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Article

Physical Activity and Nighttime Sleep in Adolescents

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ABSTRACT

Background: Previous studies show contradictory results regarding the bidirectional association between physical activity and nighttime sleep. The objective of the present study was to add knowledge to these possible relationships using autoregressive models. **Method:** 214 adolescents (117 boys and 97 girls), with a mean age of 13.31 years agreed to participate. The study variables were measured with accelerometers for 7 full days over three consecutive years. The mlVAR package was used to compute estimates from multivariate vector autoregression models. **Results:** The 5-delay models showed a better fit. Autoregressive effects were observed in sleep onset, sleep offset and sedentary behavior, which could explain the relationships found in previous studies between physical activity and sleep. Sleep onset, total sleep time, and sleep efficiency had direct effects on sedentary behavior. Moderate-to-vigorous physical activity was not related to any of the sleep variables. **Conclusions:** The hypothesis that there are bidirectional/reciprocal relationships between physical activity and sleep cannot be accepted.

Actividad Física y Sueño Nocturno en Adolescentes

Palabras clave:
Actividad física
Sueño
Modelo vectorial autorregresivo

RESUMEN

Antecedentes: Los resultados de estudios previos sobre la asociación bidireccional entre actividad física y sueño nocturno son contradictorios. El objetivo del presente estudio es intentar dar una mejor explicación a estas posibles relaciones utilizando modelos autorregresivos. **Método:** Participaron 214 jóvenes (117 varones y 97 mujeres), con una media de edad de 13,31 años. Las variables del estudio se midieron con acelerómetros durante 7 días completos, en tres años consecutivos. Se utilizó el paquete mlVAR para calcular las estimaciones de modelos vectoriales de autorregresión multivariables. **Resultados:** Los modelos de 5 retrasos fueron los que mostraron un mejor ajuste. Se observaron efectos autorregresivos en el inicio del sueño nocturno, el final del sueño nocturno y los comportamientos sedentarios, que podrían explicar las relaciones encontradas en estudios previos entre actividad física y sueño. Se observaron efectos directos entre el inicio, la duración y la eficiencia del sueño nocturno sobre los comportamientos sedentarios. La actividad física moderada-vigorosa no se relacionó con ninguna variable de sueño nocturno. **Conclusiones:** No se puede aceptar la hipótesis de que existen relaciones bidireccionales/recíprocas, entre la actividad física y el sueño.

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Physical activity and sleep are behaviors that are directly related to health. Regular and adequate physical activity, including any bodily movement that requires energy, can reduce the risk of many non-communicable diseases and disorders, such as hypertension, coronary heart disease, stroke, type 2 diabetes, breast and colon cancer, and depression (Pan American Health Organization, 2022). Previous evidence has also found that lack of sleep increases the risk of obesity, heart disease, infections, hypertension, type 2 diabetes, mood disorders, neurodegeneration, and dementia (National Institutes of Health, 2018). Consequently, knowing how these behaviors can interact with each other is a key public health aim.

So far, previous studies of the bidirectional relationship between physical activity and night sleep have attempted to answer the following questions: a) how daytime physical activity (light, moderate or vigorous) influences sleep onset (SO), sleep offset (SOF), sleep onset latency (SOL), wake time after sleep onset (WASO), sleep efficiency (SE) and total sleep time (TST), among other variables of interest; b) how SO, SOF, SOL, WASO, SE and nocturnal TST influence physical activity (light, moderate or vigorous) the following day.

Studies regarding the first issue provide inconclusive results. For instance, several studies have failed to find a positive association between MVPA → SOL (Bernard et al., 2016; Mitchell et al., 2016; Murray et al., 2017). However, other studies have observed that a greater amount of physical activity on a given day was significantly associated (inter-individual level) with a SOL increase (Nodine, 2011). Master et al. (2019) found that MVPA was positively associated with SO and SOF. There are also several studies that did not find positive associations between MVPA → TST (Baron et al., 2013; Bernard, et al., 2016; Kishida & Elavsky, 2016). On the contrary, Best et al. (2018) observed positive associations between these variables. Regarding the MVPA → SE relationship, Shepherd et al. (2018) found very small associations unlikely to reflect any clinically significant change.

Studies that have addressed the second question, the nocturnal sleep variables impact on physical activity the following day, also provide inconclusive results. Several researches have not observed a relationship between SOL → MVPA (Best et al., 2018; Dzierzewski et al., 2014; Mitchell et al., 2016). However, Baron et al. (2013) found a significant association between SOL and physical activity at the intra-individual level. Master et al. (2019) found that earlier nocturnal SO predicted greater SB the next day, however SO did not significantly predict MVPA the next day. SOF was associated with less MVPA and SB the next day. WASO was not associated with next-day MVPA in some studies (Kishida & Elavsky, 2016; Mitchell et al., 2016; Spina et al., 2017). In contrast, high WASO was significantly associated with physical activity counts the next day in other studies (Bernard et al., 2016; Bittner et al., 2018). The association between TST → MVPA has been significant and negatively associated in some occasions (Kishida & Elavsky, 2016; Knufinke et al., 2018), whereas other studies have not found this association (Bernard et al., 2016; McDonald et al., 2017). Finally, regarding SE → MVPA relationship, Nodine (2011) identified a significant positive association between these variables, although most studies have not observed a significant relationship (Best et al., 2018; Cox et al., 2019; Tang & Sanborn, 2014).

What could be the cause of these contradictory results? A possible explanation could be found in the systematic review and meta-analysis on daily associations between sleep and physical activity at the inter- and intra-individual level in adults carried out by Atoui et al. (2021). Taking into account the discrepancies observed in the selected studies, these authors encourage examining the relationship between sleep and physical activity over longer periods and with new statistical analyzes that consider their temporal dynamics. The reason is that previous studies have not addressed this temporal dependency, focusing on studying how physical activity is related to the night sleep the same day, or how night sleep is related to the physical activity the following day. Ignoring the autoregressive effects removes one of its most important dimensions from the equation: the fact that a dynamic variable can be influenced by its previous states. They also ignore the possibility that the current state of one dynamic variable is influenced by previous states of other dynamic variables.

Most of the studies on this topic commonly use linear regressions or traditional multilevel models without considering the time dependency. However, multilevel linear models have a limited ability to study multivariate models (Emerson et al., 2018). Simulation studies have shown when researchers model dynamic processes using multilevel linear models, key assumptions (e. g., observations independence) are violated by including lagged responses as predictors. Therefore, this fact can lead to biased estimates and erroneous inferences (Ruissen et al., 2021).

To overcome these difficulties, new dynamic models have appeared in recent years attempting to explain how variables changes develop over time (Bringmann & Eronen, 2018; Gelfand & Engelhart, 2012). The dynamic models fundamental characteristic is the variables *temporal dependence*. That is, the variables values in a dynamic system at a time (t) are modeled as functions of those same variables at previous times (Gelfand & Engelhart, 2012). There are two types of temporally dependent relationships: autoregressive and crossed. In the first case, the dynamic variable current state can be influenced by its previous states (Piccirillo & Rodebaugh, 2019). For instance, MVPA levels at one time-point (t) could predict MVPA levels at a later time-point ($t + 1$). In the second case, the dynamic variable current state could be influenced by other dynamic variables previous states (Piccirillo & Rodebaugh, 2019). Consequently, the variable effect at time t could predict the behavior of another variable in the future and vice versa. In summary, dynamic models use *endogenous* variables as opposed from others. This means they act as predictor and outcome variables (Brandt & Williams, 2007; Gelfand & Engelhart, 2012) and as feedback loops that develop over time (Gelfand & Engelhart, 2012).

Irish et al. (2014) studied in adult women the 24-hour temporal dynamics between health behaviors and sleep, and vice versa (e.g. past days number with greater predictive power). To conduct this, they performed Granger causality F tests from vector autoregressive (VAR) models. Results showed that a 7-day model was the best describing the temporal relationships between health behaviors and sleep characteristics. This suggested that weekly health patterns and sleep behaviors were more useful in predicting later health and sleep behaviors than more proximal models (e.g., one day). This finding was contrary to the study hypotheses and is somewhat surprising considering the nature of the many physiological mechanisms postulated to explain these associations. Although, psychosocial and behavioral patterns tend to follow a weekly cycle. Moreover, for these authors it is not yet clear to what extent this 24-hour weekly behaviors pattern will extend to other samples. It is plausible that seven days do not represent the most significant daily behaviors window for all individuals.

Furthermore, Irish et al. (2014) found that physical activity did not significantly predict any sleep variables, perhaps due to lack of sensitivity in daily physical activity measurement. For instance, physical activity duration was not assessed daily, but duration is a key factor in determining the physical activity impact on sleep. In addition, physical activity was tested with self-report measures in which women were asked to categorize their physical activity during the day as none, light (e.g., *walking, shopping*), moderate (e.g., *jogging, heavy housework*) or vigorous (e.g., *jogging, tennis*).

The main objective of the present study was to examine the temporal network of bidirectional relationships between physical activity and nocturnal sleep over three years in adolescents. For this purpose, as far as we know, this is the first study with objective measures that have used vector autoregressive model (VAR) to analyze the temporal relationships between physical activity and sleep. Based on the contributions of Atoui et al. (2021) and Irish et al. (2014), we hypothesized bidirectional/reciprocal relationships between physical activity and night sleep will not be found. Specifically, the following hypotheses were formulated: a) several days models will better explain the temporal relationships between physical activity and sleep variables; b) significant autoregressive effects will appear in the nocturnal sleep variables; c) MVPA will not be related to any nocturnal sleep variable and vice versa.

Method

Participants

A total of 214 adolescents (117 men and 97 women), aged between 12 and 14 years (M = 13.31, SD = .58) from nine schools in a city in the north of Spain agreed to participate. Considering the level of personal and family involvement required in a study of this kind and with the aim of increasing participants´ commitment, the sample technique was non-probabilistic, non-random and convenience. A stratification was carried out by the type of school and nine public and three private/private public funded schools were contacted. Of these, nine were randomly selected (seven public and two private/private public funded). From these educational centers, 12 intact 1st year secondary education classrooms were randomly selected, with an average of 21.5 students (n = 282). Eligibility criteria were the following: absence of mental and cognitive deficits and ability to provide informed consent; absence of serious cognitive disorders; absence of serious concomitant diseases. The informed consent was provided by school principals, parents and students. At T2, the sample dropped by 7.94% (n = 197) whereas at T3 it additionally dropped by 12.19% (n = 173).

Instruments

ActiGraph GT3x accelerometers (ActiGraphTM, Fort Walton Beach, FL, USA) were used to assess physical activity and sleep measures. Actigraphy data analysis was performed with Actilife v.6. (ActiGraph, Pensacola, Florida, USA).

Sleep measures: data were reintegrated in 60-second epochs and scored using Sadeh's algorithm (Sadeh et al., 1994). The use of wrist accelerometers has shown good correlations with gold standard measures (Full et al., 2018). SO: It was fixed when data indicated five consecutive epochs ≤ 10 after the last 30-second epoch of activity > 10 counts. Any interval identified that exceeded a 15 min difference between raters was reviewed by themselves until agreement was reached. SOF: Completion of nightly sleep duration was determined by accelerometer score: SOF was fixed when data indicated the first 30-second epoch of activity > 10 counts after five consecutive epochs ≤ 10. TST: It was calculated by the number of minutes between SO and SOF. SE: It was defined as the ratio between TST and total time in bed (Gillis & El-Sheikh, 2019). Only subjects with ≥ three nights were included in the sample (Kracht et al., 2020).

Physical activity measures: data were collected at a sampling rate of 30 Hz with the standard frequency extension and downloaded in 1-second epochs. Choi's algorithm (Choi et al., 2011) was used to exclude non-wear time. This procedure ensured physical activity and SB were derived from waking and usage time only. Physical activity data was categorized into MVPA and SB with Evenson cut-off points (Evenson et al., 2008), which have been shown to be a valid and reliable measure in young people (Trost et al., 2011). To be included in the analyses, participants had to wear the accelerometer for ≥ 10 hours per day and have at least ≥ four valid days (Colley et al., 2010).

Procedure

A longitudinal study was conducted to examine the temporal associations between physical activity and sleep in a cohort of adolescents for one week over three consecutive years. Participants were asked to wear an accelerometer on their waist for a full week (March of each year) except in water activities (e.g., swimming), but they were asked to move the accelerometer to the wrist of their non-dominant hand during nightly sleep. Adolescents were instructed on how to operate the accelerometer and how to complete a diary where they recorded the time they turned off the lights to go to sleep at night, the times they woke up and the times they removed the accelerometer. These data were used to help identify and confirm SO/SOF and non-wear time.

Data analysis

Statistical analysis were performed using R software (v. 3.5.3) (R Core Team, 2019) with the *mlVAR package* (v. 0.3.2) (Epskamp et al., 2019). *mlVAR* function computes estimates from the multivariate vector autoregression model. This function has been created to extract individual network dynamics by estimating a multilevel autoregression vector that models the selected variables temporal dynamics at both intra and inter-individual level at the same time unit. In a lag 1 model. (lag1), each variable at time-point t is reverted to a lagged version of itself at time-point t-1 (autoregressive effects) along with all other variables, which are set at the same time-point *t-1*. However, lags can also be extended (≥2) to preceding time-points (e.g. variables at *t-2* and *t-1* can influence variables at time t in a VAR(2) model). Based on previous studies (Irish et al., 2014), VAR models results were examined to identify the time during which associations between physical activity and sleep were maintained. Only models up to 5 days were evaluated, since the sample size limited the ability to carry out more extensive analyses. The interpretation of the significant effects direction between variables (physical activity and sleep) is complicated due to the inherent multicollinearity derived from the autocorrelation of each time series. Therefore, triad regression models were performed, in which MVPA and SB were always included with a nocturnal sleep variable (SO, SOF, TST and SE): model 1 (MVPA, SB and SO), model 2 (MVPA, SB and SOF), model 3 (MVPA, SB and TST), and model 4 (MVPA, SB and SE).

Akaike Information Criterion (AIC) was used for order selection (Shumway & Stoffer, 2011), taking into account that lower AIC values indicate a better model fit. Likelihood ratio tests comparing VAR models (2-5 days) with first-order models (that is, models in which only the previous 24 hours are included) were implemented to formally test whether the associations between night and day persisted beyond a single 24-hour period.

In a Granger causality test, X variable predicts Y variable, whether X past values predict Y after adjusting for Y past values and other covariates. The interpretation of the significant effects direction (X on Y) is complicated by the inherent multicollinearity derived from the autocorrelation of each time series. Hence, individual regression models were run to reveal the significant effects directionality of X on Y after controlling for sociodemographic and health covariates.

For the two-step multilevel vector autoregressive model (mlVAR), is recommended to obtain at least 20 measurements per subject (Epskamp, al., 2019). A total of 180 participants met this requirement.

The mlVAR assumes that each subject time series are stationary, that is, their means and variances-covariances are stable over time. The Kwiatkowski-Phillips-Schmidt-Shin test (KPSS; Kwiatkowski et al., 1992) was then used to examine the seasonality level. KPSS test indicated that all time-series were leveled and stationary.

In the network analysis the nodes were represented by the variables: moderate-vigorous physical activity (MVPA), sedentary behavior (SB), sleep onset (SO), sleep offset (SOF), total sleep time (TST) and sleep efficiency (SE); whereas the arrows represented the temporal prediction. The thickness represents the connection strength, whereas green and red means positive and negative connection respectively. In the networks, all effects that were not significant were eliminated. A significance level of $p < .05$ was used (Epskamp et al., 2018).

Results

Descriptive analysis

Table 1 shows the means and standard deviation of each variable over the three years. The information is expressed in minutes except for SE (percentage). SO and SOL are averages centered at midnight. Adolescents spend more than 10 hours per day in sedentary activities. MVPA daily time is close to the minimum recommendations (60 min) by the World Health Organization (2020). SO ranges from approximately half an hour before midnight (T1 = -31.50) to 17 minutes after midnight (T3 = 17.20). TST ranges from 7 hours and 32 minutes to 8 hours and 31 minutes.

Temporal networks between physical activity and nocturnal sleep

Table 2 shows values of the AIC, which measures the relative quality of a statistical model for a given data set. As such, it provides information for a model selection. As can be seen, all the models improve in each of the delays. According to the AIC for order selection (Shumway & Stoffer, 2011; Vallejo et al., 2010), the 5-lag models were the ones that showed the best fit. Table 3 shows the regressive effects including all possibilities (1 → 1; 1 → 2; 2 → 1; 2→ 2). In model A, there are two autoregressive effects (SO and SB) and a direct effect from the SO over the SB, whereas MVPA shows no effect. That is to say, SO in the previous days is the only predictor of the subsequent days SO and the same situation happens with SB. Additionally, SO positively predicts SB. In model B, there are only two autoregressive effects (SOF and SB). That is, the only positive predictor of SO and SB are these same variables in the previous days. In model C, there are again two new autoregressive effects (TST and SB). In addition, there is a negative effect between TST and SB. That is, a longer sleep leads to spending less time on SB. In model D, there is no autoregressive effect in the sleep variable (SE) unlike the previous models, which may indicate SE has greater variability. There is one autoregressive effect (SB) as it happened in the rest of the models. Moreover, there are two direct effects (SE → SB; MVPA → SB). In other words, less SE leads to spending more time in SB and performing more MVPA leads to spending more time in SB on subsequent days.

Figure 1 presents the four tested lag-5 models. Autoregressive effects occur in three of the sleep variables: SO, SOF, and TST. The SB autoregressive effect is significant in all tested models. Neither SE nor MVPA showed any autoregressive effect. Regarding the direct crossover effects, neither SB nor MVPA predicted any nocturnal sleep variable. None of the nocturnal sleep variables predicted MVPA. That is to say, physical activity (MVPA) is not related to any sleep variable. On the contrary, there were direct effects of SO, TST and SE on SB.

Table 1.
Descriptive analysis.

	T1		T2		T3	
	M	*SD*	*M*	*SD*	*M*	*SD*
SB	610.33	118.52	659.50	103.75	675.99	94.52
MVPA	59.94	65.65	60.74	32.22	58.92	34.21
SO	-31.50	73.69	-3.54	71.38	17.20	65.17
SOF	480.54	81.41	469.81	72.83	489.70	71.94
TST	511.67	79.25	473.35	68.43	472.50	68.30
SE	91.50	2.74	90.88	3.06	90.36	9.07

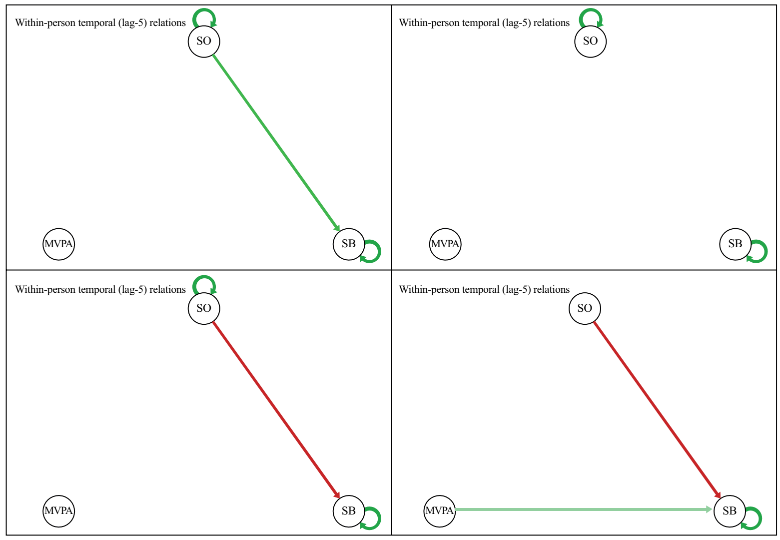
Note: SB = sedentary behavior; MVPA = moderate-vigorous physical activity; SO = sleep onset; SOF = sleep offset; TST = total sleep time; SE = sleep efficiency.

Table 2.
Akaike Information Criterion (AIC) for each Time Effects Networks in the Four Models.

		Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Model A	SO	10265.31	6685.08	6875.43	5675.72	4230.28
	SB	10221.98	7885.87	7059.99	5755.49	4234.27
	MVPA	10189.45	8350.65	7126.56	5789.49	4429.57
	SOF	10640.86	7876.83	7584.21	6320.09	4743.50
Model B	SB	10439.59	7979.84	7225.02	5894.34	4418.13
	MVPA	10284.82	8366.74	7176.01	5826.09	4361.77
	TST	10254.51	8012.23	7140.57	5839.09	4462.97
Model C	SB	10200.90	7861.84	7044.93	5760.07	4310.71
	MVPA	10330.61	8358.52	7114.84	5771.17	4319.91
	SE	10438.78	9473.61	8140.97	6865.64	4624.46
Model D	SB	10263.88	8053.12	7215.07	5881.64	4412.11
	MVPA	11072.76	8413.46	7160.98	5810.50	4348.82

Note: SB = sedentary behavior; MVPA = moderate-vigorous physical activity; SO = sleep onset; SOF = sleep offset; TST = total sleep time; SE = sleep efficiency.

Figure 1.
Temporal Effects Networks in the Four Models.



Note: A, B, C y D: from top to bottom and from left to right. SB = sedentary behavior; MVPA = moderate-vigorous physical activity; SO = sleep onset; SOF = sleep offset; TST = total sleep time; SE = sleep efficiency.

Table 3.
Temporal Effects between the Variables Analyzed in the Four Models.

		B	*SE B*	*p*
Model A	SO → SO	.204	.049	.000
	SO → SB	.163	.047	.001
	SO → MVPA	-.075	.046	.106
	SB → SO	-.003	,089	.630
	SB → SB	.210	.055	.000
	SB → MVPA	.085	.050	.087
	MVPA → SO	.074	.045	.098
	MVPA → SB	.067	.049	.247
	MVPA → MVPA	.064	.046	.169
Model B	SOF → SOF	.230	.080	.004
	SOF → SB	.012	.081	.880
	SOF → MVPA	.004	.075	.954
	SB → SOF	-.086	,060	.149
	SB → SB	.291	.054	.000
	SB → MVPA	.038	.047	.416
	MVPA → SOF	.014	.054	.790
	MVPA → SB	.096	.049	.051
	MVPA → MVPA	.048	.045	.294
Model C	TST → TST	.176	.054	.001
	TST → SB	-.170	.049	.001
	TST → MVPA	.082	.048	.087
	SB → TST	-.118	,064	.066
	SB → SB	.187	.058	.001
	SB → MVPA	.102	.053	.052
	MVPA → TST	-.070	.053	.184
	MVPA → SB	.056	.051	.272
	MVPA → MVPA	.072	.047	.125
Model D	SE → SE	-.107	.158	.499
	SE → SB	-.205	.066	.002
	SE→ MVPA	.056	.070	.423
	SB → SE	.043	,089	.630
	SB → SB	.287	.053	.000
	SB → MVPA	.041	.046	.372
	MVPA → SE	-.015	.052	.780
	MVPA → SB	.108	.049	.027
	MVPA → MVPA	.062	.045	.171

Note: SB = sedentary behavior; MVPA = moderate-vigorous physical activity; SO = sleep onset; SOF = sleep offset; TST = total sleep time; SE = sleep efficiency.

Discussion

The main objective of the present study was to examine the temporal network of bidirectional relationships between physical activity and nocturnal sleep over three years in adolescents. For this purpose, as far as we know, this is the first study with objective measures that have used vector autoregressive models (VAR) to analyze the temporal relationships between physical activity and sleep.

The results are consistent with the first specific hypothesis that was formulated (a): models with several days delays would better explain the temporal relationships between physical activity and sleep. Findings from the present study suggest that the physical activity-sleep association should not be examined with a 1-delay (e.g., association with the night or the day before), but rather with a greater delay between sleep and physical activity (Irish et al. al., 2014). The temporal dynamics of the physical activity-sleep behaviors throughout 24 hours allowed us to identify the time-period with the greatest predictive power. The results showed that a lag-5 had the best fit for possible accumulation effects and sample size (Atoui et al., 2021). This finding highlights the predictive value of the variables measured in previous days on the current results. Physical activity and sleep patterns seem to follow a weekly cycle. Unfortunately, due to the sample size, it was not possible to measure delays beyond the fifth day.

The second specific hypothesis formulated (b) was that significant autoregressive effects would appear in the nocturnal sleep variables. The results show that three nocturnal sleep variables (SO, SOF and TST) show important autoregressive effects. This means that students usually fall asleep and wake up regularly, maintaining a constant sleep time, probably associated with human circadian rhythms (Adan et al., 2012) and academic demands. Different studies that analyzed sleep habits in children and adolescents conclude that only 20% do not have regular sleep schedules on a regular basis (García-Jiménez et al., 2004). Family and school environments could explain, in part, the differences between individuals (Collado et al., 2012). However, this does not happen with SE. One possible explanation is that sleep is reduced in adolescence by scheduled school hours that do not coincide with the circadian phase, which could lead to compensatory adjustments in SE (Swaab et al., 1996).

MVPA did not have autoregressive effects, which seems to indicate that the weekly regularity of MVPA, which is a health indicator (WHO, 2020), is not met in adolescents. On the contrary, SB showed significant autoregressive effects in all tested models. That is, the reproduced behaviors over time are the sedentary ones, whereas physical activity behaviors appear sporadically.

The third hypothesis formulated (c) was that MVPA would not be related to any nocturnal sleep variable and vice versa. The results are consistent with this statement. In fact, regarding cross-effects, MVPA does not predict any nocturnal sleep variable. This finding has been observed in other studies that used a different methodology (Breneman, 2016; Mitchell et al., 2016). Similarly, none of the nocturnal sleep variables predicted MVPA. In this sense, different studies have also observed the lack of relationship between sleep variables and MVPA: SO and MVPA (Bernard et al., 2016; Best et al., 2018; Dzierzewski et al., 2014; Lambiase et al., 2013; Mitchell et al., 2016); SOF and MVPA (Baron et al., 2013; Dzierzewski et al., 2014; Kim, 2018; Kishida & Elavsky, 2016; Mitchell et al., 2016); TST and MVPA (Baron et al., 2013; Bernard et al., 2016; Cox et al., 2019; Dzierzewski et al., 2014; Irish et al., 2014; Mitchell et al., 2016; Spina et al., 2017); SE and MVPA (Baron et al., 2013; Bernard et al., 2016; Irish et al., 2014; Kishida & Elavsky, 2016; Mitchell et al., 2016; Spina et al., 2017).

As well as MVPA, SB did not predict any nocturnal sleep variable. These results are consistent with previous studies (Mitchell et al., 2016). However, SO positively predicted SB, that is, delaying sleep phase potentially reduces SB the following day. Accordingly, the present study results also showed a negative association between TST and SB. This relationship has also been observed in other studies (Gabriel et al., 2017; Heiland et al., 2021). Lastly, SE also negatively predicts SB activity, as found previously (Thosar et al., 2021).

In a recent multilevel meta-analysis on the bidirectional relationships between physical activity and sleep (Atoui et al., 2021), overall, the qualitative and quantitative analyzes did not support a bidirectional association. Likewise, authors warned that their findings should be interpreted with caution due to the various methodological approaches used in the included studies. To overcome the contradictory findings, they suggested that physical activity-sleep associations should not be examined with a delay-1 (association with the night or the day before), but with an increased delay between physical activity-sleep from vector autoregressive models. The present study results using VAR models reinforces the conclusions obtained in their meta-analysis: the hypothesis that there are bidirectional/reciprocal relationships between SO, SOF, TST, SE and MVPA and SB cannot be accepted (general hypothesis formulated in the present research).

The main limitation from the present study is that sample size was not sufficient to carry out delays beyond the fifth day, so important questions remain unanswered. For instance, Irish et al. (2014) found that bivariate lag-7 models had a better fit than lag-1 models in describing temporal associations between physical activity and sleep. Indeed, possible effects of hoarding, social, or hormonal rhythms have been proposed in studies examining the behavioral circadian rhythm (Monk, 2010). However, the present study may have important repercussions on the topic, since the results showed the importance of analyzing autoregressive effects. These results seem to indicate that the direct effects observed in other studies disappear when autoregressive effects are introduced, so this could be a key question to resolve discrepancies between studies. In the future, new network analyzes should be carried out including other physical activity and sleep variables and long time series (>50 time-points or days of observation). Intervention studies combining daily physical activity and sleep and should also be conducted to compare their effects.

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