Diurnal switching of physical activity reduces depression-related behaviors: A time-series analysis of wearable device data

Satoshi YOKOYAMA
Hiroshima University
Fumi KAGAWA
Hiroshima Prefectural Mental Health Center
Masahiro TAKAMURA
Shimane University
Koki TAKAGAKI
Hiroshima University
Kohei KAMBARA
Doshisha University
Yuki Mitsuyama
Hiroshima University
Ayaka Shimizu
Hiroshima University
Go OKADA
Hiroshima University
Yasumasa OKAMOTO (oy@hiroshima-u.ac.jp)
Hiroshima University

Research Article

Keywords: Time-series analysis, Physical activity, Wearable device, Depressive behavior

Posted Date: August 1st, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1875917/v1

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at BMC Public Health on January 6th, 2023. See the published version at https://doi.org/10.1186/s12889-023-14984-6.

Abstract

Background

Wearable devices have been widely used in research to understand the relationship between habitual physical activity and mental health in the real world. However, little attention has been paid to the temporal variability in continuous physical activity patterns measured by these devices. Therefore, we analyzed time-series patterns of physical activity intensity measured by a wearable device and investigated the relationship between its model parameters and depression-related behaviors.

Methods

Sixty-six healthy individuals used the wearable device for one week and then answered a questionnaire on depression-related behaviors. A seasonal autoregressive integral moving average (SARIMA) model was fitted to the individual-level device data and the best individual model parameters were estimated via a grid search.

Results

Out of 64 hyper-parameter combinations, 21 models were selected as optimal, and the models with a larger number of affiliations were found to have no seasonal autoregressive parameter. Conversely, about half of the optimal models indicated that physical activity on any given day fluctuated due to the previous day's activity. In addition, both irregular rhythms in day-to-day activity and low-level of diurnal variability could lead to avoidant behavior patterns.

Conclusion

Automatic and objective physical activity data from wearable devices showed that diurnal switching of physical activity, as well as day-to-day rhythms, reduced depression-related behaviors. These time-series parameters may be useful for detecting behavioral issues that lie outside individuals' subjective awareness.

Background

Healthy behavior can be understood as a sequence of habitual behaviors, and habit-related physical activities are predictive of mental health [1]. For example, an engagement in moderate-to-vigorous physical activity (MVPA), such as brisk walking, during the past 7days, reduces odds of experiencing depression among adolescents [2]. And it is known that not only low MVPA but also high sedentary behavior is a prominent feature of people with depression, and that overall daily physical activity patterns have an influence on depression [3]. These studies have used total or mean values for intensity or

duration of a physical activity. In addition, these were subjective and often focused on an activity domain of interests, including leisure time, household, transportation, and work [2, 4, 5]. Therefore, objective and comprehensive information about habitual physical activity in daily life has not been accurate enough because of overly compressed and subjective information prone to memory bias [6]. The development of technologies for highly accurate measurements without subjective biases will enhance our understanding of the association between habitual behavior, including unconscious activity, and mental health.

Certain technological advances have enabled us to measure the sequential intensity of physical activity using wearable devices such as a smart watch. These allowed researchers to conclude an association between physical activity and health risk without the problem of subjective reporting [7, 8]. A current concern is the lack of an analytic strategy to extract relevant information from the large amount of time-series raw data generated by the device, compared to the improvements in data collection technology [9]. One solution is to use machine learning-based pattern recognition to classify physical activity, which is useful in detecting mental health problems by automatically labeling to physical activity [10]. However, the recognized patterns are often remained in the black box, and it is difficult to get suggestions for improving the mental health problem. Digital wearable devices generate a vast amount of high-frequency high-dimensional time-series data that require new methods of analysis [11].

Among the many time-series models being proposed, the Autoregressive Integrated Moving Average (ARIMA) model is the most widely used and well-known [12]. ARIMA is a linear model for time-series forecasting that expresses the difference in time-series data using autoregressive (AR) and moving averages (MA) parameters [13]. The seasonal ARIMA(SARIMA) model [13], which adds cyclicality to the ARIMA model, may better reflect the habituation of the physical activities that people perform in a day-to-day cycle (24 hours). In particular, the two seasonal parameters in the 24-hour cycle model, seasonal AR (sAR) and seasonal MA (sMA), indicate habituation in terms of the effect of the previous day's physical activity on current physical activity. However, to the authors' knowledge, no report has examined the physical activity habituation in wearable device data using the SARIMA model.

The current study aimed to extract habitual physical activity patterns from sequential data obtained from wearable devices using the SARIMA model with a 24-hour cycle, and to examine the relationship between these patterns and depression-related behaviors, as an indicator of mental health, in the real world. We believe that such findings from automated measurements in everyday environments may contribute to the development of future health management tools.

Methods

Participants

Sixty-six healthy volunteers (mean age = 21.7 ± 1.60) were recruited from among the students of Hiroshima University. They attended a research briefing and provided written informed consent for participation. Accelerometers were distributed on the first day of the study, and physical activity was measured continuously for 165 hours from midnight the next day to 21:00 on the eight day. After the

completion of the measurement, the experimenter recovered the device and extracted the recorded data. Participants' personal information was protected because the device recorded only 3-axis acceleration and did not have any information about their lives, such as location (where they stayed, or how far they traveled).

Physical activity

Participants were asked to wear the Device Arm Triaxial Accelerometry system (UW-301BT Life Log, Hitachi Ltd, Tokyo) on their non-dominant wrist for seven days, except while bathing. This device can record 3-axis acceleration with a 20 Hz sampling rate [14]. The recoding signal was integrated to calculate the intensity of physical activity at each minute, referred to as metabolic equivalents (METs), via conversion algorithms [15, 16] provided in the device.

Since one MET is equivalent to the energy cost of sitting quietly, we were able to assume zero MET as non-wearing time such as bathing. We defined a missing period as any non-wearing time of more than 30 consecutive minutes. Since 22 participants had the defined missing period, 44 (mean age = 21.5 ± 1.02; females = 18; BMI = 20.9 ± 2.94) were included in the analysis excluding them. And data for non-wearing time of less than 30 minutes were substituted with the mean of the previous 15 minutes. The complemented data were totaled every hour, leading to a total of 165 time points (since the mounting start time was uneven on the first day, midnight of the second day was the measurement start time). The total intensity of hourly physical activity was entered into the SARIMA model.

Questionnaires

Japanese version of Beck's Depression Inventory-II (BDI-II)

The BDI-II is a widely used scale for assessing depressive symptoms, and consists of 21 self-report items. The items are scored using a 4-point scale. The Japanese version of the scale has demonstrated reliability and validity [17].

Japanese version of the Behavioral Activation for Depression Scale (BADS)

The BADS [18] measures depression-related behavior patterns based on behavioral theories of depression. It consists of 25 items rated on a 7-point scale (0: Not at all to 6: Completely). The four subscales of the BADS are Activation (AC: 7 items) representing goal-directed activation and completion of scheduled activities; Avoidance/Rumination (AR: 8 items) representing avoidance of negative aversive states and engaging in rumination; Work/School Impairment (WS: 5 items); and Social Impairment (SI: 5 items). The Japanese version of the BADS has demonstrated reliability and validity [19].

SARIMA model

A SARIMA model is formed by including seasonal elements in the ARIMA models [20]. The terms for non-seasonal and seasonal elements in a SARIMA model are as follows: SARIMA(p, d, q, P, D, Q, m), where, p,

d, and q are non-seasonal delays of AR type, non-seasonal delays of MA type, and non-seasonal integration order, respectively. AR (p) means that the past values of itself until t-p time points are included as predictor variables of value at t point, and MA (q) means that the noise values until t-q time points are also included as predictor variables of value at t point. Then, the dependent variable is usually integrated for stationary form by a sequence of differences from the value at t-d time. The SARIMA model includes the seasonal element as a hyper-parameter (P, D, Q, m), where, P, D, Q, and m are seasonal delays of AR type, seasonal delays of MA type, seasonal integration order, and length of seasonality cycle, respectively. Since people are usually active in 24-hour cycles, we fixed the parameter m to 24 (24 hours), that is SARIMA (p, d, q, P, D, Q, 24) model, to obtain time-series information about daily habitual physical activity.

Grid search for an individual optimal model

We performed a grid search of the model order values, (p, d, q, P, D, Q, 24), for all parameter combinations for each individual. In order to narrow down the range of candidate parameters, we asked participants to report their average daily physical activity time ("On average, how much time in total did you usually spend doing physical activities on one day?"). Since the mean value was 2.3 hours (mode = 2.0 hours), the range of influence of past physical activity was limited to 0-3 hours. Hence, there were four candidate values for the hyper-parameters (p, q) between 0 and 3, respectively. The seasonal hyper-parameter determines the influence of the 24-hour cycle. To specify whether the previous day's cycle should be included in the model, the candidate hyper-parameters (P, Q) were denoted by 0 or 1. The hyper-parameters (d, D) that specify the range of the difference were set to 1 in order to reduce the calculation cost. We tried to include the distinction between weekdays and holidays as an exogenous regressor in the model, but this had no effect and did not change the goodness of fit of the model. Therefore, we did not include a regressor for the weekend in the model, but estimated it using fewer explanatory variables.

Finally, the number of candidate combinations for hyper-parameters of SARIMA (p, d, q, P, D, Q, 24) was 64 (4x1x4x2x1x2x1). After fitting all candidate models to the data, a model with the lowest Akaike's information criterion (AIC) was determined as the optimal model a paticipant.

Interpretability of model parameters

From the individuals' optimal model, we obtained the weight estimates of each term, AR(p), MA(q), sAR(P) and sMA(Q), as indicators that reflected the time-series information of physical activity. Our SARIMA models had fixed the seasonal/non-seasonal difference to one (i.e. d = D = 1). Therefore, each weight estimate of the parameters explained the change in physical activity intensity on a daily or hourly basis.

Two seasonal parameters, sAR and sMA, may reflect daily habituation. When P = 0, sAR has no weight, which reflected that "changes" in activity are not affected by the previous day's activity. If the hyper-parameter P = 1, the sAR(1) weights reflected that daily physical activity varied depending on the previous day's physical activity. Therefore, unlike P = 0, the physical activity pattern fluctuated (increased or decreased) from day to day, which indicated unstable habitual behavior (irregularity). The weights of

sMA(1) reflected the degree to which the change in physical activity from the previous day could be explained by the residual of the predicted value due to the past physical activity. When this weight value was high, the increase in activity from the previous day was proportional to the change in the previous day, but it depended on the non-linear increase in the previous day. Therefore, the parameter sMA also indicated the unstable physical activity patterns from day to day. The non-seasonal parameters indicated whether activity in the closer past (here, 0 to 3 hours ago) influenced the change in one-hour interval.

Statistical analysis

We performed regression analyses for the scores of each questionnaire using the weights of the parameters in the SARIMA model as explanatory variables. In order to maintain analytical power, we avoided grouping or selection based on optimal models that would identify participants who did not have the order of the parameter (e.g., $p = 0$). Instead, we substituted the weight of the non-existent parameter as zero in the regression model. The significance threshold was set at $p < 0.05$. All analyses were done via the Python library “statsmodels” (ver.0.11.0).

Results

Selection of optimal SARIMA models for individuals

Out of the 64 candidate models based on combinations of the orders of the seven hyper-parameters, 21 models were estimated as optimal models with the lowest within-individual AIC in at least one participant. The physical activity records of the members belonging to each model are illustrated in Supplementary figure (Figure S1). The model numbers are a formality and do not reflect superiority or inferiority.

The results for nine participants (20.5%) showed SARIMA (1, 1, 1, 0, 1, 1, 24), model #22, as the best model, and this model was selected most frequently (Fig. 1: top panel). SARIMA (3, 1, 3, 0, 1, 1, 24), model #62, and SARIMA (2, 1, 2, 0, 1, 1, 24), model #42, were selected by five (11.4%) and four (9.1%) participants, respectively (Supplementary Figure: Figure S1). These high-ranked models took zero as the seasonal autoregressive parameter, sAR($P = 0$), and orders for the non-seasonal parameters, AR and MA, in the model were of equal value ($p = q$). Comparing the time-series plots between models with the same hyper-parameters other than P (e.g., model #6 vs model #8; model #22 vs model #24), we can visually assess that the model with $P = 0$ was more stable in the diurnal cycle (Fig. 1 and Figure S1). High-ranked models had $P = 0$, indicating that a majority of college students (65.9%) were engaged in habitual physical activity.

Whereas, the number of models with $P = 1$ was 11 (model #7, 8, 12, 15, 16, 23, 24, 44, 56, 63, 64) out of the 21 optimal models obtained, and these were judged to be the optimal models for 15 participants (34.1%).

Relationships between the weights of parameters and depression-related behaviors

Only the regression model for the BADS-AR was supported by the significance test (R^2 = .34, $F(8,35)$ = 2.28, $p < 0.05$). The estimation results for all the regression models and the partial residual plots for significant explanatory variables on the BADS-AR are shown in Table 1 and Fig. 2.

Table 1
Results of regression analyses for the weights of model parameters on depressive symptoms and depression-related behaviors.

	Dependent variables					
	BDI-II	BADS-AC	BADS-AR		BADS-WS	BADS-SI
AR(1)	0.27	-0.70	0.73		1.25	0.20
AR(2)	-0.16	0.21	-0.13		0.11	-0.47
AR(3)	-0.30	0.03	-0.11		-0.01	-0.10
MA(1)	-0.27	1.64	-2.99		-0.26	-0.25
MA(2)	-0.41	1.69	-2.71	*	-0.91	-0.43
MA(3)	-0.22	1.38	-2.01		-0.85	0.07
sAR(1)	0.25	-0.18	0.75	*	1.03	-0.09
sMA(1)	0.38	-0.34	1.03	*	0.98	0.16
R^2	0.11	0.14	0.34		0.33	0.12
F	0.53	0.69	2.28	*	2.15	0.60

Note: AR = Auto-regression parameter, MA = Moving-average parameter, prefix “s” = seasonal, BDI-II = Beck Depression Inventory-II, BADS = Behavioral Activation for Depression Scale, BADS-AC = BADS Activation subscale, BADS-AR = BADS Avoidance/Rumination subscale, BADS-WS = BADS Work/School Impairment subscale, BADS-SI = BADS Social Impairment subscale.

*p < 0.05

Significant positive regression coefficients for the weights of sAR(1) and sMA(1) indicate that physical activity patterns with irregular fluctuations can lead to more avoidance and rumination behaviors. Conversely, the regression coefficients for MA(2) weight was a significant negative value, suggesting that avoidance and rumination behaviors are reduced if the residual before two hours contributes to fluctuation in physical activity over the last hour.

Discussion

This study extracted habituation data by modeling the time course of physical activity in the real-world. Model selection showed that more than 60% of healthy college students had stable physical activity patterns that were not affected by the previous day. However, not all college students necessarily had a

regular daily routine. Irregular day-to-day activity patterns may increase depression-related behaviors such as avoidance and rumination. Interestingly, we observed that a linear continuity with the nonlinear change that occurred two hours earlier might lead to healthy physical activity. Consistent with the theory of psychological interventions, prolonged intra-day activity engagement may increase depression-related behaviors. While much evidence has already shown a relationship between lifestyle rhythms and depression based on limited measurements or cognitive experiments [21–23], this is the first study that has demonstrated it using temporal characteristics of real-world physical activity.

Irregular social rhythm has been individually noted as a negative predictor of mental health in several life domains including meals, social contacts, and sleep and wake times [24]. However, some life domains are often continuous and complementary. In addition, the irregularity of a particular behavior may be substituted by another, as when a man who is out on his usual day off enjoys a meal in a restaurant on a rainy day. Our study revealed a simplified weekly variation in the intensity of physical activity without subjective ratings, instead of breaking it down into separate behavioral domains. Regardless of what behaviors the participants engaged in or what behavioral rhythms they disrupted, less day-to-day variability contributed to a reduction in depression-related behaviors such as avoidance and rumination. Our findings provide a perspective of overall lifestyle adjustment, supporting many of the previous findings on lifestyle rhythms and mental health.

Avoidance and rumination behaviors frequently predict depression even in non-clinical samples such as the participants in this study, and their effects are sometimes more powerful than that of anxiety, which is well known to be associated with depression [25]. Avoidance behavior seeks to decrease distress in life situations where a person perceives negative consequences, and rumination refers to repetitive and continuous negative thinking [26]. In college life, where there is little coercion, it may be assumed that experiencing failure, in academic or interpersonal relationships, for example, will lead to a change in behavior patterns, such as absences from school or part-time jobs, to avoid the negative situation. In fact, irregular daily life is one of the sub-scales on a mental health scale among Japanese university students [27]. In addition, repetitive thinking about a negative experience may inhibit positive/active behaviors, consequently, changes behavioral patterns. In this manner, these depression-related behaviors may emerge as inconsistent activity patterns, and this irregularity predicts students' mental health problems.

In a shorter time span such as diurnal variability, continuation of physical activity for more than two hours could be less healthy. Regardless of the amount, the more physical activity varied two hours earlier, the more it increased in the next hour, suggesting less avoidance or rumination behaviors. The importance of the two-hour period is not clear in this study, but the healthy participants most frequently reported engaging in an activity for two hours, as described for a candidate model parameter in the Methods section. Therefore, it can be argued that the unit of their conscious activity was often two hours, and that this may have been reflected in the results. Maintaining the same intensity of physical activity exceeding the natural engagement time for conscious activity may indicate boredom or overload. Both boredom and overload might lead to emotional exhaustion and disengagement in the future via an

increase in emotional rumination [28]. The involvement of this non-seasonal MA parameter may reflect these associations.

Limitations

The present study has several limitations. First, we summarized physical activity in terms of total METs per hour, whereas several previous studies have reported that minute-long activity promotes health [29]. We did not perform time-series analysis of minute-by-minute activity data, that is, METs, because of the trade-off with analysis cost, but the development of analytical technology will make this possible in the future. Second, sampling only a non-clinical group may limit the interpretation of the association with the BADS-AR. Although the present study focused on depression-related behaviors in healthy individuals, future studies among patients with depression may be needed. Finally, participants used the wearable device for only a week. Further understanding of habitual behavior demands more long-term measurement. However, even with the one-week period, there was a large amount of missing data, as in other studies using wearable devices. Further research may be needed to understand physical activity patterns over a longer cycle, after issues such as device management and continuous data sampling are resolved.

Conclusion

In summary, the objective data automatically measured by the wearable device showed that regular day to day rhythms and moderate diurnal switching of physical activities reduced depression-related behaviors such as avoidance and rumination. In addition, this study clarified the relationship between time-series patterns of physical activity and depression-related behaviors, providing insights not only into the detection of mental health problems but also the measures to improve them. It may accelerate the delivery of care by detecting the likelihood of depression-related behaviors that are outside individuals' subjective awareness.

Abbreviations

ARIMA: Autoregressive Integrated Moving Average model

SARIMA: Seasonal Autoregressive Integrated Moving Average model

BDI-II: Beck's Depression Inventory-2nd edition

BADS: Behavioral Activation for Depression Scale

Declarations

Ethics approval and consent to participate

The study was conducted according to the guidelines of the declaration of Helsinki. In addition, all procedures and the research proposal were approved by the Ethical Committee for Epidemiology of Hiroshima University (approval No. E-172-35). Participants of this study attended a research briefing and provided written informed consent.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available due to do not have consent from all patients to publish this data, but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

This work was supported by AMED [grant number JP22dm0307002]; JSPS [Grants-in-Aid for Scientific Research on Innovative Areas, grant numbers 16H06395, 16H06399], [Grant-in-Aid for Early-Career Scientists, grant number 21K13727]; and JST [JST-Mirai Program, grant number JPMJMI20D6].

Authors' contributions

SY, FK, MT, and YO designed study and wrote the first draft of the article. SY, KT, KK, and GO developed the methodology and analyzed data. All authors contributed to manuscript preparation and review, and all authors approved the submitted manuscript.

Acknowledgements

The authors acknowledge the contributions of Akira Saito and Yurie Miyawaki, students in Hiroshima University, who helped with the data collection. We would like to thank Editage (www.editage.com) for English language editing.

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Figures

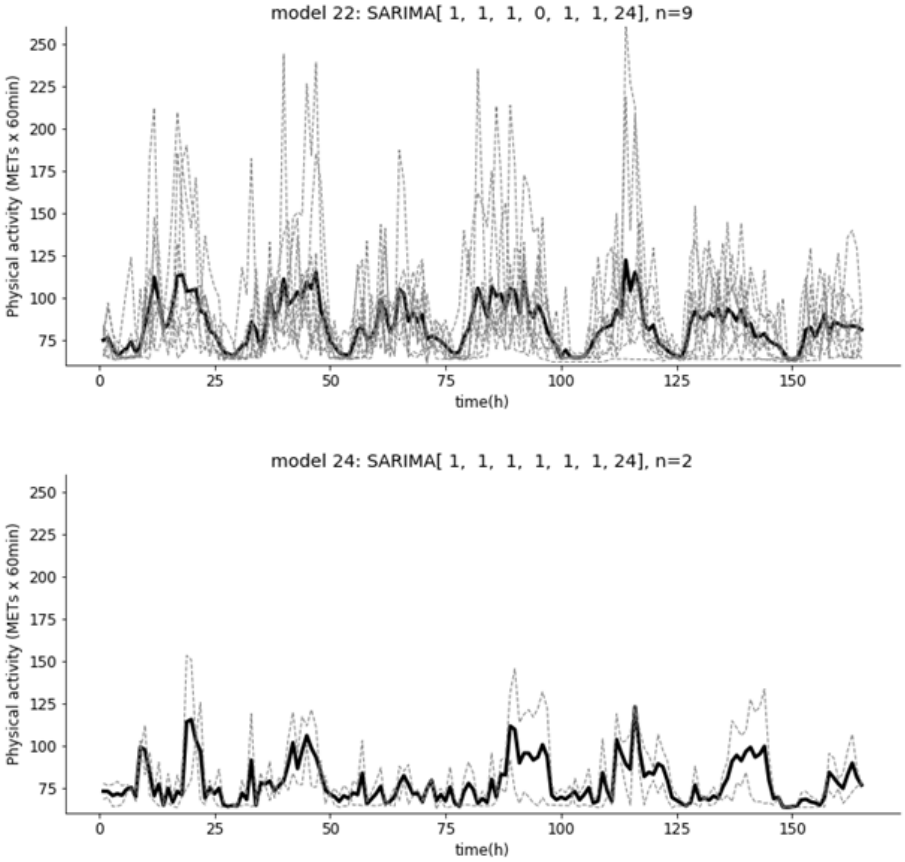

Figure 1

Time-series plot of the physical activity of participants belonging to representative models.

Note: The dashed lines show the physical activity of each participant, and the solid lines show their mean values. The model with the most affiliations (model # 22) is shown in the upper panel. The lower panel is

a comparison model that differs only in P from the upper panel (model # 24). All optimal models and their physical activity are shown in Supplementary Figure (Figure S1).

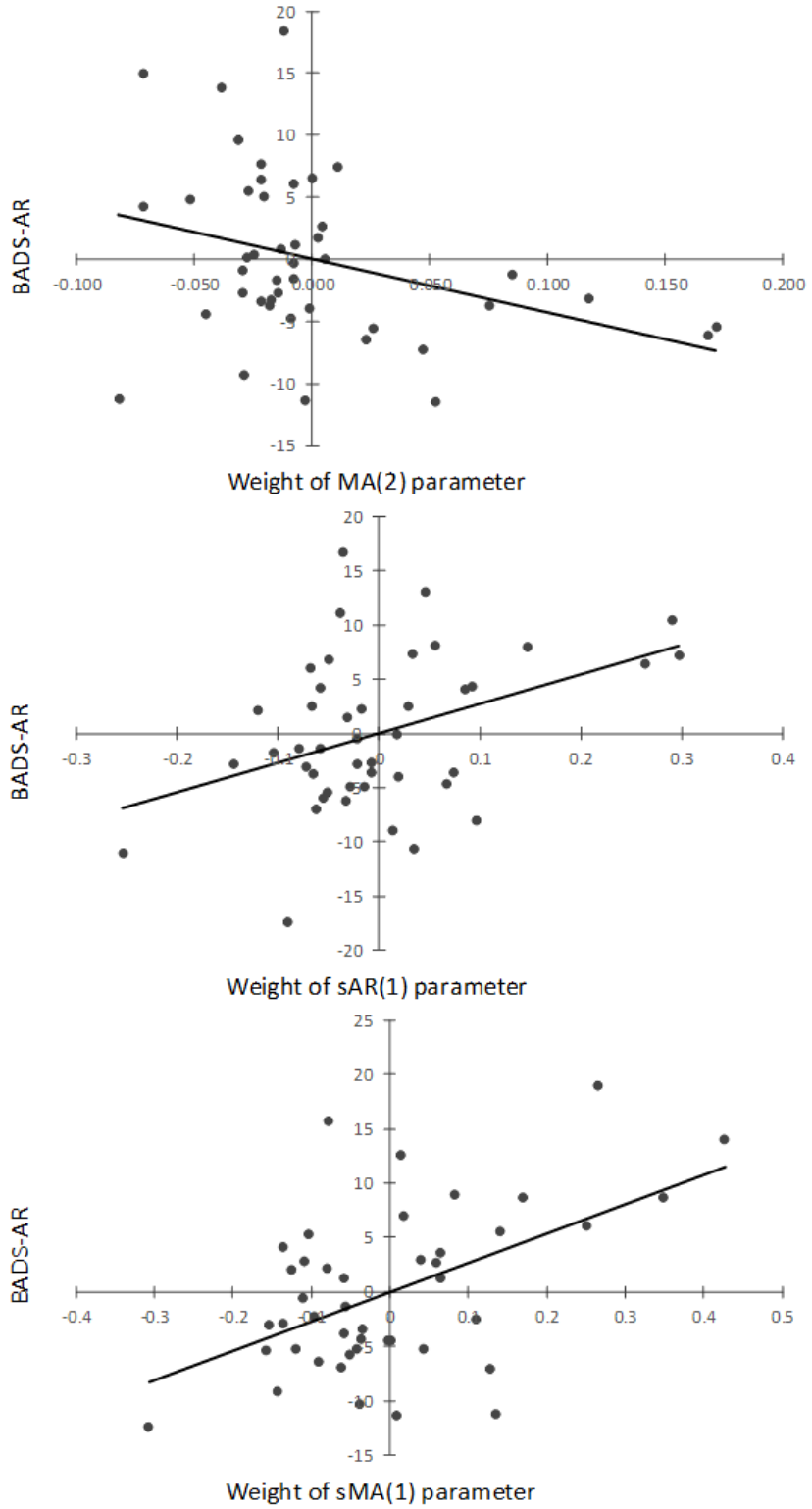

Figure 2

Partial residual plots between significant explanatory variables and the BADS-AR.

Note: The values on the axes show the centered partial residuals. sAR = seasonal auto-regression, MA/sMA = non-seasonal/seasonal moving-average, BADS-AR = Avoidance/Rumination subscale of the Behavioral Activation for Depression Scale (BADS).

Supplementary Files

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- SupplementaryFile.docx