JAN JOURNAL OF ADVANCED NURSING

ORIGINAL RESEARCH

The relationship between in-hospital mortality, readmission into the intensive care nursing unit and/or operating theatre and nurse staffing levels

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Accepted for publication 9 July 2011

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DIYA L., VAN DEN HEEDE K., SERMEUS W. & LESAFFRE E. (2012) The relationship between in-hospital mortality, readmission into the intensive care nursing unit and/or operating theatre and nurse staffing levels. *Journal of Advanced Nursing* **68**(5), 1073–1081. **doi: 10.1111/j.1365-2648.2011.05812.x**

Abstract

Aim. The aim of this article was to assess the relationship between (1) in-hospital mortality and/or (2) unplanned readmission to intensive care units or operating theatre and nurse staffing variables.

Background. Adverse events are used as surrogates for patient safety in nurse staffing and patient safety research. A single adverse event cannot adequately capture the multi-dimensional attributes of patient safety; hence, there is a need to consider composite measures. Unplanned readmission into the postoperative Intensive Care nursing unit and/or operating Theatre and in-hospital mortality can be viewed as measures that incorporate the effects of several adverse events.

Methods. We conducted a Bayesian multilevel analysis on a subset of the 2003 Belgian Hospital Discharge and Nursing Minimum Data sets. The sample included 9054 patients who underwent coronary artery bypass surgery or heart valve procedures from 28 Belgian acute hospitals. Two proxies of patient safety were considered, namely postoperative in-hospital mortality in the first postoperative intensive care unit and unplanned readmission into the intensive care and/or operating theatre (including mortality beyond the first postoperative intensive care unit) after the first-operative intensive care nursing unit.

Results. There is an association between in-hospital mortality and/or unplanned readmissions and nurse staffing levels, but the relationship is moderated by volume and severity of illness respectively. In addition, the relationship differs between the two endpoints.

Conclusion. Higher nurse staffing levels on postoperative general nursing cardiac surgery units protected patients from unplanned readmission to intensive care units or operating theatre and in-hospital mortality.

Keywords: Bayesian analysis, multilevel analysis, nurse staffing, patient safety, posterior predictive checks

Introduction

Many studies across the globe have shown that there exists a relationship between nursing resources, in particular nurse staffing levels (Aiken *et al.* 2002, Rafferty *et al.* 2007, Van den Heede *et al.* 2009a) and patient safety. Adverse events are often used as proxies for patient safety. However, as most studies make use of routinely collected administrative databases, numerous measurement problems exist. An important weakness of many administrative databases is that the information about the sequence in which events occurred during the course of a patient's hospitalization is not coded. Therefore, when and where (i.e. which nursing unit) the adverse events occurred are unknown. Moreover, the presence on admission of secondary diagnosis is not recorded, making it difficult to distinguish co-morbidities from complications.

As a result of these measurement problems authors frequently use 'mortality' as indicator of patient safety. After all, mortality can be clearly defined and in combination with a length-of-stay variable, the moment (and sometimes the place) when (and where) a patient died can be calculated (Diya *et al.* 2010). The main aim of this article is therefore to explore the relationship between nurse staffing and patient safety using an indicator that expands on mortality. 'Unplanned readmission to the intensive care unit or operating theatre' was selected as the indicator, as this indicator is assumed to highlight various patient safety problems and can technically be derived from most administrative databases used in this field of research.

The study

Aim

The specific objectives of this article are: (1) to study the relationship between in-hospital mortality and nurse staffing variables for cardiac patients in the first-operative intensive care nursing unit and (2) to study the relationship between, on one hand, nurse staffing variables and, on the other hand, a composite end-point of patient readmission to the intensive care unit (ICU) and/or the operating theatre (OT) and in-hospital mortality for cardiac surgery patients who stayed in the first-operative general nursing unit (and beyond).

Design

A retrospective analysis of cross-sectionally collected multi-level data was conducted.

Sample

The study sample consists of 9054 patients aged between 20 and 85 years who were electively admitted to a Belgian acute hospital ($n = 28$) in 2003 for a coronary artery bypass graft (CABG) or heart valve procedure. Patients were considered as having a CABG or heart valve procedure, if they were assigned to one of the following categories from All Patients Refined Diagnosis-Related-Group (APR-DRG), version 15.0: 162 (heart valve procedure with heart catherization); 163 (heart valve procedure without heart catherization); 165 (CABG with heart catherization); and 166 (CABG without heart catherization) (Van den Heede *et al.* 2008). The selected cardiac procedures involved specialized care that is delivered in 29 of the 115 Belgian acute care facilities. One hospital was dropped from the analysis, because there was no link between the two administrative databases.

The pre-operative nursing units were not considered here, as there are very few events occurring in this period, and also it is highly unlikely that nurse staffing levels have a major effect during this period. The operating theatre was also dropped, as there were only three deaths in the operating theatre and no nurse staffing variables were available. So this article will concentrate on the period starting with the first postoperative intensive care nursing unit as shown in Figure 1 below.

The first postoperative intensive care nursing unit is the first intensive care nursing unit that a patient enters immediately after coming from the operating theatre. The first postoperative general nursing unit is also the first general nursing unit that a patient enters after a surgical procedure is done.

Data collection

Two routinely collected administrative databases (i.e. the Belgian Nursing minimum Dataset and the Belgian Hospital Discharge Dataset) for the year 2003 are used. Both datasets are described in more detail, elsewhere (Van den Heede *et al.* 2009a).

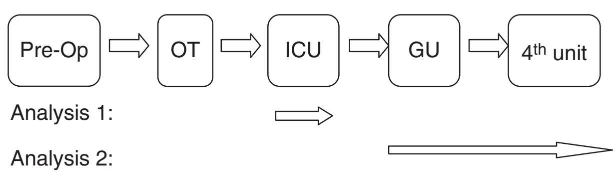

Figure 1 Cardiac surgery patient trajectory. Note: Pre-Op, pre-operative nursing units, OT, operating theatre, ICU represents the first postoperative intensive care nursing unit, GU represents the first postoperative general nursing unit and 4th unit represents the totality of units past the first postoperative general nursing unit.

Ethical considerations

The study committee appointed by the Ministry of Science Policy gave the Research Ethics Committee approval for this study. The data provided by the Ministry of Public Health of Belgium did not contain information about the identity of patients or hospitals.

Data analysis

There are two responses considered. In the first analysis, only in-hospital mortality is considered (mortality). Mortality is a binary indicator of whether a patient died in the first-operative intensive care nursing unit (mortality = 1) or the patient proceeded to the first-operative general nursing unit (mortality = 0). In the second analysis, the response is whether a patient died, readmitted into the operating theatre or the intensive care nursing unit (readmission to ICU/OT = 1). If a patient is discharged in the first-operative general nursing unit or discharged after staying in units past the first-operative general nursing units (not intensive care nursing units or the operating theatre), then readmission to ICU/OT = 0, and it is an indication that the patient is unlikely to have been exposed to an adverse event. Mortality and readmission to ICU/OT are alternative surrogates to using only one of the traditional adverse events, as they can be considered as indirect measures of various adverse events (e.g. pneumonia, sepsis, shock, delirium). To establish the relationship between nurse staffing variables and readmission to ICU/OT or mortality, there is a need to control for confounders. The considered covariates (including confounders) in this study were taken at (a) patient level (b) nursing unit level, and (c) hospital level.

The patient characteristics are age of patient (age), gender of patient (male = 1 for males or 0 otherwise), diagnosis (APR-DRG, 4 categories), severity of illness (SOI; 1 = minor, 2 = moderate, 3 = major, 4 = extreme) and risk of mortality (ROM; 1 = minor, 2 = moderate, 3 = major, 4 = extreme). The ROM categories represent the likelihood for a given patient to die and were based initially on all available secondary diagnoses (Weingart *et al.* 2000) and calculated using the 3M grouper software (Averil *et al.* 1997). Unfortunately, secondary diagnoses may represent co-morbidities and complications. This might lead to an over-correction of the relationship between staffing variables and in-hospital mortality. Therefore, the final ROM and SOI categories were calculated without in-hospital complications.

The nursing unit characteristics considered include: nurse staffing levels (i.e. nursing hours per patient day or NHPPD), educational level (i.e. percentage of bachelor prepared nurses) of nurses and an intensity of nursing care (Sermeus *et al.* 2008). In particular, the variables are intensive care nurse staffing levels, general nursing unit nurse staffing levels, percentage of nurses with a bachelor degree in intensive care nursing unit, percentage of nurses with a bachelor degree in general nursing unit, intensity of nursing care for intensive care nursing unit and intensity of nursing care for general nursing unit.

For hospital characteristics, we considered the yearly volume of the cardiac procedures (volume), the average intensive care nurse staffing levels, the average general nursing unit nurse staffing levels, the average percentage of intensive care nursing unit nurses with a bachelor degree and the average percentage of general nursing unit nurses with a bachelor degree.

Note that the raw nurse staffing levels variable (NHPPD) is log transformed before being split into the within-part (intensive care nurse staffing levels and general nursing unit nurse staffing levels) and the between-part (average intensive care nurse staffing levels and average general nursing unit nurse staffing levels) respectively. A multilevel approach that does not partition the covariate effect into the between- and within-cluster effects, can lead to misleading inferences (Neuhaus & Kalbfleisch 1998). By including the nurse staffing variables at nursing unit level and averaging them over the nursing units to create mean nurse staffing variables at the hospital level, one allows that the effect of these covariates might not be the same on the between- and within-cluster level. For easy of computation, all continuous variables were centred and standardized (SD = 1). This implies that the parameter estimates obtained are expressed in standard deviation units.

Statistical modelling

In this article, a 3-level (patient, nursing and hospital level) logistic model was used (see appendix). The dependency between patients in the same hospital was captured through the use of random effects, that is, random intercepts (and random slopes).

Multilevel logistic models, for the two responses, are fitted to the data by making use of the Bayesian approach employing Markov Chain Monte Carlo (MCMC) techniques (Gelman *et al.* 2003). The statistical importance of an effect, in a Bayesian model, is assessed by checking if the 95% credible interval (CI) of that effect does not contain zero. The variables volume, male, age, diagnosis, severity of illness, or risk of mortality, intensity of nursing care for intensive care nursing unit and intensity of nursing care for general nursing unit were considered as risk adjusters, and hence these variables were retained in the final models irrespective of their statistical importance. In building up the model for readmission to ICU/OT, risk of mortality and severity of illness were compared to check which of the two is a better risk adjuster, as only one of these risk adjusters can be included in the model. However, in building up the model for mortality, only risk of mortality was considered. In this model, risk of mortality categories 1 and 2 were combined (as there is no event for ROM 1 patients).

Model assessment

An essential step in constructing and finalizing a statistical model (Bayesian or frequentist) is to have a critical assessment of whether the model is robust against certain model assumptions (sensitivity analysis) and also whether the model fits the data well. The deviance information criterion (DIC) (Spiegelhalter *et al.* 2002) is utilized for comparing models, with a smaller value indicating a more appropriate model. As a rule of thumb, if two models have a difference of about 5 in their DIC values, then this provides substantial support for the model with the smaller DIC. The sensitivity analysis will include a check of the link functions (logit, clog–log and probit), the linearity assumption and the prior specifications with a focus on the random effects distribution (normal or *t*-distributions). To check the linearity assumption, one could transform the covariate (e.g. by log or square root transformations) and check (by e.g. DIC) the improvement of the model. However, there are no clear cut guidelines on how to choose the transformation and even if one can embark on this exercise, there are many possible transformations to try. So a possible solution is to assume that the continuous risk adjusters possibly exhibit a non-linear relationship, and hence use smoothing splines to capture this non-linearity. A smoothing spline is a function that captures the curvature in the relationship between the response (or link transformed response) and the covariates of interest. For more technical details pertaining to splines, see (Crainiceanu *et al.* 2005).

Posterior predictive checks (Gelman *et al.* 2003) are used to evaluate the goodness-of-fit of the model. This approach allows taking of any user-defined characteristic of the data and compare that characteristic obtained from the observed data with that obtained from simulated data under the assumed model. Herein, we have taken the predicted number of events in each hospital, diagnosis group, ROM category and SOI category and compared them with their respective observed frequency. The Bayesian *P* value is then calculated as the proportion of times (from a Bayesian simulation) the predicted events are greater (or less) than the observed events. For a particular characteristic of the data to be judged as being fitted well by the model, the Bayesian *P* values for that attribute should be $>0{\cdot}1$ or $<0{\cdot}9$.

Software

The model fitting was done in R (R Development Core Team, 2010) using the R2WinBUGS package (Sturtz *et al.* 2005) that is an interface between R and WinBUGS (Lunn *et al.* 2000).

Results

Descriptives

The volume of cardiac procedures ranged from 134 to 945 with a mean (SD) of 403 (244) and a median of 316. The patients' age ranged from 20 to 85 years with an average age (SD) of 67 (10) years and a median age of 69 years.

First postoperative IC unit

In the first postoperative intensive care nursing unit, there were 6225 men and 2593 women. The NHPPD ranged from 5·75 to 16·36 with a mean (SD) of 11·12 (2·39) and a median of 11·23. The mean (SD) of the percentage of Bachelor prepared nurses is 92% (9%), the median being 94% and the minimum (maximum) being 55% (100%). Diagnosis categories APR-DRG 162, APR-DRG 163, APR-DRG 165 and APR-DRG 166 contained 500, 2348, 1692 and 4278 patients respectively. As for Risk of Mortality, 2608, 3036, 1970 and 1204 patients were categorized as ROM 1 (minor), ROM 2 (moderate), ROM 3 (major) and ROM 4 (extreme) respectively. A total of 185 patients died in the first-operative intensive care nursing unit.

First postoperative general nursing unit

In the first-operative general nursing unit, there were 6127 men and 2506 women. The NHPPD ranged from 1·25 to 13·02 with a mean (SD) of 3·13 (0·95) and a median of 2·99. The mean (SD) of the percentage of Bachelor prepared nurses is 72% (15%), the median being 70% and the minimum (maximum) being 24% (100%). Diagnosis categories APR-DRG 162, APR-DRG 163, APR-DRG 165 and APR-DRG 166 contained 474, 2279, 1654 and 4226 patients respectively. As for severity of illness 368, 2684, 3979 and 1602, patients were categorized as SOI 1 (minor), SOI 2 (moderate), SOI 3 (major) and SOI 4 (extreme) respectively. The number of patients who were readmitted to ICU/OT or died after staying in the first general nursing unit is 429.

In Table 1, the percentage of readmissions to ICU/OT is classified by severity of illness and nurse staffing levels is shown. Severity of illness is split into two categories, that is, SOI 1 (minor) and compared with SOI 2 (moderate) to SOI 4 (extreme). Nurse staffing is also split into two categories, low nurse staffing levels and high nurse staffing levels. The cut-off

Table 1 Percentage of readmissions by severity of illness and nurse staffing levels

	SOI 1	SOI 2, 3and 4
Low nurse staffing levels	0·020	0·056
High nurse staffing levels	0·005	0·050

SOI, severity of illness.

point is the average nurse staffing levels, that is, low (high) nurse staffing levels are staffing levels that are smaller (larger) than the average nurse staffing levels. Notice that low nurse staffing levels is associated with a high percentage of deaths compared with high nurse staffing levels. Also, the combined categories of SOI 2, 3 and 4 have a high percentage of deaths compared with SOI 1. However, the difference in percentage of deaths under SOI 1 is more pronounced (difference = 0·015) than under the other SOI categories combined (difference = 0·006).

Model results

For analysis 1, a sensitivity analysis was done followed by a goodness-of-fit assessment employing posterior predictive checks. There was not that much difference between the logit (DIC = 1124·0) and the complementary log–log link (DIC = 1125·7); however, the probit link fared poorly (DIC = 1132·7). Specifying the random effects as coming from a normal distribution (DIC = 1124·0) or a t-distribution with 4 degrees of freedom (DIC = 1123·1) did not lead to a great difference in DIC. The need for random slopes was also assessed. We found that the random slopes add no value to the model. For instance, the model with a random slope for age at both hospital and nursing unit level had a DIC of 1122·4 compared with a value of 1124·0 for a model with just random intercepts. As the difference in DIC is <2, the simplest model, i.e. with just random intercepts is preferred. For the continuous risk adjusters, the linearity assumption was assessed using splines. Like the random slopes, splines did not add much value to the model, and hence not invalidating the linearity assumption (Age: DIC = 1122·7; Volume: DIC = 1124·0). Therefore, the final model for analysis 1 used a logit link and had only random intercepts. Using posterior predictive checks (Bayesian P values), the model was considered as a good fit for the data at hand.

Sensitivity analyses were also done for analysis 2 followed by goodness-of-fit assessment employing posterior predictive checks. The logit link was superior to both the complementary log–log link (DIC = 2830·8) and the probit link (DIC = 2845·3). Adding a random age slope into the model did not lead to any improvement in the model, but actually led to a greater DIC value of 2831·0 compared with a value of 2829·9 for a model with just random intercepts. There was no need to incorporate splines for volume (DIC = 2829·6) and age (DIC = 2935·0), as there was no major improvement in the DIC. Therefore, the final model for analysis 2 is a random intercept logistic model. From the considered posterior predictive checks, the model appeared to fit the data well.

Analysis 1

Table 2 represents the results of the relationship between in-hospital mortality and nurse staffing variables in the first-operative intensive care nursing unit. That is, Table 2 shows the posterior means and the 95% CIs, for the covariate effects in the final model. The between-nursing units staffing variables were retained in the model if their respective within-nursing units staffing variables 95% CIs did not include zero. The interaction term between volume and intensive care nurse staffing levels appears to be important in predicting mortality, i.e., the relationship between in-hospital mortality and intensive care nurse staffing levels changes with volume.

Table 2 Analysis 1: Results of Bayesian analysis of the multilevel logistic model of in-hospital mortality for patients in the first post-operative intensive care nursing unit

Effect	Mean (SD)	95% CI
Intercept	−7·423 (0·647)	(−8·826; −6·262)
Male	−0·386 (0·176)	(−0·724; −0·039)
Age	0·215 (0·108)	(0·005; 0·428)
Volume	−0·162 (0·196)	(−0·572; 0·214)
APR-DRG 162		
APR-DRG 163	0·262 (0·302)	(−0·313; 0·863)
APR-DRG 165	−0·167 (0·303)	(−0·738; 0·429)
APR-DRG 166	−0·257 (0·309)	(−0·863; 0·362)
ROM 1 & 2		
ROM 3	2·370 (0·617)	(1·241; 3·649)
ROM 4	5·754 (0·565)	(4·774; 7·004)
IC-intensity	0·339 (0·228)	(−0·066; 0·821)
Average IC-Staff	−0·204 (0·185)	(−0·575; 0·159)
IC-Staff	0·319 (0·210)	(−0·089; 0·739)
IC-Staff × Volume	−0·457 (0·188)	(−0·839; −0·095)
σ^2_{b0}	0·353 (0·329)	(0·001; 1·152)
σ^2_{u0}	0·343 (0·264)	(0·007; 0·970)
DIC	1124·000	

Mean is posterior mean, SD is posterior standard deviation and 95% CI represents equal-tail 95% credible interval. σ^2_{b0} and σ^2_{u0} are the variance components for the hospital and nursing units random intercepts respectively.
DIC, deviance information criteria; APR-DRG, All Patient Diagnostic Related Group; ROM, risk of mortality; IC-intensity, intensity of care in intensive care nursing unit; IC-Staff, intensive care nurse staffing levels.

Namely, for hospitals with a large volume of cardiac procedures, there is a more pronounced negative association between staffing levels and in-hospital mortality (i.e. higher staffing levels, less mortality).

Analysis 2

Table 3 represents the results of the relationship between readmission to ICU/OT and/or in-hospital mortality on the one hand and nurse staffing variables on the other hand, for patients who stayed past the first-operative intensive care nursing unit. This table shows the posterior means and their associated 95% CIs, for the effects in the final model. The 95% CIs for the log odds of the risk adjusters male, volume and intensity of care for general nursing unit contains zero. However, there appears to be an association between readmission to ICU/OT and the other risk adjusters (95% CIs do not contain zero). The between-nursing units staffing variables were retained in the model if their respective within-nursing units staffing variables 95% CIs does not contain zero. There is an interaction effect between within-nurse staffing levels and severity of illness. The negative association between nurse staffing and readmission to ICU/OT decreased when a patient is classified into the moderate to extreme risk category.

Table 3 Analysis 2: Results of Bayesian analysis of the multilevel logistic model of readmissions to ICU/OT for patients in the first postoperative general nursing unit

Effect	Mean (SD)	95% CI
Intercept	−5·365 (0·742)	(−6·967; −4·061)
Male	0·013 (0·115)	(−0·211; 0·241)
Age	0·129 (0·059)	(0·018; 0·249)
Volume	0·221 (0·176)	(−0·111; 0·587)
APR-DRG 162		
APR-DRG 163	0·016 (0·214)	(−0·399; 0·444)
APR-DRG 165	0·241 (0·216)	(−0·177; 0·671)
APR-DRG 166	−0·188 (0·220)	(−0·613; 0·241)
SOI 1		
SOI 2	0·432 (0·729)	(−0·845; 2·034)
SOI 3	1·836 (0·706)	(0·622; 3·389)
SOI 4	3·804 (0·708)	(2·577; 5·368)
G-Intensity	0·197 (0·155)	(−0·107; 0·499)
Average G-Staff	0·003 (0·205)	(−0·389; 0·428)
G-Staff	−3·095 (1·357)	(−5·681; −0·369)
G-Staff* SOI 1		
G-Staff* SOI 2, 3 & 4	2·955 (1·386)	(0·268, 5·551)
σ^2_{b0}	0·219 (0·218)	(0·001; 0·781)
σ^2_{u0}	0·597 (0·345)	(0·082; 1·440)
DIC	2829·9	

Mean is posterior mean, SD is posterior standard deviation and 95% CI represents equal-tail 95% credible interval. σ^2_{b0} and σ^2_{u0} are the variance components for the hospital and nursing units random intercepts respectively.

DIC, deviance information criteria; APR-DRG, All Patient Diagnostic Related Group; SOI, severity of illness; G-intensity, intensity of care in general nursing unit; G-Staff, general nursing unit nurse staffing levels.

Discussion

In this study, the relationship between nurse staffing levels and mortality and unplanned readmission to ICU/OT was studied and therefore contributes to the current body of knowledge in different ways.

First of all, using ‘Readmission to ICU/OT’ as a potential nurse sensitive indicator in itself is innovative. After all, in most studies, the relationship between nurse staffing and in-hospital mortality is studied. Some studies include other single adverse events (Needleman *et al.* 2002, Van den Heede *et al.* 2009b). Readmission to ICU/OT, however, is a summary measure of patient safety. This composite measure gives a broad view of patient safety issues instead of a narrow view emanating from considering single adverse events. However, the disadvantage of using readmission to ICU/OT is that it is not specific on which adverse event has the greatest influence on patient safety standards.

Secondly, this article acknowledges that there is a possibility that factors affecting patient safety changes as the patient moves across nursing units and also that different proxies can be used to quantify patient safety at various stages during the patient’s hospital stay.

The analyses in this article resulted in new findings. It was found that nurse staffing levels of postoperative general nursing units are related with the composite measure ‘Readmission to ICU/OT’. This relationship was only found in the patient group with a low severity of illness. A potential explanation for this observation is the fact that readmissions to ICU of severely ill patients are rather caused by their underlying comorbidities (Elliott *et al.* 2006) than by organizational factors like, for example, staffing levels. In addition, hospitals with a large yearly volume of cardiac procedures have a more pronounced negative association between nurse staffing levels and in-hospital mortality, a relationship that was masked in previous analyses (Van den Heede *et al.* 2009a, Diya *et al.* 2010).

From a methodological point of view, the use of composite measures is ideal when a lot of adverse events are considered. Although the use of several univariate multilevel models can account for the clustered nature of the data, they neglect to account for the dependencies between several adverse events, and it is often hard to make a simple statement about the nature of patient safety from these

What is already known about this topic

- High nurse staffing levels are associated with low in-hospital mortality rates.
- In Belgium, much of the variability in nurse staffing levels is at the nursing unit level and not at the hospital level.

What this paper adds

- Readmission into the postoperative intensive care and/ or operating theatre is a composite measure for all the adverse events a patient can undergo in a hospital and can be used as a proxy for patient safety.
- Splines can be used as a flexible approach in building risk adjustment models in studying the relationship between patient safety and nurse staffing variables.

Implications for practice and/or policy

- The risk associated with a patient in different nursing units is different. There is need to acknowledge the heterogeneity in risk in assessing the relationship between patient safety and nurse staffing variables, as neglecting this heterogeneity in risk might lead to wrong policy decisions.

analyses. The use of composite measures as done in this article also allows for the inclusion of unobserved, yet important adverse events.

Furthermore, the use of two analyses allows for the effects of the covariates to be different in the two periods. Unlike in previous research (Diya *et al.* 2010) where the covariate effects are kept the same for the postoperative intensive care nursing units and the postoperative general nursing unit periods, in this study all the covariate effects are permitted to be different over the considered periods. That is, the nature and effect of the risk associated with in-hospital mortality (in the first-operative intensive care nursing units) and the risk associated with readmission to ICU/OT (in the first-operative general nursing units and units beyond) are allowed to be different.

Finally, the applied analyses refine the traditionally used analyses in this field. In this article, splines have been used as a sensitivity analysis tool. Despite their lack of importance, the authors nonetheless advise that the assessment for non-linear relationships should be part of any model building step. Ideally, one would consider splines for all continuous covariates and then gauge their necessity in the model. The use of splines will also lead to flexible risk adjustment of models in nursing research. This should not only be limited to splines alone but also the modelling of random effects (slopes) should follow the same approach.

Conclusion

There is a relationship between nurse staffing levels and in-hospital mortality and between nurse staffing levels and a composite measure of unplanned readmissions into ICU/OT and in-hospital mortality. Patient safety concerns can be identified through different proxies of patient safety at various stages of the patient's hospital stay. Readmission into ICU/OT does not only capture the patient safety issues identified by the recorded adverse events but also the adverse events which skips the eye of the health authorities. This might to, some extent, eliminate coding biases inherent in administrative data sets.

In policy formulations, there is a need to consider the needs of different nursing units differently. Taking a blanket proposal for all nursing units might not lead to any improvement in the healthcare delivery system. That is, units that have optimal staffing will not benefit from further staffing levels increments, whereas those units that greatly need improvements in staffing levels will have modest improvement in patient safety.

Funding

The Belgian Federal Science Policy Office in collaboration with the Belgian Federal Ministry of Public Health provided the funding of the original research project (framework of the research program Agora 2005 AG/HH/123 Quali-Nurse), which served as the observed data in this paper.

Conflict of interest

No conflict of interest has been declared by the authors.

Author contributions

LD, KVDH, WS and EL were responsible for the study conception and design. KVDH and WS performed the data collection. LD and EL performed the data analysis. LD and KVDH were responsible for the drafting of the manuscript. LD, KVDH, WS and EL made critical revisions to the paper for important intellectual content. LD and EL provided statistical expertise. WS obtained funding. WS and EL provided administrative, technical or material support. EL supervised the study.

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Appendix

Multi-level logistic regression model

Consider a three-level random coefficient model with only one covariate. Let y_{ijk} represent the response for the k^{th} patient in the j^{th} nursing unit of the i^{th} hospital and x_{ijk} the associated covariate. The three-level random coefficient logistic model is given by

$$\text{logit}(\pi(x_{ijk})) = \beta_0 + b_{0i} + u_{0ij} + \beta_1 x_{ijk} + b_{1i} x_{ijk} + u_{1ij} x_{ijk} \quad (1)$$

where $b_i = [b_{0i}, b_{1i}] \sim \text{MVN}(0, \Sigma_b)$, $u_{ij} = [u_{0ij}, u_{1ij}] \sim \text{MVN}(0, \Sigma_u)$ independent of each other and

$$\Sigma_b = \begin{bmatrix} \sigma^2_{b0} & \sigma_{b01} \\ \sigma_{b01} & \sigma^2_{b1} \end{bmatrix},$$

$$\Sigma_u = \begin{bmatrix} \sigma^2_{u0} & \sigma_{u01} \\ \sigma_{u01} & \sigma^2_{u1} \end{bmatrix}.$$

$\pi(x_{ijk}) = \Pr(y_{ijk} = 1 | x_{ijk}, b_i, u_{ij})$ is the probability of in-hospital mortality or readmission and

$$\log\text{it}(\pi(x_{ijk})) = \log\left(\frac{\pi(x_{ijk})}{1 - \pi(x_{ijk})}\right).$$

β_0 and β_1 are the fixed intercept and the effect of the covariate on the log-odds scale, respectively. u_{0ij} and b_{0i} are the random nursing unit intercept and the random hospital intercept, respectively. That is, these quantities represent the proneness to die/readmission of patients in the j^{th} nursing unit (of hospital i) and the proneness to die/readmission of patients in the i^{th} hospital, respectively. u_{1ij} and b_{1i} are the random slopes, i.e. they indicate that the proneness of the patients changes with the value of the covariate. Hence the random intercepts and slopes reflect the residual variation between hospitals and the heterogeneity of the effect of the covariate across hospitals, respectively.

