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Nurse staffing practices and adverse events in acute care hospitals: The research protocol of a multisite patient-level longitudinal study

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Abstract

Aims: We describe an innovative research protocol to: (a) examine patient-level longitudinal associations between nurse staffing practices and the risk of adverse events in acute care hospitals and; (b) determine possible thresholds for safe nurse staffing.

Design: A dynamic cohort of adult medical, surgical and intensive care unit patients admitted to 16 hospitals in Quebec (Canada) between January 2015–December 2019.

Methods: Patients in the cohort will be followed from admission until 30-day post-discharge to assess exposure to selected nurse staffing practices in relation to the subsequent occurrence of adverse events. Five staffing practices will be measured for each shift of an hospitalization episode, using electronic payroll data, with the following time-varying indicators: (a) nursing worked hours per patient; (b) skill mix; (c) overtime use; (d) education mix and; and (e) experience. Four high-impact adverse events, presumably associated with nurse staffing practices, will be measured from electronic health record data retrieved at the participating sites: (a) failure-to-rescue; (b) in-hospital falls; (c) hospital-acquired pneumonia and; and (d) venous thromboembolism. To examine the associations between the selected nurse staffing exposures and the risk of each adverse event, separate multivariable Cox proportional hazards frailty regression models will be fitted, while adjusting for patient, nursing unit and hospital characteristics, and for clustering. To assess for possible staffing thresholds, flexible non-linear spline functions will be fitted. Funding for the study began in October 2019 and research ethics/institutional approval was granted in February 2020.

Discussion: To our knowledge, this study is the first multisite patient-level longitudinal investigation of the associations between common nurse staffing practices and the risk of adverse events. It is hoped that our results will assist hospital managers in making the most effective use of the scarce nursing resources and in identifying staffing practices that minimize the occurrence of adverse events.

1 | INTRODUCTION

Research over the past decades has suggested that many nurse staffing practices in acute care hospitals (e.g., using higher nurse-to-patient ratios, overtime hours or less qualified staff) are associated with higher rates of mortality and adverse events (AEs) (Audet et al., 2018; Bae & Fabry, 2014; Griffiths, Recio-Saucedo, et al., 2018; Stalpers et al., 2015). While these studies have made important contributions to the field, the validity of the evidence they have provided has been questioned for two main reasons (Rochefort et al., 2020).

First, most these studies relied on cross-sectional designs which preclude the assessment of the temporal sequence linking an exposure to its presumed outcome (Costa & Yakusheva, 2016; Rochefort et al., 2020). Consequently, whether the occurrence of an AE can be attributed to patient antecedent exposure to a suboptimal nurse staffing practice is uncertain (Audet et al., 2018). Second, most of these studies were multisite investigations that used large administrative databases to determine if hospital-level measures of nurse staffing were associated with mortality and AE rates after controlling for hospital case-mix (Griffiths, Recio-Saucedo, et al., 2018; Needleman et al., 2011). However, this approach entails averaging staffing and AE data over time and across all types of units and patients in a hospital (Audet et al., 2018; Costa & Yakusheva, 2016). As a result, the ability of these studies to guide daily nurse staffing decisions at the bedside has been limited.

To move the field forward, there is a strong need to determine the optimal staffing practices (i.e. the required number of nurses and mixes of skills, education and experience) that are required to decrease the risk of AEs. This is particularly relevant because the current international shortage of nurses is expected to aggravate in the near future (Scheffler & Arnold, 2018; Squires et al., 2017; Tomblin Murphy et al., 2016) and because nursing managers are compelled to apply a variety of staffing practices – for which limited empirical support is currently available – to alleviate the shortage and maintain the accessibility to healthcare services (e.g., using overtime hours, hiring less qualified and less costly workers such as licensed practical nurses [LPNs]) (Everhart et al., 2013; Garner & Boese, 2017; Yakusheva et al., 2013). In addition, given the stretched public finances, many hospitals are urged to identify more affordable staffing plans, thus hastening the routine use of less skilled nursing workers and of overtime hours during periods of peak staffing demand (Garner & Boese, 2017; Yakusheva et al., 2013). To help hospital managers optimize current staffing practices, the next step in investigation is to determine the temporal relationships between these practices and the incidence of AEs and the thresholds for safe staffing. To this end, patient-level longitudinal studies are required.

1.1 | Background

In 2014, we received funding from the Canadian Institutes of Health Research to assemble a cohort of all adult medical, surgical and intensive care patients admitted to a large university health centre in Quebec (Canada) (Rochefort et al., 2015). Using digitized payroll and patient data, we examined how shift-to-shift variations in several nurse staffing practices were related to the risk of all-cause in-hospital death. We found that every 5.0% increase in the cumulative proportion of understaffed shifts since hospital admission was associated with a 1.0% increase in the risk of death (Rochefort et al., 2020). Moreover, we noted that every 5.0% increase in the cumulative proportion of worked hours by baccalaureate-prepared Registered Nurses (RNs) decreased the risk of death by 2.0%. Last, we found that RNs' levels of experience and the proportion of non-RN staff were not related to the risk of death (Rochefort et al., 2020).

To the best of our knowledge, our study was the first patient-level longitudinal investigation conducted in Canada and, as of today, only two other international teams of investigators have conducted similar studies (Griffiths, Maruotti, et al., 2018; Needleman et al., 2011). Although these three studies included extensive controls for potential sources of an increased risk of in-hospital mortality other than variations in nurse staffing practices, our results have been inconsistent. For instance, while we noted that the increased proportion of non-RN staff (e.g., LPNs, patient care attendants [PCAs]) was unrelated to the risk of all-cause in-hospital mortality, Griffiths et al. (2018) reported a significant curvilinear association, which suggests the existence of an optimal threshold for that specific nurse staffing practice. Two explanations have been proposed for these inconsistencies.

First, these longitudinal investigations were all single-site studies. Consequently, they were highly vulnerable to the effect of baseline local staffing practices. For example, the hospital in our study was characterized by a very low usage of non-RN staff across its various units, whereas non-RNs were highly prevalent in Griffith's et al. hospital (Griffiths, Maruotti, et al., 2018; Rochefort et al., 2020). To address this limitation and generate more robust evidence on the potential impact of nurse staffing practices on patient outcomes, an important contribution of this study is to propose a patient-level multisite investigation.

Second, while all-cause mortality is a common indicator of healthcare quality (Diley et al., 2014; Ngantcha et al., 2017), it has been criticized by several scholars for its lack of sensitivity to nursing interventions (Audet et al., 2018; Stalpers et al., 2015), which may also have contributed to the aforementioned inconsistencies. To address this limitation and better elucidate the mechanisms by which nursing contributes to safer patient care, many have called for greater research attention to 'nursing-sensitive' AEs (i.e., AEs

that can plausibly be linked to lapses in nursing interventions potentially attributable to suboptimal staffing practices) (Sim et al., 2018; Stalpers et al., 2016). Therefore, another important contribution of this study and a direct extension to our prior work in this area (Rochefort et al., 2020), will be to model the effect of selected nurse staffing practices on a set of nursing-sensitive AEs.

2 | THE STUDY

2.1 | Aims

The objectives of this study are to: (a) examine the associations between nurse staffing practices and the risk of AEs; and (b) determine thresholds for safe nurse staffing.

2.2 | Settings

This study builds on a unique research partnership among researchers and decision-makers from 16 hospitals selected from three distinct university health networks and from various regions in the Province of Quebec (Canada). Together, these hospitals receive more than 225,000 admissions per year and employ more than 25,000 RNs, LPNs and PCAs.

2.3 | Design and population

The design for this study builds on our prior research work on the topic (Rochefort et al., 2020; Rochefort, Buckeridge, et al., 2015). Specifically, a dynamic cohort of all adult patients admitted to the study hospitals between 1 January 2015–31 December 2019 will be assembled. Patients in the cohort will be followed during the inpatient and 30-day postdischarge period to assess exposure to selected nurse staffing practices in relation to the subsequent occurrence of four AEs: (a) failure-to-rescue (FTR); (b) in-hospital falls; (c) hospital-acquired pneumonia (HAP); and (d) venous thromboembolism (VTE). Patient follow-up time will stop at 30 days postdischarge to allow enough time for AEs 'incubating' at the time of discharge to occur (e.g., HAP, VTE, FTR) and for patients to return to the hospital (Figure 1) (Rochefort, Buckeridge, et al., 2015). Because in-hospital falls, by definition, cannot occur after discharge, the follow-up period for this particular AE will stop at hospital discharge. Patients will be enrolled in the cohort if they were: (a) admitted on a medical, surgical or intensive care unit at the participating sites; (b) not initially admitted for one of the AEs of interest; and (c) not hospitalized in the previous 30 days (Figure 1). Re-hospitalizations by the same patient, occurring after the end of the follow-up period for a hospitalization episode, will be eligible for inclusion (Figure 1) (Rochefort, Buckeridge, et al., 2015).

Adverse events and their dates of occurrence will be ascertained from electronic health record data retrieved at the participating sites. For patients experiencing multiple AEs, or relapses of the same AE over a given hospitalization, only the first AE will be selected (Rochefort, Buckeridge, et al., 2015). Patients with no records of a hospitalization in the previous 30 days and presenting to the hospital with one of the AE of interest (e.g., pneumonia, VTE), or developing such an AE within 48 hr of admission (with the exception of in-hospital falls), will be excluded from the cohort as these AEs are most likely community-acquired and therefore totally unrelated to in-hospital staffing practices (Rochefort, Buckeridge, et al., 2015). Last, patients: (a) with no AE until the end of the follow-up period; (b) dying of causes other that FTR; or (c) readmitted to the hospital
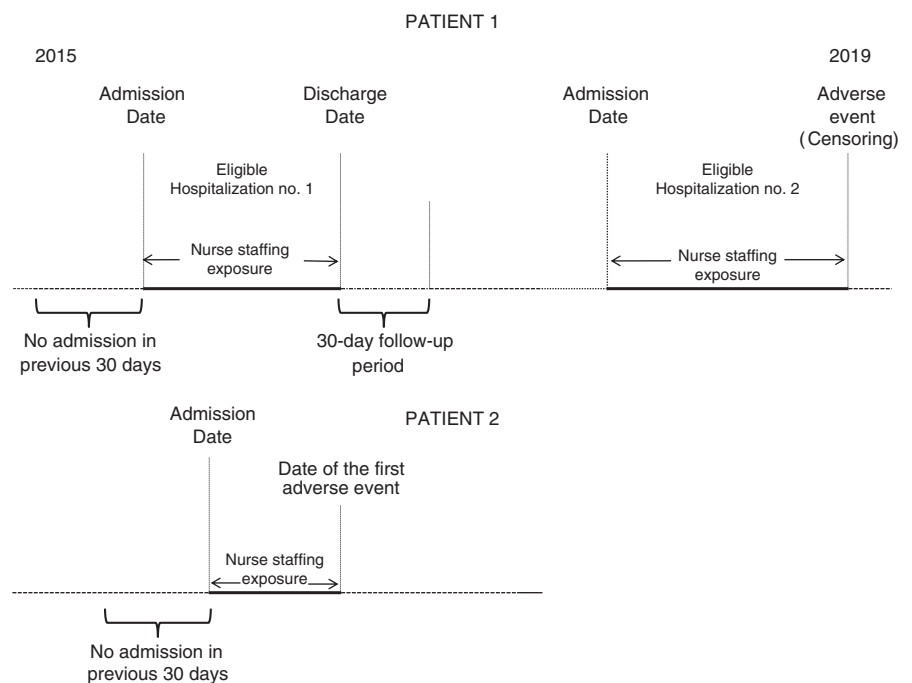

FIGURE 1 Study design

during the follow-up period for any reasons other than the AEs of interest, will be censored at that time (Figure 1).

2.4 | Data sources

Patient and AE data required for this study will be extracted from the clinical data warehouses at the participating sites, which are relational databases containing demographic, administrative and clinical (e.g., laboratory, radiology) data obtained from major information systems. The *Payroll Database* will give data on all worked hours (regular and overtime) by members of the nursing staff by shift and nursing unit, and staff's levels of experience and education. Patient, AE and staffing data will be linked by date, nursing unit and shift.

2.5 | Measures

2.5.1 | Adverse events

The four AEs of interest are defined as: (a) *FTR*: death following a set of potentially preventable AEs (Needleman & Buerhaus, 2007; Needleman et al., 2002); (b) *in-hospital falls*: an unplanned descent to the floor, with or without injury, occurring during a hospitalization (Agency for Healthcare Research & Quality, 2019); (c) *HAP*: an infection of the lung parenchyma occurring 48 hr or more after hospital admission in patients with no evidence of pneumonia on admission (Kalil et al., 2016; Torres et al., 2017) and; (d) *hospital-acquired VTE*: a thrombus identified in the deep veins of the upper or lower extremities or in the pulmonary arteries 48 hr or more after hospital admission in patients with no evidence of VTE on admission (Assareh et al., 2016).

These AEs were selected for their potential associations with nurse staffing practices and nursing interventions (i.e., nursing-sensitive AEs) (Audet et al., 2018; Stalpers et al., 2015) and for their major impacts on patient outcomes and healthcare costs (Lyman et al., 2018; Pradarelli et al., 2016; Roquilly et al., 2015; Siracuse et al., 2012). Moreover, they also all have high incidence rates: FTR occurs in 5–7% of patients experiencing potentially preventable AEs (Assareh et al., 2014; Ou et al., 2014), whereas falls characterize 2–3% of all hospitalizations (Bouldin et al., 2013). HAPs have an incidence of 1–2% and represent 15% of all hospital-acquired infections (Giuliano et al., 2018; Torres et al., 2017). Last, in patients receiving thromboprophylaxis, the incidence of VTE ranges from 2–30% (Fanikos et al., 2011; Grosse et al., 2016).

Failure-to-rescue will be measured from discharge diagnostic and procedure codes, which represent the most valid approach currently available for measuring this specific AE (Needleman & Buerhaus, 2007; Needleman et al., 2002). The occurrence of in-hospital falls, HAP and VTE (and the date and time of their occurrence) will be ascertained by applying natural language processing models to electronic health record data retrieved at the participating sites (Chapman et al., 2001; Rochefort et al., 2015; Toyabe, 2012). This approach has been shown to be more accurate than discharge diagnostic codes for measuring these AEs (Dublin et al., 2013; Stanfill et al., 2010).

2.5.2 | Nurse staffing practices

Nurse staffing practices in a given hospital vary from one unit to the next and in a given unit on a shift-by-shift basis as a function of the fluctuations in patients' demands for nursing care and due to unpredictable absenteeism (Rochefort, Buckeridge, et al., 2015). For this reason, updated patient exposure to nurse staffing practices will be measured on every shift of a hospitalization episode using the following time-varying indicators:

Staffing intensity, an indicator of the overall availability of the nursing staff, will be defined as the number of nursing worked hours per patient per shift (NWHPPS) (Patrician et al., 2011; Van den Heede et al., 2007). NWHPPS will be calculated by dividing the total number of worked hours by all members of the nursing staff (i.e., RNs, LPNs, PCAs) on the unit and shift where the patient is currently hospitalized by the start-of-shift patient census for that unit and shift (Patrician et al., 2011; Van den Heede et al., 2007).

RN skill mix is an indicator of the extent of availability of RNs among the nursing staff and richer RN skill mixes have been linked to better patient outcomes (Aiken et al., 2017; Van den Heede et al., 2007). RN skill mix will be measured, for each unit and shift of a hospitalization, as the proportion of NWHPPS reported by RNs (Griffiths, Recio-Saucedo, et al., 2018; Van den Heede et al., 2007).

Overtime use has been associated with increased fatigue and reduced vigilance, which may induce lapses in care processes and, consequently, increase the likelihood of AEs (Bae & Fabry, 2014; Stimpfel et al., 2012). Overtime use will be measured for each unit and shift of a hospitalization as the proportion of NWHPPS worked in overtime (Drebit et al., 2010).

RN experience: For each nursing unit and shift, the average number of years of experience held by all RNs who reported worked hours for that unit and shift will be measured (Van den Heede et al., 2007). This measure is meant to reflect the fact that RNs typically give patient care as a team on a given unit and shift (Kalisch et al., 2013; Rochefort et al., 2011).

RN education: Baccalaureate degree education is expected to offer RNs with better knowledge, skills and interventions for preventing AEs or reducing their impact (Blegen et al., 2013; Kutney-Lee et al., 2013). For each nursing unit and shift, the observed proportion of baccalaureate-prepared RNs' worked hours among all RNs' worked hours (education mix) will be calculated (Audet et al., 2018; Van den Heede et al., 2007).

2.5.3 | Duration and intensity of patient exposure to nurse staffing practices

Four alternative approaches will be used to represent each nurse staffing practice in the analyses: (a) *current exposure* on the present

shift; (b) *mean recent exposure* over the previous *n* hours (e.g., 24, 48, 72 & 96 hr); (c) *mean exposure* since hospital admission and (d) *weighted cumulative exposure*, a novel analytic approach developed by our research team that combines information on timing, duration and intensity of past exposures into a single metric (Danieli & Abrahamowicz, 2019; Danieli et al., 2019; Sylvestre & Abrahamowicz, 2009). It is hoped that these approaches will give further insights on the specific mechanisms by which time-dependent patterns of nurse staffing exposure influence the risk of AEs.

2.5.4 | Potential confounders common to all AEs

Several patient and organizational characteristics may increase the likelihood of FTR, in-hospital falls, HAP or VTE. These characteristics, listed below, will be measured and adjusted for in the analyses.

2.5.5 | Patient characteristics

Patient age on admission and sex will be measured from the discharge abstract database. Comorbidities will be measured on admission using the Charlson Comorbidity Index (Charlson et al., 1987; Quan et al., 2011). Comorbidities will be identified from discharge diagnostic codes from all prior hospitalizations at the participating sites since 2010 (i.e., the earliest date for which complete data are available). Severity of illness on admission will be estimated using the Laboratory-based Acute Physiology Score (LAPS), which integrates the results of 14 laboratory tests performed in the first 24 hr of hospital admission into a continuous variable (Escobar et al., 2008). Possible LAPS values range from 0-256, with higher ones indicating a higher severity of illness (Escobar et al., 2008). The type of hospital admission (i.e. urgent, semi-urgent and elective/non-urgent) will be obtained from discharge abstracts. To adjust for possible temporal trends, the year and month when a hospitalization took place will be accounted for in the analyses.

2.5.6 | Nursing unit and hospital characteristics

To adjust for unit-specific work environment characteristics that may have an impact on nurses' work (Rochefort et al., 2020; Stalpers et al., 2015), a time-varying variable representing the current unit of hospitalization will be measured. In addition, time-varying covariates will be used to characterize the current: (a) unit of hospitalization as a medical, surgical, or intensive care unit, (b) day (weekday or weekend); (c) shift of hospitalization (night, day or evening); and (d) unit occupancy as observed at the beginning of the current shift. To quantify nursing workload on a given nursing unit and shift, a time-varying measure of patient turnover rate will be used (Needleman et al., 2011). Patient turnover rate will be measured as the total number of admissions and discharges observed during a given shift on the unit where the patient is currently hospitalized divided by the

start-of-shift patient census on that unit and that shift (Needleman et al., 2011). Last, to test for possible differences across hospitals and to adjust for the effect of unmeasured hospital-level characteristics (e.g. volume, size, location) that may also have an impact on outcomes, a fixed-in-time covariate representing the hospital at which the patient is located will be measured.

2.5.7 | Other AE-specific confounders

In addition to the confounders common to all AEs, AE-specific confounders will also be measured and adjusted for in the analyses. These AE-specific confounders will be measured using discharge diagnostic codes or hospital pharmacy data. *Falls*: (a) history of previous falls; (b) mobility impairments; (c) cognitive impairments; and (d) usage (yes vs. no) of selected drugs associated with a higher risk of falls (Fernando et al., 2017; Kropelin et al., 2013); *VTEs:* (a) history of previous VTEs; (b) anticoagulant drug use (yes vs. no); (c) recent surgeries; and (d) mobility impairments (Engbers et al., 2010; Previtali et al., 2011); *HAP:* (a) reduced mobility; (b) cognitive impairments; (c) length of intensive care unit stay; and (d) length of mechanical ventilation (Ewan et al., 2017; Walaszek et al., 2016).

2.6 | Statistical analyses

Descriptive statistics will be used to summarize patient, nursing unit and nurse staffing characteristics. The associations between the selected nurse staffing practices and AE occurrence will be examined using separate multivariable Cox proportional hazards regression models for each AE of interest (Cox, 1972). For each AE-specific model, time zero will correspond to the date of hospital admission and time to event will be defined as the time to the first AE of interest. Patients who had no AE by the end of the follow-up period, or who died of causes other that FTR before experiencing an AE of interest will be censored at that time. All models will adjust the effects of the nurse staffing exposures (i.e., staffing intensity, skill mix, overtime, education and experience) for the patient characteristics (i.e., age, sex, comorbidities, severity of illness, type, year and month of hospital admission) and current nursing unit and hospital characteristics (i.e., type of nursing unit, unit occupancy, shift, patient turnover rate, current hospital) described in the previous subsections, while modelling the current nursing unit of hospitalization as a random effect (frailty) (Ha et al., 2011, 2017). Each model will be further adjusted for the aforementioned AE-specific risk factors. For continuous covariates, the flexible spline-based extension of the Cox model will be used to test for non-linear effects and, if necessary, account for such non-linearities (Wang et al., 2020; Wynant & Abrahamowicz, 2014).

In each AE-specific regression model, exposure to each nurse staffing practice will be defined in four alternative ways, each using a different time-varying exposure metric: (a) *current exposure* on the present shift; (b) *mean recent exposure* over the previous *n* hours and

including the current shift; (c) *mean exposure since hospital admission up to the current shift* and d) *weighted cumulative exposure* (Sylvestre & Abrahamowicz, 2009). For the latter, the weights, that describe how the relative importance of past exposures vary depending on how long ago they occurred, will be estimated using a flexible cubic spline function to avoid any a priori assumptions on the shape of the weight function (Sylvestre & Abrahamowicz, 2009). Because nurse staffing practices vary both between and in units (and across shifts) and since patients move from unit to unit, all staffing variables will be normalized relative to the mean values for the current unit and shift (Griffiths, Maruotti, et al., 2018). As a consequence, our estimates for the effect of nurse staffing practices will reflect variations in units (and shifts) rather than variations between units, as the latter may mostly reflect systematic differences in the required levels of care (Griffiths, Maruotti, et al., 2018). The fit of the alternative exposure models will be compared with the Akaike Information Criterion (Akaike, 1974) and the best-fitting model for a given AE indicator will be selected for subsequent analyses (Abrahamowicz et al., 2012). Adjusted hazard ratios (HRs) will be estimated for the best-fitting models and the corresponding 95% confidence intervals (CIs) will be estimated using the non-parametric cluster bootstrap resampling approach (Xiao & Abrahamowicz, 2010), which will account for both additional variance due to: (a) patient clustering within nursing units, (b) data-dependent selection of the final best-fitting exposure model.

To assess for the presence of optimal nurse staffing thresholds, the aforementioned flexible extension of the Cox model that uses non-linear spline functions to estimate how the hazard varies with increasing value of the predictor (here, the five measures of nurse staffing practices), will be fitted (Abrahamowicz & MacKenzie, 2007). The null hypothesis that the effect of nurse staffing practices is linear will be tested with a non-parametric likelihood ratio test, comparing the partial deviance of the linear model with that of the non-linear one (Abrahamowicz & MacKenzie, 2007). Values of $p < .05$ for the likelihood ratio test will indicate that the non-linear model gives significantly better prediction of AEs' occurrence than the linear model, in which case the estimated spline functions may indicate the threshold effect of nurse staffing. The 95%CI for non-linear HRs derived from splines will be estimated using bootstrap resampling (Efron & Tibshirani, 1993). To assess whether the effect of a given nurse staffing practice (e.g., staffing intensity) is modified by another staffing practice (e.g., skill mix), the statistical significance of their interaction will be assessed.

The proportional hazards assumption will be verified with a non-parametric likelihood ratio test comparing partial deviance of the proportional model to a flexible time-dependant one (Abrahamowicz & MacKenzie, 2007). In the case of significant violation of the proportionality hypothesis, the flexible model will estimate how the covariate effect (adjusted HR) changes during the follow-up (Abrahamowicz & MacKenzie, 2007; Wang et al., 2020; Wynant & Abrahamowicz, 2014). To account for possible non-random (informative) censoring on death, inverse probability censoring weights will be used in sensitivity analyses (Hernan et al., 2000;

Robins & Finkelstein, 2000). For patients with repeated hospitalizations over the study period, we will randomly select one hospitalization per patient. Cox regression with frailty terms (random effects) will be implemented in SAS, whereas flexible spline-based models and the weighted cumulative exposure model will be implemented in R.

2.6.1 | Statistical power considerations

Based on historical data offered by each participating site, we expect 225,000 eligible hospitalizations per year over the 5-year follow-up period. Assuming a conservative incidence rate of 1.0% for HAP and falls (Bouldin et al., 2013; Torres et al., 2017), we estimate that the Cox regression models for the current exposure to each of the selected nurse staffing practices will have excellent 90% power (at two-tailed $\alpha = 0.05$) to detect very small effects corresponding to relative reductions in the risk of HAP or falls of: (a) 1.2% (HR = 0.988) for every 30-min increase per patient per shift in staffing intensity, (b) 1.8% (HR = 0.982) for every 5% increase per shift in RN skill mix, (c) 0.9% (HR = 0.991) for every 5% increase per shift in the proportion of baccalaureate-prepared RNs and (d) 0.7% (HR = 0.993) for each additional year of experience held by a team of RNs. In addition, these models will have 90% power to detect a risk increase of 0.7% (HR = 1.007) for every 1% increase in overtime hours per shift. Given that FTR and VTE have higher incidence rates, the power to detect associations with these events will be even higher, resulting in the detectable HRs being even closer to 1.0. Even if we account for potentially moderate clustering within nursing units, which may reduce the effective sample size, the power remains excellent. Last, in comprehensive simulation studies, the weighted cumulative exposure model has been shown to have good power, adequate precision and good ability to detect complex cumulative effects of exposure with only 250–500 events (Abrahamowicz et al., 2012; Sylvestre & Abrahamowicz, 2009). Given that a minimum of 10,000 occurrences are expected for each of the less frequent AEs (i.e., HAP, falls), our analyses using this model will also have excellent power.

2.7 | Ethical considerations and current study status

This five-year study (2019–2024) was funded by the Canadian Institutes of Health Research in late 2019. All required research ethics and institutional approvals for initiating this study were received by February 2020. Unfortunately, the study was completely stopped in March due to the COVID-19 pandemic and it is now resuming (October 2020). All data extracted for the purpose of this project will be entirely depersonalized and used strictly for research purposes. Encrypted patient medical record numbers will be used for linking all the required data sources across nursing units, shifts and time. All research data will be kept in a secured server located at the research institution of the principal investigator. No nominal data about patients will be collected or used during this study.

3 | DISCUSSION

3.1 | Knowledge dissemination and exchange activities

To facilitate the dissemination and uptake of the new knowledge that will be generated by this study, we have partnered with key decision-makers at each of the participating sites who are engaged as collaborators/knowledge users on the project, have significantly contributed to its development and to the selection of high-priority staffing practices and AE indicators. It is hoped that this level of engagement will facilitate the development of practice-relevant knowledge that will contribute to optimize the use of nursing resources and patient safety. To reach a broader audience of decision-makers and knowledge users, we have planned a series of activities, including webinars and meetings with national/provincial stakeholders (e.g., Ministry of Health, Directors of Nursing, Nursing Union representatives). In addition, we will organize community-based events to inform the population and the media about our findings. Last, the results from this study will also be communicated through conference presentations and open access publications in peer-reviewed journals.

3.2 | Potential limitations and mitigation strategies

To ease data access and ensure that this study is conducted within the proposed timelines, we have secured a research partnership with the CEOs of each site and have involved their Directors of Nursing as key collaborators / knowledge users on this project. In addition, most of the required data sources have been standardized across sites, either for reimbursement or reporting purposes (e.g., Discharge Abstract Database) or as part of the creation of Quebec's provincial electronic health record (e.g., pharmacy, microbiology and radiology data). This high level of standardization will facilitate data integration across sites for analytical purposes. Moreover, given the use of a patient-level longitudinal design involving 5 years of hospitalization data from 16 hospitals, we anticipate a very large volume of data, which cannot easily be stored nor analysed on typical desktop computers. To address this limitation, we have purchased high-capacity database and analytical servers. These servers are located in a secured server room at the research institution of the principal investigator, therefore addressing another important issue associated with this type of study: data security. Last, although the use of a multisite patient-level longitudinal design addresses many of the limitations of earlier cross-sectional studies and eliminates many plausible alternative explanations, causation cannot be inferred from the observed associations and confounding and remains an opportunity.

3.3 | Timelines

Based on our prior research work in this area and given the multisite nature of the project, it is estimated that this study will take 5 years to conduct (Figure 2). We have budgeted the first year for research ethics approval and data extraction, validation and preparation at each site. Then, we have planned four overlapping cycles of data analyses / knowledge translation (i.e., one per AE) (Figure 2). A data extraction update is planned at 24 months to ensure contemporaneous data for the analyses.
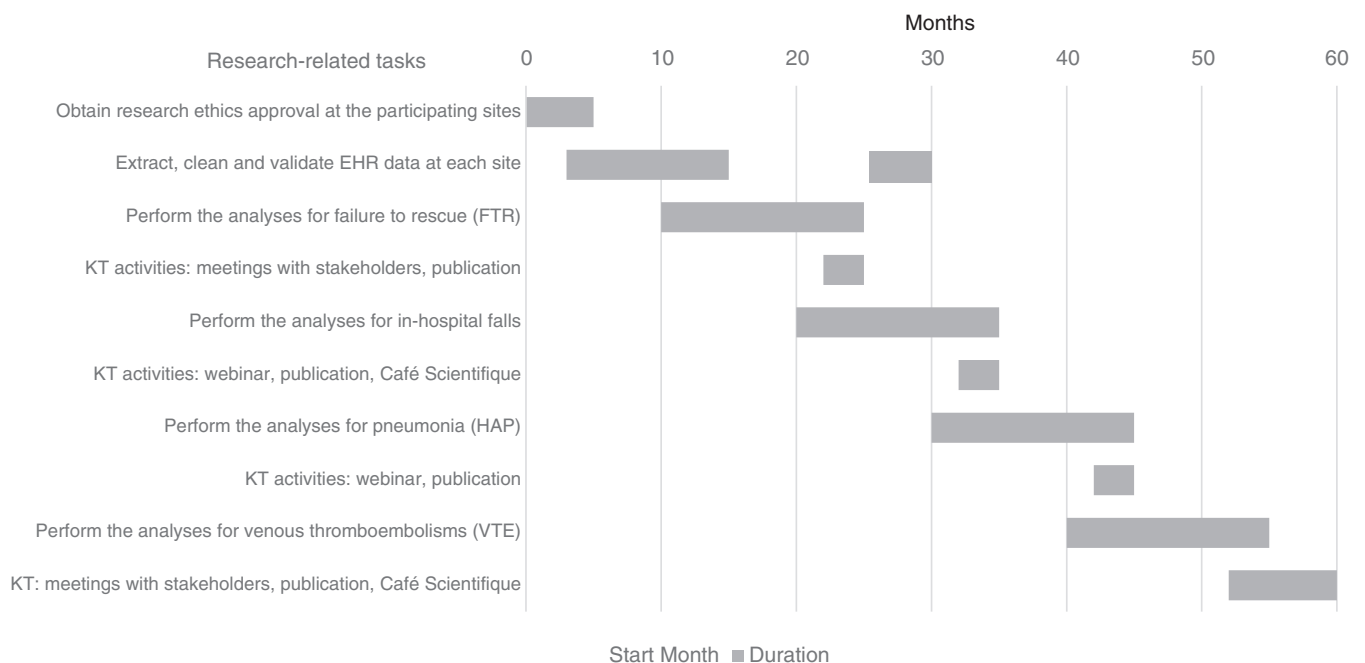

FIGURE 2 Study timelines. EHR, electronic health record; KT, knowledge transfer

4 | CONCLUSION

To our knowledge, this study is the first multisite patient-level longitudinal investigation to examine the associations between common nurse staffing practices and the risk of AEs. Our flexible analyses will permit a better understanding of the complex temporal relationships linking patterns of past nurse staffing exposures with the risks of serious AEs. The results of this study will most likely assist hospital managers in making the most effective use of the scarce nursing resources and in implementing staffing practices that minimize the incidence of AEs. Eventually, the work initiated in this study could serve as a steppingstone towards the development of a managerial decision-support system. Such a system could offer hospital managers with shift-by-shift updates on the risk of AEs on their unit given current patient characteristics and available nursing resources. Moreover, it could help select among alternative staffing options (e.g., using overtime hours or a leaner RN skill mix), the one that minimizes the risk of AEs or is the most cost-effective. Thus, our research work has the potential to lead to future research developments that will most likely help hospital managers face current economic pressures and shortages of nursing staff, while ensuring safer patient care.

CONFLICT OF INTEREST

No conflict of interest has been declared by the authors.

AUTHOR CONTRIBUTIONS

All authors have agreed on the final version and meet at least one of the following criteria (recommended by the ICMJE https://can01.safelinks.protection.outlook.com/?url=http%3A%2F%2Fwww.icmje.org%2Frecommendations%2F&data=04%7C01%7CChristian.Rochefort%40USherbrooke.ca%7Cb12bd131c80145b83a6708d88c728cc8%7C3a5a8744593545f99423b32c3a5de082%7C0%7C0%7C637413770897020032%7CUnknown%7CTWFpbGZsb3d8eyJWIjoiMC4wLjAwMDAiLCJQIjoiV2luMzIiLCJBTiI6Ik1haWwiLCJXVCI6Mn0%3D%7C1000&sdata=O5PsmNzKNdQdU437%2FoAxHTVG0vMWczxdmxqXTjpCupo%3D&reserved=0):

1. substantial contributions to conception and design, acquisition of data, or analysis and interpretation of data;
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