Improving Effect of Cooperative Learning-Based Physical Education on Children's Negative Psychology

Luobin Zhang[1*], Fei Yang[1], Qianqian Yang[1]

Abstract
Modern education has the critical responsibility of holistically fostering children's psychological and moral development. Psychological health has direct effects on the growth and development of children and indirect effects on the quality of talent training in society. Physical activity improves the negative psychology of youngsters (CNP). Both domestic and international scholars have focused on investigating and implementing cooperative learning-based innovative and successful physical education. This research presents the structural equation model (SEM) to investigate the enhancing influence of cooperative learning-based physical education (CL-PE) on CNP and analyzes children's psychology using pertinent data mining technologies and a model. First, a structural equation model (SEM) was developed to examine how CL-PE influences CNP, and the interacting, moderating, and mediating effects were investigated in depth. The proposed SEM was then transformed into a self-organized path-constrained neural network (SOPCNN), the latent variables were computed, and the observable indices were summarized. Three schools' preschool-aged students were polled to compile the set of test samples. The results of an experiment indicate that adding cooperative learning to physical education might successfully attenuate children's negative psychology.
Keywords: cooperative learning; physical education; children's negative psychology (CNP)

Introduction

Children are a country's future. The level of psychological health has direct effects on the growth and development of children and indirect effects on the quality of talent training in society (Hasan, Lukitasari, & Ernawati, 2021; Huang et al., 2021; Othman & Shilov, 2021; Pinna et al., 2018; Sekine & Ikada, 2021). Psychological health education is currently the primary focus of physical education (Chen et al., 2021; Eoh & Park, 2021). The experts in children's education are faced with a significant challenge: examining the functional attributes and characteristics of the physical education model for children that promote their negative psychological symptoms, as well as developing and implementing physical education based on cooperative learning.

To determine the cause of the psychological issues of rural left-behind children, Su et al. (2020) conducted sports intervention experiments on these issues and found that sports intervention with a fixed duration and frequency improves the negative psychological symptoms of rural left-behind children. Common intervention instruments for child psychology include questionnaire surveys, interviews, experiments, and mathematical statistics (Kazakova, Sokolova, & Farkova, 2019; Straten et al., 2020; Sun, Liu, & Yu, 2019; Zainuddin & Ihsan, 2013). Brassell et al. (2016) Investigating enrollment characteristics, age, and caring environment impact children's psychological health using an online survey and logistic regression. Hankala et al. (2017) discovered that the parent-child relationship and parenting style significantly impacted children's psychological well-being. Bronfenbrenner's ecological systems theory examined the effects of children's social status and peer relationships on their physiological health based on their parents' professions and interactions with them. Physical education has extensively adopted cooperative learning (Artishcheva, 2019; Carpenter et al., 2014; Hser et al., 2014; Minatoya et al., 2016; Peyton, Hiscock, & Sciberras, 2019). Walczak et al. (2018) streamlined the teaching model of children's tennis and produced classroom teaching tactics and cooperative learning forms that align with children's personality, physical, and psychological development characteristics.

After examining the research published in 2021 and 2022, the authors determined that the existing research has established scientific and reasonable evaluation index systems for children's psychological crisis, constructed appropriate models for evaluating the crisis, and realized appropriate evaluation and intervention of the crisis. Cooperative learning can significantly improve children's insight and cognitive ability, enable them to perform more efficiently and with self-assurance, and boost their social skills and implicit thinking (Beeber, Perreira, & Schwartz, 2008; Fergeus et al., 2017; Larriba et al., 2016; Larriba et al.,

[1] College of Education, Hebei Normal University of Science & Technology, Qinhuangdao 066004, China
E-Mail: 305220178@qq.com

2015; Turner et al., 2021). The majority of the relevant research focuses on the psychological health of youngsters. Most researchers focused on the qualitative association between physical education and mental health and the implementation path of cooperative learning in the classroom (Palit & Chatterjee, 2006; Zhang, 2020). This article, therefore, uses the structural equation model (SEM) to investigate the ameliorating effect of cooperative learning-based physical education (CL-PE) on children's negative psychology (CNP).

This study examines in depth the warning of psychological crisis precursor symptoms and the intervention of the crisis. The discussion has significant theoretical significance. The second section develops a structural equation model (SEM) to examine how CL-PE influences CNP and analyzes the interacting, moderating, and mediating effects. Section 3, the suggested SEM is transformed into a self-organized path-constrained neural network (SOPCNN), the latent variables are computed, and the observable indices are summarized. Using meticulously constructed experiments, the authors conducted t-tests on children's learning attitudes before and after the studies, as well as on the negative psychological aspects of children in the test class and control class. The results demonstrate that incorporating cooperative learning into physical education can effectively attenuate the unfavorable attitudes of the test class's students.

SEM Construction and Effect Analysis

Model construction

The SEM is not limited by the number of endogenous variables, variable measurement error, or residual terms. It solves a common shortcoming of conventional factor analysis techniques, namely their inability to assess hidden variables. The benefit of the SEM is the ability to estimate factor structure and relationships concurrently. In addition, the SEM can be transformed into a SOPCNN capable of simultaneously examining the interacting, moderating, and mediating effects of the research problem. This paper corrects the typical SEM's effect analysis flow. Figure 1 illustrates the adjusted flow.

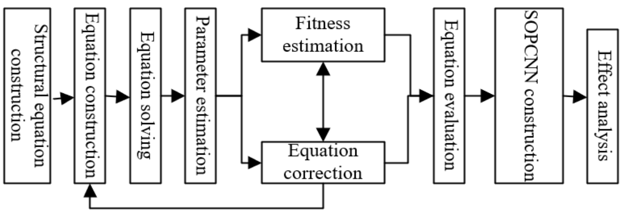


Figure 1. Effect analysis flow of the SEM

This study presents the principles, affecting factors, assessment indices, evaluation techniques, intervention measures, and intervention index systems for CNP by referencing previous research on the psychological crisis. The SEM utilized to assess the impact of CL-PE on CNP consists primarily of two models: a measurement model and a structural model. The equations of the measuring model illustrate the relationship between the problem's latent variables and observable variables. The structural model's equations describe the link between several latent variables.

Based on common CNP response scales, the exogenic observable variables of CNP are organized into vector a, and the endogenic observable variables of CNP are organized into vector b. The relationship between a and exogenic latent variables is expressed as a factor loadings matrix Ω_a, and between b and endogenic latent variables is expressed as a factor loadings matrix Ω_b. The exogenic and endogenic latent variables are organized into vectors Φ and γ. The error terms of a and b are denoted as Ψ and σ, respectively. Then, the equations of the measuring model can be constructed as:

$$a = \Omega_a \Phi + \Psi \tag{1}$$

$$b = \Omega_b \gamma + \sigma \tag{2}$$

Let ξ be the relationship between endogenic latent variables; δ be the influence of exogenic latent variables on endogenic latent variables; η be the structural equation residual for the part of γ not explained in the structural equation. Then, the equations of the structural model can be constructed as:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3}$$

$$\gamma = \xi\gamma + \delta\Phi + \eta \tag{4}$$

Let φ be the covariance matrix between exogenic latent variables. Then, the mean $AV(\Phi\Phi')$ of $\Phi\Phi'$ equals φ. Let Γ_Ψ be the covariance matrix of error vector δ. Then, we have $AV(\Psi\Psi')=\Gamma_\Psi$. Let Γ_σ be the covariance matrix of σ. Then, we have $AV(\sigma\sigma')=\Gamma_\sigma$. Let Θ be the covariance matrix of residual η. Then, we have $AV(\eta\eta')=\Theta$. Finding the covariance of both sides of equation (1):

$$\begin{aligned} COV &= AV\big((\Omega_a\Phi+\Psi)(\Omega_a\Phi+\Psi)'\big) \\ &= AV\big((\Omega_a\Phi+\Psi)(\Phi'\Omega'_a+\Psi')\big) \\ &= \Omega_a AV(\Phi\Phi')\Omega'_a + AV(\Psi\Psi') \\ &= \Omega_a\phi\Omega'_a + \Gamma_\Psi \end{aligned} \tag{5}$$

The covariance matrix of a can be expressed as:

$$\textstyle\sum_{aa}(\omega) = \Omega_a\phi\Omega'_a + \Gamma_a \tag{6}$$

Similarly, the covariance matrix of b can be obtained as:

$$\textstyle\sum_{bb}(\omega) = \Omega_b E(\gamma\gamma')\Omega'_b + \Gamma_\sigma \tag{7}$$

Let ψ be a unit matrix. If matrix ψ-ξ is revertible, formula (3) can be converted into:

$$\gamma = (\psi-\xi)^{-1}(\delta\Phi+\eta) = \xi^*(\delta\Phi+\eta) \tag{8}$$

Based on the above formula, the following mean can be solved:

$$AV(\gamma\gamma') = AV\left[\left(\xi^*(\delta\Phi+\eta)\right)\left(\xi^*(\delta\Phi+\eta)\right)'\right]$$
$$= AV[\xi^*(\delta\Phi+\eta)(\Phi'\delta'+\eta')\xi^{*\prime}]$$
$$= \xi^*[\delta AV(\Phi\Phi')\delta' + AV(\eta\eta')]\xi^{*\prime}$$
$$= \xi^*(\delta\phi\delta'+\Theta)\xi^{*\prime} \quad (9)$$

Combining the above formula with formula (7):

$$\textstyle\sum_{bb}(\omega) = \Omega_b\xi^*(\delta\phi\delta'+\Theta)\xi^{*\prime}\wedge'_b + \Gamma_\sigma \quad (10)$$

In addition, the covariance matrix between a and b can be expressed as:

$$\sum_{ba}(\omega) = AV(ba')$$
$$= AV[(\Omega_b\gamma+\sigma)(\Omega_a\Phi+\Psi)']$$
$$= AV[(\Omega_b\gamma+\sigma)(\Phi'\Omega_a'+\Psi')]$$
$$= \Omega_b AV(\gamma\Phi')\Omega_a' + AV(\sigma\Psi')$$
$$= \Omega_b AV(\gamma\Phi')\Omega_a'$$
$$= \Omega_y\xi^*\delta AV(\Phi\Phi')\Omega_x'$$
$$= \Omega_y\xi^*\delta\phi\Omega_x' \quad (11)$$

Similarly, $\Sigma_{ab}(\omega)=AV(ab')=\Omega_a\varphi\delta\xi^{*\prime}\Omega_b'$. The covariance matrix of (b', a')' can be expressed as:

$$\Sigma(\theta) = \begin{pmatrix}\Sigma_{bb}(\omega) & \Sigma_{ba}(\omega)\\ \Sigma_{ab}(\omega) & \Sigma_{aa}(\omega)\end{pmatrix} =$$
$$\begin{pmatrix}\Omega_b\xi^*(\delta\phi\delta'+\Theta)\xi^{*\prime}\Omega_b'+\Gamma_\sigma & \Omega_b\xi^*\delta\phi\Omega_a'\\ \Omega_a\phi\delta'\xi^{*\prime}\Omega_b' & \Omega_a\phi\Omega_a'+\Gamma_\sigma\end{pmatrix} \quad (12)$$

The above formula shows that the SEM of the research problem covers eight parameter matrices: Ω_a, Ω_b, ξ, δ, φ, Θ, Γ_Ψ, and Γ_σ. To solve the SEM, it is necessary to estimate the eight matrices.

Cooperative learning, which has gained popularity in education, significantly impacts traditional spoon-feeding education. Cooperative learning requires the active participation of both teachers and students, raising higher requirements for both parties. Our SEM was established based on CL-PE theory and CNP intervention experience. Let R be the covariance matrix of the observatory variable in formula (6). During the model solving process, function fitting can be adapted to import the fixed parameter values, free parameter estimates, and R to the structural equation and update the covariance matrix Σ(ω) to minimize its variation. This paper chooses the maximum likelihood estimation, an estimation method that minimizes the value of the fitting function G_{NK}. Let $tr(R\Sigma^{-1}(\omega))$ be the trace of matrix $R\Sigma^{-1}(\omega)$; log|Σ(ω)| be the logarithm of the determinant of Σ(ω); log|R| be the logarithm of the determinant of R. Then, G_{NK} can be expressed as:

$$G_{NK} = log|\Sigma(\omega)| - log|R| + tr\left(R\textstyle\sum -1(\omega)\right) - (e+s) \quad (13)$$

Effect analysis

According to the CL-PE characteristics presented in Table 1, the link between collaboration, competition, and autonomy demonstrates the unsurpassed superiority of cooperative learning above conventional learning models. Cooperative learning enhances the positive mutual help amongst children, improves their academic performance, and encourages them to share pleasant feelings and behaviors.

Concerning the influence on CNP, certain CL-PE elements support CNP from the perspectives of cognition, emotion, and behavior. Some promote CNP from a psychological standpoint, some increase the self-efficacy of CNP, and some exert favorable effects across several dimensions. This indicates that the components may interact with one another. The interactive mechanism requires additional examination.

Suppose CNP exogenic variable γ has two observable indices b_1 and b_2; the two endogenic latent variables Φ_1 and Φ_2 correspond to observable indices a_1 and a_2, and a_3 and a_4, respectively. Let β_1 be the main effect, and β_2 and β_3 be the interactive effects. Then, the SEM for the interactive effects of Φ_1 and Φ_2 on γ can be established as:

$$\gamma = \xi\gamma + \beta_1\Phi_1 + \beta_2\Phi_2 + \beta_3\Phi_1\Phi_2 + \eta \quad (14)$$

To eliminate the multicollinearity between indices, each observable index of Φ_1 is multiplied by Φ_2. The resulting four products, a_1a_2, a_1a_4, a_3a_2, and a_4a_2, serve as the observable indices of Φ_1 and Φ_2. Figure 2 shows the structure of the SEM for CNP interactive effects.

Table 1

CL-PE features

	Collaboration	Competition	Independence
Cooperation goal	Pursuing unified goal	Focusing on win or lose	Realizing own goal
Teaching activities	Adapted to the complex, abstract work requiring collaboration	Highlighting the mastery of skills, abilities, and basic knowledge	Mastery of skills and knowledge
Teacher-student interaction	Supervision, participation, guidance, and coordination	Focusing on teachers' clarification of rules, settlement of disputes, and judgment of correct answers	Correcting and optimizing behaviors
Student interaction	Mutual encouragement, assistance, and sharing within the group	Fair competition between groups	Sense of group honor and active participation
Learning space	Learning and mutual learning within the group	Fair competition between groups	Independent learning space
Evaluation standard	Evaluating intra-group performance against multiple standards	Evaluating inter-group performance against multiple standards	Comprehensive evaluation

This paper surveys preschool-age children in three schools. Under the present hypothetical conditions, the obtained data were analyzed by data analysis and statistical software.

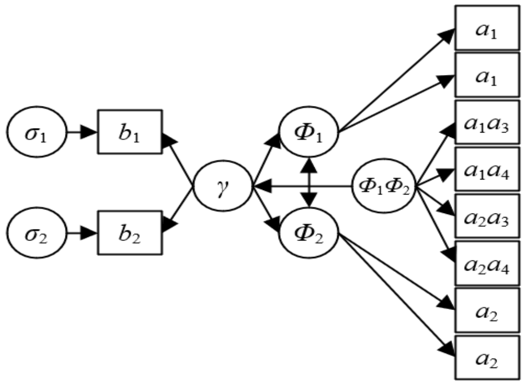


Figure 2. SEM for CNP interactive effects

The next is to analyze how the independent variable a of CNP affects the dependent variable b. It is assumed that a affects b via the mediator variable MV. Let r be the overall effect of an on b; g and h be the mediating effects generated by MV; r' be the direct effect. Then, the equations of the mediator variable can be established as:

$$B = rA + w_1 \tag{15}$$

$$MV = gA + w_2 \tag{16}$$

$$B = r'A + g \cdot MV + w_3 \tag{17}$$

If there exists only one mediator variable, formulas (16) and (17) can be combined into:

$$B = r'A + h(gA + w_2) + w_3 = (r' + gh)A + hw_2 + w_3 \tag{18}$$

Since the mediating effects satisfy r=r'+gh, the magnitude of mediating effects can be measured by r-r'=gh. In the SEM for our research problem, specific correlations and mutual effects exist between the latent variables when the CNP mediator variable and CNP moderator variable exert their effects. Unlike the mediator variable, the moderator variable is not affected by CNP's independent or dependent variable.

SOPCNN Construction

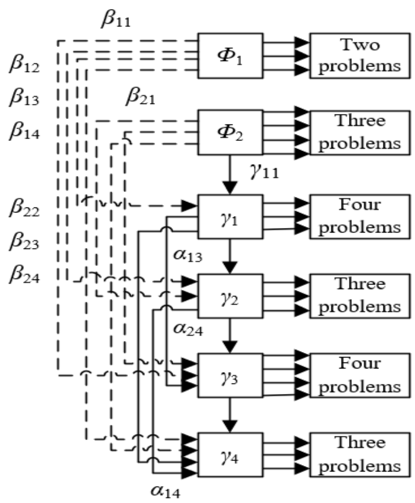


Figure 3. CNP model

As shown in Figure 3, the proposed CNP SEM involves six latent variables. The independent variables Φ_1 and Φ_2 are negative psychological symptoms and somatization, respectively. The dependent variables γ_1, γ_2, γ_3, and γ_4 refer to subjective physical education intervention, motivation of cooperative learning, peer cognition and selection, and team collaboration and guidance, respectively. Let β_m be the path coefficient from Φ_1 and Φ_2 to γ_1, γ_2, γ_3, and γ_4; α_{ij} be the path coefficients between γ_1~γ_4. The following SEM can describe the relationship between latent variables:

$$\begin{pmatrix}\gamma_1\\ \gamma_2\\ \gamma_3\\ \gamma_4\end{pmatrix} = \begin{pmatrix}0 & 0 & 0 & 0\\ \alpha_{21} & 0 & 0 & 0\\ \alpha_{31} & \alpha_{32} & 0 & 0\\ \alpha_{41} & \alpha_{42} & \alpha_{43} & 0\end{pmatrix}\begin{pmatrix}\gamma_1\\ \gamma_2\\ \gamma_3\\ \gamma_4\end{pmatrix} + \begin{pmatrix}\beta_{11} & \beta_{11}\\ \beta_{21} & \beta_{21}\\ \beta_{31} & \beta_{31}\\ \beta_{41} & \beta_{41}\end{pmatrix}\begin{pmatrix}\Phi_1\\ \Phi_2\end{pmatrix} + \begin{pmatrix}\sigma_1\\ \sigma_2\\ \sigma_3\\ \sigma_4\end{pmatrix} \tag{19}$$

Suppose $\Phi'=(\Phi'_1, \ldots, \Phi'_l)$, and $\gamma'=(\gamma'_1, \ldots, \gamma'_n)$. Let ξ be the n×n coefficient matrix of γ; δ be the n×l coefficient matrix of Φ; $\sigma_\gamma'=(\sigma'_1, \ldots, \sigma'_n)$ be the remaining vectors. Then, the SEM can be expanded as follows:

$$\gamma = \xi\gamma + \delta\Phi + \sigma_m \tag{20}$$

For CNP, every latent variable has N observable variables, each involving M observations. Then, all observations can be expressed as an M×N data matrix. Suppose there are l independent variables and n dependent variables in the latent variables. The number of observable variables for the independent variables Φ_τ can be denoted as L(τ), while the observable vector of Φ_τ can be expressed as $a_{\tau i}$, τ=1, …, l, i=1, …, L(τ). The number of observable variables for the dependent variables γ_j can be denoted as K(j), while the observable vector of γ_j can be expressed as b_{ij}, j=1, …, n, i=1, …, K(i). Then, the aggregation coefficients are denoted as Θ_{ij} and χ_{ij}, and the random error as σ with a subscript. Then, the observation equations can be established as:

$$\Phi_\tau = \sum_{i=1}^{L(\tau)} \Theta_{\tau i} a_{\tau i} + \sigma_{a\tau}, \tau = 1, \ldots, l \tag{21}$$

$$\gamma_j = \sum_{i=1}^{K(j)} \chi_{ij} b_{ij} + \sigma_{bj}, j = 1, \ldots, n \tag{22}$$

Then, a SOPCNN topology can be constructed for the proposed SEM. The input variables of the network correspond to the observable variables of our problem. The output variables are equivalent to latent variables Φ_τ, τ=1, …, l and γ_j, j=1, …, n. The output variables can be divided into an independent variable output module and a dependent variable output module. The weights of the input layer and the output layer can be respectively described as Θ_τ, τ=1, …, l, i=1, …, L(τ) and χ_{ij}, j=1, …, n, i=1, …, K(i). The relationship between output variables can be expressed as $\alpha_{\tau o}$ and $\beta_{\tau o}$, o=1, …, n. Let u_{ij} and μ_{ij} be loading coefficients. Drawing on the idea of factor analysis, the relationship between latent variables to observable variables can be illustrated by the following observation equations:

$$a_{\tau i} = u_{\tau i}\Phi_\tau + \sigma_{a\tau i}, \tau = 1,\ldots,l, i = 1,\ldots,L(\tau) \quad (23)$$

$$b_{ij} = \mu_{ij}\gamma_i + \sigma_{bij}, j = 1,\ldots,n, i = 1,\ldots,K(i) \quad (24)$$

The $\varepsilon\sigma$ with a subscript refers to the random error. Without considering the random error in formula (22), a simplified expression can be obtained:

$$\left(a_{\tau 1},\ldots,a_{\tau L(1)}\right) \approx \left(u_{\tau 1}\Phi_\tau,\ldots,u_{\tau K(1)}\Phi_\tau\right), \tau = 1,\ldots,l \quad (25)$$

Multiplying the transpose of the above matrix with the original matrix:

$$\begin{pmatrix} a_{\tau 1} \\ \vdots \\ a_{\tau L(1)} \end{pmatrix}\left(a_{\tau 1},\ldots,a_{\tau L(1)}\right) \approx \begin{pmatrix} u_{\tau 1}\Phi_t \\ \vdots \\ u_{\tau L(1)}\Phi_\tau \end{pmatrix}\left(u_{\tau 1}\Phi_\tau,\ldots,u_{\tau L(1)}\Phi_\tau\right) \quad (26)$$

The diagonal elements of the transpose matrix and the original matrix can be given by:

$$a_{\tau j}{}'a_{\tau j} \approx u_{ij}^2\Phi_\tau{}'\Phi_\tau, j = 1,\ldots,L(\tau) \quad (27)$$

If Φ_τ denotes the unit vector, then $\Phi'_\tau\Phi_\tau$ equals 1. Then, the u_{ij} can be calculated by:

$$\tilde{u}_{\tau j}{}' = \sqrt{a_{ij}^2 a_{ij}}, j = 1,\ldots,L(\tau) \quad (28)$$

On this basis, Φ_τ can be computed by formula (25). Through scalar-multiplication between the left side of formula (25) and $(u_{i1}, \ldots, u_{iL(\tau)})'$, it can be obtained that $u_{i1}a_{i1}+\ldots+u_{iL(\tau)}a_{iL(\tau)}$ is roughly equal to $(u_{i1}{}^2+\ldots+u_{iL(\tau)}{}^2)\Phi_\tau$. Assuming that $g=u_{i1}{}^2+\ldots+u_{iL(\tau)}{}^2$, we have:

$$\Phi_\tau{}^* = \frac{\tilde{u}_{\tau 1}}{g}a_{\tau 1}+\ldots+\frac{\tilde{u}_{\tau L(1)}}{g}a_{\tau L(1)} \quad (29)$$

Comparing the above formula with formula (21), $\Theta_{ij}{}^*=(\Theta_{i1}{}^*\ldots\Theta_{iL(\tau)}{}^*)$ equals $(\tilde{u}_{i1}/g, \ldots, \tilde{u}_{iL(\tau)}/g)$. Since formula (21) is an indefinite equation, and Φ_τ is not necessarily a unit vector, it is necessary to normalize Θ^*. That is, all elements in Θ^* adds up to $h=\tilde{u}_{i1}/g+\ldots+\tilde{u}_{iL(\tau)}/g$, and the estimate $\Theta''=(\Theta_{i1}''\ldots\Theta_{iL(\tau)}'')$ equals $(u_{i1}''/gh, \ldots, u_{iL(\tau)}''/gh)$. All elements in Θ^* are nonnegative and add up to 1. The latent variable Φ_τ can be estimated by:

$$\Phi_\tau'' = \frac{\tilde{u}_{\tau 1}}{gh}a_{\tau 1}+\ldots+\frac{\tilde{u}_{\tau L(1)}}{gh}a_{\tau L(1)}, \tau = 1,\ldots,l \quad (30)$$

Similarly, χ_{ij} can be estimated by formula (21).

Decision Tree (DT)-Based CNP Measurement and Evaluation

This paper measures and evaluates CNP under CL-PE intervention by the DT algorithm. The measuring and evaluation rules aim to select the metrics according to each independent variable's and dependent variable's attributes and split the data samples at the given variable node. The training set containing class labels is denoted as TS. The class label covers X different attributes, such as age, grade, school type, and degree of physical education intervention. The X classes can be defined as $LU_i\{i=1, 2, 3, \ldots, X\}$. In addition, the set of class LU_i samples in TS is denoted as $LU_{i,\varepsilon}$; the number of variable samples in TS and $TS_{i,\varepsilon}$ is denoted as $|s|$ and $|s_{i,TS}|$, respectively. Furthermore, the entropy EN(TS) of TS is introduced to characterize the chaotic degree of mediating and moderating effects. Then, the expectation required for TS sample classification can be calculated by:

$$EN(s) = -\sum_{i=1}^{X}\frac{|s_{i,TS}|}{|s|}log2\left(\frac{|s_{i,TS}|}{|s|}\right) \quad (31)$$

If attributes $SE=\{e_1, e_2, e_3, \ldots, e_Y\}$ are discrete values, then TS can be divided into Y subsets $\{s_1, s_2, s_3, \ldots, s_Y\}$ based on SE. The SE value of each variable sample in s_j ($j=1, 2, 3\ldots, Y$) is c_j. The branches of TS correspond to $\{s_1, s_2, s_3, \ldots, s_Y\}$. Then, we have:

$$EN[SE(s)] = \sum_{j=1}^{Y}\left|\frac{s_j}{s}\right| \times EN(s_j) \quad (32)$$

The decrement of variable entropy induced by SE can be calculated by:

$$\Delta EN(SE) = EN(s) - EN[SE(s)] \quad (33)$$

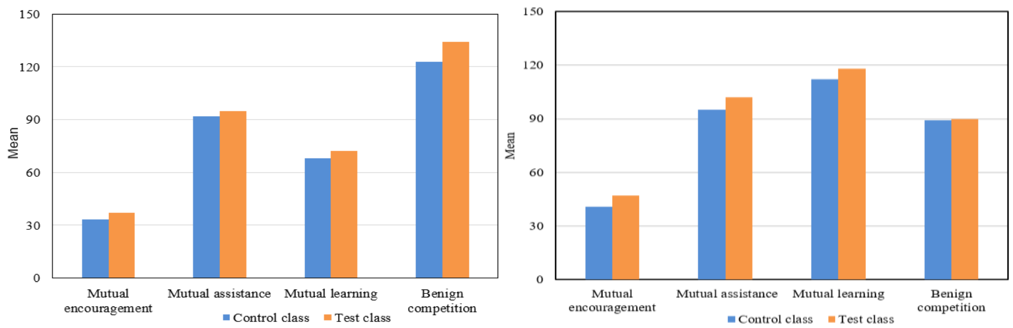
The gain ratio of SE variation can be defined as:

$$VG(SE) = \frac{\Delta EN(SE)}{PC(SE)} \quad (34)$$

where PC(SE) is the information generated by the Y outputs. These outputs are divided from TS, according to SE. The PC(SE) can be calculated by:

$$PC[SE(s)] = -\sum_{j=1}^{Y}\frac{|s_j|}{|s|}log_2\left(\frac{|s_i|}{|s|}\right) \quad (35)$$

Experiments and Results Analysis

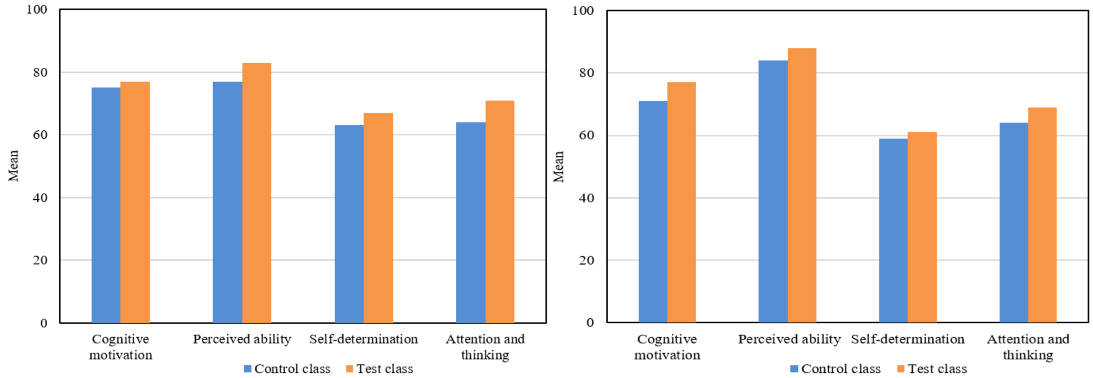


(a) Overall situation (b) Low-level situation

Figure 4. Children's learning attitudes before and after the experiment

Based on physical exercise and enhancing physical quality, the CL-PE encourages mutual encouragement, mutual aid, mutual learning, and healthy rivalry among children by providing a calm learning environment. This learning approach alleviates the high learning pressure, increases children's self-confidence, fosters an optimistic mindset and pleasant emotions, and aids in eradicating negative psychology. The group with poor mental health did better in terms of mutual learning and mutual support than the class as a whole.

Figure 4 contrasts the pre- and post-experiment learning attitudes of youngsters. Subparagraph (a) describes the general situation of the classes, while subparagraph (b) describes the situation of the group with bad psychological health (b). The comparison demonstrates that the children in the test group, which uses CL-PE based on the idea of homogeneity within groups and heterogeneity between groups, were more proactive in their approach to learning than those in the control group, which employs the conventional teaching model.



(a) Pre-experiment (b) Post-experiment

Figure 5. Children's cognition, ability, and self-efficacy before and after the experiment

Through assessing children's psychological crises, the personnel responsible for psychological crisis intervention should classify the severity of the psychological crisis and implement appropriate intervention measures, according to the relevant literature.

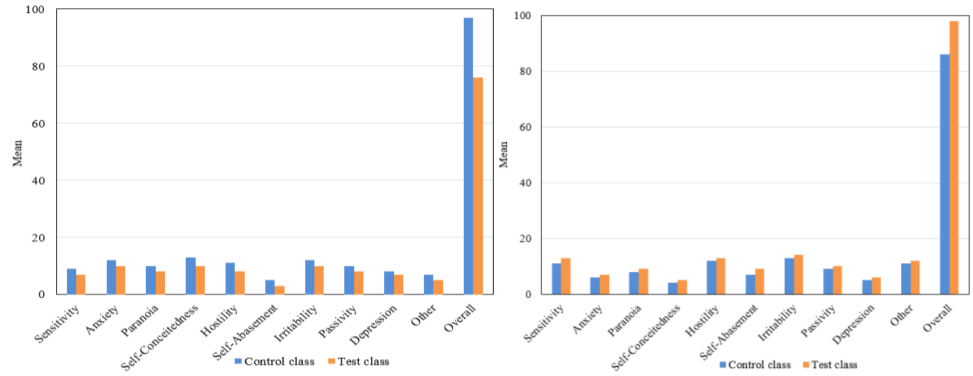
Using classroom records and observations of teachers who have adopted CL-PE, it was discovered that CL-PE could improve children's psychological health in multiple ways: cognitive motivation of sports skills, learning emotion, sports spirit, cognition of sports ability, self-determination, attention, and thinking, etc. Figure 5 contrasts children's cognitive abilities, abilities, and self-efficacy before and after the experiment. Subparagraph (a) describes the general situation of the classes, while subparagraph (b) describes the situation of the group with bad psychological health (b). Regarding cognitive motivation for sports skills, the students learned to subordinate their aims to group or class objectives and become more cognizant of the value of collaboration and group honor. The CL-PE enhanced the children's impression of their athletic abilities and taught them to enhance team competition through division of work, collaboration, and full utilization of individual strengths. The CL-PE program improved the children's concentration and ability to think critically and actively. The group with poor physical health fared well in terms of perceived ability and cognitive motivation compared to the total condition.

Table 2

T-test results on pre-experiment children's psychological health levels in a test class and control class

Negative psychological factors	Control class	Test class	t	p
Sensitivity	51.03±5.42	52.63±6.03	-1.323	0.192
Anxiety	19.36±3.07	19.42±3.82	-0.124	0.903
Paranoia	32.47±5.28	32.43±4.71	-1.008	0.319
Self-conceitedness	0.61±0.45	0.53±0.44	0.726	0.473
Hostility	1.18±0.53	1.12±0.57	0.769	0.442
Self-abasement	1.05±0.59	0.92±0.56	1.254	0.209
Irritability	0.86±0.58	0.73±0.62	1.121	0.267
Passivity	0.84±0.62	0.78±0.57	0.457	0.643
Depression	0.79±0.53	0.76±0.63	0.002	0.997
Other	0.65±0.52	0.62±0.59	0.287	0.775
Overall	0.86±0.41	0.75±0.43	1.045	0.293

Table 2 displays the t-test results on pre-experiment children's psychological health levels in the test and control classes. Before the experiment, the grouping, peer relationship, and psychological health levels of the children in the two groups were screened carefully. According to the independent samples t-test, the p-value of every dimension was greater than 0.05, i.e., there is no significant difference between negative psychological factors. Hence, the grouping, peer relationship, and psychological health levels of the children in both groups are highly homogenous before the experiment.



(a) Pre-experiment (b) Post-experiment

Figure 6. CNP factors before and after the experiment

Figure 6 compares the CNP variables before and following the experiment. Students in the test group who got CL-PE demonstrated significant improvements in various psychological characteristics, including sensitivity, anxiety, paranoia, self-conceit, anger, self-abasement, irritability, apathy, and sadness. The primary cause is as follows: Cooperative learning tries to assist students in achieving everyday tasks through teamwork and division of labor. Communication with other children may relieve symptoms such as sensitivity, anger, and inactivity. A strong sense of collective honor and a cooperative environment could significantly mitigate paranoia, irritation, and anxiety. Acceptance and acknowledgment from other children alleviate symptoms such as despair and feelings of inferiority. The teachers' varied evaluations and prompt comments could rapidly resolve student disputes and disagreements. The teachers' compliments could bolster the children's sense of accomplishment, which could also improve their attitudes toward physical activity.

The necessary index data were then processed using statistical and data analysis software. Table 3 displays the correlation matrix between CL-PE and CNP variables.

The mediator variable necessitates a weak association between the independent and dependent variables, but the moderator variable does not. According to this theory, CL-PE satisfies the moderator variable test criteria. According to Table 3, there was no significant correlation between CL-PE and CNP variables. Consequently, CL-PE is expected to function as a moderator variable.

In addition, subjective physical education intervention, motivation for cooperative learning, peer cognition and selection, and team collaboration and guidance are selected as dependent variables. In contrast, negative psychological symptoms and somatization are selected as independent variables. These variables are continuous. Table 4 displays the moderating influence of each CL-PE variable as determined via centralization and hierarchical regression. Results indicate that the R2 of team collaboration and leadership was more significant than any other component. This demonstrates the significance of teachers in implementing CL-PE.

Table 3

Correlation matrix between CL-PE and CNP factors

	Negative emotion	Negative cognition	Negative behavior	Somatization	Utilization of cooperative learning	The total score of cooperative learning
Negative emotion	1.000					
Negative cognition	-0.108	1.000				
Negative behavior	0.157	-0.105	1.000			
Somatization	0.082	-0.009	0.067	1.000		
Utilization of cooperative learning	0.073	-0.043	0.085	0.268	1.000	
The total score of cooperative learning	0.259	-0.088	0.682	0.631	0.638	1.000
Mean	16.274	5.072	10.361	7.176	7.425	23.853
Standard deviation	7.456	4.098	3.276	2.507	2.473	5.312

Table 4

Moderating effect of each CL-PE variable

	Steps	Regression equation	R^2
Subjective physical education intervention	1	Y=2.076+0.061X+0.083M	0.015
	2	Y=2.087+0.062X+0.082M+0.451XM	0.016(0.002)
The motivation for cooperative learning	1	Y=0.106+0.107X+0.108M	0.029
	2	Y=0.107+0.108X+0.107M+0.112XM	0.030(0.002)
Peer cognition and selection	1	Y=0.107+0.108X+0.109M	0.004
	2	Y=0.108+0.109X+0.110M+0.105XM	0.006(0.002)
Team collaboration and guidance	1	Y=0.103+0.104X+0.104M	0.089
	2	Y=0.103+0.103X+0.103M+0.103XM	0.103(0.017)

As shown in Tables 5-7, there was no significant difference between pre-experiment and post-experiment levels of any dimension of learning attitude for the children in the control group; their attention and thinking, as well as perceived ability, improved significantly through the experiment; their symptoms such as sensitivity, anxiety, passivity, and depression improved to varying degrees through the experiment. These findings demonstrate the effect of CL-PE.

Table 5

T-test results on children's learning attitude before and after the experiment

	Pre-experiment	Post-experiment	t	p
Mutual encouragement	51.07±5.39	52.31±7.65	-0.782	0.435
Mutual assistance	19.36±3.07	19.42±3.82	-1.978	0.057
Mutual learning	32.47±5.28	32.43±4.71	0.284	0.774
Benign competition	24.13±5.11	25.32±5.24	0.214	0.984

Table 6

T-test results on children's cognition, ability, and self-efficacy before and after the experiment

	Pre-experiment	Post-experiment	t	p
Cognitive motivation	51.07±5.39	52.31±7.65	-0.782	0.435
Perceived ability	19.36±3.07	19.42±3.82	-1.978	0.057
Self-determination	32.47±5.28	32.43±4.71	0.284	0.774
Attention and thinking	42.15±5.21	40.11±4.12	-0.656	0.921

Table 7

T-test results on CNP factors of control class and test class

Negative psychological factors	Control class	Test class	t	p
Sensitivity	0.62±0.47	0.83±0.54	-2.068	0.043
Anxiety	1.21±0.59	1.27±0.71	-0.475	0.628
Paranoia	1.05±0.58	1.02±0.66	0.336	0.742
Self-conceitedness	0.86±0.55	0.83±0.75	-0.107	0.925
Hostility	0.86±0.62	0.84±0.76	0.242	0.823
Self-abasement	0.76±0.57	0.75±0.54	0.295	0.767
Irritability	0.68±0.53	0.72±0.68	-0.343	0.749
Passivity	0.81±0.51	0.67±0.53	1.198	0.234
Depression	0.66±0.49	0.59±0.41	1.203	0.231
Others	0.63±0.56	0.66±0.62	-0.051	0.953
Overall	0.85±0.47	0.84±0.54	0.035	0.964

Regarding interpersonal communication, self-abasement, self-conceit, and anxiety, the trial results indicate that the children in the test group who adopted CL-PE saw a considerable improvement in their negative psychological characteristics. Therefore, our theoretical premise is supported: integrating cooperative learning in physical education can enhance children's negative psychology, and this improvement is directly related to the implementation elements of CL-PE.

Conclusions

This research presents the SEM to investigate the effect of CL-PE on CNP. The authors employed a structural equation model (SEM) to assess the role of CL-PE on CNP and to investigate the interacting, moderating, and mediating effects. The SEM was then transformed into a SOPCNN, generated latent variables, and summarized observable indices. The authors compared and examined the children's learning attitude, cognition, ability, self-efficacy, and CNP factors before and after each experiment, and conducted t-tests on the children's learning attitude and CNP factors in the control and test classes prior to each experiment. The experimental data indicate that the experiment significantly improved negative psychology among the test group youngsters.

This research successfully improves CNP by data mining in light of preschool-aged children's current psychological assessment needs. However, there are several limitations to the research. Creating archives for these children is essential for enhancing the psychological tracking of children experiencing psychological crises and resolving their psychological issues promptly.

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