad (1.5)$$

After determining each point in a fuzzy set, the trapezoidal membership function for each linguistic term can be presented as shown on Figure A1, step1.b.2. Graphically the membership function component x_3 "Cost of technology used" can be represented as in Figure B2.
For any quantitative valuation of the indicator, the vector from the three values of corresponding membership functions can be shown as:

$$Z^*(x_j) = \{\mu_L(x_j), \mu_M(x_j), \mu_H(x_j)\}, \qquad (1.6)$$

where: x_j - quantitative value of the indicator j, and $\mu_i(x_j)$ - membership function that links it to the fuzzy set.

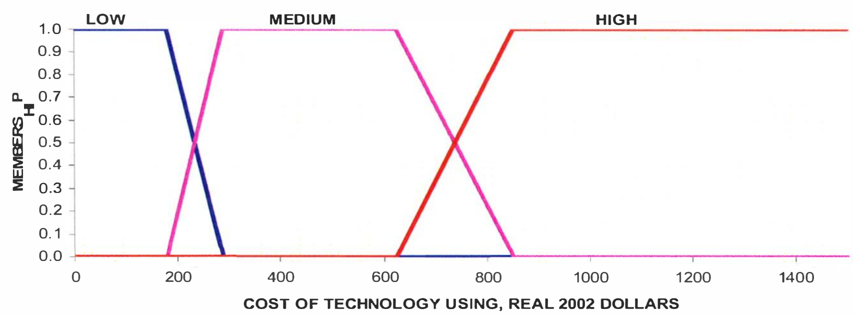

Figure B2. Membership Function for Linguistic Variable x_3 – "*Cost of technology used*"

The sum of all components of vector $Z^*(x_j)$ is equal to 1, for grey scale consistency in Pospelov's sense (Nedosekin, 2003). Thus from one to two values of a vector may be zero (the level belongs to the maximum of two qualitative descriptions with the membership, which sum to 1).

Step 2: *Determination of component importance.*

We assume that the variable weights are not equal, i.e. technological intervention or procedure (FSC) is more important than cost of technology used (P) and knowledge of the person (SP), who uses this technology for patient treatment:

$$FSC \succ SP \approx P \qquad (2.1)$$

So the weights of the components are:

$$w_1 = 0.5; w_2 = w_{.3} = 0.25 \qquad (2.2)$$

Step 3: Aggregation all components in HTI.

For aggregation we use Ordered Weighted Averaging (OWA) operators (Yager, 1993, 1996, 1998; Xu, 2008), which have the properties of commutativity, monotonicity, idempotency, boundedness, universality, and the "best to use (in some reasonable sense)" (Yager and Kleinovich, 2002).

Suppose we have N inputs that should be aggregated in one output. Thus we can aggregate all vectors for individual indicators $Z^*(x_j)$ in the model with weights W_j under the formula:

$$HTI(x_j) = \sum_{j=1}^{N} w_j \times Z^*(x_j) = \sum_{j=1}^{N} w_j \times \{\mu_{j_L}(x_j), \mu_{j_M}(x_j), \mu_{j_H}(x_j)\} = \\ \{\sum_{j=1}^{N} w_j \times \mu_{j_L}(x_j), \sum_{j=1}^{N} w_j \times \mu_{j_M}(x_j), \sum_{j=1}^{N} w_j \times \mu_{j_H}(x_j)\} \qquad (3.1)$$

This results in the aggregated vector $HTI(x_j)$ with three values of the corresponding membership functions:

$$HTI^*(p_l) = \{\mu_L(p_l), \mu_M(p_l), \mu_H(p_l)\}, \qquad (3.2)$$

where p_l is the quantitative value of *HTI*, and $\mu_j(p_l)$ is the membership function in the fuzzy set.

This aggregated vector (averaging vector) can be interpreted as follows. It is an aggregation of all combined meanings expressed by the trapezoidal numbers $Z_1,....,Z_n$ considered either of equal importance or different importance, depending on the weights w_j.

Step 4: Defuzzification.

The aggregation, defined by its trapezoidal numbers, has to be expressed by crisp (numerical) values which are best for the corresponding aggregation operation. This operation is called defuzzification (i.e. the transformation from the linguistic domain to the numerical domain

(Herrera et al, 2005)). This is an operation that produces a nonfuzzy output which is a single value $\hat{Z} = \hat{HTI}$, that adequately represents the aggregated vector $HTI^*(p_k)$. This output must then be identified for technology adoption linguistic classification and comparison. There are several widely used defuzzification methods: the Center-of-Maximum Method (COM), the Mean-of-Maximum Method (MOM), etc. (Bojadziev and Bojadziev, 1997). The COM defuzzification method was chosen for our work. When we have trapezoidal fuzzy membership functions we can use the midpoint (centre) of the range of the trapezoidal fuzzy number for each linguistic term at the maximum level, when $\mu_i = 1$. Since we use a fuzzy set with an uniformly distributed ordered set (Xu and Da, 2003) with three linguistic terms for aggregation, the centres of the maxima are $z_{i\max} = \{0.1, 0.5, 0.9\}$, and the crisp (numerical) output $\hat{HTAI}$ can be calculated in our case as follows:

$$\hat{HTI} = \frac{\sum_{i=1}^{N} \mu_i \times z_{i\max}}{\sum_{i=1}^{N} \mu_i}. \qquad (4.1)$$

The membership function for the uniformly distributed ordered set with three linguistic terms is presented in Figure B3.

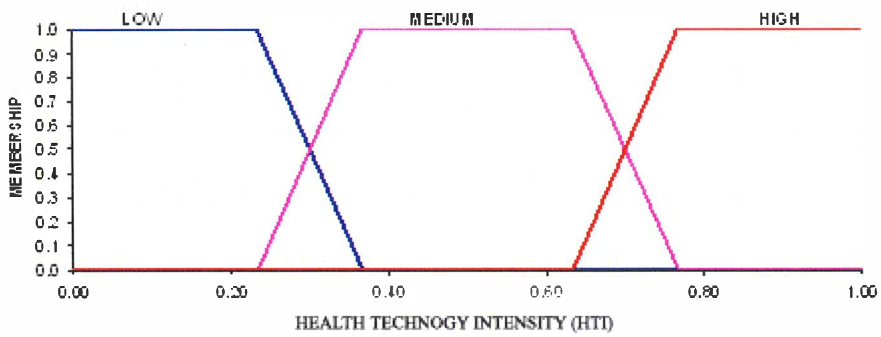

Figure B3 Membership Function for HTI.

Step 5: HTI Linguistically identification.
Every record in OHIP linked files for every person was linguistically identified, knowledge rules were generated and then aggregated by the number of health services received by each person in each year in the OHIP database.

Knowledge rules usually have the form:

IF $FSC = (L, M, H)$ and $SP = (L, M, H)$ and $P = (L, M, H)$,
THEN $HTI = (L, M, H)$ (5.1)

Step 6: HTI Aggregation by Class.

The HTI measure was aggregated by its class (L, M, H) for every unique person and every research year. Our method allows the recognition of technology level patterns used for the patient for number of services and physician expenditures.

APPENDIX C

International Databases of Clinical Guidelines and Standards of Medical Care

Country and resource name , internet address

United States of America

1 US National Guideline Clearinghouse (NGC) http://www.guideline.gov

2 Centers for Disease Control and Prevention (CDC) http://www.cdc.gov

3 Agency for Healthcare Research and Quality (AHRQ) http://www.ahrq.gov/clinic/cpgsix.htm

Health Services/Technology Assessment Text (HSTAT) and National Library of Medicine (NLM)
4 http://www.ncbi.nlm.nih.gov/books/bv.fcgi?rid=hstat

5 AMA (American Medical Association) http://www.ama-assn.org

6 American Society of Health System Pharmacists (ASHP) http://www.ashp.org/s_ashp/index.asp

7 Institute for Clinical Systems Improvement (ICSI) http://www.icsi.org

8 Guide to Clinical Preventive Services http://odphp.osophs.dhhs.gov/pubs/guidecps

American Academy of Pediatrics Policy (AAP Policy) Clinical Practice Guidelines
9 http://aappolicy.aappublications.org/practice_guidelines/index.dtl

Primary Care Clinical Practice Guidelines
10 http://medicine.ucsf.edu/education/resed/ebm/practice_guidelines.html

11 American Academy of Family Physicians (AAFP) http://www.aafp.org/online/en/home.html

12 American College of Physicians (ACP) http://www.acponline.org

13 National Institutes of Health (NIH) http://www.nih.gov

14 AIHA Network http://www.aiha.com/en/WhatWeDo/PracticeGuidelines_CPGPI.asp

15 AIHA Multilingual Library http://www.aiha.com/en/ResourceLibrary/Glossary/A.asp

Canada

Canadian Medical Association InfoBase (CMA InfoBase: Clinical Practice Guidelines (CPGs))
16 http://www.cma.ca/index.cfm/ci_id/54316/la_id/1.htm

17 Ontario Health Technology Advisory Committee http:// www.health.gov.on.ca/ohtas.

18 Health Canada http://www.hc-sc.gc.ca/index-eng.php

19 Canada Task Force on Preventive Health Care (CTFPHC) http://ctfphc.org/guide.htm

20 Medical Services Plan of British Columbia / Guidelines & Protocols http://www.health.gov.bc.ca/gpac

21 Health information Research Unit (HIRU) / McMaster University http://hiru.mcmaster.ca/hiru

22 Canadian Diabetes Association http://www.diabetes.ca/cpg2003/download.aspx

Great Britain

23 National Institute for Health and Clinical Excellence (NICE) http://www.nice.org.uk

24 NHS Quality Improvement Scotland http://www.nhshealthquality.org/nhsqis/CCC_FirstPage.jsp

25 eGuidelines http://www.eguidelines.co.uk/index.php

26 National Library of Guidelines Specialist Library (NLH) http://www.library.nhs.uk/guidelinesfinder

27 PRODIGY Knowledge http://www.prodigy.nhs.uk/home

28 Scottish Intercollegiate Guidelines Network (SIGN) http://www.sign.ac.uk

29 Core Library for Evidence Based Practice http://www.shef.ac.uk/scharr/ir/core.html

30 Royal College of Physicians (RCP) http://www.rcplondon.ac.uk

31 TRIP Database http://www.tripdatabase.com/index.html

32 Bandolier http://www.medicine.ox.ac.uk/bandolier/

Germany

33 Leitlinien.de/German Guideline Information Service (GERGIS) http://leitlinien.de/english/english/view

Finland

34 Evidence Based Medicine Resource Centre http://ebmny.org/cpg.html

Australia

35 Australian National Health and Medical Research Council (NHMRC)

http://www.nhmrc.gov.au/guidelines/health_guidelines.htm

36 eMJA/The Medical Journal of Australia http://mja.com.au/public/guides/guides.html

Monash University/Medicine, Nursing and Health Sciences/Centre for Clinical Effectiveness

37 http://mihsr.monash.org/cce

New Zealand

38 New Zealand Guidelines Group (NZGG) http://nzgg.org.nz

Russia

39 Russian society of Evidence-based medicine specialists (OSDM) / http://osdm.org

International databases of clinical guidelines

40 The Cochrane Collaboration http://www.cochrane.org/resources/training.htm

41 The Cochrane Library http://www.thecochranelibrary.com

42 International Network of Agencies for Health Technology Assessment (INAHTA) http://www.inahta.org

43 Health Evidence Network (HEN), World Health Organization (WHO) http://www.euro.who.int/hen

44 WebMD http://www.wbmd.com

45 eMedicine from WebMD http://emedicine.com

46 Medscape from WebMD http://www.Medscape.com

47 The hearth.org from WebMD http://www.theheart.org

48 MedicalMatrix http://medmatrix.org/reg/login.asp

49 ScHARR Netting the Evidence http://www.shef.ac.uk/scharr/ir/netting

50 http://www.nettingtheevidence.org.uk

The Community Research and Development Information Service (CORDIS)

51 http://cordis.europa.eu/guidance

52 Global Index Medicus WHO http://www.who.int/ghl/medicus/en

Index Medicus — abbreviations of journals titles

53 http://www2.bg.am.poznan.pl/czasopisma/medicus.php?lang=eng

54 http://www.nlm.nih.gov/pubs/techbull/mj04/mj04_im.html

55 International Guideline Library http://www.g-i-n.net/index.cfm?fuseaction=membersarea

Source: Authors finding *and* A.V. Stepanenko et al. Unified Methodology for Development of Clinical Guidelines, Standards of Medical Care, Unified Clinical Protocols of Medical Care, Local Protocols of Medical Care (Clinical Pathways) on the Principles of Evidence-Based Medicine, UKR.MED. CHASOPIS, 2009, 22. www.umj.com.ua

APPENDIX D
Clustering Results and Validity Measures

Literature suggests various cluster validity indexes for each partition, when the number of clusters is unknown a priori. The optimal partition can be determined by the point of the extrema of the validation indexes in dependence of the number of clusters (Ozer, 2005; Balasko et al., 2007). Most commonly used validation indexes include - Partition Coefficient (PC) (Bezdek et.al.,1999; Ozer, 2005; Balasko et al., 2007); Modified PC (MPC) (Roubens,1982; Bezdek et.al.,1999; Ozer, 2005); Classification (sometimes called partition) Entropy (CE) (Bezdek et.al.,1999; Ozer, 2005; Balasko et al., 2007); Modified CE (MCE) (Roubens,1982; Bezdek et.al.,1999; Ozer, 2005); Partition Index (PI) (Bensaid et all,1996; Balasko et al., 2007); Separation Index (SI) (Bensaid et all,1996; Balasko et al., 2007); Xie and Beni's Index (XB) (Xie and Beni, 1991; Ozer, 2005; Balasko et al., 2007). Empirical studies suggest that a suitable number of clusters is the one that maximizes PC, MPC, and MCE and minimizes CE, PI, SI and XB. Main description of validation indices shows that PC, CE and their modifications (MPC and MCE) are based only on clusters membership μ_{ij}, and PI, SI and XB are taking into consideration the amount compactness and separation of the clusters centers in addition to cluster membership. This additional information is supposed to increase the quality of cluster validity indices (Pedrycz, 2005; Balasko et al., 2007). Fig.D1 summarized validity indices and indicated that a three-cluster solution was appropriate for our data according the recommendation of the past studies to pay attention to interpretability of the results (Balakrishnan et al, 1996; Ozer, 2005). The main description of validation indexes can be found below.

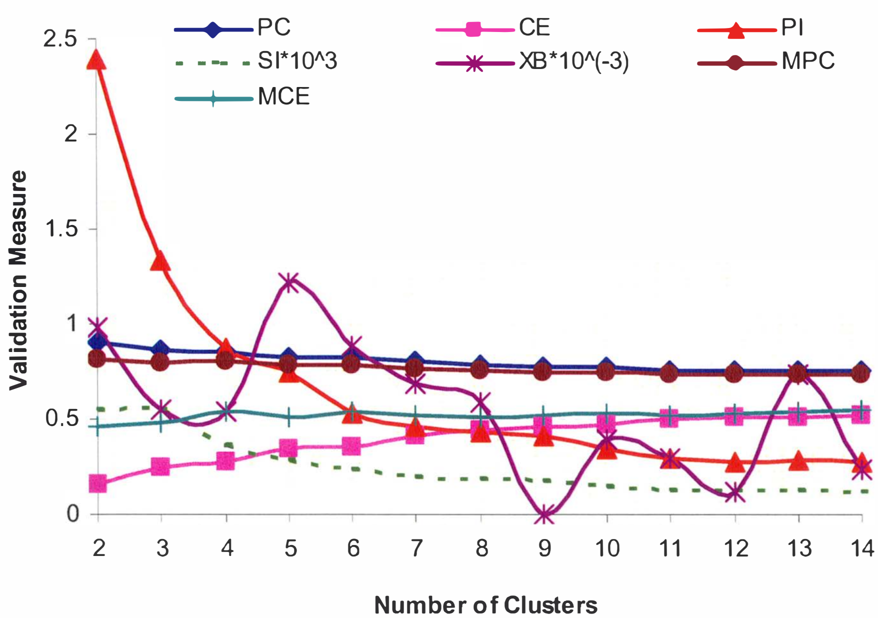

Fig D1 Value of different cluster validity indices for different numbers of clusters.

The main description of index validation was prepared from (Bezdek et.al., 1999; Xie and Beni, 1991; Bensaid et al, 1996; Ozer, 2005; Balasko et al., 2007);

1. **Partition Coefficient (PC):** measures the amount of "overlapping" between clusters. It was defined by Bezdek (Bezdek et.al.,1999) as follows:

$$PC(c) = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}(\mu_{ij})^2$$

where μ_{ij} is the membership of data point j in cluster i. The disadvantage of PC is the lack of direct connection to some property of the data themselves. ***The optimal number of clusters is at the maximum value.***

2. **Modified Partition Coefficient (MPC)**

$$MPC(c) = \frac{(cPC - 1)}{c - 1}$$

3. **Classification Entropy (CE):** measures the fuzzyness of the cluster partition only, which is similar to the Partition Coefficient.

$$CE(c) = -\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}\mu_{ij}\log(\mu_{ij})$$

4. **Modified Classification Entropy (MCE)**

$$MCE(c) = 1 - \frac{CE}{\log_a c}; a(1, \infty).$$

5. **Partition Index (PI):** the ratio of the sum of compactness and separation of the clusters. It is a sum of individual cluster validity measures normalized through division by the fuzzy cardinality of each cluster (Bensaid et al, 1996).

$$PI(c) = \sum_{i=1}^{c}\frac{\sum_{j=1}^{N}(\mu_{ij})^m\left\|x_j - v_i\right\|^2}{N_i\sum_{k=1}^{c}\left\|v_k - v_i\right\|^2}$$

SC is useful when comparing different partitions having equal number of clusters. ***A lower value of PI indicates a better partition.***

6. **Separation Index (SI):** the separation index uses a minimum -distance separation for partition validity (Bensaid et al, 1996).

$$SI(c) = \frac{\sum_{i=1}^{c}\sum_{j=1}^{N}(\mu_{ij})^2\left\|x_j - v_i\right\|^2}{N\min_{i,k}\left\|v_k - v_i\right\|^2}$$

A lower value of SI indicates a better partition.

7. Xie and Beni's Index (XB): aims to quantify the ratio of the total variation within clusters and the separation of clusters (Xie and Beni, 1991).

$$XB(c) = \frac{\sum_{i=1}^{c} \sum_{j=1}^{N} (\mu_{ij})^m \left\| x_j - v_i \right\|^2}{N \min_{i,j} \left\| x_j - v_i \right\|^2}$$

The optimal number of clusters should minimize the value of the index.

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