Identifying periodicity in nurse call occurrence: Analysing nurse call logs to obtain information for data-based nursing management

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None.

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1. ABSTRACT

Aim: To verify our hypothesis that "there is periodicity in nurse call occurrence".

Background: It is difficult to plan nursing management because nursing tasks can vary widely, seemingly at random. One of the most useful pieces of information for decision making is periodicity. If periodicity is present, it should be possible to predict the occurrence of tasks and make preventive strategies. In this study, we focused on the nurse call, which plays an important role in nursing practice.

Method: We used nurse call logs that accumulated automatically when patients pushed the button. Data were obtained from January 1, 2014 to September 30, 2017 (1,369 days) in a university hospital. The total number was 5,982,935. Periodicity was verified by the autocorrelation function.

Results: The value of the autocorrelation function increased regularly, which demonstrates there was periodicity in nurse call occurrence.

Conclusion: Our hypothesis was accepted. The presence of periodicity indicates that nurse call occurrence is not a random event but has a pattern.

Implications for Nursing Management: If we can identify patterns such as the time that nurse calls frequently occur, managers can implement two strategies: one, assigning more nurses, and two, moving tasks other than nurse calls to another time.

2. KEYWORDS

periodicity, nurse call, data-based nursing management, secondary data analysis, autocorrelation function

3. INTRODUCTION

Data-based nursing management is essential to improve nursing practices (Smaldone, & Connor, 2003: Hyun, Bakken, Douglas, & Stone, 2008). Nurse managers are required to make a variety of difficult decisions in complex and rapidly changing clinical settings, so it is crucial to provide them with useful information to ensure more effective and efficient management (Peltonen et al., 2018).

However, obtaining useful information is not easy. In recent years, digitalization has enabled the accumulation of more data than ever before. The analysis of such data is attracting attention as a methodology that can clarify important research questions quickly and with fewer monetary resources (Dunn et al., 2015). However, it is still underutilized in nursing research (Aponte, 2010), partially because, as such data are not originally collected for the purpose of research, it is unclear how they can be used in concrete ways (Brennan, & Bakken, 2015). For example, while it is easy to calculate averages if data are available, which is helpful, it is not sufficiently useful for daily nursing management. Data pertaining to nursing tasks are highly variable because they vary greatly every day due to the influence of a variety of factors (Ebright, Patterson, Chalko, & Render, 2003). As such, the actual numbers that occur may differ significantly from the average. Thus, useful information for nursing management cannot be obtained unless we examine the essential characteristics rather than simply performing calculations.

In this study, as one of the essential characteristics, we investigated whether the occurrence of nurse calls exhibits periodicity. Periodicity means the tendency of an event to happen regularly. The analysis of periodicity is a common technique used in signal processing, such as image compression and speech analysis (Ramkumar, & Anand, 1997: Rabiner, 1977). In this study, we applied the methodology to determine whether there is a periodicity in nurse call occurrence. The presence of periodicity indicates a pattern exists. Whether or not a pattern exists is an important factor in determining nursing management. If there is a pattern, it should be possible to predict nurse call occurrence and make a preventive strategy. If there is no pattern, it means the nurse call occurrence is completely random and unpredictable. In that case, the data analysis should take a probabilistic approach such as calculating the most probable or riskiest situation. In other words, providing information to nurse managers about whether there is periodicity will enable them to determine the direction of management more effectively.

Note that we need to utilize longitudinal data in this case, not short-term data. The essential characteristics of a nursing task are not easy to identify because they vary significantly from day to day, as mentioned. Due to this feature, there is a significant risk that key results may be overlooked if we utilize short-term data. This sampling bias is one of the most prevalent limitations in nursing research today. In this study, this risk might be even higher because we attempt to clarify invisible periodicity. The sampling bias is less likely to occur as the sample size is increased (Dunn, Engoren, DeKoekkoek, Jadak, & Scott, 2015). To avoid overlooking the periodicity, we therefore utilized longitudinal data.

This study is also significant in that it examines nurse calls, as the nurse call system plays an important role in nursing practice. It is a crucial communication tool between nurses and patients, and in some cases, it can be a patient's lifeline. For this reason, a prompt response to a call is always expected (Tzeng, & Yin, 2009). There is also a cultural expectation that nurses need to respond to calls straightaway as part of providing "good service" to their patients. However, this high priority could cause problems, such as delays or interruptions of work that a nurse is engaged in at the time. Studies have shown that interruption of tasks causes other task delays and human errors, such as forgetting

(Reed, Minnick, & Dietrich, 2018: Westbrook, Woods, Rob, Dunsmuir, & Day, 2010). As a result, nurse calls sometimes lead to ironic problems such as patient dissatisfaction or risks to patient safety. For a nurse call system to be utilized successfully, it is imperative that the amount of nurse call responses not exceed the capacity of the nursing system. While various studies on nurse calls have been conducted in the past (Capo-Lugo et al., 2020: Meade, Bursell, & Ketelsen, 2006: Miller, Deets, &Miller, 2001: Ongenae et al., 2014), the mechanism underlying their occurrence is not clearly understood, and as a result there is no standardized approach for how to deal with it. Therefore, the need to obtain information on the true nature of the occurrence is very great.

The purpose of this study is to verify our hypothesis that "there is periodicity in nurse call occurrence" by utilizing longitudinal data.

4. METHODS

4.1 Design and Hospital Setting

The design of this study was retrospective data analysis using longitudinal nurse call logs. Nurse call logs were the data that have recently become available. They were accumulated automatically when patients pushed a nurse call button and included information such as when and where the call happened along with some of the patient's information. As these data had already been automatically accumulated, we were able to investigate longitudinal data without any additional workload in terms of data collection. Nurse call logs were obtained from a nurse call system in a university hospital with approximately 1,000 beds on 20 different medical and surgical wards. We examined data from January 1, 2014 to September 30, 2017 (1,369 days). During this period, the total number of nurse calls was 5,982,935.

To verify the periodicity, we first needed to determine the cycle of the target. We focused on one-day and seven-day cycles in this study. A one-day cycle meant there was a pattern that repeated every day, i.e., there was a certain characteristic relating to the time of day. For example, if the number of nurse calls increased at 12:00 every day, there was periodicity in the data and the cycle was one-day. Similarly, a seven-day cycle indicates there was a pattern that repeated every seven days, i.e., there was a certain characteristic relating to the day of the week. One-day (24 hours) and seven-day cycles are major cycles for humans because the human body has a 24-hour physiological cycle and people live and work around a seven-day social cycle. We assumed that these cycles existed because nurse calls occur in response to the life of the patient.

4.2 Data Source and Data Processing

Information such as date and time, time to answer, call type, location-related data (ward, room number, bed number, etc.), patient information (medical department, etc.) was recorded in the nurse call logs. Since the nurse call logs were just usage historical data, the data had to be processed into a form that could be calculated before data analysis. This section describes the three steps involved in the data processing, which produced four types of data (Figure 1).

First, the data were divided and analyzed by ward, as the occurrence of nurse calls was very different depending on the ward. Among the 20 wards in this hospital, three were excluded from our analysis: two because they didn't contain data for the entire study period due to a delay in system implementation, and one because it didn't contain enough data due to its small number of beds. All told, the target data of this study came from 17 wards (n = 5,814,209).

Second, the data from each ward were processed from two perspectives: (1) "How many times did patients push the nurse call button?" (count) and (2) "How many patients pushed the nurse call button?" (number of patients). The nurse work flow would be different when one patient pushed the call button 100 times compared to when 100 patients pushed it once each. Periodicity might also be different depending on the point of view, so the analysis was conducted from multiple perspectives. The data did not contain personal information (e.g., patient IDs), so it was not possible to identify individual patients. For this reason, we defined the number of beds in which a call button was used at least once as the number of patients who pushed the button.

Third, data recorded in seconds were aggregated at two different intervals to match the two types of periodicity: for validation of the one-day cycle, data were aggregated every 30 minutes (n = 65,712: 48 per day for 1,369 days), and for validation of the seven-day cycle, data were aggregated every day (n = 1,369).

4.3 Analytical Method

We analyzed the following four datasets for each ward, created by data processing.

a) Count-30min: Data of the count of nurse calls aggregated every 30 minutes.
b) Count-1day: Data of the count of nurse calls aggregated every one day.
c) People-30min: Data of the number of patients who pushed the call button aggregated every 30 minutes.
d) People-1day: Data of the number of patients who pushed the call button aggregated every one day.

The autocorrelation function (ACF) was used to investigate if nurse call occurrences exhibited periodicity. Thanks to its ease of implementation and interpretation, the ACF has been widely used for the pitch detection of voice signals (Rabiner, 1977). In this study, we defined the ACF of a time-series $(X_i)_{i=1,2,\ldots,N}$ with length N as a function of a time lag τ, as

$$ACF(\tau) = \frac{\sum_{i=1}^{N-\tau}\left(X_i - \bar{X}\right)\left(X_{(i+\tau)} - \bar{X}\right)}{\sum_{i=1}^{N}\left(X_i - \bar{X}\right)^2} \qquad 1 \leq \tau \leq N-1, \quad (1)$$

where $\bar{X}$ denotes the average of $(X_i)_{i=1,2,\ldots,N}$.

The ACF evaluated at τ represents a similarity between the original time-series data and that shifted by the lag τ. For example, if the time unit of the data was 30 minutes (as in the case discussed later), the ACF value at τ = 48 would show how similar these data values were to those after one day. By definition, the ACF value is equal to the correlation coefficient between the original and shifted data. Due to the finiteness of the data length, however, the summation in the numerator of Eq. (1) was taken only over an overlapping window such that the original and shifted data had the same length of valid values (Figure 2).

As a result, the absolute value of the ACF value tends to decrease with an increase in lag τ, as the size of the overlapping window decreases along with it.

The interpretation of the ACF value was the same as that of the correlation coefficient. The closer the ACF value was to 1, the higher the similarity. Therefore, the presence of regular peaks (the increase of ACF value) implied the presence of periodicity in the original data. The length between peaks corresponded to its period (cycle length). For example, if the time unit of the data was 30 minutes, the peak of the ACF value every 48 τ indicated the existence of periodicity and that the cycle was one-day.

In the following section, we visualize the ACF calculated from nurse call data to examine its characteristics in terms of periodicity.

We used Python 3.6.5 to analyze the data.

5. RESULTS

The analysis was performed for each of the 17 wards, and four ACF results were obtained from the four types of data for each ward. The results for the presence or absence of periodicity were the same in all wards except for people-1day in the neuropsychiatry ward. Due to space limitations, only results from the neurosurgical ward were shown in the figures as a representative.

5.1 Visual Confirmation of Periodicity without Analysis

Before discussing the analysis results, we show that periodicity cannot be confirmed without analysis, by indicating how much the nurse call occurrence varied from day to day (Figure 3). In the figure, we have separated the data for each day with a dashed line for ease of confirmation. As shown, no obvious daily patterns can be found. We also separated the data by weeks in vertical arrangements of four weeks, where again, no obvious weekly patterns can be found.

5.2 Overview of ACF Results

The ACF values of count-30min and people-30min are shown in Figure 4.

The ACF values showed different trends in the different lag periods: the amplitude centered around 0 in the large lag periods while it was always positive in the small lag periods. In other words, the ACF values slanted upward in small lag periods. To examine this difference in more detail, we expanded and confirmed the periodicity in both periods. Small lag periods were set to 0–1440 lags, and large periods were set to 19,200–20,640 lags. The length of each period was set to 30 days (1,440 lags) because if there were too many ACF values, the change in the ACF values (up and down) could not be visually recognized, as shown in Figure 4. Small lag periods were set to 0–1440 lags because the trend that the ACF values slanted upward was shown in the smallest periods. Large lag periods were set to 19,200–20,640 lags because this trend was gone. In this study, we did not use the largest lag periods, as the absolute value of the ACF value tends to decrease with an increase in lag τ.

5.3 Verification of One-Day Cycle

In both count-30min and people-30min, the ACF values increased regularly and there were 30 peaks in 30 days in each lag (Figure 5).

5.4 Verification of Seven-Day Cycle

The ACF values of people-1day increased regularly and we can see four peaks in 30 days in each lag. However, the ACF value of count-1day showed no clear peaks in either period (Figure 6).

The ACF value slanted upward in the small lag period for both count-1day and people-1day (Figure 6).

6. DISCUSSION

In this study, we investigated whether one-day or seven-day cycles existed in the occurrence of nurse calls by analyzing nurse call logs. Excluding the neuropsychiatry ward, the results showed that one-day cycles were present in both count-30min and people-30min, and a seven-day cycle was present in people-1day. In contrast, no clear periodicity was exhibited in count-1day. These results demonstrate that our hypothesis, “there is periodicity in nurse call occurrence”, was accepted. The fact that these results for the presence or absence of periodicity were the same in most of the wards serves as evidence to support the reliability of this study.

6.1 Periodicity and the Cycles

Our analysis revealed that nurse call occurrences exhibited both one-day and seven-day cycles. The presence of the one-day cycle can be seen from the ACF value that had 30 peaks in 30 days of each lag in both count-30min and people-30min. The presence of 30 peaks within 30 days indicates that there was periodicity in nurse call occurrence and that the cycle was approximately one-day. Similarly, the presence of four peaks within 30 days in people-1day indicates that there was periodicity in nurse call occurrence and that the cycle was approximately seven-day. These periodicities must be verified by data that were aggregated at smaller intervals than the target cycle to confirm that the ACF value moved up or down. This is why we changed the aggregate interval according to the target cycle.

The presence of periodicity indicates that the nurse call occurrence is not a random event, but rather an event that has a pattern. Furthermore, the presence of one-day and seven-day cycles indicates that there were patterns that repeat every 24 hours and every seven days. There is various evidence that supports this. For the 24-hour cycles, patients live according to a 24-hour circadian rhythm, and the occurrence of disease is also affected by circadian rhythms (Smolensky et al., 2015a, 2015b). Considering that the most frequent nurse call reasons are related to personal care and medications (Tzeng & Yin, 2010), the presence of 24-hour patterns is likely to exist. The seven-day cycle can be explained by the management systems in hospitals. These systems are different on weekdays and weekends, and this difference has been reported to affect even the mortality rate (Bell & Redelmeier, 2001). Even within a weekday, tasks related to surgery, examinations, and day-specific nursing care might be different in some wards.

Additionally, the presence of patterns that repeat every 24 hours and every seven days indicates there are characteristics of the time of day and day of the week on nurse call occurrence, such as an increase in nurse calls at a specific time or day. However, this study did not focus on which characteristics were present. For example, there are at least two possibilities for the pattern of the seven-day cycle. The first is that every day of the week has different characteristics (e.g., the characteristics of Monday’s nurse call occurrences are different from those of the other days of the week, and the same applies to all days of the week). The second possibility is that one or several days of the week have different characteristics (e.g., only the characteristics of Monday’s nurse call occurrences are different from those of the other six days of the week, or the characteristics on weekends are different from those on weekdays). If a characteristic on the weekend is different from one on weekdays, it may suggest that a factor related to the difference between weekdays and weekends (e.g., surgeries or examinations) affects the pattern. López-Soto et al. (2016) attempted to identify temporal patterns in the falls of elderly patients for making preventive strategies. Similarly, in the future, identifying patterns in the nurse call occurrence may enable us to predict the occurrence of nurse calls and make preventive strategies.

An important point here is the possibility that data that did not show periodicity may actually have periodicity. Only the ACF values of count-1day showed no clear periodicity, but it is possible that the periodicity was simply masked. Masking is a phenomenon where the periodicity becomes invisible due to other influences, called noise (Taal, Hendriks, Heusdens & Jensen: 2011). In this study, noise may have stemmed from patients who pushed the call button frequently. This assumption is supported by the fact that the effect of such patients was largest in count-1day in all four types of data. First, people-30min and people-1day were unaffected by the personal difference of the count of nurse calls. Second, the variety in count-1day was bigger than that in count-30min because the score size was different due to the counting interval. For these reasons, the effect of these patients was the largest in count-1day. The number of nurse calls varied greatly depending on the patient, and the influence of patients who pushed the call button frequently was extremely large. In other words, if these patients did not push the call button in the seven-day cycle, even if the majority of other patients did push it in the seven-day cycle, that cycle would be masked. Further analysis (such as frequency analysis) is needed to investigate how to remove the effect of such masking.

6.2 Characteristics of Nurse Call Occurrence

This study revealed two characteristics of nurse call occurrence outside of periodicity. The first is that nurse call occurrence was similar on days that are close together. We found that the ACF values tended to slant upward when the time lag was small, which suggests that the correlation of nurse call occurrence is higher in small periods than in large periods; that is, the similarity between today and a close day (e.g., tomorrow) is higher than it is between today and a distant day (e.g., one year later). The most likely explanation is that the assumable factors affecting nurse call occurrence are similar on days that are close together. For example, most of the inpatients are the same and there is no big difference in terms of the nursing system, medical staff, or disease tendency. The high impact of patients that push the call button frequently is another important factor. While this characteristic is empirically well known by nurses, it is also important to show it objectively. Moreover, it suggests the high possibility of predicting the characteristics of tomorrow’s nurse call from the characteristics of today’s nurse call.

The second characteristic is that the existence of periodicity didn't depend on the patients. There was periodicity even in large lag periods. The ACF values in large lag periods imply a correlation between today and 400–430 days later. Considering that all inpatients have probably been discharged after 400 days, this result indicates that nurse call data have periodicity even if all inpatients change. In conclusion, this study has revealed a common rule for all patients. These two characteristics of nurse call occurrence were only revealed through the use of long-term data. Showing these characteristics objectively is extremely important in the visualization of nursing.

7. LIMITATION

This study has some limitations. First, while we verified periodicity by ACF to understand the results visually and intuitively, this method doesn't deal with cycles in numerical terms. Second, we examined data from only one hospital. Third, the results in the neuropsychiatry ward differed from those in other wards. This may have been influenced by the specificity of the treatment (e.g., treatment in the neuropsychiatric ward is less physically invasive) or by differences in patient characteristics (e.g., the life rhythms of psychiatric patients are more easily disrupted). Further investigation is needed to clarify these factors. Fourth, we do not know the clinical meaning of the absolute ACF value. Further studies are needed to clarify the meaning.

8. IMPLICATIONS FOR NURSING MANAGEMENT

The key finding of this study, as mentioned in the discussion, is that nurse call occurrence has characteristics pertaining to the time of day and day of the week. In the future, identifying which time and day characteristics exist will lead to two practical implementations for nursing management. The first is assigning more nurses to the times at which nurse calls occur frequently. Many papers have shown that proper nurse staffing improves patient outcomes and the working environment for nurses (Aiken, Clarke, Sloane, Sochalski, & Silber, 2002: Duffield et al., 2011). If staffing can be adapted to the characteristics of nurse call occurrence, both patient and nurse outcomes should improve as a result. The second is moving tasks that can be postponed to another time at which nurse calls occur less frequently. It is usually not easy to increase the number of nurses assigned, while in contrast, devising a work schedule can be done quickly. Setting up an environment that allows nurses to focus on answering nurse calls during times these calls occur more frequently will improve patient and nurse outcomes.

Some nurses may already be aware that nurse call occurrences have different characteristics depending on the time and the day of the week. However, simply realizing this is not enough to develop effective data-based nursing management in the future. Currently, nursing practices are changing to keep up with diseases that are more complex, medical technologies featuring advanced capabilities, and patient discharges that are far more frequent. The effects of an aging society are significant in Japan. To accommodate these trends, visualizing current statuses and tasks is an urgent issue. Thus, we feel that nursing managers in particular should try the method presented in this study, as they play a key role in facilitating the long-term vision of an organization.

Finally, we should emphasize that the greatest potential of this study in terms of clinical application is the fact that our method can be applied to various data accumulated in hospitals, not just nurse call logs. If our method is applied to such data, various complicated nursing phenomena may be clarified. In particular, the periodicity revealed by this research is an important viewpoint for clarifying the original nature of human beings and a key factor in considering human health. From this perspective, we believe our method can greatly contribute to the development of nursing science.

9. CONCLUSION

In this study, we determined that there is periodicity in nurse call occurrence, thus verifying our hypothesis. We also clarified that the cycles of periodicity were approximately one day and seven days. These results will contribute to more effective and efficient nursing management as a form of data-based nursing management.

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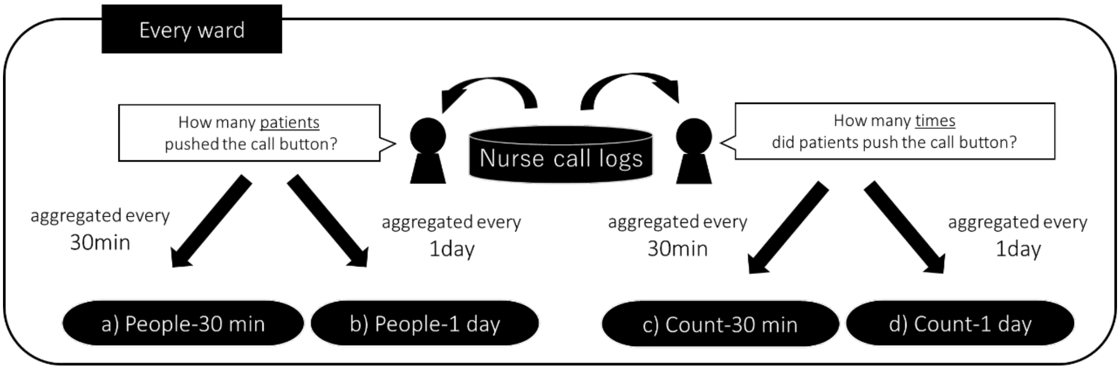

Figure 1 Data processing.

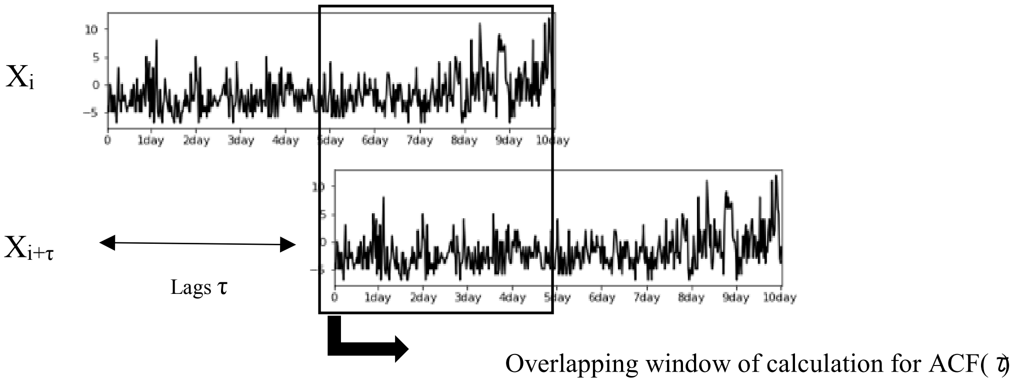

Figure 2 Overlapping window of calculation for ACF (τ).

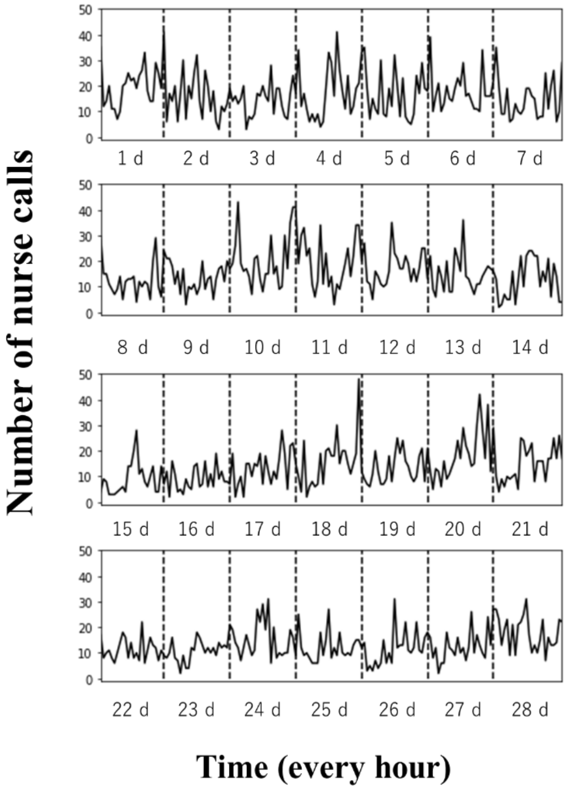

Figure 3 Nurse call counts aggregated every hour for 28 days.

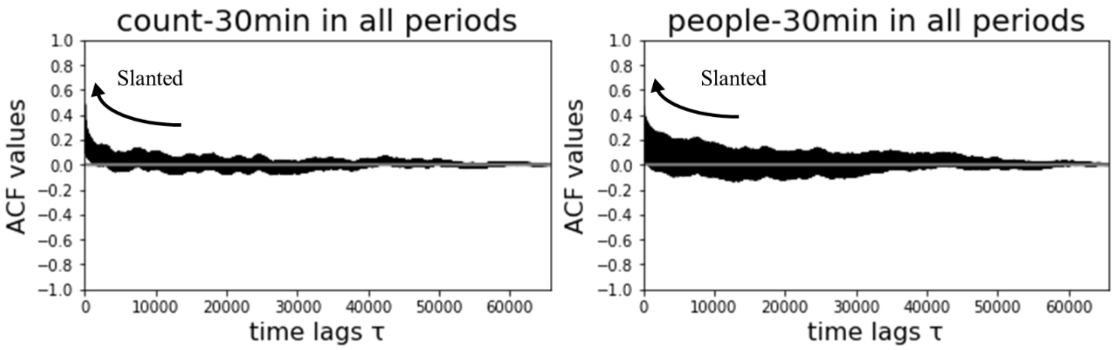

Figure 4 ACF results in small lag periods (left) and large lag periods (right).

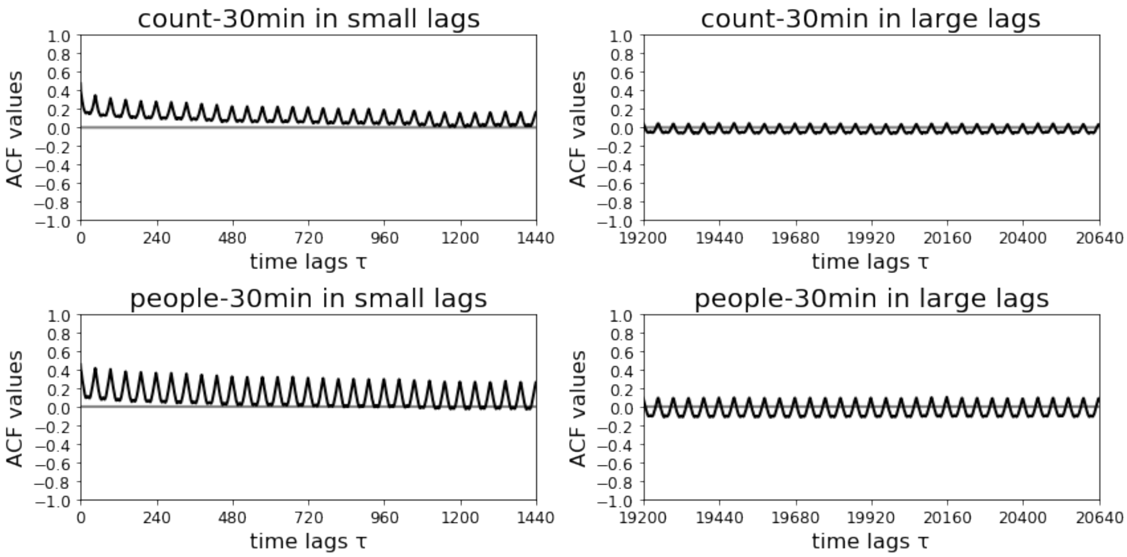

Figure 5 ACF results in small lag periods (left) and large lag periods (right).

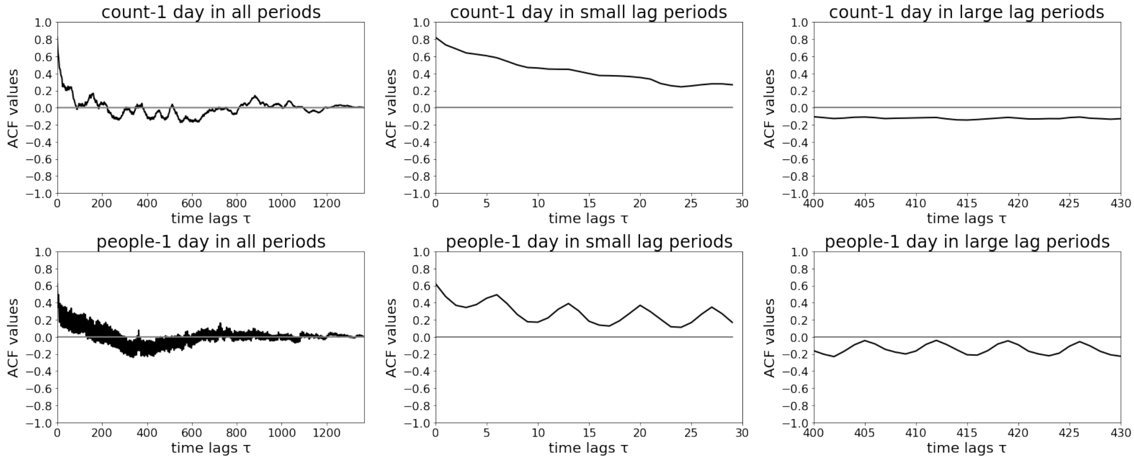

Figure 6 ACF results in all periods (left), small lag periods (center), and large lag periods (right).