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Original Article

Sleep and Circadian Health in the Justice System

Original Article

Nightshift imposes irregular lifestyle behaviors in police academy trainees

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Abstract

Study Objective: Shiftwork increases risk for numerous chronic diseases, which is hypothesized to be linked to disruption of circadian timing of lifestyle behaviors. However, empirical data on timing of lifestyle behaviors in real-world shift workers are lacking. To address this, we characterized the regularity of timing of lifestyle behaviors in shift-working police trainees.

Methods: Using a two-group observational study design ($N = 18$), we compared lifestyle behavior timing during 6 weeks of in-class training during dayshift, followed by 6 weeks of field-based training during either dayshift or nightshift. Lifestyle behavior timing, including sleep–wake patterns, physical activity, and meals, was captured using wearable activity trackers and mobile devices. The regularity of lifestyle behavior timing was quantified as an index score, which reflects day-to-day stability on a 24-hour time scale: Sleep Regularity Index, Physical Activity Regularity Index, and Mealtime Regularity Index. Logistic regression was applied to these indices to develop a composite score, termed the Behavior Regularity Index (BRI).

Results: Transitioning from dayshift to nightshift significantly worsened the BRI, relative to maintaining a dayshift schedule. Specifically, nightshift led to more irregular sleep–wake timing and meal timing; physical activity timing was not impacted. In contrast, maintaining a dayshift schedule did not impact regularity indices.

Conclusions: Nightshift imposed irregular timing of lifestyle behaviors, which is consistent with the hypothesis that circadian disruption contributes to chronic disease risk in shift workers. How to mitigate the negative impact of shiftwork on human health as mediated by irregular timing of sleep–wake patterns and meals deserves exploration.

This paper is part of the Sleep and Circadian Health in the Justice System Collection.

Key words: shift work; actigraphy; circadian rhythms

Statement of Significance

Shiftwork is essential to a productive society. However, following a shiftwork schedule may impose a lifestyle of circadian rhythm disruption that increases chronic disease risk. Despite the widespread prevalence of shiftwork, our empirical knowledge base of real-world shiftwork and the timing of lifestyle behaviors is severely lacking. This knowledge gap has delayed progress in the field toward developing disease prevention strategies specific to shift workers. Herein, we present a novel and accessible method that quantifies the regularity of timing of lifestyle behaviors in shift-working police trainees. We observed that nightshift led to irregular timing of sleep–wake cycles and meals. Future research might consider intervening in irregular timing of lifestyle behavior as a strategy to mitigate disease risk.

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Introduction

Maintaining regular circadian rhythms is an important feature of health [1–3]. Behavior and endogenous circadian clocks have a bi-directional relationship; this premise underlies the concept that maintaining optimal behavioral patterns promotes robust circadian rhythmicity and mitigates disease [4]. In contrast, a lifestyle characterized by irregular behavior patterns—particularly in which behaviors are misaligned with endogenous circadian rhythms—may increase susceptibility to chronic disease. In support, epidemiological evidence indicates that shiftwork is associated with numerous chronic diseases [5–9]. Moreover, highly controlled in-patient studies simulating nightshift demonstrate that rapid and short-term circadian misalignment negatively impacts cardiometabolic health [10–12]. It is presumed that shift workers undergo frequent and rapid shifts in behavior timing imposed by reoccurring schedule changes from work to free days. Thus, findings from experimental models that artificially simulate nightshift, imply that real-world shift workers undergo repeat, acute disruptions in health. However, the extent to which these findings translate to shift workers is not fully understood.

To address this knowledge gap, we are in need of empirical data on lifestyle behaviors in real-world shift workers. Wearable technology and smartphone devices offer promise here, enabling real-world data capture applicable over long durations and scaled up for assessment of human behaviors [13–15]. From these data, analytical approaches that quantify day-to-day regularity of behaviors can be readily applied to field settings. One previous approach developed an index scoring method to quantify the regularity of sleep–wake cycles. Termed the sleep regularity index (SRI), this metric quantifies the likelihood of sleep–wake episodes occurring at the same time within a 24-hour time scale, or day-to-day variation [16, 17]. Application of this SRI metric has shown that the irregular sleep–wake patterns are linked to poorer academic performance in students, as well as increased cardiometabolic disease risk in adults [16, 17]. In addition to sleep–wake episodes, mealtime regularity has been previously quantified by a metric termed Composite Phase Deviation (CPD) that was originally developed to quantify circadian misalignment in humans [18, 19]. Informed by these previous approaches, we sought to expand and combine these metrics to integrate a composite score accounting for three behavior patterns that are known to impact health status: sleep–wake patterns, physical activity, and meals.

The primary objective of this study was to characterize the effects of nightshift on the regularity of lifestyle behavior timing in a real-world setting. We used wearable activity trackers to assess sleep–wake patterns and physical activity patterns, and mobile devices to assess meal timing. We conducted these assessments in two groups of police trainees that followed a real-world shiftwork schedule: one group that transitioned from dayshift to nightshift, versus a comparator group that maintained a dayshift schedule. Accordingly, we assessed day-to-day behavior regularity for three behaviors: sleep–wake patterns, physical activity, and meals. We then combined these indices into a composite score, termed the Behavior Regularity Index (BRI). We hypothesized that nightshift, incorporating a cyclic pattern of night work and off days, would be characterized by irregular behavior patterns. To test this hypothesis, we compared changes in lifestyle behavior regularity (as measured by the BRI) during the transition from a dayshift to nightshift schedule relative to changes in lifestyle behavior regularity (BRI) during maintenance of a dayshift schedule.

Methods

Study design

The study design has been previously described [13]. In brief, this was a two-group observational repeated measures study design. Police trainees followed 24 weeks of in-class training and 14 weeks of field training, and the current study protocol was a short-term observational period nested within the training schedule. Specifically, we assessed behaviors during the last 6 weeks of in-class training (baseline) and the first 6 weeks of field training, totaling 12 weeks of observation.

During the first 6 weeks, all participants followed the same in-class training schedule, which involved classes held Monday to Friday during daytime hours (7:30 am–5:00 pm). During the next 6 weeks, all participants followed one of the four field-training schedules, based on occupational assignment, which involved either a day or night shiftwork schedule. Specifically, day shifts included either shift A: 6 am–5 pm ($N = 5$) or shift B: 10 am to 9 pm ($N = 2$), thus representing circadian alignment. Night shifts included either Shift C: 4 pm–3 am ($N = 5$) or shift D: 8 pm–7 am ($N = 6$), thus representing circadian misalignment. The same shift (A, B, C, or D) was maintained throughout the 6-week observation period, with trainees operating on a 4-day on, 4-day off schedule. No distinction was made in the analysis between weekdays and weekends during in-class training or days on/off during shiftwork so as to capture the level of irregularity in the trainees' behaviors, whether imposed or voluntary.

Participants.

Study inclusion criteria have been previously described [13]. These included (1) being enrolled in a local public safety training program and (2) owning a smartphone. Institutional Review Board approval was given by Duke University Health System Institutional Review Board for Clinical Investigations (IRB# Pro00077319). All participants gave informed consent prior to participation in this study.

Study protocol

As described above, this was a field-based study. During the 12-week protocol, participants wore activity trackers (Garmin vívosmart HR, Olathe, KS) and used smartphones to report recalled mealtimes. From these collection methods, we determined behavior variability for the following three behaviors: sleep–wake patterns, physical activity, and meals, which were then used to calculate the BRI.

Wearable assessments.

Activity trackers were used to assess sleep–wake patterns and physical activity during in-class training and field-based training. The Garmin vívosmart HR was worn on the wrist 24/7 (except when charging device) [13]. This activity tracker provides readouts of "activity level" and heart rate, which are used to inform sleep–wake labeling in 15-minute epochs. Garmin vívosmart HR wear time of 80% over 24 hours was the criteria used to determine data completeness. To be considered for data analysis, at least 50% of days were required to meet wear time criteria. We applied a novel sleep-labeling method to improve sleep–wake labeling completeness [13]. This method involves a post-data processing step to increase labeling accuracy of daytime sleep episodes—which we previously observed were frequently mislabeled as non-sleep among nightshift workers. We used this sleep-labeling method to determine sleep initiation time and sleep duration. Herein, all labeled sleep events were considered regardless of duration of time to enable the capture of napping periods, whereas previous approaches only considered sleep events exceeding 4 hours [13].

The Garmin vívosmart HR was also used to determine exercise/physical activity duration and intensity. For this, we used the Garmin mean motion intensity score. This is a proprietary method that takes acceleration and heart rate into account to average motion intensity levels within 15-minute epochs, resulting in values ranging from 0 to 7.

Meal timing assessments.

Self-reported mealtimes were collected throughout the duration of the study protocol. Starting the day after enrollment, participants responded to a text message prompt that inquired about the times of their major meals during the prior calendar day (or prior 24 hours). This text message prompt was sent at 4 pm regardless of shiftwork schedule, and participants replied when it was convenient for them to do so.

Regularity indices

The behaviors of interest—sleep–wake, physical activity, and meals—were separately quantified using the following 3 measures: SRI [16, 17], Physical Activity Regularity Index (PARI), and Mealtime Regularity Index (MRI). Each of these metrics range in value from 0 to 100 and are further described below.

The *SRI*, in which sleep versus awake is assessed using our sleep detection algorithm in 15-minute epochs, has been described by others [16, 17] but is reiterated here for completeness. For a given participant, the SRI is calculated across the J 15-minute epochs in K observed days as

$$\mathrm{SRI} = -100 + \frac{200}{J(K-1)} \sum_{j=1}^{J} \sum_{k=1}^{K-1} \delta(s_{kj}, s_{(k+1)j})$$

where S_{kj} denotes the participant's sleep–wake status (0 or 1) on day k during the jth 15-minute epoch, and $\delta(s_{kj}, s_{(k+1)j}) = \mathbb{I}(s_{kj} = s_{(k+1)j})$ is an indicator function that assigns the value 1 if the participant has the same status, asleep or awake, during the jth epoch on consecutive days, or 0 otherwise. Although the SRI could theoretically take values between [–100,100], the developers noted that negative values are highly unlikely to be observed and so the practical range of values is [0,100] [16].

The *PARI*, in which activity is binned within 15-minute epochs as low [0–3], medium [4–6], or high [7] by rounding mean motion intensity scores (from Garmin), is computed similar to the previously described SRI. Specifically, for a given participant, the PARI is calculated across the J 15-minute epochs in K observed days as

$$\mathrm{PARI} = \frac{100}{J(K-1)} \sum_{j=1}^{J} \sum_{k=1}^{K-1} \delta(a_{kj}, a_{(k+1)j})$$

where a_{kj} denotes the participant's physical activity level (low, medium, or high) on day k in epoch j, and $\delta(a_{kj},\ a_{(k+1)j})$ is the indicator function comparing activity levels during the same 15-minute epoch across consecutive days. The PARI is scaled to take values in [0,100] by multiplying the average similarity index by 100. This difference in scaling, relative to the SRI, is due to the increased variability associated with three possible physical activity levels rather than two, as for sleep. Scaling the PARI as the SRI would result in negative PARI values, which are not easily interpretable.

The *MRI* assesses day-to-day stability of meal timing. The MRI extends the metric CPD, which was initially used to quantify circadian misalignment in sleep patterns [19] and later applied to mealtimes [18]. CPD measures variability by combining how different meal timing is compared to that on the previous day (regularity) and how far away meal timing is from the average mealtime (alignment). For a given participant and meal, CPD is calculated across days $k = 1,\ldots, K$ as follows:

$$\Delta\ \mathrm{Regularity}_k = \Delta\ \mathrm{DD}_k = \mathrm{Meal\ time}_{k-1} - \mathrm{Meal\ time}_k$$

$$\Delta\ \mathrm{Alignment}_k = \Delta \mathrm{AT}_k = \mathrm{Average\ meal\ time} - \mathrm{Meal\ time}_k$$

$$\mathrm{CPD}_k = \sqrt{\Delta\ \mathrm{DD}_k^2 + \Delta\ \mathrm{AT}_k^2}$$

$$\mathrm{CPD} = \frac{1}{K} \sum_{k=1}^{K} \mathrm{CPD}_k$$

To scale the index value between [0,100] and invert it to indicate regularity, we let $\mathrm{CPD}_m^* = (1 - [\mathrm{CPD}_m/\mathrm{CPD}_{\max}]) \times 100$, where CPD_{max} assumes meal m alternates timing by 12 hours each day yielding $\Delta\ \mathrm{DD} = 12$, $\Delta\ \mathrm{AT} = 6$, and $\mathrm{CPD}_{max} = 6\sqrt{5}$. The MRI, which reflects a participant's average regularity across meals, in hours, relative to a perfectly regular pattern of meal timing, can then be defined for meals $m = 1,\ldots, M$ as

$$\mathrm{MRI} = \frac{1}{M} \sum_{m=1}^{M} \mathrm{CPD}_m^*.$$

Self-reported mealtimes for the first meal upon awaking and the last meal before sleep, for a maximum of two meals per waking period, were used for the MRI calculation. Intermediate meals were omitted; this resulted in mealtime windows (or duration of eating) corresponding to each waking period that was anchored by the time of first and last behavioral meals. Any meal that was the only meal reported for a given waking period was characterized as both the first meal after waking and last meal before sleeping.

Using the three indices described above, we developed the *BRI*. For a given participant, the BRI is the predicted response from a multiple logistic regression model with the SRI, PARI, and MRI as predictors and expected regularity status as the response Y, as given below:

$$\mathrm{BRI} = \Pr(Y = 1 \mid \mathrm{SRI},\ \mathrm{ARI},\ \mathrm{MRI}) = \frac{\exp(\beta_0 + \beta_1 \mathrm{SRI} + \beta_2 \mathrm{ARI} + \beta_3 \mathrm{MRI})}{1 + \exp(\beta_0 + \beta_1 \mathrm{SRI} + \beta_2 \mathrm{ARI} + \beta_3 \mathrm{MRI})}.$$

Here, the expected regularity status corresponds to whether the trainee was following a dayshift (1) or nightshift (0) schedule, regardless of actual observed behavior, with the a priori assumption that nightshift workers revert to a typical daytime schedule on days not working. Succinctly, the BRI measures the degree, ranging from 0 to 1, to which a participant is performing behaviors in a regular pattern, day to day. A BRI value of 0 indicates complete irregularity and 1 indicates perfect regularity.

Each component index was calculated separately for in-class training and field-based training. For the MRI, average mealtime was determined during in-class training as a circular mean (i.e. in polar coordinates then converted back to hours) and used for both in-class and field-based training computations. The logistic regression model producing the BRI was then trained on the component indices from the two time periods (in-class training and field-based training), where each trainee thus contributed two observations. We assumed independence of observations within participants because accounting for paired samples with a grouping covariate resulted in overfitting and the $N - 1$ grouping coefficients cannot be applied in predictions of new observations.

Statistical analysis

R version 4.2.1 was used for mathematical computation and data visualization. Statistical analyses were conducted with SAS software, Version 9.4 (SAS Institute Inc., Cary, NC, USA). We first determined the impact of transitioning from in-class training to field-based training in both the dayshift and nightshift group (within-group differences) in the SRI, PARI, MRI, and the composite BRI using the Wilcoxon signed rank test. To assess the impact of nightshift on behavior regularity, we next determined if the in-class to field-training transition was different between the dayshift and nightshift groups (between-group differences) on the same indices using the Kruskal–Wallis test of equality test. Behavior regularity during in-class training was compared between the dayshift and nightshift groups using the Wilcoxon rank sum test. Regularity indices are summarized and reported as median (Q1, Q3). Significance of within- and between-group differences was accepted at $p < 0.05$. Estimated odds ratios, 95% confidence intervals, and the corresponding *p*-values are also reported for each of the three component indices of the BRI.

Results

Participant characteristics

The current study cohort consisted of 18 individuals, which is a subset of our previous cohort [13]. Participants lacking meal timing data or who were not assigned to one of the four shiftwork schedules were excluded. The mean age was 26 (±6.7) years, and mean BMI was 26 (±3.8) kg/m^2. Representative polar plots display the impact of transitioning from a dayshift to a nightshift schedule on sleep–wake patterns, physical activity, and mealtimes, relative to maintaining a dayshift schedule (Figure 1).

Effect of shiftwork on behavior regularity: input indices

Sleep regularity index.

We have reported the SRI for the larger participant cohort elsewhere [13]. Transitioning from dayshift in-class training to dayshift field-based training did not significantly reduce the SRI (70.3 vs. 64.9; $p = 0.578$; Table 1), whereas transitioning from dayshift in-class training to nightshift field-based training significantly reduced the SRI (56.8 vs. 46.6; $p = 0.042$; Table 1). However, the changes in the SRI were not different between groups ($p = 0.342$; Table 1). No differences were observed between groups during the in-class training dayshift periods ($p = 0.147$). Figure 2 shows density plots of the SRI during all four conditions.

Physical activity regularity index.

The PARI was not significantly impacted by either transitioning from dayshift in-class training to dayshift field-based training (63.5 vs. 63.4, $p = 0.297$; Table 1) or transitioning from dayshift in-class training to nightshift field-based training (60.9 vs. 59.0, $p = 0.365$; Table 1). Thus,

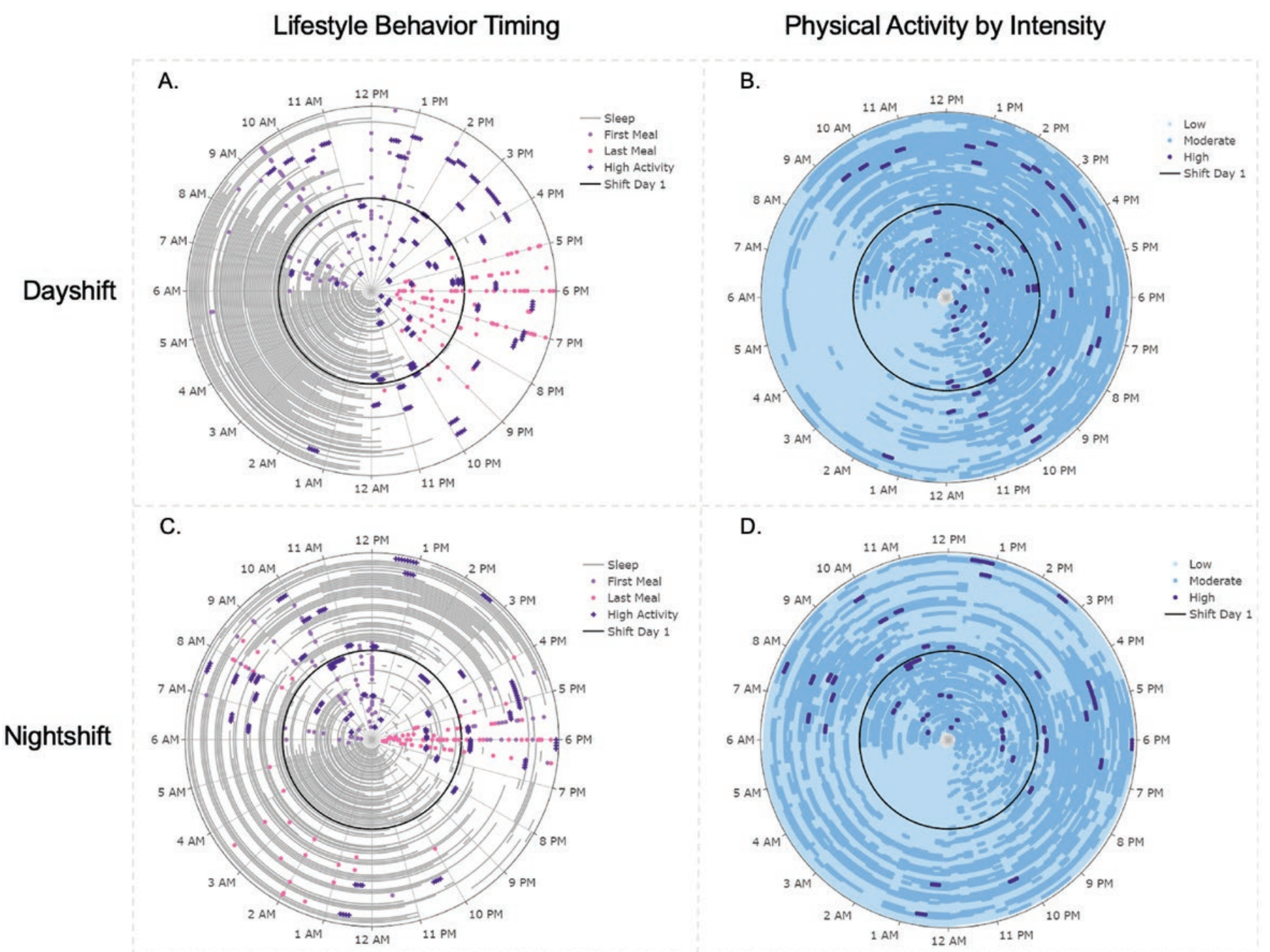

Figure 1. Panels A and B show representative polar plots for an individual participant during 6 weeks of dayshift in-class training followed by 6 weeks dayshift field-based training. Panels C and D show representative polar plots for an individual participant during 6 weeks of dayshift in-class training followed by 6 weeks nightshift field-based training. Panels A and C show the occurrence of sleep periods (gray lines), meals (light purple and pink), and physical activity bouts (dark purple). Panels B and D show the occurrence of physical activity bouts by intensity, including low (light blue), moderate (blue), and high (dark purple). The transition from in-class training to field-based training at 6 weeks is indicated by the black concentric circle.

Table 1. Lifestyle Behavior Regularity Indices on Dayshift and Nightshift

Indices	Sleep regularity	Physical activity regularity	Mealtime regularity	Behavior regularity
Circadian alignment				
In-class/day shift ($N = 7$)	70.3 (64.6, 77.1)	63.5 (61.2, 67.7)	84.5 (82.4, 88.5)	1.00 (1.00, 1.00)
Field-based/day shifts A ($N = 5$) and B ($N = 2$)	64.9 (55.1, 69.9) —	63.4 (56.6, 67.8) —	84.1 (76.8, 91.0) —	1.00 (0.82, 1.00) —
Within-group p-values	0.578	0.297	0.375	0.250
Circadian misalignment				
In-class/day shift ($N = 11$)	56.8 (48.2, 69.0)	60.9 (56.7, 65.5)	85.5 (83.6, 86.5)	1.00 (1.00, 1.00)
Field-based/night shifts C ($N = 5$) and D ($N = 6$)	46.6 (42.6, 56.7) —	59.0 (52.7, 62.1) —	49.2 (35.3, 74.0) —	0.00 (0.00, 0.24) —
Within-group p-values	0.042*	0.365	0.001*	0.001*
Between-group p-values	0.342	0.751	<0.001*	<0.001*

Values are presented as median (Q1, Q3). *$p \leq 0.05$.
Within-group p-values from Wilcoxon signed rank tests applied to within-group differences.
Between-group p-values from Kruskal–Wallis test of equality of within-group differences.

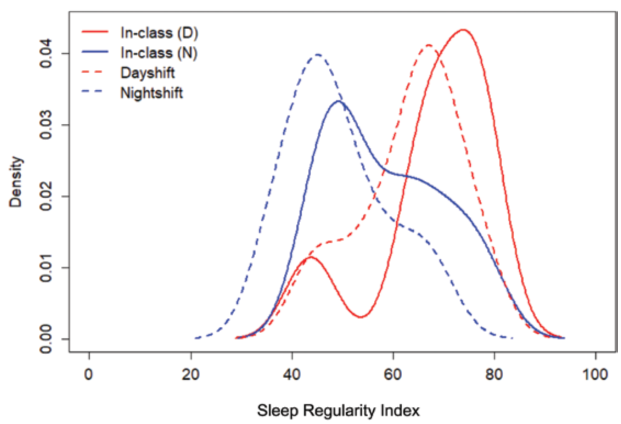

Figure 2. Figure shows density plots of Sleep Regularity Index (SRI) of the participant cohort during the transition from dayshift in-class training (in-class (D); red line) to dayshift field-training (dayshift; dashed red line), as well as during the transition from dayshift in-class training (in-class (N); blue line) to nightshift field-training (nightshift; dashed blue line). Each index is expressed as a value ranging from 0 to 100, in which 0 reflects irregularity and 100 reflects regularity.

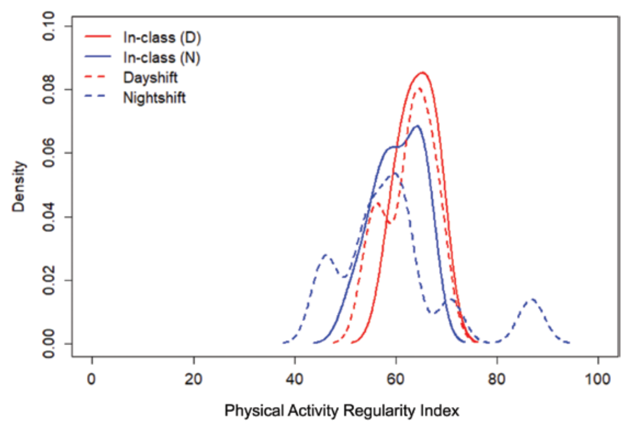

Figure 3. Figure shows density plots of Physical Activity Regularity Index (PARI) of the participant cohort during the transition from dayshift in-class training (in-class (D); red line) to dayshift field-training (dayshift; dashed red line), as well as during the transition from dayshift in-class training (in-class (N); blue line) to nightshift field-training (nightshift; dashed blue line). Each index is expressed as a value ranging from 0 to 100, in which 0 reflects irregularity and 100 reflects regularity.

changes in the PARI were not different between groups ($p = 0.751$; Table 1). No differences were observed between groups during the in-class training dayshift periods ($p = 0.085$). Figure 3 shows density plots of the PARI during all four conditions.

Meal timing regularity index.

The transition from dayshift in-class training to dayshift field-based training was not significantly different (84.5 vs. 84.1, $p = 0.375$; Table 1). In contrast, the transition from dayshift in-class training to nightshift field-based training led to a significant reduction in meal timing regularity (85.5 vs. 49.2, $p = 0.001$; Table 1). Moreover, changes in the MRI were significantly different between groups ($p < 0.001$; Table 1). No differences were observed between groups during the dayshift in-class training ($p = 0.928$). Figure 4 shows density plots of the MRI during all four conditions.

Effect of shiftwork on BRI

The transition from dayshift in-class training to dayshift field-based training on the composite BRI was not significantly different in dayshift (1.00 vs. 1.00; $p = 0.250$; Table 1). In contrast, the transition from dayshift in-class training to nightshift field-based training reduced composite BRI (1.00 vs. 0.00, $p = 0.001$; Table 1). Moreover, changes in the BRI were significantly different between dayshift and nightshift groups ($p < 0.001$; Table 1). No differences were observed between groups during dayshift in-class training ($p = 0.359$). Figure 5 shows density plots of the BRI during the transition from dayshift in-class training to dayshift field-based training (panel A) and dayshift in-class training to nightshift field-based training (panel B).

The BRI was calculated and rounded to the nearest integer to classify participant behaviors as either regular or irregular. Our a priori hypothesis was that dayshift schedules would produce a BRI classified as regular (closer to 0.5–1) and nightshift schedules would produce a BRI classified as irregular (closer to 0–0.5). As shown in the contingency table in Table 2, this hypothesis was confirmed for 24 of the 25 participant dayshift observations classified as regular and 10 of the 11 participant nightshift observations classified as irregular. The odds ratio for each behavior component index was calculated, but not significant (Table 3). Of the three indices, though, the MRI had the largest odds ratio (2.16) compared to the PARI (1.39) and SRI (1.09).

Discussion

The primary finding of this study was that nightshift reduced the regularity of lifestyle behavior timing, whereas dayshift enabled maintenance of lifestyle behavior regularity. This finding is consistent with previous work in shift-working nurses that, through the use of self-report logs, indicate a variety of sleep–wake patterns are used to cope with shiftwork demands [20]. We extended this earlier work to also consider two additional behaviors that are relevant for health, namely physical activity and meal timing. This current work addresses a knowledge gap by generating empirical data to confirm that sleep–wake patterns and meal timing are irregular during nightshift in the real-world. Controlled in-patient studies reveal that following a simulated nightshift schedule has acute detrimental consequences on cardiometabolic health [10–12]. Our findings of irregular sleep–wake patterns and meals during nightshift in sample of police trainees—for which shiftwork is unavoidable—supports the translation and relevance of in-patient studies to real-world settings of shiftwork characterized by repeated bouts of nightshift.

The novel BRI quantifies the degree of regularity with which behavior events occur at the same point in time, 24 hours apart, on a day-to-day timescale. As a test of internal validity, we compared BRI against the known shiftwork schedule, with the a priori expectation that participants on nightshift would exhibit reduced behavior regularity, whereas participants on dayshift would exhibit maintenance of behavior regularity. On average, we had successful predictions for matching of behavior regularity compared to the shiftwork schedule. Specifically, 91% of

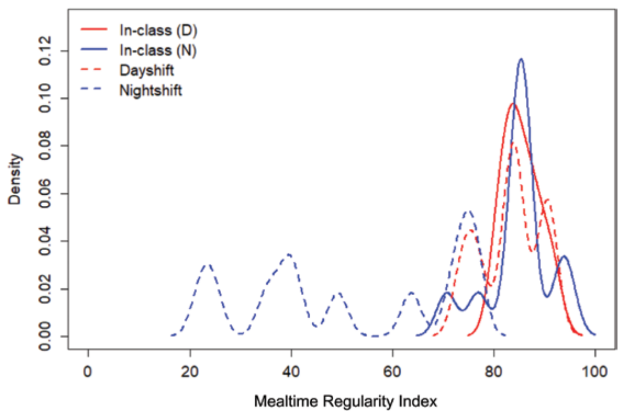

Figure 4. Figure shows density plots of Mealtime Regularity Index (MRI) of the participant cohort during the transition from dayshift in-class training (in-class (D); red line) to dayshift field-training (dayshift; dashed red line), as well as during the transition from dayshift in-class training (in-class (N); blue line) to nightshift field-training (nightshift; dashed blue line). Each index is expressed as a value ranging from 0 to 100, in which 0 reflects irregularity and 100 reflects regularity.

Table 2. Comparison of Predicted Behavior Regularity Index Versus Actual Shiftwork Schedule

	Actual shiftwork schedule	
Computed behavior regularity	**Dayshift**	**Nightshift**
Regular	24	1
Irregular	1	10

Computed behavior regularity index was calculated using linear regression. We then compared the predicted shiftwork schedule (e.g. regular behavior index was hypothesized to indicate an actual dayshift schedule), whereas an irregular behavior index was hypothesized to indicate an actual nightshift schedule).

Table 3. Odds Ratio of Component Input Indices

Parameter	Odds ratio	95% CI	P-value
Sleep regularity index	1.09	(0.89, 1.34)	0.401
Physical activity regularity index	1.39	(0.86, 2.25)	0.184
Mealtime regularity index	2.16	(0.82, 5.68)	0.119

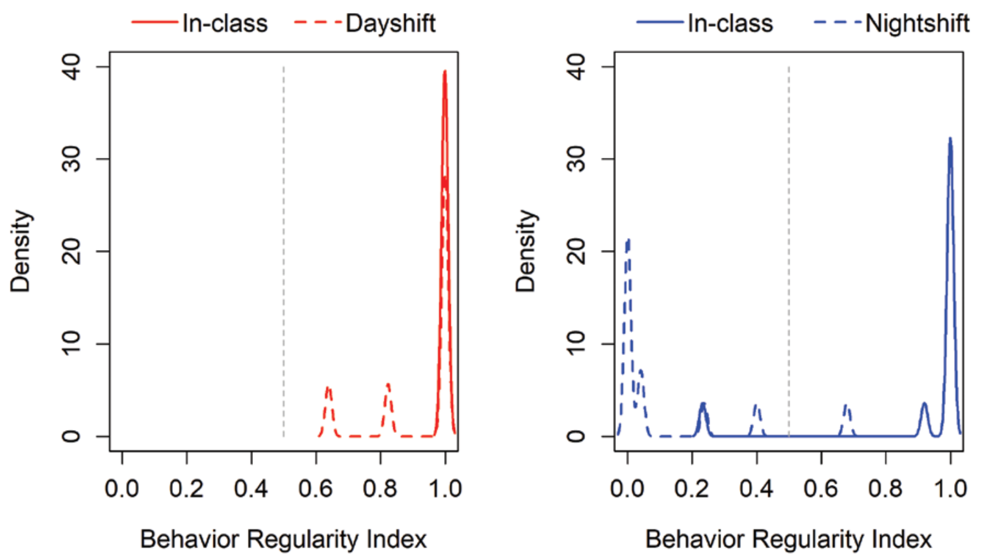

Figure 5. Panel A shows density plots of BRI of the participant cohort during the transition from dayshift in-class training (in-class; red line) to dayshift field-training (dayshift; dashed red line). Panel B shows density plots of BRI from participant cohort during the transition from dayshift in-class training (in-class; blue line) to nightshift field-training (nightshift; dashed blue line). BRI is expressed as a value ranging from 0 to 1, in which 0 reflects maximum irregularity and 1 reflects maximum regularity. The dashed gray line marks a reference point of 0.5, in which a BRI between 0.5 and 1 is classified as "regular" and a BRI between 0 and 0.49 is classified as "irregular."

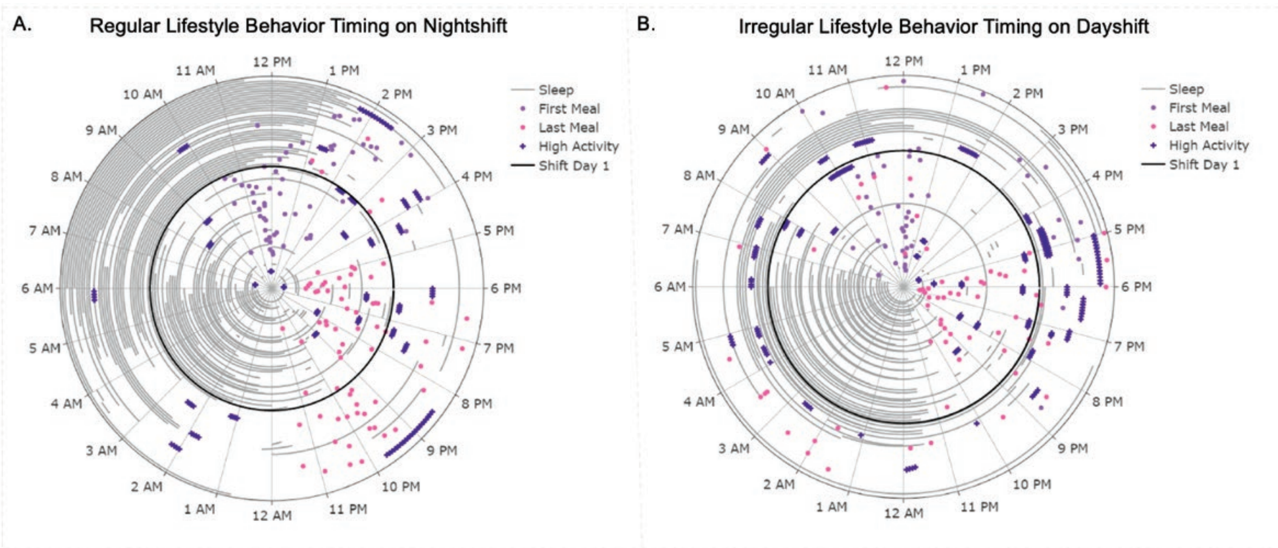

Figure 6. Representative polar plots for two instances in which BRI did not correspond with actual shiftwork schedule. Panel A shows an example of behavior regularity during the 6 weeks of nightshift, indicating that a nightshift schedule was regularity maintained during non-workdays. Panel B shows an example of behavior irregularity during 6 weeks of in-class training, despite a typical dayshift schedule.

the observations from nightshift were classified as irregular and 96% of the observations from dayshift were classified as regular. Indeed, this analysis revealed some interesting misclassifications. We observed that one participant on nightshift exhibited regularity in lifestyle behavior patterns by maintaining a "nightshift" schedule during non-workdays (Figure 6; panel A). Additionally, we observed that one participant exhibited irregularity in lifestyle behavior patterns during in-class training (Figure 6; panel B), possibly related to illness that altered sleep/wake patterns and induced irregular mealtimes (MRI = 70). Overall, these findings suggest that, on average, nightshift disrupts the regularity in lifestyle behaviors from day-to-day, whereas dayshift enables a maintenance of behavior regularity.

We primarily focused on regularity of three lifestyle behaviors, which included sleep–wake patterns, physical activity, and meals. We also calculated the odds ratio which describes the increase in likelihood that a participant will be classified as regular for a 1-point increase in a component index. Of these three behaviors, meal timing had the largest odds ratio (2.16) relative to the physical activity (1.39) and sleep (1.09), suggesting that this behavior had the strongest influence on the BRI, although not statistically significant. The observation that nightshift led to irregular meal timing may be concerning in the context of weight gain; late meal timing relative to circadian phase is associated with increased adiposity [21, 22]. Nightshift also led to irregular sleep–wake patterns, in agreement with previous work [20]. Physical activity regularity was minimally impacted by nightshift, and this finding may be explained by the low levels of physical activity in our participant cohort. Furthermore, in-class training involved some structured physical exercise (1–2 times per week), which may have contributed to increased regularity. Field training, on the other hand, did not involve structured physical exercise, and it is possible that this resulted in a slight decline in physical activity regularity by some participants. Given the well-accepted health benefits of physical activity and exercise, this finding may highlight a targetable behavior for intervention specific to shift workers. Thus, an advantage of the BRI is that it is designed to be sensitive to changes in behavior patterns in physical activity, sleep–wake, and meal timing, over a broad range of adaptations in a variety of populations.

As with any study utilizing field-based assessments, we encountered data missingness regarding self-reported mealtimes and sleep–wake patterns due to noncompliance. Since self-reported mealtimes focused on main meals, this may have resulted in missing snacking behavior. In addition, there may be some misclassification in sleep–wake patterns—specifically when the sleep detection algorithm noted sleep periods while the participant was supposedly in the classroom or on patrol due to low activity levels and heart rate. In these situations, classification of meals relative to sleep was done manually and subjectively, considering the participants' behavior patterns on surrounding days when both meal and activity data were collected. In addition, meals reported during the detected sleep periods were not accounted for in the analysis (e.g. the computation of MRI).

In summary, we observed that nightshift imposed a rapid and sustained reduction in regularity of lifestyle behavior timing as compared to dayshift. We also identified "behavior" outliers, in which the anticipated behavior regularity did not necessarily match with the shiftwork schedule, suggesting some variation in behavior strategies to cope with shiftwork. Through the use of wearable activity trackers and mobile devices, we demonstrate the use of a novel BRI metric that quantifies lifestyle behavior regularity in real-world settings of shiftwork. One advantage of this approach is that it is feasible to scale these assessments to larger participant cohorts across long time domains. Future studies might consider using the BRI to gain new insight into patterns of behavior in other populations experiencing circadian disruption.

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Author Contributions

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Data Availability

Data will be made available upon reasonable request.

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