ALC Populations in Ontario – A Data Driven Approach to Targeted Policy Design for Specific Patient Populations Using a Time-Variant State Space Model

by

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Abstract

Hospital overcrowding is a major policy issue across Ontario, Canada. Nearly 15% of all acute care hospital bed-days were used by ALC patients between April-2012 and April-2017. Patient level data on all patients in Ontario with at least one ALC day during the study window was made available by the MOHLTC. A whole system model is proposed and can used to test the impact of policies on demand for included services, while accounting for the multidimensionality of the ALC problem. A policy where 15% of patients, who would otherwise await placement in ALC to a LTCH, are discharged to community care was found to unblock 100 acute care beds at peak. A second policy examined the changes to service use patterns if ALC patients with dementia and delirium were discharged at twice the current rate, to find that between 200-250 beds would be released.
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Chapter 1

Introduction

1.1 Hospital overcrowding and its relation to LTC and ALC

Hospital overcrowding has become a major policy issue in recent decades, particularly in the most economically developed nations of the world [9]. Viewed simply, hospital overcrowding is essentially a shortage - growth in demand for hospital based healthcare services, driven by population growth and availability of treatments, has outpaced the growth in supply of such services. While this view is necessarily true, expansion of the supply of hospital based services is seldom proposed as a main policy lever to alleviate hospital overcrowding [50]. Instead, policy proposals targeting hospital overcrowding mostly focus on expansion of non-hospital healthcare services, and on better use of existing hospital resources. This seemingly skewed view on the hospital overcrowding problem is driven by two common observations: first, a small fraction of the overall population, most of whom are frail elders, consume the majority of hospital healthcare services [10]; second, hospital based care is usually more expensive than alternative modes of healthcare delivery, on a per patient basis [8]. Put together, these two observations point to the possibility of alleviating the observed shortage of hospital based services by expanding alternative services for elderly “heavy-users”, at a cost that is lower than direct expansions of hospital services. A subset of these alternative services for frail elderly patients are often referred to as “Long Term Care” (hereafter, LTC), which includes care provided in the patient’s home, community, and in institutional settings, for an extended period.

Hospitals provide a variety of different services on an emergent, outpatient, and inpatient basis. As such, a wide array of alternative services is needed to divert demand for care away from hospitals. Efficient planning for the supply of these alternatives is in itself a challenging task due to variations in patients’ needs, projections of future demand, and cost constraints [2]. When supply of these services is insufficient in meeting demand, patients revert to seeking healthcare services from hospitals, which results in overcrowding. In particular, shortage of LTC capacity has been widely cited as a primary culprit of hospital overcrowding [9]. Demand for LTC
services, mainly emanating from frail elderly patients, is expected to increase in the near future due to increases in the share of older citizens in the most economically developed nations [1,50,6,31]. Older citizens tend to require more assistance with daily activities, and as overall longevity increases, the prevalence of chronic diseases and disabilities also grows - further increasing older citizens’ demand for care [2,3]. The supply of care for the elderly can be informal or formal: informal care is provided by family, relatives, and friends; formal care is provided by healthcare professionals, social workers, and paid helpers. Contemporaneously to the increase in elders requiring care, decreasing family size and increasing female participation in the labor force resulted in reduced supply of informal care [2]. The gap between growing demand for care and diminishing supply of informal care, was left to be filled with formal care - provided either as LTC or hospital based care. In many healthcare systems, LTC capacity was not sufficiently increased to eliminate this gap, which in turn contributed to hospital overcrowding [1,11,50]. As all available LTC services were occupied, elders that could not live independently at their residence without some form of formal care deferred to waiting for such services in the hospital and became “Bed-blockers”.

1.2 ALC - definition, causes, and importance

Bed-blockers, known as Alternative Level of Care (hereafter, ALC) patients in Canada, are patients who no longer require the intensity of service provided, but continue to occupy the service provider. In the context of hospital based care, ALC patients have been designated ready for discharge from acute care but have yet to be discharged and continue to occupy an acute care bed. ALC patients cause hospital overcrowding directly by denying access to a bed to a patient in need of acute care while occupying a bed they no longer require, and indirectly by causing the blocked patient to be taken care of elsewhere while they wait for an acute bed - usually, in the emergency department [14,30,51]. This relationship between bed-blockers and hospital overcrowding has been identified in multiple economically developed nations [7,9] including Singapore [2,35], Australia [27,28], Ireland [30,31], Israel [32], the Netherlands [33,34], the United Kingdom [36,37], as well as in different provinces in Canada [1,15,17,18,19,20,12,13], and specifically to this paper, in Ontario [11,12,13,21,24,26,23]. As in the case of hospital overcrowding at large presented above, ALC patients are primarily frail elderly, with a small fraction of patients responsible for most ALC days [11,17]. Furthermore, hospital overcrowding
due to ALC has been directly linked to a lack of LTC capacity, mainly residential LTC, known in Ontario as Long Term Care Homes (hereafter, LTCH) [1,31,38,21,42,46,11,43]. These defining characteristics of ALC present policy makers with a specific course of action for reducing hospital overcrowding - identify the causes of ALC and expand capacity for the required services, to free acute hospital beds and increase patient flow within the hospital.

Patients are designated as ALC and continue to occupy an acute hospital bed due to transfer frictions, non-existence of a service providing the level of care they require outside the hospital, or due to lack of downstream capacity. Transfer frictions occur when the next service in the patient’s care pathway has capacity to accommodate the patient, but the administrative process relating to the transfer of care is not yet complete. ALC caused by transfer frictions is likely to be short and its elimination would require expansion of administrative capacity and better integration between healthcare service [12,13]. The non-existence of an alternative to hospital based care outside the hospital also results in ALC, in which case the patient must remain in the hospital in perpetuity. For example, no adequate level of care may exist in some cases for complex patients diagnosed with organic mental disorders or mental illnesses [25,37]. ALC caused by such patients is irreducible without the creation of novel services and relevant expertise. Lastly, and as previously stated, some patients are designated ALC and continue to occupy an acute care bed in hospital as they await admission to a service that has no available capacity to accommodate them. Multiple approaches have been proposed for assessing the utility and guiding the selection of policies targeting better allocation and expansion of downstream healthcare services, particularly LTC services, and are discussed below. The research presented in this article also targets ALC caused by access block to downstream services, specifically in Ontario.

Addressing the issue of ALC is important from human, economical, and political perspectives. By definition, ALC patients are not receiving the level of care that best matches their needs [31]. Prolonged length of stay in a hospital environment has negative consequences on the patient’s health outcomes, and the mismatch between need and level of care has a negative impact on both patients and hospital staff [8]. In addition, the resulting access block for patients in need of acute care beds, caused by ALC occupants, expands the mismatch of need and level of care upstream in the hospital [31]. The inappropriate level of care received by ALC patients is also
economically wasteful. This is especially true for ALC caused by lack of downstream capacity - the per patient daily cost of care in the services ALC patients await admission to are significantly lower compared to the daily cost of the acute care beds they are occupying [8,13,23,31]. The economic cost of ALC is especially important in a universal healthcare system such as in Ontario. Healthcare, and specifically hospital overcrowding - termed “hallway medicine”, was a key issue in Ontario’s provincial elections of 2018, with the ultimately winning party promising increases in healthcare spending and LTCH capacity [48]. After the elections, a specially established committee highlighted the centrality of ALC in causing hospital overcrowding and called for a new strategic planning ideology that focuses on key patient populations and their care pathways [46,47]. Overall, the need for addressing the ALC issue and motivation for policy in Ontario are both present. The next section presents previously developed tools for designing hospital and LTC capacity planning policies and discusses their relevance to the present context of Ontario.
Chapter 2
Literature Review

2.1 ALC Planning and Policies

The task of planning services and designing policies to address the ALC issue is fraught with complexities relating to variations in patients, time, and availability of healthcare resources [2]. The needs of ALC patients are not homogenous – different ALC patients require different types of services at varying care intensities, which in themselves may change over time as the patient ages and their health condition changes. Patient needs vary by health status, chronic conditions, disabilities, age, gender, socio-economic status, place of residence, availability of informal support, and other factors [11,22]. Time is also a determinant of patient need, both with respect to cyclical variations in demand for care within a given period, and changes to the patients themselves between periods [1]: Within periods, demand for healthcare services may be higher during winter months compared to summer months, and may be lower during weekends compared to weekdays; Between periods, changes in the demographic structure of the population and associated changes in the prevalence of certain health conditions, may impact the need for care if longer time horizons are considered. Furthermore, since the ALC patient population is likely to need a variety of healthcare services throughout their care pathways, prudent policies ought to be considerate of potential externalities that may arise from changes made to a specific service [49,50]. Overall, these dynamisms make projections of the demand for care posed by ALC patients difficult, which translates into difficulties in planning the supply of services to match this demand.

Previous studies on the topic of ALC and related capacity planning differ on the amount of the aforementioned variations brought into the study’s scope, and on the proposed quantification methodology. Nevertheless, all the studies presented below share a similar approach to policy design – estimate future demand for services in a given system, propose a change to the system to meet this demand, and provide a tool for future development of policy for the considered system. The studies presented below are broadly grouped as deterministic models, which offer easier application and lower computation time, and simulation base models that provide greater flexibility at the expense of ease-of-use and deployment time.
2.2 Deterministic models

The simplest method for estimating demand is presented in [1] as a “Ratio rule”. This method relies solely on yearly population growth projections per age group and on current utilization of specific services by each age group. The ratio of service users to population cohort is then calculated and applied to the growth projections to estimate future yearly demand. Clearly, this method ignores potential future changes in need for care, as it assumes that the needs of an age cohort today are representative of future needs for the same cohort. This assumption is especially problematic for the older cohorts, who are projected to both grow in size and demand higher service intensities. [1] also argues that the use of population projection data prohibits disaggregated applications of the “ratio rule” for different time periods and geographic locations. In response, [1] proposes the “Average Flow Model” – demand per period evolves as inventory, where patient departures from a service are subtracted from, and patient arrivals added to the previous period’s demand to obtain demand in the next period. This model requires estimates on flow of patients in and out of the service for each period, which can be obtained directly or as a function of average length of stay estimates. [1] applies the “Average Flow Model” for yearly estimation of demand for LTCH beds, for patients of different age and gender, for a subregion of British Colombia, Canada. The strength of this model is in its simplicity, transparency with regards to the level of aggregation, and flexibility to fit in different contexts. However, the model’s reliance on length of stay limits its ability to account for cyclical variations in demand within periods. More importantly, interactions between services are not considered, as the capacity is planned for each service independently of others.

Patient flows between multiple services can be modelled as a state space network, in which each state represents a service that the patient occupies until their transition to a different state. This approach is suitable for studying the ALC issue, as it explicitly captures the essence of ALC – blocked flow between services. [51,11] developed a markov chain model to determine the impact of LTCH capacity increases on ALC in Ontario, Canada. While this model focused on the ALC-LTCH link, the authors also included demand for LTCH emanating from non-ALC patients and home care services as an alternative service to LTCH. Furthermore, [51,11] considered daily variations in flows between services, patient preferences over specific LTCHs, and policy targets regarding wait times and hospital capacity as constraints – but did not consider specific patient
characteristics nor any form of readmissions after hospital discharge. An example of how differences between patients and readmissions can be captured in a similar framework is presented in [16]. Albeit not directly focusing on ALC, [16] uses a markov chain model to forecast future demand for public and private home care services in British Colombia, Canada. The proposed model explicitly matches patient service type demand to different groups based on age, income, and health status, as well as considers bidirectional patient flows between different home care service types as a function of changes in their characteristics. Both markov models share a common focus on the flows between services as a determinant of utilization, as does the “Average Flow Model” discussed above.

Conceptualization of the ALC problem in terms of patient flows between service “states” can be also directly expressed in queueing models, where ALC is viewed as a queue formed between two services. [20] used this natural modelling choice to develop a model for LTCH planning in Nova Scotia, Canada, with an explicit focus on the ALC to LTCH link. Specifically, the simple queueing model proposed by [20] examined the impact of LTCH capacity changes on ALC length of stay. While this model benefits from its transparency and ease of application, it neglects some of the important complexities expressed previously, such as differences between patients, time variations in demand for services, and dynamic interactions with other healthcare service. A more sophisticated model is presented in [36] using data from England, UK – differences in patients’ age, geographic variations and spillover, and costs of LTCH beds, were all considered in explaining the impact of LTCH capacity changes on ALC. Nevertheless, demand was assumed to be stationary within the studied time window, and feedback to and from other healthcare services was not included in [36]. A whole system model using queueing logic in a optimal control framework was developed by [32] for an HMO in Israel, which unlike the simpler models mentioned above did consider some variations between patients, differences in demand over time, and interactions between services: patients were grouped by age, with demographic changes were considered in forecasts; yearly cyclicality in demand was observed and included; emergency departments, hospital based acute care, hospital based LTC, inpatient rehabilitation, home care, LTCH, and deaths, were explicitly modeled, including relevant return flows between these services. With the inclusion of different cost measures, such as per diem patient service cost and patient relocation costs, the authors of [32] demonstrated how their
model can be used to determine the optimal capacity choices for the entire network. Notably, unlike the Markov models, the queueing inspired models require estimations of both flows and length of service provision to determine utilization.

2.3 Simulation models

The often cited PSSRU macrosimulation was developed in the UK to strategically guide LTC planning, with an emphasis on long term costs [39]. This model uses aggregate data on large patient groups and utilization of both formal and informal LTC to project future demand for LTCH and home care. Somewhat analogously to the “Ratio rule” approach, [39] only accounts for aggregate demographic changes in determining future need for care, and does not account for short-run fluctuations in supply and demand of services. In addition, the model’s large scale and reliance on aggregates and estimations, results in it being sensitive to effects caused by ignored variations and incorrect assumptions [40]. Nevertheless, the lax need for data may be considered a strength in the specific context of this model, which has been developed for long term projections of overall costs on a national scale – not short-run capacity planning for specific services at separate geographic locations. The relative simplicity, and resulting transparency, of the model was also used to test several “what if” scenarios regarding aggregate changes in the population, such as marital status trends, home ownership among the elderly, and inflation [39]. Despite the usefulness of the PSSRU and similar models in highlighting the urgent need for strategic long term planning of LTC services, it cannot be used for guiding policy at the granular level required for efficient planning for a heterogeneous population and service mix – more detailed models are necessary for addressing the specific problem of ALC.

Discrete event simulations (hereafter, DES) capture the evolution of each state in a given system over time and can explicitly model the flow between services, thereby making it suitable for capacity planning and scenario testing in complex and time-variants environments. Taking advantage of the high degree of granularity of the DES framework, [33] used aggregate data and estimates to model the transition between a hospital and LTCH in the Netherlands, and tested “what if” scenarios aiming at reducing frictional ALC. Specifically, faster patient transfers between services, use of interim buffer beds for ALC patients, and deployment of discharge planning policies, were tested by [33] with respect to their impact on ALC occupancy in the
hospital. The flexibility of the DES microsimulation framework was further used to capture variations between patients based on their pre-hospitalization place of residence, and to directly account for weekly and yearly variations in demand for hospital services. DES can also be applied to test capacity planning scenarios at a disaggregated level, as was done by [38] for a large geographical area in British Columbia, Canada. [38] included multiple LTC services, considered patient variation based on age and gender, allowed for year to year changes in demand for the various healthcare services represented in the model, incorporated demand for LTC by non-ALC patients, and explicitly disaggregated each service provider within the geographical area studied. This highly granular model was then used to test the impact of capacity changes in different services on wait times for placement in LTCH. Notably, the ability to account for granular patient pathways and temporal variations, as well as test narrow policies that focus on a specific process or pathway in the system, exemplifies the strength of microsimulations, such as DES, when compared to larger aggregate models, like the PSSRU. However, this same specificity also results in rapidly increasing complexity when multiple services are included and patient flows are observed over a longer period of time – DES is not well suited for capturing complex feedbacks between different pathways and processes in the long run.

System dynamics models (hereafter, SD) implicitly uncover the rules governing a system to replicate the flows between different stocks in a system. In the context of a healthcare system, the SD framework can be used to model the flow of patients between different services, where the flow rates are determined by exogenous variations, such as patient attributes, time, and transfer policies, as well as by the endogenous state of the system, as it relates to capacity constraints, priority rules, and patient choice. The focus on modeling the determinants of flow, instead of flow itself, allows SD models to circumvent the limitations of the DES framework by uncovering continuously operating rules that govern the behavior of the system, as opposed to trying to fit the flow directly. [14] advocated the use of SD in healthcare planning by arguing for its superiority over other methods in modeling complex systems – especially due to SD’s transparent ability in capturing feedback. Using data from Alberta, Canada, [14] developed a simple hospital SD model to show how population aging and LTC service shortages result in hospital overcrowding, which in turn causes ED overcrowding. The SD framework can also be
directly used for projecting future demand and for testing “what-if” scenarios regarding capacity changes, as is demonstrated by [2]. [2] championed SD models by arguing for the framework’s flexibility in answering different policy questions and its transparent mapping of the system. While accounting for patient variations based on age, gender, educational attainment, and ability to perform daily activities, [2] applied an SD model to forecast the future need for formal and informal care, and to quantify the impact of LTC capacity changes on the supply of acute care professionals in Singapore.

Unlike DES, SD models can be easily scaled up to include flows between multiple services with feedbacks resulting from a long modeling horizon. [31] developed a whole system model, which included hospitals, inpatient rehabilitation facilities, LTCH, and home care, for strategic planning on a national scale with the explicit focus on reducing hospital ALC in Ireland. The proposed SD model utilized large amounts of data to forecast future demand for all considered services, and to test the impact of capacity changes in LTCH and home care on other services, while accounting for temporal variations in the system’s behavior and for differences in service use among different age cohorts [31]. [49] developed a more expansive SD model for the totality of the healthcare system in Ontario, Canada. The large scope of this model allows testing the direct and indirect impact of different policies targeting different determinants of flow in the model, which vividly reflects the flexibility of the SD framework. As an example of a particular policy test, [49] observed the impact of best care practice observance on hospital length of stay and later service utilization of stroke patients, with consideration given to the type of stroke and yearly variations in parameters. While the SD framework is better suited then the aforementioned macrosimulation and DES methods in accurately representing large and complex systems, it relies on a large number of inputs to match the degree of complexity, which may cost in usability by planners and policy makers. Other simulation methods that were proposed for the context of strategic planning in healthcare, such as agent based models [e.g. 29] and SD-DES hybrids [e.g. 5], similarly suffer from complexity and the risk of inoperability.
Chapter 3
Motivation

The models discussed in the previous section outline the various dimensions that need to be considered in the context of hospital overcrowding. First, differences between patient groups are essential for characterizing service demand and utilization over time. While most models only use age and gender to cluster patients, other models use a more expansive list of attributes, including health status, living arrangements, and geographical location. In addition, these characteristics are likely to change over time as patients receive services and age. Second, demand for services varies within each week, within each year, and between years. The models presented above account for these variations to different extent, but all admit to the importance of considering this dimension. Third, the length of the care pathway included in each model has direct implications on its usefulness: no direct consideration of pathways is only applicable to aggregate long term planning; short pathways that only include a few services, are useful for localized consideration of policies and short term planning; long pathways that include multiple services and feedbacks necessitate more complex models, which in turn allow planning for different time horizons and scales. Fourth, the complexity and transparency of the different models presented may have an impact on their use by planners – heavy reliance on a multitude of inputs and on technical expertise might render models impractical. This consideration is especially relevant for models targeting larger scales, where explicit knowledge of the operation of the system is diffused among many decision makers. Lastly, the types of “what-if” scenarios that can be tested are directly related to the structure of the model. Given the aforementioned dimensions that need to be considered, a large number of policy scenarios can be imagined in the context of hospital overcrowding, such as policies targeting different causes of ALC, introduction of new services, and capacity expansion of existing services, for different patient populations and with different planning horizons. However, such increased flexibility must be weighed against transparency and usability by planners.

We propose a model that allows the user to choose their preferred degree of complexity and granularity, while retaining its simplicity and transparency. Specifically, the model presented in
the methodology section below can be applied to any group of patients and temporal horizon, can be easily modified to include more or less services, and relies on the estimation of a single parameter that determines flow between services. The relevant degrees of variation between patients are left to be chosen by the planner – each created patient cluster is then “flown” through the model separately, which allows the use of established patient groupers and the testing of policies tailored to specific types of patients. Temporal variations are captured by the single flow parameter, which can be estimated at any desired time step. The care pathway in the model can be expanded through the inclusion of data regarding utilization of the extra services without modification of the model itself. Transparency and flexibility are promoted by the reduction of the models function to the single flow parameter, and by the concentration of all policy impacts to be explicitly viewed in terms of their effect on patients’ transition between services: once the relevant cluster of patients, time step, and relevant healthcare services, have been chosen by the planner, varying the flow parameter from the estimated baseline would mimic the impact of policy targeting the specific patient cluster. This proposed framework can be used to estimate the effect of policies ex-post their design, or conversely observe the required changes in capacity given a desired change in the flow parameter. As such, we intend this model to be used to evaluate the impact of proposed policies at a granular level, to establish desired targets of changes to patient flow patterns for the design of policy, and to complement the existing literature on healthcare system modelling.
Chapter 4
Data and Descriptive Analysis

4.1 Data Source

Administrative data for this project was made available by Ontario’s Ministry of Health and Long Term Care (hereafter, MOHLTC). The data includes information about patient characteristics, time-stamped service use, and healthcare facility details. All patients that had occupied an acute care bed in a hospital in Ontario as ALC patients between April 1st 2012 and March 31st 2017 were included in the study cohort. Data was extracted from the following databases, each of which corresponds to a different type of healthcare service:

- Discharge Abstract Database (DAD): hospital based inpatient acute care and ALC.
- Continuing Care Reporting System (CCRS): hospital based inpatient LTC, known as Complex Continuing Care (hereafter, CCC), and residential LTCH.
- Home Care Database (HCD): home and community care.
- Registered Persons Database (RPDB): deaths.

These specific services were chosen because they encompass almost all government funded inpatient service types available in Ontario. Inpatient psychiatric services were initially considered, but later excluded due to the small number of patients in the cohort that had utilized this service during the study window. Admission and discharge times from each of the services were used to represent each patient’s care pathway as a series of transactions, with each transaction starting at admission and ending at discharge. Deaths were registered as an open transaction with admission as time of death and no discharge, such that a deceased person “occupies” the death “service” from time of death until the end of the study period. In cases where one transaction was nested in another, the latter was split into two transactions with the former placed in-between. Other overlaps between transactions were resolved by prioritizing information from one database over the other, using the following hierarchy: information from
the DAD was given the highest priority, followed by NRS, then CCRS, then HCD. Any gaps between transactions of three days or less were removed by changing the admission or discharge date of one of the transactions to close the gap – the choice of the transaction to be changed was based on the previously identified hierarchy in reverse. This action was recommended by MOHLTC data scientists as their standard practice. The remaining gaps between transactions were filled with a residual “Home” transaction to represent the time a patient was not utilizing any of the services included in the data. MOHLTC policy staff expressed special interest in patients residing in assisted living settings, a government funded supportive housing for seniors – the “Home” transaction was thus replaced with “Assisted Living” from the first date patients were identified as living in this setting.

The next section presents descriptive statistics about the ALC patient population in Ontario between April 1st 2012 and March 31st 2017. The choice of attributes to focus on was guided by interest expressed by MOHLTC policy staff and the availability of information on a sufficiently large section of the patient cohort. Notably, the aforementioned databases contain a much larger array of patient characteristics, specificities about the healthcare interventions provided, and details on the care provider – all of which can be used to better identify patient clusters in future applications of the model, as discussed in previous sections.

4.2 Descriptive Analysis of ALC patients in Ontario

4.2.1 Episode lengths and accumulated bed days

279335 distinct episodes of ALC occurred in Ontario between April 1st 2012 and March 31st 2017. These episodes were attributed to 224717 unique patients, and had accumulated a total of 4962424 days occupying a hospital bed while ALC. Notably, while these acute care with ALC episodes represented 4.82% of all acute care episodes and were attributed to 6.48% of all hospitalized patients, the number of ALC days created by this cohort corresponds to 14.77% of all care days delivered to hospital inpatients during the study period. These statistics clearly demonstrate the ALC problem in Ontario – a small number of patients are occupying a significant number of hospital beds that they no longer require. The discrepancy between the number of episodes and number of patients is explained by the fact that some patients in the cohort had more than one ALC episode during the study period; 81.53% of patients had only one
ALC episode; 14.28% had 2; 3.1% had 3; the remaining 1.09% had 4-12. These ALC readmissions are further explored in later sections of this document.

ALC episode-length percentiles are presented in figure 4.2.1. The median length of an ALC episode over the study period is 7 days – roughly half of all observed ALC episodes lasted a week or less. 88% of episodes lasted 31 days or less. However, episodes lasting less than a week or a month, account for only 10.96% and 39.59% of total ALC days respectively. In other words, while most ALC episodes were short, a small number of episodes is responsible for the majority of bed-days - 60.41% of days were accumulated by 12% of episodes lasting longer than a month. More specifically, 9% of episodes lasting between one and three months accumulated roughly 20% of all ALC days, with the remaining 3% of episodes longer than 3 months creating 40% of ALC days in the study period. The three different reasons for ALC identified previously can explain this variation: extremely short ALC episodes are caused by transfer friction; intermediate length episodes are caused by lack of capacity in downstream services; long episodes are caused by complex patients that need scarcely available specialized services, or by patients that cannot be taken care of anywhere else. Given that a small number of long duration ALC episodes is causing a large share of total ALC days, policies targeting the small number of patients attributed to these episodes may have a large impact on hospital overcrowding in Ontario. Some characteristics of this group of patients are identified later in this document.
Figure 4.2.1: ALC episode-length percentiles. Horizontal axis: bottom scale – episode-length percentile; upper scale – episode length in days. Vertical axis: right scale – bar height, number of ALC episodes in bin; left scale - dots, cumulative percentage of total ALC days over the study period, values also labeled above each dot for the corresponding bin.

4.2.2 Geographic and temporal variations

As recommended by MOHLTC policy staff, ALC episodes were grouped into six bins based on their length: 7 days of less; 7-30 days; 30-60 days; 60-90 days; 90-180 days; and more than 180 days. Figure 4.2.2-1 presents the geographical distribution of ALC episodes by Local Health Integration Networks (hereafter, LHIN), a geographical subdivision of Ontario. Clearly, the overall contribution of ALC episodes varies geographically across the province, while maintaining the high prevalence of shorter episodes within each LHIN. LHINs 4 and 8 contribute more ALC episodes than other LHINs, while LHINs 5 and 10 contribute the least. In addition, LHINs 3 and 5 contribute very few long episodes, and LHINs 11,12,13 have more ALC episodes
lasting 7-30 days than episodes of a week or less in duration. Figure 4.2.2-2 presents a similar disaggregation for accumulated ALC days, instead of episodes. Observing each LHIN’s accumulation of ALC days by cluster, LHIN 3 and 5 again stand out with relatively few ALC days overall, compared to LHINs 6, 7, 8, 9, 11, 13 that contribute many days from longer episodes. These differences between LHINs are necessarily caused by variations in demand for care and supply of services, as can be seen from the differing mappings of episode and day distributions across the length clusters for each LHIN. Thus, policies that account for the variations in patient needs and the availability of services should be uniquely tailored to each LHIN, in order to best address the ALC issue.

Figure 4.2.2-1: ALC episodes by LHIN. Horizontal axis: facets – LHIN number; bins – ALC episode length cluster ordered from shortest to longest, left to right in each facet. Vertical axis:
bin height – number of ALC episodes per length cluster; value above bin – percent of total ALC episodes in the study period.

Beside varying geographically, the ALC problem in Ontario also varies over time. Figure 4.2.2-3 presents the daily number of acute care beds occupied by ALC patients is all hospitals in Ontario. Evidently, the number of beds taken up by the ALC issue in Ontario has been increasing within the study period. ALC occupancy also varies by roughly 500 beds within each year cyclically, from a trough in spring to a peak in winter with a temporary decline in occupancy towards the winter holidays. This variation is expected due to the overall increase in demand for
healthcare services during winter months, particularly among older patients. Figure 4.2.2-4 shows daily occupancy for each episode-length cluster. First, despite accounting for half of all ALC episode within the study period, patients with ALC length of stay of a week or less occupy the smallest number of beds compared to the other length clusters, whereas patients with ALC lasting between 7 to 90 days take up the most beds. Second, the cyclical decrease in occupancy around the winter holidays is fully attributed to shorter ALC episodes. Third, the observed increase in overall ALC in Ontario shown in Figure 4.2.2-3 is caused by growth in the number of patients that occupy acute care beds as ALC for more than 90 days, whereas the number of patients with shorter ALC stays is relatively stable throughout the study period. Put together, these observations suggest that different causes of ALC, manifested here as differences in ALC episode lengths, contribute differently to the level and variance of the ALC issue within and between years.

Temporal cyclicality in ALC occupancy is also present within each week. Figure 4.2.2-5 shows a consistently large difference between weekdays and weekends for patient flows in and out of ALC. Notably, while the net flow of patient varies within each week, flows in either direction are almost stationary for each day over the study period – net flows are therefore also roughly stationary, which suggests that the growth in ALC occupancy is driven by accumulation rather than by changes to the flows. Other services in the dataset demonstrate similarly stable within week variations, albeit with different day of week effects. For example, admissions into LTCHs fall to a trickle on weekends but not discharges. Overall, the yearly and weekly cycles in ALC and other services’ use attest the importance of considering temporal variations in the design of policies, as large variations masked by averages and distributions may lead to underestimations of demand during cyclical peaks and its overestimation during troughs. Furthermore, direct examination of the temporal variations discussed above allows for their explicit incorporation in policy design.
Figure 4.2.2-3: Hospital ALC midnight occupancy. Horizontal axis: dates – April 1st 2012 to April 1st 2018. Vertical axis: hospital acute care beds occupied by ALC patients near midnight. Graphs: blue – daily data from DAD; black – monthly average from DAD; red – end of month from CCO data. Note: the discrepancy between DAD and CCO counts are due to a difference in definitions.
Figure 4.2.2-4: Hospital ALC occupancy by episode length cluster. Horizontal axis: dates – April 1st 2012 to March 31st 2017. Vertical axis: hospital acute care beds occupied by ALC patients near midnight.
Figure 4.2.2-5: Daily ALC admissions and discharges by day of week. Horizontal axis: dates – April 1st 2012 to March 31st 2017. Vertical axis: upper facet – new ALC designations of previously acute care patients; bottom facet – discharges from ALC. Graphs: number of patients by day of week.

4.2.3 Admission origins and discharge destinations

The diversity in contributions to ALC occupancy of different episode-length clusters seen in Figure 4.2.2-4 results from the different causes of ALC designation discussed previously. While information regarding the specific reason for ALC designation is not present in the data, it can be inferred from observing each patient’s care pathway. Figure 4.2.3-1 presents pre-hospitalization origin and discharge destination pairings for all ALC episodes in the study period: 63.39% of ALC episodes are attributed to patients admitted from their private home, where they receive no formal care prior to hospitalization, with an additional 20.34% arriving from other non-
institutional residential settings with a care package; 22.56% of episodes are discharged to inpatient rehabilitation, 20.17% to CCC, 17.45% to home care, and 12.86% to LTCH; 8.97% of ALC episodes conclude with patient death; Notably, many ALC episodes originate from and return to the same “location” in the patient’s care pathway. Figure 4.2.3-2 presents the same flows rescaled to represent the accumulated ALC bed days for each origin-destination pair: 59.95% of days are attributed to patients hospitalized from home without a care package, while 20.04% of days are attributed to patients originating from residences with a care package; 8.9% of days are attributed to discharges to inpatient rehabilitation, 16.22% to CCC, 11.94% to home care, and 35.54% to LTCH; as with episodes, many days were attributed to ALC patients returning to their origin. The interaction between episodes and days is further examined in Figure 4.2.3-3: while the distribution of origins remains roughly unchanged, shorter episodes are associated with discharges to inpatient rehabilitation, whereas longer episodes are primarily discharged to LTCH; discharges to home care, CCC, and returns to origin decrease with episode length.

Several conclusions regarding causes of ALC can be deduced from observing the variations in ALC episodes’ admission origins and discharge destinations. Most ALC patients are initially admitted into acute care from a non-institutional residence, some of whom return to their residence – most of these episodes are associated with shorter stays in ALC. These cases can be attributed to friction or to unavailability of short term respite or convalescence. For the remainder of episodes, the discrepancy between episodes’ and days’ association with different discharge destinations is representative of the degree of mismatch between supply and demand for each of these destinations: patients awaiting transfer to inpatient rehabilitation are numerous but have shorter ALC episodes, which implies either friction, a mild shortage in inpatient rehabilitation capacity, or both; patients discharged to CCC and home have ALC of varying lengths, suggesting moderate capacity shortages; the small number of episodes and large number of accumulated days attributed to patients discharged to LTCHs asserts the severe shortage in this service in Ontario – awaiting for placement in LTCH is a primary driver of the ALC problem, through growth in number of ALC occupants with long ALC stays. Figure 4.2.3-4 provides additional support for this interpretation: discharges to inpatient rehabilitation have the lowest mean ALC episode length, presented in red, for all origins; episodes culminating in
discharge to LTCH have the highest mean length of stay and accumulate the most ALC days, presented in black, for all origins with one exception – patients admitted from LTCH are given the highest priority for a bed upon their return to LTCH.

Figure 4.2.3-1: ALC patients’ admission origin and discharge destination in the hospital care pathway by episode. Horizontal axis: left – pre-hospitalization origins; right – discharge destination. Vertical axis: number of episodes per origin-destination pair. Graphs: width corresponds to number of episodes based on the vertical scale.
Figure 4.2.3-2: ALC patients’ admission origin and discharge destination in the care pathway by ALC days. Horizontal axis: left – pre-hospitalization origins; right – discharge destination. Vertical axis: number of accumulated ALC bed days per origin-destination pair. Graphs: width corresponds to number of episodes based on the vertical scale.
Figure 4.2.3-3: ALC patients’ origins and destination in the care pathway by days, faceted by episode length clusters. Horizontal axis: left – pre-hospitalization origins; right – discharge destination. Vertical axis: number of accumulated ALC bed days per origin-destination pair. Graphs: width corresponds to number of episodes based on the vertical scale.
Figure 4.2.3-4: ALC episode length distribution box plots by origin, faceted by destination. Horizontal axis: ALC length of stay in days. Vertical axis: admission origin. Red dot, red value: mean episode length per origin destination pairing. Black value, right of mean value: total accumulated days per origin destination pairing.

At the request of MOHLTC policy staff, a similar analysis was done for re-designated ALC patients and is presented in appendix A. Figure 4.2.3-5 and Figure 4.2.3-6 compare the distributions of ALC episodes and accumulated days per origin destination pairing, for all ALC, only first ALC, and all re-designated ALC. Compared to the first ALC episodes in patients’ care pathways, which mostly originate from home, later ALC episodes originate mostly from home care. Notably, the majority of re-designated ALC are discharged back to home care, suggesting friction or a mild shortage in home care services. Discharges to LTCH are associated with most ALC days for first and re-designated ALC. Overall, the disaggregation of ALC episodes by
origins and destinations identified shortages of LTCH capacity as the primary cause of the ALC issue in Ontario, but also presents other viable directions for policy interventions that target ALC associated with same origin and return destinations, specifically for patients arriving from home and home care.

Figure 4.2.3-5: All ALC, first ALC, and re-designated ALC episodes by origin and destination. Facets: row – admission origin; column – discharge destination. Horizontal axis: in each facet, from left to right – all ALC episodes, first ALC episodes only, all re-designated ALC episodes. Vertical axis: bar height – percent of episodes out of all ALC episodes per cluster.
Figure 4.2.3-6: All ALC, first ALC, and re-designated ALC accumulated days by origin and destination. Facets: row – admission origin; column – discharge destination. Horizontal axis: in each facet, from left to right – all ALC episodes, first ALC episodes only, all re-designated ALC episodes. Vertical axis: bar height – percent of days out of all ALC days per cluster.

4.3 Patient characteristics

4.3.1 Age, gender, marital status, and living arrangements

The ALC issue in Ontario is not caused by a single group of homogenous patients – not all ALC patients are the same. As see in Figure 4.3.1-1, most ALC episodes are attributed to older patients, which corresponds to higher demand for healthcare services towards end of life. Specifically, 83.21% of all ALC episodes in the study window were caused by patients older than 65 years. Female patients account for 55.72% of episodes, with higher representation in older groups - likely due to a longer life expectancy. Figure 4.3.1-2 further disaggregates the
cohort by marital status. While the overall predominance of females is preserved, Figure 4.3.1-2 shows that while the majority of male ALC patients are married, most female patients are not married, especially in older age groups. This observation hints at differences in the availability of informal support between patients, which can be seen in Figure 4.3.1-3 – a large share of ALC episodes is attributed to older females that live alone, while most episodes attributed to males are caused by patients that live with their spouse. Put together, the spread between female and male representation in ALC can be explained by longer life expectancy and lower availability of informal support for female patients. Notably, this distinction highlights the overall importance of informal support, particularly for females, as a potential area for targeted policy intervention.

Figure 4.3.1-1: Percent of ALC episodes by patient age and gender. Horizontal axis: patient age group; left bar – female patients; right bar – male patients. Vertical axis: percent of total ALC episodes attributed to age-gender patient group, value for each group presented above bars.
Figure 4.3.1-2: Percent of ALC episodes by patient age, gender, and marital status. Facets: upper – females; lower – males. Horizontal axis: patient age group. Vertical axis: percent of total ALC episodes attributed to age-gender-marital status patient group, value for each group presented above bars.
Figure 4.3.1-3: Percent of ALC episodes by patient age, gender, and living arrangement. Facets: upper – females; lower – males. Horizontal axis: patient age group. Vertical axis: percent of total ALC episodes attributed to age-gender-living arrangement patient group, value for each group presented above bars.

ALC patients’ characteristics also vary geographically by LHIN. In order to better account for demographic differences between the LHINs, the average population of each LHIN within the study window was used for normalization in this section. Figure 4.3.1-4 presents the number of episodes per 1000 residents, attributed to each age-gender group, disaggregated by LHIN. This figure directly speaks to the variation in service shortages across LHINs, which is expressed through different impacts of age and corresponding increases in condition complexity, on ALC designations. For example, LHINs 3 and 5 that have been identified in previous sections as having few long ALC episodes, greatly differ on how many of their elder residents are ever
designated ALC – LHIN 5 has one of the lowest ALC designations in Ontario across age groups, while LHIN 3 has one of the highest. This means that LHIN’s 3 lower contribution to the ALC problem is in fact due to a smaller population size, rather than adequate policy, as is true for LHIN 5. LHIN 14 displays the most ALC designations across all age groups, which suggests a large discrepancy between demand and supply of services, especially for older patients. Patient differences in marital status and living arrangements by LHIN are presented in figures B2.2 and B2.3. The marital status differences between female and male patients identified previously hold for all LHIN except LHINs 7 and 14, where unmarried men have a higher representation in the ALC cohort. Furthermore, Figure 4.3.1-5 reinforces the variations in ALC designations among the LHINS, with LHINs 5 and 6 having the lowest rates. Figure 4.3.1-6 explicitly demonstrates the relation of female loneliness to ALC – with the exception of LHIN 5, females that live alone account for most ALC designations. Interestingly, in LHINs 7 and 14, male patients that live alone account for more ALC designations then their married counterparts. This observation suggests that the availability of informal support for male residents of these LHINs differs from other LHINs and may be suitable for policy intervention. Overall, the geographical disaggregation of patients reveals the differing ability of LHINs in averting ALC and providing informal support.
Figure 4.3.1-4: ALC episodes per 1000 population by LHIN, for each age-gender patient group. Facets: Ontario LHINs. Horizontal axis: patient age group. Vertical axis: number of ALC episodes per 1000 population by gender, values presented above bars.
Figure 4.3.1-5: ALC episodes per 1000 population by LHIN, for each gender-marital status patient group. Horizontal axis: facets – LHIN; bars – marital status. Vertical axis: facets – gender; bars - number of ALC episodes per 1000 population by marital status, values presented above bars.
Figure 4.3.1-6: ALC episodes per 1000 population by LHIN, for each gender-living arrangement patient group. Horizontal axis: facets – LHIN; bars – living arrangement. Vertical axis: facets – gender; bars - number of ALC episodes per 1000 population by living arrangement, values presented above bars.

4.3.2 ALC patient health status

ALC patients can be further differentiated by their health status, as captured by ICD-10CA diagnostic codes relating to their ALC episodes. Special ICD-10CA codes identify specific reasons for the ALC designation: as expected, the majority of ALC is caused by waiting for admission into a different facility, corresponding to 76.64% of ALC episodes; 4.3% of ALC designations were given for end-of-life treatment; 4% for observation; 3.72% for physical therapy; the remaining 11.34% of ALC episodes were caused by a need for convalescence and respite for patients that did not have sufficient support in their homes, so as to be discharged
from the hospital. The Most Responsible Diagnosis (hereafter, MRD) corresponds to the main condition causing the acute care episode that precedes the ALC designation. Figure 4.3.2-1 presents the percent of all ALC episodes associated with ICD-10CA chapters, which group MRD codes: 17.98% of hospitalizations followed by ALC where due to injury, poisoning, and other external causes; 30.64% of hospitalizations were due to diseases of the circulatory system, respiratory system, and due to mental and behavioral disorders – the three most prevalent medical chapters; an additional 13.56% of hospitalizations were caused by lack of access to appropriate care outside the hospital and by general poor health. Overall, more than 60% of pre-ALC hospitalizations were caused by conditions identified by these 6 ICD-10CA chapters. To better examine the specific causes of hospitalizations of ALC patients, Figure 4.3.2-2 shows the percentages of ALC episodes associated with the most common MRD ICD-10CA codes. The conditions in the large injury chapter that relate to most hospitalization episodes are bones fractures and internal bleeding due to trauma - both are likely to be caused by falls, which is common among elderly patients. Congestive heart failure was the most common cause for hospitalization for acute episodes culminating is ALC, which together with strokes represents common circulatory diseases in the cohort. Similarly, pneumonia and chronic obstructive pulmonary disease are the most common respiratory diseases. Dementia and delirium, also known to be associated with advanced age and ALC, are the most common MRDs in the mental and behavioral disorders chapter. Other notable conditions are urinary tract infection and renal failure, which together account for most hospitalizations caused by diseases of the genitourinary system. Palliative care, post-surgery convalescence, and physical therapy, were the main cause of hospitalization for 5.12% of episodes with ALC, with an additional 3.4% of hospitalizations caused by a tendency to fall and general symptoms of old age such as cachexia and fatigue – all of which do not necessitate acute care. Notably, the diagnostic codes that capture the main causes of acute hospitalization, and later ALC, episodes primarily attest to specific changes in the patient’s health status. In other words, observing the ALC and MRD codes alone may not sufficiently characterize patients’ complex and chronic conditions, which may not be directly causing hospitalization but may impact the length of care and the specific services demanded during and after acute care.
Figure 4.3.2-1: percent of ALC episodes per ICD-10CA chapter, by MRD. Horizontal axis: percent of ALC episodes, bar height corresponds to value to the right of each bar. Vertical axis: ICD-10CA chapters.
In order to better capture each patient’s health status, all diagnoses associated with each hospitalization episode, including MRD and reported comorbidities, were examined to establish the prevalence of different condition in the studied cohort. Figures 4.3.2-3 and 4.3.2-4 present the most common diagnoses associated with hospitalization episodes, and their corresponding ALC length of stay distributions. Diseases of the circulatory and genitourinary systems are most common: 57.65% of episodes are attributed to patients diagnosed with hypertension, congestive heart failure, and/or atrial fibrillation; 34.29% of episodes are attributed to patients with urinary tract infections and/or renal failure. These numbers contrast with the previously reported values.
associated with MRDs – the higher number of episodes associated with a specific condition attests that while the condition was not the main cause of hospitalization for many episodes, it may have contributed to the complication of treatment and required care. For example, congestive heart failure was the main cause of hospitalization associated with 3.36% of episodes, but was prevalent in 12.74% of episodes – for urinary tract infection these values correspond to 2.27% and 20.99% respectively. The effect of these comorbidities on acute care are vividly demonstrated by the length of stay distributions associated with each diagnosis. Specifically, while the majority of the most common diagnoses present length of stay distributions that are similar to each other and the overall episode-length central tendencies, urinary tract infections, other infections, tendency to fall, and dementia stand out with higher median and average ALC episode length of stay. In other words, these conditions are related to longer ALC episodes after hospitalization.
Figure 4.3.2-3: percent of ALC episodes, by all diagnoses. Only diagnoses associated with more than 5% of total episodes are displayed. Horizontal axis: percent of ALC episodes, bar height corresponds to value to the right of each bar. Vertical axis: diagnoses descriptions. Colors: ICD-10CA chapters.
Figure 4.3.2-4: ALC length of stay boxplots, for diagnoses reported in Figure 4.3.2-3. Horizontal axis: ALC length of stay – medians in black inside boxes, means in red. Vertical axis: diagnoses descriptions. Colors: ICD-10CA chapters.

A better overview of prevalence of conditions in ALC patients in Ontario can be made by examining patients directly, as opposed to episodes. While establishing a relationship between diagnoses and length of stay requires analysis of episodes, a significant number of patients were readmitted to ALC within the study period, which results in multiple counting of certain conditions. The percentages of patients presenting with different conditions is shown in Figure 4.3.2-5: diseases of the circulatory and genitourinary systems remain most prevalent; 14.69% of patients receive some form of palliative care; at least 24.82% of patients are diagnosed with dementia, delirium, or both; type 2 diabetes, pneumonia, and infections, are also highly prevalent in ALC patients. The length of stay distributions corresponding to these conditions are shown in
Figure 4.3.2-6, and direct to similar conclusions as before – urinary tract infection, other infections, dementia, and delirium relate to longer ALC episodes. The strong relationship between these conditions and longer ALC stays is further demonstrated in Figure 4.3.2-7, which presents the number of ALC bed days associated with different conditions. Comparing the values between the three sets of plots explicitly demonstrates this fact: while only 20.99% of episodes and 23.31% of patients are associated with a diagnosis of urinary tract infection, 32.49% of the total ALC days during the study period are related to this condition; for other infections, these figures are 6.55%, 7.73%, and 10.15% respectively; for dementia and delirium – 21.99%, 24.82%, and 34.03%. The subset of ALC episodes with stays longer than 90 days are analyzed in a similar manner in appendix B. For this group of episodes and patients, the previously identified conditions that relate to longer length of stay are unsurprisingly more prevalent then in the total ALC population. In addition, dementia, delirium, and diseases on the nervous system are reported to be the main causes on hospitalization, unlike the aggregate patient cohort. This observation, along with the above discussion on patients’ health status, directly speaks to the varying contribution of different health conditions on the ALC problem in Ontario. Since different health conditions necessarily require different types of services and care intensities, policies targeting hospital overcrowding must remain cognizant of the various demands for care presented by the heterogenous ALC cohort.
Figure 4.3.2-5: percent of ALC patients, by all diagnoses. Only diagnoses associated with more than 5% of total patients are displayed. Horizontal axis: percent of ALC patients, bar height corresponds to value to the right of each bar. Vertical axis: diagnoses descriptions. Colors: ICD-10CA chapters.
Figure 4.3.2-6: ALC length of stay boxplots, for diagnoses reported in Figure 4.3.2-5. Horizontal axis: ALC length of stay – medians in black inside boxes, means in red. Vertical axis: diagnoses descriptions. Colors: ICD-10CA chapters.
Figure 4.3.2-7: percent of ALC days, by all diagnoses. Only diagnoses associated with more than 5% of total days are displayed. Horizontal axis: percent of ALC days, bar height corresponds to value to the right of each bar. Vertical axis: diagnoses descriptions. Colors: ICD-10CA chapters.
Chapter 5
Methodology

5.1 Model requirements

The ALC issue in Ontario is multidimensional, as was shown in the previous section – the ALC designated patient population is highly varied in its characteristics and its demand for services across space and time. In other words, different ALC patients at different locations require different services at different times, and would therefore respond differently, in terms of their ALC length of stay, to different policies. An effective model aimed at assisting policy designers to choose and evaluate potential policies must be able to account for these variations. Given the discussion on the state of the literature and the variations observed in the “data” section of this document, such a model is required to be able to account for:

Differences between patients - Patient characteristics, health status, and availability of informal care directly relates to their demand for service types and intensities. Release of current ALC beds, and the prevention of future ALC days, requires the matching of supply to the specific needs of patients.

Temporal and spatial variations – Unmet demand, which results in ALC, is not evenly distributed across time and space in Ontario. Seasonal variations in demand for services and weekly capacity fluctuations in service provision are predictable, cause fluctuations in ALC occupancy, and can be a target of policy intervention in themselves. Also, different subregions in the province contribute differently to overall ALC and would therefore respond differently to identical policy interventions.

Policy specificity – Once the variations above are accounted for, only a limited number of specifically tailored policies may be feasible due to operational and budgetary constraints. These policies are likely to vary in terms of the services or processes they target, the proposed rollout schedule, and in terms of their impact on the patient’s overall care pathway.

Varying availability of technical expertise and data – Sufficient transparency and flexibility is required to ensure the usability of the model by planners. Knowledge sharing between different
stakeholders in the policy design process is likely to benefit from an intuitively explainable model. In addition, flexibility in terms of scope would allow application by different groups of planners with varying data holdings and policy interests.

The model assumes that no permanent structural changes occurred during the data window and that it is sufficiently long to learn the behavior of the system. In other words, the implicit decisions made by agents in the modelled system regarding the flow of patients are stable throughout the data window: doctors did not alter their referral decisions; healthcare providers did not vary the intensity of the services they provide to similar patients; patients did not change their preferences over substitutable services. Note that this assumption allows cyclical, and therefore predictable, changes in response to the state of the modelled system – only changes to the pattern between cycles are excluded. This assumption allows the identification of policy impacts by assuming that no other exogenous variations could be the cause of the observed result, as all else is assumed to behave as it did in the past – the system does not change, except as for the impact of the enacted policy.

5.2 Assumption

The model assumes that no permanent structural changes occurred during the data window and that it is sufficiently long to learn the behavior of the system. In other words, the implicit decisions made by agents in the modelled system regarding the flow of patients are stable throughout the data window: doctors did not alter their referral decisions; healthcare providers did not vary the intensity of the services they provide to similar patients; patients did not change their preferences over substitutable services. Note that this assumption allows cyclical, and therefore predictable, changes in response to the state of the modelled system – only changes to the pattern between cycles are excluded. This assumption allows the identification of policy impacts by assuming that no other exogenous variations could be the cause of the observed result, as all else is assumed to behave as it did in the past – the system does not change, except as for the impact of the enacted policy.
5.3 Generic model structure

We propose a state space model where nodes correspond to different services and arcs identify transfers between services. Each node has a time dependent value that captures the number of patients occupying the service at the beginning of the period. At each discrete time step, patients either transition to a different node or remain at their present node – these “inflows” into nodes and “outflows” out of nodes are represented by the arcs, which tally transitions at the end of the period. The dynamics of this system is represented by:

\[ \text{Occ}_i^{t+1} = \text{Occ}_i^t + \text{Inflow}_i^t - \text{Outflow}_i^t \]

\( \text{Occ}_i^t \equiv \text{patient occupancy in node } i \text{ at time } t \)

\( \text{Inflow}_i^t \equiv \text{inflow of patients into node } i \text{ at time } t \)

\( \text{Outflow}_i^t \equiv \text{outflow of patients out of node } i \text{ at time } t \)

Given this representation, all inflows into a specific node are equivalent to outflows from other nodes. Similarly, outflow from a specific node can be disaggregated into inflows to other nodes. The law of motion is therefore equivalent to:

\[ \text{Occ}_i^{t+1} = \text{Occ}_i^t + \sum_{j \neq i} \text{Outflow}_{i\rightarrow j}^t - \sum_{j \neq i} \text{Outflow}_{j\rightarrow i}^t \]

\( \text{Outflow}_{i\rightarrow j}^t \equiv \text{outflow of patients out of node } i \text{ into node } j \text{ at time } t \)

Notably, all outflows can be similarly represented as inflows. However, in the current context of healthcare services, focusing on outflows better mimics referral and discharge decisions made by service providers, as well as “pulls” of patients that were blocked from transitioning to the next service node due to non-availability of free capacity. While the choice of variable definition is not consequential in this case, outflows are chosen in the interest of transparency.

Entry into and exit from the system can be modelled in one of two ways – exogenously from outside the scope of the model, or as special nodes that do not represent service. In the case of
exogenous entry or exit, an additional time dependent variable is added to the dynamic equation above to add patients to the period’s occupancy from without for entry, or to subtract patients for exit:

\[ \text{Occ}_{i}^{t+1} = \text{Entry}_{i}^{t} + \text{Occ}_{i}^{t} + \sum_{j \neq i} \text{Outflow}_{j \rightarrow i}^{t} - \sum_{j \neq i} \text{Outflow}_{i \rightarrow j}^{t} - \text{Exit}_{i}^{t} \]

\( Entry_{i}^{t} \equiv \text{inflow of patients into node } i \text{ at time } t \text{ from outside the scope of the system} \)

\( Exit_{i}^{t} \equiv \text{outflow of patients out of node } i \text{ at time } t \text{ out of the scope of the system} \)

Alternatively, nodes that represent “being” outside the scope of the system of interest can be added, with arcs connecting them to all other nodes. In the context of healthcare, occupancy of the entry node corresponds to the number of potential patients, which may enter the system or not at every time step. This group may also be growing in size exogenously – for example, the number of potential users of health services may be increasing due to overall population growth, or due to increases in prevalence of some diseases in a specific population. Conversely, patients occupying the exit node are no longer potential users of services – for example, deceased or inoculated patients. The law of motion for these dummy nodes is:

\[ \text{Occ}_{\text{entry}}^{t+1} = g_{\text{entry}}^{t} \text{Occ}_{\text{entry}}^{t} - \sum_{j \neq \text{ent}} \text{Outflow}_{\text{entry} \rightarrow j}^{t} \]

\( g_{\text{entry}}^{t} \equiv \text{exogenous growth in potential enterants into the system} \)

\[ \text{Occ}_{\text{exit}}^{t+1} = \text{Occ}_{\text{exit}}^{t} + \sum_{j \neq \text{exit}} \text{Outflow}_{j \rightarrow \text{exit}}^{t} \]

The specific choice of method for entry depends on whether varying the exogenous growth is relevant to policy analysis. For exit, this choice depends on whether tallying exits from the system over time is of interest.

The outflows from each node can be modelled as a fraction of the occupancy that was discharged at every period. Under the assumption outlined previously, this fraction may vary between periods but must be stationary over the entire time frame. Since the patient cohort flown through
the model is assumed to be relatively homogenous in a specific set of attributes and there are no
direct distinctions between patients within the model, the composition of patients occupying each
service node at any period varies only due to heterogeneity in pathways taken through the
system. In addition, the rules governing the decisions to transfer patients between services are
assumed constant over the long run. Put together, these assumptions imply that the number of
patients that outflow from a given node only varies due to changes in the overall occupancy of
the node. To capture this dependency, the outflow variable can be replaced by a time dependent
fraction of occupancy:

\[ \text{Outflow}_{i \rightarrow j} = \frac{\text{Outflow}_{i \rightarrow j}}{\text{Occ}_{i}} = \text{fraction of occupancy in node i at time t transferred to node j} \]

Note that this law of motion only requires an initial value of occupancies and a schedule for the
change in the fractional transfer rates over time. This fraction is the control parameter in this
model – policy impacts are captured by their impact on fractional transfer rate:

\[ \text{Outflow}_{i \rightarrow j} = \frac{\text{Outflow}_{i \rightarrow j}}{\text{Occ}_{i}} = \text{fraction of occupancy in node i at time t transferred to node j} \]

Defined in this manner, any policy can be applied to this model insofar as it is translated into a
percentage wise change in transfer rates between services. Since the policy is indexed using the
same time step as the motion of the system, time varying impacts of the policy can be directly
captured: a gradually rolled out policy can be modelled by a continuously growing value up to
full deployment of the policy, after which the value remains constant; a policy that is
implemented in phases can be modelled by a step function over time; a policy that is only
applicable for certain periods can be represented by changing the value for only those periods.
Alongside this flexibility, the interpretation of all variables in the model is transparent:
occupancy is the occupied capacity at each period; the fractional transfer rate is the percentage of
patients discharged from the service at each period; the policy parameter is the hypothesized
percentage change in the flow of patients from one service to another. Overall, the state space model developed in this section satisfies all the requirements detailed above. The next section presents the specific application of this model to the ALC issue in Ontario.

5.4 Ontario ALC model

All services present in the available data were included in the scope of the model. Specifically, 8 nodes capture bed occupancy in hospital acute care, hospital ALC, LTC, CCC, inpatient rehabilitation, assisted living, home with home care, and home without a care package as a residual node for patients in the system but not in any service bed. Since the common characteristic of the patient cohort selected for this study is ALC designation, the ALC node was naturally selected as the only entry point into the modelled system – patients only become part of the ALC cohort after passing through ALC “service”. This choice of entry point also provides a unique interpretation to the inflow into the system because all ALC episodes are preceded by an acute care episodes in a hospital – patients flow into the model from acute care once they are designated ALC for the first time in their care pathway. As the overall occupancy of acute care in Ontario was not observed due to the cohort inclusion criteria, entry was modelled as an exogenous inflow into the ALC node. Once a patient was designated ALC for the first time and was introduced into the model, they continue to circulate between the service nodes until the end of the captured time horizon, or until death. Exit from the model was modelled as a dummy node with arcs connecting to all other nodes – patients can die while occupying any of the nodes in the system.

In order to produce forecasts for the future behavior of the system, the flow parameters and entry time series were fitted. Since the only entry into the model was via the ALC node, all other nodes were initialized at zero occupancy and were left to accumulate patients as more entrants transitioned through the model – occupancy in these nodes by patients that had ALC before the study window is unknown. The first 9 months of the data were not used to fit the flow parameters – flows and occupancies were not sufficiently large to demonstrate the steady state of the system during the accumulation “warm up” phase. Unlike all other nodes, occupancy and flows for the ALC nodes were completely captured from the beginning of the series. Nevertheless, the data used to fit the entry series was also truncated to match all other nodes.
Three models were fit to all fraction and entry series: linear regression (OLS) – common and easily applied, but does not capture any cyclical patterns; Autoregressive Integrated Moving Average (ARIMA) – a common model for fitting and forecasting time series, but can only capture a single cyclicality in the series; Trigonometric Box-cox ARMA errors Trend Seasonality (TBATS) – more flexible then ARIMA and can account for both weekly and yearly cycles, as was observed to be characteristic of the modelled healthcare services [52]. Notably, other models can be used for fitting the parameter series if desired by the user. Next, the best fitting model was selected, and the model validated. Given this set up, the dynamic equation of all nodes in the model with the estimated parameters becomes:

\[
O_{cc}^{t+1} = \pi_i^t E_i^t + O_{cc}^t + \sum_{j \neq i} \pi_{i \rightarrow j} q_{j \rightarrow i}^t O_{cc}^t - \sum_{j \neq i} \pi_{i \rightarrow j} q_{i \rightarrow j}^t O_{cc}^t
\]

\[
q_{i \rightarrow j}^t = f(p_{i \rightarrow j}^t)
\]

\[
E_i^t = f(Entry_i^t)
\]

\[
E_i^t = 0, i \neq ALC \text{ and } \pi_i^t = 1, \forall i, t \text{ in base case}
\]

A 5 year forecast was created for each of the estimated parameters and run through the model to obtain a base case scenario for the system occupancy over time, under which no policy changes are made in this system. This completes the model – policy parameter values can now be manipulated to observe the changes that these policies would enact on the behavior of the system in comparison to the “no-action” base case in the forecasted period.

Chapter 6

Results

6.1 Aggregated Model on Entire ALC population of Ontario

This section details the application of the Ontario ALC model to the aggregate ALC patient cohort and to a subset of patients diagnosed with dementia and delirium. The aggregate model is deployed to produce forecasts for service demand for the entire province and can be used for
testing broad non-patient-type-specific policies. While more accurate measures of demand and impact of policy can be achieved by focusing on specific patient clusters, the aggregate model is useful as a first step in exploring the state of the system and policy directions at large, which in turn can guide the focus on unique services and patient groups. The application to the dementia and delirium patient cluster is presented as a demonstration of the model’s ability to test the effect of narrower policies that target specific types of patients – dementia and delirium were chosen as an example due to the high prevalence of these conditions in long stay ALC patients. Notably, this patient group can be disaggregated further, for example by LHIN or living arrangements, to explore even more narrowly defined policies. Lacking direct guidance on such policies, the dementia and delirium application is merely presented here as an example of the model’s potential.

To validate the aggregate model, the data was split into a three year training set and a one year validation set. OLS, ARIMA, and TBATS were used to fit flow parameters in the training set. The fitted values were then applied in the model and the resulting occupancy time series for each service were compared to the data series. Daily Absolute Percentage Errors (APE) for each service series are presented in Figure 6.1-1. Mean APE across all services was lowest for the TBATS fits at 1.54%, followed by OLS and ARIMA, at 2.07% and 2.51% respectively. Figure 6.1-2 shows daily APE for the forecast relative to the validation series. Mean APE values for the forecast are 2.17%, 4.01%, and 6.34% for TBATS, OLS, and ARIMA. TBATS’s superior performance in both fitting the data and accurately extrapolating a forecast is likely the result of the algorithm’s ability to directly account for the weekly and yearly cyclicality observed in the data for all services. Furthermore, the accuracy of the TBATS forecasts attests to the stability of these cycles over periods. The higher estimation and forecast errors observed in the non-residential services, specifically acute care, ALC, and Rehabilitation, are expected since demand for these services is more sensitive to random events like emergencies. Overall, it can be concluded that the model preforms well, with TBATS being the best fitting procedure for this data – the model can now be used for out of sample forecasts and “what-if” scenario analysis.
Figure 6.1-1: Daily absolute percentage error (APE) per service, 3 year training set. Facets: modelled services. Colors: fitting procedure used for flow parameters - OLS, ARIMA, TBATS. Horizontal lines: mean APE across all services per fitting procedure.
Figure 6.1-2: Daily absolute percentage error (APE) per service, 1 year validation set. Facets: modelled services. Colors: fitting procedure used for flow parameters - OLS, ARIMA, TBATS. Horizontal lines: mean APE across all services per fitting procedure.

Daily 5 year forward forecasts for the occupancy of each node on the model were created using a TBATS fit for the parameters. The forecast for ALC occupancy is presented in Figure 6.1-3 – ALC is predicted to increase from nearly 3100 at peak during winter 2017, to more than 3300 at peak during winter 2022. Occupancy of acute care beds is also forecasted to increase from just over 2000 at the winter peak of 2017 to 2700 at the winter peak of 2022, which brings the total hospital beds forecasted to be occupied by patients with any ALC history to 6000 at winter 2022 – more than a quarter of overall current capacity in the province. LTCH, CCC, and inpatient rehabilitation occupancies will increase from 25000 to 32500, 3000 to 3400, and 1400 to 1600 respectively. Patients in the cohort that reside in the community and receive some government funded care package will also grow in numbers: assisted living occupancy will increase from
14000 to 19000; home with home care occupancy will increase from 24000 to 31000. Notably, these figures represent demand for services by the modelled ALC patient cohort and not the entire population of Ontario, so overall demand for healthcare services posed by the entire population of the province is undoubtedly higher. The forecasted occupancy values can now be used as a baseline in “what-if” scenario analysis, which will alter some flow parameter and observe the change in occupancies over time that this intervention will have, compared to the “no-intervention” baseline.

Figure 6.1-3: ALC occupancy April 2013 to February 2022. Dashed vertical line – end of data at February 2017, later values are forecasted.

In order to represent a realistic policy rollout, which in this model can be thought of as a shock to flow parameters that govern the dynamics of the system, all tested policies assume a linear rollout of 2 years followed by permanent deployment of the policy. In other words, the impact of
an enacted policy increases linearly for 730 days, after which the full impact of the policy is achieved and the corresponding change to the flow parameter remains constant, at the policy impact “value”, for the remainder of the forecasted period. Linear rollout was chosen here due to its simplicity and is merely demonstrative – other schedules can also be used and should match the specificities of proposed policy. For example, step wise rollout is best for representing capacity changes since new capacity is likely to be added intermittently and drastically, while sigmoidal rollout is a better fit for policies that effect the allocative decisions of healthcare staff and patients because diffusion of the policy’s “uptake” is likely to be gradual and continuous.

At the request of MOHLTC policy staff, the proposed policy tests the effects of diverting 15% of ALC patients that await admission to LTCH to a home setting with a care package. This policy was motivated by a finding reported by MOHLTC staff – 15% of LTCH residents were found to be sufficiently well to have had been taken care of in the community instead of in the LTCH they reside in. Diversion is hypothesized to reduce demand for LTCH and to relieve some ALC beds as patients are discharged home with a care package immediately after the acute care episode that would otherwise result in ALC in anticipation of LTCH placement. In essence, this policy seeks to increase the availability of residential care in the community so as to allow some patients to wait for LTCH placement in their homes, instead of in an acute care bed as ALC. Within the confines of the model, the policy is captured by determining the fraction of patients that enter the model as ALC that would eventually be discharged to a LTCH, decreasing that fraction by the impact of the policy according to the linear deployment schedule, and “entering” these subtracted patients into the model through a residential node. Thus, some number of patients that have completed an acute care episode that would lead to their first ALC episode in the baseline case, are discharged to a residential node instead. Notably, only the first ALC in the diverted patient’s care pathway is affected – no interventions are made in later ALC episodes. Two scenarios are examined: all patients are diverted to their private home with home care services; half of the patients are diverted to home care, and half to assisted living.

The impacts of the first scenario on ALC, LTCH, and home care occupancies are presented in figures 6.1-4,5,6: ALC occupancy is reduced by 100 beds at peak winter demand after the full rollout of the policy; daily demand for LTCH decreases by 80 by the end of the rollout period and continues to decrease for another year to a maximal decrease of roughly 120 beds, after
which demand begins to grow as more diverted patients eventually enter LTCHs; Home care occupancy increases by nearly 550 at end of the policy rollout, and continues to grow to reach a 770 increase from baseline by the forecast horizon. Impacts of the second scenario are shown in figures 6.1-7,8,9: reduction in ALC is similar to the first scenario, as the same number of patients are diverted from first ALC – the feedback from changed pathways on later ALC admissions is very small; LTCH demand also decreases by 80 by the end of the rollout period, but continues to decrease only until the end of winter 2019 to a peak of roughly 90 beds, after which it begins to rapidly return to baseline; Assisted living occupancy increases by 400 by rollout end and continues to increase to reach 670 by the end of the forecast horizon; Due to the decreased diversion rate, home care occupancy only increases by 170 by end of rollout and 250 by the end of the forecast period. While the two scenarios achieve nearly identical effects on ALC occupancy, the second scenario requires an overall larger expansion of residential with care package services and results in a lower and less permanent freeing of LTCH beds. This observation can be explained as shorter stays in assisted living prior to eventual LTCH placement – patients diverted to assisted living enter LTCH faster than patients diverted to home care. Despite the weakened impact on LTCH capacity, the policy investigated in the second scenario might still be preferred to the first scenario policy if expansion of assisted living is sufficiently cheaper than home care.
Figure 6.1-4: ALC occupancy change from baseline due to diversion from LTCH demand. Scenario: all diverted to home care.
Figure 6.1-5: LTCH occupancy change from baseline due to diversion from LTCH demand. Scenario: all diverted to home care.
Figure 6.1-6: Home care occupancy change from baseline due to diversion from LTCH demand. Scenario: all diverted to home care.
Figure 6.1-7: LTCH occupancy change from baseline due to diversion from LTCH demand. Scenario: half diverted to home care, half diverted to assisted living.
Figure 6.1-8: Assisted living occupancy change from baseline due to diversion from LTCH demand. Scenario: half diverted to home care, half diverted to assisted living.
Figure 6.1-9: Home care occupancy change from baseline due to diversion from LTCH demand. Scenario: half diverted to home care, half diverted to assisted living.

6.2 Dementia and delirium subgroup

The diversion policy discussed above exemplifies a use case of the model for broad policies, where a specific scenario is examined for its impact on patient flows through the modelled healthcare system. While this approach may be useful for initial exploration, it does not consider the specific patients that this policy targets and therefore cannot provide insights into the type of needs that would be needed to be met by the policy to achieve its goals. In addition, the care pathways characterized by the aggregate model are not necessarily representative for the patients that would be affected by the policy, as was argued previously by observing the heterogeneity present in the ALC cohort. To exemplify the model’s use for more narrowly defined subsets of the population, a sub cohort of patients was created – only patients with a diagnosis of Dementia, Delirium, or both,
were included. The model was validated as before – TBATS fit and forecast Mean APE across all services was 2.38% and 5.58% respectively. 5 year forecasts were then produced for all services to serve as baseline for the policy analysis. A different policy is proposed for this group to demonstrate an alternative approach to policy interpretation that can be tested using the model – the change in the flow parameter is explicitly set as a desirable target to be achieved by the full deployment of the policy, while the observed changes in occupancies across services are interpreted as the capacity expansions needed to achieve this target. In this manner, desirable outcomes can be used to guide resource allocation without the need for a priori policy design. This approach might be especially attractive to planners that are primarily concerned with strategic guidance and resource allocation, while preferring to delegate specific policy design to subordinates. Two scenarios, or targets to be achieved, of patient outflows from ALC are examined below, where the target is assumed to be achieved after 2 years following a linear attainment trajectory, as before.

The first scenario targets a doubling of the number of daily discharges from ALC to LTCH for patients with dementia and delirium in 2 years. Impact on ALC and required expansion of LTCH capacity that can specifically accommodate these patients are shows in figures 6.2-1,2: ALC occupancy is permanently decreased by 200 once the target is attained; 1100 LTCH beds are required after 2 years to attain the target, and an additional 500 for the 3 years after in order to maintain it. Furthermore, demand for assisted living and home care drops by 300 and 350 respectively, due to greater availability of LTCH beds. The second scenario targets doubling discharges from ALC to both assisted living and home care in 2 years. Impact on ALC and LTCH demand are presented in figures 6.2-3,4: around 250 ALC beds are permanently freed in 2 years; Several months after the target attainment, demand for LTCH beds that can accommodate patients with dementia and delirium is lessened by more than 250 compared to baseline, but then begins to increase and returns to baseline level by the end of the forecast horizon. Similar to the policies tested for the aggregate population, assisted living and home care only provide a temporary reduction in demand for LTCH beds, as patients’ health eventually deteriorates and they require LTCH placement. The expansions of assisted living and home care capacities that are needed to meet the target are 450 and 550 after 2 years, and increase to 720 and 780 respectively after 5 years. Comparing the two scenarios reveals that while both require an addition of services to
accommodate 1500-1600 patients in 5 years to produce a permanent 200-250 reduction in ALC occupancy, targeting discharges to LTCH also permanently releases 650 “beds” in assisted living and home care, whereas targeting discharges to assisted living and home core only provides a temporary reduction in occupancy of LTCH beds. As with the diversion policies tested previously, the ultimate choice between these policies would depend on costs. However, unlike the previous policies, the capacity changes required to attain the targets must specifically be accommodative for the needs of patients with dementia and delirium – in this case the larger LTCHs may be more cost effective than decentralized care in the patients’ private residences, since these patients are likely to be complex and require specialized around the clock care.

Figure 6.2-1: Dementia/delirium ALC occupancy change from baseline due to increased discharges from ALC. Scenario: double daily discharges to LTCH.
Figure 6.2-2: Dementia/delirium LTCH occupancy change from baseline due to increased discharges from ALC. Scenario: double daily discharges to LTCH.
Figure 6.2-3: Dementia/delirium ALC occupancy change from baseline due to increased discharges from ALC. Scenario: double daily discharges to assisted living and home care.
Figure 6.2-4: Dementia/delirium LTCH occupancy change from baseline due to increased discharges from ALC. Scenario: double daily discharges to assisted living and home care.
Chapter 7

Discussion

7.1 Discussion

Several caveats regarding the policy tests presented above and the overall structure of the modelling framework are noteworthy. First, the patient cohort selected as an input in the model must be representative of the population that will benefit from the proposed policy. While this issue may not be relevant to narrowly defined patient groups, more broadly defined cohorts are likely to be made up of multiple patient groups with heterogenous needs and consequent care pathways. Once input in the model, patients in the chosen cohort become undistinguishable from each other and policies applied to the cohort will impact patients indiscriminately. Therefore, any mismatch between the input cohort and the hypothesized policy beneficiaries is likely to result in inaccurate estimation of the policy’s affect, as patients that should not benefit from the specific policy are in fact influenced directly by its deployment. For example, the 15% diversion policy tested on the aggregate ALC cohort was proposed to impact patients that are on the waitlist for LTCH placement but are sufficiently independent to be cared for in their own residence with some assistance, instead of awaiting LTCH placement in ALC. The flow parameters that characterize the care pathway of this able patient group likely differ from the aggregate pathways captured by the aggregate ALC cohort model. Thus, the effect of the modelled policy on these parameters may have been biased. Nevertheless, the use of broad cohorts is useful for initial exploration of the system and potential policy effects, which in turn can direct planners’ focus on specific policies and services. Data constraints may also justify approximations using aggregated cohorts, as was the case here – reliable data on patient independence and waitlist status was not available. On the other hand, overly specific selection of patient grouping variables is also undesirable, as cohorts must be sufficiently large to create regular flow patterns that can be well fitted and forecasted forward.

The tradeoff between narrowly defining homogenous cohorts, which promotes confidence in the policy tests, and broadly capturing larger cohorts that flow through the modelled services in a more regular manner, which in turn enables accurate forecasting, represents the second noteworthy caveat. Planners should select the specific cohort that matches their postulated
interest – broad cohorts for high level characterization of the healthcare system and goal identification, and narrow cohorts for specific “what-if” scenario tests. The variable selection for the construction of the cohorts is in some cases obvious – for example, geographical grouping of patients by LHIN of residence or demographic grouping by age and gender. In other cases, expert opinion provided by healthcare providers or data coders may be necessary, as would be in the case of grouping patients by functional ability or illness - incorrect assumptions about the similarity in need for care across different levels of independence or ICD codes will result in heterogenous cohorts and subsequent biases in estimation of policy effects and their interpretation. In other words, flawed assumptions of homogeneity can result in incorrect interpretations of predictions made by the model.

Notably, one such flawed assumption is implicit in the method used to estimate the effect of policy in the model, and presents itself as a key limitation of the models design: changes to the care pathway of patients caused by policy intervention does not alter the flow parameters of services downstream from the service that was directly affected by the policy. This assumption is unlikely to hold since the introduction on new patients as “occupants” in specific service node changes the case mix of patients using that service, which in turn is likely to be reflected in different flow parameters to downstream nodes. For example, increasing daily discharges from ALC into private residences with a care package for the dementia and delirium cohort undoubtedly impacted the case mix of patients occupying these services, while retaining the services’ pre-policy flow parameters. It is likely that the arriving ALC patients have greater needs than the patients with dementia and delirium that used assisted living and home care services in the pre-policy period, which was used to estimate the flow parameters. The addition of more complex patients into the case mix of these services is likely to increase outflow, as these patients demand additional care – this effect is not captured, with the flow parameters remain fixed to their pre-policy levels. The biasing effect of post policy intervention changes in the case mix of service nodes is probably negligible in models run on sufficiently large cohorts, in which the intervention results in the addition of a relatively small number of new service occupants. These uncaptured policy effects present an additional consideration for the selection of the input patient cohort.
The final caveat pertains to elements excluded from the model and policy analysis due to the lack of data. While the model’s design allows the incorporation of exogenous growth in the number of entrants into the modelled system, this parameter was not estimated because only data on ALC patients was available. Overall population aging and a corresponding increase in the prevalence of dementia and delirium are likely to have had an impact on the rate of entry into the model for the two input cohorts used in the policy testing section. The non-observation of this potential growth may have resulted in an underestimation of demand over the 5-year forecast horizon. Estimating these values from the available data was ruled out, as the ALC population is not representative of the overall population of Ontario – contingent on the availability of data, these parameters can be easily applied to the model to recalculate the reported results. Direct impact of capacity changes on flow parameters was also excluded due to the lack of detailed data on historical capacity flux. If such data is made available, impulse response functions can be estimated for the impact of capacity changes on discharges from services directly upstream. The exclusion of such effects means that occupancy relieved by a scenario is not immediately occupied by members of the modelled cohort through an increase in flow into the vacated service. This behavior may be acceptable for models run with narrowly defined cohorts, by assuming that the much larger remainder of the unmodelled population rapidly occupies the vacated services. In the case of the aggregate ALC cohort, this remainder consists of all other Ontario residents that use the modelled services but had never had an ALC episode. However, it may not necessarily be true that this remainder is sufficiently large and is so highly prioritized so as to warrant the assumption that all vacated capacity is rapidly occupied by patients from this remainder “cohort”. Therefore, the inclusion of capacity feedback for large patient cohorts requires data from the totality of service users for accurate specification of an impulse response. In other words, including capacity feedback while retaining the model’s flexibility requires data on all users in Ontario.
Chapter 8

Conclusion

Resolving the ALC problem that causes hospital overcrowding in Ontario is critical but is complicated by the large scale of the problem and the multitude of variations that require consideration when designing a solution. However, the large and comprehensive administrative data holdings of the MOHLTC can be effectively used to understand the needs of the patient population that gives rise to the ALC problem, identify the lacking supply for meeting these needs, and test the potential impact of policies aiming to match demand with supply using a mathematical model. The present document outlines such application using data on the all ALC patients in Ontario between April 2012 and April 2017. Large variations between patients and in terms of the behavior of the system were observed – patients with different characteristics, different geographies and time, as well as varying histories of service use, contribute to the overall ALC problem to differing extent and for different reasons. MOHLTC administrative data holding provide enough detail to provide planners with a deep understanding of the specific patient groups that should be most effectively targeted by policy to reduce their contribution to the ALC problem. Disaggregated examination of ALC across space and time can also highlight local successes in managing this problem, which in turn can be investigated to infer potential policies that can be used globally. Once a specific group of patients has been selected, the model presented above can be used to forecast the future use of services by this cohort and to test “what-if” scenarios to observe the influence of different policies on the future matching of demand and supply of healthcare services. Two examples of patient cohorts and four scenarios were presented to demonstrate the models functional ability and flexibility. The design of the model itself was guided by an understanding that transparency, relative simplicity, and applicability to different contexts, are all crucial for successful future adoption and application of the framework above by healthcare planners. We envision that this framework will be used to guide policy design from a patient perspective by tailoring supply of services to care needs, with the help of insights gained from describing the data and scenarios run through our model. Desired targets of for future states of the healthcare system can also be developed using our framework, to strategically guide resource allocation and the overall direction of ALC policy in the healthcare system in Ontario. Overall, the framework outlined in this document presents a
comprehensive approach to leveraging the MOHLTC’s administrative data holding for addressing the ALC problem in Ontario.
References


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Appendix B
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<td>Other and unspecified dysphagia</td>
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<td>6.04</td>
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<tr>
<td>Enterococcus as the cause of diseases classified to other chapters</td>
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<td>5.90</td>
</tr>
<tr>
<td>Type 2 diabetes mellitus with established or advanced kidney disease</td>
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<tr>
<td>Enterococcus due to Clostridium botulinum</td>
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<td>Dementia in Alzheimer's disease, unspecified</td>
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<td>Hypo-osmolality and hyponatraemia</td>
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- Certain infectious and parasitic diseases
- Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism
- Diseases of the circulatory system
- Diseases of the digestive system
- Diseases of the genitourinary system
- Diseases of the nervous system
- Diseases of the respiratory system
- Endocrine, nutritional and metabolic diseases
- Factors influencing health status and contact with health services
- Mental and behavioural disorders
- Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified