Modeling for Change of Daily Nurse Calls After Surgery in an Orthopedics Ward Using Bayesian Statistics

Modeling for Change of Daily Nurse Calls After Surgery in an Orthopedics Ward Using Bayesian Statistics

Noguchi Hiroshi[1], Miyahara Maki[2], Takahashi Toshiaki[3], Sanada Hiromi[2,4], Mori Taketoshi[5]

1 Department of Electric Information, Graduate School of Engineering, Osaka City University

2 Department of Gerontological Nursing/Wound Care. Management, Graduate School of Medicine, The University of Tokyo

3 Department of Life Support Technology (Molten), Graduate School of Medicine, The University of Tokyo

4 Division of Care Innovation Office for Global Nursing Research Center, Graduate School of Medicine, The University of Tokyo

5 Division of Care Innovation Office for Global Nursing Research Center, Graduate School of Medicine, The University of Tokyo

Citation	CIN: Computers, Informatics, Nursing. 39(7); 375-383
Issue date	2021-07
Corresponding Author	Hiroshi Noguchi. Ph.D. Osaka City University. 3-3-138 Sugimito, Sumiyoshi-ku, Osaka. JAPAN.
Type	Journal article
Textversion	Author
Relation	This is the Accepted article version. This is a non-final version of an article published in final form in CIN: Computers, Informatics, Nursing. The final, published version is available at https://doi.org/10.1097/CIN.0000000000000712.
Acknowledgements	The authors have no conflicts of interest directly relevant to the content of this article. This work was supported by JSPS KAKENHI Grant Number 17H02130
DOI	10.1097/CIN.0000000000000712

Abstract

Nurse call data may be used to evaluate the quality of nursing. However, traditional frequency-based statistics may not easily apply to nurse calls due to the large individual variability and daily call changes. We aim to propose a probabilistic modeling of nurse calls based on Bayesian statistics. We constructed the model including nurse call daily changes, individual variability, and adjustment according to characteristics (age and sex). Nurse call differences after surgery were analyzed based on data from the orthopedic ward from April 2014 to October 2017. Results show that there were differences in nurse calls from the first to the 10th day after surgery between patients who had undergone orthopedic surgery and those who had undergone other surgeries such as tumor surgery. Furthermore, there were differences in nurse calls from the first to the eighth day after surgery between patients using extra pain relief medicine and those who did not. Although the analysis required multiple comparisons regarding daily nurse call changes and fixed data samples per day, our approach using Bayesian statistics could detect the periods and significant differences. This suggests that our nurse call modeling based on Bayesian statistics may be used to analyze nurse call changes.

Key words: time-series analysis; big data analysis; recovery after surgery

Introduction

The nurse call system is essential for hospitalized patients to inform nurses in case of assistance or emergency. It is a critical communication method between patients and nurses. Thus, the use of a nurse call system affects both hospitalized patients and nurses. Indeed, several reports have indicated that patient satisfaction is related to the number of nurse calls and response time to the calls.[1] On the other hand, other reports suggested that frequent nurse calls cause unfavorable effects, such as an increase in work time and disruption of nursing care, which results in burnout and job dissatisfaction among nurses.[2] In order to reduce the number of nurse calls, there have been attempts to change the system of nursing rounds. Several studies, including systematic reviews, reveal that frequent nursing rounds (especially hourly rounds) reduce nurse calls and increase patient satisfaction.[3,4] However, having more frequent nursing rounds increases the nurses' burden, and it is challenging to satisfy the urgent demands of the patients. The problem with the current approach to reduce nurse calls is that no consideration is given to the individual characteristics of the patients and nursing management factors except rounding. Developing a new method to reduce nurse calls, in light of the disadvantages mentioned above, requires a detailed analysis of nurse calls with relevant information, such as patient characteristics and nursing management. However, limited research exists to date because of the lack of relevant databases.

Fortunately, in the hospital, there exist several electric databases. For example, in Japan, the government promotes the Diagnosis Procedure Combination (DPC) as a bundled payment for hospitalized medical services. To calculate the medical fee, a database for DPC exists in a hospital. The database includes multifarious information such as a patient's primary disease and hospitalization duration. Also in Japan, nurses regularly and uniformly record the amount of nursing care needed per patient every day. The data were then amassed into a database managed by a nursing department as a nursing necessity database. Thus, if these databases are integrated, the factors related to the number of nurse calls may be detectable through analysis of the integrated database. However, since there is no method to integrate these databases, the establishment of database construction is needed.

However, database construction is insufficient to detect factors related to the number of nurse calls. The development of a new analysis method is also required because of the large number of records and how complicated the items are. Nurse calls change hourly and daily according to the duration of hospital admission. Additionally, the calls might change non-linearly because the physiological condition of patients is fundamentally unstable throughout the hospitalization duration. Traditional frequency-based statistics cannot address these problems. We focused on an analysis based on Bayesian statistics. Bayesian analysis requires the pre-design of the statistical model but permits fixable model configuration based on various probabilistic distributions, which means that Bayesian analysis can overcome the problems related to nurse calls.

We chose to limit our population of interest to the orthopedic ward because our pre-analysis indicated that the orthopedics ward has a large number of nurse calls and there is a demand to improve nursing management for nurse call reduction since the exceeded nurse calls interrupt regular nursing care in the ward. In an orthopedics ward in a Japanese acute care hospital, not only there were patients with orthopedic disorders, but also patients with other diseases such as neurological diseases and malignant tumors. As for the analysis, the type of surgery (orthopedic surgery or not) was considered in order to investigate how surgery type affects the number of nurse calls and time-series, as orthopedic surgery causes more intense pain than other surgeries such as tumor surgery. If differences in calls and duration were identified, particular nursing rounds and care could be applied for patients who had undergone orthopedic surgery. Furthermore, the use of extra pain relief medicine was selected because it is a simple indicator of pain management.

Thus, our research purpose was to construct a statistical model for nurse call data analyses. Since the model was constructed based on Bayesian statistics, the model has its merits for nurse call analysis, such as being able to handle a large variability and the irregularity of nurse calls, based on the fundamental properties of Bayesian statistics.

Using the model, we investigated how differently the number of nurse calls changes between 1) patients who have undergone orthopedic surgery and those who have undergone other surgeries, and 2) patients who do or do not use extra pain-relief medicine.

Method

We conducted a retrospective cohort study including patients in the orthopedic ward who had undergone surgery between April 2014 and October 2017 in order to examine the nurse difference between patients who underwent orthopedic surgery and those who had undergone other surgeries.

Integrated database

The database at the University of Tokyo Hospital was used for analysis. The hospital is a type of acute hospital that includes approximately 1000 beds. There were 44 beds in the orthopedic ward. The mean hospitalization duration was approximately 14 days. The mean number of nurses in the ward ranged between five and six in the daytime shift, and four in the night shift. The clinical course in the ward was introduced and the method of care was uniform for patients who underwent surgery.

This research was approved by the ethical committee of the medical department of the

University of Tokyo. Each database for analysis was separated from the hospital electric system, and patient IDs from records in the database were replaced by anonymized IDs. Data from April 2014 to October 2017 were used. A total of 21,447 records from nurse calls were extracted. The last day was decided according to the electric system replacement and hospital department arrangement. Finally, six databases were used for analysis: 1) DPC database, 2) patient movement database, 3) nurse call database, 4) surgery database, 5) patient record database in the nursing station, and 6) nursing necessity database. The details of each database are shown in Table 1.

Since each individual database contains anonymized IDs, the databases were easily combined, with data corresponding to individual patients. However, this differed for hospitalization durations and filling in data for nurse calls which had values of 0 was difficult. Therefore, we developed the software to integrate the databases into one dataset using Java 8, a popular programming language. After construction of one dataset, we analyzed the database using Python 3.6, which is often utilized in information science and is one of the suitable program languages for Bayesian analysis implementation.

Analysis

To confirm the status of the dataset, fundamental statistics were calculated from the database. The mean and variance of nurse calls one day after surgery and age were calculated between groups. The difference was determined using the Kolmogorov Smirnov test considering data distribution. The number of females and males was also compared using Fisher's extract test. To confirm the relationship between nurse calls and other variables, Pearson's correlation coefficient was calculated. In the analyses, the significance level was set at 0.05.

We assumed the following items related to nurse call properties for statistical modeling of nurse calls based on Bayesian statistics.

- The number of nurse calls depends on the number of nurse calls on the previous day.
- The change in nurse calls differed between the two comparable groups.
- The patient-dependent variability exists apart from the baseline change of nurse calls (this is equivalent to a random effect in the hierarchical model in the aspect of traditional statistics)
- The number of patient-nurse calls per day depends on the Poisson distribution.

To model that the number of nurse calls depends on the number of nurse calls on the previous day, the number of nurse calls was derived from the normal distribution of nurse calls a day before. To calculate patient-dependent variability, the values delivered by the normal distribution of individual patients were added to the number of nurse calls. The final statistical models were as follows:

$$
\begin{aligned}
X_d^{(g1)} &\sim Normal(X_{d-1}^{(g1)}, s_w) \\
X_d^{(g2)} &\sim Normal(X_{d-1}^{(g2)}, s_w) \\
r_i &\sim Normal(0, s_r) \\
log(m) &= \begin{cases} X_d^{(g1)} + r_i + s_v(group1) \\ X_d^{(g2)} + r_i + s_v(group2) \end{cases} \\
Y &\sim Poisson(m)
\end{aligned}
$$

Xd signifies the number of nurse calls at day d g1, and g2 represents individual groups. In other words, the upper two terms indicate that the nurse calls changes according to one day after surgery, and the change was different among groups g1 and g2. The equation illustrated in the third line defines patient-dependent variability. The mean value of the Poisson distribution was calculated by summing the number of nurse calls per day, patient-dependent variably, and the base variability of nurse calls in the fourth and fifth lines. The last line indicates that the observed number of nurse calls Y was derived from the Poisson distribution with mean m. Sw, Sv, and Sr were the standard deviations, which were derived from a non-informative prior distribution. In our case, a uniform distribution was used as a non-informative prior distribution.

If age and sex were different between the two groups, the adjusted sex and age model was used. For adjustment, lines 4 and 5 were modified by adding age and sex linearly. This approach is similar to the adjustment method in multiple regressions.

$$
\begin{aligned}
X_d^{(g1)} &\sim Normal(X_{d-1}^{(g1)}, s_w) \\
X_d^{(g2)} &\sim Normal(X_{d-1}^{(g2)}, s_w) \\
r_i &\sim Normal(0, s_r)
\end{aligned}
$$

$$
log(m) = \begin{cases} X_d^{(g1)} + b_1 * age + b_2 * sex + r_i + s_v (group1) \\ X_d^{(g2)} + b_1 * age + b_2 * sex + r_i + s_v (group2) \end{cases}
$$

$$
Y \sim Poisson(m)
$$

For implementation, Stan was used for coding conveniently. The Stan module was called from Python 3.6 through the PyStan module.

In the statistical model, there is no explicit model of the difference between the two groups per day. To resolve this problem, we defined the difference parameters Dd as

$$
D_d = X_d^{(g1)} - X_d^{(g2)}
$$

The distribution of Dd was deterministically generated from the estimated Xd values of each group during the estimation of Xd distribution from each data sample. If the group difference Dd with the credible interval is over 0, it means the existence of a significant difference between groups in the aspect of traditional statistics. Moreover, while distance from 0 in frequent-based statistics does not mean the magnitude of significance, the distance in Bayesian statistics represents the magnitude itself. This is because the difference distribution was not a probability of the null hypothesis but was directly estimated in Bayesian statistics. Thus, a large distance from 0 indicates the magnitude of not only significance but also difference.

The model was estimated using the Markov chain Monte Carlo (MCMC) method. To estimate the model, 5000 MCMC calculation cycles were performed during the warm-up period, and an additional 5000 calculation cycles were used to estimate the final distribution. Owing to the limitations of our computer device, only one chain was used for calculation. Duration of d was defined from 0 to 14, according to the mean score of hospitalization duration, which was 14 days. Patients who underwent orthopedic surgery and those who had undergone other surgeries and who did and did not use extra pain relief medicine were compared as g1 and g2.

In order to confirm the convergence of MCMC, the Rhat value was calculated. A value below 1.1 indicated that the estimated statistical distribution was well converged[5]. To confirm the model complexity, the AIC and BIC were often utilized in multiple regression. The AIC and BIC require that posterior distribution was normal, meaning that these scores were not available in Bayesian statistics. Hence, the widely applicable information criterion (WAIC)[6] was used to evaluate the error of model fitting because of its generalized nature. Leave-one-out (LOO)[7] was also used for model fitting. Namely, both WAIC and LOO could be indicators that represent the total difference between the estimated statistic model and real data points. Therefore, in this study, these values were only used for comparison between the models with and without adjustment.

Result

Overall, the boxplot of raw nurse calls is shown in Fig. 1. The figure indicates that nurse calls were at the peak one day after surgery, and after that day, the number of nurse calls gradually decreased. The number of data per day is shown at the bottom of the figure. Some patients moved to the ICU or discharged after surgery, denoting the data numbers gradually decreased.

The characteristics of the patients are shown in Table 2. Comparison of nurse calls between patients who had undergone orthopedic surgery and those who had undergone other surgeries, and whether extra pain relief medicine was consumed one day after surgery, are shown in the same table. There are significant differences between sex and age in patients who have undergone orthopedic surgery and those who have undergone other surgeries. However, there was no significant difference between using and not using pain relief medicine. The correlation coefficient r of nurse calls to age was 0.106 ($p < 0.001$).

The result of nurse call difference between patients who had undergone orthopedic surgery and those who had undergone other surgeries is shown in Fig. 2. The value Rhat, which indicates how the model fitted to the dataset per variable was below 1.10, which means that the proposed model fitted the dataset well and that the statistical model was stable. The WAIC was 11.5, and LOO was 15.1. The upper part of the figure exemplifies the change in nurse calls after surgery, and the lower part of the figure illustrates the difference. The band of the graph indicates a 95% credible interval. In other words, the band of difference over y-axis 0 in the lower part of the figure specifies that the difference is over 0 in the 95% credible interval.

The most significant difference was observed at one day after surgery. The means with credible intervals (2.5%, 97.5%) of individual nurse calls by patients who had undergone orthopedic surgery and those who had undergone other surgeries were 6.5 (7.5, 6.9) and 4.5 (5.1, 4.8), respectively. Figure 2 illustrates that patients who had undergone orthopedic surgery called nurses more frequently than those who had undergone other surgeries between 1 and 10 days after surgery. The calls and differences gradually decreased after the first day of surgery.

Considering the basic statistics, age and sex were significantly different between patients who had undergone orthopedic surgery and those who had undergone other surgeries. The model adjusting for age and sex is shown in Fig. 3. The RHat values were below 1.10. The WAIC was 11.53 and LOO was 10.38, respectively. The beta values of mean and 95% credible intervals of age and sex were 0.180 (0.004, 0.259) and 0.006 (0.001, 0.008), respectively.

The results of the comparison between patients using and not using extra pain-relief medicine is shown in Fig. 4. The RHat values of all variables were below 1.10, which implies a stable estimation of the statistical model. The figure illustrates that the change in nurse calls was similar to the difference between patients who had undergone orthopedic surgery and those who had undergone other surgeries. However, the differences were smaller than those in the previous analysis. The duration at which 95% credible intervals were over 0 was from 1 to 4 days after surgery. Besides, even the highest difference was below one nurse call. The means with 95% credible intervals of the patients using and not using extra pain-relief medicine were 6.3 (6.0, 6.5) and 5.0 (4.7, 5.3), respectively.

Discussion

The proposed Bayesian statistical model could estimate a sequential change in nurse calls after surgery. The model also detected the differences between patients who had undergone orthopedic surgery and those who had undergone other surgeries, and between patients who did and did not use extra pain-relief medicine.

The traditional approach (i.e., frequent-based statistics) to investigate the significant difference in nurse calls between the two conditions (e.g., the difference of disease) is the null hypothesis significance test. However, in order to investigate when the number of calls was different between the two groups after admission, multiple comparisons were required. It is well known that multiple comparisons fundamentally contain the occurrence of the alpha error problem, which means that the test can increase the possibility of misdetection concerning days when the number of calls varies significantly. In order to detect all combinations during hospitalization, the number of combinations increased drastically. Such an approach is impractical, and in order to resolve this problem, analysis of variance (ANOVA) is commonly used. However, the number of samples is different for all days because the hospitalization duration varies considerably among patients. Thus, the application of ANOVA to nurse call analysis is difficult. Another approach is to extract parameters from time-series changes. In the example of blood flow analysis, frequency parameters are extracted for performing comparisons using fast, frequent transform and wavelet transform, methodologies[8]. However, the extracted parameters lose the source data themselves (in this case, the raw number of nurse calls). Hence, the approach is not suitable for conducting the analysis. To overcome this problem, we introduced Bayesian analysis, which attracts attention as a new analysis method in the context of computational power increase, enhancement of tools' software, and development of efficient solution methods. For example, in the psychological research area, Bayesian methods are utilized to overcome the limited availability of data samples and complications associated with the experiment design. Primarily, Bayes factors were used for the comparison of models[9]. As an example use in medical areas, Bayesian statistics were used for estimating model construction from an evidence-based questionnaire score[10]. However, no research has applied Bayesian analyses to nurse call data. Thus, our research results indicated that Bayesian analysis could become a powerful tool to investigate differences in nurse calls, including large variabilities.

It is known that Bayesian analysis requires the pre-design of the statistical model but permits fixable model configuration based on various probabilistic distributions. Our model clarified the difference between daily nurse calls between the two groups. The X value itself is hard to interpret as the value that directly denotes the number of nurse calls because of the exponential value. For example, the difference in nurse calls one day after surgery indicated that patients who had undergone orthopedic surgery called the nurses approximately twice as many as those who had undergone other surgeries. The SD values of nurse calls one day after surgery indicated that nurse calls vary inherently and largely owing to fundamental body characteristics condition, personality in nurse call use (i.e., some patients often use the nurse calls, and some patients rarely call the nurse), and changes in body condition based on patients' recovery from surgery or disease. This large variability suggests that the simple introduction of basic statistics could not vividly reveal the difference between nurse calls. Our proposed model could incorporate individual baseline characteristics and changes in these, through the introduction of individual variation (in general Gaussian mixture model, random effect) and time-series change model. This introduction removed variability related to individual patients and time-series, and identified differences between two groups based on the number of days that had passed after surgery.

The graph of nurse calls adjusted by age and sex demonstrated that baseline daily nurse calls changed smoothly, and the differences between groups were flat from the first to the 10th day after surgery. This smooth transition denotes that the baseline difference between the two groups continued from the first to the 10^{th} day after surgery, and that the difference might be independent of time series. Thus, the proposed model detected potential differences in nurse calls between patients who had undergone orthopedic surgery and those who had undergone other surgeries, although only the average number of nurse calls could not depict the difference. Therefore, our proposed model has the capability of detecting potential differences in nurse calls in interventions, such as changes in the nursing management system.

As a first step in introducing Bayesian statistics into nurse call data analysis, we focused on the change of nurse calls after surgery because the number of calls might change according to recovery. Almost 80% of patients report feeling pain after surgery[11,12]. This pain might drastically affect the number of nurse calls. On the other hand, the pain of only 2-10% of patients becomes chronic or severe after surgery[13]. This fact indicates that almost all patients gradually recover from the painful condition after surgery. The research reported that the peak of pain strength was at one day after surgery and the pain gradually decreased afterwards[14]. As pain decreases after surgery, the number of nurse calls may also decrease. It is known that pain after surgery in obstetrics departments is the most severe[15]. However, the obstetrics department is a particular kind of department and is not suitable for general analysis because all patients are women. Thus, we focused on the orthopedic department, where pain after surgery is ranked second in terms of severity[15]. Besides, it is known that pain management in orthopedics is vital for nursing because many patients are suffering from severe pain[16]. In addition, almost all patients in the orthopedic department can call the nurses themselves, which indicated that body condition and/or nursing management directly affected the number of nurse calls. Therefore, our detected difference could be applied to nursing management. For example, the nurse calls from patients who had undergone orthopedic surgery were significantly larger than the patients who had undergone other surgeries. It is known that frequent nurses around the patient's room decrease nurse calls[3]. If a patient has undergone orthopedic surgery, frequent nurse rounds for the patient would reduce the number of nurse calls, which might lead to patient satisfaction.

As per the results of the analysis, the number of nurse calls of patients who had undergone orthopedic surgery was significantly larger than those who had undergone other surgeries. Age and sex were significantly different between patients who had undergone orthopedic surgery and those who had undergone other surgeries. It has also been reported that older women have a high risk of fracture[17]. This might have caused a significant difference. On the other hand, even after adjusting these characteristics, the nurse calls varied significantly. The findings imply that surgery might affect nurse calls more strongly than any other factors. Nurses' calls decreased with a decrease in the incidence of pain in patients after surgery, as has been validated by previous research[14]. This finding suggested that nurse calls due to pain and need for assistance (i.e., need to go to the toilet) might decrease, causing a reduction in total nurse calls. In other words, the decrease in nurse calls might indicate patients' recovery from surgery and may even be an indicator of patients' body condition. In traditional research, nurse calls were used as an indicator of patient satisfaction and business of nurses[1]. This research outlines how nurse calls are an indicator of patient status as well.

The difference in duration between patients who had undergone orthopedic surgery and those who had undergone other surgeries was longer than that between patients using and not using extra pain-relief medicine. This difference indicated that different surgeries drastically worsened a patient's body condition, thus increasing the number of nurse calls. On the other hand, the nurse call difference between patients using and not using extra pain-relief medicine immediately approached zero after surgery, which suggested that patients' body conditions were well managed, and the severe condition became similar to that of patients who were receiving routine management in the ward. Based on these findings, our proposed model of nurse calls clarified the presence of differences and the duration of these differences, which might indirectly reflect nursing management and care strategies. In addition, our model would be applicable for the evaluation of other studies using nurse calls as an indicator. Examples of applied research include a study on the effectiveness of special devices and care approaches introduced temporarily in a particular duration, and an investigation of how long the introduced method continues in the ward.

One of the research limitations is outcome identification. In our analysis, the surgery type was identified from the primary disease code in the DPC database because surgical names were disorganized. However, the patient genuinely receiving the surgery related to the primary disease was unobservable. In addition, when a patient had undergone multiple surgeries during hospitalization, only the last surgery day was used. However, multiple surgeries themselves might affect pain, which might be related to nurse calls. Moreover, extra pain relief medicine was recorded if the patient received extra pain-relief medicine in addition to usual treatment. However, some types of medicine that the patients received themselves were not recorded in the medical chart at the nurse station. These points should be considered when interpreting the results. The proposed methodology contains a simple model wherein the number of nurse calls on the previous day affects the number of nurse calls on the present day. There are several approaches to model temporal sequences, such as a bi-gram. Investigation of optimal modeling for temporal changes in nurse calls is required for further research using nurse calls as an indicator.

Conclusion

A new model based on Bayesian statistics was proposed to model the temporal changes in nurse calls after surgery. The model can be treated according to time-sequential change, individual characteristics for nurse call usage, and differences in nurse calls between the two groups. The model was applied to the nurse calls dataset in the orthopedic ward. The model identified the difference between nurse calls and days, including differences after surgery between patients who had undergone orthopedic surgery and those who had undergone other surgeries, and between patients who used and did not use extra pain-relief medicine. In future analysis, based on Bayesian statistics, it is imperative to analyze the change in nurse calls after hospital admission and its pattern classification.

References

1. Meade CM, Bursell AL, Ketelsen L. Effects of nursing rounds: on patients' call light use, satisfaction, and safety. The American journal of nursing. 2006;106:58–70.
2. Roszell S, Jones CB, Lynn MR. Call bell requests, call bell response time, and patient satisfaction. Journal of nursing care quality, 2009;24:69–75.
3. Culley T. Reduce call light frequency with hourly rounds. Nursing management. 2008;39:50–52.
4. Nelson JJ. Staffileno BA. Improving the patient experience: Call light intervention bundle. Journal of pediatric nursing. 2017;36:37–43.
5. Gelman A, Carlin JB, Stern HS, Dunson DB, Vehtari A, Rubin DB. Bayesian Data Analysis. Chapman and Hall / CRC, 2013.
6. Watanabe S. Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory, Journal of Machine Learning Research, 2009:11;3571–3594.
7. Vehtari A, Gelman A, Gabry J, Practical Bayesian model evaluation using leave-one-out cross-validation and waic, Statistics and Computing, 2017;27(5):1413 – 1432.
8. Liao F, Burns S, Jan Y.-K. Skin blood flow dynamics and its role in pressure ulcers. Journal of tissue viability, 2013;22:25–36.

9. Etz A, Vandekerckhove J. Introduction to Bayesian inference for psychology. Psychonomic bulletin & review, 2018;25:5–34.

10. Kharroubi SA. Use of Bayesian methods to model the sf-6d health state preference based data. Health and quality of life outcomes. 2018:16:234.

11. Gan TJ, Habib AS, Miller TE, White W, Apfelbaum JL. Incidence, patient satisfaction, and perceptions of post-surgical pain: results from a us national survey. Current medical research and opinion. 2014;30:149–160.

12. Meissner W, Huygen F, Neugebauer EAM, Osterbrink J, Benhamou D, Betteridge N, Coluzzi F, De Andres J, Fawcett W, Fletcher D, Kalso E, Kehlet H, Morlion B, Montes Prez A, Pergolizzi J, Schfer M. Management of acute pain in the postoperative setting: the importance of quality indicators. Current medical research and opinion. 2018;34:187–196.

13. Kehlet H, Jensen TS, Woolf CJ. Persistent postsurgical pain: risk factors and prevention. Lancet. 2006;367:1618–1625.

14. Sommer M, de Rijke JM, van Kleef M, Kessels AGH, Peters ML., Geurts JWJM, Gramke HF, Marcus MAE. The prevalence of postoperative pain in a sample of 1490 surgical inpatients. European journal of anaesthesiology. 2008;25:267–274.

15. Gerbershagen HJ, Aduckathil S, van Wijck AJM, Peelen LM, Kalkman CJ, Meissner W. Pain intensity on the first day after surgery: a prospective cohort study comparing

179 surgical procedures. Anesthesiology, 2013;118:934–944.

16. Pasero C, McCaffery M. Orthopaedic postoperative pain management. Journal of perianesthesia nursing. 2007;22:160–72.

17. Liang W, Chikritzhs T. The Effect of Age on Fracture Risk: A Population-Based Cohort Study. J Aging Res. 2016:5071438.

Figure 1: Boxplot of raw nurse calls: The number patient entries per day is described at the bottom.

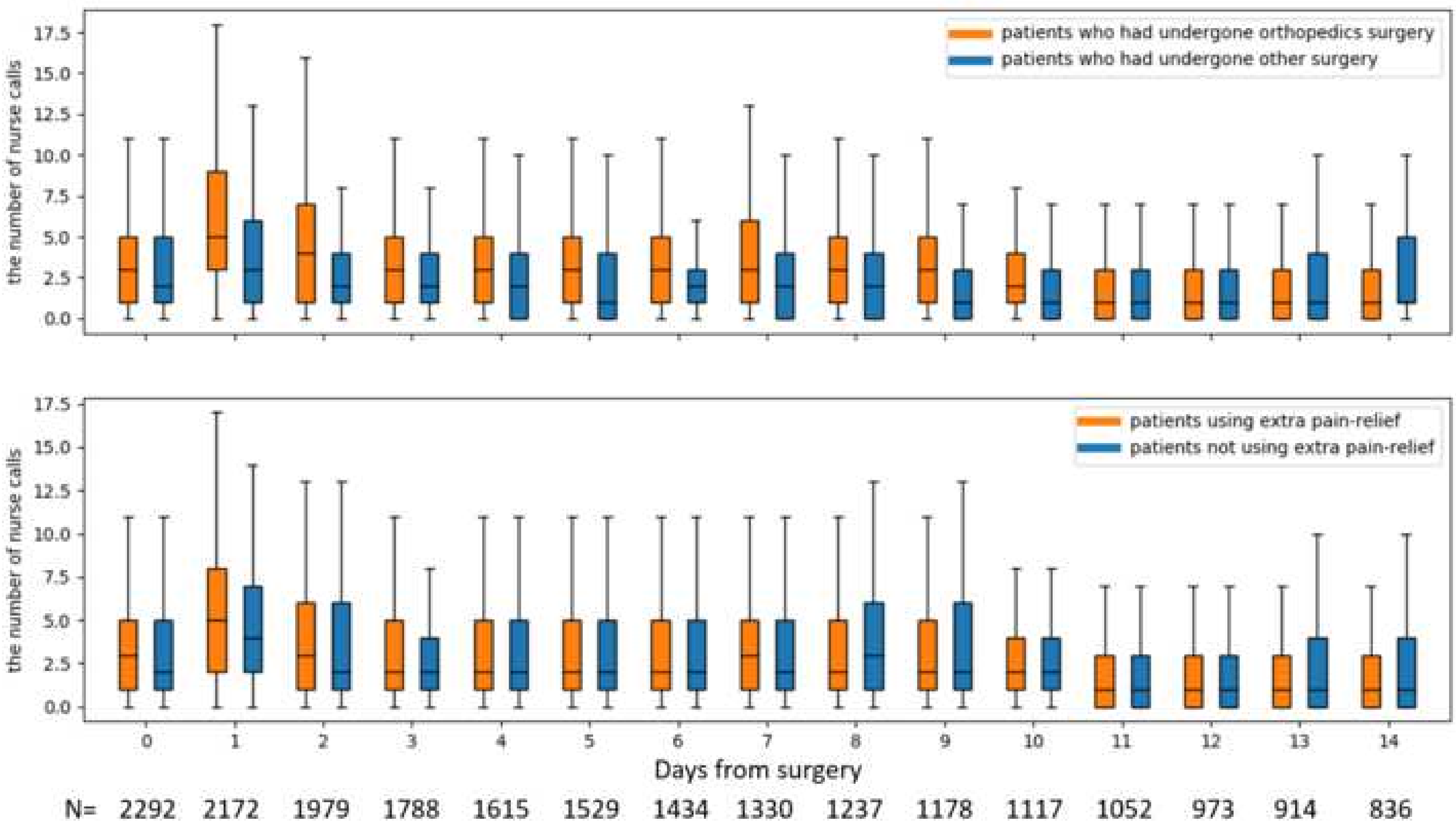

Figure2: Difference in nurse calls between patients who had undergone orthopedic surgery and those who had undergone other surgery

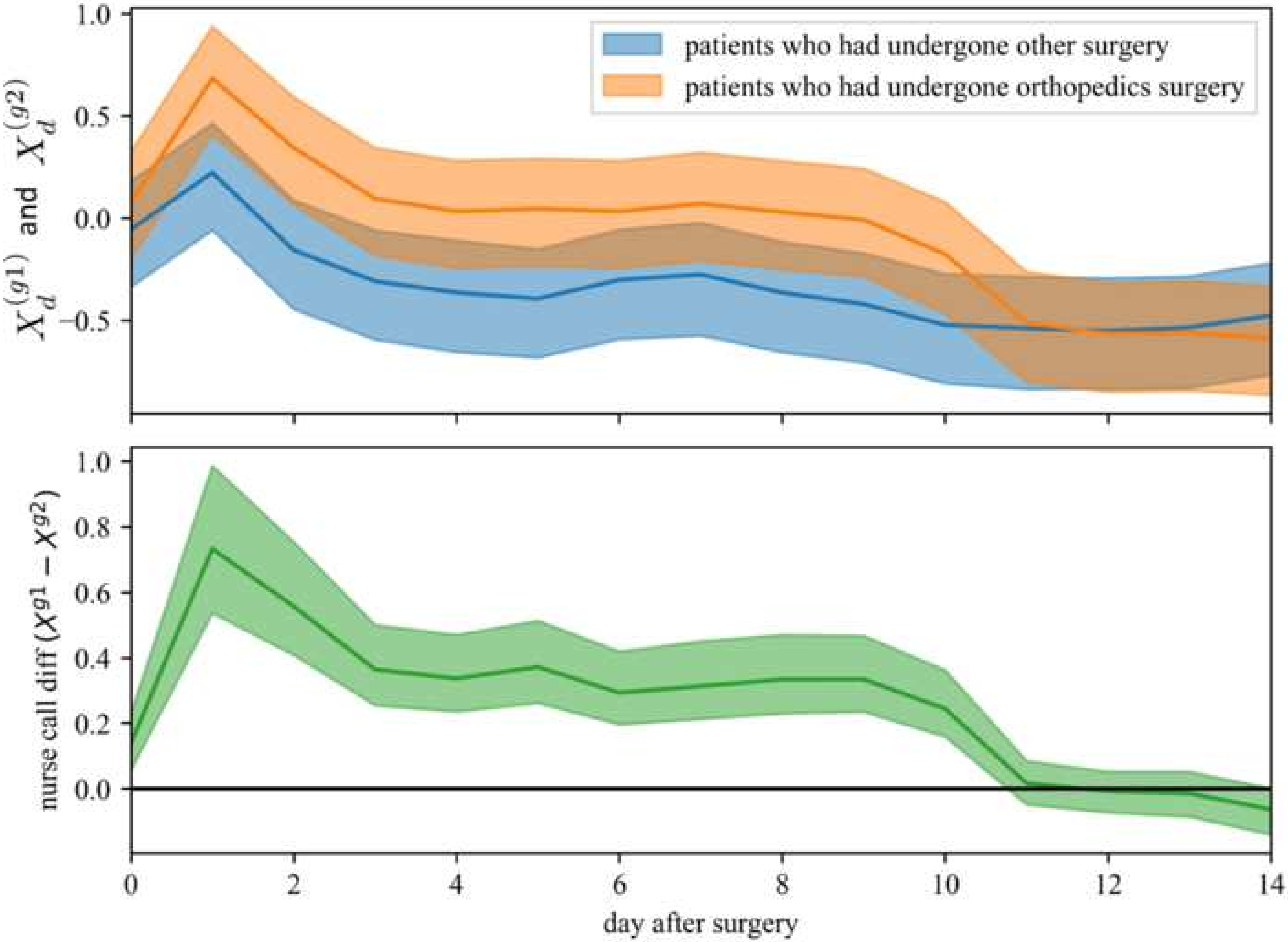

Figure 3: Difference in nurse calls between patients who had undergone orthopedic
surgery and those who had undergone other surgery adjusted according to age and

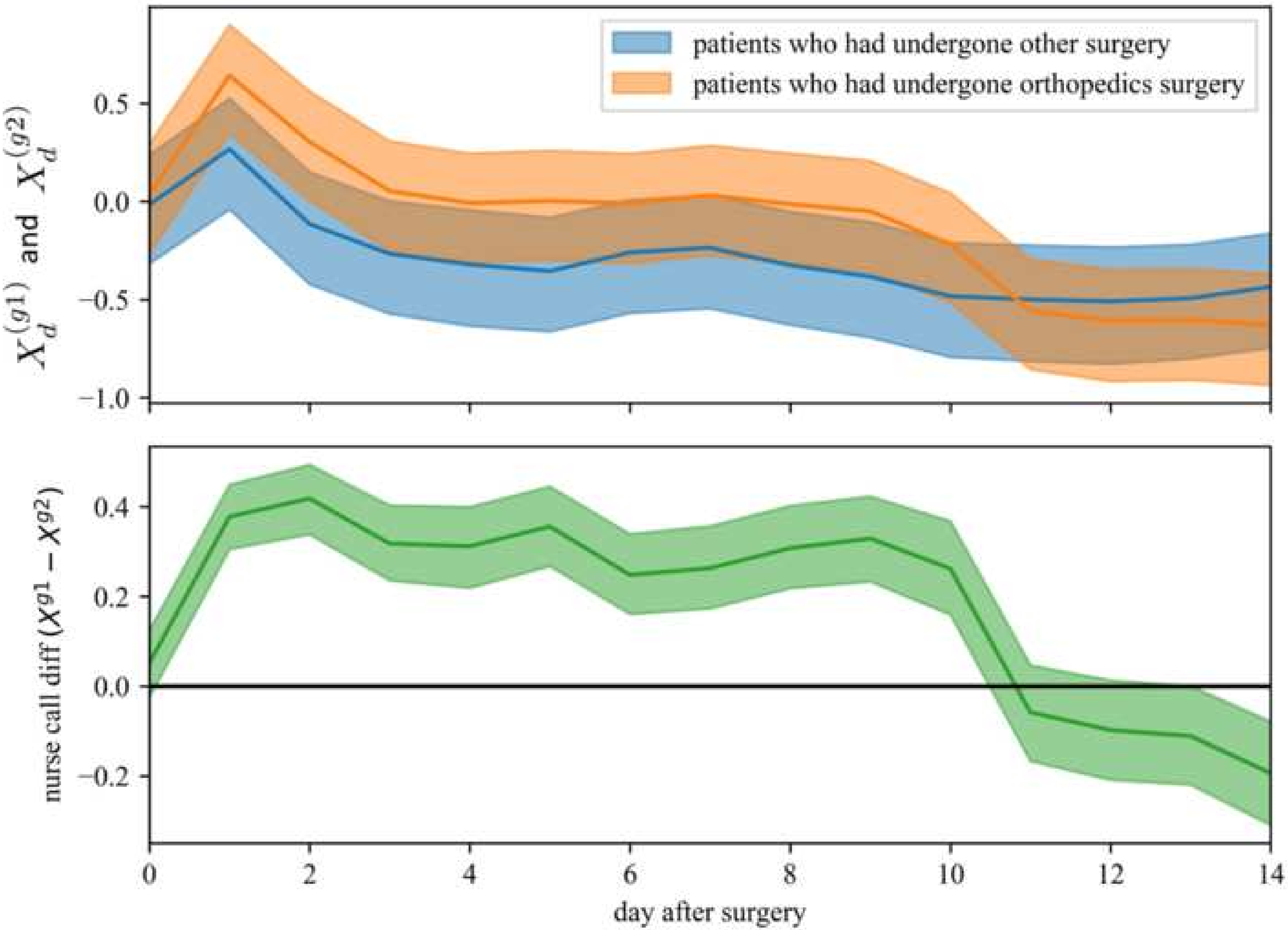

Figure 4: Difference in nurse calls between patients using and those not using extra pain relief medicine

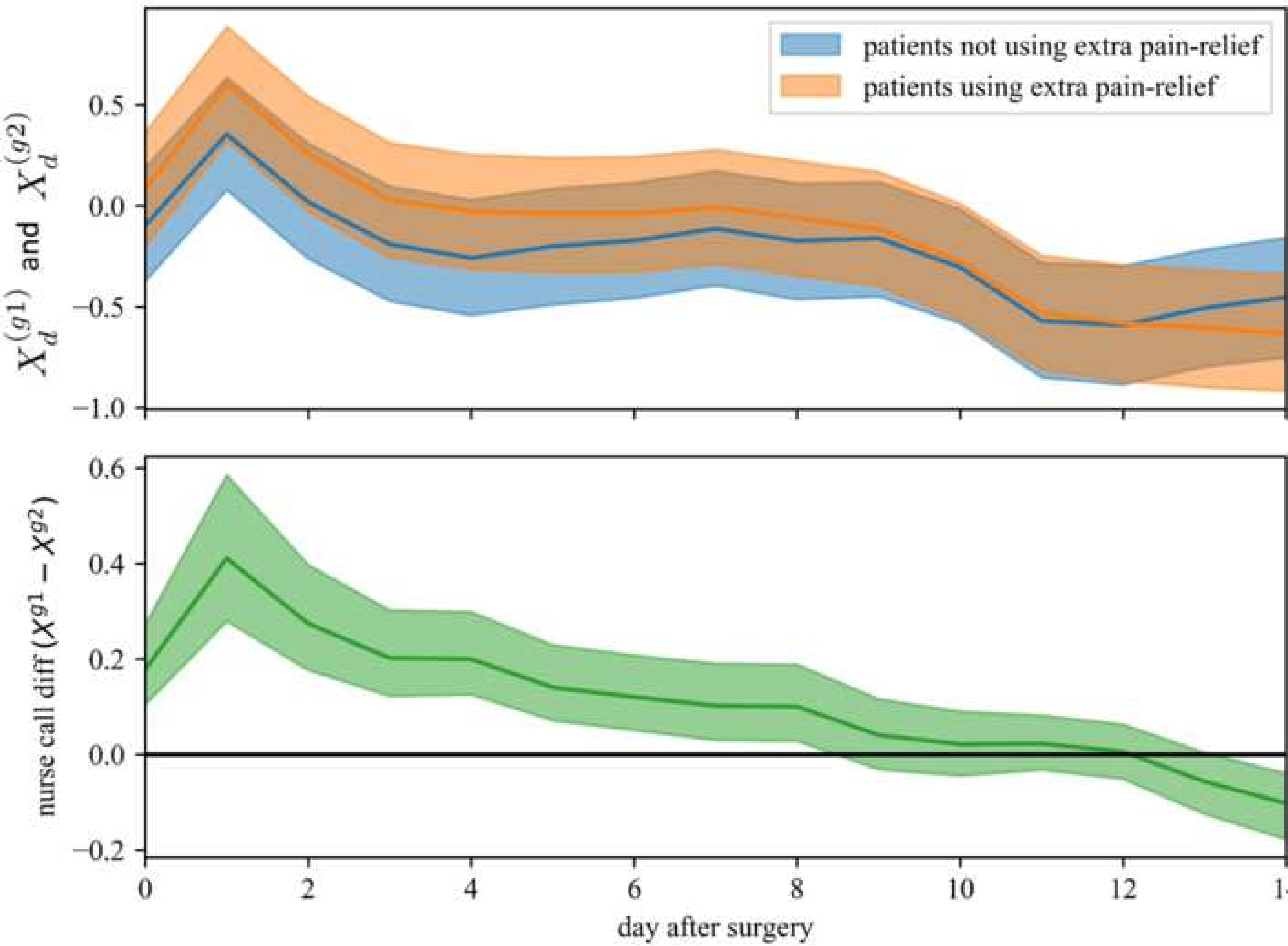

Table 1: Individual databases used for the integrated database

No.	Database Name	Data Columns	Remarks
1	DPC database	Anonymized ID, ward, room, bed number, hospital admission or discharge information, date, and code of primary disease	The code of primary disease was used for surgery identification.
2	Patient movement database	Anonymized ID, source ward, source room, source bed number, destination ward, destination room, destination bed, and movement type (e.g., admission, discharge, movement of bed, temporal discharge)	The details of patients staying at the hospital could be tracked from this database.
3	Nurse call database	Anonymized ID, ward, room, bed number, hourly nurse calls and nurse call type (general calls, special calls, emergency calls, toilet calls, and dropout calls)	One record was written per patient in one day. In the research, only general call type was used. The general call was only counted when the patients pushed the nurse call system buttons. The nurse call system only updates the patient record when there is existence of a nurse call to save storage space. In the other words, the system does not produce a record unless the patient uses nurse call. Therefore, there is no record with “0” calls, which may violate statistical analysis such as the accuracy of calculating the mean. After the admission and discharge days were identified from the movement database, hospitalization duration was calculated. If no records were detected over the duration, the number of nurse calls was filled in as 0.

4	Surgery database	Anonymized ID, surgery date, department, and name of surgery	This database was used along with the DPC database. By combining the admission day from the DPC and the surgery day from the surgery database, the surgery day was also appended into the respective database. Moreover, information about the surgery day was integrated into the database. If multiple surgeries were performed during hospitalization, the last surgery was selected as the surgery day. This information was also used for identifying whether the patients received surgery or not. If the DPC code about the primary disease included "M", which indicated that the disease is a kind of orthopedic disease, the surgery was regarded as orthopedic.
5	Patient record database in the nursing station	Information such as anonymized ID, date, kinds of medicine (e.g., pain relief), name of the medicine, and others.	The database contains shared information on the time-series of the patients' status displayed in nursing station. In the target ward, if extra pain relief medicine (which should be managed by nurses as needed) was provided, the information on the medicine was recorded. If the medicine was provided after surgery day and its description in the medicine column included the term "pain relief," we regarded it as an indication that the patient received extra pain relief medicine.
6	Nursing necessity database	Anonymized ID, sex, age, and total of nursing necessity scores A, B, and C	Score A consists of several items related to special care such as wound care. Score B consists of items related to patients status such as ability of transfer. Score C consists of items related to medical conditions such as bone surgery history. Since items under scores A, B, and C were revised during the retrospective cohort study, the total scores were meaningless for analysis. Thus, only age and sex data were used for analysis.

Table 2: Characteristics of patients

Table 2: Characteristics of patients

n= 2061				Surgery					Pain relief medicine				
		All		Orthopedics		Other			Use		No Use		
Sex	female	1233	(0.60)	868	(0.66)	365	(0.49)	p < 0.001*1	875	(0.61)	358	(0.57)	p = 0.087*1
	male	828	(0.40)	450	(0.34)	378	(0.51)		558	(0.39)	270	(0.43)	
Age		58.2 ±	19.7	63.6 ±	19.5	48.5 ±	21.1	p < 0.001*2	58.2 ±	19.5	58.1 ±	20.3	p = 0.134*2
Nurse call at one day after surgery		5.9 ±	5.9	6.7 ±	5.8	4.5 ±	4.7	p < 0.001*2	6.2 ±	6.2	5.2 ±	4.9	p < 0.001*2

*1 fisher's extract test *2 Kolmogorov Smirnov test