RESEARCH PAPER

Estimating Population Benefits of Prevention Approaches Using a Risk Tool: High Resource Users in Ontario, Canada

Estimation des avantages, pour la population, du recours à une trousse d'outils pour la prévention du risque : grands utilisateurs de ressources en Ontario, Canada

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Abstract

Background: Healthcare spending is concentrated, with a minority of the population accounting for the majority of healthcare costs.

Methods: The authors modelled the impact of high resource user (HRU) prevention strategies within five years using the validated High Resource User Population Risk Tool.

Results: The authors estimated 758,000 new HRUs in Ontario from 2013–2014 to 2018–2019, resulting in $16.20 billion in healthcare costs (Canadian dollars 2016). The prevention approach that had the largest reduction in HRUs was targeting health-risk behaviours.

Conclusions: This study demonstrates the use of a policy tool by decision makers to support prevention approaches that consider the impact on HRUs and estimated healthcare costs.

Résumé

Contexte : Les dépenses de santé sont concentrées, une minorité de la population représente la majorité des coûts de santé.

Méthode : Les auteurs ont modélisé l'impact des stratégies de prévention des grands utilisateurs de ressources (GUR) sur une période de cinq ans à l'aide de l'outil d'évaluation de risque des grands utilisateurs de ressources.

Résultats : Les auteurs estiment qu'il y a eu 758 000 nouveaux GRU en Ontario de 2013–2014 à 2018–2019, ce qui a entraîné des coûts de santé de 16,20 milliards de dollars (dollars canadiens, 2016). Le type de prévention qui a entraîné la plus forte réduction des GRU ciblait les comportements à risque pour la santé.

Conclusion : Cette étude fait état de l'utilisation d'un outil par les décideurs pour soutenir les démarches de prévention qui prennent en compte l'impact sur les GRU et les coûts de santé estimés.

Background

It is widely acknowledged that healthcare spending is overwhelmingly concentrated, with a minority of the population accounting for the majority of healthcare costs (Zook and Moore 1980). In Ontario's single-payer universal healthcare system, the top 5% of healthcare users account for almost 50% of healthcare spending (Rais et al. 2013; Wodchis et al. 2016). This pattern of healthcare use has been observed across several health systems, including Canada, the US and Australia (Berk and Monheit 2001; Billings et al. 2006; Calver et al. 2006; Ehrlich et al. 2010).

In light of this phenomenon, high resource users (HRUs) are common targets for health system improvement or interventions with the goal of reduction in healthcare spending and improved quality of care. This focus has led to clinical intervention programs that have largely concentrated on older adults, managing individuals with multiple comorbidities and improved coordination and delivery of care (Ali-Faisal et al. 2017; Bleich et al. 2015), groups that are overrepresented in HRU studies. To date, such programs have had favourable results in quality of care and health outcomes and mixed results in their ability to reduce health system costs and outcomes (Blumenthal and Abrams 2016; Mondor et al. 2017). Existing interventions typically target patients who are already HRUs, with limited recognition of the role of upstream determinants, specifically those that are non-clinical in nature. The prevention of HRUs is an important component of population health management given that the healthcare system has historically failed patients with the most complex needs. In addition, prior work has also demonstrated stability in HRU status once the initial transition has occurred (Wodchis et al. 2016).

The inconclusive evidence and limited impact of most clinical interventions aimed at HRUs have compelled policy makers to revisit program strategies and to seek subgroups of the population that may benefit from certain interventions more than others (Figueroa et al. 2017). A proactive approach to address health system efficiency and sustainability includes targeting interventions toward individuals who are at the greatest risk of becoming a new HRU in the future. Research has shown that the impact and efficiency of intervention programs increase when they are targeted at groups that are most likely to benefit (Anderson et al. 2015; Blumenthal et al. 2016). Prediction models can inform such approaches by allowing for the modelling of future burden and the impact of potential interventions before substantial avoidable costs have incurred. In a financially constrained system, the ability to assign cost estimates to how intervention approaches influence the number of future HRUs in the population represents a major advantage in planning and prevention.

The High Resource User Population Risk Tool (HRUPoRT) is a validated tool that estimates the future risk of an individual becoming a new HRU and quantifies the impact of prevention strategies by applying routinely collected data from population surveys to a validated risk-prediction algorithm (Rosella et al. 2018). The HRUPoRT is unique from other risk prediction algorithms for HRUs that have traditionally been designed for applications in a clinical setting. Specifically, existing algorithms have focused on individual patients (Billings and Mijanovich 2007; Chang et al. 2016; Chechulin et al. 2014), using data that are not widely accessible to policy makers (for e.g., electronic medical records) (Chang et al. 2016; Frost et al. 2017) and have given little consideration to the impact of health behaviours on shaping healthcare spending (Billings and Mijanovich 2007; Chang et al. 2016; Frost et al. 2017; Hu et al. 2015; Lauffenburger et al. 2017). There are currently no other population risk tools for HRUs designed for application on publicly available survey data, allowing users to tailor the impact of interventions to the populations they serve. This article represents the first application of such a tool in a population covered under a single health system.

To date, to the best of the authors' knowledge, no study has focused on modelling the fiscal impact of multiple health behaviours on HRU, although a large subset of studies has attempted to determine risk factors for HRU, which consist of older age, comorbid health conditions, low socio-economic status and the presence of health risk behaviours (Alberga et al. 2018; Fitzpatrick et al. 2015; Rosella et al. 2014). The association between health risk behaviours and spending is well supported in the context of Ontario where physical inactivity and smoking are estimated to cost the province 22% of all health-related expenditures, amounting to $4.9 billion in healthcare spending that could be averted through policy or program interventions (Manuel et al. 2016). The aim of the current study was twofold: (1) to apply the HRUPoRT to the Ontario portion of the Canadian Community Health Survey (CCHS) and model the potential impact of two different prevention scenarios aimed at individuals with health risk behaviours and multimorbidity; and (2) to estimate how reducing risk among population subgroups impacts HRU spending.

Methods

High Resource User Population Risk Tool

To estimate the predicted risk and number of new HRU cases, we used the HRUPoRT (Rosella et al. 2018). The HRUPoRT is a predictive algorithm that estimates the five-year risk of becoming an HRU, defined as persons in the top 5% of total annual healthcare utilization expenditures. The absolute definition of an HRU was adopted from our original development and validation paper and has not changed in the current application of the HRUPoRT. In Canada, there is no established or defined indicator for an HRU; however, a 5% threshold is commonly used in studies of HRUs locally and internationally (Clough et al. 2016; Guilcher et al. 2016; Muratov et al. 2017; Wodchis et al. 2016). The HRUPoRT was originally developed in a cohort of 58,617 Ontarians who responded to the 2005 and 2007–2008 CCHS and was validated in an external cohort of 28,721 Ontarians in the 2009–2010 CCHS. The predictive performance of the model was evaluated based on discrimination (i.e., the ability of the model to distinguish between individuals with and without the event) and calibration (i.e., the agreement between observed and predicted outcomes). The best prediction model for a five-year transition to HRU status had good discrimination (*c*-statistic = 0.8213) and calibration (HL χ^2 = 18.71) in the development cohort. The model performed similarly in the validation cohort (*c*-statistic = 0.8171; HL χ^2 = 19.95). Close approximation between predicted and observed number of HRUs by deciles of risk was observed, specifically for individuals in high deciles of risk. Overall, the HRUPoRT was shown to accurately project the proportion of individuals in the population that will transition to a HRU over a five-year time period. Predictive variables in the HRUPoRT algorithm include perceived health status, presence of a chronic condition, age group, sex, ethnicity, immigrant status, household income, food security, body mass index (BMI), smoking status, physical activity quartile and alcohol consumption (Table A1, available online at longwoods.com/content/26433). All variables that were used to derive the HRUPoRT were also available in the study data. To ensure the model was representative of the Ontario population, survey weights were incorporated into the analysis that also took into account non-response rates at baseline and follow-up. Healthcare costs were calculated by applying a person-level costing algorithm to the linked provincial health administrative databases, including in-patient hospitalizations, physician visits, complex continuing care, long-term care, home services and assistive devices. Full details on model specification and validation can be found in existing literature (Rosella et al. 2018).

Data sources and study population

For this study, we used the HRUPoRT to generate predictions based on responses to the Ontario portion of the 2013–2014 CCHS. The province of Ontario is located in central Canada and is the most populous province, representing approximately 40% of the Canadian population (Statistics Canada 2018). Briefly, the CCHS is a cross-sectional survey administered at the sub-provincial level, used to gather estimates of health determinants, health status and healthcare utilization. The CCHS is administered by Statistics Canada and is representative of 98% of the Canadian population aged ≥12 years, living in private dwellings. Detailed survey methodology is available in existing literature (Statistics Canada 2018). The sample size for this survey was 40,199; excluding respondents under 18 years of age, the final sample size used in analyses for this study was 36,920, representing 10,732,847 when weighted. For individuals missing covariate information (n = 117) that is required for the probabilities calculation (i.e., missing information on at least one variable required for the calculation), they were assigned the mean predictive probability from the overall cohort, as recommended by Harrell (2001). This approach was chosen because it would not change the overall predicted risk and allows for the number of cases to reflect the entire population without excluding those with missing values, which is important for estimating the HRU burden.

Descriptive statistics were calculated for sociodemographic and health behaviours at baseline (i.e., CCHS interview year) according to the overall cohort (Table 1). The HRUPoRT was used to estimate the five-year predicted risk by important population subgroups, including sex, age group, ethnicity, immigration status, BMI, education, household income, smoking status, physical activity, alcohol consumption, number of health risk behaviours and the number of chronic conditions. The risk of becoming an HRU was calculated by multiplying individual probabilities estimated by the HRUPoRT (ranging from 0 to 1) by 100. Statistics Canada sample weights were applied to each individual probability to generate the number of new HRU cases that is reflective of the Ontario population.

Intervention scenarios

In addition to the baseline estimates, we ran two intervention scenarios to examine how implementing prevention programs aimed at reducing new HRUs would affect the total predicted number of HRUs and the cost to the healthcare system.

First, we modelled a high-risk strategy in which individuals (65+) with multimorbidity and individuals (65+) without multimorbidity were targeted. A respondent was defined as having multimorbidity if they reported having two or more of the following conditions: self-reported asthma, arthritis, back problems, migraine headaches, chronic obstructive pulmonary disease, diabetes, hypertension, heart disease, cancer, stomach or intestinal ulcers, stroke, urinary incontinence, bowel disorder, mood disorder and anxiety disorder. The second intervention scenario was a community-wide strategy that targeted those with "any one" or "any two" health risk behaviours (including heavy alcohol consumption, overweight/obesity, current smoking and physical inactivity). Heavy drinking behaviour was specified using cut-points for daily alcohol consumption and the presence of bingeing behaviour. The definition of overweight/obesity was based on the World Health Organization cut-offs (WHO 2000). Smoking behaviour was defined by combining separate questions about smoking status, daily cigarette consumption and past smoking behaviour. We categorized current smokers as heavy or light smokers. Physical inactivity was calculated using average metabolic equivalent of task (MET) per day derived from an aggregate list of leisure-time physical activities (frequency and duration) that were examined in the CCHS. The definition used to capture each risk factor variable can be found in Table A2, available online at longwoods.com/content/26433. These intervention scenarios were specifically selected based on efforts to generate the greatest returns on investment as indicated by the high baseline risk associated with increasing age, the presence of multiple chronic conditions and health risk behaviours. In addition, these scenarios were chosen due to prior work that suggests health behaviours are meaningful risk factors for incurring costs associated with HRUs (Alberga et al. 2018; Rosella et al. 2014), interest in these subgroups from knowledge users in local health departments and to demonstrate the utility of the HRUPoRT in providing evidence to support the best candidates for prevention.

Application of risk reductions to target intervention groups

For each intervention scenario, we subtracted 2.5%, 5% and 10% from an individual-level risk (ranging from 0 to 100) of transitioning to an HRU in five years as specified by the HRUPoRT (Table A1, available online at longwoods.com/content/26433). For example, if an individual were assigned a risk of 20%, their respective risk would be reduced to 15%, applying a 5% absolute risk reduction. To aggregate individual-level risk to estimate the total number of new HRUs at the population level, we applied bootstrap replicate survey weights provided by Statistics Canada to accurately reflect the Ontario population and account for the complex survey design of the CCHS. Weighted 95% confidence limits were calculated for all descriptive analyses. All statistical analyses were carried out using SAS version 9.4 (SAS Institute Inc., Cary, North Carolina, US).

Attributable cost estimates

To calculate healthcare costs of HRUs, including the associated costs averted with each prevention scenario, we used cost estimates from a previous study of ours that linked Ontario CCHS respondents to administrative data, estimated healthcare spending and ranked individuals in Ontario according to gradients of cost based on the top 1%, the top 2–5%, the top 6–50% and the bottom 50% (Rosella et al. 2014). The healthcare spending captured costs accrued by each person covered by the single-payer government insurer, Ontario Ministry of Health and Long-Term Care, including in-patient hospital stay, emergency department visits, same-day surgery, stays in complex continuing care hospitals, in-patient rehabilitation, long-term care, home care, in-patient psychiatric admissions, physician services and prescriptions for individuals eligible for the Ontario Drug Benefit program; the costing methodology is described in Wodchis et al. (2013). All costs are reported in 2016 Canadian dollars.

To determine total healthcare costs of HRUs in our study, we took 20% of 758,000 to ascertain the top 1% of HRUs and multiplied this value by $53,150 (i.e., the average per-person expenditure across healthcare services for the top 1%). We then took the remaining HRUs and multiplied this value by $13,450 (i.e., the average per-person expenditure across healthcare services for the top 2–5%). To determine cost estimates associated with the population subgroups, we took 20% of the number of HRUs averted (i.e., the results from the HRUPoRT after baseline reductions to risk were applied) to ascertain the top 1% of HRUs and multiplied this value by $53,150 (i.e., the average per-person expenditure across healthcare services for the top 1%). We then took the remaining HRUs and multiplied this value by $13,450 (i.e., the average per-person expenditure across healthcare services for the top 2–5%). The same approach was repeated for each prevention scenario. For further details on how cost reductions associated with each prevention scenario were estimated, see Table A3, available online at longwoods.com/content/26433.

In recognizing that not all healthcare costs among HRUs are avoidable, we present the five-year total cost of each prevention scenario and the five-year total cost that accounts for a baseline level of costs per person. To account for a baseline level of costs, we applied the average cost per person ($1,935) of a non-HRU to the predicted number of HRUs averted and subtracted this value from the five-year total cost. All cost estimates are presented with associated ranges to show uncertainty in the estimates.

Results

Overall, based on the 2013–2014 population in Ontario, the risk of transitioning to an HRU is 7.09%, translating to 758,000 new HRU cases in Ontario by 2018–2019. The five-year baseline risk for HRUs in the overall population and by important subgroups is reported in Table 1. Males are at a greater risk of transitioning into HRU status (five-year HRU risk of 7.42%) than females (five-year HRU risk of 6.78%) and are predicted to amount to 14,000 more HRU cases than females. Five-year HRU risk varies by age, whereby as age increases, the risk of becoming an HRU also increases with a risk of 1.10% among those 18-34 years compared to a risk of 21.20% among those 65 years and older. Individuals of white ethnicity are at a greater risk of becoming an HRU (five-year HRU risk of 8.14% compared to 4.29% among visible minorities) and are predicted to contribute the greatest number of HRU cases (n = 608,000), compared to visible minorities (n = 124,000). With the exception of being underweight, as BMI increases the predicted risk of becoming an HRU also increases (five-year HRU risk of 5.29% among normal weight compared to 7.96% among individuals who are overweight/obese). The largest number of HRU cases is predicted to occur among individuals with post-secondary education (n = 352,000); however, the greatest risk of becoming an HRU is among those with less than secondary school education (risk of 15.56% compared to a 5.53% risk among post-secondary graduates). Those in the lowest household income group are predicted to have the greatest HRU risk (five-year HRU risk of 10.18%) and the greatest number of cases (n = 222,000).

Considering health risk behaviours, former smokers are predicted to have the greatest risk of becoming an HRU (five-year HRU risk of 10.59%). However, the greatest absolute number of HRU cases is predicted to occur among non-smokers (n = 348,000) given that most of the population are non-smokers. This finding demonstrates that the number of predicted cases is both a function of level of risk and the distribution of risk among the population. Risk of becoming an HRU is greater among individuals who are physically inactive (five-year HRU risk of 8.31%). Individuals who are physically inactive are also predicted to contribute the greatest number of HRU cases (n = 416,000) compared to those who are active (n = 283,000). Those who are non-drinkers have both the greatest risk of becoming an HRU (five-year HRU risk of 7.65%) and are expected to contribute the largest number of cases (n = 469,000). As the number of health risk behaviours increases, the risk of becoming an HRU also increases (from 6.14% among those with zero health risk behaviours to 8.20% among those with ≥3 health risk behaviours). The largest number of new HRUs is expected to occur among those with 1–2 health risk behaviours. Finally, those with multimorbidity have three times the risk of becoming a new HRU than those with zero chronic conditions (five-year HRU risk of 12.99% compared to 4.35%, respectively). The number of predicted cases reflects the variation in risk across the population, in addition to the distribution of subgroups within the Ontario population.

TABLE 1. Baseline HRU risk overall and by important subgroups in the CCHS 2013–2014 Ontario cohort

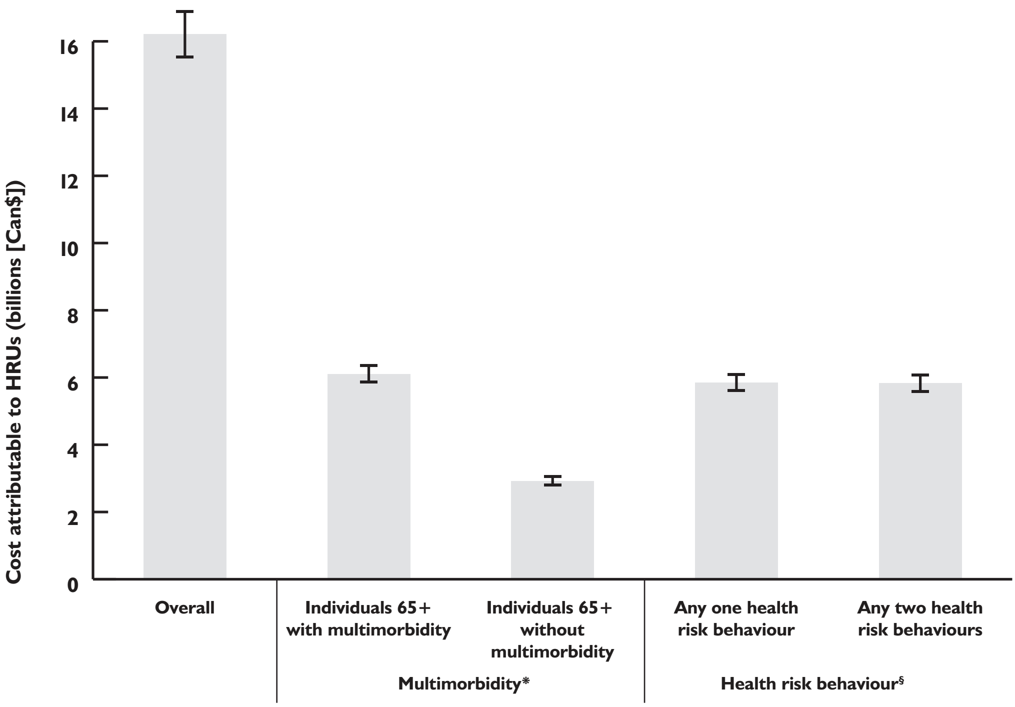
	Overall (36,920) 10,732,847	Five-year HRU risk (%)	Number of new HRU cases (thousands)
	Percent of population*	Estimate	Estimate
Overall	100	7.09	758
Sex (male)	48.67 (48.54, 48.78)	7.42	386
Sex (female)	51.34 (51.22, 51.46)	6.78	372
Age group (years)			
18–34	28.75 (28.22, 29.28)	1.10	32.8
35–49	25.99 (25.21, 26.78)	2.37	65.6
50–64	26.62 (25.99, 27.26)	8.33	237
65+	18.63 (18.58, 18.68)	21.2	422
Ethnicity			
White	69.79 (68.75, 70.84)	8.14	608
Visible minority	27.09 (26.04, 28.13)	4.29	124
Immigration status			
Canadian-born	63.40 (62.34, 64.46)	6.71	455
Immigrant	32.93 (31.86, 34.01)	7.69	271
BMI			
Underweight	2.50 (2.21, 2.79)	5.74	15.3

	Overall (36,920) 10,732,847	Five-year HRU risk (%)	Number of new HRU cases (thousands)
Normal weight	40.54 (39.65, 41.42)	5.29	229
Overweight or obesity	50.81 (49.93, 51.69)	7.96	433
Individual education			
Less than secondary school graduation	11.94 (11.29, 12.60)	15.56	199
Secondary school graduation	21.62 (20.81, 22.44)	7.12	165
Some post-secondary	5.25 (4.80, 5.69)	3.97	22.3
Post-secondary graduation	59.74 (58.75, 60.72)	5.53	352
Equivalized household income quintile			
Lowest	20.34 (19.51, 21.17)	10.18	222
Low-middle	19.51 (18.75, 20.27)	9.09	190
Middle	19.68 (18.96, 20.39)	6.64	140
High-middle	19.68 (18.89, 20.47)	5.70	120
Highest	20.79 (20.05, 21.54)	3.96	87.5
Smoking status			
Current smokers	17.87 (17.17, 18.56)	7.05	134
Former smokers	20.57 (19.86, 21.28)	10.59	233
Non-smoker	57.56 (56.64, 58.47)	5.67	348
Physical activity			
Physically active (≥1.5 METs/day)	52.20 (51.19, 53.21)	5.20	283
Physically inactive (<1.5 METs/day)	47.80 (46.79, 48.81)	8.31	416
Alcohol consumption			
Heavy drinker	7.44 (7.00,7.89)	4.86	38.5
Moderate drinker	18.66 (17.91, 19.41)	6.45	129
Light drinker	13.15 (12.46, 13.83)	6.21	87.4
Non-drinker	57.38 (56.44, 58.32)	7.65	469
Number of health risk behaviours§			
0	22.26 (21.52, 23.00)	6.14	146
1	40.74 (39.81, 41.68)	6.29	274
2	29.53 (28.67, 30.38)	8.63	273
>3	7.47 (6.96, 7.98)	8.20	65.6
Number of chronic conditions¶			
0	68.25 (67.42, 69.08)	4.35	316
>1	31.75 (30.92, 32.57)	12.99	443

* Weighted using bootstrap weights as described by Statistics Canada. Column percentages do not total 100% where missing values are not reported.
§ Including heavy alcohol consumption, overweight/obesity, current tobacco use and physical inactivity.
¶ >1 chronic condition, including self-reported asthma, arthritis, back problems, migraine headaches, chronic obstructive pulmonary disease, diabetes, hypertension, heart disease, cancer, stomach or intestinal ulcers, stroke, urinary incontinence, bowel disorder, mood disorder and anxiety disorder.

Overall, the HRUPoRT predicted 758,000 new HRU cases in Ontario by 2018–2019, resulting in $16.20 billion in healthcare costs (Figure 1). Without intervention, the HRUPoRT estimated 286,000 new HRU cases among those 65+ with multimorbidity and 137,000 among those 65+ without multimorbidity. Altogether, these two segments of the population are estimated to cost $6.11 billion and $2.93 billion, respectively. Moreover, without intervention, the HRUPoRT estimated 273,000 new HRU cases among those with "any one" health risk behaviour and "any two" health risk behaviours, resulting in a cost of $5.85 billion and $5.83 billion to the healthcare system, respectively.

FIGURE 1. Baseline scenario of healthcare costs attributable to HRUs and corresponding costs associated with each prevention scenario, Ontario, 2011–2012 to 2018–2019



* >1 chronic condition, including self-reported asthma, arthritis, back problems, migraine headaches, chronic obstructive pulmonary disease, diabetes, hypertension, heart disease, cancer, stomach or intestinal ulcers, stroke, urinary incontinence, bowel disorder, mood disorder and anxiety disorder.
§ Including heavy alcohol consumption, overweight/obesity, current tobacco use and physical inactivity.

If a targeted intervention approach were put in place that resulted in a 5% reduction in risk among those 65+ with multimorbidity, it is estimated that we would save 59,100 new HRUs, resulting in $1.26 billion in savings (Table 2). In contrast, if a targeted intervention approach were implemented that resulted in a 5% reduction in risk among those 65+ without multimorbidity, we would prevent approximately 40,400 new HRUs producing a savings of $863 million.

Alternatively, if a population-level intervention were carried out that resulted in an average 5% reduction in the risk of becoming an HRU among those with "any one" health risk behaviour in the population, the total number of HRU cases prevented would amount to approximately 125,000, equating to $2.67 billion in healthcare savings for Ontario. Finally, an intervention targeting individuals with "any two" health risk behaviours that produced a 5% reduction in risk would avert approximately 109,000 new HRUs and save $2.34 billion in healthcare costs. Reference costs are also provided for context, which include the baseline estimate among non-HRU within the target group (see Table 2).

TABLE 2. Healthcare costs averted with estimated five-year costs according to two intervention scenarios: Ontario 2011–2012 to 2018–2019

	Number of HRUs averted (thousands)	Five-year total cost reductions in billions (range) Can$	Five-year baseline total cost in billions (range; reference) Can$*
Individuals 65+ with multimorbidity§			
2.5%	29.6	$0.632 (0.606–0.659)	$0.575 (0.550–0.600)
5%	59.1	$1.26 (1.21–1.31)	$1.15 (1.10–1.20)
10%	117	$2.50 (2.40–2.61)	$2.27 (2.18–2.37)
Individuals 65+ without multimorbidity§			
2.5%	20.2	$0.432 (0.414–0.451)	$0.393 (0.376–0.410)
5%	40.4	$0.863 (0.827–0.900)	$0.785 (0.752–0.819)
10%	76.1	$1.63 (1.56–1.70)	$1.48 (1.42–1.54)
Any one health risk behaviour¶			
2.5%	79.8	$1.71 (1.63–1.78)	$1.55 (1.49–1.62)
5%	125	$2.67 (2.55–2.78)	$2.42 (2.32–2.53)
10%	182	$3.90 (3.74–4.07)	$3.55 (3.40–3.70)
Any two health risk behaviours¶			
2.5%	66.2	$1.42 (1.36–1.48)	$1.29 (1.23–1.34)
5%	109	$2.34 (2.24–2.44)	$2.13 (2.04–2.22)
10%	166	$3.54 (3.39–3.69)	$3.22 (3.08–3.36)

* The average per-person cost for all Ontarians was applied to the number of HRUs averted and subtracted from the five-year total cost to account for a baseline level of cost.
§ >1 chronic condition, including self-reported asthma, arthritis, back problems, migraine headaches, chronic obstructive pulmonary disease, diabetes, hypertension, heart disease, cancer, stomach or intestinal ulcers, stroke, urinary incontinence, bowel disorder, mood disorder and anxiety disorder.
¶ Including heavy alcohol consumption, overweight/obesity, current tobacco use and physical inactivity.

Discussion

Between 2013–2014 and 2018–2019, new HRU cases are estimated to result in $16.20 billion in Ontarian healthcare costs. To our knowledge, this is the first study to model the impact of prevention approaches to reduce the burden of HRUs of the health system. These models can help estimate the population impact of a range of intervention scenarios. To improve population and public health while containing costs, it is important to define populations that can be targeted to potentially impactful interventions. Appropriate and timely public health interventions can lead to considerable savings in future healthcare spending; however, due to scarce resources, decisions must be made to identify the best candidates for such interventions.

Despite recent literature that identifies behavioural risk factors to be associated with hospitalization, prolonged hospital stay, and overall high-cost utilization in the healthcare system (Manuel et al. 2014, 2016; Rosella et al. 2014), no prevention programs designed to target HRUs have addressed upstream health behaviours. Our study provides further evidence to support that health promotion and prevention strategies designed to reduce the burden of health risk behaviours at the population level, which in turn mitigate the pathway to HRUs, would have a more meaningful impact on conserving health system costs than targeting individuals after they develop chronic disease and multimorbidity. This population risk tool is particularly useful because it assists in identifying high-risk groups, whereby public health interventions may offer the greatest return on investment and considerable cost savings (Masters et al. 2017). However, population-wide efforts to encourage behaviour change are complex and nested within the broader socio-political context. Successful policy and program interventions aimed at targeting population health behaviours require multi-stakeholder and multi-sectoral collaboration, making such approaches difficult to initiate and sustain (Rosella and Kornas 2018).

Alternatively, reducing the risk of becoming an HRU among individuals with multimorbidity may also represent a meaningful approach but to a lesser extent than targeting health risk behaviours. The challenges associated with reducing healthcare use among individuals who have already developed multimorbidity are exacerbated by health systems that are siloed and have been designed to treat individual diseases with many treatments being medically necessary to sustain or increase quality of life (Barnett et al. 2012). In most cases, suitable interventions for individuals with multimorbidity are multi-faceted and oriented toward a person-centred perspective while acknowledging an individual's broader social and historical context (Poitras et al. 2018). Multimorbidity is more than just a health systems issue; it is also largely driven by health behaviours and the upstream social determinants. To that effect, investments in improving health behaviours and social supports, such as housing and basic income, are likely to translate into reductions in multimorbidity (Rosella and Kornas 2018).

In April 2019, the Government of Ontario announced efforts to restructure the healthcare system into an integrated model for organizing and delivering healthcare. These changes include the creation of Ontario Health Teams comprising groups of providers and organizations that are clinically and fiscally accountable for delivering care to a defined population (Ontario Ministry of Health and the Ontario Ministry of Long-Term Care 2019). These system changes have galvanized the attention of health decision makers leading Ontario Health Teams to identify population segments that consume a high proportion of costs. As such, population-based risk tools that can model the effect of interventions on containing costs become important decision-making tools. Furthermore, a strength of the HRUPoRT is the ability to incorporate upstream social determinants of health that have been identified as important targets in early reflections from Ontario Health Teams (Downey et al. 2020).

This work has important implications for policy makers seeking to improve healthcare spending in Ontario. First, our findings suggest that individuals with multiple health risk behaviours should be considered in population approaches to reduce the burden of HRUs. This study also demonstrates the use of a population-based risk prediction tool (HRUPoRT) that can be leveraged using routinely collected representative population data to predict HRUs. Given that this algorithm is built on population survey data, the risk prediction model can be used by a broad audience, such as decision makers in local health departments to help understand characteristics of HRUs, including overall population risk, distribution of risk in the population and the total number of new cases in the population, which facilitates evidence-based decision making.

Limitations

One limitation of the HRUPoRT is that while the tool was applied to CCHS data that are representative of the majority of the Ontario population, some population subgroups were not surveyed by the CCHS, most notably on-reserve Indigenous peoples. This is an important consideration because the ability to generalize our results to important populations at risk, who may have greater health behaviour risk factors, is limited. Due to the sampling frame, the estimated number of new HRUs and corresponding costs is likely an underestimate, given that CCHS respondents are typically healthier than the general population (Keyes et al. 2018). In addition, this study used self-reported exposure to health risks, which can result in misclassification. It is possible that self-reported behaviours are an underestimate of the true risks (Newell et al. 1999), although several validation studies have been carried out to show good agreement (Wong et al. 2012). Despite this limitation, the use of self-reported risk factor measurements leveraged in the HRUPoRT algorithm were found to be accurate for HRU transitions (Rosella et al. 2018).

Healthcare costs were estimated based on publicly funded healthcare coverage in Ontario using an established costing methodology at ICES, Ontario, that captures new HRUs across the main domains of spending. The HRUPoRT does not capture spending in domains that are not covered in a single-payer system, including dental visits, eye care, physiotherapy, chiropractic and other allied health professions, such as drug claims for those under 65 years old (Rosella et al. 2018). In addition to the direct health system costs, the model does not capture costs for HRUs that may include out-of-pocket expenses or indirect emotional and social costs for patients, family and friends. Avoidable healthcare costs due to HRUs by population subgroups may have been overestimated given that not all healthcare costs are avoidable. To facilitate a balanced interpretation of this estimate, we have supplemented this information with an estimate that accounts for a baseline cost per person. Finally, individuals who experience several HRU transitions or new transitions to HRU status within the first year are not captured, although prior literature suggests that HRU status remains relatively stable (Wodchis et al. 2016). Given this, the HRUPoRT projections are likely to underestimate the true HRU burden in the population. Furthermore, we acknowledge that HRU risk-reduction values associated with modifying health risk behaviours are not well established; however, one risk prediction tool estimated that a weight-loss intervention targeted at severely obese individuals was expected to reduce the risk of high medical spending in the subsequent year by 1.5–27.4% depending on the baseline level of overweight/obesity (Snider et al. 2014).

Conclusions

Containing healthcare spending has been identified by governments in multiple health systems as a top priority for improving efficiency and sustainability. Population risk tools, such as the HRUPoRT that considers the upstream determinates of HRUs, can be leveraged to improve health planning and to explore the impact of different prevention strategies and associated cost savings up to five years in the future. In addition, predictive tools such as the HRUPoRT can assist in using evidence-based planning to identify optimal population subgroups for intervention and provide insight into how extensive a strategy must be to achieve the desired risk reduction in the number of new HRU cases.

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