Biological, behavioral, and social correlates of executive function in low-income preschoolers: Insights from the perspective of the networks

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Abstract

Behavioural, biological, and social correlates may be related to the association between executive function (EF) and physical activity (PA), when considering such variables as an integrated and non-linear system. Thus, the aim of the present study was to investigate the relationships between EF, PA and associated correlates in low-income preschoolers according to a network perspective. Thus, 142 preschoolers of both sexes, age 3-to-5-years-old (51% girls) were analysed. Light, moderate and vigorous PA, cardiorespiratory fitness (CRF), body mass index, family income, preterm birth, presence of siblings, presence of other children at home and the child's primary caregiver were assessed. Our results showed that EF was positively associated with age (b = 0.47), child´s primary caregivers (b = 0.37), moderate PA (b = 0.30) and CRF (b = 0.25). Negative associations were seen with preterm birth (b = -0.50), vigorous PA (b = -0.34), presence of other children at home (b = -0.25), and sex (b = -0.33). The network's centrality indicators highlighted preterm birth and moderate PA as the most important variables in the network. Future interventions aiming to increase low-income preschoolers' EF should focus on increasing moderate PA, with special attention to preterm children.

Keywords: Executive function; preschoolers; physical activity; preterm birth; cardiorespiratory fitness;

Introduction

Executive function (EF) refers to cognitive processes that are responsible for planning and solving complex tasks (Bell & Cuevas, 2016), through three central skills: working memory, inhibitory control, and cognitive flexibility (Adele Diamond, 2015). During childhood, EF better predicts reading and math skills rather than IQ (Intelligence Quotient) (Alloway & Alloway, 2010), and is associated with academic and personal success in adulthood (Moffitt et al., 2011). In the early childhood, an increase in information processing capacity is observed, which is functionally essential for neural plasticity (Kurth et al., 2016). Moreover, the prefrontal cortex, the EF's brain basis, is in upward maturation and neural plasticity, what may potentiate EF skills due to environmental and behavioural factors (Adele Diamond, 2015).

Different studies have associated behavioural factors, such as physical activity (PA), with brain functioning, including EF (Donnelly et al., 2016), brain development (Batouli & Saba, 2017), better cognition and higher volume of specific brain structures (C. Hillman, Khan, & Kao, 2015). Underlying mechanisms involved in its beneficial effects on cognitive health are linked to angiogenesis, synaptogenesis, and neurogenesis, and the regulation of brain derived neurotrophic factor (Vaynman & Gomez-Pinilla, 2006). Further, regular PA improves cardiorespiratory fitness (CRF), which is related to a higher information processing speed, EF, whole-brain volumetric and cognition (Esteban-Cornejo et al., 2017; C. H. Hillman, Erickson Ki Fau - Kramer, & Kramer, 2008; Nieto-López et al., 2020). These advantageous influence have been observed even in obese children (Ruiz-Hermosa et al., 2019), whose negative effects of obesity on brain development have been previously reported (Anderson et al., 2019; Ruotsalainen et al., 2020; Scheurer et al., 2018). However, it is noteworthy that the existing systematic reviews were based on studies conducted with adult participants (Batouli & Saba, 2017; Vaynman & Gomez-Pinilla, 2006), or middle-childhood children (Donnelly et al., 2016;

Hillman, Khan, & Kao, 2015; Hillman, Erickson, Kramer, & Kramer, 2008). The existing studies covering cross-sectional designs were conducted with adolescents (Ruotsalainen et al., 2020), or middle-childhood children (Ruiz-Hermosa et al., 2019), and only the cross-sectional study conducted by Nieto-López et al., (2019) investigated preschoolers.

Despite the existing studies, data documenting the interaction between PA, CRF, body mass index (BMI), and EF in children remain inconclusive (Tandon et al., 2018; Wen et al., 2018). According to Pate et al. (2019), results on the relationship between PA and EF do not provide enough evidence to determine the modifying effects of socio-demographic correlates on child´s EF. Previous studies have also shown an isolated association between parental relationships (Walker & Macphee, 2011), social vulnerability (Sektnan, McClelland, Acock, & Morrison, 2010), socioeconomic status (Lawson, Hook, & Farah, 2017), preterm birth (Linsell et al., 2017), and poverty (Raver, Blair, & Willoughby, 2013) with EF. For instance, parent´s exacerbated coercion, belonging to an ethnic minority, low family income, and lower mother´s educational level may negatively influence children´s EF. Further, a systematic review by Zysset et al. (2018) reported primary caregivers, and child´s relationship with parents and siblings as important social correlates of EF in preschoolers.

Additionally, the existing studies have analyzed individual linear relationships between EF and its biological, behavioural and social correlates. This linear perspective neglects the complex nature of non-linear and dynamic interrelationships that the several correlates may interplay on children´s EF. The presence or absence of a single variable within a model of analysis may completely change the nature of a system (Borsboom & Cramer, 2013). Thus, when examining interrelationships between EF and PA in children it is important to simultaneously consider known correlates of both.

A network approach seems to be an useful tool for proposing appropriate solutions within a complex system (Schmittmann et al., 2013), such as the one seen between EF and its correlates. By providing theoretical and statistical knowledge on the non-linear interrelationships between all elements that are complexly interrelated by their very nature, this approach allows identifying crucial correlates to intervening. The Network Analysis estimates partial correlation coefficients by examining the variables (nodes) and their relationships (edges), while controlling for all the other variables presented in the network (Polishchuk, 2021). Therefore, by applying a Network Analysis, this study aimed to analyze the relationships among PA, CRF, BMI, psychosocial correlates, and EF in low-income preschoolers.

Methods

Study Description

This cross-sectional study used baseline data from the project "Movement's cool," aiming to analyze the association between PA and health outcomes in preschoolers. All the ethical aspects were followed. The evaluation methods and procedures were approved by the Research Ethics Committee of Health Science Center (protocol n. 2,727,698), and by the Education Board of the João Pessoa, Brazil city.

Participants and Context

Preschool children aged three-to-five-years-old, of both sexes, and registered in Early Education Childhood Centres (EECC) of João Pessoa / Brazil were eligible. The preschool public education zone is organized in nine districts, where the fifty-five EECC three-to-five-years-old registered students, are located. Ten institutions, located in impoverished areas of six different districts agreed to participate in the study. For this study, three EECC, situated in three different districts, were randomly selected. The three preschools were located in deprived areas, and comprise children from low-income families with low socioeconomic status (SES): 50.5% of the mothers or fathers were unemployed, and over 71.8% of mothers have not finished the high school. The Human Development Index of the EECC areas ranges from 0.4 to 0.5 (Brasil, 2010).

All children of 3-to-5 years old enrolled in the EECC selected, with no medical diagnosis of physical or mental problems that could compromise the study´s protocol and outcomes, were invited (283 children), and 146 accepted to participate. Four children didn't complete the entire study's protocol, and 142 children comprised the study´s final sample.

Study design

Measurements were performed for four months (August to October 2019, and March 2020). All the schools and parents were informed about the project's protocols and procedures in meetings with the project coordinator and agreed to participate. All children authorized by their parents were evaluated. A prior meeting with the school's manager was conducted during the first day at schools. On the second day, the socio-demographic and social data were provided by parents. On the third day, EF data was collected, and an accelerometer was given to each child.

Variables and protocols

<u>Physical activity</u>

PA was assessed using accelerometer (Actgraph® wGT3x). The accelerometer was placed on the child's waist for a period of eight consecutive days. For data validation, at least three days of use were considered, with at least eight valid hours daily. Of the days of use, at least two were on weekdays and one on weekend (Reilly et al., 2004). Sixty minutes of consecutive zeros were considered non-use time and excluded of the analysis. This procedure has been used previously in a similar study (Andersen et al., 2017). Data reduction was performed using the Actlife software, version 6.11.7. Data were downloaded in 15-second epoch, and reintegrated to 60-seconds epochs for further processing (Microsoft Excel software).

To measure PA at different intensities, the cutoff points established by Butte and collaborators (2014), derived from the magnitude vector, which is the average resulting from the movement in the three axes of the accelerometer, were used. The calculation is the result of the square root of the arithmetic sum of the three squared axes (Sasaki; Silva; Gonçalves, 2018). According to the following cutoffs: light physical activity (LPA) from 820 to 3907 counts/min; moderate physical activity (MPA) between 3908 and 6111 counts/min; vigorous physical activity (VPA) above 6112 counts/min. For the time spent in each of the PA intensities in the week and at the weekend, the weighted average was performed. For analysis purposes, the time in minutes of PA was considered.

Cardiorespiratory Fitness

CRF was assessed using the adapted protocol (Cadenas-Sanchez et al., 2014) of the 20-meter Shuttle Run test (Leger, Mercier, Gadoury, & Lambert, 1988). This adapted protocol consists of running a distance of 20 meters at a previously determined speed (6.5 km / h), that increases 0.5 km / h every minute. The number of completed laps is multiplied by 20 to determine the total distance covered in meters, which was considered for analysis.

Body Mass Index

Height (cm) and weight (kg) were determined using a Holtain stadiometer and digitized weighing scales (Seca 708), respectively, while the participant was lightly dressed and barefoot, following a standardized procedure (de Onis, 2006). BMI was calculated by dividing body weight by the squared height in meters (kg/m^2), and the continuous value was used for analysis.

Child´sex, age and preterm birth

Sex, age and preterm birth information was collected through a face-to-face interview with the parents / primary caregivers. Sex was dichotomized as 1) boys *x* 2) girls. Parents / primary caregivers provided children's date of birth, which was transformed into months, and analyzed as a continuous variable. Then, parents / primary caregivers were asked about how many weeks of gestation the child was born. For analysis, information was dichotomized into: 1) term birth *x* 2) preterm birth (< 37 weeks of gestation).

Social correlates

Children's parents/guardians reported information regarding family income, presence of siblings (if yes, how many?), child's primary caregivers (mother, father, uncles, siblings, grandparents, neighbors or others), the presence of other children at home (if yes, how many?), and play time with parents (Do parents have some time to play with the child?). Response categories were dichotomized as follow: **a) family income** – 1) up to $190,00 per month *x* 2) more than $190,00 per month; **b) presence of siblings** – 1) no *x* 2) yes; **c) child's primary caregivers** – 1) mother *x* 2) others (father, grandparents; brothers; uncles, neighbors or others); **d) presence of children at home** – 1) only one *x* 2) two or more; **e) play time with parents –** 1) no *x* 2) yes.

Executive function

EF was assessed using Early Years Toolbox – EYT (Howard & Melhuish, 2016), which is a battery of computerized tasks that was developed to specifically assess the EF of children aged three-to-five-years-old. The battery consists of five tasks assessed from games in an app designed for iPad. Preschoolers have less differentiated EF skills, where inhibitory control, working memory and cognitive flexibility do not fully dissociate (Adele Diamond, 2012). Indeed, cognitive flexibility shares common processes that are challenging to differentiate (Willoughby et al., 2012). Moreover, it is relevant to consider that in early childhood, these components are strongly related to inhibition, both at the representational level, and to the maintenance of objectives (Karr et al., 2018; Miyake et al., 2000; Willoughby et al., 2012). For this study, we have considered the score computed in Go / No Go task as a global EF indicator (Karr et al., 2018; Willoughby et al., 2012). A previous study has shown that the Go / No Go task may activate the entire prefrontal cortex, and is a more robust task than others to establish EF performance (Smith et al., 2017; Willoughby et al., 2012). Moreover, based on Wiebe, Sheffield, & Espy (2008), inhibitory control, assessed using the Go / No Go task, was considered a global indicator of preschool children's EF. In this regard, the Go/No-Go scores have been employed as a surrogate measure of global EF in preschoolers (Bezerra et al., 2020; Wiebe, Sheffield, & Espy, 2012).

Inhibitory control was indexed by an impulse control score that represents the product of the Go and No-Go accuracy, representing the strength of the prepotent response to tapping whenever a no-go trial is presented, concerning their ability to overcome this response. For analysis, one point was assigned for each correct answer, with the score ranging from 0 to 75 points. This protocol presents satisfactory reliability values with Cronbrach's $\alpha = 0.95$ (Howard & Melhuish, 2016). In the present study, the composite reliability values for Go/No-Go was 0.78 considered an adequate value (Valentini & Damásio, 2016).

Data analysis

A network analysis was conducted to assess the pattern of relationship among PA, CRF, BMI, social correlates, and EF. The "Fruchterman-Reingold" algorithm was applied. Therefore, the data were shown in a relative space in which variables with strong permanent statistics are together, and with weak applied variations repelled one another (Fruchterman & Reingold, 1991).

In the present study, there is a set of variables of different natures (dichotomous and continuous) in this sense we use the model "random fields of pairwise Markov" to improve the accuracy of the network and mitigate the possible loss of information. The algorithm adds an "L1" (regularized neighbourhood regression) penalty. Regularization is achieved by a less full contraction and selection operator (Lasso) (Friedman, Hastie, & Tibshirani, 2008), who works by controlling the sparse network. We use the Extended Bayesian information criterion (EBIC) to select the Lambda of the regularization parameter. EBIC uses a hyperparameter (*y*) that determines how much EBIC selects sparse models (Chen & Chen, 2008; Foygel & Drton, 2010). We determine the *y* value at 0.25 (range from 0 to 0.50), which is a more parsimonious value when we have exploratory networks, as in the present study. These procedures guarantee that the Lasso operator selects the best network model, considering the sample size (Krämer, Schäfer J Fau - Boulesteix, & Boulesteix, 2009).

We used three centrality indicators to understand the role of each variable in the pattern that emerged from the network. (1) betweenness centrality, estimated from the number of times that a node is part of the shortest path among all the others pairs of nodes connected to the network; (2) closeness centrality, which is determined from the inverse of the distances from one node to all others; (3) strength (degree/centrality), which is the sum of all the weights of the paths that connect a node to the others (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). The *qgraph* package of R was used (Epskamp et al., 2012).

Results

A total of 142 children met all inclusion criteria (50.7% female, 4.0 ± 0.8 years old, 61.9% preterm). The children spent approximately 28.6% in LPA, 5.5% in MPA, and 2.7% in VPA (Table 1).

*************Table 1*************

The network configuration is presented in Figure 1. The green color expresses positive relationships between the variables, and negative relationships are presented by the red color. The thickness of the graph indicates the weight of the ratio.

*************Figure 1*************

The network prediction matrix (Table 2) indicated a positive association of EF with age (b = 0.47), non-maternal child´s primary caregiver (b = 0.37), MPA (b = 0.30) and cardiorespiratory fitness (b=0.25), and negative associations were seen with preterm birth (b = -0.50), VPA (b=-0.34), presence of other children at home (b=-0.25), and female sex (b= -0.33). Preterm birth showed negative relationships with sex (b=-0.70), VPA (b=-0.57) presence of other children at home (b=-0.49) and income (b = -0,37), and positive association with child´s primary caregivers (b=0.81) and presence of siblings (b = 0.44).

*************Table 2*************

The network's centrality indicators highlighted preterm birth (btw = 2.221), VPA (btw = 0.898), and EF (btw = 1.228) with the highest betweenness values. The greater closeness and strength were seen for preterm birth (cls. = 1.459; str = 1,462) and child´s primary caregivers (cls. = 1.276; str = 1,162), while presence of siblings (str= 0.807) and VPA (str = 0.766) also showed significant strength values (Table 3).

*************Table 3*************

Discussion

As far as the authors are aware, this is the first study to consider the relationships between PA, cardiorespiratory fitness, BMI, social correlates, and EF as a network system, in low-income preschoolers. As a consequence, the results of the current study advance understanding of this topic by providing an overview of the aforementioned variables as a non-linear and dynamic network. Our results demonstrate a positive association between age, MPA, CRF, and primary caregivers (not being the mother) with EF. Conversely, preterm birth, female sex, VPA and having other children at home were negatively associated with preschoolers´ EF.

Hierarchically, the prefrontal cortex has a late-maturing process, compared to other brain regions (Adele Diamond, 2002). During this maturation period, increases in information capacity, such as integration with a task, and managing information, as well as processing speed occur, which are functionally essential for neuronal plasticity (Khan & Hillman, 2014), and may partially justify the fact that older children have higher EF than younger ones.

Moreover, lifestyle behaviours, such as PA and exercise, leads to a higher cerebral vascularization (da Silva et al., 2017) and may be a triggering factor for brain changes, due to its role in neurogenesis (C. Hillman et al., 2015), mediated by the Brain-Derived Neurotrophic Factor (Khan & Hillman, 2014). Batouli and Saba (Batouli & Saba, 2017) stated that 82% of the brain's grey matter is associated with PA effects, especially when increasing CRF levels. Although a recent review study has reported a lack of evidence regarding these mechanisms in young children (Stillman, Esteban-Cornejo, Brown, Bender, & Erickson, 2020), the current results highlighted that PA is intrinsically present in different pathways that link it with the assessed variables. Further exploration is needed to determine the direction of these paths.

When considering the relationship between PA intensities and cognitive processes, the inverted U theory supports that cognition improvements occur during MPA and that such effects tend to decrease with increasing intensity (McMorris, 2016). McMorris (McMorris, 2016) states that in acute PA of light intensity, the stimulus is low, and the energy expended to concentrate on cognitive tasks is also low. During moderate-intensity activities, cognitive performance is optimized. However, during acute vigorous intensities, the cognitive performance returns to its initial levels, due to the affected ability to concentrate during the performed cognitive task (McMorris, 2016). Although this rational is based on results from adults' samples, it is possible to speculate that in preschoolers, the same hypothesis should be considered. Simirlaly, Chang and Etnier (Chang & Etnier, 2009) observed that EF tasks are impaired by acute VPA and benefited by acute MPA, though there remains a lack of existing evidence on the chronic effects of different PA intensities on EF (Pontifex et al., 2018). Besides that, our results are somehow in line with Kamijo et al. (2004), who have reported a positive effect of moderate exercise in P300 amplitude (a measure of attentional resource demands for a specific task), when compared to low and high exercise intensity conditions. It is important to note that in the current study, we evaluated the association between cumulative PA during the whole day and EF, and not its effect derived from one exercise session.

In the present study, being a boy was associated with a higher EF. Conversely, Klenberg et al. (Klenberg, Korkman, & Lahti-Nuuttila, 2001) showed that girls have higher EF than boys, though they did not consider the role of PA in this association. Considering that in this study, boys spent more time in moderate to vigorous PA than girls, we can hypothesize that PA partially explain the higher observed EF of boys compared to girls. Also, the higher CRF usually seen in boys when compared to girls (Fedewa & Ahn, 2011), and their higher proficiency in fundamental motor skills (Bezerra et al., 2021), may reinforce the current results. Indeed, socially boys tend to be more encouraged to PA engagement (Barnett et al., 2016) than girls, especially in sports practice, what may contribute to higher fundamental motor skills proficiency and consequently, EF (A. Diamond & Ling, 2016; Koziol & Lutz, 2013).

The network analysis showed that the child's primary caregivers and the presence of other children at home were also related to EF. Indeed, the parental relationship is significant for EF's development during childhood (Hughes & Devine, 2019). Nonetheless, Zysset et al. stated the importance of time-quality, even more than time-quantity in this relationship (Zysset et al., 2018). Previous studies show that caregiver sensitivity can influence the volume of the preschoolers' hippocampus, which is directly related to cognitive performance (Rao et al., 2010; Wang et al., 2019). So, for those low-income children whose mothers work outside home, the time spent with the child may be compromised. The assessed children spend 10 hours per day at preschools settings, so it is essential to report a previous study which highlighted that the affective bond with teachers could provide positive effects on EF (Vandenbroucke, Spilt, Verschueren, & Baeyens, 2017).

The centrality indicators provide essential information on the role of the variables in the network, making possible to identify the variables most sensitive to changes, and influence the network on a greater extent (Polishchuk, 2021). Variables with higher betweenness values are more sensitive to changes and may act as a hub, connecting other pairs of variables. A variable with a high Closeness value will be quickly affected by changes in any part of the network and may also affect other parts. The Strength indicator is essential to understand which variables present the most robust connections in the network pattern (Watts & Strogatz, 1998). Besides the negative association between preterm birth and EF, the current results highlighted preterm birth as the variable with the greatest centrality values in the emerged observable pattern. Indeed, preterm children have lower total brain volume (de Kieviet, Zoetebier, Elburg, Vermeulen, & Oosterlaan, 2012), and present compromising changes in grey and white matter volumes (Counsell & Boardman, 2005). Although preterm is an unmodifiable variable in its nature, when properly stimulated, a natural catch-up is expectable for preterm children in relation to their EF when early interventions are provided (Nordhov et al., 2010).

The results also highlighted EF as the variable with the highest Betweenness value in the network. This index considers the number of times a node connects to other nodes in the network, demonstrating that EF is the variable that connects the most with the others in the network. Moreover, another variable that emerged with high centrality values in the network was the Primary Caregiver. Previous studies show that caregiver sensitivity can influence the volume of the preschoolers' hippocampus, which is directly related to cognitive performance (Rao et al., 2010; Wang et al., 2019). Indeed, parental relationship models EF development during childhood (Hughes & Devine, 2019), though stated the importance of time-quality, even more than time-quantity in this relationship. As the assessed children spend 10 hours per day at preschools settings, it is also important to consider that the affective bond with teachers during the long preschool-journey could provide positive effects on children´s EF (Vandenbroucke et al., 2017).

Further, the current results showed that BMI did not emerge as a central variable in the network. Even considering its importance for the analyzed variables, the assessed children showed similar weight status characteristics, with little variability. So, in psychometric terms, it is possible that this variable loses the power to differentiate children by different BMI values.

The overarching strength of the present study is the assessment of the relationship between PA, CRF, BMI, social correlates and EF in a low-income sample of preschool children, from a middle-income country. Also, having based this study on a network approach, which allows a look at the variables as a dynamic, reciprocal, and non-linear system. The network perspective used have been fundamental to investigate relationship patterns between variables in a developmental model (Borsboom & Cramer, 2013). However, the present study has some limitations that must be reported. The lack of data on parental and teachers' relationships can limit the knowledge on the contribution of these relationships to the emerged pattern. Moreover, the lack of information on types of PA and sports that children usually performed may be considered an area to adapt or refine for future research. At preschools setting, variability in children´s characteristics and behaviours are seen, and the lack of generalization of these results for boys and girls separately, and for children with special needs that are closely linked to EF development, such as hyperactivity / impulsivity, should be covered in future research. Additional information on other correlates that may also affect children´s EF during early childhood, such as parental marital status (divorced or married), preschool and home-literacy environment, for example, should be further explored. Finally, as the emergent patterns are non-deterministic, the low external validity and lack of generalizability should be highlighted, although this fact reinforces the need for more studies to identify the critical correlates of EF across different subgroups and contexts.

Thus, considering the assessed social, biological, and behavioral correlates linked to EF in low-income preschoolers, the network approach used has allowed a multidimensional look at this phenomenon. The results of the current study suggest that when analyzed simultaneously, modifiable correlates, such as MPA, and non-modifiable correlates, such as preterm birth were identified as the most important variables on the emerged pattern highlighted. Future studies should focus on longitudinal designs to identify the interrelationships of EF and its correlates through a developmental trajectory. Further, interventions aiming to increase low-income preschoolers EF should focus on increasing MPA, with special attention to preterm children.

Declarations

Funding: N/A

Conflicts of interest/Competing interests: N/A

Availability of data and material: N/A

Code availability: N/A

Ethics approval: All procedures were approved by the university committee and the board of education. The Helsinki Declarations' ethical aspects were followed. The Research Ethics

Committee of the Health Science Center of the Federal University of Paraiba and the local board of education approved the study (protocol n. 4.102.806).

Consent to participate: All the preschools' staff and parents were informed about the research's goals, protocols, and procedures in meetings with the project coordinator (one session in each school) and agreed to participate in the present study through an informed consent form.

Consent for publication: All preschool staff and parents were informed about the research objectives, protocols, and procedures in meetings with the project coordinator (one session at each school) and agreed to publish the data, maintaining the confidentiality of the participants, through an informed consent form.

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Tables and Figures

Table 1. Sample's characteristics stratified by sex.

Variable	Boys (n = 70) Mean ± SD	Girls (n = 72) Mean ± SD	p	Cohen's d
LPA (%)	28.8 ± 11.43	28.6 ± 9.4	0.877	0.03
MPA (%)	5.8 ± 2.1	5.4 ± 1.8	0.329	0.21
VPA (%)	3.2 ± 1.4	2.4 ± 1.1	0.004*	0.65
MVPA (%)	8.9 ± 2.6	7.7 ± 2.3	0.024*	0.50
Cardiorespiratory fitness (meters)	370.8 ± 181.7	327.0 ± 150.8	0.120	0.26
BMI (kg/m²)	15.3 ± 1.4	15.5 ± 1.8	0.477	-0.12
EF (scores)	60.7 ± 9.5	60.6 ± 9.3	0.941	0.01

LPA = Light physical activity; MPA = Moderate physical activity; VPA = Vigorous physical activity; MVPA = Moderate to vigorous physical activity; BMI = Body mass index; EF = Executive Function.
* Student Test T.

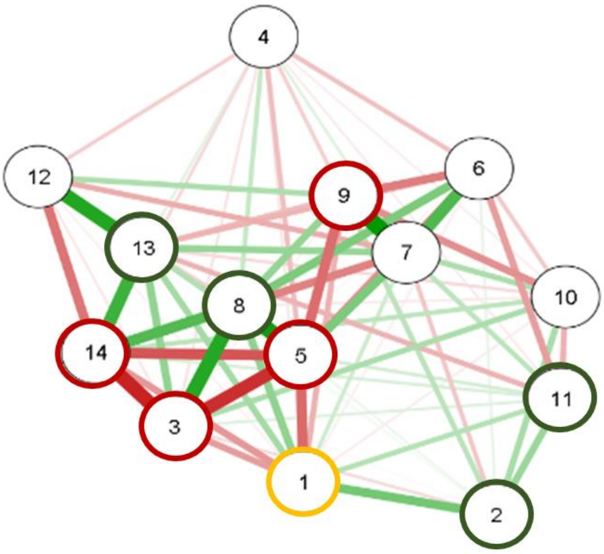
Table 2. Weight matrix of variables physical activity, cardiorespiratory fitness, BMI, age, sex, social correlates and executive function. João Pessoa-PB. Year 2019/2020

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1														
2	0,47													
3	-0,33	-0,12												
4	-0,07	0,06	-0,09											
5	-0,50	-0,04	-0,70	-0,21										
6	-0,05	0,08	-0,03	-0,20	-0,37									
7	0,16	-0,19	0,01	0,10	0,44	0,59								
8	0,37	0,06	0,73	0,19	0,81	0,44	-0,42							
9	-0,25	0,23	-0,04	-0,15	-0,49	-0,43	0,86	0,36						
10	-0,06	0,29	0,28	-0,06	0,00	-0,17	0,27	-0,07	-0,37					
11	0,25	0,33	0,11	-0,06	0,14	-0,32	0,22	-0,01	-0,10	-0,26				
12	-0,05	0,02	-0,07	-0,16	0,03	0,00	-0,27	-0,07	0,27	0,00	-0,02			
13	0,30	0,04	0,36	0,09	0,26	-0,25	0,34	-0,15	-0,22	-0,12	-0,25	0,74		
14	-0,34	-0,02	-0,74	-0,12	-0,57	0,00	-0,05	0,58	0,00	0,22	0,12	-0,46	0,65	

1: Executive function; **2**: Age; **3**: Sex; **4**: BMI; **5**: Preterm birth; **6:** Income; **7:** Siblings; **8:** child's primary caregivers; **9**: Children at home; **10**: Play with parents; **11**: Cardiorespiratory fitness; **12**: Leve physical activity; **13**:Moderate physical activity; **14**:Vigorous physical activity.

Table 3: Centrality measures of the network analysis between physical activity, cardiorespiratory fitness, BMI, age, sex, social correlates and executive function. João Pessoa-PB. Year 2019/2020.

	Centrality Measures		
Variables	**Betweenness**	**Closeness**	**Strength**
Executive Function	1.228	0.212	0.066
Age	-0.756	-0.973	-1.259
Sex	-0.756	0.590	0.483
BMI	-1.087	-2.074	-1.606
Preterm birth	2.221	1.459	1.462
Income	0.898	0.063	-0.209
Siblings	-0.425	0.590	0.807
Child´s primary caregivers	-0.094	1.276	1.162
Children at home	0.236	0.583	0.648
Cardiorrespiratory fitness	-0.756	-1.014	-0.976
Physical activity			
Light physical activity	-0.756	-0.480	-1.004
Moderate physical activity	0.236	0.179	0.664
Vigorous physical activity	0.898	0.671	0.766



Legend: 1: Executive function; **2**: Age; **3**: Sex; **4**: BMI; **5**: Preterm birth; **6:** Income; **7:** Siblings; **8:** child's primary caregivers; **9**: Children at home; **10**: Play with parents; **11**: Cardiorespiratory fitness; **12**: Light physical activity; **13**:Moderate physical activity; **14**:Vigorous physical activity. The green nodes are the variables with positive association with executive function and red the negative association.

Figure 1. Network perspective physical activity, cardiorespiratory fitness, BMI and social correlates of executive function in low-income preschoolers