BMJ Open

Transfer from long-term care to acute care and risk of new permanent cognitive or physical disability among long-term care residents in Canada: protocol for a retrospective cohort study

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To cite: Yin CY, Scott MM, Talarico R, *et al*. Transfer from long-term care to acute care and risk of new permanent cognitive or physical disability among long-term care residents in Canada: protocol for a retrospective cohort study. *BMJ Open* 2025;**15**:e086932. doi:10.1136/bmjopen-2024-086932

► Prepublication history for this paper is available online. To view these files, please visit the journal online (https://doi.org/10.1136/bmjopen-2024-086932).

Received 26 March 2024
Accepted 19 December 2024

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ABSTRACT

Introduction Long-term care (LTC) residents are frequently transferred to acute care hospitals. Transfer decisions should align with residents' wishes and goals. Decision to transfer to hospital, when not aligned with the resident's wishes, can result in transfers that are harmful to residents, leaving residents in a state of disability that could be considered worse than death. We aim to examine whether transfer to an acute care hospital is associated with subsequent new onset of severe permanent physical and cognitive disability in LTC residents.

Method and analysis We will conduct a retrospective cohort study of all LTC residents ≥65 admitted to LTC homes between 1 April 2013 and 31 March 2018 in Ontario, Canada. We will use health administrative data from the Continuing Care Reporting System (CCRS), National Ambulatory Care Reporting System (NACRS) and Registered Persons Databases (RPDB), which include data on emergency department visits, hospitalisations, demographic information and mortality. All participants will be followed until 31 March 2023. The exposure is any transfer from LTC to an emergency department or acute care hospital. The outcomes are (1) subsequent new permanent physical disability, (2) subsequent new permanent cognitive disability and (3) all-cause mortality. Due to the time-varying nature of the exposure and confounders, we will use an extended cause-specific Cox regression model to explore this relationship. We will fit marginal structural models (MSMs) to account for the known shortcomings of traditional regression modelling, such as collider bias. Lastly, we will use a preference-based instrumental variable approach to address unmeasured confounders.

Ethics and dissemination Ethics approval was obtained through Bruyère Research Institute Ethics Committee (REB#M16-23-030). Study findings will be submitted for publication in a peer-reviewed journal. Findings will be disseminated in conferences and seminars.

Trial registration Open Science Framework (https://doi.org/10.17605/OSF.IO/JCDEY).

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ This study uses a population-based cohort with comprehensive information on comorbidities to study care transitions.
⇒ This study uses three modelling approaches to address measured and unmeasured confounders to increase our confidence in determining the direction of the effect.
⇒ Coding inconsistencies may result in misclassification.
⇒ The exact date that the outcome occurred is unknown and is estimated using the 92-day assessment window.

INTRODUCTION

Long-term care (LTC) residents experience frequent transfers to acute care hospitals.[1] It is estimated that 25% of LTC residents have at least one transfer to a hospital every 6 months.[2 3] While transfers to hospital allow LTC residents to receive timely investigation or treatment when they become acutely ill, transfers can also result in negative health outcomes,[4 5] poor quality of life[6] and adverse events[5 7] due to complications, stress and the burden of extensive treatments.[4 7–9]

Ideally, transfers should promote the resident's best interests and well-being. Transfers should meaningfully prolong life while preserving the resident's cognitive and physical functioning, ensuring they maintain their dignity and minimise stress. However, transfer decisions are often made without accounting for the natural downward trajectory of health towards the end of life or the resident's wishes,[10 11] resulting in transfers

that may be more harmful than helpful to LTC residents. In some cases, standard care practice can leave residents in a state of disability that reduces quality of life in a way that some residents consider worse than death.[12 13] Improving the care planning process requires incorporating shared decision-making that helps LTC residents, families and healthcare providers anticipate prepare for future changes so they can make informed transfer decisions.

We aim to examine if transfer to an acute care hospital is associated with the subsequent new onset of a permanent physical and cognitive disability in LTC residents. We hypothesise that transfer to acute care hospital will prolong life in states of disability. The protocol outlines the planned steps for data preparation and analysis. Our study findings will support LTC residents, caregivers and staff to make informed transfer decisions and have the potential to guide LTC policies regarding transfer decisions.

METHODS AND ANALYSIS

Patient and public involvement

Caregivers of LTC residents were involved in the design, conduct and selection of the outcomes of this study. Eight LTC caregivers were engaged through the Patient and Family Advisory Council at the Ottawa Hospital Research Institute and Bruyère Health Research Institute. One LTC caregiver is part of the research team and coauthor. During the study design phase, we involved caregivers of LTC residents to select cognitive and physical disability measures that were meaningful and resident-important. They also played important roles in selecting covariates for modelling. We will continue to engage with caregivers of LTC residents through research and focus group meetings. Once the study is completed, we will present our findings in the meetings to gain feedback and ensure that our study findings are presented to the general public.

Causal inference with observational data

Our objective is to examine whether transfer from LTC to acute care hospital prolongs residents' life but increases the chance of being alive with severe disability. Estimating causation requires knowledge of the counterfactual. That is, what would have happened to this person if they had not been transferred to hospital? Rubin's causal model describes the challenge of estimating outcomes that would have occurred under the observed and the unobserved counterfactual.[14] With no ability to observe the outcome of both decisions, the best we can do is compare those who are transferred to those who are not while adjusting for differences that could also affect the outcome.

Any causal inference based on observational data requires assuming the completeness and accuracy of measured confounders as well as the nature of the relationships between confounders and the outcome. Because these assumptions cannot be tested, we cannot be certain of the alignment between statistical estimands and causal effects. One way to address concerns about these assumptions is to use multiple modelling approaches and to explore whether the direction of the effect is consistent across approaches.

To address both measured and unmeasured confounders related to residents' health and well-being, we will use multiple analytical approaches to examine the association between transfer to acute care hospital and physical and cognitive disabilities. By leveraging the Rubin causal model, we will use three approaches: (1) an instrumental variable (IV) approach, (2) a marginal structural model and (3) an extended cause-specific hazard model. Each of these methods will allow us to approximate the unobservable counterfactual under different assumptions.

Data source

We will conduct a retrospective cohort study using administrative health data to examine the association between all-cause transfer and the subsequent onset of a permanent physical and cognitive disability. We will obtain our data from the Institute for Clinical Evaluative Sciences (ICES). ICES is an independent, non-profit research institute whose legal status under Ontario's health information privacy law allows it to collect and analyse healthcare and demographic data, without consent, for health system evaluation and improvement. The use of the data in this project is authorised under section 45 of Ontario's Personal Health Information Protection Act (PHIPA) and does not require review by a Research Ethics Board. ICES conducts routine data quality assessments to ensure data completeness, reliability and accuracy.[15]

We will use the following databases: the National Ambulatory Care Reporting System (NACRS), the Canadian Institute for Health Information (CIHI) Discharge Abstract Database (DAD), Registered Persons Database (RPDB) and Continuing Care Reporting System (CCRS). These datasets are linked using unique encoded identifiers and analysed at ICES. NACRS collects information on emergency department visits and DAD records hospitalisations. RPDB tracks demographic information and vital status for Ontario residents. CCRS collects information on health status and care characteristics based on the resident assessment instrument- minimum data set 2.0 (RAI-MDS 2.0) assessments.

Study population

We will include LTC residents ≥65 who entered LTC homes between 1 April 2013 and 31 March 2018 in Ontario, Canada. We will follow participants for a minimum of 5 years, with the maximum follow-up date of 31 March 2023. We will exclude non-Ontario residents at index and those who entered an LTC home prior to April 2013 to ensure we are capturing a cohort of incident admissions and all residents are indexed from their first-ever admission assessment. Residents receive assessments using the RAI-MDS 2.0 schedule that provides these assessments at admission, quarterly, and with full assessments annually or

when a resident has a vital change in status.[16] Based on this schedule, we created a longitudinal within resident time series where every resident is followed for discrete 92-day periods beginning from admission (period 0) to the end of follow-up. Assessment information is then captured once every 92-day period and updated accordingly. The end of follow-up is marked by either death, administrative censoring in March 2023 or discharge from LTC, where the resident was not readmitted within 123 days and thus missed their subsequent assessment period.

Exposure

Our exposure includes all transfers to an emergency department, regardless of type (planned or unplanned), after the index admission to LTC. Residents can transition in and out of an exposed state during their follow-up. We linked their transfer history to each resident's assessment period cycle, treating it as a binary time-varying exposure. An exposed period is defined as the 92-day period in which a resident had a transfer. An unexposed period is a 92-day period with no transfers.

Outcomes

Our outcomes are (1) permanent physical disability, (2) permanent cognitive disability and (3) all-cause mortality. We defined permanent physical disability as total dependence in performing personal hygiene, toilet use, eating and locomotion (equivalent to activities of daily living (ADL)—self-performance hierarchy=6) with no improvement in subsequent assessments once the outcome is achieved (table 1). We defined permanent cognitive disability as comatose, or severely impaired in decision-making skills, and total dependence in eating (equivalent to Cognitive Performance Scale (CPS)≥5; Mini Mental State Examination (MMSE)≤5) with no improvement in subsequent assessments once the outcome is achieved (table 1). The outcome will be assessed in the immediate subsequent assessment period, since it contains the assessment information that occurs entirely after the exposure and is clinically relevant for interpreting the association.

Other variables

We selected covariates based on existing literature that examined factors associated with cognitive and functional decline in institutionalised older adults,[17–21] and the team's previous work in developing a predictive algorithm for life expectancy in frail older adults.[22 23] Covariates for adjustment will include sociodemographic factors, health stability measures, comorbidities, medication use and other functional measures (table 2). We obtained covariate data using the RAI-MDS 2.0 assessment in the CCRS. The RAI-MDS 2.0 is a comprehensive assessment with more than 160 items and is administered to every LTC resident on admission, every 3 months and when there is a change in residents' health status. Age will be treated as a continuous linear term. Sex will be categorised into two groups (female vs male). We will categorise education into four groups: less than high school, high school or equivalents, technical or trade school, college and above.

We will use weight loss/gain of 5% or more in the last 30 days, or 10% or more in the last 180 days, and changes in health, end-stage disease and signs and symptoms (CHESS) score as a measure of health stability. Other functional measures will include hearing and vision impairment, which will be categorised into five groups: adequate, impaired, moderately impaired, highly impaired and severely impaired. All comorbidities will be determined using data from CCRS. Variable definitions are listed in table 2.

Statistical analyses

To address concerns with both measured time-varying confounding and unmeasured confounders and to determine the direction of effect, we will use a staged approach with three analyses: extended cause-specific Cox regression model, marginal structural models (MSMs) and instrumental variable analysis (figure 1). Each method improves on the previous one by how the model adjusts for measured and unmeasured confounding, allowing for increasingly robust causal inference. Our primary analysis will be the IV analysis. The IV analysis for causal inference accounts for measured and unmeasured confounding using a third variable, which mimics randomisation to isolate the effect of the exposure on the outcome.[24] We selected the IV model to be our primary analysis because it adjusts for unmeasured confounders, primarily the resident's health instability at the time of the transfer.

Extended cause-specific Cox regression models

We will fit a traditional extended cause-specific Cox regression model to model both the time-varying exposure and confounder histories. However, this model has several known and documented methodological shortcomings. This approach is often biased when there are

Table 1 Physical and cognitive outcomes

Physical outcome	Variable	Definition
Loss of independence in physical function	Activities of daily living score=6	Total dependence in performing personal hygiene, toilet use, eating and locomotion
Cognitive outcome		
Loss of independence in cognitive function	Cognitive Performance Scale≥5	Comatose, or severely impaired in decision-making skills and total dependence on eating

Table 2 Covariates for modelling

Variable	Scale	Range/levels
Sociodemographic		
Age	Continuous	65–105 years
Sex	Categorical	Female, male
Education	Categorical	<High school Completed high school Technical or trade school Some college and ≥Bachelor's Unknown
Health stability		
Weight loss of 5% or more in the last 30 days, or 10% or more in the last 180 days	Categorical	0=No 1=Yes 9=Unknown
Weight gain of 5% or more in the last 30 days, or 10% or more in the last 180 days	Categorical	0=No 1=Yes 9=Unknown
CHESS score	Discrete	0–5
Hip fracture in last 180 days	Binary	0=No 1=Yes
Fell in the past 30 days	Binary	0=No 1=Yes
Comorbidities		
Dementia	Dichotomous	Yes, no
Delirium	Dichotomous	Yes, no
Emphysema/COPD	Dichotomous	Yes, no
Cancer	Dichotomous	Yes, no
Kidney failure	Dichotomous	Yes, no
Congestive heart failure	Dichotomous	Yes, no
Arteriosclerotic heart disease	Dichotomous	Yes, no
Depression	Dichotomous	Yes, no
Anxiety	Dichotomous	Yes, no
Pressure ulcer	Dichotomous	Yes, no
Stroke	Dichotomous	Yes, no
Seizure disorder	Dichotomous	Yes, no
Anaemia	Dichotomous	Yes, no
Parkinson's disease	Dichotomous	Yes, no
Multiple sclerosis	Dichotomous	Yes, no
Oxygen therapy	Dichotomous	Yes, no
Kidney dialysis	Dichotomous	Yes, no
Incontinence	Dichotomous	Yes, no
Number of chronic conditions	Discrete	0–18
Medications		
Antipsychotic: the number of days during the last 7 days	Categorical	0, 1, 2+
Number of medications	Discrete	0–13
Other functions		
BMI	Continuous	0–40 kg/m^2
Pain scale	Discrete	0–3

Continued

Table 2 Continued

Variable	Scale	Range/levels
Vision impairment	Categorical	Adequate, impaired, moderately impaired, highly impaired, severely impaired
Hearing impairment	Categorical	Adequate, impaired, moderately impaired, highly impaired, severely impaired
Index of Social Engagement	Discrete	0–6
Depression Rating Scale	Discrete	0–14
CPS score	Discrete	0–6
ADL—Self-Performance Hierarchy Scale Score	Discrete	0–6

ADL, activities of daily living; BMI, body mass index; CHESS, Changes in Health, End-Stage Disease and Signs and Symptoms; COPD, chronic obstructive pulmonary disease; CPS, Cognitive Performance Scale.

time-dependent confounders that are risk factors for the outcome and predict future exposure or when past exposure history itself predicts the current exposure and/or risk factors.[25] Furthermore, with longitudinal repeated measures data, the same variable can act as a confounder, mediator or collider, and this can change over time in ways that traditional conditional estimates are unable to account for.[25]

Marginal structural models

To address the methodological shortcomings of the extended cause-specific Cox models, we will use MSMs, which provide a propensity score-weighted framework for longitudinal exposures. MSMs are especially useful in this context because they allow us to control for confounders that change over time and are influenced by prior exposures. Unlike traditional models, MSMs reduce bias by accounting for confounding variables at each time point.

We will use stabilised weights estimated from a sequence of logistic regression models that will be subsequently computed as products of both the inverse probability of treatment weights at each assessment period and inverse probability of censoring weights based on the probability of being censored at a current assessment period. These stabilised weights are cumulatively carried forward to account for the entire exposure and confounder history when connecting transfers to the rate of subsequent disability and/or death.

To ensure we have a mean stabilised weight of approximately one, we will experiment with trimming of the

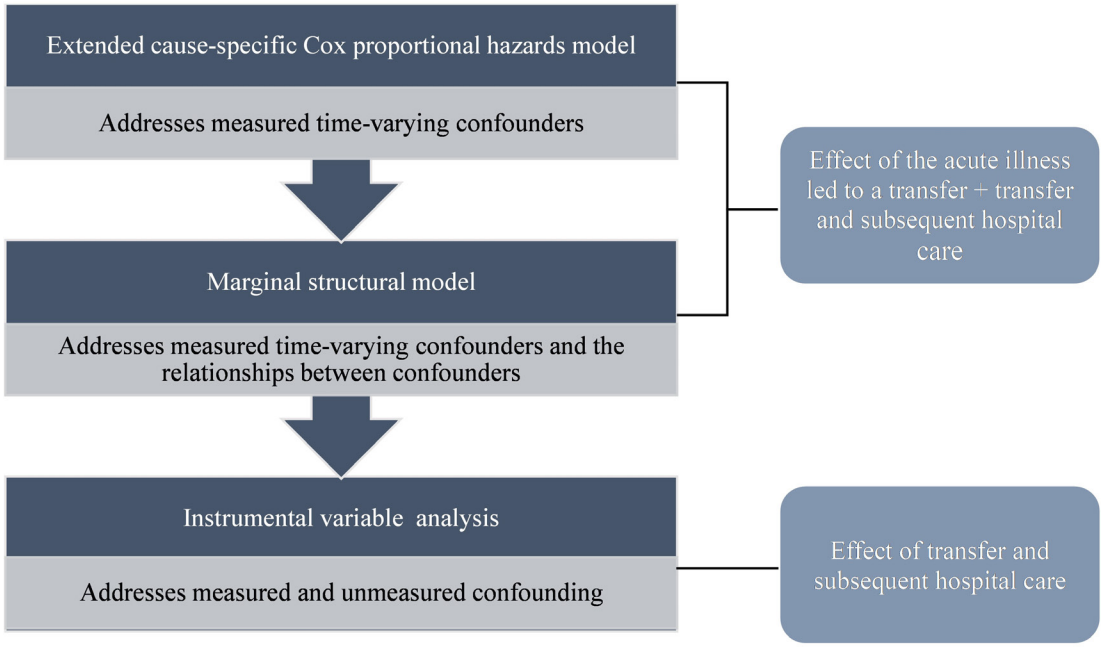

Figure 1 Staged analytical approach. Staged approach with three analyses: extended cause-specific Cox proportional hazard model, marginal structural model and instrumental variable analysis.

stabilised weights, starting at the 1st and 99th percentiles and moving out to the extremes. The last step of the MSMs analysis will be to fit a weighted cause-specific extended Cox model and estimate a weighted HR and 95% CI with robust sandwich covariance estimators. Both the MSMs and extended Cox models will account for clustering at the LTC home level by incorporating a random intercept. Through these methods, we aim to provide reliable estimates of the impact of transfers on disability and death while accounting for complex confounding. Neither of these approaches will adjust for the acute health event that led to the transfer.

Instrumental variable approach

While MSMs account for time-varying covariates, they cannot adjust for unmeasured confounding, such as the acute health event, that led to a transfer. The IV analysis addresses both measured and unmeasured confounding, allowing us to estimate the average treatment effect of transfer for residents. Our conceptual instrument is the preference for transfer at LTC home level, which will be operationalised as homes' hospital transfer rate. We defined the annual transfer rate as the proportion of residents in an LTC home who are transferred to the hospital within the last year. We will examine the consistency of the transfer rate over a 5-year period from 2013 to 2018, assessing the temporal stability of the transfer rate variable and changes in LTC facility characteristics over time to ensure the robustness of our IV.

For the transfer rate to be a valid instrument, there are three assumptions (relevance, exogeneity and exclusion assumption) that need to be satisfied. Transfer rate is (1) strongly associated with the exposure, (2) unrelated to the error in the outcome model and (3) associated with the outcome only through the exposure. For the relevance assumption to be supported, our instrument (ie, transfer rate) should be strongly associated with the exposure (ie, transfer event). Our preference IV is logically sound because the transfer rate of LTC homes reflects directly their preference for transfer. Transfer rates are known to vary widely due to culture and practices within the home.[26 27] Thus, the preference for hospital transfer at the LTC home level can be expected to have a strong and direct impact on transfer events, making it a suitable instrument. We will use descriptive statistics to summarise the transfer rate across LTC homes and the number of actual transfers to test the relevant assumption. Although directly unverifiable, adherence to the exogeneity assumption will be supported if the baseline residents' characteristics are similar between homes, which have been shown previously.[28] We will perform a balance test to compare baseline residents' characteristics across LTC homes with varying transfer rates to examine if systematic differences exist. For exclusion assumption to be supported, the transfer rate needs to be unrelated to physical or cognitive function other than through its association with the transfer event. Although we cannot directly test this assumption, evidence from prior studies, such as from Hébert *et al*, indicated that the LTC home transfer rate is primarily determined by systemic factors (ie, institutional policies and practice patterns), but not directly driven by residents' health status.[29] We will compare residents' physical and cognitive functions across LTC homes with different transfer rates to explore this assumption.

Our IV analysis will use two-stage least squares regression analysis. We will first model the probability of hospital transfers as a function of the transfer rate. Then, we will use the predicted probabilities as an instrument in the time-to-event analysis using a Cox proportional hazard model, further adjusting for LTC home characteristics and health stability factors. We will use the ivtools package in R and use the two-stage estimators with a control function to obtain HR estimates along with 95% CI.

Primary model selection

We anticipate that the results will be different between the extended Cox model, MSMs and IV analysis because of model assumptions and approach to account for confounding.

The extended Cox model is widely used and well understood. However, it cannot fully adjust to the complex relationship between time-varying covariates and unmeasured confounding, particularly the acute health condition that led to a transfer. The acute health condition leading to the transfer is critical in our analysis. This acute health condition refers to the sudden deterioration in health or onset of symptoms that necessitate a hospital transfer from the LTC home. It influences the subsequent health trajectory of the residents and precipitates disability,[30] affecting physical and cognitive functioning and mortality. However, the acute health condition in the moments leading up to the hospital transfer is not measured. It is a major unmeasured confounder. The MSMs improve on the extended Cox models by using inverse probability weighting to better adjust for time-varying covariates. However, like the Cox models, they cannot adjust for the unmeasured acute illness that led to a transfer. As a result, we expect both the extended Cox models and MSMs to reflect the combined effect of the transfer and the acute illness that led to such transfer. In this case, we hypothesise that both the extended Cox models and MSMs will reveal a positive association between transfer and our outcomes (ie, physical disability, cognitive disability and mortality) because the acute illness leading to the transfer will not be accounted.

The IV analysis is designed to address unmeasured confounding to provide unbiased effect estimates.[24] It will account for the acute health condition that led to a transfer. Thus, our primary research question regarding the association between hospital transfer and new permanent cognitive and physical impairments will be addressed through the IV analysis. We will use the instrumental variable analysis as our primary model. We hypothesise that the IV analysis will reveal a protective effect of hospital transfer for survival. For physician and cognitive disability outcomes, we hypothesise that the IV analysis will reveal

a positive association with the most accurate estimates of the causal effect of hospital transfer, given its ability to adjust for both measured and unmeasured confounding.

Anticipated challenges and mitigation strategies

We anticipate several challenges that might affect us, including the potential for a weak IV, computational demands of our modelling approaches, limitations in the RAI-MDS assessment cycle, and inherent constraints of administrative health data. We have developed strategies to address these issues to ensure that our findings are robust.

In the unlikely event that our IV is weak, we will refine our instrument by using multiple instrument variables.[31 32] LTC home level factors we will consider as IVs include LTC home staff ratios, geographical location and for-profit status. Additionally, we may use near-far matching in our IV analysis to further control for confounding. In this approach, residents with similar measured confounders who differ by level of their LTC home transfer rate will be matched.[33 34] The inclusion of near-far matching will improve robustness by further reducing bias from residual confounding.

Our modelling approaches are computationally complex. All of the models will require significant processing power due to the large data volume. If this is an issue, we will conduct initial analyses on smaller subsets of data to optimise codes and refine model specifications before applying to the full dataset.

The RAI-MDS assessment cycle is every 92 days. Therefore, the exact date that physical disability or cognitive disability outcome occurred is unknown but can only be assigned to a 92-day assessment window. This limitation means that residents who had a new permanent physical or cognitive disability after a transfer that occurred during the same window as the transfer but then died prior to their next assessment will not be classified as having had the outcome. We will make this limitation clear when the model is presented. The 92-day assessment period reflects the standard clinical practice at LTC homes, and more frequent assessments are not feasible in the LTC setting. While the exact time cannot be determined, the assessment cycle captures a clinically relevant timeframe that reflects changes occurring after a transfer.

Administrative datasets may have inconsistencies due to coding errors or delayed data entry, which could lead to misclassification. To address these issues, we will conduct rigorous data quality checks during the data cleaning stage to identify and correct any inconsistencies in coding. Where possible, we will use validated definitions for our variables, maintaining consistency with existing studies. We expect that any issues with data quality will be minimal because ICES data undergo regular quality control procedures to ensure data accuracy and completeness.[35]

By examining the association between transfer to an acute care hospital and subsequent onset of disabilities, we hope to provide evidence that encourages healthcare providers to foster an environment for shared decision-making for LTC residents. Study findings will provide average treatment effects for those who are transferred from LTC to hospital and will not be directly applicable to individual patients, but our study will generate two pieces of useful information to support policymakers and inform decisions. The Cox and MSM models will provide estimates of the relative risk of death and disability for those who become unwell enough for a transfer to be considered compared with those who did not become unwell enough to consider transfer. Our IV will provide estimates of the relative risk of death and disability caused by the transfer itself, which could be avoided if a resident is not transferred. Our study will be the largest and best used to optimise transfer decisions by supporting residents, caregivers and LTC staff in making informed decisions, improving care coordination between LTC and hospitals to improve quality of life outcomes for LTC residents, and influencing LTC practice and policies on making transfer decisions.

ETHICS AND DISSEMINATION

Ethics approval was obtained through the Bruyère Research Institute Ethics Committee on 21 June 2023 (REB#M16-23-030). Study findings will be disseminated through conferences, seminars and in published journals. Caregivers of LTC residents will be informed of the study findings through focus team meetings.

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Acknowledgements This study was supported by ICES, which is funded by an annual grant from the Ontario Ministry of Health (MOH) and the Ministry of Long-Term Care (MLTC). The analyses, conclusions, opinions and statements expressed in this study are solely those of the authors and do not reflect those of the funding or data sources; no endorsement is intended or should be inferred. MMS contributed to this work through her role at the Ottawa Hospital Research Institute, and this work does not reflect the opinion of the Public Health Agency of Canada.

Contributors All authors (CYY, MMS, RT, RH, JK, CW, SK, AM, DM, AH, PT, CF, SK, FM, SS, DIM and DK) contributed substantially to the conception of this study. CYY, RT, MMS, JK, DM, AH and DK contributed substantially to the design of the study. CYY, MMS and DK drafted the manuscript for review. All authors reviewed the manuscript and made significant contribution to manuscript revision. All authors

gave final approval for publication and agreed to be accountable for all aspects of the study. DK is the guarantor of the study.

Funding This study was supported by ICES, which is funded by an annual grant from the Ontario Ministry of Health (MOH) and the Ministry of Long-Term Care (MLTC). This work was also supported by the Canadian Institutes of Health Research (CIHR; reference number 184572).

Competing interests None declared.

Patient and public involvement Patients and/or the public were involved in the design, or conduct, or reporting, or dissemination plans of this research. Refer to the Methods section for further details.

Patient consent for publication Not applicable.

Ethics approval Ethics approval was obtained through Bruyère Research Institute Ethics Committee on June 21, 2023 (REB#M16-23-030).

Provenance and peer review Not commissioned; externally peer reviewed.

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REFERENCES

1 Information CI for H. Profile of residents in residential and hospital-based continuing care 2018-2019. Continuing Care Reporting System; 2019.
2 Gruneir A, Bell CM, Bronskill SE, *et al*. Frequency and pattern of emergency department visits by long-term care residents--a population-based study. *J Am Geriatr Soc* 2010;58:510–7.
3 Hoben M, Chamberlain SA, Gruneir A, *et al*. Nursing Home Length of Stay in 3 Canadian Health Regions: Temporal Trends, Jurisdictional Differences, and Associated Factors. *J Am Med Dir Assoc* 2019;20:1121–8.
4 Vognar L, Mujahid N. Healthcare transitions of older adults: an overview for the general practitioner. *R I Med J* 2013;98:15–8.
5 Coleman EA. Falling Through the Cracks: Challenges and Opportunities for Improving Transitional Care for Persons with Continuous Complex Care Needs. *J Am Geriatr Soc* 2003;51:549–55.
6 Heyland DK. What matters most in end-of-life care: perceptions of seriously ill patients and their family members. *Can Med Assoc J* 2006;174:627–33.
7 Snow V, Beck D, Budnitz T, *et al*. Transitions of Care Consensus Policy Statement American College of Physicians-Society of General Internal Medicine-Society of Hospital Medicine-American Geriatrics Society-American College of Emergency Physicians-Society of Academic Emergency Medicine. *J Gen Intern Med* 2009;24:971–6.
8 Baker GR. The Canadian Adverse Events Study: the incidence of adverse events among hospital patients in Canada. *Can Med Assoc J* 2004;170:1678–86.
9 Storm M, Siemsen IMD, Laugaland K, *et al*. Quality in transitional care of the elderly: Key challenges and relevant improvement measures. *Int J Integr Care* 2014;14:e013.
10 Ernecoff NC, Zimmerman S, Mitchell SL, *et al*. Concordance between Goals of Care and Treatment Decisions for Persons with Dementia. *J Palliat Med* 2018;21:1442–7.
11 Comer AR, Hickman SE, Slaven JE, *et al*. Assessment of Discordance Between Surrogate Care Goals and Medical Treatment Provided to Older Adults With Serious Illness. *JAMA Netw Open* 2020;3:e205179.
12 Rubin EB, Buehler AE, Halpern SD. States Worse Than Death Among Hospitalized Patients With Serious Illnesses. *JAMA Intern Med* 2016;176:1557–9.
13 Auriemma CL, O'Donnell H, Jones J, *et al*. Patient perspectives on states worse than death: A qualitative study with implications for patient-centered outcomes and values elicitation. *Palliat Med* 2022;36:348–57.
14 Rubin DB. Causal Inference Using Potential Outcomes: Design, Modeling, Decisions. *J Am Stat Assoc* 2005;100:322–31.
15 Iron K, Manuel DG. Quality Assessment of Administrative Data (QuAAD): An Opportunity for Enhancing Ontario's Health Data. *Inst Clin Eval Sci* 2007.
16 Morris JN. Resident assessment instrument (rai) rai-mds 2.0. user's manual. canadian version. Canadian Institute for Health Information; 2010.
17 Kwan RYC, Kwan CW, Kor PPK, *et al*. Cognitive decline, sensory impairment, and the use of audio-visual aids by long-term care facility residents. *BMC Geriatr* 2022;22:216.
18 Casanova R, Saldana S, Lutz MW, *et al*. Investigating Predictors of Cognitive Decline Using Machine Learning. *The J Gerontol* 2020;75:733–42.
19 Palese A, Menegazzi G, Tullio A, *et al*. Functional Decline in Residents Living in Nursing Homes: A Systematic Review of the Literature. *J Am Med Dir Assoc* 2016;17:694–705.
20 Jerez-Roig J, de Brito Macedo Ferreira LM, Torres de Araújo JR, *et al*. Functional decline in nursing home residents: A prognostic study. *PLoS One* 2017;12:e0177353.
21 Grueso S, Viejo-Sobera R. Machine learning methods for predicting progression from mild cognitive impairment to Alzheimer's disease dementia: a systematic review. *Alzheimers Res Ther* 2021;13:162:162:.
22 Manuel DG, Rosella LC, Hennessy D, *et al*. Predictive risk algorithms in a population setting: an overview. *J Epidemiol Community Health* 2012;66:859–65.
23 Hsu AT, Manuel DG, Spruin S, *et al*. Predicting death in home care users: derivation and validation of the Risk Evaluation for Support: Predictions for Elder-Life in the Community Tool (RESPECT). *CMAJ* 2021;193:E997–1005.
24 Widding-Havneraas T, Zachrisson HD. A Gentle Introduction to Instrumental Variables. *J Clin Epidemiol* 2022;149:203–5.
25 Williamson T, Ravani P. Marginal structural models in clinical research: when and how to use them? *Nephrol Dial Transplant* 2017;32:ii84–90.
26 Bowers B, Roberts T, Nolet K, *et al*. Inside the Green House "Black Box": Opportunities for High-Quality Clinical Decision Making. *Health Serv Res* 2016;51 Suppl 1:378–97.
27 Grant KL, Lee DD, Cheng I, *et al*. Reducing preventable patient transfers from long-term care facilities to emergency departments: a scoping review. *CJEM* 2020;22:844–56.
28 Tanuseputro P, Chalifoux M, Bennett C, *et al*. Hospitalization and Mortality Rates in Long-Term Care Facilities: Does For-Profit Status Matter? *J Am Med Dir Assoc* 2015;16:874–83.
29 Hébert PC, Morinville A, Costa A, *et al*. Regional variations of care in home care and long-term care: a retrospective cohort study. *CMAJ Open* 2019;7:E341–50.
30 Covinsky KE, Pierluissi E, Johnston CB. Hospitalization-associated disability: "She was probably able to ambulate, but I'm not sure". *JAMA* 2011;306:1782–93.
31 Mogstad M, Torgovitsky A, Walters CR. The Causal Interpretation of Two-Stage Least Squares with Multiple Instrumental Variables. *Am Econ Rev* 2021;111:3663–98.
32 Hansen C, Hausman J, Newey W. Estimation With Many Instrumental Variables. *J Bus Econ Stat* 2008;26:398–422.
33 Baiocchi M, Small DS, Yang L, *et al*. Near/far matching: a study design approach to instrumental variables. *Health Serv Outcomes Res Methodol* 2012;12:237–53.
34 Rigdon J, Baiocchi M, Basu S. Near-Far Matching in R: The nearfar Package. *J Stat Softw* 2018;86.
35 ICES. Data repository requirements. data repository requirements. Available: https://www.ices.on.ca/data-repository-requirements/ [Accessed 30 Oct 2024].