

The Pulse of Renewal: A Focus on Nursing Human Resources



Published as a special report by the *Canadian Journal of Nursing Leadership*
with the kind support of the Office of Nursing Policy, Health Canada

May 2005

Hospital Service Utilization: Implications for Nursing Human Resource Planning

Final Report, March 31, 2004
Submitted to the Office of Nursing Policy, Health Canada

Principal Investigators: Professor Gail Tomblin Murphy and
Dr. Linda O'Brien-Pallas
Co-Investigators: Dr. Stephen Birch and Dr. George Kephart
Project Staff: Adrian MacKenzie

Background

In the face of growing expectations and technological innovations in healthcare, and an aging population with varying and different needs than previous generations, decision-makers are increasingly challenged to improve efficiency in the use of healthcare resources. This challenge includes consideration of changing the level and mix of health human resources (HHR) delivering the services and ensuring an adequate supply of human resources to meet the needs of the population. Given the relative labour intensity of healthcare services, the attention of researchers and decision-makers is often focused on changing the level of health human resources in isolation from other human and non-human resources (Vujicic 2003). Little, if any, attention is given to the notion of health human resources as inputs in a healthcare services production function in which input-output relationships (or the rate of productivity of human resources) may be sensitive to the levels of other healthcare inputs and methods of production (Birch et al. 2003). Instead, decisions about the level and deployment of health human resources are often made in response to short-term financial pressures or opportunities, without any evidence of the effect of changing the use of human resources on health outcomes in the context of the prevailing needs of patient groups and availability of other healthcare inputs. Greater attention needs to be paid to how changes in levels of inputs affect the levels of delivery of services and patient outcomes. Moreover, because healthcare is delivered through a range of different inputs (i.e., human and nonhuman resources), these effects cannot be determined without consideration of the available levels of other inputs.

Birch et al. (2003) argue that health human resource requirements should be considered in the context of the relationship between the levels and mix of resources used to produce healthcare services and the quantity and quality of services produced. Health human

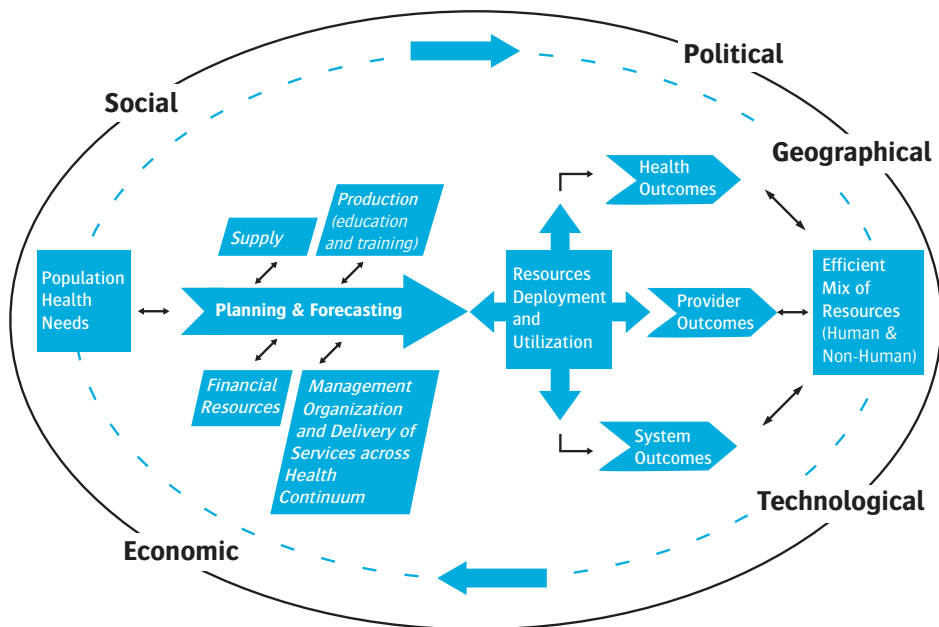
resource planning (HHRP) cannot be performed effectively in isolation from broader healthcare policy processes (O'Brien-Pallas, Tomblin Murphy et al. 2001; CIHI 2001).

In recent research in Ontario (Tomblin Murphy et al. 2004), we considered the impact of different levels of hospital-based nursing provision on healthcare outcomes, in particular: (1) whether greater levels of nursing inputs are associated with lower levels of other inputs, such as bed days, indicating a substitution of human for nonhuman resources in the production of inpatient services as opposed to a “pure add-on” to existing resources, and (2) whether the use of more nursing inputs to support reductions in bed days is achieved at the expense of reduced health outcomes. Reductions in bed days may be introduced in response to fiscal pressures on hospital management. It is important to determine the changes in production that are used to support these changes (e.g., by use of additional nurse time to increase the intensity of care) and whether these changes in production are sufficient to maintain service outcomes (i.e., are not implemented at the expense of poorer patient outcomes). In that work, we found that hospitals with greater levels of nursing inputs per patient day had, on average, shorter inpatient lengths of stay after controlling for variations in population and patient characteristics. However, we found no evidence that this relationship was associated with poorer patient outcomes as measured by higher rates of readmissions, hospital mortality or reduced levels of patient satisfaction with care.

We also explored the association between the number of days in hospital and the self-assessed health status at the individual level after controlling for age, sex and chronic conditions. We hypothesized that if patient outcomes were not affected by the substitution of nurses for hospital days, after controlling for health conditions, the number of days in hospital should not affect individuals' self-assessed health status. In order to deal with endogenous relationships (i.e., levels of healthcare provision may respond to levels of need in the population as well as influencing those levels of need), we compared self-reported number of hospital days with the number that hospitals expected based on age, sex, income group, education level, employment status, location type, living arrangement, depression score and presence of chronic conditions at the individual level. The estimated relationship between individual self-assessed health status and the difference between reported and expected bed days allowed us to consider whether individuals with fewer than expected bed days reported poorer levels of health status, as might be expected if a lower than expected number of bed days represented poorer quality of care. However, the estimated relationship between “observed minus expected” bed days and health status was negative. In other words, since a higher than expected number of bed days was associated with slightly poorer patient health status, a lower than expected number of bed days would be associated with slightly *higher* patient health status. In our previous work in Ontario, a greater level of nursing intensity to support fewer bed days was associated with greater levels of patient health status. These results suggest that the substitution of more nursing input for fewer days might represent a more efficient mix of healthcare inputs in the production of inpatient episodes of care.

The present study extends our work in Ontario through further refinements in our analytical approach and an analysis that is expanded to the national level. Specifically, our primary objective was to assess whether patient outcomes were sensitive to differences in the observed minus expected number of hospital days after controlling for age, sex and chronic health conditions. Because information on nursing intensity levels was not available for all provinces, the analysis is performed in the context of our findings on the association between length of stay and nursing intensity in Ontario. As a secondary objective, our analysis provides a basis for assessing the extent of provincial variation in the days of hospital care (and, by proxy, utilization of hospital nursing care) based on the age and sex distribution of provincial populations and the relative levels of prevalence of major chronic health conditions in those populations. Such evidence is needed to determine the degree to which population characteristics translate into different levels of need for acute care services between the provinces.

Figure 1. Framework for analyzing health human resources
(for definition of key elements, see Appendix A)



Source: O'Brien-Pallas, Tomblin Murphy, Baumann and Birch 2001
(adapted from O'Brien-Pallas and Baumann 1992)

Theoretical Framework

This study is informed by, and tests elements of, a conceptual framework developed by O'Brien-Pallas et al. (Figure 1). The framework has been adapted from previous work by O'Brien-Pallas and Baumann (1992), and has built upon earlier work including Anderson's (1995) service utilization model, Donabedian's (1966) quality-of-care

framework, Leatt and Schneck's (1981) conceptualization of technology in human service organizations and the work of a Canadian think tank summarized by Kazanjian et al. (1992). The framework is designed to include the essential elements of the HHRP process in a way that captures the dynamic interplay among factors that have previously been conceptualized in isolation from one another. (Definitions of the framework's key elements appear in Appendix A.)

The framework provides researchers and planners with a guide to decision-making that takes account of current circumstances (e.g., supply of workers) as well as those factors that need to be accounted for in making predictions about future requirements (e.g., fiscal resources, changes in worker education and training). This open-system framework considers factors that, though important in the HHRP process, have not always been included in the analyses to date. These include social, political, geographic, economic and technological factors. At the core of the framework is the recognition that health human resources must be matched as closely as possible to the health needs of the population.

The framework highlights the need to conceptually differentiate the issues of (1) measuring the relative need for healthcare between regions and segments of the population as a basis for allocating healthcare resources among different populations (i.e., the link between population needs and healthcare resources in the framework) and (2) how best to deploy healthcare resources to meet population needs (the link between resource deployment and patient outcomes in the framework).

The present study focuses primarily on the relationship between resources deployment and patient outcomes in order to provide an evidence base for the consequences of policies that affect the availability and use of healthcare inputs. For example, reductions in bed numbers may be an important policy goal for a fiscally constrained government, but we need to know what other inputs are required to support the required reconfiguration of services without reducing patient outcomes. In addition to addressing the relationship between resources deployment and utilization and patient outcomes, this study also provides insights on the importance of considering relative population health needs in planning for acute care delivery between provinces.

Estimating the relative need for health services between populations and regions poses a challenge, as it requires the selection of appropriate indicators of population health need. Based on the theoretical framework driving this work, indicators of need ideally ought to be independent of the level and deployment of healthcare services. Accordingly, the use of measures that are independent of healthcare utilization and provide global assessments of population health status is preferred. Although we have made only limited use of such measures here, our results highlight the potential benefits of further incorporating such measures into HHR planning and research.

In addition to supply, the conceptual framework guiding this study highlights that utilization is a function of not just supply, but how human and technological resources are

deployed and organized. Moreover, it emphasizes that relative health needs, and thus utilization, are in part driven by outcomes from the health system itself. Ultimately, it seems logical that estimates of relative population health need derived from utilization-based models will also need to distinguish variation in relative need generated by the health system itself (i.e., differences in relative need resulting from the effectiveness of health services) from variation in relative need reflecting variation in the more exogenous determinants of health. Thus, the focus of the present study on estimating the link between utilization and health outcomes is an important step in the development of methods for needs-based approaches to health human resource planning.

Goal of the Study

This study extends our study “Health Human Resource Planning: An Examination of Relationships among Nursing Service Use, an Estimate of Population Health, and Overall Health Status Outcomes in the Province of Ontario” (Project Identifier: RC1-0618-06), funded by the Canadian Health Services Research Foundation (CHSRF) (Tomblin Murphy et al. 2003). Using an open systems framework, this study estimated the association between the number of hospital days and patient outcomes in acute care hospitals in Canada. Because utilization is influenced, in part, by non-need factors (local availability of hospital beds, local practice patterns, etc.), we use the difference between reported and expected bed days as the measure of utilization. Expected days are estimated from data on the presence of chronic conditions and demographic factors, independent determinants of the need for services. The expected use model is estimated at the national level in order to “liberate” expected use from the influences of local availability of resources and practice patterns.

It is important to emphasize that this study is a step in the process of developing and testing a population health needs-based approach to HHRP; since health needs, demand for healthcare services and utilization of services are inextricably linked, understanding differences in the utilization of and expected demand for healthcare services across provinces (which we investigate here) is crucial to understanding differences in health needs across the same jurisdictions. That is, full understanding of need, demand and utilization is necessary. In this study we address some new issues and extend our work in the following ways: (1) expanding our examination beyond Ontario to all of Canada, (2) using the Canadian Community Health Survey (CCHS) to increase our sample size, to increase power while doing jurisdictional estimates and (3) using improved modelling techniques to adjust for local variations in non-need factors such as health services supply and access.

Objectives and Research Questions

In this study we addressed two questions:

1. How does health vary as a function of actual levels of inputs (days of hospital care and, by proxy, exposure to nursing care) compared to those given a patient’s

- age, sex, income level, employment status, education level, location type, living arrangement, depression score and chronic health conditions?
2. How does the expected utilization of hospital services per capita vary between provinces and territories as a function of differences in the provincial populations by age, sex, income level, employment status, education level, location type, living arrangement, depression score and major chronic health conditions?

In approaching these research questions, we focused primarily on the deployment and utilization components of the model, as well as population health status and health outcomes. Although controlling for supply, management practices and financial resources for health services is a key component of our model, it is important to note that development of national-level measures of these factors, and thus incorporation of them into our study, was not feasible given the three-month preparation time. Despite such constraints, this study explored some of the very difficult methodological issues associated with need.

Methods

Data

Analysis was restricted to respondents 18 years of age and older, and the CCHS sample size for adult respondents in Canada was 117,825. (Full descriptive statistics of the CCHS appear in Table 1 of Appendix B.) The gender split in this sample was 46% males to 54% females. The 40–44 age group was the largest in the CCHS at about 11%, followed by the 35- to 39-year-olds at just under 11%. About 20% of respondents were seniors (aged 65 and over), and only 2% were over 85. Thirty-eight percent of respondents resided in major metropolitan areas, with 23% residing in urban, nonmetropolitan areas and the remainder in rural areas. Fifty-eight percent of respondents were employed, with 35% out of the labour force and 5% unemployed. Twenty-seven percent of respondents had no high school diploma; 14% had a university degree. Roughly 27% of respondents had a high school diploma only, and 31% had earned a community college or trade school diploma. The CCHS was afflicted with a high rate of nonresponse on income-related questions (roughly 11% nationally). Income level was missing for about 10% of our sample. Fifty-four percent of respondents were classified as living in an upper-middle or upper income household (about 31% and 22% each), compared to about 14% in the lower-middle and lower income groups (about 9% and 4%, respectively). About 25% of respondents reported living alone, with roughly 6% living in single-parent homes. The remaining respondents did not fall into either category.

Variables

Table 2 (Appendix B) lists and describes the variables used in the study. Independent variables included sex, age (in five-year groups), adequacy group, education (less than high school education, high school diploma with no further certification, community college or trade school diploma, university degree), employment status (employed,

unemployed, not in labour force), location type (census metropolitan area, urban nonmetropolitan area, rural nonmetropolitan area), living arrangement (living alone, single parent, other), depression score (0–8) and chronic conditions (cancer, heart disease, chronic obstructive pulmonary disease, high blood pressure, diabetes or ulcers).

The dependent variables in the first stage of our model were self-reported overnight hospital use (versus nonuse) and self-reported hospital days, with self-reported health status (poor/fair, good, very good, excellent) and dichotomous Health Utilities Index (HUI) score (less than 0.8, 0.8 or greater) as the dependent variables in the second stage of the model.

Models

As discussed above, in order to reduce the influence of non-need factors (e.g., local availability of care, local practice patterns, etc.) we estimate the relationship between patient health status and “excess” hospital days, where excess days is the difference between observed hospital days and the number of hospital days expected based on the individual’s age, sex and presence of chronic conditions. Using this approach, we investigate whether there is any evidence that reporting more hospital days than expected is associated with better health status.

Two steps are necessary in calculating a respondent’s expected number of hospital days. First, we use a random-effects logit regression model to generate each respondent’s predicted probability of having at least one hospital day. Second, we estimate the number of hospital days each respondent is likely to have, given that they’ve each had at least one, using a negative binomial regression model. The product of these results yields the expected number of hospital days for each respondent in the year preceding the survey.

Both models in the first stage used the same independent variables: age group, sex, education level, employment status, income group, location type, living arrangement, depression score and chronic conditions. Census subdivision (CSD) was used as the unit variable in the random-effects logit model. The dependent variable in the logit model was whether respondents had spent at least one night in hospital in the year preceding the survey. In the negative binomial model, the dependent variable was the number of nights respondents spent in hospital in the year preceding the study (given at least one such night).

Once each respondent’s expected number of hospital days is obtained, the difference between that value and the actual number of hospital days is calculated for each respondent, and this figure is the key independent variable in the final stage of the model. Here, a separate regression model is run for each of two dependent variables: respondent self-reported health status and dichotomized HUI score. In addition to the difference between respondents’ actual and expected nights in hospital, independent variables include age group, sex, employment status, education level, income group, location type and living arrangement. The decision to use random-effects in the use/

nonuse model and not in the days of care model was based on the belief that the geographically clustered non-need variables we are attempting to capture are significant in predicting whether a person will have an overnight hospital stay, but not in predicting how many days in hospital a person will spend, given that the patient spends at least one (Raudenbush and Bryk 2002; Snijders and Bosker 1999).

Findings

Full interpretation of these findings is more easily achieved by examining them in the context of findings from our previous work for Ontario. In particular, because nursing utilization data are not available at the individual patient level for all provinces, we are unable to use nursing data directly. Instead, we draw on the evidence from our previous work, which suggests that after controlling for other system, patient and population factors, hospitals with lower average lengths of stay have higher levels of nurse utilization per patient. So although our principal focus in this study is on the relationship between hospital bed days and outcomes, the findings can be used to derive messages about nursing human resources. Time constraints also prohibited the use of longitudinal data, which would have helped to eliminate or reduce problems with endogeneity.

Results

When interpreting regression results, it is important to be aware that all results are relative to those for respondents in the control categories for each independent variable. In our models, these control categories were males, age group 18–24, those without high school diplomas, those in the lowest income group, employed respondents, respondents residing in census metropolitan areas (CMAs), respondents living alone, those with depression scores of zero (not depressed) and those without self-reported heart disease, cancer, chronic obstructive pulmonary disease (COPD), ulcers, diabetes or high blood pressure.

Stage 1 results

Stage 1 results estimated the relative odds of receiving hospital care and the number of days of hospital care used (given that some care was used). Table 3 (Appendix B) shows the parameter estimates of the random-effects logistic regression model predicting the odds of receiving hospital care as a function of age, sex, education, income, depression and chronic health conditions. Respondent age, sex, employment status, education, depression score and chronic conditions were all significant predictors of having at least one overnight hospital stay in the year preceding the survey. After controlling for all other variables in the model, only male respondents aged 85 and over were significantly more likely than male respondents aged 18–24 to have had an overnight hospital stay. Young females (aged 18–34) were significantly more likely than young males to have had a hospital stay, but apart from these reproductive age groups, females had lower odds of having a hospital stay than males. The results show that after controlling for all other variables in the model, women's odds of having a hospital stay were actually highest during the reproductive years.

Respondents classified as being unemployed or out of the labour force were significantly more likely than employed respondents to have had an overnight hospital stay, with the difference being much more pronounced for out-of-labour-force respondents than for unemployed respondents; unemployed respondents had roughly 1.29 times higher odds than employed respondents to have had an overnight hospital stay, whereas respondents who were out of the labour force were almost three times as likely as employed respondents to have had an overnight hospital stay.

Those respondents living outside CMAs were significantly more likely to have had an overnight hospital stay than those living in CMAs. Both rural and urban non-CMA residents had roughly 1.2 times higher odds than their metropolitan counterparts to have had an overnight hospital stay.

Although respondents at all income levels were less likely to have had a hospital stay than those in the levels below them, this difference was not statistically significant. Respondents who had university, community college, trade school and/or high school diplomas were less likely to have had an overnight hospital stay than respondents without a high school diploma. This difference was significant for respondents with high school diplomas and for those with university degrees (at only 0.88 and 0.85 times the odds, respectively, for respondents without high school diplomas), although not for those with trade school or community college diplomas (at 0.96 times the odds). Neither single parents nor respondents living alone were significantly different from other respondents in their likelihood of having an overnight hospital stay.

As respondents' depression scores increased, so did their likelihood of having an overnight hospital stay; respondents with a depression score of 1 had odds of having an overnight hospital stay about 1.12 times higher than respondents with a zero score, whereas respondents with a depression score of 8 had odds roughly three times as high as respondents with a score of zero to have had an overnight hospital stay. This difference was significant for respondents with depression scores of 3 and higher. Respondents with cancer, diabetes, chronic obstructive pulmonary disease (COPD), high blood pressure and/or ulcers had significantly higher odds of having had an overnight hospital stay than respondents not affected by any of these conditions (1.54 times higher for COPD sufferers, 1.27 for respondents with hypertension, 13.29 for diabetics, 2.54 for heart disease sufferers, 2.72 for cancer sufferers and 1.50 for those with ulcers). Results indicate that diabetics were about equally likely as to have had an overnight hospital stay regardless of their age. The same was true for respondents with heart disease.

While between-CSD variation in the odds of having an overnight hospital stay (as represented by the model intercept) was statistically significant, the random effect accounted for a fairly small proportion (about 4%) of the total variation in probability of a hospital stay. Thus, while we may have controlled for the effects of geographically clustered non-need factors through use of a CSD random effect, the degree to which this effect explains residual variation in the hospital use (versus nonuse) is small.

Table 4 (Appendix B) shows results from the negative binomial regression model predicting the number of days of care conditional on having received hospital care. Among respondents with at least one overnight hospital stay, older respondents had higher rates of hospital days per year than younger respondents. This difference was significant for respondents aged 30–39 and 44 and over. Females had significantly higher rates of nights in hospital per year than males at younger ages (34 and under), while at older ages (55 and up), males had significantly higher rates of nights spent in hospital than females.

Unemployed respondents and those out of the labour force had significantly higher rates of hospital days per year than employed respondents, at 1.20 times higher for unemployed respondents and 1.35 for respondents out of the labour force. Respondents living outside metropolitan areas, in both urban and rural areas, had significantly higher (about 1.07–1.08 times each) rates of hospital days than respondents living in metropolitan areas. Respondents in each income level had lower rates of hospital days per year than respondents in each income level below them; that is, higher income was associated with lower rates of hospital days per year.

This difference was significant for respondents with high-middle and high incomes. Respondents with high school diplomas or university degrees had lower rates of hospital days than respondents without a high school diploma, significantly so (odds about 0.93 times those for respondents without high school diplomas) for university graduates. Other than single parents, who had significantly lower rates of nights spent in hospital (about 0.89 times those for respondents living alone), respondents living alone had rates of hospital stays similar to those not living alone.

Depression was a strong predictor of rates of hospital days per year, much as it was a strong predictor of incidence of a hospital stay. Respondents with higher depression scores (4 and above) had significantly higher rates (1.15 to 1.87 times higher) of nights in hospital per year than respondents with lower scores. Several chronic conditions were also strong predictors of overnight hospital stays. Respondents with COPD, diabetes, heart disease and/or cancer had significantly higher predicted rates of hospital days per year (1.09, 1.24, 1.24 and 1.29 times higher, respectively) than those not afflicted with any of these conditions.

Table 5 (Appendix B) displays mean and median predicted and actual number of hospital days by province. Note that the median actual number of hospital days is zero for each province. This is expected, since only about 10% of respondents reported spending one or more nights in hospital in the year preceding the survey. New Brunswick, Yukon and PEI have the highest mean actual number of hospital days, respectively, while Nova Scotia, New Brunswick and Newfoundland have the highest mean predicted number of hospital days, respectively. At the lower end of the spectrum, Ontario, Alberta and British Columbia have the lowest mean actual number of hospital days, respectively, while Northwest Territories, Nunavut and Yukon have the lowest mean predicted number of hospital days.

Stage 2 results

The difference between actual and expected hospital days (and therefore the difference between actual and expected exposure to nursing care) had an odds ratio of 0.956 in predicting self-reported health status, which means that for each day spent in hospital beyond the number of such days predicted by our models, a respondent's likelihood of being in a higher self-reported health category decreased by about 4%. (See Table 6, Appendix B, for detailed results from this model.) Respondents in each age group were significantly more likely to be in a lower health status category than respondents in each age group below them. This was true for both males and females. Younger (29 and under) female respondents were significantly less likely to report better health status compared to males the same age. Females over 30, however, were significantly more likely to report better health status than males the same age.

Unemployed respondents and respondents out of the labour force were each significantly less likely than employed respondents to report better health (at 0.86 and 0.56 times, respectively, the odds for employed respondents). Respondents living in non-metropolitan urban areas were significantly more likely (1.08 times) to report better health status than respondents living in CMAs, while this difference was not significant between respondents in rural areas and respondents in CMAs. Higher-income respondents were significantly more likely than lower-income respondents to report better health; respondents in each income category were more likely to report better health than respondents in each category below them. Lower-middle income respondents were 1.14 times more likely than low-income respondents to report better health, whereas high-income respondents were 2.42 times more likely than low-income respondents to do so. As with income, there was an increasing relationship between education level and likelihood of reporting better health. Respondents with a high school diploma were 1.58 times more likely than respondents without a high school diploma to report better health status, with university graduates 2.50 times more likely than non-high school graduates to report better health status. Neither single parents nor respondents living alone were significantly different from other respondents in terms of their likelihood of reporting better health status.

Respondents living in nonmetropolitan urban areas were significantly more likely (by 1.08 times) to report better health status than respondents living in CMAs, while this difference was not significant between respondents in rural areas and respondents in CMAs. Neither single parents nor respondents living alone were significantly different from other respondents in terms of their likelihood of reporting better health status.

With regard to predicting respondents' dichotomized HUI scores, the difference between their actual and expected numbers of hospital days had an associated odds ratio of 0.973. This means that an extra day spent in hospital beyond the number of days predicted by our models is associated with a respondent's odds of being healthy (having an HUI score of 0.8 or higher) as opposed to "not healthy" (HUI below 0.8), decreasing

by about 3%. (See Table 7, Appendix B, for complete results for this model.) In general, older respondents had lower odds of being healthy than the youngest respondents (aged 18–24). This difference was significant for respondents aged 35 and over, with respondents aged 45–49 and 85 and over having the lowest odds (relative to the 18- to 24-year-olds) of being healthy. There was no significant difference between males and females in their odds of being healthy.

Unemployed respondents and respondents out of the labour force were significantly less likely than employed respondents to be healthy (odds for unemployed respondents were only 0.72 times those of employed respondents, 0.43 times for respondents out of the labour force). Respondents living in nonmetropolitan areas were significantly more likely than respondents living in CMAs to be healthy. The odds of being healthy for rural nonmetropolitan residents were 1.09 times higher than those for respondents living in CMAs, and 1.20 times higher for urban nonmetropolitan dwellers.

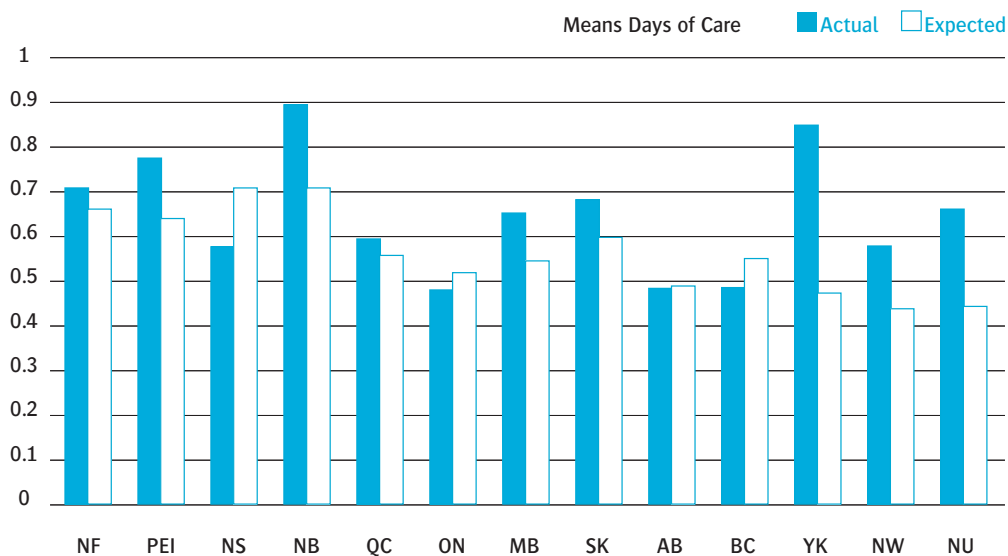
Higher-income respondents were more likely to be healthy than lower-income respondents, and respondents with high school, community college or trade school diplomas or university degrees were more likely to be healthy than those without high school diplomas. Single parents were less likely to be healthy than respondents living alone, although this difference was not significant.

Discussion

Stage 1

Figure 2 displays the mean actual and predicted hospital days for each province. From this graph, it is clear that the mean predicted days of care for Quebec, Ontario, Alberta and British Columbia are closest to their actual means. This is somewhat expected, given the relatively large representation (see Table 8, Appendix B) of each of these provinces within the CCHS sample. Conversely, it is apparent that the predicted means for Yukon, Northwest Territories and Nunavut are the most different from their actual means, which may be a product of their comparatively small representation within the CCHS sample.

Figure 2. Actual vs. expected mean reported hospital days

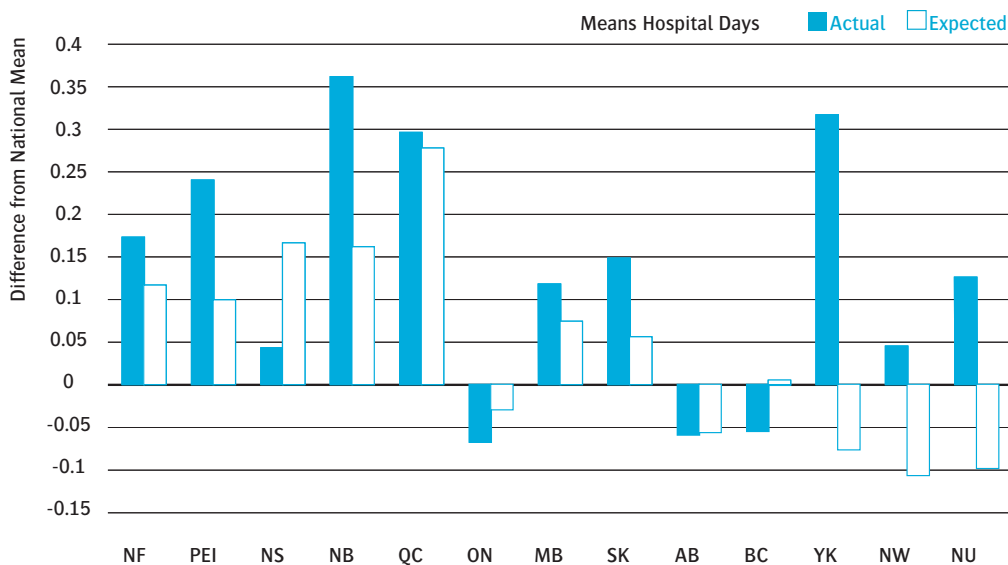


It is also interesting to note that the mean actual hospital days is higher than the expected mean in Newfoundland, PEI, New Brunswick, Quebec, Manitoba, Saskatchewan, Yukon, Northwest Territories and Nunavut, while in Nova Scotia, Ontario, Alberta and British Columbia, the reverse is true; in these four provinces, the mean expected hospital days is higher than the actual mean hospital days. Ontario, Alberta and British Columbia are widely recognized as being “healthier” in general than the other provinces, so the fact that these provinces seem to have lower than expected hospital utilization is not necessarily surprising. Nova Scotia, however, is widely regarded as one of the least “healthy” provinces in the country. While the reason for its lower than expected utilization is not apparent from our results, it may be related to issues of access, supply or both, specific to Nova Scotia.

Also apparent from Figure 2 is that several provinces, especially the territories and New Brunswick, have much higher mean actual utilization than expected. In the case of the

territories, this disparity may be due to the relative “youth” of their age distributions compared to the other provinces (see Table 9, Appendix B), coupled with their comparatively low life expectancy (2–9 years lower than the national average; see Table 10, Appendix B). It may be that in the territories, life expectancy is more important than age as a predictor of health utilization. This difference may also be a function, in part, of lower self-reported chronic disease prevalence rates in the territories compared to Canada as a whole (CIHI 2003). Since our models use self-reported chronic conditions as an important predictor of health utilization, it is not surprising that for regions with low self-reported chronic disease prevalence (such as Newfoundland and the territories) our models predict lower than actual levels of utilization. Our models cannot control for the chronic conditions of respondents who do not report them.

Figure 3. Mean and expected reported hospital days, relative to national means



We find other interesting results when we compare the mean actual and expected number of hospital days for each of the provinces to the actual and expected means for Canada (Figure 3). While Ontario, Alberta and British Columbia have slightly lower actual mean reported hospital days than the national average, all other provinces, on average, have reported hospital days much higher than Canada as a whole. This result likely reflects two underlying factors. First, part of the reason the means for Ontario, Alberta and British Columbia are so much closer than the other provinces’ to the national mean may be that these three provinces have the largest, fourth largest and third largest (respectively) representations in the CCHS, and collectively account for roughly 62% of the entire sample. It is not surprising, then, that their mean values are closer than those of the other provinces to the national mean. Second, these three provinces are generally accepted as being “healthier” than the rest of the country, and therefore people living in them spend less time per capita in hospitals than people living the rest of the country. This second factor may explain why the actual mean utilizations are so

much lower in those three provinces than in the Atlantic provinces, Quebec, Manitoba, Saskatchewan and the territories.

Perhaps the most striking result apparent in this display is the differences in the territories between their mean expected hospital days and their mean actual hospital days, relative to the national means. Under our models, each of the territories is expected to have much lower mean hospital days than the rest of Canada. In fact, the reverse is true; the actual mean number of hospital days for each of the territories is much higher than the national average.

Given these results, it is clear that significant differences exist among the provinces both in terms of their health service utilization (in the form of hospital days) and in their expected demand for said services. Further, given the inherent links between need for health services, demand and health service utilization, it seems likely that these differences between provinces in demand and utilization relate to differences between provinces in need for health services. It is also clear that factors other than age, sex, income, education, location type, employment status, living arrangement and chronic conditions can be strong predictors of health utilization (if this were not the case, the actual and expected values would be much closer).

It is interesting to note that younger females (aged 18–34) were significantly more likely to have had a hospital stay than males of the same age group. We attribute this to hospitalization associated with childbearing. Also noteworthy is the finding that out-of-labour-force respondents were significantly more likely than employed respondents to have had an overnight stay. This is most likely attributable to the fact that people out of the labour force may be experiencing illness, disability or injury requiring hospitalization. People living outside census metropolitan areas were significantly more likely to have had an overnight hospital stay than those living in CMAs. This may be because clinicians prefer to hospitalize people with marginal health status and reduced access to other services (outpatient, community health clinics), who are thus admitted for observation. There is an inverse relationship between level of education and overnight hospital stays, perhaps because more highly educated people have more knowledge regarding their health status and have developed better access networks.

The finding that people who suffer from all levels of depression experience increased overnight hospital stays is important. It is generally recognized that one in four people in Canada experiences some form of depression in his or her lifetime; our results suggest such individuals also have increased odds of an overnight stay. The higher the depression score, the more likely people would be to have an overnight stay. In most provinces/territories, major restructuring has limited access to inpatient beds, leaving one to wonder if the relationship between increasing depression score and higher odds of being hospitalized is associated with being admitted to hospital care for a different primary diagnosis or chronic condition.

Even though the effects of chronic condition were controlled for in the first phase of the model, the high odds ratios for all the chronic conditions in the second part of the analysis suggests that when the conditions are severe they are more likely to warrant an overnight stay. In particular, these findings would suggest the need to pay attention to preventative strategies for diabetes and heart disease to reduce the incidence of hospitalization and the costs of services. We recognize that it takes time to realize the impact of preventative strategies on population health and utilization, but in the meantime we need to plan for human and nonhuman resource requirements to meet the needs of these people.

Among respondents who have at least one overnight stay, the rate of hospital days per year is greater in young women of childbearing years and in older men. This is consistent with other findings and our finding for having an overnight stay. While there were no differences in the probability of an overnight stay for respondents in different living arrangements, single-parent family members were 15% less likely to have more hospital days per year than others. This finding suggests that familial obligations influence the number of hospital days per stay and suggests the need to have community resources available to provide support for familial obligations or to deliver care at home. It also highlights the need for special discharge planning with this group of people.

As much as depression was a strong predictor of incidence of hospitalization, we note that higher probabilities of depression are associated with more days of stay per year than lower rates of depression. Consistent with other studies (e.g., Klabunde et al. 2002), all the chronic conditions studied were strong predictors of hospital overnight stays and hospital days per year. Worthy of comment is the finding that cancer and heart disease result in 343% and 306% higher rates of hospital days per year. Hypertension, COPD, diabetes and/or ulcers were also predictors of increased rates of hospital days per year (ranging from 30% for hypertension, 190% for diabetes), but like the incidence of overnight stay, did not have as high an influence as diabetes and heart disease.

Stage 2

In the CHSRF study carried out in Ontario, we concluded that increased nursing intensity (measured by increased nurses per bed day) reduced length of stay, but not at the expense of system and health outcomes. This study supports our finding from the earlier study in that there was no evidence that lowered numbers of nights of stay were associated with lower levels of health status after controlling for other population-based factors. In fact, the opposite was true; once in hospital, the more hospital days a person has the lower his or her self-reported health status and the lower the probability of having an HUI score greater than 0.8.

One of the key results of this analysis was that for each day people had stayed in hospital longer than the days predicted by our model, their odds of scoring a higher self-reported health status decreased by 5%. Although this finding might appear counter-intuitive, more hospital care is associated with poorer health status. After other factors are

controlled for, it is important to consider what might explain the longer than expected hospital stay. In particular, relative shortages of other healthcare inputs, such as nursing human resources, may lead to delays in the rate of recovery of patients and hence delayed discharge. In other words, it is not necessarily the additional days that cause lower health status. On the contrary, inadequate levels of other inputs, such as nursing services, may be responsible for both the higher than expected number of days and lower health status. It is also possible that this result may relate, in part, to increased exposure to iatrogenic effects of hospitalization with increased hospital bed days and/or to some aspects of health needs not captured by our models.

The finding that unemployed people and people out of the labour force were significantly less likely than employed people to report better health likely reflects the fact that people who are injured or sick and unable to work have lower self-reported health status because of their particular conditions. Consistent with findings of other studies (Evans et al. 1994; Mustard and Frohlich 1995; Roos et al. 1995), both higher income and education levels are associated with higher ratings of self-reported health status.

The finding that older people are less healthy than younger people is consistent with the findings of many studies. Similarly, the result that people living in nonmetropolitan areas were more likely to be healthy than people living in CMAs identifies the impact of location on health status and has been reported before (CIHI 2003).

Conclusion: Policy Messages

The authors believe that the findings of this study have important policy implications and suggest that policy makers consider and integrate the following six policy messages into health human resource planning:

1. There was no evidence that lowered numbers of nights of stay were associated with lower levels of health status after controlling for other population-based factors. Our results reflect associations between variables, not cause–effect relationships; that is, they do not suggest that extra hospital bed days cause decreases in health status. Rather, they point to the existence of some relationship between extra hospital days and health status that is not captured by our models. It is important to note that this conclusion is based on one healthcare input (hospital days). In the CHSRF study, where we examined the relationship between nursing intensity and lengths of stay in Ontario, lower lengths of stay were associated with increased levels of nursing input.
2. Populations that have higher rates of chronic conditions (such as diabetes and heart disease) have higher numbers of hospital days, and numbers of hospital days differ by jurisdiction.
3. Significant investment is needed in creating and maintaining readily accessible databases and methods that allow HHR researchers and planners to compare differences between and across jurisdictions, to understand the health needs of the population and to determine whether the system is working effectively and ef-

- ficiently to meet these needs. More effective ways to access data on healthcare use and factors that influence needs for healthcare are essential.
4. Planning for health human resources should be based on the needs of the population in the context of the availability of other healthcare human and nonhuman resources, and it should consider as many factors that affect use of services as possible, including social, political, geographical, technological and economic factors.
 5. This study highlights the potential benefit of intensive preventative initiatives to reduce overall hospital admissions and lengths of stay for people suffering from chronic conditions, depression or both.
 6. HHRP cannot depend on simple solutions to provide short-term answers. To gain a better understanding of health human resources, planning must be comprehensive, and the complexity of the work demands partnerships that include policy makers and researchers who have different perspectives.

References

- Aiken, L.H., H.L. Smith and E.T. Lake. 1994. "Lower Medicare Mortality among a Set of Hospitals Known for Good Nursing Care." *Medical Care* 32(8): 771–87.
- Amick, B.C., I. Kawachi, E.H. Coakley, D. Lerner, S. Levine and G.A. Colditz. 1998. "Relationship of Job Strain and Iso-strain to Health Status in a Cohort of Women in the United States." *Scandinavian Journal of Work, Environment and Health* 24(1): 54–61.
- Andersen, R.M. 1995. "Revisiting the Behavioral Model and Access to Medical Care: Does It Matter?" *Journal of Health and Social Behavior* 36(1): 1–10.
- Birch, S., L. O'Brien-Pallas, C. Alksnis, G. Tomblin Murphy and D. Thomson. 2003. "Beyond Demographic Change in Health Human Resources Planning: An Extended Framework and Application to Nursing." *Journal of Health Services Research and Policy* 8(4): 225–29.
- Blegen, M.A. 1993. "Nurses' Job Satisfaction: A Meta-analysis of Related Variables." *Nursing Research* 42(1): 36–41.
- Blegen, M.A., C.J. Goode and L. Reed. 1998. "Nurse Staffing and Patient Outcomes." *Nursing Research* 47(1): 43–50.
- Blegen, M.A. and T. Vaughn. 1998. "A Multisite Study of Nurse Staffing and Patient Occurrences." *Nursing Economic\$* 16(4): 196–203.
- Brooten, D. and M.D. Naylor. 1995. "Nurses' Effect on Changing Patient Outcomes." *Journal of Nursing Scholarship* 27(2): 95–99.

Canadian Institute for Health Information (CIHI). 2001. *Future Development of Information to Support the Management of Nursing Resources: Recommendations*. Ottawa: Author. Retrieved March 22, 2005. <http://secure.cihi.ca/cihiweb/dispPage.jsp?cw_page=GR_149_E>.

Canadian Institute for Health Information (CIHI). 2003. Summary Report: *Improving the Health of Canadians*. Ottawa: Author.

Donabedian, A. 1966. "Evaluating the Quality of Medical Care (Review)." *Milbank Memorial Fund Quarterly* 44(3 Suppl.): 166–206.

Evans, R., M. Barer and T. Marmor. 1994. *Why Are Some People Healthy and Others Not? The Determinants of Health of Populations*. New York: Aldine De Gruyter.

Josephson, M. and E. Vingard. 1998. "Workplace Factors and Care Seeking for Low-Back Pain among Female Nursing Personnel. MUSIC–Norrtalje Study Group." *Scandinavian Journal of Work, Environment and Health* 24(6): 465–72.

Kazanjian, A., I.R. Pulcins and K. Kerluke. 1992. "A Human Resources Decision Support Model: Nurse Deployment Patterns in One Canadian System." *Hospital and Health Services Administration* 37(3): 303–19.

Klabunde, C.N., J.L. Warren and J.M. Legler. 2002 (August). "Assessing Comorbidity Using Claims Data: An Overview." *Medical Care* 40(8 Suppl.): IV-26–35.

Kovner, C. and P.J. Gergen. 1998. "Nurse Staffing Levels and Adverse Events Following Surgery in U.S. Hospitals." *Image: The Journal of Nursing Scholarship* 30(4): 315–21.

Kramer, M. and C.E. Schmalenberg. 2003. "Magnet Hospital Staff Nurses Describe Clinical Autonomy." *Nursing Outlook* 51(1): 13–19.

Leatt, P. and R. Schneck. 1981. "Nursing Subunit Technology: A Replication." *Administrative Science Quarterly* 26: 225–36.

Leiter, M.P., P. Harvie and C. Frizzell. 1998. "The Correspondence of Patient Satisfaction and Nurse Burnout." *Social Science and Medicine* 47(10): 1611–17.

McGillis Hall, L., D. Irvine, G.R. Baker, G. Pink, S. Sidani, L. O'Brien Pallas and G. Donner. 2001. *A Study of the Impact of Nursing Staff Mix Models and Organizational Change Strategies on Patient, System and Caregiver Outcomes. Final Report*. Toronto: Faculty of Nursing, University of Toronto.

Mustard, C. and N. Frohlich. 1995. "Socioeconomic Status and the Health of the Population." *Medical Care* 33(12): DS43–DS54.

O'Brien-Pallas, L. 2002. "Where To from Here?" (Editorial). *Canadian Journal of Nursing Research* 33(4): 3–14.

O'Brien-Pallas, L. & A. Baumann. 1992. "Quality of Nursing Worklife Issues – A Unifying Framework." *Canadian Journal of Nursing Administration* 5(2): 12–16.

O'Brien-Pallas, L., A. Baumann, S. Birch and G. Tomblin Murphy. 2000. "Health Human Resource Planning in Home Care: How to Approach It – That Is the Question." *Healthcare Papers* 1(4): 53–59.

O'Brien-Pallas, L., D. Thomson, C. Alksnis and S. Bruce. 2001. "The Economic Impact of Nurse Staffing Decisions: Time to Turn Down Another Road?" *Hospital Quarterly* 4(3): 42–50.

O'Brien-Pallas, L., D. Thomson, L. McGillis Hall, G. Pink, M. Kerr, S. Wang, X. Li and R. Meyer. 2004 (September). *Evidence-based Standards for Measuring Nurse Staffing and Performance*. Toronto: Canadian Health Services Research Foundation. Retrieved March 22, 2005. <http://www.chsrf.ca/final_research/ogc/pdf/obrien_e.pdf>.

O'Brien-Pallas, L., G. Tomblin Murphy, A. Baumann and S. Birch. 2001. "Figure 1: Framework for Analyzing Health Human Resources." *Future Development of Information to Support the Management of Nursing Resources: Recommendations* (p. 6). Ottawa: CIHI. Retrieved March 22, 2005. <http://secure.cihi.ca/cihiweb/dispPage.jsp?cw_page=GR_149_E>.

Ozcan, S., Y. Taranto and P. Horney. 1995. "Shaping the Labor Efficiency among American Hospital Markets." *Annals of Operations Research* 67: 61–81.

Raudenbush, S.W. and A.S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods* (2nd ed.) (pp. 388–89). Thousand Oaks, CA: Sage Publications.

Roos, N., C. Black, N. Frohlich, C. Decoster, M. Cohen, D. Tataryn, C. Mustard, F. Toll, K. Carriere, C. Burchill, L. MacWilliam and B. Bogdanovic. 1995. "A Population-based Health Information System." *Medical Care* 33(12): DS13–DS20.

Snijders, T. and R. Bosker. 1999. *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling* (p. 45). Thousand Oaks, CA: Sage Publications.

Tomblin Murphy, G. and L. O'Brien-Pallas. 2002. "A Health Human Resources Discussion Paper: How Do Health Human Resource Policies and Practices Promote or Inhibit Change?" In R.J. Romanow, *Building on Values: The Future of Health Care in Canada: Final Report*. Ottawa: Government of Canada.

Tomblin Murphy, G., L. O'Brien-Pallas, C. Alksnis, S. Birch, G. Kephart, M. Pennock, D. Pringle, I. Rootman and S. Wang. 2003 (November). *Health Human Resource Planning: An Examination of Relationships among Nursing Service Utilization, an Estimate of Population Health and Overall Health Status Outcomes in the Province of Ontario*. Final Report. Toronto: Canadian Health Services Research Foundation. Retrieved March 22, 2005. <http://www.chsrf.ca/final_research/ogc/tomblin_e.php>.

Tomblin Murphy, G., L. O'Brien-Pallas, S. Birch and G. Kephart. 2004. *Needs-based Health Human Resource Planning: The Relationship between Population Health and Nursing Service Utilization*. Presented at the 57th International Atlantic Economic Society, Lisbon, Portugal, 10–14 March.

Vujicic M. 2003. "The Nursing Labour Market in Canada during a Period of Restructuring." Paper presented to the 2nd International Conference on Health Economics and Health Management, Kalamata, Greece, 29–31 May.

World Health Organization. 2000. *The World Health Report 2000. Health Systems: Improving Performance*. Geneva, Switzerland: Author.

Appendix A: Elements of the HHR Framework

- **Population health needs** reflect the multivariate characteristics of individuals in the population that create the requirements for curative as well as preventive health services. Addressing population health needs provides the motive, context and justification for HHRP practices.
- The **production** element of the framework highlights the fact that in order to ensure future capacity to meet population health needs, these needs must be considered in setting production targets for health education and training programs.
- The **supply** element reflects the actual number, type and geographic distribution of regulated and unregulated providers. It recognizes that supply is fluid and is related to production elements as well as to such factors as recruitment, retention, licensing, regulation and scope of practice.
- **Planning and forecasting** reflect the varieties of available HHRP practices and models, their assumptions, methods, data requirements and limitations.
- **Management, organization and delivery of health services** are key variables that influence how care is delivered across the continuum. Management and organizational characteristics influence the amount and quality of care provided, provider health and satisfaction, and costs associated with delivery of services. Organization characteristics such as structural arrangements, the degree of formalization and centralization, environmental complexity and culture influence the way work gets done and affects outcomes. In nursing, for example, numerous studies have demonstrated that resource allocation decisions made by managers can have a negative impact on nurse job satisfaction (Kramer and Schmalenberg 1988; Blegen 1993; O'Brien-Pallas et al. 2004) and health (Josephson and Vingard 1998; Amick et al. 1998; O'Brien-Pallas et al. 2004), as well as on patient outcomes (Aiken et al. 1994; Brooten and Naylor 1995; Blegen et al. 1998; Blegen and Vaughn 1998; Kovner and Gergen 1998; O'Brien-Pallas et al. 2004) and patient satisfaction with the care received (Leiter et al. 1998; McGillis Hall et al. 2001), the level of productivity (O'Brien-Pallas, Thomson et al. 2001; O'Brien-Pallas et al. 2004) and the number of visits a client receives in the community (O'Brien-Pallas, Thomson et al. 2001). In fact, decisions on such matters as scheduling and number of shift changes, continuity of care providers and support for providers and others have been shown to have significant influences on system, patient and provider outcomes (O'Brien-Pallas et al. 2004).
- **Resource deployment** reflects the amount and nature of the resources deployed to provide health services to the population at large; **resource utilization** reflects the nature and type of resources utilized by the population to meet health needs. The efficiency and effectiveness of service delivery depend to a great extent on the effective deployment and use of personnel (Ozcan et al. 1995). The World Health

Organization (2000) notes that provision of healthcare involves putting together a considerable number of resource inputs to deliver an extraordinary array of service outputs. Decisions made about the deployment and use of personnel across all sectors of the system influence access to services and utilization by the population and outcomes. Working nurses beyond specific productivity standards leads to poorer patient and nurse outcomes, increased costs per relative-intensity weight and longer lengths of stay (O'Brien-Pallas et al. 2004).

- **Health, provider and system outcomes** refer to establishing the effectiveness and quality of HHR practices by examining the effect on population health, provider health, job satisfaction, etc., and system costs and efficiencies.
- **Efficient mix of human and nonhuman resources** (e.g., fiscal resources, physical plant, space, supplies, equipment and technology) reflects the number and type of resources that must be developed in order to achieve the best population, provider and system outcomes.
- **Context** elements (represented in the outer broad band of the framework) speak to the need to recognize factors outside the healthcare system that influence population health, the health system and the HHRP process.

Appendix B: Tables from Study

Table 1. Canadian Community Health Survey

Sex	Frequency	Percentage
Male	53,970	45.81
Female	63,855	54.19
Age Group		
18–24	12,029	10.21
25–29	8,786	7.46
30–34	10,335	8.77
35–39	12,486	10.60
40–44	12,944	10.99
45–49	11,429	9.70
50–54	10,287	8.73
55–59	8,377	7.11
60–64	7,145	6.06
65–69	6,819	5.79
70–74	6,322	5.37
75–79	5,174	4.39
80–84	3,387	2.87
85+	2,305	1.96
Location Type		
Census Metropolitan Area	44,444	37.72
Nonmetro, Urban	27,669	23.48
Nonmetro, Rural	45,712	38.80
Employment Status		
Employed	68,171	68,171
Unemployed	5,409	5,409
Not in Labour Force	41,628	41,628
Missing	2,617	2,617
Income Level		
Low	5,276	4.48
Low-Middle	10,988	9.33
Middle	25,928	22.01
High-Middle	37,032	31.43
High	26,296	22.32

Continued...

Income Level	Frequency	Percentage
Missing	12,305	10.44
Education		
No High School Diploma	31,769	26.96
High School Diploma	32,145	27.28
Community College or Trade School Diploma	36,650	31.11
University Degree	16,021	13.60
Missing	1,240	1.05
Living Arrangement		
Unattached Individual Living Alone	28,879	28,879
Single Parent with Children	6,607	6,607
Neither Single Parent Nor Living Alone	75,549	75,549
Missing	6,790	6,790
Total	117,825	100.00

Table 2. Description of study variables

Variable Name	Description
Self-reported hospital use*	Self-reported number of nights spent in hospital, nursing home, or convalescent home in year preceding survey
Age group**	5-year groups (18–24, 25–29, ... 80–84, 85+)
Sex**	Male, female
Income**	Five categories of income adjusted for household size
Education level**	No high school diploma, high school diploma only with no further certification, community college or trade school diploma, university degree
Current employment status**	Employed, unemployed but in the labour force, not in the labour force
Location type**	Major metropolitan area, nonmetro urban area, nonmetro rural area
Chronic conditions**	One or more of chronic bronchitis or emphysema, high blood pressure, diabetes, heart disease, cancer, ulcers
Living arrangement**	Living alone, single parent, other
Depression**	Integer scores ranging from 0 (low probability of depression) to 8 (high probability of depression)
Derived health status index*	HUI† score greater or lower than 0.8
Self-assessed health status*	Poor/fair, good, very good, excellent

*Dependent variable **Independent variable †HUI = Health Utilities Index

Table 3. Logit regression results (use/nonuse)

Variable	Coefficient	Standard Error	95% Confidence Interval		Odds Ratio
			Lower Confidence Limit	Upper Confidence Limit	
Age 25–29	–0.005	0.111	–0.223	0.213	0.995
Age 30–34	–0.060	0.106	–0.267	0.147	0.942
Age 35–39	0.068	0.097	–0.123	0.259	1.070
Age 40–44	–0.021	0.097	–0.211	0.169	0.979
Age 45–49	0.040	0.098	–0.152	0.232	1.041
Age 50–54	0.050	0.100	–0.146	0.246	1.051
Age 55–59	0.020	0.102	–0.180	0.221	1.021
Age 60–64	–0.001	0.103	–0.202	0.201	0.999
Age 65–69	–0.182	0.104	–0.387	0.022	0.833
Age 70–74	–0.130	0.104	–0.334	0.074	0.878
Age 75–79	0.051	0.109	–0.162	0.264	1.052
Age 80–84	0.224	0.122	–0.015	0.463	1.251
Age 85+	0.486	0.138	0.216	0.756	1.626*
Female	0.816	0.084	0.652	0.980	2.261*
Female, Age 25–29	0.429	0.127	0.179	0.678	1.535*
Female, Age 30–34	0.186	0.122	–0.053	0.425	1.204
Female, Age 35–39	–0.404	0.117	–0.633	0.176	0.668*
Female, Age 40–44	–0.615	0.118	–0.847	0.383	0.541*
Female, Age 45–49	–0.881	0.122	–1.120	0.642	0.414*
Female, Age 50–54	–0.827	0.122	–1.066	0.589	0.437*
Female, Age 55–59	–1.063	0.124	–1.307	0.819	0.345*
Female, Age 60–64	–1.137	0.124	–1.379	0.894	0.321*
Female, Age 65–69	–1.095	0.122	–1.334	0.856	0.335*
Female, Age 70–74	–1.036	0.119	–1.270	0.803	0.355*
Female, Age 75–79	–0.867	0.121	–1.105	0.630	0.420*
Female, Age 80–84	–0.955	0.135	–1.220	0.690	0.385*
Female, Age 85+	–0.995	0.152	–1.294	0.696	0.370*
Unemployed	0.255	0.061	0.136	0.374	1.291*
Out of Labour Force	1.097	0.032	1.035	1.160	2.996*
Nonmetro, Urban	0.199	0.037	0.126	0.271	1.220*
Nonmetro, Rural	0.179	0.035	0.111	0.247	1.196*
Low-middle Income	–0.028	0.054	–0.134	0.078	0.972
Middle Income	–0.069	0.052	–0.170	0.032	0.933
Upper-middle Income	–0.089	0.053	–0.192	0.014	0.915
Upper Income	–0.108	0.058	–0.222	0.006	0.898
High School Diploma	–0.131	0.033	–0.195	0.066	0.878*

Continued...

Variable	Coefficient	Standard Error	95% Confidence Interval		Odds Ratio
			Lower Confidence Limit	Upper Confidence Limit	
Community College/ Trade School Diploma	-0.045	0.032	-0.107	0.017	0.956
University Degree	-0.172	0.045	-0.260	0.084	0.842*
Single Parent	-0.008	0.052	-0.109	0.094	0.993
Other Not Living Alone	0.060	0.031	0.000	0.121	1.062
Depression Score 1	0.117	0.296	-0.464	0.698	1.124
Depression Score 2	0.093	0.178	-0.256	0.442	1.097
Depression Score 3	0.495	0.107	0.284	0.706	1.641*
Depression Score 4	0.316	0.086	0.147	0.486	1.372*
Depression Score 5	0.414	0.070	0.277	0.550	1.512*
Depression Score 6	0.602	0.060	0.485	0.719	1.826*
Depression Score 7	0.645	0.062	0.523	0.767	1.906*
Depression Score 8	1.129	0.084	0.963	1.294	3.091*
COPD	0.433	0.035	0.364	0.501	1.541*
Hypertension	0.241	0.031	0.181	0.301	1.272*
Diabetes	2.587	0.318	1.964	3.211	13.295*
Heart Disease	0.932	0.331	0.283	1.581	2.540*
Cancer	1.000	0.054	0.894	1.106	2.719*
Ulcer	0.404	0.049	0.308	0.499	1.497*
Diabetes, Age 25–29	-2.299	0.467	-3.215	-1.384	0.100
Diabetes, Age 30–34	-1.890	0.400	-2.673	-1.107	0.151
Diabetes, Age 35–39	-2.347	0.406	-3.143	-1.552	0.096
Diabetes, Age 40–44	-2.085	0.378	-2.826	-1.345	0.124
Diabetes, Age 45–49	-2.048	0.360	-2.755	-1.342	0.129
Diabetes, Age 50–54	-2.280	0.353	-2.972	-1.589	0.102*
Diabetes, Age 55–59	-2.033	0.345	-2.709	-1.358	0.131*
Diabetes, Age 60–64	-2.455	0.345	-3.132	-1.778	0.086*
Diabetes, Age 65–69	-2.250	0.339	-2.914	-1.586	0.105*
Diabetes, Age 70–74	-2.033	0.335	-2.689	-1.377	0.131*
Diabetes, Age 75–79	-2.294	0.337	-2.954	-1.633	0.101*
Diabetes, Age 80–84	-2.520	0.351	-3.207	-1.832	0.080*
Diabetes, Age 85+	-2.336	0.365	-3.052	-1.621	0.097
Heart Disease, Age 25–29	-0.379	0.514	-1.387	0.628	0.684
Heart Disease, Age 30–34	-0.228	0.451	-1.112	0.656	0.796
Heart Disease, Age 35–39	0.028	0.419	-0.793	0.849	1.028
Heart Disease, Age 40–44	0.254	0.381	-0.494	1.001	1.289
Heart Disease, Age 45–49	0.576	0.364	-0.138	1.290	1.779
Heart Disease, Age 50–54	0.306	0.357	-0.394	1.005	1.357
Heart Disease, Age 55–59	0.136	0.351	-0.552	0.824	1.145

Continued...

Heart Disease, Age 60–64	0.012	0.349	–0.673	0.696	1.012
Heart Disease, Age 65–69	0.145	0.345	–0.531	0.821	1.156
Heart Disease, Age 70–74	–0.048	0.343	–0.721	0.624	0.953
Heart Disease, Age 75–79	–0.269	0.343	–0.942	0.403	0.764
Heart Disease, Age 80–84	–0.003	0.347	–0.684	0.678	0.997
Heart Disease, Age 85+	–0.252	0.354	–0.947	0.443	0.777
Sigma					0.202
Rho					0.039
N					95,304

*Significant at 0.05 level

Table 4. Negative binomial regression results (days of care)

Variable	Coefficient	Standard Error	95% Confidence Interval		Odds Ratio
			Lower Confidence Limit	Upper Confidence Limit	
Age 25–29	0.206	0.103	0.003	0.409	1.229
Age 30–34	0.239	0.097	0.048	0.430	1.270*
Age 35–39	0.293	0.089	0.118	0.468	1.341*
Age 40–44	0.125	0.089	–0.049	0.300	1.134
Age 45–49	0.341	0.087	0.171	0.511	1.406*
Age 50–54	0.304	0.088	0.132	0.477	1.356*
Age 55–59	0.415	0.086	0.245	0.584	1.514*
Age 60–64	0.459	0.087	0.288	0.630	1.583*
Age 65–69	0.407	0.086	0.238	0.576	1.502*
Age 70–74	0.501	0.086	0.333	0.669	1.650*
Age 75–79	0.545	0.089	0.372	0.719	1.725*
Age 80–84	0.576	0.095	0.389	0.763	1.779*
Age 85+	0.705	0.105	0.498	0.911	2.023*
Female	–0.028	0.078	–0.181	0.124	1.029
Female, Age 25–29	–0.271	0.118	–0.501	–0.040	1.311*
Female, Age 30–34	–0.213	0.112	–0.433	0.007	1.238
Female, Age 35–39	–0.176	0.107	–0.386	0.033	1.193
Female, Age 40–44	0.082	0.109	–0.131	0.295	1.085
Female, Age 45–49	–0.098	0.110	–0.313	0.117	1.103
Female, Age 50–54	0.116	0.109	–0.097	0.328	1.123
Female, Age 55–59	–0.111	0.109	–0.324	0.103	1.117
Female, Age 60–64	–0.093	0.109	–0.306	0.121	1.097
Female, Age 65–69	0.040	0.106	–0.169	0.248	1.040
Female, Age 70–74	0.020	0.103	–0.183	0.222	1.020
Female, Age 75–79	–0.095	0.104	–0.299	0.110	1.099

Continued...

Female, Age 80–84	0.011	0.113	–0.210	0.232	1.011
Female, Age 85+	–0.018	0.124	–0.261	0.224	1.019
Unemployed	0.178	0.054	0.072	0.285	1.195*
Out of Labour Force	0.301	0.026	0.250	0.352	1.351*
Nonmetro, Urban	0.065	0.027	0.012	0.117	1.067*
Nonmetro, Rural	0.076	0.023	0.031	0.121	1.079*
Low-middle Income	–0.046	0.044	–0.132	0.039	1.047
Middle Income	–0.061	0.042	–0.144	0.021	1.063
Upper-middle Income	–0.159	0.044	–0.244	–0.073	1.172*
Upper Income	–0.221	0.049	–0.317	–0.125	1.247*
High School Diploma	0.025	0.028	–0.029	0.079	1.026
Community College/ Trade School Diploma	–0.002	0.027	–0.054	0.049	0.998
University Degree	–0.070	0.040	–0.148	0.008	1.073
Single Parent	–0.116	0.044	–0.202	–0.030	0.891
Other Not Living Alone	–0.045	0.026	–0.097	0.007	1.046
Depression Score 1	–0.413	0.265	–0.932	0.105	1.512
Depression Score 2	–0.064	0.155	–0.367	0.240	1.066
Depression Score 3	0.093	0.089	–0.082	0.269	1.098
Depression Score 4	0.143	0.073	0.001	0.286	1.154
Depression Score 5	0.222	0.058	0.109	0.335	1.248*
Depression Score 6	0.381	0.048	0.287	0.475	1.463*
Depression Score 7	0.432	0.049	0.336	0.528	1.540*
Depression Score 8	0.626	0.062	0.504	0.747	1.870*
COPD	0.083	0.028	0.029	0.138	1.087*
Hypertension	0.025	0.025	–0.023	0.074	1.026
Diabetes	0.213	0.032	0.150	0.276	1.238*
Heart Disease	0.215	0.027	0.162	0.268	1.240*
Cancer	0.253	0.039	0.176	0.330	1.288*
Ulcer	0.023	0.038	–0.052	0.098	1.024
N					95304
Pseudo-R-Squared					0.0341

*Significant at 0.05 level

Table 5. Actual and predicted days of care by province

Jurisdiction	Days of Care			
	Actual Median	Actual Mean	Predicted Median	Predicted Mean
Newfoundland and Labrador	0	0.701	0.308	0.652
Prince Edward Island	0	0.770	0.285	0.636
Nova Scotia	0	0.571	0.275	0.703
New Brunswick	0	0.890	0.297	0.699
Quebec	0	0.584	0.228	0.547
Ontario	0	0.464	0.207	0.506
Manitoba	0	0.646	0.217	0.534
Saskatchewan	0	0.675	0.241	0.592
Alberta	0	0.470	0.203	0.479
British Columbia	0	0.473	0.226	0.539
Yukon	0	0.843	0.211	0.455
Northwest Territories	0	0.570	0.228	0.423
Nunavut	0	0.654	0.277	0.433
Canada	0	0.528	0.220	0.536

Table 6. Ordinal logit regression results (self-reported health)

Variable	Coefficient	Standard Error	95% Confidence Interval		Odds Ratio
			Lower Confidence Limit	Upper Confidence Limit	
Actual (Expected Days of Care)	-0.045	0.003	-0.051	-0.039	0.956*
Age 25–29	-0.261	0.060	-0.379	-0.143	0.770*
Age 30–34	-0.420	0.060	-0.537	-0.303	0.657*
Age 35–39	-0.523	0.055	-0.630	-0.416	0.593*
Age 40–44	-0.666	0.057	-0.778	-0.554	0.514*
Age 45–49	-0.858	0.059	-0.975	-0.742	0.424*
Age 50–54	-0.910	0.064	-1.035	-0.785	0.403*
Age 55–59	-0.898	0.069	-1.033	-0.762	0.407*
Age 60–64	-1.102	0.072	-1.243	-0.962	0.332*
Age 65–69	-0.937	0.076	-1.087	-0.788	0.392*
Age 70–74	-1.175	0.082	-1.335	-1.015	0.309*
Age 75–79	-1.314	0.089	-1.488	-1.140	0.269*
Age 80–84	-1.478	0.110	-1.693	-1.263	0.228*
Age 85+	-1.445	0.140	-1.719	-1.171	0.236*
Female	-0.395	0.055	-0.503	-0.288	0.673*
Female, Age 25–29	0.380	0.080	0.222	0.537	1.462*
Female, Age 30–34	0.570	0.079	0.414	0.725	1.768*
Female, Age 35–39	0.502	0.074	0.357	0.648	1.653*
Female, Age 40–44	0.492	0.075	0.344	0.640	1.636*
Female, Age 45–49	0.426	0.082	0.265	0.586	1.531*
Female, Age 50–54	0.355	0.085	0.189	0.521	1.426*
Female, Age 55–59	0.433	0.092	0.253	0.613	1.542*
Female, Age 60–64	0.684	0.095	0.498	0.869	1.981*
Female, Age 65–69	0.628	0.098	0.435	0.821	1.873*
Female, Age 70–74	0.611	0.103	0.410	0.812	1.842*
Female, Age 75–79	0.508	0.110	0.293	0.723	1.662*
Female, Age 80–84	0.612	0.140	0.337	0.886	1.844*
Female, Age 85+	0.697	0.166	0.372	1.023	2.009*
Unemployed	-0.153	0.046	-0.244	-0.063	0.858*
Out of Labour Force	-0.600	0.029	-0.658	-0.543	0.549*
Nonmetro, Urban	0.076	0.022	0.033	0.119	1.079*
Nonmetro, Rural	0.015	0.019	-0.021	0.052	1.015
Low-middle Income	0.135	0.058	0.021	0.249	1.145
Middle Income	0.411	0.053	0.308	0.514	1.509*
Upper-middle Income	0.654	0.052	0.552	0.756	1.924*
Upper Income	0.890	0.054	0.783	0.996	2.434*
High School Diploma	0.461	0.028	0.406	0.515	1.586*

Continued...

Variable	Coefficient	Standard Error	95% Confidence Interval		Odds Ratio
			Lower Confidence Limit	Upper Confidence Limit	
Community College/ Trade School Diploma	0.537	0.027	0.484	0.591	1.711*
University Degree	0.919	0.034	0.853	0.985	2.506*
Single Parent	0.010	0.045	-0.077	0.097	1.010
Other Not Living Alone	0.024	0.023	-0.022	0.070	1.024
N					91,894
Pseudo-R-squared					0.0613

*Significant at 0.05 level

Table 7. Logistic regression results (dichotomized HUI† score)

Variable	Coefficient	Standard Error	95% Confidence Interval		Odds Ratio
			Lower Confidence Limit	Upper Confidence Limit	
Actual (Expected Days of Care)	-0.012	0.003	-0.015	-0.009	0.973*
Age 25–29	-0.043	0.108	-0.145	0.059	0.905
Age 30–34	-0.021	0.103	-0.113	0.070	0.952
Age 35–39	-0.158	0.066	-0.240	-0.077	0.695*
Age 40–44	-0.200	0.059	-0.280	-0.120	0.631*
Age 45–49	-0.264	0.052	-0.344	-0.183	0.545*
Age 50–54	-0.323	0.047	-0.406	-0.240	0.475*
Age 55–59	-0.215	0.061	-0.300	-0.131	0.609*
Age 60–64	-0.183	0.068	-0.271	-0.095	0.656*
Age 65–69	-0.024	0.100	-0.114	0.066	0.947
Age 70–74	-0.197	0.067	-0.287	-0.108	0.635*
Age 75–79	-0.243	0.064	-0.338	-0.147	0.572*
Age 80–84	-0.441	0.047	-0.551	-0.331	0.362*
Age 85+	-0.684	0.032	-0.816	-0.553	0.207*
Female	-0.019	0.097	-0.105	0.067	0.958
Female, Age 25–29	0.046	0.172	-0.086	0.178	1.111
Female, Age 30–34	-0.008	0.140	-0.130	0.113	0.981
Female, Age 35–39	0.067	0.150	-0.043	0.176	1.167
Female, Age 40–44	-0.001	0.127	-0.109	0.108	0.998
Female, Age 45–49	-0.033	0.121	-0.144	0.078	0.927
Female, Age 50–54	0.004	0.133	-0.108	0.117	1.010
Female, Age 55–59	0.019	0.143	-0.098	0.135	1.044
Female, Age 60–64	0.089	0.171	-0.030	0.208	1.227

Continued...

Variable	Coefficient	Standard Error	95% Confidence Interval		Odds Ratio
			Lower Confidence Limit	Upper Confidence Limit	
Female, Age 65–69	0.012	0.146	–0.108	0.133	1.029
Female, Age 70–74	0.117	0.182	–0.002	0.235	1.308
Female, Age 75–79	0.033	0.155	–0.090	0.155	1.078
Female, Age 80–84	0.060	0.190	–0.082	0.201	1.147
Female, Age 85+	0.095	0.240	–0.069	0.260	1.245
Unemployed	–0.172	0.047	–0.231	–0.113	0.673*
Out of Labour Force	–0.401	0.014	–0.432	–0.370	0.397*
Nonmetro, Urban	0.086	0.038	0.060	0.113	1.220*
Nonmetro, Rural	0.029	0.028	0.006	0.051	1.068
Low-middle Income	0.085	0.076	0.031	0.138	1.215*
Middle Income	0.177	0.087	0.127	0.226	1.502*
Upper-middle Income	0.277	0.110	0.227	0.327	1.892*
Upper Income	0.361	0.150	0.305	0.417	2.296*
High School Diploma	0.126	0.049	0.095	0.158	1.338*
Community College/ Trade School Diploma	0.145	0.049	0.115	0.175	1.396*
University Degree	0.293	0.102	0.249	0.337	1.963*
Single Parent	–0.066	0.050	–0.115	–0.017	0.859*
Other Not Living Alone	0.063	0.037	0.036	0.090	1.157*
N					91,906
Pseudo-R-squared					0.0912

*Significant at 0.05 level

†HUI = Health Utilities Index

Table 8. CCHS sample composition by province

Jurisdiction	Sample Size
Newfoundland and Labrador	3,870
Prince Edward Island	3,651
New Brunswick	5,319
Nova Scotia	4,996
Quebec	22,667
Ontario	39,278
Manitoba	8,470
Saskatchewan	8,009
Alberta	14,456
British Columbia	18,302
Yukon	809
Northwest Territories	1,001
Nunavut	707
Total	131,535

Table 9. Proportional age distribution by jurisdiction

Jurisdiction	Age group %		
	0–14	15–64	65+
Newfoundland and Labrador	16.3	71.1	12.6
Prince Edward Island	18.7	67.5	13.9
Nova Scotia	17.0	69.1	13.9
New Brunswick	16.9	69.6	13.5
Quebec	17.2	69.5	13.4
Ontario	18.9	68.5	12.6
Manitoba	20.2	66.2	13.6
Saskatchewan	20.4	64.8	14.8
Alberta	19.8	69.9	10.3
British Columbia	17.0	69.4	13.5
Yukon	19.4	74.2	6.4
Northwest Territories	25.4	70.4	4.2
Nunavut	35.3	62.4	2.3
Canada	18.3	68.9	13

Table 10. Life expectancy at birth by province

Jurisdiction	Life Expectancy
Newfoundland and Labrador	78.3
Prince Edward Island	78.9
Nova Scotia	79.0
New Brunswick	79.0
Quebec	79.4
Ontario	79.9
Manitoba	78.6
Saskatchewan	79.3
Alberta	79.7
British Columbia	80.6
Yukon	77.3
Northwest Territories	76.8
Nunavut	70.4
Canada	79.7