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Article

The Impact of Physical Education Teachers' Digital Teaching Competencies, Empowered by Smart Education, on Student Participation in Physical Activity: A Time Series Analysis

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Abstract: With the rapid development of information technology and intelligent systems, smart education has emerged as a key direction in modern education, providing both technological support and practical pathways for cultivating core physical education and health competencies. In light of this, this study utilizes statistical data on physical education teachers' digital teaching capabilities and students' physical activity participation from 2010 to 2025 in a certain city. It establishes a vector autoregressive model between physical education teachers' digital teaching capabilities and students' physical activity participation, and employs unit root tests, cointegration analysis, impulse response functions, and variance decomposition to analyze and predict the interactive dynamics and time-series relationships between the two. The results indicate that a bidirectional Granger causality relationship exists between physical education teachers' digital teaching capabilities and students' physical activity participation. The contribution rate of students' physical activity participation to changes in physical education teachers' digital teaching capabilities is relatively high in the short term and then gradually decreases. The contribution rate of physical education teachers' digital teaching capabilities to fluctuations in student physical activity participation showed a rapid upward trend after the second period, reaching 72.08104% by the eighth period. The variance contribution rate of physical education teachers' digital teaching capabilities was significant and exhibited a continuous upward trend over time.

Keywords: Vector autoregressive model; Impulse response function; Variance decomposition method; Digital teaching competence; Physical activity participation

1. Introduction

The information revolution is reshaping the concepts, models and methods of education in an unprecedented manner [1]. Digitalization acts as a catalyst, accelerating the modernization process of education and prompting comprehensive and profound changes in school education in aspects such as teaching methods, resource integration, and teacher-student interaction, bringing unprecedented opportunities and challenges to school education and making the digital transformation of physical education teaching imperative [2]. Various educational practices indicate that the comprehensive application of digital teaching methods in school education can inject new vitality into physical education teaching [3-4]. Based on this, in-depth research on the impact of physical education teachers' digital teaching ability on students' participation in physical activities in the era of smart education will better help physical education teachers adapt to the teaching needs of the information age and promote the high-quality development of school physical education [5].

In the research on the digital teaching ability of physical education teachers, literature [6] based on the European educators' digital competence model, through questionnaire verification, concluded that the digital teaching ability of physical education teachers includes four aspects: using digital technology to communicate with students, developing remote learning, creating complex technical content, and information retrieval. Literature [7] with 50 middle school physical education teachers as the survey subjects, using a mature scale, explored the digital teaching resources allocation, teaching application difficulties of physical education teachers, as well as the professional training and teaching method strategies needed to adapt to the new era of physical education teaching, and analyzed the differences in digital literacy among teachers in terms of gender, age, and teaching experience. Literature [8] believes that the integration of digital technology into physical education can help students develop physical fitness and improve the quality and efficiency of courses, physical education teachers are the core entities implementing digital physical education, and must possess professional qualities suitable for modern digital education to support the implementation of digital teaching in the classroom. Literature [9] aims to investigate the self-perceived level of physical education teachers' ability to apply digital classrooms, the results show that physical education teachers' self-assessed digital teaching ability is generally low, and personal factors and school objective conditions have jointly hindered the integration and application of digital technology in physical education classes; the study suggests that the relationship between teaching methods and technology in physical education is more complex, the existing digital literacy framework is partial and cannot fully adapt to the actual digital teaching of the physical education subject. Literature [10] believes that physical education teachers generally recognize and are willing to use digital technology in campus physical education, and support extending learning to outside the school; the application motivation covers five aspects: learning evaluation, physical exercise, teaching assistance, home-school communication, and student teamwork and collaboration. Literature [11] with 35 pre-service physical education teachers from an Australian university as the subjects, found that pre-service physical education teachers recognize the teaching value of digital technology, which can help with professional learning, enhance digital application ability, broaden international perspectives, and enhance collaboration and communication.

Regarding the research on the impact of teachers' digital teaching ability on students' participation in physical activities, literature [12] found that the digital teaching literacy of physical education teachers and students' motivation for learning physical activities have a moderately strong positive correlation, the stronger the teacher's digital ability, the more effectively they can mobilize students' learning enthusiasm, and the teacher's subject professional knowledge level is also significantly related to students' physical education grades, solid professional foundation can positively enhance students' academic performance. Literature [13] found that compared with traditional teaching, digital teaching methods can slightly to moderately improve students' partial physical skills levels, and deeply explored the teaching efficacy of various digital platforms, the long-term retention effect of skills, and the impact of digital teaching on students' learning motivation. Literature [14] found that digital teaching can effectively assist in physical education professional teaching, learning, and physical practice, positively promoting students' participation in physical activities and learning outcomes, playing an important role in the sustainable development of higher physical education, and also assisting physical education educators in better conducting professional teaching and knowledge dissemination. Reference [15] found that academic performance, the frequency of physical education classes per week, family and school information resources, and the social cognition of information and communication technology are the key factors influencing students' participation in digital sports, and there are obvious threshold characteristics. Reference [16] found that teachers' application of digital teaching innovations effectively helps students prepare for pre-class experiments and classroom participation, improves the level of interaction and collaboration between teachers and students as well as among students, and realizes timely and efficient teaching feedback; at the same time, it broadens students' access to learning resources and significantly enhances their learning motivation and classroom participation.

The article first introduces the vector autoregressive (VAR) model, followed by a description of the variables selected for this study and their measurement methods. These include two main variables—student physical activity participation (SP) and physical education teachers’ digital teaching competence (TDC)—as well as five control variables: student gender, grade level, school facility quality, family support, and teacher seniority. It then describes the distribution of student physical activity participation levels in physical education classes, covering both the overall distribution across the sample population and the multidimensional distribution of participation levels. Finally, using statistical data on physical education teachers’ digital teaching capabilities and student physical activity participation from 2010 to 2025 in a certain city, the study empirically examines the dynamic effects between physical education teachers’ digital teaching capabilities and the development of student physical activity participation, and analyzes the underlying mechanisms.

2. Research Design

2.1. Fundamentals of Vector Autoregressive Models

2.1.1. Vector Autoregressive Model

The analytical framework for univariate time series can be extended to multivariate time series to construct vector autoregressive (VAR) models. VAR models are typically used to describe the relationships between variables in multivariate time series; they do not require an economic theory as a foundation but are built directly from the data, making them unstructured models. Their general form is as follows:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \varepsilon_t \tag{1}$$

In the equation:

$$y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{dt} \end{bmatrix}, \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{dt} \end{bmatrix}, \quad A_0 = \begin{bmatrix} a_{10} \\ a_{20} \\ \vdots \\ a_{d0} \end{bmatrix} \tag{2}$$

$$A_i = \begin{bmatrix} a_{11}(i) & a_{12}(i) & \cdots & a_{1d}(i) \\ a_{21}(i) & a_{22}(i) & \cdots & a_{2d}(i) \\ \vdots & \vdots & \vdots & \vdots \\ a_{d1}(i) & a_{d2}(i) & \cdots & a_{dd}(i) \end{bmatrix} \left(i = 1, 2, \cdots, p\right) \tag{3}$$

y_t is a d -dimensional variable sequence. $A_i\left(i = 1, \cdots, p\right)$ is a $d \times d$ -dimensional coefficient matrix. ε_t has d dimensions, all independent and identically distributed, while the components within it do not need to be mutually independent. The variance-covariance matrix of the disturbance term $[\varepsilon_{1t}, \varepsilon_{2t}, \cdots \varepsilon_{dt}]'$ is expressed as:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1d} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_{d1} & \sigma_{d2} & \cdots & \sigma_d^2 \end{bmatrix} = E\left(\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{dt} \end{bmatrix} \left[\varepsilon_{1t}, \varepsilon_{2t}, \cdots \varepsilon_{dt}\right]\right) \tag{4}$$

In this case, $\sigma_{ij} = \sigma_{ji}\left(i, j = 1, 2, \cdots, n\right)$ and Σ are symmetric matrices.

2.1.2. Determining the Order of the Model

In practical applications, we generally want the lag order p to be sufficiently large so that the dynamic characteristics of the constructed model are better captured; however, as the lag order p increases, the number of parameters to be estimated in the model increases, and the degrees of freedom decrease. When the p value is too large, without a sufficient sample size, the required parameters cannot be estimated effectively. Therefore, it is usually necessary to compare the estimated values of the six metrics—likelihood ratio test, AIC, SC, HQ, LogL, and final prediction error—across different lag orders. The lag order with the highest number of minimum values across these six criteria is selected as the model's lag order.

2.1.3. Estimation of Model Coefficients

For each equation in the vector autoregressive model system, the OLS (least squares estimation) method can be used for estimation, and the estimators have consistency and unbiasedness. In a d -dimensional p -order vector autoregressive model, the lag periods of all explanatory variables in each equation are the same, all being p periods of lag, thus a total of $pd^2 + d$ coefficients are estimated.

2.1.4. Unit Root Tests

A non-stationary time series is one in which its mean or autocovariance function changes over time. Random process $\{R_t, t=1,2,\cdots\}$, if:

$$R_t = \rho R_{t-1} + \xi_t \tag{5}$$

In particular, if $\rho = 1$ and $E(\xi_t)=0$, $Cov(\xi_t, \xi_{t-s}) = \mu_t < \infty$, and $s=0,1,\cdots$ hold, then the process is a unit-root process. A unit-root process is a very common type of non-stationary process. If $|\rho| < 1$ holds, then the process described by Equation (1) is a stationary process.

2.1.5. Granger Causality Test

The Granger causality test uses the following approach to verify whether a relationship is truly causal:

(1) Estimate the extent to which the current value of variable Y can be explained by the lagged values of variable Y.

(2) Examine whether the degree of explanation for variable Y increases after including the lagged values of variable X.

(3) If condition (2) is satisfied, then X is a Granger cause of Y, and the lag coefficient of X is statistically significant.

Specifically, this is tested by examining whether all the coefficients of the lag terms in the vector autoregressive (VAR) model system are zero. Take a 2-dimensional, p th-order stationary VAR model as an example:

$$\begin{aligned} y_{1t} &= a_{10} + a_{11}(1)y_{1,t-1} + a_{11}(2)y_{1,t-2} + \cdots + a_{11}(p)y_{1,t-p} \\ &\quad + a_{12}(1)y_{2,t-1} + a_{12}(2)y_{2,t-2} + \cdots + a_{12}(p)y_{2,t-p} + \varepsilon_{1t} \\ y_{2t} &= a_{20} + a_{21}(1)y_{1,t-1} + a_{21}(2)y_{1,t-2} + \cdots + a_{21}(p)y_{1,t-p} \\ &\quad + a_{22}(1)y_{2,t-1} + a_{22}(2)y_{2,t-2} + \cdots + a_{22}(p)y_{2,t-p} + \varepsilon_{2t} \end{aligned} \tag{6}$$

Test the null hypothesis: y_{2t} is not a Granger cause of y_{1t}. Then, use test F to test the joint hypothesis:

$$a_{12}(1) = a_{12}(2) = \cdots = a_{12}(p) = 0 \tag{7}$$

If the test results reject the null hypothesis—that is, reject the Granger causality of y_{2t} over y_{1t}—then y_{2t} is typically said to be a Granger cause of y_{1t}.

Test the null hypothesis: y_{2t} is not a Granger cause of y_{1t}, then use test F to test the joint hypothesis:

$$a_{21}(1) = a_{21}(2) = \cdots = a_{21}(p) = 0 \tag{8}$$

If the test results lead to a rejection of the null hypothesis—that is, a rejection of the Granger causality of y_{1t} over y_{2t}—then it is generally said that y_{1t} is a Granger cause of y_{2t}.

2.1.6. Overall Model Validation

Generally speaking, vector autoregressive (VAR) models are constructed based on data and are used to simulate the dynamic patterns of multivariate time series. Therefore, since this model does not rely on variables with different lag orders to explain the dependent variable, tests of parameter significance are not particularly important.

In practical applications, when building a vector autoregressive model, we focus more on the overall model test results, primarily by comparing the log-likelihood function with various information criteria; this can be combined with the selection of the optimal lag order.

If the model passes the test, it can be used for forecasting. Before performing out-of-sample forecasting, one can first use the established model to estimate the values at each time point within the training period, compare them with the actual values, and evaluate the accuracy of the model's estimates.

After the model is established, assuming its predictive accuracy is satisfactory, it can be used for out-of-sample forecasting. When actually building a predictive model, if a large amount of data has been collected, the first portion of the data can be used for modeling, while the latter portion is reserved to validate the model's predictive performance.

2.1.7. Impulse Response Analysis

By using a vector autoregressive (VAR) model to represent the relationships between variables, we can not only make predictions but also analyze how the entire system responds dynamically when a disturbance term changes; this is known as the impulse response. The specific impulse response model is as follows:

$$\begin{aligned} y_{1,t} &= \beta_{10t} + \beta_{11} y_{1,t-1} + \beta_{12} y_{2,t-1} + \varepsilon_{1t} \\ y_{2,t} &= \beta_{20t} + \beta_{21} y_{1,t-1} + \beta_{22} y_{2,t-1} + \varepsilon_{2t} \end{aligned} \tag{9}$$

The impulse response examines the impact on the entire model system when a disturbance term changes; it describes how a change in one variable affects all other variables in the model.

Since there are a large number of parameters to be estimated in the vector autoregressive model, and each coefficient reflects only a local relationship, the coefficients in the vector autoregressive model are of limited analytical significance. However, examining the dynamic relationships among variables—that is, the system's dynamic response—when a disturbance term changes or is subject to an interference or shock is of considerable significance.

2.2. Research Design

2.2.1. Variable Selection and Measurement Methods

This study primarily investigates the impact of physical education teachers' digital teaching competencies on students' physical activity participation. The main variables selected for this study are as follows:

Dependent variable: Student physical activity participation (SP), assessed using the Physical Activity Rating Scale (PARS-3). Physical activity scores are calculated based on three dimensions—intensity, duration, and frequency—enabling a relatively objective assessment and classification of students' physical activity levels.

Independent variable: Physical education teachers' digital teaching competence (TDC). Teaching competence empowered by smart education is a dynamic and evolving process. Physical education teachers' digital teaching competence should encompass five key competencies: digital knowledge, digital application and innovation, digital teaching and learning, personal traits, and digital ethical literacy. These elements reinforce, influence, and promote one another in a bidirectional manner, constituting essential components of physical education teachers' digital teaching competence.

Regarding the selection of methods for measuring physical education teachers' digital teaching competence, there are many options available, such as the commonly used locational entropy method, as well as input-output analysis, principal component analysis, clustering methods, and the Gini coefficient. This paper employs the locational entropy method for calculation, as shown in Formula (10). A higher locational entropy index indicates a higher level of digital teaching competence among physical education teachers in that region.

$$Q = \frac{M_j / \sum M_j}{N_j / \sum N_j} \tag{10}$$

Control variables: Student gender (Gender); generally speaking, gender differences significantly influence interest in and participation in sports. Student grade level (Grade); generally speaking, academic pressure and physical development vary across different educational stages. School facility level (Facility); the quality of equipment on school sports fields affects the objective conditions for sports participation. Additionally, family support (Family); the degree to which parents value physical education also influences students' participation in sports. Teacher experience (Exp): The teaching experience of veteran teachers may exert an influence independent of digital competence.

2.2.2. Model Development

(1) Panel Data Model

We establish an equation for student physical activity participation, where SP is the dependent variable (student physical activity participation), TDC is the independent variable representing physical education teachers' digital teaching proficiency, and the control variables include Gender (student gender), Grade (student grade level), Facility (school facility level), Family (family support), and Exp (teacher years of experience):

$$\begin{aligned}\log(SP) = \beta_0 + \beta_1 \log(TDC) + \beta_2 \log(Gender) + \beta_3 \log(Grade) \\ + \beta_4 \log(Facility) + \beta_5 \log(Family) + \beta_6 \log(Exp)\end{aligned} \tag{11}$$

In the above equation, panel data were used for regression estimation. Since there is a causal relationship between physical education teachers' digital teaching capabilities and students' physical activity participation, OLS regression estimates would be ineffective; therefore, instrumental variables from statistical theory are required to adjust for this. Consequently, in the regression analysis of this paper, SYS-GMM was employed for further statistical analysis, with the instrumental variables represented by the first-order lagged values of the variables in the study.

(II) Panel Vector Autoregression Model

Since its introduction, the VAR model has been widely used by economists and has undergone continuous refinement based on the characteristics of data structures. The P-VAR model has now evolved into a mature econometric model and is widely applied across various fields, including agriculture, economics, finance, and technology. The P-VAR model adopted in this paper can be expressed as:

$$Y_{i,t} = A_{i,0} + \sum_{l=1}^{m} A_{i,l} Y_{i,t-l} + u_{i,t} \tag{12}$$

Here, $i = 1, 2, \cdots, n$ represents the number of cross-sectional data points at time t, $A_{i,t}$ denotes the $k \times nk$ -dimensional coefficient matrix to be estimated, $u_{i,t} \sim (0, \sigma_i^2)$ is the residual term, and if $i \neq j$ holds, then $E(u_{i,t} u_{j,t}) = 0$ is satisfied. The model shown in Equation (12) exhibits three fundamental characteristics: First, the model coefficients change as time evolves. Second, this model intuitively illustrates the dynamic changes in each data unit of the cross-sectional data. Finally, the model can measure the dynamic feedback relationship between the current period and the lagged period of the cross-sectional unit.

This paper employs a vector autoregressive (VAR) panel model to examine the dynamic relationship between physical education teachers' digital teaching competencies and students' participation in physical activity. The vector autoregressive (VAR) model treats all variables as endogenous, which is appropriate given the interrelationship between physical education teachers' digital teaching competencies and students' physical activity participation. While regression coefficients derived from panel data reflect only overall relationships, the VAR model utilizes impulse response functions to more accurately capture the long-term impact of physical education teachers' digital teaching competencies on students' physical activity participation.

2.2.3. Description of Data Sources

This study focuses on universities in Province A, a model region for smart education. All data were obtained from the Province A Department of Education for the period 2010–2025.

3. Descriptive Analysis of Students' Participation in Sports

3.1. Distribution of the Overall Sample Population by Level of Physical Activity Participation

The subjects of this experimental study were 3,116 college students from a university in Province A. In the context of physical education, "physical activity participation" refers to the behavior or state of students' physical and mental engagement within the setting of physical education classes, encompassing three dimensions: intensity, duration, and frequency. This study assessed the level of physical activity participation among students in physical education classes. The distribution of students' physical activity participation levels consists of two parts: the distribution of the total sample population and the multidimensional distribution of participation levels.

To understand the overall level of student physical activity participation in physical education classes and identify existing issues, the mean scores and standard deviations of the total sample's participation levels are analyzed below. The average scores for physical activity participation and its various dimensions are shown in Table 1. As shown in the table, the overall score for student physical activity participation in physical education classes is 4.67 ± 0.52, with an average score of 4.67. This indicates that, in physical education classes, students generally participate quite actively in classroom learning activities.

Table 1. Sports participation and average scores in each dimension

Indicator	M±SD
Participation in sports	4.67±0.52
Strength	4.45±0.67
Time	4.59±0.74
Frequency	4.53±0.72

3.2. Multidimensional Differences in Levels of Physical Activity Participation

One of the main focuses of this study is to examine whether the four factors—grade level, gender, class size, and teaching method—interfere with the effectiveness of physical education teachers' digital teaching abilities in influencing physical activity participation. According to statistical requirements, only if there are significant differences in physical activity participation levels within these factors—such as grade level, gender, and class size—can they be considered potential factors that interfere with the influence of physical education teachers' digital teaching abilities on physical activity participation. Therefore, it is necessary to conduct a comparative analysis of the distribution of physical activity participation levels within each of these factors.

(1) Grade-Level Differences in Physical Activity Participation Levels

The comparison of physical activity participation levels across grade levels is shown in Table 2. The p-values for the associations between all indicators were all <0.001, with η^2 being 0.004, 0.007, 0.004, and 0.002, respectively. The analysis of variance (ANOVA) indicated that there were significant differences in physical activity participation and its various dimensions between at least one group and the other two groups among the freshman, sophomore, and junior cohorts. Since the variances of the indicators were not homogeneous across groups ($P < 0.05$), post-hoc multiple comparisons of the means were conducted using Tamhane's method. The results showed that, in terms of overall physical activity participation scores, first-year students performed significantly better than second-year students, and second-year students performed significantly better than third-year students. Further comparisons of the scores across the three dimensions of physical activity participation revealed that, regarding intensity, first-year students performed significantly better than both second- and third-year students, while no significant difference was found between second- and third-year students. Regarding duration, both first-year and second-year students scored significantly higher than third-year students, while no significant difference was found between first- and second-year students. Regarding frequency, both first-year and second-year students scored significantly higher than third-year students, while no significant difference was found between first- and second-year students. These findings indicate that as students progress through their academic years, their levels of physical activity participation begin to decline, with intensity showing the most significant decrease first. By the third year, students' intensity, duration, and frequency of physical activity participation have all decreased significantly.

Table 2. Grade comparison of sports participation levels

	Grade	n	M±SD	F value	P	η^2
	Junior year	859	4.82±0.46			
Participation in sports	Sophomore year	1032	4.74±0.67	18.707	<0.001	0.004
	Junior year	1225	4.53±0.68			
	Junior year	859	4.83±0.47			
Strength	Sophomore year	1032	4.78±0.48	23.805	<0.001	0.007
	Junior year	1225	4.51±0.61			
	Junior year	859	4.83±0.66			
Time	Sophomore year	1032	4.69±0.74	20.312	<0.001	0.004
	Junior year	1225	4.12±0.76			
	Junior year	859	4.47±0.79			
Frequency	Sophomore year	1032	4.38±0.66	10.022	<0.001	0.002
	Junior year	1225	4.29±0.7			

(2) Gender Differences in Physical Activity Participation Levels

A comparison of physical activity participation levels between genders is shown in Table 3. The

P-values for comparisons of scores between male and female students in terms of participation, intensity, duration, and frequency were all <0.001, with Cohen's d values of 0.2, 0.08, 0.27, and 0.16, respectively. Analysis of variance (ANOVA) indicates highly significant differences between male and female students, with males scoring significantly higher than females on total physical activity participation, intensity, duration, and frequency. Numerous studies have confirmed that female students exhibit lower levels of physical activity participation than male students in sports settings. Research on physical education indicates that, compared to male students, female students face greater challenges regarding physical education teachers' digital teaching capabilities. Specific reasons include poor teacher-student relationships, insufficient enjoyment of physical activity, and peer acceptance biases.

Table 3. Gender comparison of sports participation levels

	Gender	n	M±SD	T value	P	Cohen's d
Participation in sports	Male	1981	4.59±0.66	8.98	0.000	0.2
	Female	1135	4.46±0.49			
Strength	Male	1981	4.54±0.58	5.98	0.000	0.08
	Female	1135	4.47±0.51			
Time	Male	1981	4.73±0.6	10.63	0.000	0.27
	Female	1135	4.46±0.79			
Frequency	Male	1981	4.66±0.81	7.81	0.000	0.16
	Female	1135	4.22±0.74			

(3) Differences in Teaching Methods Regarding Levels of Physical Activity Participation

A comparison of teaching methods regarding levels of physical activity participation is shown in Table 4. The p-values for the ANOVA tests on physical activity participation, intensity, duration, and frequency were all <0.001. The p-values for η^2 were 0.008, 0.002, 0.004, and 0.009, respectively. The analysis of variance indicated that there were significant differences in physical activity participation and its various dimensions between at least one group and the other two, or even all three groups, across the co-ed, all-boys, and all-girls classes. A test for homogeneity of variances revealed that the variances of physical activity participation and its various dimensions were not equal across groups, with P-values all <0.001. Post-hoc multiple comparisons of the means across groups using Tamhane's method revealed that the boys' class scored significantly higher than the co-ed class and the girls' class in terms of total physical activity participation scores, as well as intensity, duration, and frequency scores. The co-ed class scored significantly higher than the girls' class in total physical activity participation scores, duration, and frequency, except for intensity, where no significant difference was observed.

Table 4. Comparison of teaching methods for sports participation levels

	Grade	n	M±SD	F value	P	η^2
	Co-educational class	1851	4.63±0.57			
Participation in sports	Boys' Class	551	4.78±0.57	26.785	<0.001	0.008
	Girls' class	714	4.54±0.67			
	Co-educational class	1851	4.47±0.56		<0.001	
Strength	Boys' Class	551	4.54±0.46	9.344		0.002
	Girls' class	714	4.39±0.54			
	Co-educational class	1851	4.52±0.72		<0.001	
Time	Boys' Class	551	4.54±0.75	40.06		0.004
	Girls' class	714	4.41±0.9			
	Co-educational class	1851	4.47±0.68		<0.001	
Frequency	Boys' Class	551	4.51±0.78	19.653		0.009
	Girls' class	714	4.24±0.95			

(4) Differences in Class Size by Level of Physical Activity Participation

A comparison of class sizes by level of physical activity participation is shown in Table 5. The p-values for the ANOVA tests on physical activity participation, intensity, duration, and frequency were 0.013, 0.007, 0.069, and 0.025, respectively. Among these, the p-value for duration was >0.05, while those for the other three indicators were <0.05; the η^2 effect size was 0.001 for all. The analysis of variance indicates that there are no significant differences in duration among groups with different class sizes; however, significant differences exist among groups regarding the three indicators of exercise participation, frequency, and intensity.

A test for homogeneity of variances revealed that the variances of exercise participation, frequency, and intensity are homogeneous across all groups, with P-values all >0.05. A post-hoc LSD test comparing the means across groups revealed that classes with fewer than 20 students had the highest total scores for physical activity participation. When class size exceeded 31 students, students' scores for participation and frequency declined significantly; for class sizes exceeding 26 students, students' intensity scores also declined significantly. Therefore, in physical education instruction, keeping class sizes within 20 students yields optimal levels of student participation, with 25 students being the recommended upper limit. When class sizes exceeded 25 students, students' exercise intensity began to be hindered. When class sizes exceeded 31 students, students' frequency, duration, and intensity were all hindered, and overall exercise participation scores declined.

Table 5. Comparison of the number of students attending classes

	Grade	**n**	**M±SD**	**F value**	**P**	η^2
Participation in sports	≤20	857	4.71±0.6	3.554	0.013	0.001
	21~25	645	4.33±0.65			
	26~30	768	4.22±0.62			
	≥31	846	4.07±0.7			
Strength	≤20	857	4.71±0.41	3.838	0.007	0.001
	21~25	645	4.67±0.58			
	26~30	768	4.53±0.39			
	≥31	846	4.48±0.69			
Time	≤20	857	4.85±0.62	2.522	0.069	0.001
	21~25	645	4.47±0.57			
	26~30	768	4.41±0.77			
	≥31	846	4.36±0.75			
Frequency	≤20	857	4.49±0.65	3.144	0.025	0.001
	21~25	645	4.41±0.74			
	26~30	768	4.33±0.69			
	≥31	846	4.31±0.68			

4. Empirical Analysis

4.1. Stability Test

To determine whether the two time series are stationary in their original form or become stationary after differencing, this paper employs the ADF unit root test. The results of the stationarity tests are shown in Table 6. The p-values indicate that the original series TDC and SP are both non-stationary; however, the series D(TDC) and D(SP), obtained after first-order differencing, both pass the stationarity test at the 5% significance level and are both first-order integrated sequences.

Table 6. The results of the stationarity test

Variable	**Test value**	**P value**	**1% threshold**	**5% threshold**	**10% threshold**	**Conclusion**
TDC	-1.288	0.883	-4.369	-3.606	-3.246	Unstable
D(TDC)	-2.316	0.013	-2.536	-1.732	-1.325	Stable
SP	-2.51	0.778	-4.38	-3.601	-3.241	Unstable
D(SP)	-3.891	-0.001	-2.533	-1.727	-1.329	Stable

4.2. Selection of the Optimal Order of Lagging Terms

Since the VAR model includes lag terms, it is necessary to determine the optimal lag order to improve the model's estimation performance. In this paper, five information criteria—LR, FPE, AIC, HQIC, and SBIC—are used to select the optimal lag order. The results of this selection are shown in Table 7. As can be seen from the table, all five criteria indicate lag(3); therefore, the VAR model established in this paper has a lag order of three.

Table 7. The result of selecting the optimal lag order

Lag (hysteresis)	LR (Likelihood test)	FPE (Final prediction error)	AIC (Red pool information code)	HQIC (Hannan quinn information code)	SBIC (Schwartz guidelines)
0	NA	1.159	2.979	3	3.023
1	109.225	0.003	-2.657	-2.647	-2.555
2	4.28	0.006S	-2.787	-2.756	-2.624
3	7.918	0.001	-3.092	-3.063	-2.899
4	1.832	0.006	-3.077	-3.03	-2.836

4.3. Cointegration Tests

Although the original time series used in this paper are non-stationary, there may still be a common random trend between the two series, i.e., a cointegration relationship. In this case, the random trend can be eliminated through a linear combination; therefore, a cointegration test is a necessary prerequisite for performing regression on non-stationary series. This paper employs the Johansen test to calculate the trace statistic and conducts a cointegration test on the two non-stationary series, TDC and SP. The results of the cointegration test are shown in Table 8. As shown in the table, when assuming no cointegration between TDC and SP, the trace statistic is 31.79, which is greater than the 1% critical value of 31.26, and the p-value is 0.008. This indicates that the null hypothesis is rejected, meaning that a cointegration relationship exists between TDC and SP. When assuming that a cointegration relationship exists between TDC and SP, the trace statistic is 7.159, which is less than the 5% critical value of 12.33, and the p-value is 0.211, indicating that the null hypothesis is accepted, i.e., a cointegration relationship exists between TDC and SP. Thus, the results of the trace statistic under both hypotheses indicate that a cointegration relationship exists between TDC and SP.

Table 8. The result of the cointegration test

Cointegration hypothesis	Trace statistics	5% critical value	1% critical value	P value	Conclusion
There is no cointegration relationship	31.79	25.31	31.26	0.008	Refuse
There exists a cointegration relationship	7.159	12.33	16.14	0.211	Accept

4.4. Granger Causality

To further determine whether the cointegration relationship between TDC and SP manifests as unidirectional or bidirectional causality, this study conducted Granger causality tests to establish causality. The results of the Granger causality tests are shown in Table 9. As can be seen from the table, the p-values corresponding to the F-statistics for both tests are <0.05, indicating that the null hypothesis is rejected in both cases. This suggests that a causal relationship exists between TDC and SP, and that it is a bidirectional causal relationship, meaning that TDC and SP are causally related to each other.

Table 9. Granger causality test results

Null hypothesis	F value	P value	Conclusion
TDC is not SP's granger reason	6.26541	0.008	Refuse
SP is not the granger reason of TDC	3.78494	0.039	Refuse

4.5. Estimation of the VAR Model

The regression results for the three-order lagged VAR model are shown below:

TDC=0.8885×L.TDC+0.4436×L2.TDC×0.4366×L3.TDC-0.2582×L.SP-0.2825×L2.SP+0.6359×L3.SP+1.4555

SP=4566×L.TDC+0.2196×L2.TDC+0.2618×L3.TDC+0.3634×L.SP+0.2558×L2.SP+0.2724×L3.SP+0.6188

Furthermore, the R2 values for the two equations are 0.9996 and 0.9976, respectively, and the F-values are 4435.325 and 1156.771, respectively. These results indicate a high degree of goodness of fit, suggesting that the model specification is reasonable and that there is a significant correlation between SP and TDC.

4.6. Stationarity Tests for the VAR Model

To perform impulse response and variance decomposition analyses based on the VAR model, it is necessary to first test the model's stationarity. The results of the eigenvalue test are shown in Figure 1. As can be seen from Figure 1, all six eigenvalues of the model lie within the unit circle, indicating that the model passes the stationarity test.

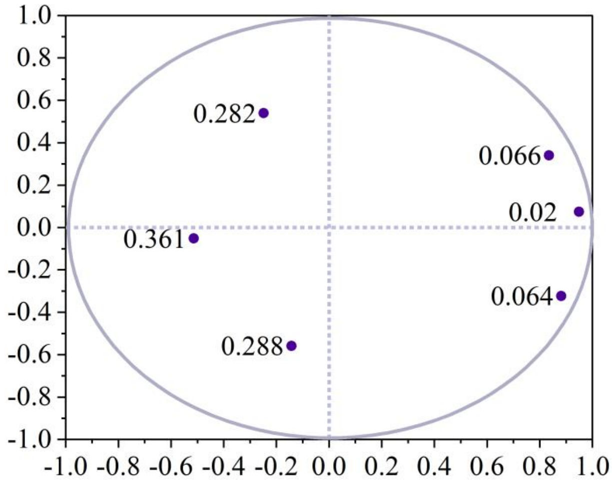
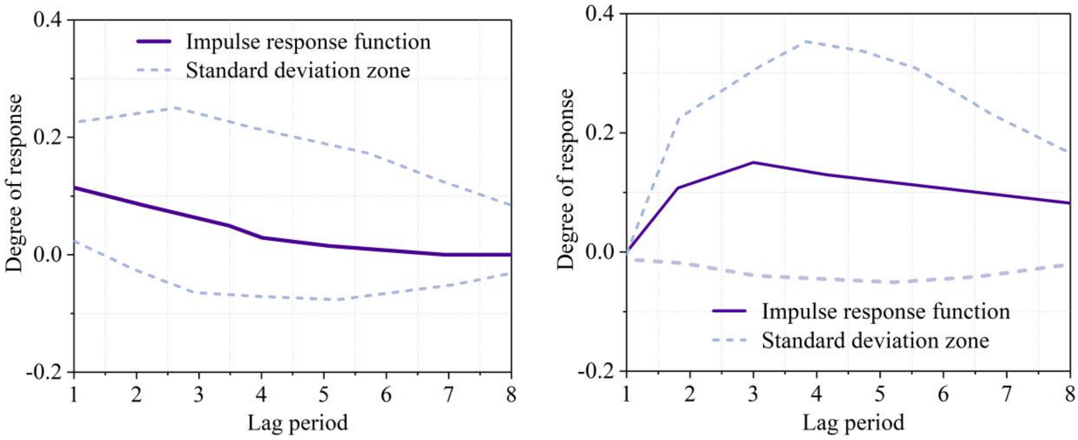


Figure 1. Results of characteristic root test

4.7. Impulse Response Analysis

Impulse response functions are commonly used to analyze the causal relationships among variables in time series models. They illustrate the current and future responses of a variable, as well as the trajectory of its impact, following a one-standard-deviation shock from any new information within the system. By measuring the current and future effects of a one-standard-deviation shock from a random disturbance term on endogenous variables, impulse response analysis provides a relatively intuitive description of the dynamic interactions between variables. Based on the established VAR model, we apply a one-standard-deviation shock to each of the two variables—physical education teachers' digital teaching competence (TDC) and student physical activity participation (SP). Following the AIC and SC principles, we set the impulse response period to 8 periods to examine the dynamic interaction response paths between physical education teachers' digital teaching competence and student physical activity participation over the next 8 periods.

The impulse response paths of student physical activity participation to shocks to itself and to physical education teachers' digital teaching competence are shown in Figure 2. Figure (a) displays the impulse response path of student physical activity participation following a one-standard-deviation shock to itself. As shown in the figure, the impulse response of student physical activity participation to a one-standard-deviation shock to itself is positive. Furthermore, this impact effect peaks in the first period, then declines gradually; after the fourth period, its influence continues to weaken, gradually approaching zero. This indicates that the response of student physical activity participation to a shock to itself has a positive effect, which peaks in the first two periods and then gradually weakens over time until it disappears. Figure (b) displays the impulse response path of student physical activity participation following a one-standard-deviation shock to physical education teachers' digital teaching capabilities. As shown in the figure, the response to a one-standard-deviation shock in student physical activity participation regarding physical education teachers' digital teaching capabilities is zero in the first period—indicating no initial response—followed by a rapid increase in response. It peaks in the third period, maintains a strong positive effect from the third to the fifth periods, and then declines gradually while still retaining a strong positive effect. These results align with the interactive pathways and patterns between student physical activity participation and the development of physical education teachers' digital teaching competencies in China. Physical education teachers' digital teaching competencies serve as a crucial foundation for promoting the development of student physical activity participation.

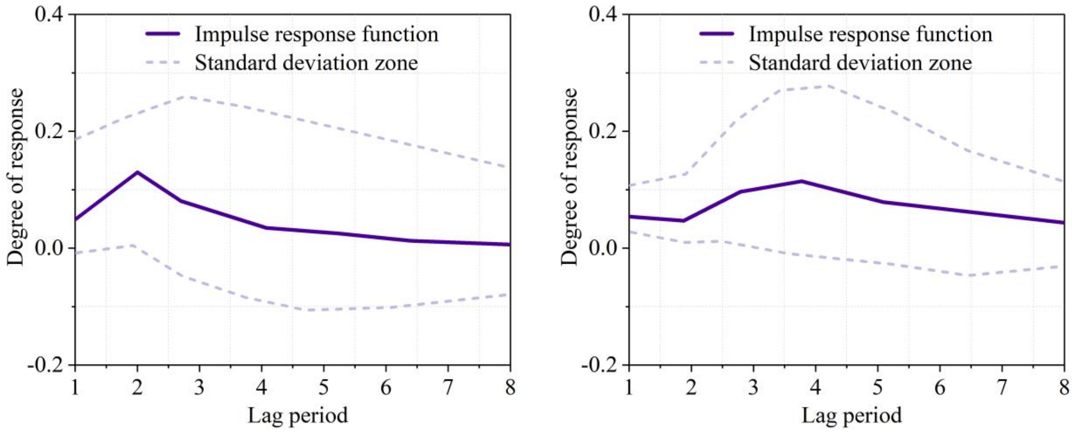


(a) The student movement participates in the pulse response path of itself

(b) The student movement participates in the pulse response path of the impact

Figure 2. The pulse response path of the student movement

Figure 3 illustrates the impulse response paths of physical education teachers' digital teaching competencies on students' physical activity participation and their own performance. Figure (a) illustrates the impulse response path of physical education teachers' digital teaching competencies following a one-standard-deviation shock to student physical activity participation. As shown in the figure, the response path of physical education teachers' digital teaching competencies to the shock on student physical activity participation remains positive throughout, reaching a maximum in the second period before gradually declining toward zero. This indicates that the development of student physical activity participation has a positive promotional effect on the development of physical education teachers' digital teaching competencies, and this positive effect gradually weakens over time until it disappears. Figure (b) illustrates the impulse response path of physical education teachers' digital teaching capabilities to a one-standard-deviation shock to their own capabilities. The impulse response curve indicates that the response to this self-shock remains relatively stable in the first and second periods, then rapidly amplifies, and begins to decline slowly from the fifth period onward; however, the positive effect persists for a relatively long period. This indicates that physical education teachers' digital teaching competencies exhibit a positive response to a one-standard-deviation shock to their own competencies, and this positive response is highly significant with a long-lasting effect. In summary, physical education teachers' digital teaching competencies generate positive responses to both student physical activity participation and shocks to their own competencies, with stable effects that persist over a relatively long period.



(a) The pulse response path of the student movement

(b) The ability of physical education teachers to respond to their impact

Figure 3. Pulse response path of the digital teaching ability of PE teachers

4.8. Analysis of Variance

The impulse response function describes the impact of a one-standard-deviation shock to an endogenous variable on other endogenous variables in a vector autoregressive (VAR) model. To further analyze the contribution of shocks to endogenous variables to changes in those variables—and thereby assess the importance of different endogenous variables and the dynamic characteristics of each variable—we introduce variance decomposition. Variance decomposition provides information on the relative importance of each random term generated by each variable in a VAR model.

The results of the variance decomposition are shown in Table 10. The data indicate that the contribution rate of students' physical activity participation to their own behavior was 100% in the first period, rapidly declined to 75.88448% in the second period, and continued to decline at a relatively fast pace in subsequent periods. It gradually stabilized in the seventh and eighth periods, dropping to 33.27835% by the eighth period. Regarding the contribution rate of physical education teachers' digital teaching capabilities to fluctuations in student physical activity participation, this rate showed a rapid upward trend after the second period, reaching 72.08104% in the eighth period. This indicates that as the lag period lengthens, the influence of physical education teachers' digital teaching capabilities on fluctuations in student physical activity participation exhibits a steady upward trend and sustained growth, characterized by a gradually widening rate of increase. It is evident that among the factors influencing the development of student physical activity participation, changes in physical education teachers' digital teaching capabilities make a highly significant contribution, with a long-lasting impact and substantial effect. These findings demonstrate that the development of physical education teachers' digital teaching capabilities plays a crucial role in promoting the development of student physical activity participation.

Regarding changes in physical education teachers' digital teaching competencies, the contribution rate of student participation in physical activities reached 19.46843% in the first period, rose to 54.71508% in the second period, and then gradually weakened until it disappeared. The self-contribution rate of physical education teachers' digital teaching competencies reached 82.01387% in the first period, before suddenly dropping in the second period and then gradually recovering, rising to 83.42624% in the eighth period. It can thus be seen that, among the factors influencing changes in physical education teachers' digital teaching competencies, the contribution rate of student participation in physical activities should not be underestimated, particularly given its significant contribution at the levels lagging by 2, 3, and 4 periods, which reflects the guiding role of student participation in the development of physical education teachers' digital teaching competencies.

Table 10. Variance decomposition results

Lag period	SP variance decomposition		TDC variance decomposition	
	SP	**TDC**	**SP**	**TDC**
1	100.0000	0.000000	19.46843	82.01387
2	75.88448	25.97037	54.71508	45.26657
3	56.5691	44.14538	36.66554	63.8423
4	41.43125	54.64176	28.3505	69.85754
5	38.51865	63.42155	23.80207	77.61346
6	34.65317	65.2894	21.49556	79.34818
7	33.5162	68.29683	19.47462	83.42624
8	33.27835	72.08104	18.27613	83.77394

5. Conclusion

This study examines the digital teaching competencies of physical education teachers and students' physical activity participation as research variables. Using vector autoregression (VAR) models, impulse responses, and Granger causality tests, it explores the mutual driving effects and response pathways between these two variables. The findings are as follows:

(1) In the gender comparison analysis of physical activity participation levels, the Cohen's d values for male and female students in terms of participation, intensity, duration, and frequency were 0.2, 0.08, 0.27, and 0.16, respectively. Variance tests indicated that male students scored significantly higher than female students in total participation scores, intensity, duration, and frequency. Therefore, in physical education instruction, physical education teachers should adopt proactive approaches to address female students' negative attitudes toward physical education and stimulate their willingness to actively participate in physical activities.

(2) The positive impact of student physical activity participation on physical education teachers' digital teaching competencies is strong initially but weakens over time. The impact of physical education teachers' digital teaching competencies on student physical activity participation manifests

rapidly in the short term, but this effect gradually diminishes and eventually disappears as time passes.

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