

Associations of hospital unit occupancy with inpatient falls and fall-risk assessment completion: a retrospective cohort study

Jared Chiu^{1,2}, Vahid Sarhangian^{1,2,*}, Sarah Tosoni³, Laura Danielle Pozzobon^{4,5,6,7}, Lucas B. Chartier^{3,8}

¹Department of Mechanical and Industrial Engineering, University of Toronto, 5 King's College Road, Toronto, Ontario M5S 3G8, Canada

²Centre for Healthcare Engineering, University of Toronto, 5 King's College Road, Toronto M5S 3G8, Canada

³University Health Network, 190 Elizabeth St., Toronto, Ontario M5G 2C4, Canada

⁴Quality & Safety, University Health Network, 620 University Avenue, Toronto, Ontario M5G 2M9, Canada

⁵School of Medicine, Cardiff University, UHW Main Building, Heath Park Cardiff CF14 4XN, UK

⁶Lawrence S. Bloomberg Faculty of Nursing, University of Toronto, 155 College St., Toronto, Ontario M5T 1P8, Canada

⁷School of Graduate Studies, Queen's University, 74 Union St., Kingston K7L 3N6, Canada

⁸Department of Medicine, Division of Emergency Medicine, University of Toronto, 27 King's College Cir., Toronto, Ontario M5S 1A1, Canada

*Corresponding author. Department of Mechanical and Industrial Engineering, University of Toronto, Toronto, Ontario, Canada.

E-mail: sarhangian@mie.utoronto.ca.

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Abstract

Background: Inpatient fall assessment and prevention efforts are primarily performed by nursing teams. Operating at high occupancy levels may, therefore, reduce the care team's ability to deliver these efforts in a timely and effective way. We investigated the associations of unit-level hospital occupancy with the rate of inpatient fall and the completion of patient fall-risk assessment.

Methods: We conducted a retrospective cohort study using data from a large teaching hospital network in Ontario, between 2017 and 2020. We used a multi-state semi-Markov model to represent the time from admission to inpatient care to primary outcomes of first inpatient fall, and completion of fall-risk assessment in the presence of other competing events. Unit-level occupancy was defined as the time-dependent maximum ratio of unit census to unit capacity and further categorized based on whether it was below or above a given threshold or "tipping point". We estimated the tipping point as well as the association between unit-level occupancy below and above the tipping point with the cause-specific hazard rate of each outcome, adjusting the estimates for confounders.

Results: The final cohort had 83 839 inpatient stays for the fall outcome and 83 853 inpatient stays for the fall-risk assessment outcome. Unit occupancy levels above the estimated tipping point of 95% were associated with an increased rate of falls [Hazard Ratio (HR): 2.10, 95% Confidence Interval (CI): 1.05–4.20], whereas occupancy levels above the estimated tipping point of 77% were associated with a decreased rate of completion of fall-risk assessment [HR: 0.87, 95% CI: 0.82–0.91].

Conclusions: Our study provides evidence for a significant increase in the rate of falls and decrease in the rate of assessment completion when occupancy levels exceed certain tipping points. The results motivate the design of safety protocols tailored for periods of high-capacity strain to support nursing teams and prioritize delivery of assessments and interventions to patients at high risk of fall.

Keywords: falls and injuries; workforce and workload; risk management

Introduction

Patient falls in hospitalized settings are common hospital-acquired conditions, with an estimated rate of three to five falls per 1000 bed days [1]. Falls could result in serious injuries or even death. Injurious falls are associated with increased hospital length-of-stay (LOS) [2] and substantial costs for the health system [3, 4]. Multifactorial fall-prevention strategies can reduce rates of falls and related injuries [5, 6], in particular

those that ensure patient adherence [7]. Fall prevention strategies are described as a three-step process in the literature [8]: (1) fall-risk assessment; (2) developing a personalized prevention plan; and (3) consistently executing the plan. The Morse Fall Scale, for instance, is a common fall-risk assessment used to categorize patients as with low, moderate, or high fall-risk by assessing their history of falls, secondary diagnosis, ambulatory aids, intravenous therapy, gait, and mental status [9].

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Personalized prevention plans subsequently target the identified risk factors with interventions (human and equipment resourced).

Fall assessment and prevention efforts are primarily performed by nursing teams, and their success has been linked to quantity and quality of nursing care [10, 11]. Hence, operating at high occupancy levels may reduce the nursing team's ability to deliver the three-step process in a timely and effective way. While the relationship between hospital capacity strain and increased patient safety incidents has been studied in the literature, the primary focus has been on mortality as the outcome [12–14]. As such, evidence for the relationship between capacity strain and patient falls is lacking. Understanding this relationship could have important implications for the design of fall-prevention strategies. As addressing hospital capacity strain [15, 16] and maintaining a robust nursing workforce [17, 18] continue to be important challenges for healthcare systems worldwide, understanding their implications for patient falls is timely and important.

Examining the associations between capacity strain and patient falls using observational data is challenging due to the existence of competing events (that either preclude or change the risk of fall) as well as potential existence of a “tipping point” on unit occupancy levels, beyond which increased occupancy can be associated with substantially higher rate of falls. We used a flexible survival modeling framework to examine the associations between unit-level occupancy, rate of fall-risk assessment completion, and rate of inpatient falls using data from a large academic health system in Ontario.

Methods

Study design

We conducted a retrospective study using data from a cohort of patients admitted to two acute care sites (Site A with 439 beds and Site B with 280 beds) of a large teaching hospital network in Toronto, Ontario. We followed the strengthening the reporting of observational studies in epidemiology (STROBE) reporting guideline [19]. The research ethics boards of the University Health Network (UHN) and the University of Toronto approved this study. Informed consent was not required, in accordance with section 45 of Ontario's Personal Health Information Protection Act.

Data sources

Data were obtained from deidentified electronic medical records and from four sources: the Discharge Abstract Database (DAD), the Admission, Discharge, and Transfer database (ADT), Medication Administration Records (MAR), and the patient Safety Events Reporting and Review system (SERR). These records included patient demographics and clinical characteristics; nursing units where the patients received care and transfer information (if any) between the units; medications prescribed; fall-risk assessment completion time; fall interventions and their delivery times; and whether a fall was observed during their stay. Inpatient fall records included all reported falls that occurred in the two hospital sites, including near misses and with any level of impact on patients; see [Supplementary Material](#), Section 1.

Study cohort

We identified all inpatient admissions between 1 January 2017 and 3 June 2022, to general internal medicine, surgery, arthritis care, neurology, cardiology, and multi-organ transplant programs. We used the complete dataset to calculate the hourly census of all units. Because data included records for patients admitted and discharged during the period, we excluded the 95th percentile of each cohort's LOS (approximately 23 days) from the beginning and end of the period to ensure census is accurately calculated. This is referred to as the truncation period.

Patient stays starting in other hospital care areas of psychiatry and intensive care were excluded. Other exclusion criteria included inpatient stays with an LOS above the 99th percentile of the cohort's LOS; those who experienced a fall, had a fall assessment completed, or received a fall-related intervention before inpatient admission; and those with atypical fall prevention practice (i.e. with fall-related intervention with either an assessment recorded after the intervention or no assessment). We further excluded inpatient stays with admission or discharges after the onset of the COVID-19 pandemic (defined as 1 March 2020) because care models and delivery adapted to COVID-19 requirements during this period; see [Supplementary Material](#), Section 2.

Exposure

The exposure of interest was the (time-varying) maximum unit-level occupancy during the inpatient hospital stays of patients. Unit-level occupancy was defined as the ratio of unit census to unit capacity. Because unit capacity was not fixed, we used the 80th percentile of the midnight census in each year as the capacity of each unit. We chose the 80th percentile as it was close to the most common midnight census (mode) for most units. Occupancy level was categorized into two levels of below or above a given threshold or “tipping point” to account for potential nonlinear effects of exposure to high occupancy levels following Kuntz *et al* [12].

At each point in time, occupancy was measured with respect to the unit the patient was staying in. We assumed that patients who were temporarily relocated to other areas of the hospital after being admitted to inpatient care (e.g. the emergency department for imaging or other services) continued to be exposed to the occupancy levels of their primary inpatient units.

Follow-up and outcomes

Primary outcomes of interest were the first inpatient fall and first completion of a fall-risk assessment. Timestamps for inpatient falls and fall-risk assessments were extracted from the SERR and Electronic Health Record databases, respectively. A fall-risk assessment was defined as the first MORSE Fall Scale risk assessment completed in an inpatient setting.

For both outcomes, follow-up started at the time of first admission to inpatient care and continued for the minimum of 7 days and time until either the patient experienced the outcome or a competing event. Competing events for the fall outcome were receiving a fall-prevention intervention, discharge (to home, another acute facility, long-term care, rehabilitation, or death), or transfer to non-inpatient or intensive care setting. Competing events for the completion of fall-risk assessment outcome were experiencing a fall, discharge, or

transfer to a non-inpatient or intensive care setting. Inpatient stays that did not experience any of the outcomes within 7 days were assumed to be right-censored.

Covariates

Covariates included demographic and clinical characteristics of patients, time-related fixed effects of their inpatient stay, and follow-up time.

Patient characteristics included age-category, sex, admitting inpatient medical program, most responsible diagnosis, fall-risk-related comorbidities, entry mode to the hospital, number of bed transfers within a unit, count of prescribed fall-risk inducing drugs (FRIDs), and poly-pharmaceutical use of FRIDs. We categorized age at admission into five categories of less than 50, 50–59, 60–69, 70–79, and 80 or above. The admitting inpatient medical program was defined as the first inpatient stay's medical program. The most responsible diagnosis and pre-admit comorbidities were defined by the Canadian Institute of Health Information Diagnosis Type [20], using the ICD-10 code chapters as disease categorizations [21]. We defined fall-risk-related comorbidities as diabetes (with and without complications), obstructive pulmonary disease, dementia, and cerebrovascular disease [22]. Entry mode to the hospital was either from the emergency department or direct. The number of bed transfers within a unit was defined as the total number of physical bed location changes in that unit. Medications were categorized as FRIDs if they were reported to be associated with increasing the risk of fall in the literature, and included benzodiazepines, antidepressants, antipsychotic agents, antihypertensive agents, anti-arrhythmic agents, and opioid analgesics [23]. The count of FRIDs was defined as the number of FRID categories from which medications were administered and having more than one category was defined to be a poly-pharmaceutical use of FRIDs.

Time-related covariates included year and month of admission, whether it was a weekend or weekday, and time-of-admission categorized as morning (00:00–10:00), afternoon (11:00–17:00), and evening (18:00–23:00).

Statistical analysis

We used a parametric (multi-state) semi-Markov model [24, 25] to analyze the time from admission to each primary outcome in the presence of competing events (Fig. 2). We estimated the association of the exposure with the cause-specific hazard rates of time-to-fall (Model 1) and time-to-assessment (Model 2). We assumed that holding time follows a Weibull distribution.

We adjusted the estimates for confounders and covariates impacting the risk of fall or fall-risk assessment completion using a Cox-like proportional hazard model [24]. Covariates correlated with the outcomes were added iteratively and kept only if reduced the estimated model's Akaike information criterion.

The exposure was modeled using time-dependent covariates representing the occupancy levels below and above a tipping point threshold. The first covariate was the maximum of the tipping point threshold and the time-dependent occupancy level at each point in time, whereas the second covariate was the excess occupancy above the tipping point, i.e. maximum of zero and the time-dependent occupancy level minus the tipping point. To estimate the tipping point threshold, we

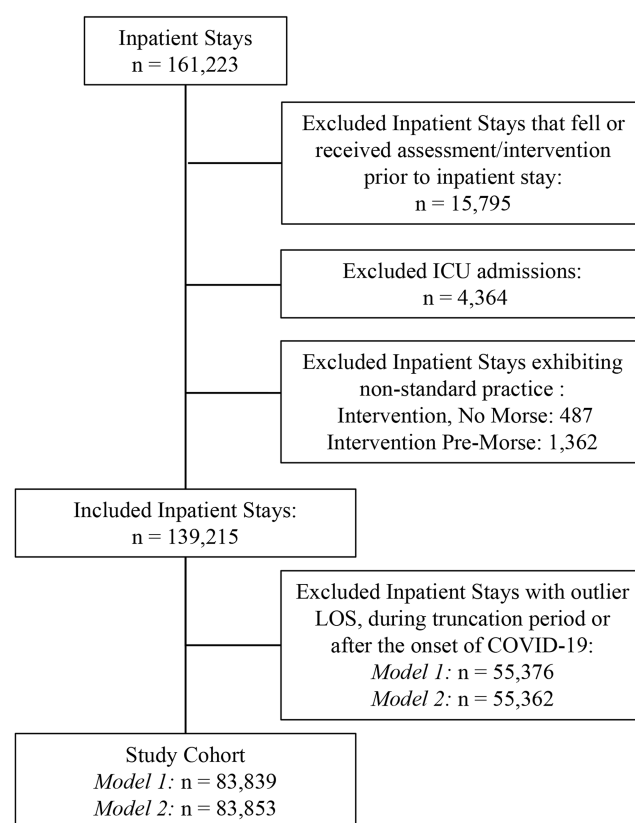


Figure 1 Study design flow chart.

re-estimated each model using thresholds between 0.70 and 1.20 (in increments of 0.01) and chose the threshold resulting in the maximum log-likelihood [12]. We reported the Hazard Ratios (HRs) with 95% Confidence Intervals (CIs) for the exposures and covariates.

Data were analyzed using R software version 4.2.1 (R Project for Statistical Computing) and the estimations were conducted using the *flexsurv* package [25].

Sensitivity analysis

We used a cubic spline model [26] with three knots to examine the robustness of our results to the choice of Weibull distribution for the holding times. We also used an alternative definition of unit capacity, namely the 90th percentile of the midnight census in each year.

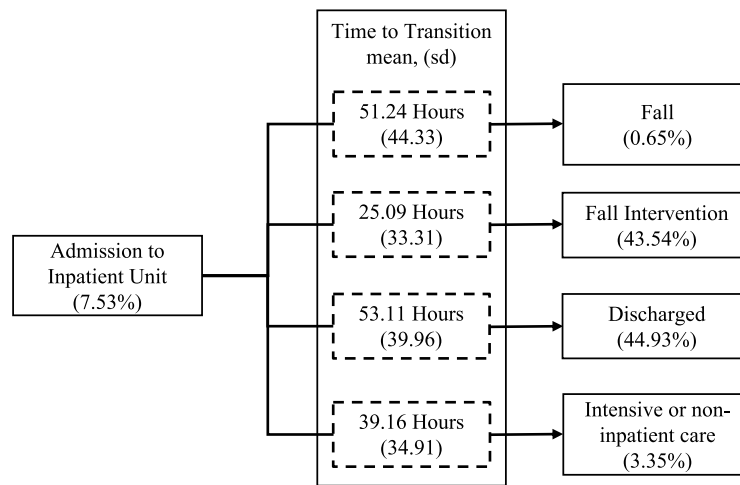
Results

Patient characteristics and time to outcomes

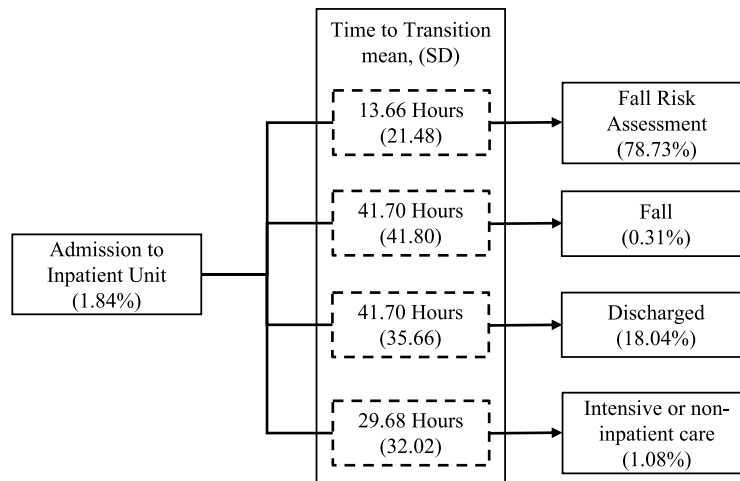
The final cohort included 83 839 inpatient stays for the first fall outcome (Model 1), and 83 853 inpatient stays for the fall-risk assessment completion outcome (Model 2) (Fig. 1). The observed fall rate (considering only the first fall) was approximately 3 falls per 1000 bed days.

Figure 2 summarizes the transitions and mean time to transitions for all outcomes. Summary statistics on the exposure variable are presented in [Supplementary Material](#), Section 3.

For both cohorts, female patients represented 46.76% of the records; the most common age-category was less than 50 years old (23.80%). Table 1 provides a summary of



Model 1: Time to Fall; Time to transition and proportion of visits in each end state



Model 2: Time to Assessment; Time to transition and proportion of visits in each end state

Figure 2 An illustration of the two models and summary of transitions.

patient characteristics stratified by the two models' outcomes. Unstratified characteristics are summarized in [Supplementary Material](#), Section 4.

Time to fall

The estimated tipping point for the fall outcome was 95%; see [Supplementary Material](#), Section 5 for details. [Table 2](#) summarizes the estimated hazard ratios. Exposure to occupancy levels below the tipping point was not associated with the rate of transition to fall (HR: 0.52, [95% CI: 0.21–1.28]), while exposure to occupancy above the tipping point was associated with a statistically significant increase in the hazard rate of transition to fall (HR: 2.24, [95% CI: 1.05–4.20]).

Other covariates with a positive association included all age categories above 50 years old; a most responsible diagnosis of mental, behavioral, and neurodevelopmental disorder; and disease of the nervous system (reference: diseases of the circulatory system); the number of fall-related comorbidities; the number of bed transfers within a unit; and entry to hospital through the emergency department. Covariates with a

statistically significant negative association included patients initially admitted to site: program pairs of A: Multi-organ transplant, A: Cardiology, A: Surgery, B: GIM and B: Surgery (reference of A: GIM); follow-up time; and years 2018, 2019, and 2020 (reference: 2017).

Time to fall-risk assessment

The estimated tipping point for fall-risk assessment completion was 77%; see [Supplementary Material](#), Section 5. [Table 3](#) summarizes the estimated hazard ratios. Exposure to occupancy levels below the tipping point was associated with a statistically significant increase in the hazard rate of transition to fall-risk assessment completion (HR: 1.27, [95% CI: 1.10–1.47]), whereas exposure to occupancy levels above the tipping point was associated with a statistically significant decrease (HR: 0.87, [95% CI: 0.82–0.91]).

Other covariates with a statistically significant positive association were all age categories above 50 years old; site: program pairs of A: GIM—Oncology, A: MOT, A: Cardiology, B: Neurology, and B: GIM (reference: A: GIM); entering

Table 1. Patient characteristics stratified by model outcomes.

Outcome	Model 1: time to fall				Model 2: time to assessment					
	Remain ^a	Fall	Fall-risk intervention	Discharged/death	Intensive or non-IP setting ^b	Remain	Fall	Fall-risk assessment	Discharged/death	Intensive or non-IP setting
n (%)	6313 (7.53)	547 (0.65)	36 503 (43.54)	37 666 (44.93)	2810 (3.35)	1545 (1.84)	262 (0.31)	66 016 (78.73)	15 125 (18.04)	905 (1.08)
Female (%)	46.41	40.77	48.29	46.30	34.98	48.70	40.80	46.80	46.80	39.10
Age (%)										
<50	27.50	11.70	16.40	30.90	19.60	17.30	9.90	22.90	29.30	20.10
50–59	18.30	16.10	15.20	18.80	20.40	14.80	14.90	17.10	18.10	19.60
60–69	22.50	23.00	23.20	22.50	30.10	20.50	26.30	23.10	22.60	27.30
70–79	17.40	21.00	22.10	16.80	21.20	21.90	21.80	19.60	17.40	22.10
80+	14.40	26.10	23.00	11.10	8.70	23.40	27.10	17.30	12.60	10.90
Emergency department hospital entry (%)	70.58	81.90	63.33	52.92	31.21	88.10	82.80	59.70	48.90	45.50
Site of admission (%)										
Hospital A	67.00	56.30	54.30	60.80	79.80	58.30	54.20	59.20	57.90	68.10
Hospital B	33.00	43.70	45.70	39.20	20.20	41.70	45.80	40.80	42.10	31.90
Admitting medical program (%) ^c										
General internal medicine	33.60	44.10	32.60	22.30	9.89	3.95	5.73	6.49	10.50	2.87
General internal medicine—oncology	3.29	3.47	2.51	1.82	0.57	12.80	14.90	10.20	7.39	17.50
Multi-organ transplant	17.30	8.78	12.20	14.90	23.40	49.10	49.20	28.20	21.70	16.10
Surgery	16.00	13.50	23.70	29.60	9.32	0.06	1.53	2.69	0.38	0.22
Arthritis care	1.73	3.84	9.31	6.40	1.07	15.50	9.54	13.70	15.40	25.20
Neurology	15.70	14.60	9.93	8.58	12.10	6.99	7.63	13.70	15.90	27.00
Cardiology	12.40	11.70	9.77	16.40	43.70	11.50	11.50	25.00	28.70	11.20
Bed moves in unit, mean (SD) ^d	0.8 (1.01)	0.62 (0.92)	0.48 (0.84)	0.22 (0.52)	0.28 (0.57)	0.76 (1.03)	0.68 (1.01)	0.4 (0.76)	0.18 (0.47)	0.29 (0.59)
Five most prevalent diagnosis (%)										
Mental, behavioral, and neurodevelopmental disorders	20.66	34.00	2.05	11.74	16.69	25.50	35.50	17.43	12.32	19.56
Disease of the circulatory system	14.62	14.81	13.45	15.29	40.78	13.33	12.98	15.43	14.13	28.40
Neoplasms	11.20	9.32	15.24	12.61	9.43	9.00	9.16	14.14	11.54	11.27
Diseases of the digestive system	9.03	8.04	8.66	11.23	7.54	7.90	7.63	9.64	10.86	8.29
Diseases of the musculoskeletal system and connective tissue	4.26	3.11	8.35	7.56	2.06	5.24	3.44	6.84	10.62	3.44
Other diseases and disorders	49.26	30.72	52.25	41.57	23.50	39.03	31.29	36.52	40.53	29.04
Fall-risk-related comorbidities (%)										
Diabetes	2.41	3.29	1.40	0.64	2.63	3.45	0.34	1.27	0.49	2.32
Diabetes (complications)	3.06	3.47	1.82	1.00	3.00	3.62	0.34	1.67	0.86	3.98
Dementia	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chronic obstructive pulmonary disease	0.76	0.18	0.75	0.31	1.00	1.30	0.00	0.62	0.20	1.33
Cerebrovascular disease	0.48	0.18	0.34	0.16	0.39	0.32	0.38	0.30	0.13	0.55
No fall-risk comorbidity	93.68	93.425	95.86	97.94	93.13	91.97	93.13	96.29	98.35	92.04
Fall-risk inducing drug count, mean (SD)	0.58 (0.89)	0.44 (0.78)	0.39 (0.69)	0.44 (0.71)	0.37 (0.71)	0.25 (0.70)	0.31 (0.69)	0.31 (0.60)	0.35 (0.64)	0.24 (0.64)
Poly-FRID pharmaceutical use (%)	16.50	11.52	7.51	8.64	8.86	7.70	8.40	4.89	6.29	6.00

^aThe Remain outcome refers to inpatient stays who were right-censored after 7 days.^bNon-IP setting are non-inpatient settings, such as post-operation care units.^cPrograms are specific to a site, modeled as a site-program covariate.^dValue is reported as the maximum movement observed in any unit during a stay.

Table 2. Estimated hazard ratios for Model 1 (time to fall).

Covariates	Hazard ratio (95% CI)	P-value
Exposure		
Occupancy below 0.95 threshold	0.52 (0.21–1.28)	.154
Occupancy above 0.95 threshold	2.10 (1.05–4.20)	.037
Time to transition (hours)	0.95 (0.94–0.95)	<.001
Admitting site and medical program		
A: GIM—oncology	1.00 (0.61–1.63)	.996
A: Multi-organ transplant	0.57 (0.40–0.81)	.002
A: Cardiology	0.72 (0.52–1.01)	.054
A: Surgery	0.38 (0.27–0.55)	<.001
B: Arthritis care	0.47 (0.29–0.75)	.002
B: Neurology	1.10 (0.82–1.48)	.534
B: GIM	0.56 (0.44–0.73)	<.001
B: Surgery	0.42 (0.28–0.64)	<.001
A: GIM	1.00 (reference)	
Age category		
50–59	2.05 (1.48–2.83)	<.001
60–69	2.43 (1.80–3.27)	<.001
70–79	2.39 (1.76–3.26)	<.001
80+	2.78 (2.06–3.77)	<.001
<50	1.00 (reference)	
Sex (1 = male)	1.23 (1.04–1.47)	.017
Entry mode (1 = emergency department)	2.51 (1.94–3.26)	<.001
Most responsible diagnosis		
Mental, behavioral, and neurodevelopmental disorder	2.26 (1.69–3.01)	<.001
Disease of the nervous system	1.84 (1.08–3.12)	.024
Other diseases and disorders	1.01 (0.77–1.32)	.960
Disease of the circulatory system	1.00 (reference)	
Count of fall-related comorbidities	2.02 (1.42–2.86)	<.001
Count of bed transfers in unit	1.42 (1.32–1.53)	<.001
Count of fall-risk inducing drugs administered	1.23 (0.93–1.63)	.143
Day of inpatient admission (1 = weekend)	0.91 (0.73–1.13)	.394
Inpatient entry time		
Morning (00:00–10:00)	1.15 (0.92–1.44)	.220
Afternoon (11:00–17:00)	1.01 (0.82–1.25)	.906
Evening (18:00–23:00)	1.00 (reference)	
Inpatient entry year		
2018	0.77 (0.62–0.95)	.016
2019	0.70 (0.56–0.88)	.002
2020	0.47 (0.27–0.83)	.009
2017	1.00 (reference)	
Inpatient entry month		
February	1.04 (0.70–1.55)	.846
March	0.98 (0.65–1.49)	.930
April	1.08 (0.71–1.65)	.716
May	1.12 (0.74–1.69)	.594
June	1.07 (0.70–1.63)	.748
July	0.77 (0.49–1.21)	.252
August	0.96 (0.63–1.47)	.844
September	0.89 (0.58–1.38)	.610
October	0.68 (0.43–1.06)	.091
November	0.81 (0.52–1.26)	.350
December	0.76 (0.49–1.19)	.238
January	1.00 (reference)	

through the emergency department; most responsible diagnosis of mental, behavioral or neurodevelopmental disorders, diseases of the nervous system, and other disorders and diagnosis (reference: diseases of the circulatory system); count of bed transfers in unit; count of fall-related comorbidities; entry to hospital from the emergency department; all years

Table 3. Estimated hazard ratios for Model 2: time to assessment.

Covariates	Hazard ratio (95% CI)	P-value
Exposure		
Occupancy below 0.77 threshold	1.27 (1.10–1.47)	<.001
Occupancy above 0.77 threshold	0.87 (0.82–0.91)	<.001
Time to transition in hours	0.90 (0.9–0.91)	<.001
Admitting site and medical program		
A: General internal medicine—oncology	1.29 (1.22–1.36)	<.001
A: Multi-organ transplant	1.13 (1.10–1.17)	<.001
A: Cardiology	1.04 (1.00–1.07)	.050
A: Surgery	1.01 (0.98–1.04)	.554
B: Arthritis care	1.00 (0.96–1.04)	.900
B: Neurology	1.11 (1.07–1.15)	<.001
B: General internal medicine	1.13 (1.09–1.16)	<.001
B: Surgery	0.73 (0.71–0.76)	<.001
A: General internal medicine	1.00 (reference)	
Age category		
50–59	1.04 (1.02–1.07)	<.001
60–69	1.06 (1.04–1.09)	<.001
70–79	1.05 (1.03–1.08)	<.001
80+	1.05 (1.02–1.08)	<.001
<50	1.00 (reference)	
Sex (male = 1)	0.98 (0.97–1.00)	.014
Entry mode (1 = emergency department)	1.33 (1.30–1.35)	<.001
Most responsible diagnosis		
Mental, behavioral, and neurodevelopmental disorders	1.14 (1.10–1.17)	<.001
Disease of the nervous system	1.20 (1.13–1.27)	<.001
Other diseases and disorders	1.07 (1.05–1.10)	<.001
Disease of the circulatory system	1.00 (reference)	
Poly-FRID pharmaceutical use (1 = yes)	0.84 (0.82–0.85)	<.001
Count of bed transfers in unit	1.09 (1.08–1.10)	<.001
Count of fall-related comorbidities	1.05 (1.01–1.10)	.012
Day of inpatient admission (1 = weekend)	1.05 (1.02–1.07)	<.001
Inpatient entry time		
Morning (00:00–10:00)	1.06 (1.03–1.08)	<.001
Afternoon (11:00–17:00)	1.12 (1.10–1.14)	<.001
Evening (18:00–23:00)	1.00 (reference)	
Inpatient entry year		
2018	1.75 (1.71–1.78)	<.001
2019	2.06 (2.01–2.10)	<.001
2020	2.49 (2.39–2.61)	<.001
2017	1.00 (reference)	
Inpatient entry month		
February	1.02 (0.98–1.05)	.358
March	1.26 (1.21–1.31)	<.001
April	1.38 (1.33–1.44)	<.001
May	1.40 (1.34–1.45)	<.001
June	1.40 (1.35–1.46)	<.001
July	1.37 (1.32–1.43)	<.001
August	1.36 (1.31–1.42)	<.001
September	1.37 (1.32–1.43)	<.001
October	1.34 (1.29–1.40)	<.001
November	1.35 (1.29–1.40)	<.001
December	1.40 (1.35–1.46)	<.001
January	1.00 (reference)	

(reference: 2017) and all months (reference: January) except February.

Covariates with a statistically significant negative association included the follow-up time; male sex; site: program pair of B: Surgery (reference: A: GIM); and the use of multiple fall-risk inducing drugs (reference: less than 2).

Sensitivity analysis

The estimates from the spline models were consistent with the baseline model, except that the association with fall-risk assessment completion below the threshold was no longer significant. The estimated tipping point for the fall outcome was 100%, and exposure to higher occupancy above the tipping point was associated with a statistically significant increase in the hazard rate of transition to fall (HR: 2.21, [95% CI: 1.04–4.72]). The estimated tipping point for the fall-risk assessment outcome was 78%, and exposure to occupancy above the tipping point was associated with a statistically significant decrease in the hazard rate of fall-risk assessment completion (HR: 0.83, [95% CI: 0.79–0.88]). Association below the tipping point was not statistically significant for both the fall outcome (HR: 0.53, [95% CI: 0.24–1.15]), and the fall-risk assessment completion outcome (HR: 0.97, [95% CI: 0.85–1.11]); see [Supplementary Material](#), Section 6.

Under the alternative definition of unit capacity, the estimated tipping point for the fall outcome was 85%, and exposure to higher occupancy above the tipping point did not have a statistically significant association with rate of transition to fall (HR: 2.39, [95% CI: 0.92–6.22]). The estimated tipping point for fall-risk assessment completion was 70%. Increased occupancy above the tipping point was associated with a statistically significant decrease in rate of transition to fall-risk assessment completion (HR: 0.91, [95% CI: 0.85–0.98]), whereas increased occupancy below the tipping point was associated with a statistically significant increase in rate of transition (HR: 1.29, [95% CI: 1.10–1.51]).

Discussion

Statement of principal findings

We found significant associations between unit-level hospital occupancy, increased rate of fall, and reduced rate of fall-risk assessment completion. The associations for both outcomes were significant above an estimated tipping point, which was 95% for the fall outcome and 77% for the fall-risk assessment completion outcome. The association of occupancy level below the tipping point was insignificant for the fall outcome, but significant and positive for the fall-risk assessment completion outcome. The results point to existence of thresholds, below which the nursing teams are resilient and can cope with increased occupancy level, possibly even with increased rate of fall-risk assessment completion. However, increased unit occupancy beyond the thresholds could result in substantial burden on nursing teams and compromise their ability in providing care related to fall-risk assessment and prevention.

Strengths and limitations

We used multiple granular datasets together with innovative applications of semi-Markov models to examine the relationship between hospital occupancy levels, fall-risk assessment, and inpatient falls. A key strength of our study is identifying tipping points on the impact of high occupancy.

Our study also has some limitations. First, the positive association with increased rate of fall was not significant when using an alternative definition of unit occupancy, although the value of the estimate was consistent with the base model. We suspect that this is due to the relatively small number of falls in our data. Second, we did not have access to nurse staffing levels similar to previous studies on occupancy effects

[12] Nevertheless, we suspect that by adjusting the estimates for shift of admission as well as other seasonal effects (day of week, month of the year) we controlled for some of the variations in staffing. Finally, our study relied on data from a single hospital system and limited information on social determinants of health. Extension of the analysis to a more comprehensive patient history and multi-institutional dataset to examine the robustness of the results should be considered in future work.

Interpretation within the context of the wider literature

Previous studies have investigated demographic and clinical determinates of fall risk [27, 28]. In addition to these patient-related factors, our study provides evidence for significant associations of a system-level variable, namely unit-level occupancy, on the rate of fall. While high occupancy levels and capacity strain have been previously linked to poor outcomes in various settings [13–15], to our knowledge, associations with inpatient falls and delivery of fall-risk assessment have not been studied before.

Implications for policy, practice, and research

Our results have important implications for health system capacity planning and design of fall prevention strategies. First, the association between high occupancy and increased rate of fall indicates a cascading effect: higher occupancy results in increased rate of fall incidents, which in turn results in increased LOS and higher capacity strain. Considering the current health human resource crisis, our results reinforce the importance of maintaining adequate nursing capacity to ensure timely and consistent delivery of fall prevention efforts.

Second, the results point out the need for customized guidelines to mitigate the increased risks when hospitals experience or anticipate high levels of capacity strain. Such guidelines could be in form of additional support for the nursing teams, as well as prioritization protocols for allocating the limited available resources to patients at high risk. Machine learning-based predictive models that use routinely collected patient data to provide predictions of surge in occupancy [29] or identify patients at high-risk of fall at the time of admission [30] could support the design and implementation of such guidelines.

Conclusion

Hospital capacity strain could have significant impacts on inpatient falls. Fall prevention strategies should provide tailored guidelines for episodes of high occupancy.

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Author Contributions

Conceptualization: JC, VS, LDP, ST, LBC
Data curation: JC, LDP
Formal analysis: JC, VS

Funding acquisition: VS, LBC
 Investigation: all authors
 Methodology: JC, VS
 Supervision: VS, LBC
 Validation: all authors
 Visualization: JC
 Writing—original draft: JC, VS
 Writing—review and editing: all authors

Supplementary data

Supplementary data is available at *IJQHC* online.

Conflict of interests

No known conflict of interests.

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Data availability

The data underlying this article cannot be shared publicly due to the privacy of individuals that participated in the study.

Ethical approval

The study was approved by the Research Ethics Boards of the University Health Network (UHN) and the University of Toronto.

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