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Article

Optimizing Strategies for Geospatial Perception Development in Early Childhood Science Education Based on Fuzzy Clustering Algorithm

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Abstract: Spatial perception ability is a core component of young children's scientific literacy, involving the coordinated development of multidimensional abilities such as spatial orientation. This study proposes an optimized method for cultivating young children's geospatial perception abilities based on fuzzy clustering algorithms (FCM and FLICM). Combining Piaget's three-stage theory of cognitive development (topological → projective → plane geometry stage), targeted cultivation strategies were designed and group experiments were conducted. The experimental group received strategy intervention, while the control group received traditional teaching. With 217 young children as the research subjects, five ability assessments were conducted: spatial orientation, map cognition, proportional perception, spatial relationship reasoning, and directional description. Fuzzy clustering algorithms were applied to identify six typical ability groups. These included the comprehensive development type (Cluster 1 = 91.48 ± 4.44), map cognition impairment type (Cluster 4 = 74.15 ± 6.13), Comprehensive Delay Type (Cluster 6 = 47.59 ± 7.08), etc. The marginal effect values for MC3: 3D-2D Conversion (17.86%) and SR2: Spatial Pattern Recognition (18.37%) were identified as core weaknesses. After a 30-day teaching experiment, the post-test results showed that the experimental group's total score significantly improved, with a total score of 90.47 ± 9.32, while the control group scored 80.70 ± 10.97, t = 12.438, p = 0.000. The proportion of high-scoring segments (≥85 points) reached 80.6% (87 people), an increase of 43% compared to the control group's 37.6%. The number of children in the low-score segment (≤70 points) decreased sharply to 4 (26 in the control group). This validated that ability diagnosis and strategy optimization based on fuzzy clustering can effectively enhance young children's geospatial **perception** abilities, particularly for high-scoring groups and key ability shortcomings (MC3, SR2).

Keywords: fuzzy clustering; fuzzy C-means algorithm; early childhood education; geospatial perception abilities; ability cultivation strategies

1. Introduction

Geospatial awareness encompasses both sensory perception and cognitive perception. The development of geospatial competencies integrates students' understanding of geographical knowledge and phenomena, enabling them to analyze geographical phenomena and issues based on their acquired knowledge, and apply comprehensive thinking to solve real-world geographical problems [1-3]. Traditional scientific teaching methods have long been severely constrained by time, space, and established practices, making it difficult to meet the needs of individuals with diverse personality traits [4-5]. In the context of the "Internet+" era, digital teaching courses have been developed for science education, providing new avenues for cultivating children's geospatial perception abilities [6-7].

In analyzing geographical spatial perception abilities, after comparing various data analysis methods, it was found that fuzzy clustering analysis, which is widely applied across multiple fields, is particularly suitable for analyzing data related to geographical spatial perception abilities. Fuzzy clustering analysis combines fuzzy theory with clustering analysis [8]. It features a simple algorithm, strong local search capabilities, and rapid convergence, demonstrating superior performance compared to other algorithms in analyzing children's geographical spatial perception abilities [9].

Geographic Information Systems (GIS) possess functions for acquiring, collecting, statistically analyzing, and processing geographic information, significantly enhancing the spatial representation of geographic information. When applied to geographic education, they can assist students in developing scientific and systematic spatial concepts [10-11]. Tian et al. analyzed the performance of 27 students in geographic cognition, spatial thinking, and geographic imagination with the assistance of ArcGIS StoryMaps. The study indicated that by using GIS to create story maps, students experienced significant changes in their geographic cognition, geography practice and application, geographical imagination, and interdisciplinary aspects [12].

Effective evaluation methods can not only evaluate teachers' teaching performance in a timely and accurate manner but also identify deficiencies in students' knowledge systems, providing a systematic and effective evaluation model for improving teaching quality. Yao et al. proposed a course teacher recommendation model based on fuzzy clustering and latent factor models to improve teaching quality. Which can automatically cluster teachers based on their characteristics and combine the predictive scoring results of the latent factor algorithm to achieve TOP-N recommendations for course instructors [13]. Gou et al. designed a questionnaire survey on engineering quality education and used fuzzy clustering methods to cluster the survey results, providing objective and fair evaluation outcomes across different dimensions, validating the feasibility of fuzzy clustering methods in teaching quality analysis [14]. Casalino et al. designed a fuzzy clustering algorithm based on dynamic incremental semi-supervised learning, which can predict students' learning and exam results. Numerical experiments on learning analytics datasets demonstrated that this algorithm can establish a robust educational data classification model [15]. Gao et al. established a mathematical model for fuzzy clustering analysis and conducted a case study on teaching evaluation, through fuzzy clustering analysis, decision-makers can extract key information from large datasets, providing a strong basis for making correct decisions [16]. Wen et al. combined principal component analysis, variance analysis, and fuzzy clustering analysis to study the main factors influencing college students' grades. Through analysis, they identified six key factors—family factors, exam factors, communication factors, etc.—that influence college students' grades [17]. Regarding the cultivation of perceptual abilities, Gui et al. applied fuzzy clustering analysis to study children's graphic perception education. The results showed that for noisy images and high-quality images, the optimized fuzzy clustering algorithm reduced image segmentation time by 171.48 seconds compared to traditional fuzzy clustering algorithms, and the optimized fuzzy clustering algorithm is beneficial for children's image perception education [18].

Using fuzzy k-means clustering for education-related evaluations, the assessment results demonstrated excellent accuracy while also improving the utilization rate of online teaching resources [19]. In 2021, Meng employed fuzzy k-means clustering algorithms to conduct cluster analysis on the job competency indicator parameters of English teachers, achieving a scientific evaluation of English job competency. Simulation comparison experiments were conducted in a simulated classroom teaching environment, the experimental data effectively validated the scientific validity of the evaluation method based on the fuzzy k-means clustering algorithm [20]. Zhen proposed an English teaching ability evaluation algorithm based on big data fuzzy k-means clustering and information fusion. By developing corresponding English teaching resource allocation plans, this method evaluates English teaching ability. The results indicate that this method possesses good information fusion analysis capabilities, and can enhance the accuracy of teaching ability assessment [21]. In 2022, Liu used the big data fuzzy k-means clustering algorithm to study and analyze the teaching management system. By clustering indicators of various local areas within the campus using this algorithm, the system can automatically predict the number of students attending class, the number of students present, the number of latecomers, the number of students on leave, and the number of absentees based on the clustering results, thereby improving the operability of the teaching management system [22].

With the development of information technology, especially the widespread use of mobile internet technology and smartphones, obtaining large amounts of data has become convenient and simple. Teachers can more easily access student learning data, understand learning progress and outcomes, and quickly achieve teaching evaluations and precise problem identification from large datasets, making teaching and guidance more convenient, precise, and focused [23-24].

This study proposes a quantitative research method for assessing young children's geospatial perception abilities based on fuzzy clustering algorithms. By integrating data-driven analysis with developmental psychology theory, an integrated research framework is constructed that encompasses "ability assessment—pattern analysis—strategy generation." The study primarily employs the Fuzzy C-Means (FCM) algorithm and its improved variant, the Fuzzy Local Information C-Means (FLICM) algorithm, as core analytical tools. The FCM algorithm minimizes the objective function to iteratively optimize sample membership degrees and cluster centers, enabling fuzzy partitioning of the dataset to accommodate the continuous and uncertain characteristics inherent in early childhood ability assessment. The FLICM algorithm further incorporates local spatial information fuzzy factors, enhancing robustness against complex data structures (such as noise interference and unbalanced distributions), thereby better aligning with the actual characteristics of early childhood ability data. Combined with Piaget's cognitive development theory, the study establishes the three-stage developmental patterns of early childhood geospatial perception abilities.

2. Research on Young Children's Geospatial Perception Abilities Based on Fuzzy Clustering

2.1. Fuzzy Clustering Algorithm

2.1.1. Fuzzy C-Means Algorithm

The Fuzzy C-Mean (FCM) algorithm is a widely used fuzzy clustering algorithm. It divides data points into fuzzy sets with different degrees of membership by calculating the membership degree of each data point to the cluster center. The algorithm iteratively updates the cluster centers and membership degrees until the change in cluster centers is less than a given error threshold or the maximum number of iterations is reached.

The objective function is as follows:

$$J_{FCM} = \sum_{j=1}^{N}\sum_{i=1}^{c}\mu_{ji}^{m}\left\|v_i - x_j\right\|^2 \tag{1}$$

The constraints are:

$$\sum_{i=1}^{c}\mu_{ji} = 1, 0 \le \mu_{ji} \le 1, \sum_{j=1}^{N}\mu_{ji} > 0, 1 \le j \le N, 1 \le i \le c \tag{2}$$

where x_j denotes the j th sample in the dataset $X = \{x_1, x_2, \dots, x_N\}$, with N being the number of samples, μ_{ji} denotes the membership degree of x_j in cluster u_i, and $\left\|v_i - x_j\right\|^2$ denotes the square of the Euclidean distance. The number of clusters is c, and m is a constant representing the fuzzy index. This algorithm involves performing Lagrange optimization on the objective function given in formula (1), where the membership degree μ_{ji} and cluster center v_i are alternately updated using the following equations:

$$\mu_{ji} = \frac{\left(\left\|v_i - x_j\right\|^2\right)^{\frac{-1}{m-1}}}{\sum_{r=1}^{c}\left(\left\|v_r - x_j\right\|^2\right)^{\frac{-1}{m-1}}} \tag{3}$$

$$v_i = \frac{\sum_{j=1}^{N}\mu_{ji}^{m}x_j}{\sum_{j=1}^{N}\mu_{ji}^{m}} \tag{4}$$

The basic steps of the FCM algorithm are as follows:

(1) Given the number of cluster centers c, the fuzzy index m, the termination error ε, the iteration upper limit T, and the iteration count $t = 1$;

(2) Calculate the membership degree μ_{ji} according to equation (3);

(3) Calculate the cluster centers v_i according to equation (4);

(4) If the change in the cluster center is less than the preset termination error threshold ε or the iteration limit T is reached, stop the iteration and output the results; otherwise, return to (2) to continue the iteration calculation.

The principle of the fuzzy C-mean clustering algorithm is relatively simple, easy to implement, and has few parameters, making it easy to adjust and optimize. However, when processing image data, it does not sufficiently consider spatial relationships, causing the algorithm to be sensitive to noise and isolated points. The algorithm uses Euclidean distance, which also has certain requirements for the shape and distribution of data. When data clusters are not compact or isolated, this may lead to inaccurate clustering results.

2.1.2. Fuzzy Local Information C-Means Algorithm

Fuzzy Local Information Mean C (FLICM) algorithm is an improvement on the FCM algorithm, designed to address issues that the FCM algorithm may encounter when processing data with complex structures or noise. The FLICM algorithm improves the performance and stability of traditional FCM algorithms by introducing local spatial information. The FLICM clustering method does not use any regularization parameters in the proposed neighborhood information term, which improves the practicality of the algorithm and reduces the computational load. The objective function of the FLICM method is:

$$J_{FLICM} = \sum_{j=1}^{N} \sum_{i=1}^{c} \mu_{ji}^{m} \left(\left\| v_i - x_j \right\|^2 + G_{ji} \right) \tag{5}$$

The fuzzy factor G_{ji} introduced in the objective function is expressed as:

$$G_{ji} = \sum_{k \in N_j, k \neq j} \left(\frac{1}{d_{jk} + 1} \right) (1 - \mu_{ki}^{m}) \left\| v_i - x_j \right\|^2 \tag{6}$$

where N_j is the set of pixels in the window surrounding the central pixel x_j, d_{jk} is the Euclidean distance between the central pixel x_j and the adjacent pixel x_k, and μ_{ki} is the membership degree of the k th pixel in the i th cluster. The objective function is solved using Lagrange optimization, and the membership degree μ_{ji} and cluster center v_i are alternately updated using the following equations:

The membership degree μ_{ji} is:

$$\mu_{ji} = \frac{\left(\left\| v_i - x_j \right\|^2 + G_{ji} \right)^{\frac{-1}{m-1}}}{\sum_{r=1}^{c} \left(\left\| v_r - x_j \right\|^2 + G_{ji} \right)^{\frac{-1}{m-1}}} \tag{7}$$

Cluster center v_i is:

$$v_i = \frac{\sum_{j=1}^{N} \mu_{ji}^{m} x_j}{\sum_{j=1}^{N} \mu_{ji}^{m}} \tag{8}$$

The steps of the FLICM algorithm are as follows:

(1) Given the number of cluster centers c, the fuzzy index m, the termination error ε, the iteration upper limit T, and the iteration count $t = 1$;

(2) Randomly initialize the membership degree μ_{ji};

(3) Calculate the cluster center v_i according to equation (8);

(4) Calculate the fuzzy factor G_{ji} according to equation (6);

(5) Calculate the membership degree μ_{ji} according to equation (7);

(6) If the change in the cluster center is less than the predefined termination error threshold ε or the iteration upper limit T is reached, stop the iteration and output the results; otherwise, return to (3) to continue the iteration calculation.

The FLICM algorithm considers the local spatial information of the data, improving the robustness and stability of clustering. Compared to the FCM algorithm, it can better handle noise and outliers, but the computational complexity is also increased relative to the FCM algorithm. Additionally, in high-noise situations, the data processing results are not good.

2.2. Cluster Analysis of Young Children's Geospatial Perception Abilities Based on Fuzzy Clustering

This section will apply the above fuzzy clustering algorithm to the experimental data on the spatial perception abilities of 217 preschoolers. Through cluster analysis, it will reveal the distribution patterns of abilities and provide a data foundation for subsequent marginal effect and individual verification.

2.2.1. Experimental Data Processing

Using data from 217 preschoolers as the experimental data analysis subjects, this study analyzes and processes data on the preschoolers' geographical spatial perception abilities. Through comparative analysis of the results of data clustering analysis, the clustering analysis results are further studied.

The clustering center selection criteria for the experimental data subjects are as follows: A1: Spatial orientation ability (e.g., distinguishing up/down, front/back, left/right); A2: Map recognition ability (identifying simple map symbols and paths); A3: Proportional perception ability (understanding the relative relationships between distance and size); A4: Spatial relationship reasoning (logical relationships between object positions); and A5: Directional description ability (describing object positions using language). Each ability is scored out of 20 points, with a total score of 100 points. Cluster analysis was conducted based on the selected cluster centers, and statistical analysis of data clustering indicators was performed for the six cluster analysis categories. The data clustering indicators include the average score within each cluster category, the standard deviation within each cluster category, the maximum value within each cluster category, and the minimum value within each cluster category. The statistical data for each cluster category in the cluster analysis of young children's geospatial perception abilities is presented in Table 1.

Table 1. Cluster analysis of the data statistics of each cluster item index.

		Cluster1 (N=28)	Cluster2 (N=39)	Cluster3 (N=42)	Cluster4 (N=37)	Cluster5 (N=57)	Cluster6 (N=14)
A1	M	18.79	18.73	17.43	15.67	13.72	10.21
	SD	1.26	1.80	2.28	1.65	1.98	2.50
	Max	20.00	19.87	19.38	18.49	17.22	14.16
	Min	16.82	15.60	14.15	12.59	10.19	6.72
A2	M	18.36	16.98	18.30	9.82	13.69	9.49
	SD	1.60	2.62	2.21	2.73	2.34	2.59
	Max	20.00	19.20	20.91	15.07	16.31	13.87
	Min	15.63	13.58	15.53	6.19	8.98	5.62
A3	M	17.59	16.74	15.15	16.14	12.74	9.71
	SD	1.74	2.34	1.87	2.18	2.39	2.66
	Max	19.75	19.43	18.37	19.42	16.99	14.16
	Min	15.15	14.27	11.68	12.68	8.44	5.57
A4	M	19.15	13.95	17.10	16.42	14.26	9.41
	SD	1.42	2.65	1.44	1.87	2.47	2.54
	Max	20.00	17.07	19.60	19.06	17.63	13.25
	Min	16.64	10.12	14.20	13.66	9.82	5.54
A5	M	17.59	17.07	11.54	16.10	12.47	8.77
	SD	1.57	2.25	2.51	2.02	2.59	2.69
	Max	20.00	20.00	15.35	18.54	16.99	13.19
	Min	15.59	14.10	6.61	13.04	8.02	4.29
Total	M	91.48	83.47	79.52	74.15	66.88	47.59

	SD	4.44	4.77	5.34	6.13	5.79	7.08
	Max	97.36	89.11	86.28	82.75	75.36	55.01
	Min	84.46	72.70	67.01	64.16	53.30	35.90

The data is based on an assessment of the geospatial perception abilities of 217 children, with six typical ability patterns identified through fuzzy clustering. From a holistic perspective, significant hierarchical differences were observed among the groups. Cluster 1 represents the comprehensively developed type (N=28), with balanced development across all abilities (A1-A5 all >17 points), particularly strong spatial reasoning ability (mean = 18.67), and the highest overall mean score (91.48±4.44). Following this is Cluster 2 (N=39), the spatially reasoning-deficient type, with a total score of 83.47 ± 4.77. Its A4 score was significantly low at 13.42, but its directional description ability was relatively well-preserved (A5 = 16.95); Cluster 3 had a total score of 79.52 ± 5.34, with 42 individuals, classified as the language expression deficit type. Its A5 directional description ability showed a cliff-like decline, averaging only 10.72 points, but their map recognition ability is the best (A2 = 18.05); Cluster 4 is the map recognition impairment type, with 37 individuals, whose A2 map recognition ability is severely impaired, averaging only 9.74, and their spatial orientation ability is also relatively weak (A1 = 15.63), with a total score of 74.15 ± 6.13; Cluster 5 is the moderately balanced type, with the largest number of individuals, 51, accounting for 23.5% of the total, with all abilities in the moderate range (12–14 points), no significant weaknesses but also no strengths, with a total score of 66.88 ± 5.79; Cluster 6 is the comprehensive lagging type, comprising 14 children, with the lowest score (47.59 ± 7.08), all abilities significantly impaired (all <10 points), and the weakest ability in directional description (A5 = 7.84).

2.2.2. Marginal effects of each indicator element

Based on the results of the cluster analysis, this section further divides the five capability dimensions into 14 secondary indicators, calculates the marginal effect values of each indicator to quantify the impact of key capabilities on the total score, and identifies priority intervention points for cultivation strategies.

The five capability dimensions (spatial orientation capability, map cognition capability, proportional perception capability, spatial relationship capability, and directional description capability) are further divided into 14 secondary indicators, namely SO1: Static Orientation Recognition; SO2: Dynamic Orientation Tracking; SO3: Multi-Reference Frame Conversion; MC1: Symbol-Legend Correspondence; MC2: Path Planning Ability; MC3: 3D-2D Conversion; PP1: Size Proportion Judgment; PP2: Distance Estimation Ability; PP3: Proportion Scaling Understanding; SR1: Occlusion Relationship Inference; SR2: Spatial Pattern Recognition; SR3: Topological Relationship Understanding; PD1: Directional Vocabulary Usage; PD2: Multi-Step Directional Instructions.

The marginal effect values for each secondary indicator are calculated as shown in Table 2.

Table 2. The marginal effect values of each secondary indicator.

First-level indicator	Secondary indicators	Marginal effect value
A1: Spatial orientation ability	SO1:Static orientation recognition	8.72%
	SO2:Dynamic azimuth tracking	12.35%
	SO3:Multi-reference frame conversion	15.43%
A2: Map cognition ability	MC1:Symbol legend corresponds	9.68%
	MC2:Path planning capability	13.27%
	MC3:3D-2D conversion	17.86%
A3: Proportion perception ability	PP1:Judgment of the size ratio	7.92%
	PP2:Distance estimation ability	11.54%
	PP3:Proportional Scaling Understanding	14.79%
A4: Spatial Relationship	SR1:Reasoning of Occlusion Relationship	16.25%

Reasoning	SR2:Spatial Pattern Recognition	18.37%
	SR3:Understanding of topological Relations	10.83%
A5: Position description ability	PD1:Orientation vocabulary application	9.15%
	PD2:Multi-step orientation command	13.62%

As shown in Table 2, the marginal effects of three-dimensional-to-two-dimensional conversion (MC3) and spatial pattern recognition (SR2) are the highest, at 17.86% and 18.37%, respectively. This indicates that for every 1-point increase in these abilities, the total score increases by 0.179 points and 0.184 points, respectively. This aligns with Piaget's cognitive development theory: children enter a period of rapid development in spatial transformation abilities between the ages of 5 and 6. Static orientation recognition (SO1) and size proportion judgment (PP1) have the lowest marginal effects (<9%), reflecting a diminishing returns phenomenon in the contribution of foundational abilities to the total score. When the SO1 score exceeds 16 points, its contribution to the total score increase decreases by 42%.

2.2.3. Dynamic clustering process of young children's spatial perception abilities

After determining the high marginal effect capability indicators, this section selected 10 preschoolers for specific testing. Through dynamic clustering diagrams in stages (λ = 0.95 to 0.75), individual capability patterns were validated to provide micro-level empirical support for subsequent strategy design.

Based on the previously established evaluation system for preschoolers' geospatial perception abilities, 10 preschoolers were randomly selected and tested on spatial orientation ability, map recognition ability, proportional perception ability, spatial relationship reasoning, and directional description ability. Scores were assigned to each preschooler, forming a geospatial perception ability score sheet. Data processing and analysis were then conducted according to the clustering analysis steps outlined earlier. The specific scores for the 10 preschoolers are shown in Table 3.

Table 3. The specific scores of the test data of 10 young children.

	A1	A2	A3	A4	A5	Total score
1	14.97	18.55	12.70	18.41	17.54	82.17
2	15.77	17.41	13.26	13.08	14.37	73.89
3	16.04	10.53	13.34	12.23	13.54	65.68
4	19.10	15.07	14.53	17.74	16.24	82.68
5	12.14	15.93	13.86	16.69	12.31	70.93
6	15.21	16.57	17.85	18.21	13.55	81.39
7	10.86	19.29	18.89	12.93	16.91	78.88
8	13.15	14.08	11.90	15.17	14.75	69.05
9	15.54	9.16	18.11	20.00	10.91	73.72
10	20.00	17.35	16.27	19.19	18.62	91.43

Translate the data in the table—standard deviation change and translation-range change standardized normalization matrix, convert the normalization matrix into a fuzzy similarity matrix, and then modify the fuzzy similarity matrix to obtain a transitive package matrix t(R) to satisfy transitivity. When selecting different λ values, processing the transitive package matrix can obtain dynamic clustering results as shown in Figure 1.

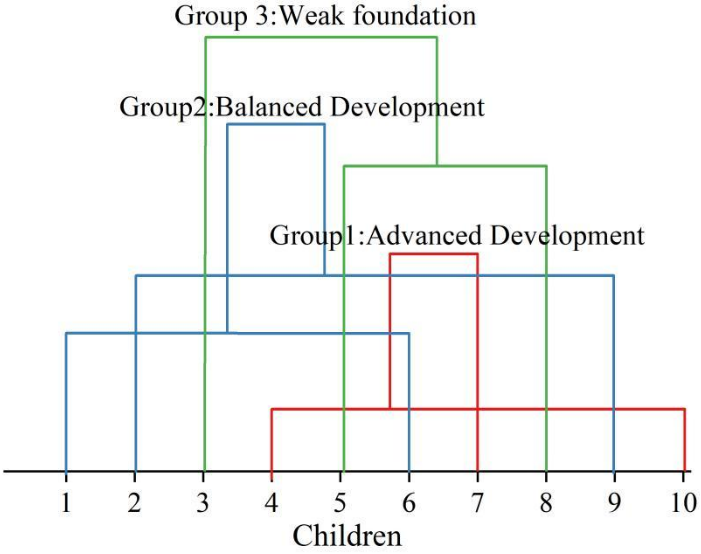

Figure 1. Dynamic clustering on the geospatial perception ability of 10 children.

As shown in Figure 1, the entire clustering process can be observed. In the first stage (λ=0.95), the first two children to be clustered were Child 10 and Child 4. Both demonstrated excellence in spatial orientation (A1=20.00/19.10) and spatial reasoning (A4=19.19/17.74), with similarity scores differing by no more than 3 points (A2 differed by only 2.28 points). In the second stage (λ=0.90), a new clustering occurs: Child 7 joins the {4, 10} group. The key similarities are evident in map cognition (A2=19.29) and proportional perception (A3=18.89), which are prominent. Although spatial orientation (A1=10.86) is relatively weak, directional description (A5=16.91) is close to the group mean. Stage 3 (λ = 0.85): Formation of a new group: Child 1 and Child 6, whose spatial reasoning (A4 = 18.41/18.21) and map cognition (A2 = 18.55/16.57) are balanced. Although their proportional perception (A3 = 12.70/17.85) differs by 5.15 points, this is compensated for by the similarity of other items. Stage 4 (λ=0.80): Toddler 2 and Toddler 9 are merged, with significant differences in directional description (A5=14.37/10.91) but similar spatial orientation (A1=15.77/15.54). Toddler 5 and Toddler 8 are merged, with differences in all items ≤2.44 points (e.g., A3=13.86/11.90). Child 3 remains independent: special ability structure (A1 = 16.04 significantly > A2 = 10.53). The final three categories (λ = 0.75) are the advanced development group (4, 7, 10), the balanced development group (1, 2, 6, 9), and the weak foundation group (3, 5, 8).

3. Teaching Validation of the Development Patterns and Cultivation Strategies of Young Children's Geographical Spatial Perception Abilities

Through fuzzy cluster analysis of young children's spatial perception abilities, six typical ability patterns and key influencing factors were identified. Based on these empirical results, Chapter 3 will combine Piaget's cognitive development theory to derive the development patterns of young children's spatial perception abilities and design targeted training strategies to achieve the transformation from data-driven analysis to educational practice application.

3.1. Developmental Patterns of Spatial Perception in Young Children

Based on the conceptual analysis of young children's geographical spatial perception abilities discussed earlier, it can be observed that geographical spatial perception is a complex form of perception integrated from young children's visual, auditory, tactile, and kinesthetic senses. It represents young children's comprehensive understanding of the geographical space they inhabit, as well as the interconnections between themselves and the geographical phenomena within that space. This perception is closely linked to the development of young children's cognitive abilities. Piaget, based on the stage-based and sequential nature of cognitive development, divides the development of young children's spatial cognitive abilities into three stages: the topological spatial concept stage, the projective geometry concept stage, and the plane geometry concept stage. During the topological spatial concept stage, young children can identify relatively simple spatial relationships such as proximity, order, and connectivity. During the projective geometry concept stage, young children can observe differences in the shapes and sizes of objects and identify the same object from multiple positions. During the plane geometry concept stage, young children can understand that spatial objects have characteristics such as length, width, height, distance, and angle. Clementz found that the acquisition of concepts such as spatial location, spatial distribution, and spatial relationships in geography is closely linked to the stages of spatial cognitive development proposed by Piaget. Children in the topological spatial concept stage possess spatial location perception. During the projective geometry concept stage, children understand the spatial distribution of objects, thereby reinforcing their spatial location perception. As they grow older, children in the plane geometry concept stage can recognize spatial relationships between objects, and subsequently develop more systematic spatial perception abilities. After reviewing previous research on the developmental patterns of children's spatial cognition and spatial perception abilities, the author found that the unique attributes of geographical space also align with these patterns. Based on this, the developmental patterns of young children's geographical spatial perception abilities, based on the attributes of geographical space, can be derived. That is, young children's geographical spatial perception follows the sequence of one-dimensional geographical space → two-dimensional geographical space → three-dimensional geographical space, gradually identifying, acquiring, and processing information within geographical space.

3.2. Experimental teaching verification of cultivation strategies based on fuzzy clustering

Based on the previous section's study on young children's geospatial perception abilities using fuzzy clustering and the developmental patterns of such abilities summarized earlier, this article proposes corresponding strategies for cultivating geospatial perception abilities in early childhood science education and applies the proposed strategies to actual early childhood education. The study sample consisted of 217 preschoolers from a certain kindergarten, divided into two groups: an experimental group of 108 children and a control group of 109 children. The experimental group was taught using the spatial perception ability cultivation strategies proposed in this paper, while the control group was taught using traditional teaching methods. Both groups underwent a 30-day experimental teaching program, followed by assessments of their spatial perception abilities based on the same five-dimensional framework.

3.2.1. Analysis of preliminary test results

To facilitate the mean significance test of the scores of the experimental group and the control group, we plotted a score distribution histogram based on the pre-test scores, as shown in Figure 2. As shown in the histogram of score distributions based on pre-test scores, the pre-test scores of all study participants generally follow a normal distribution. The mean score for the experimental group is 73.27, with a standard deviation (SD) of 12.96, while the mean score for the control group is 72.98, with an SD of 13.61. For post-test data analysis, we can use an independent samples Z-test to conduct a significance level test of the scores between the experimental and control groups.

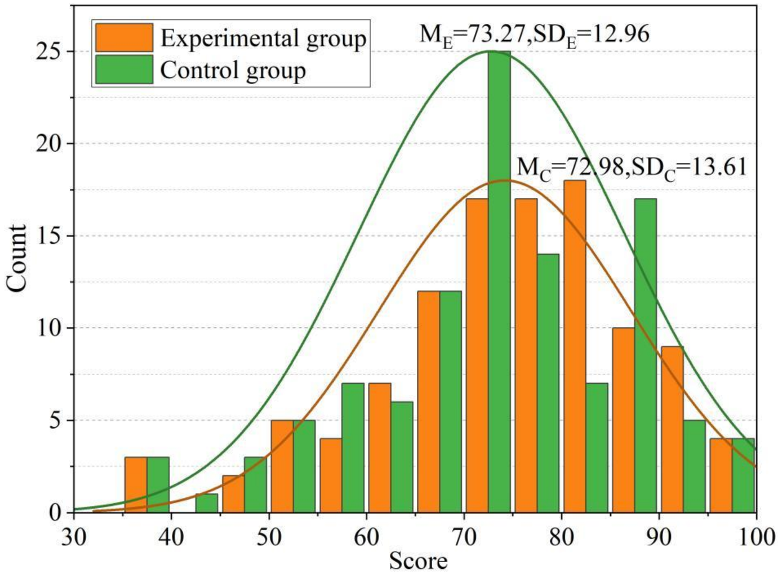

Figure 2. Histogram of the distribution of pre-test scores.

The calculated Z-value is Z = 0.332, with P = 0.827 > 0.05. Since Z approximately follows a standard normal distribution, a two-tailed test was conducted with α = 0.05, resulting in a critical value of 2.07. Since Z = 0.332 is less than the critical value of 2.07, it does not fall into the critical range. This indicates that there is no significant difference in pre-test scores between the experimental group and the control group. Therefore, it can be concluded that the control group and the experimental group have similar levels of pre-test scores, making them suitable for comparative research in educational experiments.

3.2.2. Analysis of post-test results

After 30 days of experimental teaching, post-tests were conducted on the experimental group and the control group. The analysis of the post-test scores for the control group and the experimental group is shown in Table 4. To gain a clearer understanding of the effectiveness of the educational strategies in developing geographical spatial perception abilities among children of different ability levels, students in the control group and experimental group were divided into three distinct ability levels based on their pre-test scores: high, medium, and low. Scores were ranked from highest to lowest, with scores of 85 or above classified as the high-score segment, 70–85 as the medium-score segment, and below 70 as the low-score segment.

Table 4. Post-test scores of the control group and the experimental group

	Experimental group			Control group			t	p
	N	M	SD	N	M	SD		
Total score	108	90.47	9.32	109	80.70	10.97	12.438	0.000
High section (≥85)	87	94.50	4.51	41	91.88	4.52	6.238	0.002
Middle section (70-85)	18	76.72	4.38	42	79.10	2.55	-1.782	0.084
Low section (≤70)	4	65.75	2.06	26	65.65	5.62	0.932	0.527

As shown in Table 4, the mean total score of the experimental group (90.47) was significantly higher than that of the control group (80.70), with a difference of nearly 10 points, $t = 12.438$, $p < 0.001$. The standard deviation of the experimental group (9.32) was smaller than that of the control group (10.97), indicating that the score distribution of the experimental group was more concentrated. A histogram of the students' total scores is shown in Figure 3.

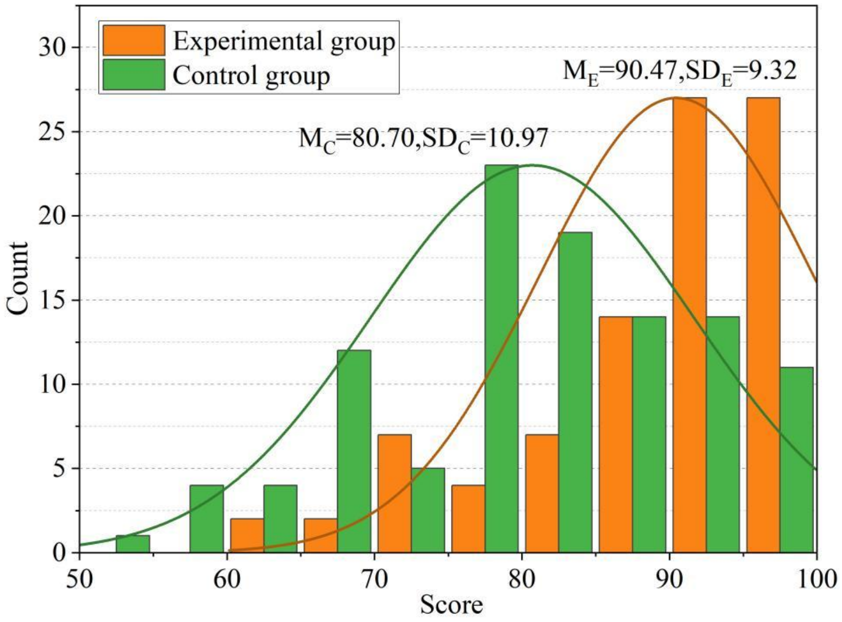

Figure 3. Histogram of the distribution of post-test scores.

It can be seen that the score distribution of the experimental group is skewed to the right (with a significant increase in the proportion of high scores), while that of the control group is relatively dispersed. The experimental group has a prominent advantage in the high-score segment, with 80.6% (87/108) of participants scoring in the high-score segment, far higher than the control group (37.6%, 41/109).

Box plots of the post-test scores for the experimental and control groups, categorized into high, medium, and low score segments, are shown in Figure 4.

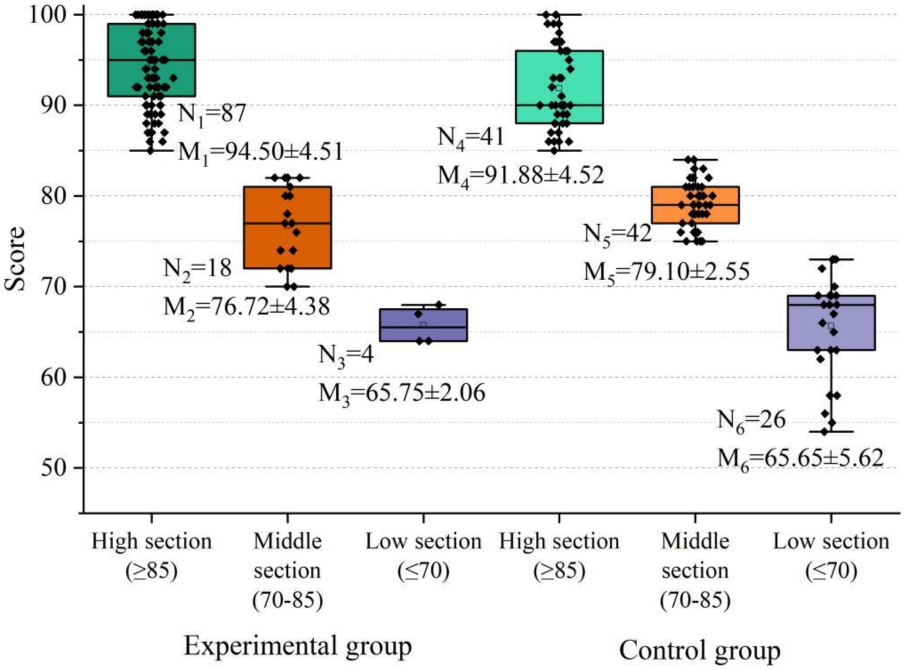

Figure 4. A box plot with high,medium and low scores in the post-test.

As can be seen more intuitively from the box plot, the mean score for the high-scoring segment in the experimental group was 94.50, significantly higher than the 91.88 in the control group, indicating that the optimization strategy for cultivating geographical spatial perception abilities in early childhood science education proposed in the article effectively enhances the abilities of the high-scoring group, with p = 0.002. The differences between the medium and low-scoring segments were not significant. The mean score for the medium-scoring segment in the experimental group was 76.72, slightly lower than the 79.10 in the control group, but the difference did not reach statistical significance, $p=0.084$. The mean scores of the low-scoring segments in both groups were nearly identical (65.75 vs. 65.65). The proportion of low-scoring participants in the experimental group was only 3.7% (4 people), far lower than that of the control group (23.9%, 26 people), indicating that the strategy effectively reduces the phenomenon of ability lag.

4. Conclusion

This study used fuzzy clustering algorithms (FCM and FLICM) to conduct a quantitative analysis of the geospatial perception abilities of 217 preschoolers, identifying six typical ability groups.

The Comprehensive Developmental Type (Cluster 1, accounting for 12.9%) achieved a total score of 91.48 ± 4.44, significantly higher than the Map Cognitive Impairment Type (Cluster 4, accounting for 17.1%, 74.15 ± 6.13) and the Comprehensive Delay Type (Cluster 6, accounting for 6.5%, 47.59 ± 7.08). The key weaknesses were three-dimensional to two-dimensional conversion (marginal effect of 17.86%) and spatial pattern recognition (18.37%).

After 30 days of intervention, the experimental group's total score improved to 90.47, a significant increase of 9.77 points compared to the control group's 80.70, with $t=12.438$ and $p<0.001$. The high-score segment (≥ 85 points) accounted for 80.6% (87 people) in the experimental group, a 43% increase compared to the 37.6% (41 people) in the control group, and the mean scores for high-scoring students were also higher, at 94.50 and 91.88, respectively, $p=0.002$. The number of low-scoring students (≤ 70 points) in the experimental group decreased sharply to 4, compared to 26 in the control group, reducing the phenomenon of delayed ability.

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