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A network analysis involving mental difficulties, cognition, physical fitness, 24-hour movement components, fatness, and sociodemographic factors in children[☆]

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ABSTRACT

Background: Evidence supports the beneficial linear influence of diverse lifestyle behaviors on brain health since childhood; however, multiple behaviors -and not only one-simultaneously affect such outcomes. Therefore, the aim was to explore the multivariate relationship through a network analysis among mental difficulty and cognitive function with physical fitness (PF), 24-h movement components, fatness, and sociodemographic factors in children.

Methods: Cross-sectional study involved 226 children (52.2 % boys) aged between six and 11 years. Mental difficulties were evaluated through the Strengths and Difficulties Questionnaire and cognitive function by the Raven's Colored Progressive Matrices Test. The body mass index and PF were assessed according to the procedures suggested by the Proesp-Br, while moderate-to vigorous-intensity physical activity (MVPA) using accelerometry. The socioeconomic level, sleep, and screen time were evaluated by questionnaires. A network analysis was carried out to evaluate the associations among variables and establish centrality measures.

Results: Age and PF moderated the negative relationship between cognitive function and MVPA. Furthermore, the direct and inverse relationship between cognitive function and mental difficulties appears to be affected by the 24-h movement components. Finally, age, PF, and screen time are the nodes with higher values of expected influence, indicating more sensitivity to interventions for decreasing mental difficulty and improving cognitive function.

Conclusion: Mental health and cognitive function were moderated by the multivariate interaction among age, PF, and the three 24-h movement components. Nonetheless, centrality measures from the network analysis suggest that PF, MVPA, and screen time are crucial nodes in order to implement future interventions.

☆ (i) all authors agree with the content of the article and approve of its submission to the journal; (ii) the material contained in the manuscript has not been previously published and is not being concurrently submitted elsewhere; (iii) the experiments reported in the article were undertaken in compliance with the current laws of the country in which the experiments were performed.

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1. Introduction

Current evidence supports the beneficial influence of lifestyle behavior associated with brain health since childhood.[1,2] Among brain health conditions, psychological aspects such as mental health disorders and cognitive function are essential in children's inclusion in social life.[3] For instance, several studies in children have shown that moderate-to vigorous-intensity physical activity (MVPA), physical fitness, and sports effects on brain health indicators, including a greater hippocampal and basal ganglia volume, greater white matter integrity and more efficient patterns of brain activity, reduced anxiety and depression, superior cognitive functioning, and even better academic performance.[4,5] On the other hand, a greater amount of time spent in sedentary behaviors (i.e., watching television, video games, and cellphone) is associated with lower cognition[6] and inadequate sleep quality in children,[7,8] as it can reduce time spent on activities that promote cognitive growth, such as physical play, reading, and social interactions.[9]

In this sense, researchers have shown negative associations of not adopting a daily habit-balanced profile, including less than 2 h in sedentary behavior, at least 1 h in MVPA, and respect sleep time for age, with cognition and mental health of children and adolescents.[10] Moreover, other factors affect mental health and cognition, such as obesity.[11,12] For instance, Esteban-Cornejo et al. (2020) identified that children with obesity were related to deficiencies in brain structure and function, executive function, and academic performance, while having a low socioeconomic status has been associated with impaired cognitive functions.[13,14] In this sense, children of low-income backgrounds may face various stressors and limited access to resources, potentially impacting their mental health and cognitive development.[15]

In addition to the mentioned and accumulated knowledge regarding these linear associations,[16–19] it is crucial to understand these approaches critically and cautiously due to their complex nature.[13] In other words, when we deal with living systems ("the real world"), it is necessary to consider that an outcome is the product of several interactions that take place simultaneously. Thus, it is essential to comprehend these mechanisms under a multivariate view to elucidate the relationships involved and how they are organized in a shared space. Based on this understanding, the justification for carrying out this work and the statistical choice is that the network analysis, on the one hand, allows verifying the simultaneous relationships between variables, unlike traditional methods, such as regression analysis and principal component analysis. On the other, it permits establishing variables more sensitive to future interventions.[20,21]

Therefore, bearing in mind the importance of knowing the more appropriate approach to promote brain health in children through behavioral interventions, this study aimed to explore through a network analysis [20,21]the multivariate relationship among mental difficulties and cognitive function with physical fitness, 24-h movement components, fatness, and sociodemographic factors in children. Based on the literature, we hypothesize that the MVPA and physical fitness will be the most relevant nodes in this model and those that connect mental health variables with the other nodes.

2. Methods

2.1. Study design and participants

This cross-sectional study used baseline data from a project that aimed to verify the effects of an intervention with football in several aspects of children's health. Participated 226 schoolchildren (118 boys) between 1st to 5th grade (6–11 years old, mean 8.42 ± 1.49) from a state-funded school in southern Brazil. This school was selected by convenience criteria. Because it is a teaching establishment, all children were invited to participate in the research to address the ethical issue related to this aspect. Thus, the inclusion criteria adopted were: being between six and 11 years old, being enrolled in school, have completed questionnaires and other assessments. Exclusion criteria included: having some physical impediment for the physical assessments and not having answered all the questionnaires. Finally, parents and children who agreed to participate in the study had to sign the terms of consent and assent, respectively (Fig. 1). The present research was approved by the Ethics and Research Committee of the Federal University of Rio Grande do Sul (number 2. 611.180).

2.2. Measurements procedures

All measures were taken at the school by trained researchers and psychologists. Initially, the parents were invited to a school meeting to present the project's objectives, solve doubts, and fill out some questionnaires and anamneses related to the study. For those unable to attend the session, we contacted them by phone and set individual appointments when they were available.

2.3. Mental difficulties

Mental difficulties were evaluated through the Strengths and Difficulties Questionnaire (SDQ), which consists of an epidemiological tool for the behavioral screening of children.[22] In addition, this questionnaire was validated and presented satisfactory psychometric quality with positive indices of validity and reliability in the general population,[23] and in children and adolescents from Brazil (validity: variations between 0.63 and 0.88) and (reliability: ranged from 0.59 to 0.88).[23] The SDQ addresses behavioral issues in children between three and 12 years old. It contains 25 items subdivided into five domains: emotional symptoms (anxiety and depression), conduct problems, hyperactivity-inattention, peer relationship problems, and pro-social behavior. Each dimension contains five items, and respondents rate the frequency of each item on a scale from 0 to 2, ("True," "More or less true," and "False"), considering several sentences, such as "Often unhappy, depressed or tearful", "Easily distracted, concentration wanders", and "Many fears, easily scared", resulting in scores ranging from 0 to 10 for each dimension. To calculate the total difficulty score, the scores from the 20 items related to difficulties (excluding prosocial behavior) are summed up. The questionnaire was answered by the guardian, who considered the child's last six months. The internal consistency (Cronbach's alpha) of the SDQ was 0.79.

2.4. Cognitive function

Cognitive function was accessed through Raven's Colored Progressive Matrices Test, which is a valid and reliable measure for this population.[24] It measures children's non-verbal intelligence and is related to diverse cognitive abilities, from basic attentional skills to the more complex ones that require perceptual or analogical reasoning.[25] This psychological test consists of three series of 12 items (A, Ab, and B), organized in increasing difficulty. In Part A, the demand for attention to visual details predominates. In Part Ab, the ability to recognize and reason in relationships that include patterns is required. In Part B, some components of analysis and reasoning about relationships between non-verbal stimuli constitute the main demand. The child must choose between six options to complete an incomplete matrix correctly. Thus, the fluid intelligence is determined by scoring the number of correct responses. Each correct response earns one point, and the total score is calculated by summing the correct answers across all matrices. Higher scores indicate better abstract reasoning ability. The children were allocated to small groups in a room fully supervised by psychologists.

2.5. 24 -hour movement components

MVPA was measured using an ActiGraph accelerometer (wGT3X-BT model, ActiGraph, FL, USA). The accelerometer was placed, by the researchers, on the child's waist with an elastic belt in the middle axillary

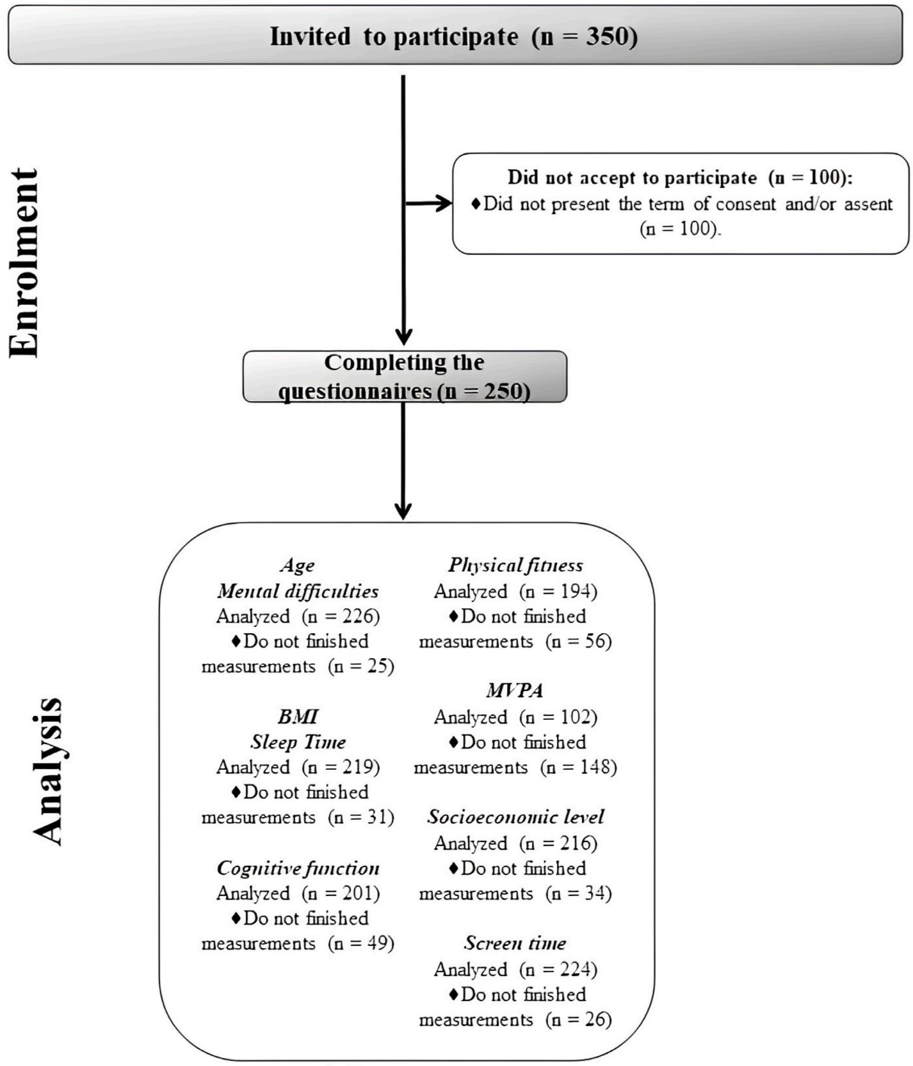

Fig. 1. Flow diagram of the study participant.

line on the right side. Participants used it for seven consecutive days and were encouraged to keep it for the 24-h day, removing it only when performing water activities. Sleep data was removed from the data analysis, considering the non-wear period of 20 min motionless. The minimum amount of accelerometer data considered acceptable for analysis purposes was five days (including at least one weekend day), with at least 10 h/day of usage time. After the last day of data collection, the research team returned to the school to remove the accelerometers and verify that the data was complete using the Actilife software (ActiGraph®, version 5.6, EUA), which was also used for data analyses. The data were collected at a sampling rate of 80 Hz, downloaded in periods of 1 s, and aggregated for periods of 15 s. We used the counts count for accelerometer cutoff points for periods of 15 s (<574 counts/15 s for moderate to vigorous physical activity) proposed by Evenson (2008).[26]

To assess screen time and sleep time, children's parents were invited to participate in a meeting to present the study's objectives. On the same occasion, they were able to answer some questionnaires, and for those unable to attend, individualized meetings were arranged over the telephone at available times. Thus, they answered the following questions: "On average, how long does your child watch TV, play video games, stay on the computer or cell phone?" The response options were "up to 30 min", "1 h", "2 h", "3 h," and "more than 3 h". For analysis purposes, they were recategorized into ≤2 h or >2 h according to guidelines for this population.[11] The questions regarding sleep time were: "On average, what time does your child lie down?" and "On average, what time does your child get up?" Afterward, the child's sleep hours were calculated.

2.6. Anthropometry and physical fitness

Anthropometric and physical fitness measures were evaluated according to the procedures suggested by Proesp-Br (https://lume.ufrgs.br/handle/10183/217804).[27] To calculate body mass index (BMI), height was measured with the help of a tape fixed on the wall and extended from the bottom up. The child was placed barefoot, standing, and touching the entire body on the wall surface. With the help of a square positioned transversely to the wall, the height was recorded in meters with two decimal places. The weight assessment was performed on a digital scale with a precision of 0.1 kg, with a maximum weight of 150 kg, being recorded in two decimal places. The child was asked to wear light clothes and was barefoot. Then, the formula (weight [kg]/height[m]^2) was applied.

The square test was used to assess agility. A square with 4 m side was demarcated, with a cone positioned at each angle. At the signal, the students moved as fast as possible, diagonally, then to the left (or right), then to the other diagonal, and finished towards the initial cone, always touching the cones with their hands. The children had two opportunities, and the best time was noted.[27]

To check the speed, the 20-m run test was used. Three parallel lines were marked, one starting line, one 20 m from the first (timeline), and one 21 m from the start (a finish line). The third line was a reference for the child not to slow down before crossing the 20 m. At the signal, the children moved as quickly as possible, and the time was recorded in seconds with two decimal places.[27]

The children underwent the 6-min running and walking test to assess cardiorespiratory fitness. The students were divided into small groups suitable for the multisport court dimensions (usually 10). The importance of maintaining a constant running pace has been reinforced, avoiding walks, and running spikes and guiding them to run as long as possible. During the test, the passage of 3 and 5 min was reported. Through a signal, at the end of the test, the students interrupted the test remaining in the place where they were, so that the distance covered during the 6 min (in meters) could be noted (the number of laps multiplied by the size of the court, added to the meters the last lap).[27]

The Sit-up test was used to determine abdominal resistance. In this test, the child must perform the largest number of sit-ups in 1 min. Then, they were positioned supine, with the knees flexed at 45° and the arms crossed over the chest. At the signal, children initiated the trunk flexion movements until touching the elbows on the thighs and returning to the initial position. The evaluator remained to hold the child's ankles throughout the test.[27]

Lower limb strength was determined by the horizontal jump test. A measuring tape was attached to the floor, perpendicular to the starting line. The students were asked to remain to stand with their feet parallel, behind line.[27] They jumped as far as possible at the signal with both feet simultaneously. Each child had two attempts, and the longest distance was recorded in centimeters.

The medicine ball pitch was used to measure the strength of the lower limbs. A measuring tape was fixed to the floor perpendicular to the wall, the zero point of the measuring tape being fixed to the wall. Then, the child was asked to sit with the knees extended, legs together, and the back fully supported on the wall. After flexing their arms, they should play the ball as far as possible, keeping their backs against the wall. The distance was recorded in centimeters from the zero point to the place where the ball hit the ground for the first time in two attempts, the best of which was noted.[27]

Then, z-scores for each component of physical fitness were calculated and added to a total z-score. The direction of the variables agility and speed was inverted, multiplying them by −1.

2.7. Sociodemographic data

Socioeconomic status was assessed using a method based on the guidelines provided by the Brazilian Association of Research Companies.[28] This method takes into account two main factors: the educational level of the head of the household and the ownership of specific items such as bathrooms, washing machines, and cars, among others. Each response was assigned a score, and the total of these scores was used as a measure of the family's social class. As a result, participants were categorized into three distinct economic classes: low (D-E), medium (C), and high (A-B).

2.8. Statistical analysis

Mean, standard deviations, and frequency were used to characterize the sample. Independent T-test and chi-square were applied to examine sex differences (the network analyses were not split by sex because we aimed to examine how the sex variable would interact within the model), and an alpha of 0.05 was used. The Machine Learning technique, Network Analysis, was used to analyze associations and establish interactions between variables from a graphical representation. A network is a set of nodes (variables) connected by an edge (partial correlations in the present study) that can be positive (blue) or negative (red), the strength of the correlations ranges from −1 to 1. The stronger the relationship the greater the edge thickness and color intensity. In the present study, we carried out a weighted and undirected network analysis of variables of different natures (ordinal, continuous), network analysis allows adding variables of different types to the same model, in addition, the analysis is not configured as an inferential test, the relationships are evaluated based on their theoretical importance.

To increase reliability and limit the number of possibly spurious relationships in the network, we use statistical regularization techniques that consider the complexity of the model to minimize the small sample, non-normal distribution of the data, and missing data. It was used a 'least absolute shrinkage and selection operator' (LASSO)[29] applied to the estimation of partial correlation networks. LASSO performs well in estimating partial correlation networks,[30] and this results in some small weak edge estimates being reduced to exactly zero, resulting in a sparse network.[31] LASSO produces a more parsimonious graph (fewer connections between nodes) that reflects only the most important empirical relationships in the data.

The "Fruchterman-Reingold" algorithm was used so that the data were presented in the relative space in which variables with stronger relationships were together and with less strong variations applied repelled to each other. We use the "random fields of pairwise Markov" model to improve the accuracy of the network. The algorithm adds an "L1" penalty (regularized neighborhood regression). The regulation is estimated by a less complete selection and contraction operator (Lasso) that controls the sparse network. The Extended Bayesian Information Criterion (EBIC) for selecting the Lambda of the regularization parameter was observed. The EBIC uses a hyperparameter (y) that determines how much the EBIC selects sparse models.[21,30,32] We set the y value to 0.50 (range 0–0.50). The network analysis uses regularized minus absolute shrinking and selection operator (LASSO) algorithms to obtain the precision matrix. This matrix, when standardized, represents the associations between the variables.

To quantify the importance of each node in the network, betweenness, closeness, and strength centrality indices were calculated, being 1) Expected influence: able to point out the variables that are more sensitive to interventions, as they have more connections with the other network variables; 2) Closeness: refers to the degree to which a node is closely connected to other nodes in the network through the shortest paths. Thus, it is possible to perceive the variables that would spread the effect of an intervention more quickly; 3) Strength: denotes the sum of the weights (for example, correlation coefficients) of the edges connected to a node. The centrality of the force is important as it reflects the probability that the activation of a given node will be followed by the activation of other nodes. The moderations and mediators were identified through the observation of the network's graphics analyzed, meaning that the variables function as mediators or moderators of all interrelationships. This methodology offers a holistic view of the interactions between variables. Positive correlations were represented in blue and negative correlations in red. In weighted networks, the lines vary in color (direction of association) and thickness or intensity of the color (magnitude of association). The analyses were performed in JASP (0.13.1).

3. Results

3.1. Descriptive results

Table 1 presents the main characteristics of the study sample. Overall, non-significant differences were found; nonetheless, girls showed lower MVPA and physical fitness than boys ($p < 0.05$).

3.2. Network analysis results

Fig. 2 shows the multivariate relationships among all study variables from a network perspective. Mental difficulties presented negative and direct relationships with screen time and total hours slept. Besides,

Table 1
Main participants' characteristics.

Characteristics of sample	Total		Boys	Girls	
	n	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	p
Age (years)	226	8.42 (1.49)	8.42 (1.45)	8.44 (1.53)	0.920
BMI (kg/m^2)	219	17.94 (3.80)	17.93 (3.51)	17.96 (4.10)	0.953
Mental difficulties (points)	226	11.43 (6.18)	11.58 (6,61)	11.28 (5.69)	0.718
Sleep time (h)	219	9.48 (1.31)	9.46 (1.29)	9.49 (1.35)	0.846
Cognitive function (rough points)	201	24.77 (6.07)	25.58 (6.20)	23.91 (5.84)	0.051
MVPA (min/day)	102	62.77 (25.99)	69.59 (29.83)	57.17 (21.01)	0.016
Physical fitness (z-score)	194	0.15 (3.66)	1.23 (3.81)	−0.91 (3.18)	<0.001
Wear time (hours)	102	16.72 (1.17)	16.88 (1.33)	16.57 (0.98)	0.139
	N	**%**	**%**	**%**	**p**
Socioeconomic level					
Middle	69	31.9	32.5	31.4	0.885
Low	147	68.1	67.5	68.6	
Screen time					
≤2 h	107	47.8	47.0	48.6	0.894
>2 h	117	52.2	53.0	51.4	

BMI: body mass index; WC: waist circumference; CRF: cardiorespiratory fitness; MVPA: moderate-to vigorous-intensity physical activity; *n*: Sample Size; SD: Standard Deviation.

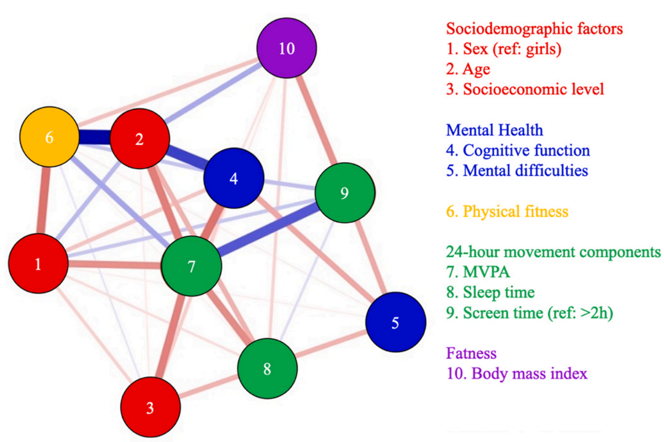

Fig. 2. Multivariate relationships among all study variables from a network perspective. Blue lines: positive associations; red lines: negative associations. The thickest lines indicate the higher magnitude of association MVPA: moderate-to vigorous-intensity physical activity.

mental difficulties and cognition showed a direct and inverse association. However, this association could be modified by MVPA, sleep time, and screen time variations. Also, it is possible to verify a weak relationship between fatness and mental difficulties being this relationship is mediated by screen time.

Fig. 2 also presents the importance of age in this network, considering that the relationship between MVPA and physical fitness with cognitive function was mediated for this sociodemographic variable. Nonetheless, physical fitness and age mediate the association between MVPA and cognitive function (weights matrix presented in supplement material).

Variables' centrality measures are presented in Table 2. Our results showed that age, physical fitness, and screen time are the nodes with higher values of expected influence, indicating a larger sensitivity to

Table 2
Centrality measures per variable.

Variables	Centrality measures		
	Expected Influence	Closeness	Strength
Sex	−0.678	−0.560	−0.612
Age	**1.851**	**1.238**	**1.297**
Socioeconomic level	−0.843	−0.497	−0.767
Cognitive function	0.302	0.575	0.474
Mental difficulties	−0.657	−1.191	−1.192
Physical fitness	**1.164**	0.087	**0.521**
MVPA	−1.166	**1.792**	**1.740**
Sleep time	−0.587	−0.826	−0.985
Screen time	**0.870**	0.422	−0.140
Body mass index	−0.256	−1.039	−0.612

MVPA: moderate-to-vigorous physical activity. Bold denotes higher values of each centrality measure.

interventions. Regarding closeness and strength, age, MVPA, and physical fitness presented the major values, pointing that its activations will be able to activate other nodes on the network automatically, indicated these variables would spread the effect of the intervention more quickly.

4. Discussion

4.1. Summary & contributions

The present study aimed to explore the multivariate relationship through network analysis focusing on the association of mental difficulties and cognition function with physical fitness, 24-h movement components, and sociodemographic factors in children. Several studies were previously developed to investigate the linear associations between these variables.[33–36] However, to our knowledge, this study contributes a unique insight addressing the multivariate relationship among all these variables through a network analysis in a population with specific characteristics (Brazilian children between six and 11 years old with low socioeconomic status). Overall, this study points to a direction in which an intervention considering modifiable habits in conjunct (in particular physical fitness, MVPA, and screen time) could potentiate gains in mental health and cognitive function within a network model.

Regarding to the pathways that can elucidate the relationship found between physical fitness and cognitive function, the literature presents numerous potential mechanisms, such as cerebral blood flow, the release of pivotal chemical compounds including BDNF, dopamine, and serotonin, stimulus to neuroplasticity and neurotransmission, improve of sleep and reduced stress and anxiety.[37]

To cognitive function, the main findings of our study indicate a negative relationship between cognitive function and MVPA, opposite to what is traditionally declared in the literature.[38,39] However, based on a network perspective, this relationship seems mediated by age and physical fitness, which is supported by literature that has indicated a tendency to decrease MVPA and physical fitness[40–42]; thus, the association between MVPA and cognitive function could play a key role as fitness declines as children age. This mediation by age suggests that as children grow, age-related factors may influence the association between MVPA and cognitive function. For example, changes in priorities, interests, or opportunities for engaging in physical activity may occur as children transition into adolescence or other developmental stages. These changes can affect the frequency or quality of MVPA, thereby impacting cognitive function in turn. In practice, our findings reinforce early development strategies to increase MVPA and physical fitness to promote cognitive health[43] of children with similar characteristics.

Concerning the indicator related to mental health, our data indicated a direct and inverse relationship between cognitive function and mental difficulties, in agreement with the literature[44] since children with better mental health will also have better cognition parameters. It is essential to highlight that this relationship seems mediated by the three 24-h movement components (i.e., screen time, sleep time, and MVPA). In brief, we identify an inverse and direct association between meeting screen recommendations and sleep time with lower mental difficulties risk. Besides, MVPA seems to affect mental difficulties indirectly, mediating children's cognitive function.

Therefore, first, these results agree with the literature pointing out that high screen time was associated with a greater prevalence of anxiety, depression, psychopathologic symptoms, and brain development problems in childhood.[7,45–47] Second, regarding sleep time and its link to mental health, a systematic review[18] mentioned that this association could be explained by the decrease in the release of neurotransmitters that are related to mental health, heightened stress reactivity, and the difficulty in maintaining a healthy active life due to daytime sleepiness and fatigue. And third, despite the direct relationship only with cognition and not mental difficulties, several studies have appointed the role of MVPA through sports and regular involvement of children in physical activity to prevent and treat mental disorders.[48,49] Finally, our mental health findings align with the systematic review by Sampasa-Kanyinga et al. (2020).[18] They declare that "meeting the screen time and sleep duration recommendations appeared to be associated with more mental health benefits than meeting the physical activity recommendation." Finally, the present study contributes to the literature by proposing an indirect effect of MVPA on mental health indicators mediated by cognitive improvement in children.

Centrality measures are crucial to identify variables having the most significant potential for future interventions[50] for each data group. In our network analysis, three variables reach higher values of the expected influence, age, physical fitness, and screen time. This finding indicates that these three variables are sensitive to possible intervention in a population like ours and, when modified, reconfigure the network closer to the ideal. It is essential to highlight that although age is not modifiable, it is highly recommended to consider it because it can play a moderator role in the network. For instance, the other two nodes, physical fitness and screen time, are modifiable behaviors that decrease and increase according to age.[42,51,52] Concerning closeness and strength centrality measures, MVPA (i.e., closeness and strength) and physical fitness (i.e., expected influence and strength) presented the most expressive values. Closeness measure refers to the degree to which a node is connected to others through the shortest paths, while strength indicates the sum of the weights of the edges connected to a node. With that in mind, from an intervention in this population, the effect would be spread more quickly to the other nodes through the MVPA, and the physical fitness being activated (that is, modified), other nodes would also suffer this activation of other nodes.

4.2. Strengths and limitations

The main strength of this study was the novel statistical approach for elucidating relationships among different elements through network analysis, a simple but powerful tool to describe complex systems and establish target interventions. However, a fundamental limitation is that caution must be taken when interpreting our findings due to the study's cross-sectional design. This is important to understand because both directions of causality are equally plausible, and reciprocal causation is also possible. In this sense, future interventions would help to elucidate these questions. In future research employing network analysis, it would be beneficial to explore additional factors, such as developmental stage, exploring sex and individual difference, educational background, and others, by expanding the sample size to investigate other populations. Our study was limited to one school, but by including more diverse samples, we can obtain a broader perspective. Finally, it is crucial to take into account lifestyle habits assessed through direct assessment, such as screen time and sleep, as they provide more accurate data.

4.3. Potential practical applications

Our findings provide valuable insights into the direction that interventions should take, especially within this specific population, to enhance the effectiveness of promoting and improving mental health and cognitive function in children. It is crucial to underscore the significance of modifiable behavior components that must be worked together for additional gain in this model.

4.4. Future work

Further research is warranted, particularly considering the limitations inherent in our current study. For instance, utilizing direct assessments to variables sleep and screen time. Additionally, studies involving populations of children with characteristics different from ours spanning different countries, cultures, and socioeconomic status. Finally, interventions could help in elucidating the possibilities of causality and in what direction the relationships happen.

5. Conclusions

Our findings provide valuable insights for developing interventions to enhance children's health and well-being. First, the network analysis showed that age and physical fitness seem to mediate the direct and negative relationship between cognitive function and MVPA. Thus, early interventions are necessary. Second, our data indicated a direct and inverse relationship between cognitive function and mental difficulties mediated by screen time, sleep time, and MVPA. This reinforces the relevance of keeping an adequate balance among these three behaviors. Finally, according to centrality findings, addressing these three factors simultaneously (i.e., physical fitness, MVPA, and screen time) could elicit a relevant modification on the whole network, positively influencing children's mental and cognitive health. Due to the nature of this cross-sectional study, future interventions are necessary to corroborate our results.

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Author statement

C.F.F: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing; C.C.M: Conceptualization, Investigation, Final review; P.F.R.B: Formal analysis, Methodology, Writing; C.B: Data curation, Formal analysis, Funding acquisition, Methodology, Writing. A.F.D: Investigation, Writing. D.R.B: Conceptualization, Methodology, Final review; J.M: Conceptualization, Methodology, Final review; A.C.A. G: Conceptualization, Methodology; A.R.G: Conceptualization, Data curation, Investigation, Methodology, Project administration, Resources, Final review.

Declaration of competing interest

The authors have no conflicts of interest relevant to this article.

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Appendix A. Supplementary data

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