JMIR Publications
The Leading eHealth Publisher

Integrating Human-Smartphone Interactions and Actigraphy in Digital Phenotyping: Exploring Social-Physical Coherence in Relation to Obesity and Depression

Yu-Hsuan Lin, Chen Lin, Hai-Hua Chuang, Hsiang-Chih Chang, I-Ming Chen, Tien-Yu Chen

Submitted to: Journal of Medical Internet Research
on: May 22, 2024

Disclaimer: © The authors. All rights reserved. This is a privileged document currently under peer-review/community review. Authors have provided JMIR Publications with an exclusive license to publish this preprint on it's website for review purposes only. While the final peer-reviewed paper may be licensed under a CC BY license on publication, at this stage authors and publisher expressively prohibit redistribution of this draft paper other than for review purposes.

Table of Contents

Preprint
JMIR Publications

Integrating Human-Smartphone Interactions and Actigraphy in Digital Phenotyping: Exploring Social-Physical Coherence in Relation to Obesity and Depression

Yu-Hsuan Lin[1, 2, 3] MD, PhD; Chen Lin[4] PhD; Hai-Hua Chuang[5, 6, 7, 8] PhD; Hsiang-Chih Chang[1] PhD; I-Ming Chen[2, 3] MD; Tien-Yu Chen[9] PhD

[1]National Health Research Institutes Miaoli County TW
[2]National Taiwan University Hospital Taipei TW
[3]National Taiwan University Taipei TW
[4]National Central University Taoyuan City TW
[5]Chang Gung Memorial Hospital Taoyuan TW
[6]National Taipei University of Technology Taipei TW
[7]National Tsing Hua University Hsinchu TW
[8]Chang Gung University Taoyuan TW
[9]National Defense Medical Center Taipei TW

Corresponding Author:
Yu-Hsuan Lin MD, PhD
National Health Research Institutes
No.35, Keyan Rd., Zhunan Township
Miaoli County
TW

Abstract

Methods: The research encompassed 135 participants (average age: 43.8±12.3 years; 65.2% female), including individuals with a history of major depression, those with obesity, and health-care professionals participating in a workplace health program. Body Mass Index (BMI) and the Patient Health Questionnaire-9 (PHQ-9) scale were employed to determine obesity and depression levels, respectively. Activity data were collected over a minimum of four weeks using wrist actigraphy devices and the Rhythm app, yielding 3,973 person-days of data. The Rhythm app tracked human-smartphone interactions and computed rest-activity rhythm (RAR) patterns, including interdaily stability (IS), from both standard actigraphy and app-derived data, thus offering two distinct RAR measurements. Social-physical coherence was assessed by combining physical activity data from actigraphy with social activity data derived from human-smartphone interactions.

Results: Findings demonstrated a significant positive correlation between social-physical coherence and IS, particularly significant in app-derived IS (ISapp) over a period of 1-6 weeks. Analysis of the relationship with BMI revealed a significant negative correlation for both social-physical coherence and ISapp within the first 2-4 weeks, whereas no notable correlation was found with actigraphy-based IS (ISact). Regarding depressive symptom scores, a borderline-significant negative correlation was observed with ISact when examining data from the first 1, 3, 4, or 5 weeks (P=.054 to .062). No significant correlation was found between social-physical coherence or ISapp and PHQ-9 scores across all timeframes studied.

Conclusions: This study leveraging digital phenotyping through actigraphy and human-smartphone interactions, reveals an inverse relationship between social-physical coherence and obesity, and a more complex association with depression.

(JMIR Preprints 22/05/2024:60798)
DOI: https://doi.org/10.2196/preprints.60798

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?
- ✓ **Please make my preprint PDF available to anyone at any time (recommended).**
- Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
- Only make the preprint title and abstract visible.

No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Preprint JMIR Publications

Original Manuscript

Preprint
JMIR Publications

Original Paper

Integrating Human-Smartphone Interactions and Actigraphy in Digital Phenotyping: Exploring Social-Physical Coherence in Relation to Obesity and Depression

Chen Lin[1], Hai-Hua Chuang[2,3,4,5], Hsiang-Chih Chang[6], I-Ming Chen[7,8], Tien-Yu Chen[9], Yu-Hsuan Lin[6,7,8*]

Affiliations

[1] Department of Biomedical Sciences and Engineering, National Central University, Taoyuan City, Taiwan.

[2] College of Medicine, Chang Gung University, Taoyuan, Taiwan.
[3] Department of Family Medicine, Chang Gung Memorial Hospital, Taipei Branch and Linkou Main Branch, Taoyuan, Taiwan.
[4] Department of Industrial Engineering and Management, National Taipei University of Technology, Taipei, Taiwan.
[5] School of Medicine, National Tsing Hua University, Hsinchu, Taiwan.
[6] Institute of Population Health Sciences, National Health Research Institutes, Miaoli County, Taiwan.
[7] Department of Psychiatry, National Taiwan University Hospital, Taipei, Taiwan.
[8] Department of Psychiatry, College of Medicine, National Taiwan University, Taipei, Taiwan.
[9] Department of Psychiatry,Tri-Service General Hospital, School of Medicine, National Defense Medical Center, Taipei, Taiwan

Corresponding author

Yu-Hsuan Lin, MD, PhD

Institute of Population Health Sciences

National Health Research Institutes

35 Keyan Road, Zhunan, Miaoli County, Taiwan

Phone: +886 37-206-166 ext. 36383

Email: yuhsuanlin@nhri.edu.tw

Abstract

Introduction: The interrelationship between physical and social activities plays a crucial role in influencing health outcomes, particularly in populations with obesity and depression. This study aims to develop the "social-physical coherence" method for measuring the alignment between physical and social activities, investigating its association with obesity and depression.

Methods: The research encompassed 135 participants (average age: 43.8±12.3 years; 65.2% female), including individuals with a history of major depression, those with obesity, and health-care professionals participating in a workplace health program. Body Mass Index (BMI) and the Patient Health Questionnaire-9 (PHQ-9) scale were employed to determine obesity and depression levels, respectively. Activity data were collected over a minimum of four weeks using wrist actigraphy devices and the Rhythm app, yielding 3,973 person-days of data. The *Rhythm* app tracked human-smartphone interactions and computed rest-activity rhythm (RAR) patterns, including interdaily stability (IS), from both standard actigraphy and app-derived data, thus offering two distinct RAR measurements. Social-physical coherence was assessed by combining physical activity data from actigraphy with social activity data derived from human-smartphone interactions.

Results: Findings demonstrated a significant positive correlation between social-physical coherence and IS, particularly significant in app-derived IS (IS_{app}) over a period of 1-6 weeks. Analysis of the relationship with BMI revealed a significant negative correlation for both social-physical coherence and IS_{app} within the first 2-4 weeks, whereas no notable correlation was found with actigraphy-based IS (IS_{act}). Regarding depressive symptom scores, a borderline-significant negative correlation was observed with IS_{act} when examining data from the first 1, 3, 4, or 5 weeks (P=.054 to .062). No significant correlation was found between social-physical coherence or IS_{app} and PHQ-9 scores across all timeframes studied.

Conclusions: This study leveraging digital phenotyping through actigraphy and human-smartphone interactions, reveals an inverse relationship between social-physical coherence and obesity, and a more complex association with depression.

Keywords: phase coherence, social jetlag, circadian rhythm, rest-activity rhythms, human-smartphone interaction, actigraphy

Introduction

Circadian rhythms are near-24-hour oscillations that regulate various physiological processes in the human brain and body. These rhythms are found in essentially every aspect of our physiology, and disruptions in circadian rhythms, known as circadian dysregulation, have been linked to an increased risk of various diseases, including mood disorders and metabolic diseases [1]. One key factor influencing circadian dysregulation is the misalignment between our social clock and our biological clock. The greater the misalignment between these clocks, the higher the likelihood of developing certain diseases [2]. This misalignment has been quantified using the concept of "social jetlag," which measures the difference between our social and biological clocks [2]. However, to comprehensively understand the impact of circadian misalignment on health outcomes, it is crucial to develop methods that directly measure the alignment between physical activity and psycho-social activity.

Rest-activity rhythms (RARs) have emerged as crucial indicators of circadian disruptions and can be measured using actigraphy in real-world settings. Unlike traditional measurements that focus solely on sleep or physical activity, RAR measures quantify the regularity and timing of 24-hour sleep-wake cycles. Actigraphy, the standard tool for assessing RAR, primarily relies on physical activity measured by wrist-worn accelerometers [3]. However, recent research has explored the use of digital footprints, specifically human-smartphone interactions, as a potential new method for observing human circadian rhythms. Smartphone usage captures a wider range of social and mental activities, which are integral components of circadian rhythms and provide richer insights compared to actigraphy alone. While previous studies [4, 5] have compared sleep-wake estimations derived from human-smartphone interaction patterns with those derived from standard actigraphy, there is a lack of research utilizing human-smartphone interaction patterns to delineate well-established RAR indicators, such as interdaily stability, relative amplitude, and intradaily variability, which have been extensively studied using actigraphy-based analyses. Moreover, the existing research has predominantly focused on healthy participants and has not validated their algorithms in patients with sleep disturbances or disrupted circadian rhythms in clinical settings. This limited clinical evidence restricts the

Preprint JMIR Publications

application of circadian knowledge in diagnostic and therapeutic opportunities. By combining actigraphy and human-smartphone interaction patterns in measuring RAR, we can obtain a more comprehensive understanding of the alignment between physical activity and psycho-social activity, addressing the gaps in current research.

The aim of this study was to develop a method for directly measuring the alignment and interaction between physical activity andsocial activity. Actigraphy was used to quantify physical activity, while human-smartphone interaction patterns were used to quantify psycho-social activity. By quantifying the phase coherence of these two activities, we examined the associations between this "social-physical coherence" and clinical indicators such as obesity and depression. Additionally, we investigated the correlation between the alignment measure and traditional RAR indices, such as interdaily stability. Furthermore, we determined the optimal measurement period for these indices and explored their associations with clinical indicators.

Methods

Study population

A total of 135 participants were recruited for the study from various sources, including three psychiatric outpatient clinics (n=57), an obesity outpatient clinic (n=25), and a workplace health promotion program at seven hospitals in northern Taiwan (n=53). The participants had a mean age of 43.8±12.3 years, and 65.2% of them were women. The study was conducted between September 2021 and February 2023. This diverse sample allowed us to examine the associations between RAR profiles and major depression, obesity, and their comorbid conditions. Upon giving informed consent, all participants were asked to install the Rhythm app and wear a wrist actigraphy device for a minimum of four weeks, resulting in a total of 3,973 person-days of data collection. Only participants with Android operating smartphones were eligible to participate, with the condition that their phones were to be exclusively used by them during the study period. Participants were instructed to wear their actigraphy device continuously. The study was approved by the Institutional Review Boards of the National Taiwan University Hospital (IRB No. 202004005RIND), Tri-Service General Hospital (IRB No. B202205050), and Chang-Gung Memorial Hospital (IRB No. 202002452A3 and 202100434B0A3) and was conducted in

Preprint JMIR Publications

accordance with the ethical principles outlined in the Declaration of Helsinki.

Actigraphy, physical activity and sleep indicators

The participants were instructed to wear a research-grade wrist actigraphy device on their non-dominant wrist. The actigraphy device gathered acceleration data along three axes and calculated the Euclidean distance of the deviations from zero. The data were then bandpass filtered from 0.5-3 Hz, and zero values above a pre-defined threshold were integrated within 2 seconds. Activity counts were derived by averaging the integrated segments over one minute [3, 6]. The algorithm was run on MATLAB software (MathWorks, Natick, USA) using pre-existing codes.

Human-smartphone interaction patterns

The app, *Rhythm*, was designed to collect data on smartphone usage by tracking three key variables: screen on/off events, notifications, and the app being used [5, 7]. The data were collected in the background without interfering with the smartphone operation or affecting battery life (less than 1%). To represent patterns in app usage, the number of apps used per minute was aggregated into 5-minute epochs that did not overlap (288 epochs per day) to eliminate excessive zero count segments. This data was then used to mimic the activity data obtained from the wrist actigraphy device and estimate the near-24-hour cycle of the circadian rhythm (Figure 1).

Rest-activity rhythm measures

We used the non-parametric method to calculate circadian rhythm indicators based on the varying time-windows from one-week to six-week dataset of app-counts or acti-counts (Figure 2). The non-parametric method was used to calculate three of the circadian rhythm indicators: interdaily stability (IS), intradaily variability (IV) and relative amplitude (RA) [8].

IS quantified the stability of the rhythms between days representing the coupling strength of the rhythms to the supposedly stable environmental factors. It could vary between 0 and 1, with higher values indicating more stable daily rhythms.

$$\mathrm{IS} = \frac{\sum_{h=1}^{p}(x_h - \bar{x})^2\, N}{\sum_{i=1}^{N}(x_i - \bar{x})^2\, p}$$

IV indicated the fragmentation of the rhythms representing the frequency and extent of transitions between rest and activity. It could vary roughly between 0 and 2, with higher values indicating higher fragmentation.

$$\mathrm{IV} = \frac{\sum_{i=2}^{N}(x_i - x_{i-1})^2 \, N}{\sum_{i=1}^{N}(x_i - \bar{x})^2 \, (N-1)}$$

RA, the ratio of the differences between the most active 10 continuous hours (M10) and the least active 5 continuous hours (L5) over the summation of M10 and L5, was calculated as a measure of the amplitude of rest-activity rhythms while considering the daily variations and unbalanced amplitudes of peak and trough in daily activity or app-usage rhythms.

$$RA = \frac{M10 - L5}{M10 + L5}$$

IS, IV and RA were calculated for a minimum period of one week [8].

Clinical outcomes

1. Weight status: All participants had their weight (in kilograms) and height (in centimeters) measured without shoes following standard protocols. The body mass index (BMI) was calculated by dividing the body weight (in kilograms) by the square of the body height (in meters), resulting in units of kg/m^2. The BMI categories used were: overweight, defined as a BMI between 24.0 and 26.9 kg/m^2; and obesity, defined as a BMI equal to or greater than 27.0 kg/m^2 [9].

2. Depressive symptoms: The Patient Health Questionnaire (PHQ-9) is a widely used, self-administered instrument for detecting depressive symptoms. For each of the nine depressive symptom criteria, subjects indicate the extent to which the symptoms bother them using options like “not at all,” “several days,” “more than half the days,” or “nearly every day.” Each criterion yields a score between 0 and 3 so the PHQ-9’s total score ranges from 0 to 27. A PHQ-9 score of 10 or greater has a sensitivity of 93% and a specificity of 88% for the diagnosis of major depressive disorder[10]. The diagnostic validity of the Chinese version of PHQ-9 is comparable to clinician-administered assessments [11].

Preprint JMIR Publications

Statistical Analysis

Coherence is a measure that describes the degree of relationship or association between two biological signals that may potentially interact with each other. Examples include the relationship between blood pressure and heart rate signals [12] or heart rate and respiration signals [13], which exhibit linear statistical dependence at specific frequency components. In this study, we utilized the magnitude-squared coherence (MSC) [14] to quantify the linear relationship between the temporal changes in the amplitudes of physical activity (PA) and social activity (SA), as measured by human-smartphone interaction patterns. The MSC considers whether there is a constant phase alignment between the two signals.

To extract the interactions of the circadian rhythms between PA and SA, we calculated the MSC within a frequency band ranging from 16 hours to 28 hours using the following formula:

$$MSC(f)=\frac{|S_{PA-SA}(f)|}{S_{PA}(f)*S_{SA}(f)}$$

Here, where $S_{PA}(f)$ and $S_{SA}(f)$ represent the autospectrum of changes in physical activity and smartphone usage, respectively. $|S_{PA-SA}(f)|$ denotes the amplitude of the cross-spectrum between the two signals. The MSC value ranges from 0 to 1, where 0 indicates no coherence or correlation between the signals, and 1 represents perfect coherence or correlation at specific frequency components.

Pearson's correlation coefficients were calculated to examine the relationships between social-physical coherence and the rest-activity rhythm (RAR) indicators, namely interdaily stability (IS), intradaily variability (IV), and relative amplitude (RA). These indicators were measured using both actigraphy (IS_{act}, IV_{act}, RA_{act}) and human-smartphone interaction patterns (IS_{app}, IV_{app}, RA_{app}). The correlation coefficients were calculated for different duration, ranging from 1 to 6 weeks, to assess the strength and direction of these associations.

To investigate the associations between social-physical coherence, BMI, and PHQ-9 depressive symptom scores, multiple linear regression models were employed. The models were adjusted for potential confounding factors, including age and gender. The analysis focused on the associations between social-physical coherence, BMI, and the RAR indicators (IS_{app} and IS_{act}). Correlation coefficients were calculated for each duration to evaluate the strength and direction of these associations. Furthermore, additional analyses were conducted to explore the impact of depressive symptom scores on the relationships between social-physical coherence, RAR indicators, and BMI. Multiple linear regression models were used, controlling for age, gender, and PHQ-9 depressive symptom scores.

Statistical significance was determined using a significance level of $\alpha = 0.05$. All data arrangement and statistical analyses were performed using IBM SPSS Statistics 25.

Results

Among the 135 participants in this study, 53.3% (72/135) met the criteria for being overweight, defined as having a BMI greater than 24. Additionally, 40.7% (55/135) of participants met the criteria for obesity, defined as having a BMI greater than 27. Furthermore, 19.7% (26/132) of participants had major depression, as indicated by a PHQ-9 score of 10 or higher. When examining the overlap between BMI and major depression, only 6% (8/132) of participants with a BMI over 24, indicating overweight, also had major depression. Similarly, only 4.5% (6/132) of participants with obesity (BMI > 27) also had major depression.

Figure 2 presents the Pearson's correlation coefficients between social-physical coherence and the RAR indicators measured by actigraphy and human-smartphone interactions across different time scales. The correlation analysis revealed that social-physical coherence exhibited the highest significant positive correlation with IS_{app} in the 1-6 week time scale, with significant positive correlation coefficients exceeding 0.5. The next highest correlation was observed with IS_{act}. On the other hand, social-physical coherence showed a significant negative correlation with IV_{app}, while no significant correlations were found with the other RAR indicators.

Considering the highest correlation of social-physical coherence with IS_{app} and IS_{act} among all RAR indicators, they were compared in terms of their associations with BMI and PHQ-9 depressive symptom scores at the same time scale. Figure 3

Preprint JMIR Publications

illustrates a significant negative correlation between social-physical coherence, IS_{app}, and BMI when considering the first 2, 3, or 4 weeks. This indicates that a higher alignment of social-physical activities or high cross-daily stability of social activities (measured by human-smartphone interaction patterns) was associated with a lower degree of obesity. Even when considering only one week of data, a significant negative correlation between IS_{app} and BMI persists, while the association with social-physical coherence is only borderline and did not reach statistical significance. In contrast, the association between IS_{act} and BMI did not show a significant correlation at any time scale ranging from one week to six weeks.

If we additionally controlled for depressive symptoms (PHQ-9) scores, along with age and gender, in the aforementioned correlation analysis, the findings remained consistent (Figure 4). There was still a significant negative correlation between social-physical coherence, IS_{app}, and BMI when considering the first 2, 3, or 4 weeks of cumulative data. However, when using only one week of data, IS_{act} and IS_{app} showed a significant negative correlation with BMI. In contrast, the association between social-physical coherence calculated at the same one-week data time scale remained only borderline and did not reach statistical significance.

Figure 5 presents the association between the three indicators and depressive symptom scores. When considering IS_{act} calculated from the first 1, 3, 4, or 5 weeks of data, a statistically borderline-significant negative correlation with PHQ-9 scores was observed (*P*=.054 to .062). Regarding social-physical coherence or IS_{app}, there was no statistically significant correlation with PHQ-9 scores across all time scales examined.

Discussion

The key findings of our study revolve around the development of an indicator called "social-physical coherence," which directly measured the alignment between the biological clock, represented by physical activity, and the social clock, represented by social activity measured through human-smartphone interactions. We observed a significant correlation between this coherence indicator and adiposity, highlighting its relevance in understanding the relationship between the alignment of social and physical activities and weight status. In comparison to the concept of "social jetlag," which quantifies the discrepancy in mid-sleep times between work days and work-free days, our coherence indicator offers a more direct measurement of the coupling between social activity and physical activity, without relying on assumptions about differences between work days and work-free days. Coherence, in a mathematical sense, represents the consistency of phase and amplitude between two time series when compared simultaneously. This concept has been previously applied in diverse domains, such as central/peripheral circadian rhythm coupling [15, 16], cardio-respiratory dynamics [13], and blood pressure and heart rate signals [12]. Within the context of our study, coherence serves as a direct measure of the alignment and interaction between social activity and physical activity, capturing the extent to which these two domains synchronize.

Our study revealed significant positive correlations between social-physical coherence and interdaily stability (both IS_{act} and IS_{app}), with the strongest association observed with IS_{app}. This finding suggests that individuals with greater stability in their rest-activity rhythms also exhibit higher alignment between their social and physical activities. These results align with previous research emphasizing the importance of maintaining a regular pattern of daily activities, especially social activities, for overall health [17-22]. In contrast to the correlation patterns observed between social-physical coherence and interdaily stability across the time window from 1 to 6 weeks, our study revealed a significant negative correlation between social-physical coherence, IS_{app}, and BMI specifically within the first 2, 3, or 4 weeks. This specific time window provided insights into the association between disrupted circadian rhythmicity and adiposity. Previous studies investigating the impact of circadian rhythm disruption on obesity were often limited by utilizing actigraphy with a measurement period of only 7 days [23-27], which might not capture the full variability of circadian rhythms. In contrast, our findings suggest that an optimal measurement period of 2 to 4 weeks is needed to more accurately capture the association between disrupted circadian rhythmicity and adiposity, particularly in individuals with obesity who often exhibit disrupted rhythms. Furthermore, our research underscores the significance of tracking the 7-day cycle over a longer period of time for a comprehensive and stable measurement of the social rhythm.

Our findings contribute to the existing body of research by demonstrating a significant negative correlation between social-physical coherence, IS_{app}, and BMI. This

Preprint JMIR Publications

correlation aligns with previous studies highlighting the importance of cross-daily stability in circadian rhythms for maintaining a healthy weight [28-36]. Additionally, our results provide more specific evidence by indicating that a higher cross-daily stability of social activities, as captured by human-smartphone interaction patterns, and the alignment of social-physical activities are associated with a lower degree of obesity. Interestingly, we did not observe a significant correlation between actigraphy-measured interdaily stability (IS_{act}) and BMI. This discrepancy may be attributed to the app's ability to capture additional factors such as finer finger movements [4] and exposure to smartphone light, which can influence melatonin secretion [37]. The inclusion of these additional factors in our comprehensive assessment of circadian rhythms, provided by the app, highlights the advantages of utilizing smartphone-based measurements over standard actigraphy, which solely focuses on recording physical activities. By combining measurements of physical activity and human-smartphone interactions, our approach offers a comprehensive assessment of social-physical coherence, capturing the interaction and alignment of social and physical activities. This integrated evaluation provides a more holistic understanding of the relationship between mind-body alignment and health outcomes, particularly in the context of obesity. Our findings contribute to the growing recognition of the importance of considering both social and physical aspects when examining the impact of circadian rhythms on health.

Although this study did not find a statistically significant correlation between social-physical coherence and IS_{app} or social-physical coherence and PHQ-9 scores across all time scales examined, a statistically borderline-significant negative correlation (P=.054 to .062) between IS_{act} and depressive symptom scores was observed when considering IS_{act} calculated from the first 1, 3, 4, or 5 weeks of data. This finding is consistent with some previous research that has reported a negative correlation between depressive symptoms and interdaily stability s [23, 38-43]. However, it is important to note that the current sample size was relatively small, and the inclusion criteria for obesity and depression differed in this study. Participants with obesity or overweight were enrolled before treatment, while participants with depression were enrolled during a stable treatment period. Despite these limitations, the study provides valuable evidence by considering both obese individuals and those with comorbid

Preprint JMIR Publications

depression, which is clinically significant. Furthermore, when controlling for depressive symptoms (PHQ-9) scores, age, and gender in the correlation analysis, a significant negative correlation between social-physical coherence, IS_{app}, and BMI persisted when considering the first 2, 3, or 4 weeks of data. This highlights the robustness of the findings and strengthens the evidence supporting the association between social-physical coherence, rest-activity rhythms, and obesity.

In interpreting the results, it is important to acknowledge several limitations of our study. Firstly, the cross-sectional design and convenience sample used may limit our ability to establish causal relationships between social-physical coherence and obesity. Future longitudinal studies are warranted to gain a deeper understanding of these associations and to identify potential underlying mechanisms. Secondly, the interpretation and validity of the derived RAR profiles, which categorize activities as "mental activities" or "social activities," require further exploration and validation. It is crucial to develop a comprehensive understanding of the meaning and reliability of these profiles to ensure accurate measurement of circadian rhythms. Thirdly, the Rhythm app used in our study was limited to the Android operating system. Developing versions of the app for other operating systems, such as iOS and Windows, would enhance the generalizability of our findings and allow for broader applicability across different smartphone users.

In conclusion, our study contributes to the understanding of social-physical coherence and its relevance in rest-activity rhythms and obesity. The positive correlation between social-physical coherence and interdaily stability indicates the importance of aligning social and physical activities for stable rest-activity rhythms. Furthermore, the negative correlation between social-physical coherence, IS_{app}, and BMI within the first 2 to 4 weeks highlights the association between disrupted circadian rhythmicity and adiposity. These findings emphasize the need for longer measurement periods and consideration of both social and physical aspects when assessing circadian rhythms and their impact on health outcomes, particularly in individuals with obesity. Future research should explore underlying mechanisms and address the limitations identified to advance our understanding of the relationship between social-physical coherence, rest-activity rhythms, and overall health.

JMIR Publications Preprint

Acknowledgements

We express our gratitude for Ms. Hsiao-Han Lin's excellent technical assistance

Conflicts of interest

All authors declare no financial or non-financial competing interests.

Availability of data and material

The authors cannot make this study's raw data publicly available due to restrictions imposed by informed consent from participants in this study, which has been approved by the Institutional Review Boards of the Chang Gung Memorial Hospital. Data are available from the Institutional Review Board of the Chang Gung Memorial Hospital for researchers who meet the criteria for access to confidential data.

Funding

This research was supported by the National Health Research Institutes of Taiwan [11A1-PHSP12-014, 11A1-PHPP14-014], the National Science and Technology Council of Taiwan [MOST 110-2314-B-182-062, 111-2314-B-182 -019 -MY2]; and Chang Gung Medical Foundation of Taiwan [CMRPG1H0061-63, CORPG1L0011, CORPG3C0011-13, CORPG1I0021].

Consent to participate

All subjects provided informed consent for inclusion before they participated in the study.

Consent for publication

Participants signed informed consent forms regarding the publication of their data.

Ethics approval

The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Institutional Review Boards of the Chang-Gung Memorial Hospital (IRB No. 202100434B0A3 and 202002452A3).

Abbreviations

BMI: body mass index

IS: interdaily stability

IV: intradaily variability

MSC: magnitude-squared coherence

PA: physical activity

PHQ-9: Patient Health Questionnaire

RA: relative amplitude

Preprint JMIR Publications

RAR: rest-activity rhythm

SA: social activity

Preprint
JMIR Publications

References

1. Allada R, Bass J. Circadian Mechanisms in Medicine. N Engl J Med. 2021 Feb 11;384(6):550-61. PMID: 33567194. doi: 10.1056/NEJMra1802337.

2. Roenneberg T. How can social jetlag affect health? Nat Rev Endocrinol. 2023 Jul;19(7):383-4. PMID: 37221400. doi: 10.1038/s41574-023-00851-2.

3. Ancoli-Israel S, Cole R, Alessi C, Chambers M, Moorcroft W, Pollak CP. The role of actigraphy in the study of sleep and circadian rhythms. Sleep. 2003 May 1;26(3):342-92. PMID: 12749557. doi: 10.1093/sleep/26.3.342.

4. Borger JN, Huber R, Ghosh A. Capturing sleep-wake cycles by using day-to-day smartphone touchscreen interactions. NPJ Digit Med. 2019;2:73. PMID: 31372507. doi: 10.1038/s41746-019-0147-4.

5. Lin YH, Wong BY, Pan YC, Chiu YC, Lee YH. Validation of the Mobile App-Recorded Circadian Rhythm by a Digital Footprint. JMIR Mhealth Uhealth. 2019 May 16;7(5):e13421. PMID: 31099340. doi: 10.2196/13421.

6. Cole RJ, Kripke DF, Gruen W, Mullaney DJ, Gillin JC. Automatic sleep/wake identification from wrist activity. Sleep. 1992 Oct;15(5):461-9. PMID: 1455130. doi: 10.1093/sleep/15.5.461.

7. Lin YH, Wong BY, Lin SH, Chiu YC, Pan YC, Lee YH. Development of a mobile application (App) to delineate "digital chronotype" and the effects of delayed chronotype by bedtime smartphone use. J Psychiatr Res. 2019 Mar;110:9-15. PMID: 30611008. doi: 10.1016/j.jpsychires.2018.12.012.

8. Witting W, Kwa IH, Eikelenboom P, Mirmiran M, Swaab DF. Alterations in the circadian rest-activity rhythm in aging and Alzheimer's disease. Biol Psychiatry. 1990 Mar 15;27(6):563-72. PMID: 2322616. doi: 10.1016/0006-3223(90)90523-5.

9. Health Promotion Administration MoH, Welfare. Taiwan’s Obesity Prevention and Management Strategy. Health Promotion Administration, Ministry of Health and Welfare Taipei, Taiwan; 2018.

10. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. J Gen Intern Med. 2001 Sep;16(9):606-13. PMID: 11556941. doi: 10.1046/j.1525-1497.2001.016009606.x.

11. Liu SI, Yeh ZT, Huang HC, Sun FJ, Tjung JJ, Hwang LC, et al. Validation of Patient Health Questionnaire for depression screening among primary care patients in Taiwan. Compr Psychiatry. 2011 Jan-Feb;52(1):96-101. PMID: 21111406. doi: 10.1016/j.comppsych.2010.04.013.

12. Ticcinelli V, Stankovski T, Iatsenko D, Bernjak A, Bradbury AE, Gallagher AR, et al. Coherence and Coupling Functions Reveal Microvascular Impairment in

Preprint JMIR Publications

Treated Hypertension. Front Physiol. 2017;8:749. PMID: 29081750. doi: 10.3389/fphys.2017.00749.

13. Lin C, Lin PF, Wang CH, Juan CH, Tran TT, Pham VT, et al. Probing age-related changes in cardio-respiratory dynamics by multimodal coupling assessment. Chaos. 2020 Mar;30(3):033118. PMID: 32237792. doi: 10.1063/1.5134868.

14. Zhang R, Zuckerman JH, Giller CA, Levine BD. Transfer function analysis of dynamic cerebral autoregulation in humans. Am J Physiol. 1998 Jan;274(1 Pt 2):H233-41. PMID: 9458872. doi: 10.1152/ajpheart.1998.274.1.h233.

15. Bordyugov G, Abraham U, Granada A, Rose P, Imkeller K, Kramer A, et al. Tuning the phase of circadian entrainment. J R Soc Interface. 2015 Jul 6;12(108):20150282. PMID: 26136227. doi: 10.1098/rsif.2015.0282.

16. Yamazaki S, Kerbeshian MC, Hocker CG, Block GD, Menaker M. Rhythmic properties of the hamster suprachiasmatic nucleus in vivo. J Neurosci. 1998 Dec 15;18(24):10709-23. PMID: 9852606. doi: 10.1523/jneurosci.18-24-10709.1998.

17. Alloy LB, Boland EM, Ng TH, Whitehouse WG, Abramson LY. Low social rhythm regularity predicts first onset of bipolar spectrum disorders among at-risk individuals with reward hypersensitivity. J Abnorm Psychol. 2015 Nov;124(4):944-52. PMID: 26595474. doi: 10.1037/abn0000107.

18. Brown LF, Reynolds CF, 3rd, Monk TH, Prigerson HG, Dew MA, Houck PR, et al. Social rhythm stability following late-life spousal bereavement: associations with depression and sleep impairment. Psychiatry Res. 1996 May 17;62(2):161-9. PMID: 8771613. doi: 10.1016/0165-1781(96)02914-9.

19. Frank E, Kupfer DJ, Thase ME, Mallinger AG, Swartz HA, Fagiolini AM, et al. Two-year outcomes for interpersonal and social rhythm therapy in individuals with bipolar I disorder. Arch Gen Psychiatry. 2005 Sep;62(9):996-1004. PMID: 16143731. doi: 10.1001/archpsyc.62.9.996.

20. Malkoff-Schwartz S, Frank E, Anderson B, Sherrill JT, Siegel L, Patterson D, et al. Stressful life events and social rhythm disruption in the onset of manic and depressive bipolar episodes: a preliminary investigation. Arch Gen Psychiatry. 1998 Aug;55(8):702-7. PMID: 9707380. doi: 10.1001/archpsyc.55.8.702.

21. Shen GH, Alloy LB, Abramson LY, Sylvia LG. Social rhythm regularity and the onset of affective episodes in bipolar spectrum individuals. Bipolar Disord. 2008 Jun;10(4):520-9. PMID: 18452448. doi: 10.1111/j.1399-5618.2008.00583.x.

22. Sylvia LG, Alloy LB, Hafner JA, Gauger MC, Verdon K, Abramson LY. Life events and social rhythms in bipolar spectrum disorders: a prospective study. Behav Ther. 2009 Jun;40(2):131-41. PMID: 19433144. doi: 10.1016/j.beth.2008.04.003.

23. Luik AI, Zuurbier LA, Hofman A, Van Someren EJ, Tiemeier H. Stability and fragmentation of the activity rhythm across the sleep-wake cycle: the importance of

Preprint
JMIR Publications

age, lifestyle, and mental health. Chronobiol Int. 2013 Dec;30(10):1223-30. PMID: 23971909. doi: 10.3109/07420528.2013.813528.

24. Sohail S, Yu L, Bennett DA, Buchman AS, Lim AS. Irregular 24-hour activity rhythms and the metabolic syndrome in older adults. Chronobiol Int. 2015;32(6):802-13. PMID: 26061588. doi: 10.3109/07420528.2015.1041597.

25. Qian J, Martinez-Lozano N, Tvarijonaviciute A, Rios R, Scheer F, Garaulet M. Blunted rest-activity rhythms link to higher body mass index and inflammatory markers in children. Sleep. 2021 May 14;44(5). PMID: 33249510. doi: 10.1093/sleep/zsaa256.

26. Quante M, Cespedes Feliciano EM, Rifas-Shiman SL, Mariani S, Kaplan ER, Rueschman M, et al. Association of Daily Rest-Activity Patterns With Adiposity and Cardiometabolic Risk Measures in Teens. J Adolesc Health. 2019 Aug;65(2):224-31. PMID: 31056236. doi: 10.1016/j.jadohealth.2019.02.008.

27. Heckler B, Lee M, Stone K, Bauer C, Xiao Q. Cross-sectional and Prospective Associations of Rest-Activity Rhythms With Body Mass Index in Older Men: A Novel Analysis Using Harmonic Hidden Markov Models. J Biol Rhythms. 2023 Feb;38(1):87-97. PMID: 36416436. doi: 10.1177/07487304221134163.

28. Li J, Vungarala S, Somers VK, Di J, Lopez-Jimenez F, Covassin N. Rest-activity rhythm is associated with obesity phenotypes: A cross-sectional analysis. Front Endocrinol (Lausanne). 2022;13:907360. PMID: 35837304. doi: 10.3389/fendo.2022.907360.

29. Qian J, Martinez-Lozano N, Tvarijonaviciute A, Rios R, Scheer FAJL, Garaulet M. Blunted rest–activity rhythms link to higher body mass index and inflammatory markers in children. Sleep. 2020;44(5). doi: 10.1093/sleep/zsaa256.

30. Fárková E, Schneider J, Šmotek M, Bakštein E, Herlesová J, Kopřivová J, et al. Weight loss in conservative treatment of obesity in women is associated with physical activity and circadian phenotype: a longitudinal observational study. Biopsychosoc Med. 2019;13:24. PMID: 31673283. doi: 10.1186/s13030-019-0163-2.

31. Cespedes Feliciano EM, Quante M, Weng J, Mitchell JA, James P, Marinac CR, et al. Actigraphy-Derived Daily Rest–Activity Patterns and Body Mass Index in Community-Dwelling Adults. Sleep. 2017;40(12). doi: 10.1093/sleep/zsx168.

32. Rogers-Soeder TS, Blackwell T, Yaffe K, Ancoli-Israel S, Redline S, Cauley JA, et al. Rest-Activity Rhythms and Cognitive Decline in Older Men: The Osteoporotic Fractures in Men Sleep Study. Journal of the American Geriatrics Society. 2018;66(11):2136-43. doi: https://doi.org/10.1111/jgs.15555.

33. Luik AI, Zuurbier LA, Hofman A, Van Someren EJW, Tiemeier H. Stability and Fragmentation of the Activity Rhythm Across the Sleep-Wake Cycle: The

Preprint JMIR Publications

Importance of Age, Lifestyle, and Mental Health. Chronobiology International. 2013 2013/12/01;30(10):1223-30. doi: 10.3109/07420528.2013.813528.
34. Mitchell JA, Quante M, Godbole S, James P, Hipp JA, Marinac CR, et al. Variation in actigraphy-estimated rest-activity patterns by demographic factors. Chronobiology International. 2017 2017/09/14;34(8):1042-56. doi: 10.1080/07420528.2017.1337032.
35. Sohail S, Yu L, Bennett DA, Buchman AS, Lim ASP. Irregular 24-hour activity rhythms and the metabolic syndrome in older adults. Chronobiology International. 2015 2015/07/03;32(6):802-13. doi: 10.3109/07420528.2015.1041597.
36. Xiao Q, Qian J, Evans DS, Redline S, Lane NE, Ancoli-Israel S, et al. Cross-sectional and Prospective Associations of Rest-Activity Rhythms With Metabolic Markers and Type 2 Diabetes in Older Men. Diabetes Care. 2020;43(11):2702-12. doi: 10.2337/dc20-0557.
37. Chang AM, Aeschbach D, Duffy JF, Czeisler CA. Evening use of light-emitting eReaders negatively affects sleep, circadian timing, and next-morning alertness. Proc Natl Acad Sci U S A. 2015 Jan 27;112(4):1232-7. PMID: 25535358. doi: 10.1073/pnas.1418490112.
38. Smagula SF, Zhang G, Gujral S, Covassin N, Li J, Taylor WD, et al. Association of 24-Hour Activity Pattern Phenotypes With Depression Symptoms and Cognitive Performance in Aging. JAMA Psychiatry. 2022 Oct 1;79(10):1023-31. PMID: 36044201. doi: 10.1001/jamapsychiatry.2022.2573.
39. Smagula SF, Krafty RT, Thayer JF, Buysse DJ, Hall MH. Rest-activity rhythm profiles associated with manic-hypomanic and depressive symptoms. J Psychiatr Res. 2018 Jul;102:238-44. PMID: 29705489. doi: 10.1016/j.jpsychires.2018.04.015.
40. Smagula SF. Opportunities for clinical applications of rest-activity rhythms in detecting and preventing mood disorders. Curr Opin Psychiatry. 2016 Nov;29(6):389-96. PMID: 27636598. doi: 10.1097/yco.0000000000000283.
41. Robillard R, Hermens DF, Naismith SL, White D, Rogers NL, Ip TK, et al. Ambulatory sleep-wake patterns and variability in young people with emerging mental disorders. J Psychiatry Neurosci. 2015 Jan;40(1):28-37. PMID: 25203899. doi: 10.1503/jpn.130247.
42. Smagula SF, Ancoli-Israel S, Blackwell T, Boudreau R, Stefanick ML, Paudel ML, et al. Circadian rest-activity rhythms predict future increases in depressive symptoms among community-dwelling older men. Am J Geriatr Psychiatry. 2015 May;23(5):495-505. PMID: 25066948. doi: 10.1016/j.jagp.2014.06.007.
43. Smagula SF, Boudreau RM, Stone K, Reynolds CF, 3rd, Bromberger JT, Ancoli-Israel S, et al. Latent activity rhythm disturbance sub-groups and longitudinal

Preprint JMIR Publications

change in depression symptoms among older men. Chronobiol Int. 2015;32(10):1427-37. PMID: 26594893. doi: 10.3109/07420528.2015.1102925.

Preprint JMIR Publications

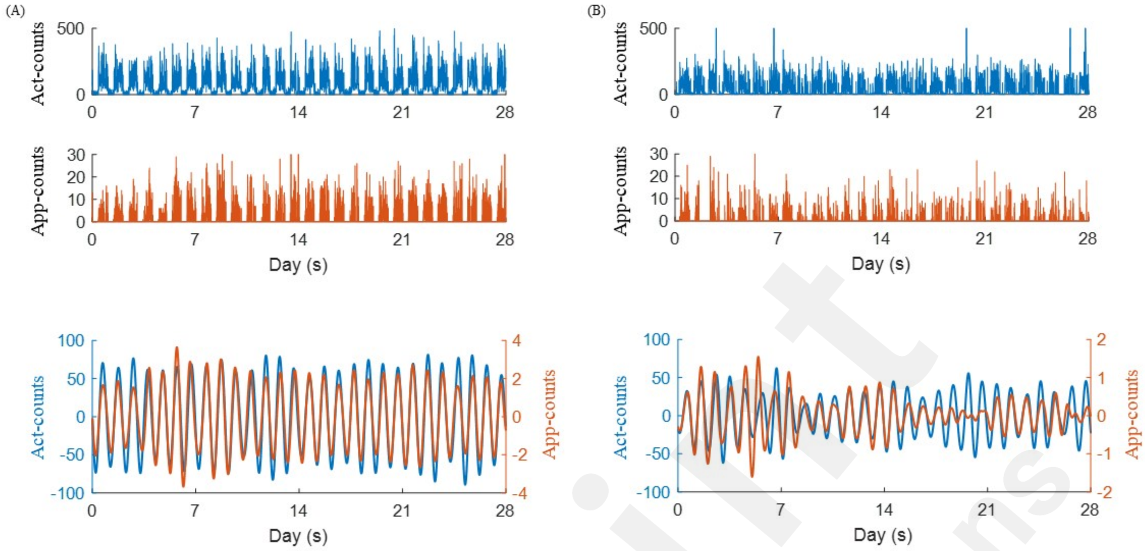


Figure 1. Illustration of physical activities, social activities, and the social-physical coherence. The top blue data represents the raw data of physical activities recorded by wrist-worn actigraphy. The red data below represents the frequency of app switches, obtained from the Rhythm app's human-smartphone interaction records, serving as a proxy for social activity. These data were used to simulate activity levels comparable to wrist actigraphy measurements over a 28-day period. Interdaily stability (IS) can be calculated for both physical activity and social activity. The bottom section demonstrates an example of calculating the social-physical coherence by filtering the data for cycles between 16 to 28 hours. This process retains approximately 24-hour cycles of physical activity (shown in blue) and social activity (shown in red).

(A) Participant with high social-physical coherence (0.907), high interdaily stability measured by actigraphy (IS_{act}=0.710) and high interdaily stability measured by the Rhythm app (IS_{app}=0.475), with a Body Mass Index (BMI) of 21.6 falling within the normal range.

(B) Participant with low social-physical coherence (0.525), high interdaily stability measured by actigraphy (IS_{act}=0.187) and high interdaily stability measured by the Rhythm app (IS_{app}=0.373) with a BMI of 30.5 indicating obesity.

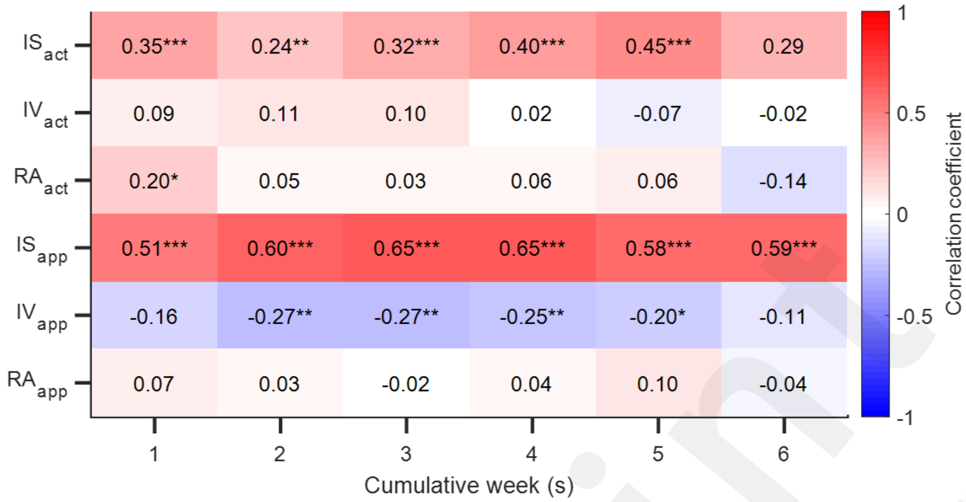


Figure 2. Pearson's correlation coefficients between social-physical coherence and rest-activity rhythm (RAR) indicators measured in different time windows. RAR indicators, include interdaily stability (IS), intradaily variability (IV), and relative amplitude (RA), measured using both actigraphy (IS_{act}, IV_{act}, RA_{act}) and the *Rhythm* app (IS_{app}, IV_{app}, RA_{app}). * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

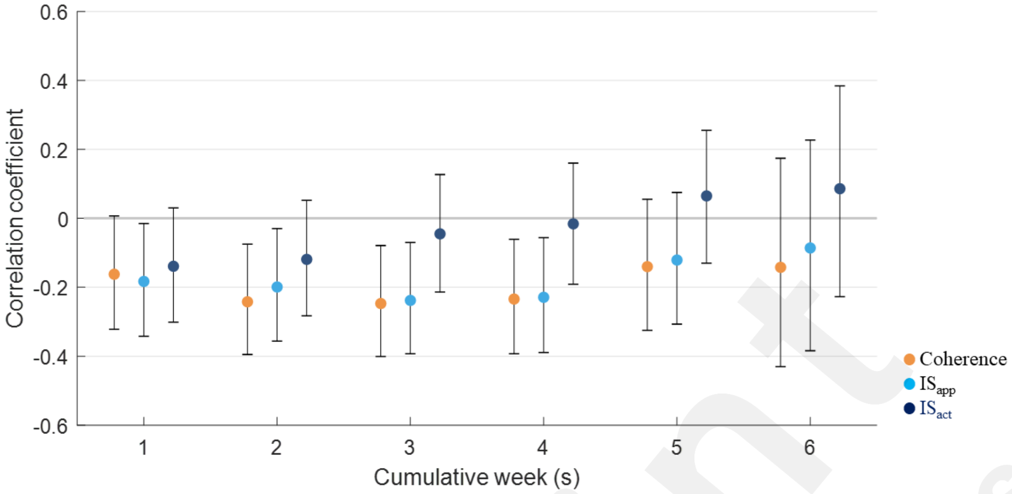


Figure 3. Coefficients of social-physical coherence, interdaily stability, and Body Mass Index (BMI) measured in different time windows. The outcome variable in the models was BMI, with age and gender included as control variables. Interdaily stability indicators were measured using actigraphy (IS_{act}) and the Rhythm app (IS_{app}).

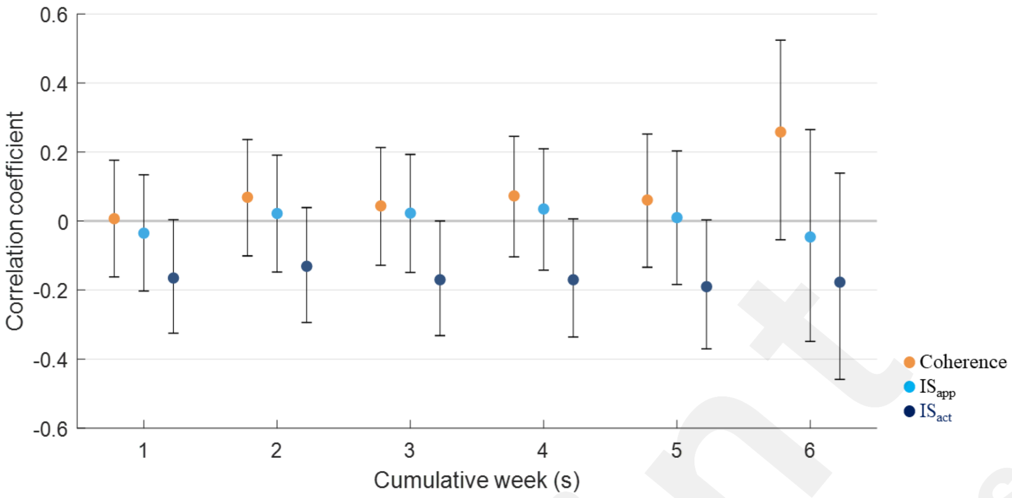


Figure 4. Coefficients of social-physical coherence, interdaily stability, and depressive symptoms measured in different time windows. The outcome variable in the models was depressive symptom scores (The Patient Health Questionnaire, PHQ-9), with age and gender included as control variables. Interdaily stability indicators were measured using actigraphy (IS_{act}) and the Rhythm app (IS_{app}).

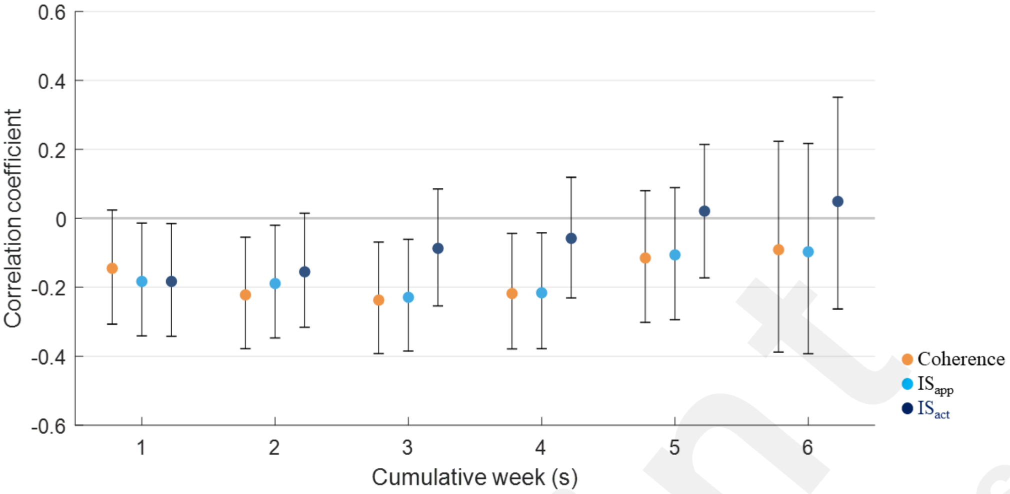


Figure 5. Coefficients of social-physical coherence, interdaily stability, and Body Mass Index (BMI) measured in different time windows. The outcome variable in the models was BMI, with age, gender and depressive symptom scores (the Patient Health Questionnaire, PHQ-9) included as control variables. Interdaily stability indicators were measured using actigraphy (IS_{act}) and the Rhythm app (IS_{app}).

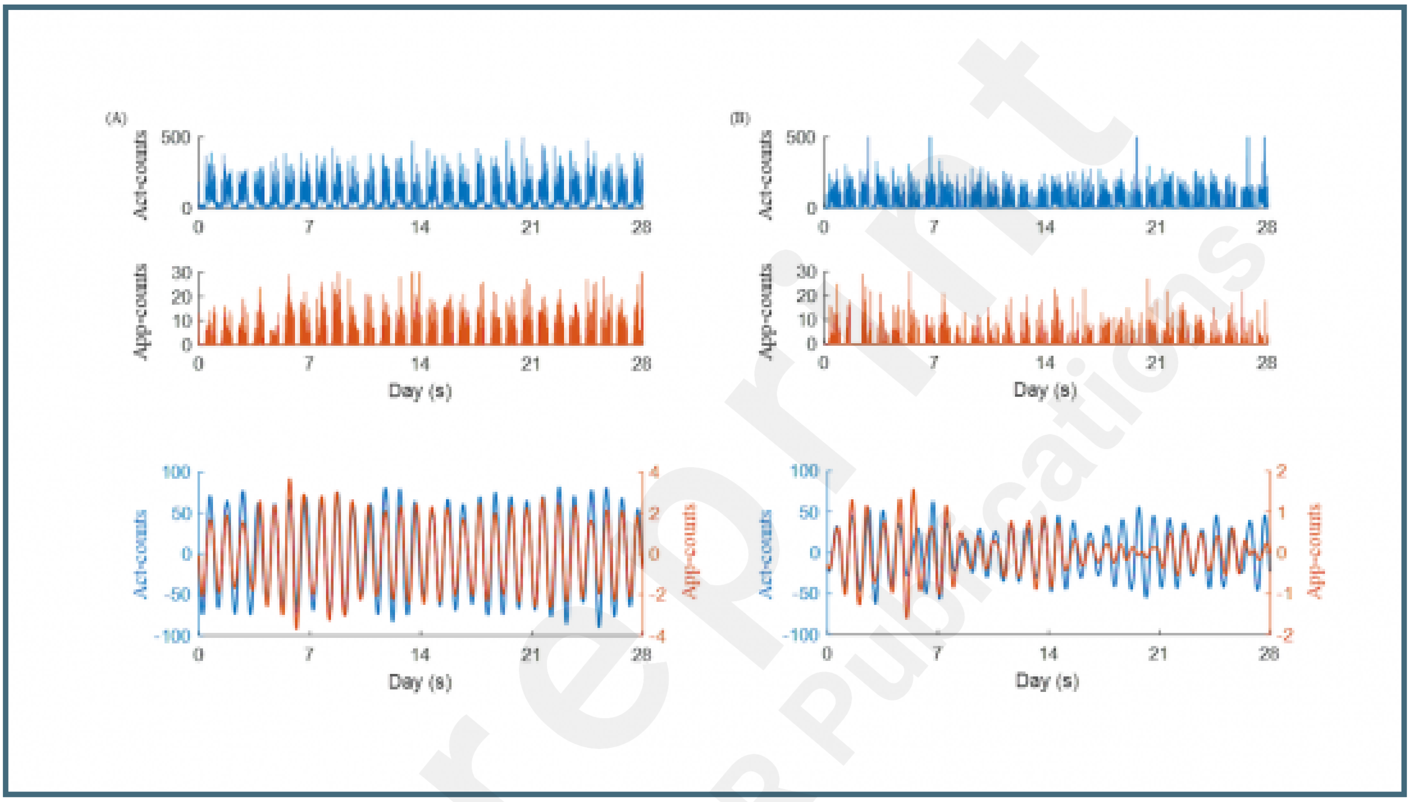
Preprint JMIR Publications

Supplementary Files

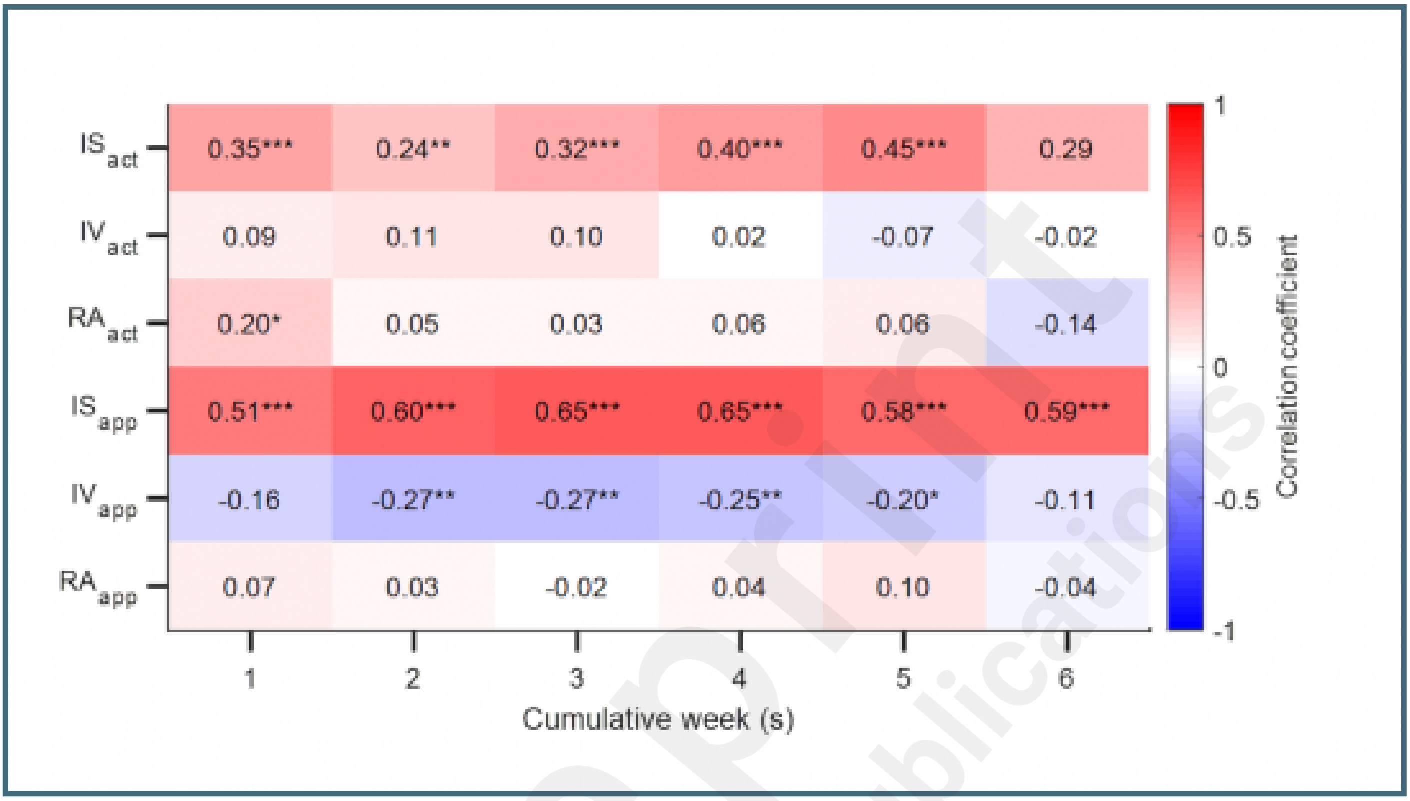
Figures

Preprint JMIR Publications

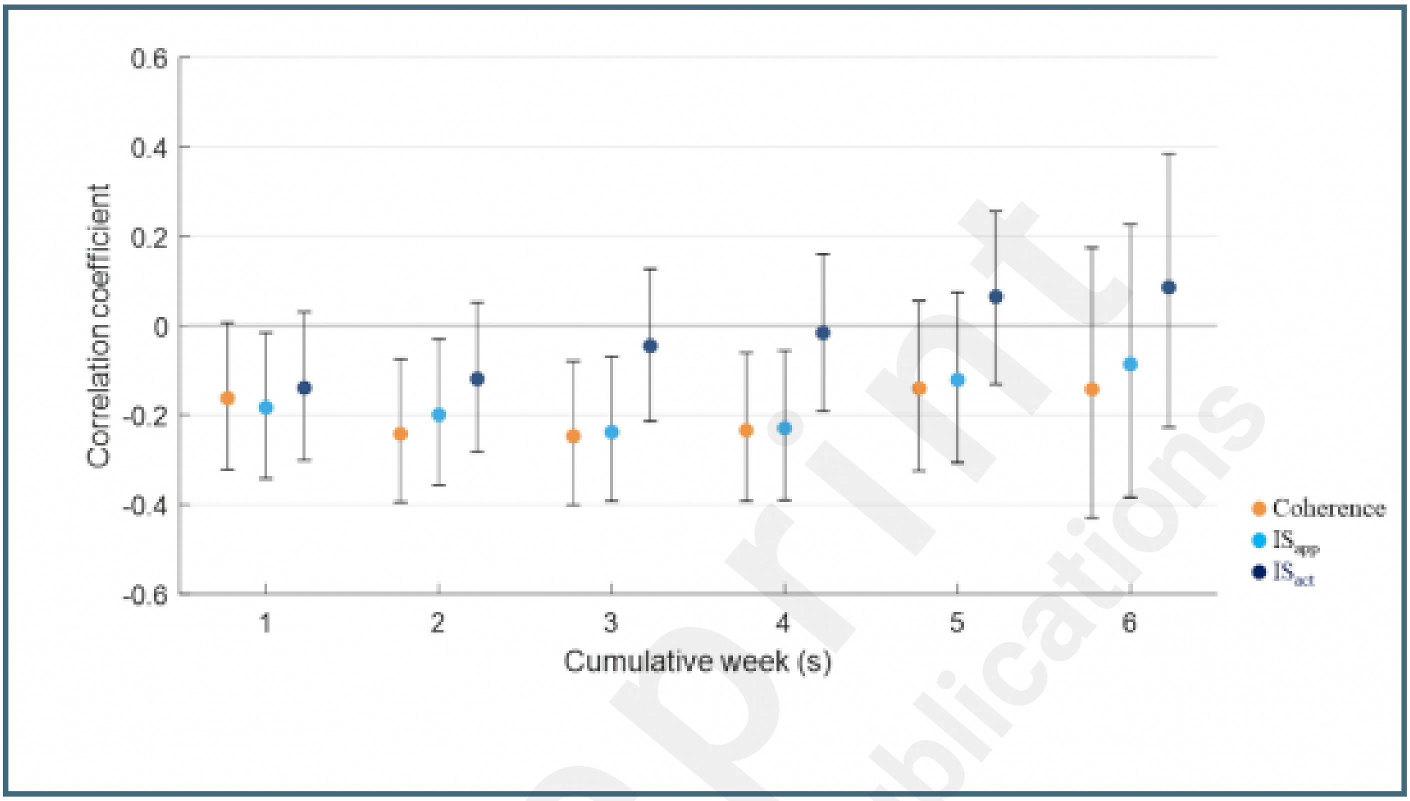
Illustration of physical activities, social activities, and the social-physical coherence. The top blue data represents the raw data of physical activities recorded by wrist-worn actigraphy. The red data below represents the frequency of app switches, obtained from the Rhythm app's human-smartphone interaction records, serving as a proxy for social activity. These data were used to simulate activity levels comparable to wrist actigraphy measurements over a 28-day period. Interdaily stability (IS) can be calculated for both physical activity and social activity. The bottom section demonstrates an example of calculating the social-physical coherence by filtering the data for cycles between 16 to 28 hours. This process retains approximately 24-hour cycles of physical activity (shown in blue) and social activity (shown in red).



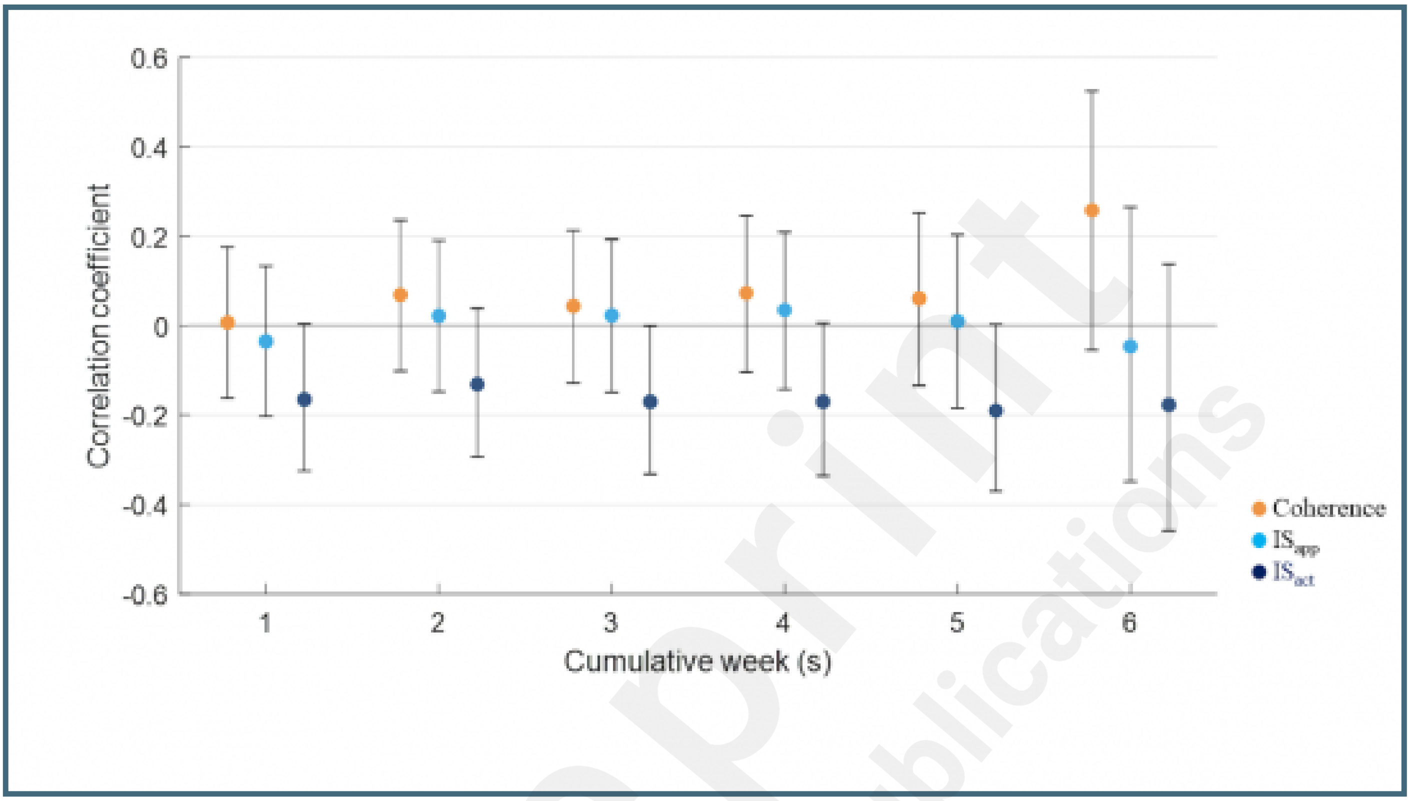
Pearson's correlation coefficients between social-physical coherence and rest-activity rhythm (RAR) indicators measured in different time windows. RAR indicators, include interdaily stability (IS), intradaily variability (IV), and relative amplitude (RA), measured using both actigraphy (ISact, IVact, RAact) and the Rhythm app (ISapp, IVapp, RAapp). * P < 0.05, ** P < 0.01, *** P < 0.001.



Coefficients of social-physical coherence, interdaily stability, and Body Mass Index (BMI) measured in different time windows. The outcome variable in the models was BMI, with age and gender included as control variables. Interdaily stability indicators were measured using actigraphy (ISact) and the Rhythm app (ISapp).



Coefficients of social-physical coherence, interdaily stability, and depressive symptoms measured in different time windows. The outcome variable in the models was depressive symptom scores (The Patient Health Questionnaire, PHQ-9), with age and gender included as control variables. Interdaily stability indicators were measured using actigraphy (ISact) and the Rhythm app (ISapp).



Coefficients of social-physical coherence, interdaily stability, and Body Mass Index (BMI) measured in different time windows. The outcome variable in the models was BMI, with age, gender and depressive symptom scores (the Patient Health Questionnaire, PHQ-9) included as control variables. Interdaily stability indicators were measured using actigraphy (ISact) and the Rhythm app (ISapp).