Drastic hourly changes in hand hygiene workload and performance rates: a multicenter time series analysis

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Background

Hand hygiene (HH) is an evidence-based practice that has been recognized as one of the most important measures to prevent the spread of infection in healthcare facilities.[1-2] Despite considerable efforts, achieving and sustaining substantial HH improvement continues to be a challenge, and performance rates remain unacceptably low.[3-4]

Multimodal strategies are recommended to improve HH, among which is the task of determining healthcare personnel's (HCP) barriers or reasons for noncompliance and developing countermeasures for improvement.[1] Although many obstacles have been identified, high HH workload as measured by the number of HH opportunities (HHO) is a commonly cited barrier to achieving optimal rates.[3,5] However, only a few studies have reported on the relationship between HHO and HH rates,[6-11] and we know of no studies that have compared HHO and HH rates continuously over 24 hours in a day over long periods of time.

Measuring HHO and performance rates over hours in a day is hindered, in part, by utilization of direct observation (DO) to collect HH data. DO is often performed over short periods of time predominantly on weekdays during day shift and captures less than 1%-3% of all HHO making it very difficult to estimate HH workload (as defined by HHO) and HH performance over a 24-hour period or longer.[4] This, in turn, makes it difficult to develop and deliver targeted interventions commensurate with the trends of workload and performance rates over hours in a day.

An automated HH monitoring system (AHHMS) provides a means to continuously capture hourly HH data during all shifts and all days of the week eliminating the challenges of short observation periods and small sample sizes associated with DO.[12] Data from an AHHMS can be analyzed to provide valuable information concerning variations and trends of HHO and performance rates. Dai et al.,[13] used AHHMS data to assess hourly HH rates during HCP shifts. Yet, we are unaware of any studies utilizing AHHMS data to specifically analyze and compare variations and trends in both HHO and performance rates over hours in a day, days in a week and months in a year.

Identifying variation and trends of HHO and HH rates over different time scales may be helpful in guiding the strategic development and timely delivery of HH improvement interventions adapted to time of day and workload. For example, activities such as team huddles, real-time feedback of HH data, unit-led Just-in-Time Coaching, etc., may be more effective if targeted at times of the day when most needed. The purpose of this study was to analyze AHHMS data with a large multicenter database to identify and compare trends of HHO (a surrogate for HH workload) and HH performance rates over different time scales including 24-hours in a day, 7 days in a week, and months in a year.

Methods

We retrospectively analyzed data collected from a group-based AHHMS (PURELL SMARTLINK® Activity Monitoring System, GOJO Industries, Inc.)[14] Elements of this system have been previously described.[15] This system records alcohol-based hand rub and soap dispense events (from any monitored dispenser in the unit) and HHO as patient room entries (a proxy for World Health Organization Moment 1 [before touching patient])[4] and patient room exits (a proxy for World Health Organization Moment 4 and 5 combined [after touching patient or the environment])[4] by all individuals (e.g., HCP, patients, visitors). Performing HH upon room entry and room exit (regardless of touching the patient or environment) was a minimum HH expectation in each of the 10 hospitals in the study. The timing of dispense events and HHO were recorded continuously by the AHHMS, and the number of dispenses and HHO were summed by the hour. Performance rates per hour were expressed as the number of dispense events divided by the number of HHO x 100. In this study, we defined HH workload as the total number of HHO during a given time period. AHHMS data were collected from 1,085 rooms in 58 units in 10 North American acute care hospitals which utilized the AHHMS for varying periods of time between July 2014 through December 2019 (Table 1S, Supplementary Material). Data were not collected for the entirety of time between these two dates for all units/hospitals because each hospital independently decided the period of AHHMS use and their approach (e.g., which units installed AHHMS). Outpatient units (including emergency departments) were excluded. In this study, weekend hours were defined as starting at 7 PM on Fridays and ending at 7 AM on Mondays. All other hours were defined as occurring on a weekday. Day shift hours were defined as starting at 7 AM and ending at 7 PM. All other hours were defined as night shift hours (i.e., 7 PM to 7 AM).

Statistical Analysis

The AHHMS in each patient care unit in each hospital generated a time series of dispense events (soap or alcohol-based hand rub) and HHO by the hour. Mixed effects general additive models (GAMM)[16] were fit to the time series of log-transformed hourly performance rates for each hospital separately. Random effect smoothers were included to model differences between patient care units in each hospital. Auto-regressive-moving average (ARMA) models were used to estimate the serial correlation of log-transformed HH rates over time. Model fit was assessed by normal probability, scatter, autocorrelation function (ACF) and partial auto-correlation function (PACF) plots of the model's residuals. The assumption of stationarity was assessed graphically and by Augmented Dickey-Fuller (ADF) Unit Root Tests. Assuming independence of the facilities, the GAMM outputs for the facilities separately were weightedly averaged together, with weights equal to the number of HHO, to provide estimates and standard errors to assess the comparisons over all facilities. All statistical calculations were performed using the software R v 4.0.1.[17] The mixed effects time series approach used is computationally efficient, which is important because conventional R software tools were not able to analyze this large SMARTLINK® data set for even a single hospital. The following R packages were used: *mgcv*[18] was used to fit the GAMMs, *tseries*[19] to perform ADF tests, *forecast*[20-21] to find the ARMA model that maximized Akaike information criterion (AIC), and *stats*[17] to fit the ARMA models. Individual two-sided t p-values and 95% two-sided t CIs were reported. To maintain a 95% family-wise false discovery rate over statistical tests, the Benjamini-Hochberg method[22] was applied. Our computationally efficient approach can utilize a conventional desktop or laptop to analyze the full data set in 8.5 hours.

Results

All 58 units used the AHHMS for a minimum of 12 months. A total of 108,426,417 dispense events and 242,551,785 HHO were captured across all 58 units combined over the entire study period. Figure 1 shows the HH dispenses and HHO for all 10 hospitals over the 5.5-year study period. During the 5.5 years, HH rates among hospitals ranged from 20 to 60, with all facilities reporting under 500,000 HHO (Figure 1B) except hospital #1 which had AHHMS in 24 patient care units (Table 1S, Supplementary Material).

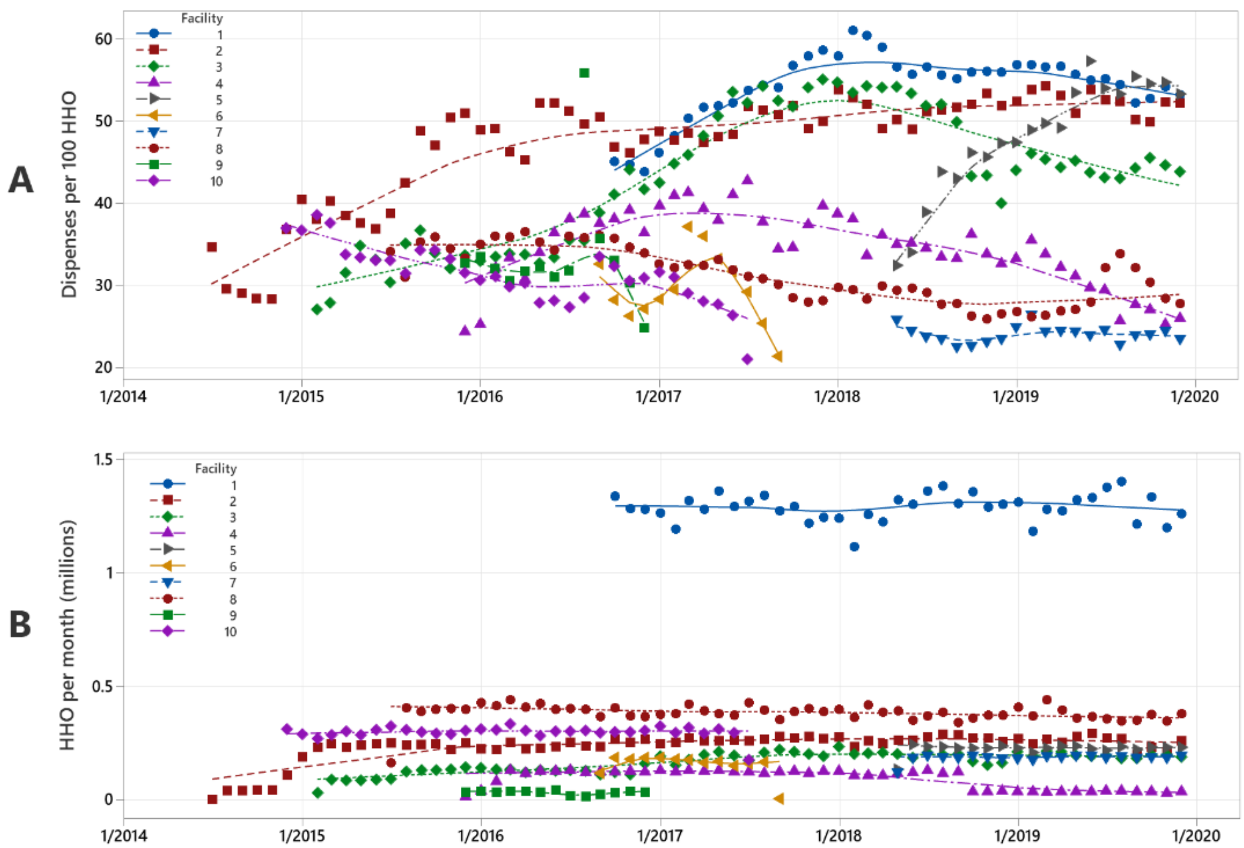

Figure 1. A. Monthly HH dispenses by hospital over the full study period. B. Monthly HHO by hospital over the full study period.

Figure 2 shows HH rates for each individual hospital aggregated by 12-hour shifts during weekdays and weekends, which shows that three of the higher performing hospitals (1, 2 and 5) consistently maintained their highest HH rates throughout both day and night shift, while hospitals 3 and 9 had relatively large increases in HH rates during night shift compared to day shift.

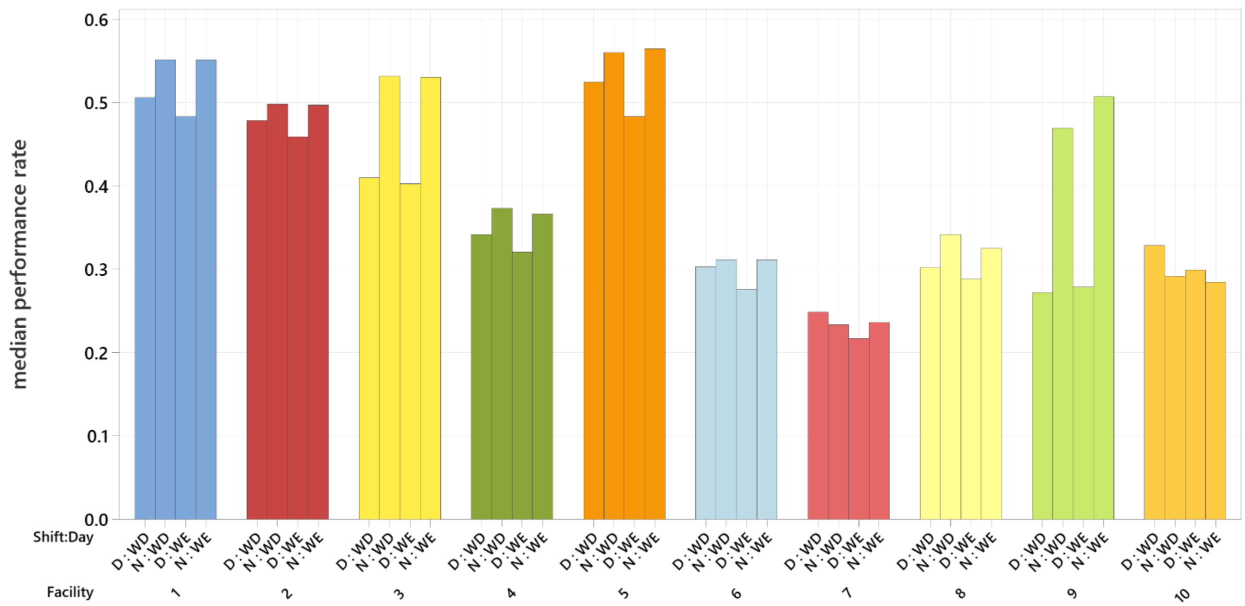

Figure 2. At each hospital separately, comparison of median HH performance rates between 12-hr shifts (day shift weekday (D:WD) vs night shift (N:WD) and day shift weekend (D:WE) vs night shift (N:WE)).

The largest fluctuations in HH rates and HHO occurred over hours in a day (Figure 3A) compared to fluctuations over days in a week (Figure 3B) or months in a year (Figure 3C). HH rates over hours in a day (Figure 3A) peaked at 50.0 (an increase of 14% from the overall median of 43.8) just before the beginning of day shift (6-7 AM) decreasing throughout the shift with the lowest rate of 38.2 (a decrease of 13%) occurring at around 5 PM, with a similar trend for all days of the week (Figure 4A). Fluctuations in HH rates over days in a week were much smaller with rates highest on Tuesdays at 44.8 (an increase of 2.3%) decreasing to 42.8 (a decrease of 2.3%) on weekends (Figure 3B). HH rates by month were highest in April at 44.2 and lowest in October at 43.4 (Figure 3C).

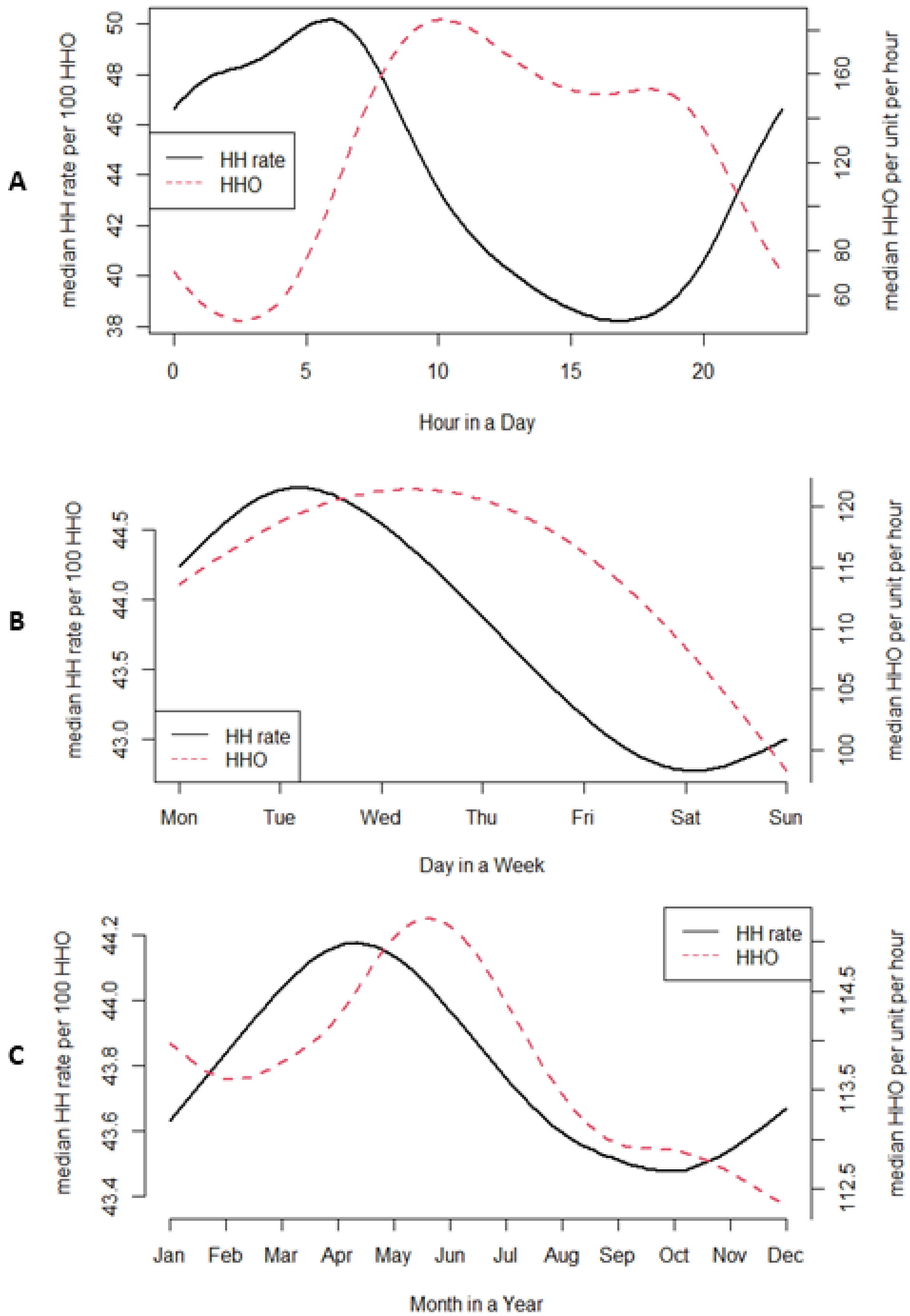

Figure 3. A. Fluctuation of median HH performance rates (black solid curve) and HHO (red dashed curve) over hours in a day. B. Fluctuation of median HH performance rates (black solid curve) and HHO (red dashed curve) over days in a week. C. Fluctuation of median HH performance rates (black solid curve) and HHO (red dashed curve) over months in a year.

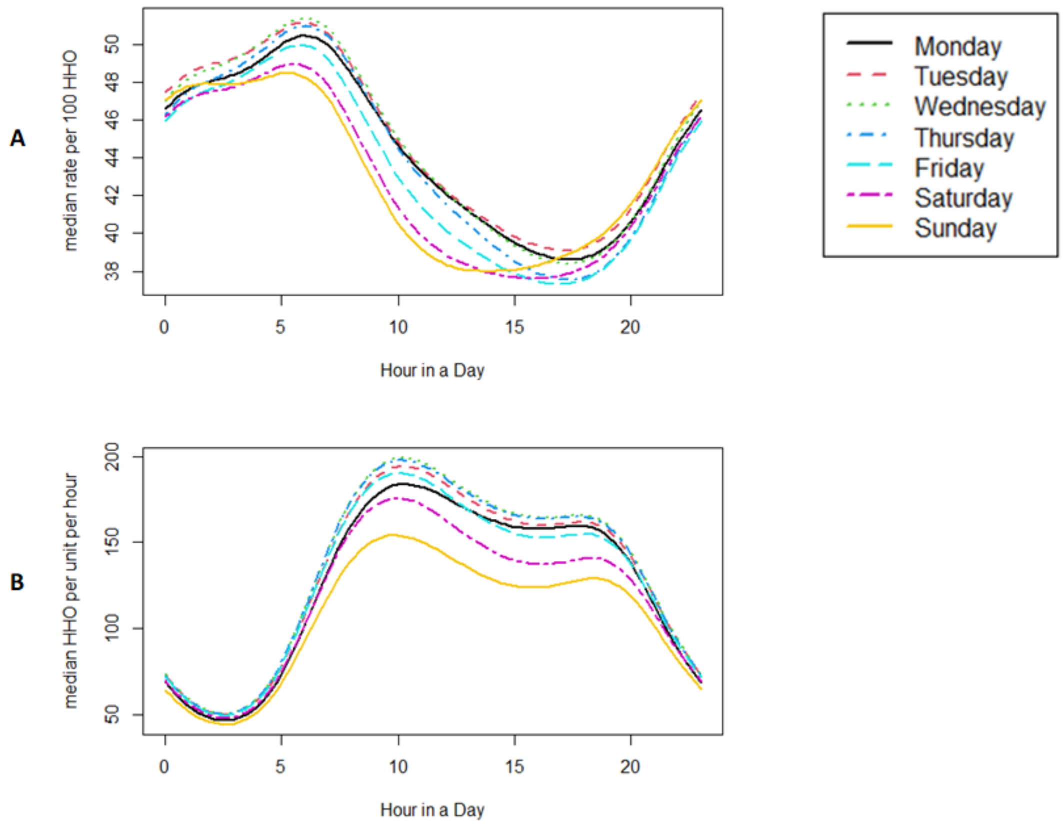

Figure 4. A. Fluctuation of hourly median HH performance rates over hours in a day by day of the week. B. Fluctuation of hourly median number of HHO over hours in a day by day of the week.

HHO over hours in a day (Figure 3A) were the lowest at 49 per hospital unit per hour (a 57% decrease from the overall median of 113.7 per unit per hour) from 2 AM – 3AM then increasing sharply thereafter, peaking at 184 per hospital unit per hour (an increase of 62%) at about 10 AM and then sharply declining at about 8 PM after night shift began. This trend was similar for all days of the week (Figure 4B). The median number of HHO per patient room per hour was 7.26. Fluctuations in HHO over days in a week were much smaller, peaking Wednesdays at 121 (an increase of 6.4%) and decreasing to 98 (a decrease of 14%) on Sundays (Figure 3B). Changes over months in a year were even smaller, with HHO highest in June at 115.3 (1.4% increase) and lowest in December at 112.3 (a 1.5% decrease) (Figure 3C).

Aggregated over all 10 facilities, the median HH rate was 43.2 for weekdays (95% CI 23.6-79.1) and 42.7 for weekends (95% CI 23.1-78.8) ($p = 0.083$), and 40.8 for day shift (95% CI 21.5-77.4) and 45.5 for night shift (95% CI 25.4-81.6) ($p = 0.079$). Among all four shift and day combinations (day shift or night shift, weekdays or weekends), the weekend day shift had the lowest median HH rate of 39.4 compared to any other combination (95% CI 20.4-76.3, $p \leq 0.1018$) (Table 1) with no statistically significant differences among the other three combinations ($p \geq 0.1441$).

	Number of Dispenses	Number of Opportunities	Median Performance Rate	95% CI
Days/Weekdays	51,625,075	118,085,657	41.4	[22,0, 77.9]
Nights/Weekdays	24,138,210	50,543,536	45.7	[25.6, 81.8]
Days/Weekends	1,6341,113	39,309,839	39.4	[20.4, 76.3]
Nights/Weekends	16,322,019	34,612,753	45.2	[25.2, 81.2]

Table 1: Summary of HH data for 12-hour shifts during weekdays and weekends.

Discussion

In this multicenter study, we used existing AHHMS data to examine trends in HH workload (as defined by HHO) and HH performance rates over multiple time scales. To our knowledge, this study is the first to compare both HHO and HH rates using a time series analysis of hourly data examining variations across hours, days, and months among multiple hospitals over multi-year periods. Others have used time series analysis to examine HH trends, but they only looked at HH rates over time.[23-28] In this study, time series analysis quantified the fluctuation of HHO and HH rates over hours in a day, days of the week and months of the year. Hourly data is a much finer time scale than what is typically reported for HH rates. The challenge with analyzing hourly data is that the results are highly serially correlated over time. In other words, dispense events and HHO tend to come in bursts because of the high correlation that a period of activity (or inactivity) by AHHMS will be followed by another period of activity (or inactivity). The time series approach explicitly models the serial correlation over time which is crucial to provide proper measures of uncertainty (i.e., error bars, confidence intervals, p-values). If one were to use a simple statistical model that ignored the serial correlation, the resulting error bars, confidence intervals and p-values would be artificially too small.

As expected, we identified a negative correlation between HHO and HH rates over hours in a day (Figure 3A). Pittet et al.,[6] reported similar findings when assessing the relationship between HHO and HH rates during 20-minute observation periods during both day and night hours. Chang et al.,[11] observed HH inside patient rooms for 30-minute time periods and found that HH rates were statistically significantly lower during high workload periods (>20 HHO/hour) compared to low workload periods (≤12 HHO/hour). Scheithauer et al.,[7] compared HH performance rates with high workload (>30 HHO/2 hours) in a neonatal intensive care unit and with high workload (>20 HHO/2 hours) in a pediatric intensive care unit and did not find a statistically significant relationship over three shifts. Their HH rates may have been inflated, however, by the use of only one observer for 96 observation periods each lasting two hours. Similarly, Stahmeyer et al.,[5] and Lebovic et al.,[9] did not find the number of HHO/hour to be associated with lower HH rates. Their findings might also be attributed to the use of DO and resultant Hawthorne effect leading to an overestimation in HH rates. In addition, their sample sizes were small and data collection occurred only during day shift. Interestingly, when we looked at the relationship between HHO and HH rates over days and months, we observed a positive correlation between HHO and HH rates (Figures 3B and 3C) suggesting that the variation between rates and HHO smooth out over longer periods of time.

As anticipated, HHO were substantially higher on day shift compared to night shift. On day shift, we observed 150-180 HHO per unit per hour which was associated with a rapid decline in HH rates with a trough at 5 PM (about 10 hours into the day shift). The steady downward trend of hourly HH rates on day shift may be due to multiple factors including HCP frequent use of HH products leading to HH fatigue,[12] progressive skin irritation over the course of a shift,[1] general fatigue as the shift progresses,[29-31] and heavy patient care workload which may result in HCP prioritizing other patient care tasks in lieu of HH.[11,13] Dai et al.,[13] analyzed over 13 million HHO from 35 hospitals using a badge-based AHHMS and explained their findings of decreasing HH rates throughout day shift as being due to the length of time HCP were at work suggesting a cumulative deleterious effect of workload on HH performance. Consistent with our findings, they found a 10% increase in HH performance within one hour of the beginning of the shift (corresponding to our finding at 6-7 AM) and a 20% decrease by the end of a 12-hour shift. They did not find a trough like we did after 10 hours into the day shift at 5 PM. This could be because they pooled the night and day shifts when investigating hourly fluctuations in HH rates.

Night shift showed the opposite effect with a rapid downward trajectory of HHO (150 HHO per unit per hour at the outset of the night shift, dropping precipitously to 50 HHO per unit per hour at approximately 3 AM), with HH rates steadily rising throughout the shift with a peak at the end of the shift. We hypothesized, as did Chang et al.,[11] that this decrease in HHO was likely the result of overall patient care workload decreasing on night shift, thereby reducing the HH workload. We expected that this decrease in HHO would position night shift as fertile ground for HH improvement leading to higher rates on night shift as compared to day shift. Intriguingly, however, despite the disproportionate HH workload between the two shifts (day shift 157,395,496 HHO, night shift 85,156,290 HHO), we did not identify a statistically significant difference in median HH rates (day shift 40.8, night shift 45.5). This finding may, in part, be due to a reduced Hawthorne effect on night shift with fewer peers in close proximity to room entry and exit.[25,30] This finding may also be attributed to less direct patient care on night shift (i.e., patients sleeping) with HCP perception that HH is not necessary upon room entry and exit.

Other studies have also used AHHMS data to compare HH rates between shifts and did not find a statistically significant difference.[32-33] Conversely, Ellison et al.,[25] compared HH rates between shifts in two ICUs in a single hospital using AHHMS data and found statistically significantly higher HH rates on day shift. In their study, like ours, they also used a group-based AHHMS to capture room entries/exits and dispenser activity of all HCP, patients and visitors. Scheithauer et al.,[7] found statistically significantly higher rates at night compared to day shift and afternoon shift, but only in the neonatal intensive care unit; no relationship was identified between HH rates and shifts in the pediatric intensive care unit. Pittet et al.,[6] also found statistically significantly higher HH rates at night and Sahay et al.,[31] reported statistically significantly lower HH rates at night; however, both studies used DO with much smaller sample sizes compared to studies using AHHMS. Interestingly, we found no statistically significant difference in median HH rates between weekdays (43.2) and weekends (42.7). Similar to our study, Cheng et al.,[32] did not find a statistically significant difference between weekdays and weekends. Pittet et al.,[6] found HH rates to be higher on weekends compared to weekdays, again using DO with a relatively small sample size. Scheithauer et al.,[8] reported higher HH performance on weekdays (with estimated HHO from electronic medical records based on patient-care procedures performed by HCP).

In our study, the highest HH rate achieved in this study was 50, and this occurred on the night shift when HHO were at their nadir at <40 per unit per hour. When HHO peaked between 150-180 per unit per hour during the day shift, HH rates maxed at approximately 43. This finding suggests that there may be limits to the number of HH events that HCP can incorporate into their workday.[11,34]

There are a variety of ways to define HH workload. We measured HH workload in terms of HHO. Edmond et al.,[33] estimated the number of HHO per nursing hour. Haac et al.,[35] and Woodard et al.,[36] quantified HH workload by estimating HHO per patient interaction. Conway et al.,[37] quantified HH workload by estimating HHO per patient observation hour. Dai et al.,[13] quantified workload as the cumulative average frequency of patient encounters and cumulative average percentage of time spent in patient rooms. Scheithauer et al.,[8] defined workload as nursing time output (total hours of activities performed by nurses per electronic health record) relative to nursing time input (total worked hours).

Others have measured workload based on patient characteristics.[38] Muller de Magalhaes, et al.,[39] expressed workload as the ratio between the number of nursing staff and the number of patients during a shift, noting that a lower nurse-to-patient ratio was associated with outcomes considered negative for patient safety. Still others have subjectively measured HCP perceived workload relative to patient safety using the NASA task-load index (TLX) concluding that higher workload is statistically significantly associated with missed patient care tasks and patient harm.[40] Clearly, documenting and measuring the impact of workload on patient safety is a critical concept in healthcare, but there is no standardized way of measuring workload.

This retrospective analysis of AHHMS data is limited by the fact that it used data from only one type of AHHMS. Additionally, it has been cited that HH rates from a group-based

AHHMS may be underestimated due to the impact of patients and visitors on HHO.[15,41] However, a recent observational study showed that 83.6% of all HHO were attributed to HCP.[41] This suggests that the true HH rate may be 19.6% (1/0.0836=1.196) larger than AHHMS estimated rates. Finally, thisAHHMS estimates only room entry and exit (proxies for WHO Moments 1, 4 and 5). This is commensurate, however, with the many hospitals in the United States that observe HH performance based only on room entry/exit rather than all of the WHO 5 Moments due to the challenges of mitigating the Hawthorne effect and preserving patient privacy while capturing Moments 2 and 3.[12] Nevertheless, with over 350 million data analyzed from 10 facilities over different time scales and multiple years, this study adds valuable insight into the relationship between HH workload and HH performance rates.

Our analyses demonstrated that HH workload (e.g., HHO) does appear to have a negative impact on optimal hand hygiene performance during both day and night shift despite the substantially lower HH workload on night shift. We further demonstrated that HH workload and performance rates vary greatly over 24 hours in a day compared to days in a week or months in a year. This is important for facilities utilizing DO to capture HH data where it is recommended that observers stay in one place for a maximum of 15 minutes per observation period to mitigate the Hawthorne effect.[2] Observers may be tempted to gather HH data only during times of day when patient care workload is high to capture as many observations as possible within that limited timespan. Based on our findings, it is important to consider not only the span of time for data collection but also the time of day in which data is captured as both HHO and HH rates vary drastically throughout the day.

Conclusion:

Healthcare facilities may benefit from a deeper understanding of the relationship between HH workload and HH performance rates over hours in a day. Such an awareness can help guide the strategic development and delivery of performance improvement interventions (e.g., real-time feedback, team huddles, HH Champions, Just-in-Time coaching) targeted at hours when they are needed the most. Importantly, special attention should be given to the potential cumulative effect of HHO on performance rates over the duration of a worked shift. Efforts to increase HH activity (dispense events) should be balanced with strategies to decrease HH workload (e.g., ensuring adequate staffing, bundling patient care activities, direct gloving as deemed appropriate).

Supplementary Material

Hospital	Patient Population	Hospital Type	# of Units	# of Rooms	Unit Types[1]	Earliest Date	Latest Date
1	Adult	Academic	24	536	ICU, MS, O	1 Oct. 2016	31 Dec. 2019
2	Pediatric	Academic	7	106	ICU, MS, O, SD	30 July 2014	31 Dec. 2019
3	Adult	Community	4	66	ICU, MS, SD	17 Feb. 2015	31 Dec. 2019
4	Adult	Community	3	37	ICU, O, SD	18 Dec. 2015	31 Dec. 2019
5	Adult	Academic	3	58	MS, O	13 May 2018	31 Dec. 2019
6	Adult	Community	4	36	ICU	9 Sept. 2016	1 Sept. 2017
7	Adult	Academic	2	34	ICU, MS, O	13 May 2018	31 Dec. 2019
8	Adult	Community	8	118	ICU, MS, O	7 July 2015	31 Dec. 2019
9	Pediatric	Community	1	38	ICU, MS, O	1 Dec. 2015	31 Dec. 2019
10	Adult	Academic	2	56	ICU, MS, O	1 Dec. 2014	31 Dec. 2016

Table 1S. Summary of Hospitals
[1]Note. ICU, intensive care unit; MS, medical surgical; O, oncology; SD, stepdown.

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