Online-Journals.org

iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 23 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i23.45637

PAPER

Exploring Virtual Reality's Impact on Spatial Perception and Creativity in Environmental Design Education

Yu Xiao(✉), Yong Wang, Fangzhi Guo

College of Communication and Art Design, Shanghai for Science and Technology University, Shanghai, China

213513027@usst.edu.cn

ABSTRACT

Virtual reality (VR) technology has been widely used in various industries, and its potential in the field of education has been increasingly recognized and explored in recent times. In environmental design education, spatial perception and creativity are fundamental skills for students. However, there are certain limitations in certain aspects of current evaluation and teaching methods. In light of these concerns, this study aims to reassess these methods and investigate ways to improve the fundamental competencies of students through VR-based landscape education. At first, the entropy weight method and the technique for order of preference by similarity to ideal solution (TOPSIS) method were adopted to develop a new evaluation system for assessing students' spatial perception and creativity. Then, the influence mechanism model of landscape education on students' competencies was constructed and validated. At last, the results have verified that VR technology can effectively enhance students' spatial perception and creativity.

KEYWORDS

virtual reality (VR), landscape education, spatial perception, creativity, entropy weight method, technique for order of preference by similarity to ideal solution (TOPSIS) method, structural equation model (SEM)

1 INTRODUCTION

Virtual reality (VR) is currently a rising star in the field of science and technology these days, creating unprecedented experiences in people's daily lives [1]. Now, VR has been widely used in various fields, including gaming, medicine, and engineering, showcasing its immense potential for application in the education sector. Especially in the education of design majors, the immersive experience provided by VR creates a more realistic and comprehensive learning environment for students [2–10]. Environmental design is a discipline that heavily relies on spatial perception and creative thinking. The use of VR technology to enhance

Xiao, Y., Wang, Y., Guo, F. (2023). Exploring Virtual Reality's Impact on Spatial Perception and Creativity in Environmental Design Education. *International Journal of Emerging Technologies in Learning (iJET)*, 18(23), pp. 84–98. https://doi.org/10.3991/ijet.v18i23.45637

Article submitted 2023-07-06. Revision uploaded 2023-09-29. Final acceptance 2023-10-20.

© 2023 by the authors of this article. Published under CC-BY.

these two competencies in students has become a focal point for educators and researchers.

Landscape education is not only about teaching students' professional knowledge; the more important aspect is to cultivating their observation, perception, and creative abilities. Despite the accumulation of history and experience, traditional teaching methods can hardly meet the needs of modern education in some aspects. The new education tools and methods, such as VR, have provided us with an opportunity to re-examine and reform traditional teaching [11–15]. Exploring and applying VR-based landscape education not only provides environmental design students with more vivid three-dimensional learning experiences but also fundamentally enhances their spatial perception and creativity.

Landscape education has a long history of research, and numerous scholars have proposed a variety of evaluation and teaching methods for it [16–18]. However, with social and technological changes, some traditional methods have begun to reveal their limitations. These methods are subjective and cannot accurately reflect the real abilities of students. Some methods are too simple in terms of methodology and fail to evaluate students' abilities from multiple aspects [19, 20]. In the constantly maturing context of VR technology, the conventional research methods of landscape education can hardly meet the needs of modern education.

The discussion in this study is divided into two parts. In the first part, the entropy weight method and technique for order of preference by similarity to ideal solution (TOPSIS) method were introduced to create a more objective and comprehensive evaluation system for assessing the spatial perception and creativity of students majoring in environmental design. In the second part, we discussed the specific mechanism by which landscape education influences students' competences. We constructed a corresponding hypothetical model and conducted verification using a structural equation model (SEM). The objective of this research is to create a new perspective and tool for landscape education. This will help educators better develop students' core competencies and provide a useful reference for research in related fields.

2 EVALUATION OF SPATIAL PERCEPTION AND CREATIVITY OF ENVIRONMENTAL DESIGN STUDENTS

Figure 1 represents a diagram illustrating the research route of this study. At first, several evaluation criteria for assessing the spatial perception and creativity of environmental design students were proposed. Specifically, three layers of evaluation criteria are included. The first evaluation criterion layer has five indicators, the second evaluation criterion layer has four indicators, and the third evaluation criterion layer also has four indicators.

2.1 Spatial cognition and interpretation

Indicator A: Spatial structure recognition ability—students can accurately recognize and interpret the fundamental structure of space.

Indicator B: Perception of spatial proportion and scale refers to students' sensitivity to spatial proportion and scale, as well as their ability to apply these concepts.

Indicator C: Understanding of spatial relationships and continuity—how to comprehend and apply the relationships and continuity between spaces.

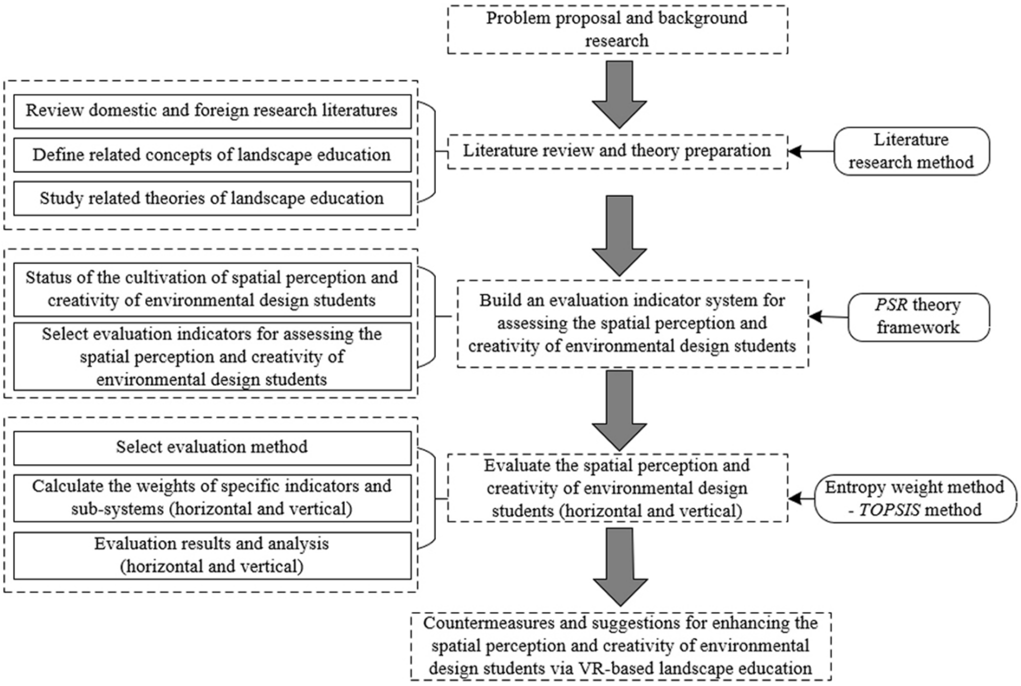

Fig. 1. Research route

Indicator D: Perception of colors and materials in space—the ability to use and perceive colors and materials in space.

Indicator E: Contextual experience of spatial environment—students' ability to perceive and interpret the context and ambiance of a space from the user's perspective.

2.2 Creativity and design expression

Indicator A: Novelty of the design—evaluate whether a student's design is innovative and distinctive.

Indicator B: Functionality of the design—assess whether a student's design is practical and can meet functional requirements.

Indicator C: Presentation skills—students' ability to utilize various tools and techniques to articulate their design concepts.

Indicator D: Balance between the whole and its parts—the ability to pay attention to and balance the whole and its parts in the design.

2.3 Communication and cooperation

Indicator A: Teamwork ability—students' ability to collaborate and communicate effectively in a team.

Indicator B: Design interpretation and presentation—the ability to clearly and persuasively explain and present design schemes to others.

Indicator C: Acceptance of feedback and suggestions—the ability to accept external feedback and suggestions and incorporate them into future designs.

Indicator D: Interdisciplinary communication—the ability to integrate and apply knowledge from other disciplines in designs.

When evaluating the spatial perception and creativity of environmental design students, having a comprehensive and precise indicator system is particularly crucial. In this research, the spatial perception and creativity of environmental design students involve multiple indicators of varying importance. If weight assignment is influenced by subjective preferences, then the evaluation results may deviate from the actual situation. The introduction of the entropy weight method can ensure the objectivity of assigned weights, thereby improving the accuracy of evaluation.

The entropy weight method assigns weights to indicators based on the principles of information entropy theory and the distribution characteristics of data, thereby avoiding the influence of subjective preferences. Additionally, the method fully considers the differences in information among all indicators, ensuring that the importance of each indicator is accurately reflected during the assignment of weights.

The entropy weight method is a weight calculation method based on the principle of information entropy. It ensures the objectivity of indicator weights by utilizing of data information effectively. For the research content and objective of this paper, the determination of the weight of evaluation indicators for spatial perception and creativity of environmental design students was carried out according to the following steps:

Step 1: Data standardization. Since multiple indicators are involved in this research, and these indicators may have different scales and units, the first step is to standardize the data. This will ensure that all indicators are on the same scale, making them comparable. Assuming that Z_{uk} represents the score of the *i*-th indicator of the *u*-th object, where u ranges from 1 to b and k ranges from 1 to l, the specific formulas are:

For positive indicators

$$Z'_{uk} = \frac{Z_{uk} - MIN(Z_{1k}, Z_{2k}, \ldots, Z_{bk})}{MAX(Z_{1k}, Z_{2k}, \ldots, Z_{bk}) - MIN(Z_{1k}, Z_{2k}, \ldots, Z_{bk})} \tag{1}$$

For negative indicators

$$Z'_{uk} = \frac{MAX(Z_{1k}, Z_{2k}, \ldots, Z_{bk}) - Z_{uk}}{MAX(Z_{1k}, Z_{2k}, \ldots, Z_{bk}) - MIN(Z_{1k}, Z_{2k}, \ldots, Z_{bk})} \tag{2}$$

Step 2: Calculate indicator weights. The standardized data is used to calculate the weight of each indicator. Specifically, for each indicator, calculate the mean value across all samples, and then determine its proportion based on this mean value. Assuming that O_{uk} represents the proportion of the *u*-th object in the *k*-th indicator, the formula is:

$$O_{uk} = \frac{Z'_{uk}}{\sum_{u=1}^{b} Z'_{uk}} \tag{3}$$

Step 3: Calculate the entropy of each indicator. The information entropy can reflect the degree of difference or dispersion of indicators. For each indicator, its information entropy r_k can be calculated using the following formula:

$$r_k = \frac{\sum_{u=1}^{b} [O_{uk} LN(O_{uk})]}{[-LN(b)]} \tag{4}$$

Step 4: Calculate the weight of each indicator. Calculate the objective weight of each indicator based on their respective information entropy. The objective weight of each indicator, Q_k^p, can be calculated using the following formula:

$$Q_k^p = \frac{1 - r_k}{\sum_{k=1}^{l}(1 - r_k)} \tag{5}$$

In this study, the level of spatial perception and creativity of environmental design students was evaluated using the TOPSIS method, which involved a comprehensive weight assignment. The TOPSIS method is a commonly used multi-indicator decision-analysis method. Considering that environmental design students' spatial perception and creativity have multiple indicators across different dimensions, the use of the TOPSIS method can ensure that appropriate weight values are assigned to each indicator. The comprehensive analysis would result in more objective and accurate evaluation results.

The TOPSIS method takes into account the distance from the ideal solution to the negative ideal solution and fully integrates the information of each indicator, thereby achieving more comprehensive evaluation results. Through calculation and comparison, the TOPSIS method can effectively sort objects based on spatial perception and creativity. The following are the specific steps for evaluating the spatial perception and creativity of environmental design students using the TOPSIS method with comprehensive weight assignment:

Step 1: Construct the normalization matrix. Convert the raw data into a normalized form to eliminate the influence of dimensions on indicators. Assuming that $C_{uk} = Z'_{uk} * Q_k$ represents the comprehensive score of each indicator, the commonly used normalization formula is:

$$C = \{C_{uk}\} = \begin{Bmatrix} C_{11} & C_{12} & \cdots & C_{1l} \\ C_{21} & C_{22} & \cdots & C_{2l} \\ \vdots & \vdots & \vdots & \vdots \\ C_{b1} & C_{b2} & \cdots & C_{bl} \end{Bmatrix} \tag{6}$$

Step 2: Calculate positive and negative ideal solutions. After obtaining the normalization matrix, determine the positive and negative ideal solutions. The positive ideal solution represents the most desirable value for each indicator, while the negative ideal solution represents the least desirable value for each indicator. Assuming that C^+ and C^- represent the positive and negative ideal solutions, respectively, their formulas are as follows:

$$C^+ = \left\{ \underset{u=1,2,\ldots,b}{MAX c_{uk}} \mid k = 1,2,\ldots,l \right\} = \{c_1^+, c_2^+, \ldots, c_l^+\} \tag{7}$$

$$C^- = \left\{ \underset{u=1,2,\ldots,b}{MIN c_{uk}} \mid k = 1,2,\ldots,l \right\} = \{c_1^-, c_2^-, \ldots, c_l^-\} \tag{8}$$

Step 3: Calculate the distance between the evaluation object and the positive and negative ideal solutions. For each evaluation object, calculate its Euclidean distance from the positive and negative ideal solutions. Assuming that F_u^+ and F_u^-

respectively represent the distances from the evaluation object to the positive and negative ideal solutions, then their formulas are:

$$F_u^+ = \sqrt{\sum_{k=1}^{l}(C_{uk} - C_k^+)^2} \tag{9}$$

$$F_u^- = \sqrt{\sum_{k=1}^{l}(C_{uk} - C_k^-)^2} \tag{10}$$

Step 4: Calculate the degree of proximity. Calculate the degree of proximity based on the distance between each evaluation object and the positive and negative ideal solutions, and use it to represent the overall evaluation value of each evaluation object. Assuming that C_iV_u represents the degree of proximity, then its formula is:

$$V_u = \frac{F_u^-}{F_u^+ + F_u^-} \tag{11}$$

In this way, each evaluation object is assigned a proximity value ranging from 0 to 1. The closer the nearness value is to 1, the better the overall performance of an evaluation object. Conversely, the closer the nearness value is to 0, the worse the overall performance of the evaluation object.

3 MODELLING OF THE INFLUENCE MECHANISM OF LANDSCAPE EDUCATION ON THE SPATIAL PERCEPTION AND CREATIVITY OF ENVIRONMENTAL DESIGN STUDENTS

To investigate VR-based landscape education and build a hypothetical model, this paper established three metrics:

1. The metric for evaluating the VR landscape simulation experience (VR-LSE): This metric is used to assess students' and overall experience during VR landscape simulation. Specifically, it is measured from three aspects: the realistic feeling perceived by students in VR, the similarity between VR landscape simulation and the real landscape, and the participation and interaction of students in virtual reality.
2. The VR design experiment capability (VR-DEC) metric: This metric assesses students' ability to experiment and innovate in landscape design using VR technology. Specifically, it is measured from three aspects: the frequency of students attempting different design schemes in VR, the students' ability to make design corrections based on VR feedback, and the novelty of VR-aided design schemes compared to conventional methods.
3. The metric for VR technology acceptance and adoption (VR-TAA): This metric assesses students' acceptance and attitude towards the use of *VR* in landscape education. Specifically, it is measured from three aspects: students' attitudes towards the application of VR in landscape education, students' cognition of the usability and practicality of VR, and students' willingness to continue using or recommending the use of VR technology in the future.

These three metrics create a comprehensive evaluation framework for VR-based landscape education. They can effectively guide the subsequent construction of the hypothetical model, thereby exploring the actual influence of VR technology on the spatial cognition and creativity of environmental design students.

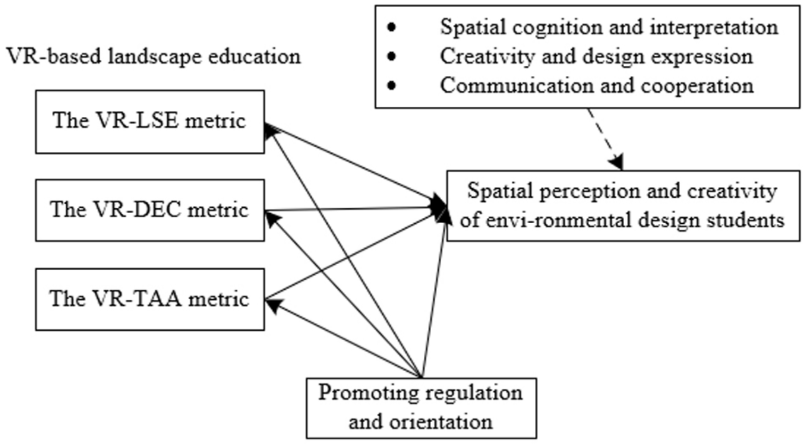

Fig. 2. The research model

Figure 2 presents a diagram illustrating the research model. When constructing a hypothetical model, the first step is to identify each variable and its corresponding metrics. In this paper, the constructed hypothetical model considers the three evaluation criteria of VR-based landscape education and the spatial perception and creativity of environmental design students as variables. The three metrics set for VR-based landscape education and the 13 evaluation indicators of spatial perception and creativity for environmental design students were used as the metrics for the constructed hypothetical model. Then, a hypothetical model was constructed to explain the influence of landscape education on the spatial perception and creativity of environmental design students. The specific hypotheses are as follows:

H1: VR-based landscape education (VR-LE) positively affects the spatial cognition and interpretation of students studying environmental design.
H2: VR-based landscape education (VR-LE) positively affects the creativity and design expression of environmental design students.
H3: VR-based landscape education (VR-LE) positively affects the communication and cooperation of environmental design students.

This hypothetical model can help us gain a deeper understanding of the aforementioned influence mechanism, and it can be validated and expanded upon in subsequent empirical research

The test of a SEM is a comprehensive statistical method for assessing the causal relationship between unobservable latent variables. For the aforementioned hypothetical model, the steps of the SEM test are elaborated below.

At first, an initial SEM was established based on relevant theories and previous studies. The relationships between observed variables and latent variables were then determined.

$$\begin{cases} \lambda_1 = \alpha_{11}\zeta_1 + \varsigma_1 \\ \lambda_2 = \alpha_{21}\zeta_1 + \varepsilon_{21}\lambda_1 + \varsigma_2 \\ \lambda_3 = \alpha_{31}\zeta_1 + \varepsilon_{31}\lambda_1 + \varepsilon_{32}\lambda_2 + \varsigma_3 \end{cases} \tag{12}$$

Assuming that λ_1 represents students' spatial cognition and interpretation, λ_2 represents their creativity and design expression, λ_3 represents their communication and cooperation, ζ_1 represents VR-based landscape education, α represents the path coefficient between endogenous and exogenous variables, ε represents the path coefficient between endogenous variables, and ς represents the residual term of endogenous variables, the matrix expression of the SEM is given by the following formula:

$$\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} = \begin{bmatrix} \alpha_{11} \\ \alpha_{21} \\ \alpha_{31} \end{bmatrix} \begin{bmatrix} \zeta_1 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ \varepsilon_{21} & 0 & 0 \\ \varepsilon_{31} & \varepsilon_{32} & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} + \begin{bmatrix} \varsigma_1 \\ \varsigma_2 \\ \varsigma_3 \end{bmatrix} \tag{13}$$

Data were collected using appropriate research tools, such as questionnaires. In this study, to ensure a sufficiently large sample size, 200 observed values were collected. For each free parameter, there were at least 5–10 observed values. Then, factor analysis was conducted to verify the correlations between metrics and their corresponding latent variables. Assuming: z_1, z_2, z_3 represent the metrics of VR-based landscape education; η_{z11}, η_{z21}, η_{z31} represent factor loads of metrics of VR-based landscape education; σ_1, σ_2, σ_3 represent random errors of metrics of VR-based landscape education; t_1, t_2, t_3, t_4, t_5 represent metrics of spatial cognition and interpretation of students; η_{t11}, η_{t21}, η_{t31}, η_{t41}, η_{t51} represent factor loads of metrics of spatial cognition and interpretation of students; γ_1, γ_2, γ_3, γ_4, γ_5 represent random errors of metrics of spatial cognition and interpretation of students; t_6, t_7, t_8, t_9 represent metrics of creativity and design expression of students; η_{t62}, η_{t72}, η_{t82}, η_{t92} represent factor loads of metrics of creativity and design expression of students; γ_6, γ_7, γ_8, γ_9 represent random errors of metrics of creativity and design expression of students; t_{10}, t_{11}, t_{12}, t_{13} represent metrics of communication and cooperation of students; η_{t103}, η_{t113}, η_{t123}, η_{t133} represent factor loads. The metrics model includes metrics of communication and cooperation among students, represented by; γ_{10}, γ_{11}, γ_{12}, and γ_{13}, which account for random errors. The matrix expression of the metrics model is given by the following formula:

$$\begin{gathered} \begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \end{bmatrix} = \begin{bmatrix} \eta_{z11} \\ \eta_{z21} \\ \eta_{z31} \end{bmatrix} \begin{bmatrix} \zeta_1 \end{bmatrix} + \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \sigma_3 \end{bmatrix} \\ \begin{bmatrix} t_1 \\ t_2 \\ t_3 \\ t_4 \\ t_5 \\ t_6 \\ t_7 \\ t_8 \\ t_9 \\ t_{10} \\ t_{11} \\ t_{12} \\ t_{13} \end{bmatrix} = \begin{bmatrix} \eta_{t11} & 0 & 0 \\ \eta_{t21} & 0 & 0 \\ \eta_{t31} & 0 & 0 \\ \eta_{t41} & 0 & 0 \\ \eta_{t51} & 0 & 0 \\ 0 & \eta_{t62} & 0 \\ 0 & \eta_{t72} & 0 \\ 0 & \eta_{t82} & 0 \\ 0 & \eta_{t92} & 0 \\ 0 & & \eta_{t103} \\ 0 & & \eta_{t113} \\ 0 & & \eta_{t123} \\ 0 & & \eta_{t133} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix} + \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \\ \gamma_6 \\ \gamma_7 \\ \gamma_8 \\ \gamma_9 \\ \gamma_{10} \\ \gamma_{11} \\ \gamma_{12} \\ \gamma_{13} \end{bmatrix} \end{gathered} \tag{14}$$

Next, the SEM was fitted based on the available data, and appropriate statistical methods, such as the maximum likelihood method, were adopted to estimate the model parameters. The path coefficients in the model were examined, and the significance of each path was assessed. At last, the model was adjusted (by adding or deleting paths) to achieve a higher degree of fit. In the test, to ensure an adequate sample size, the samples were selected randomly to ensure the model's universality. In particular, to avoid overfitting caused by overly complex modeling, it is necessary to ensure that each modification of the model is based on a solid theoretical foundation. In the meantime, it is also necessary to ensure that there is no significant correlation between the independent variables, as this could impact the accuracy of parameter estimation.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Nearness value and rank of the evaluation of environmental design students' spatial perception and creativity under different metrics conditions

Rank	Year	Metric	Nearness Value of Each Subsystem	Comprehensive Nearness Value
1	Dataset 4	*VR-LSE*	0.632 (Good)	1.000 (Excellent)
		VR-DEC	0.729 (Good)	
		VR-TAA	0.798 (Good)	
2	Dataset 3	*VR-LSE*	0.612 (Good)	0.625 (Good)
		VR-DEC	0.478 (Average)	
		VR-TAA	0.759 (Good)	
3	Dataset 2	*VR-LSE*	0.328 (Average)	0.259 (Poor)
		VR-DEC	0.345 (Average)	
		VR-TAA	0.421 (Average)	
4	Dataset 1	*VR-LSE*	0.326 (Average)	0.000 (Poor)
		VR-DEC	0.368 (Average)	
		VR-TAA	0.000 (Poor)	

According to Table 1, there are variations in the proximity value of the assessment of spatial perception and creativity among environment design students under different datasets and metric conditions. This suggests that the impact of VR-based landscape education is influenced by various factors. As evident from the data in the table, students in Dataset 4 achieved the highest performance in VR-based landscape education, with a comprehensive nearness value of 1.000, indicating an excellent level. Therefore, it can be concluded that students in Dataset 4 had the best overall performance in VR-based landscape education. They also attained good or excellent levels in VR-LSE, VR-DEC, and VR-TAA, suggesting a high acceptance degree of VR technology among these students or that the quality of VR-based landscape education they received was the highest. Students in Dataset 1 exhibited significant deficiencies across all metrics, particularly in terms of VR-TAA. Their value is 0.000, indicating a low acceptance degree for VR technology. This could be attributed to the quality of the VR-based landscape education they received, or their background knowledge and skills, which hindered their ability to fully utilize or experience VR technology. Overall, VR-based landscape education has significant potential for enhancing the spatial perception and creativity of environmental design students. However, attention must be given to factors such as education quality and students' background knowledge and skills in order to maximize the educational impact.

According to Table 2, all variables yielded good or very good results in terms of factor load, Cronbach's α, composite reliability, and mean variance extraction. This suggests that the variables and their metrics were valid and reliable. Two variables, VR-based landscape education and communication and cooperation, performed the best on all indicators. This means that they had the most significant correlation with other metrics, and their internal consistency and validity were both high. In summary, these variables and metrics are effective tools for assessing the spatial perception and creativity of environmental design students. This provides a solid foundation for further research and practical application.

Table 2. Reliability and validity analysis results

Variable	Metric	Factor Load	*Cron.a*	Composite Reliability	Mean Variance Extraction
VR-based landscape education	*VR-LSE*	0.92	0.91	0.85	0.61
	VR-DEC	0.88			
	VR-TAA	0.92			
Spatial cognition and interpretation	1-*A*	0.87	0.88	0.77	0.57
	1-*B*	0.88			
	1-*C*	0.83			
	1-*D*	0.84			
	1-*E*	0.86			
Creativity and design expression	2-*A*	0.85	0.72	0.73	0.66
	2-*B*	0.86			
	2-*C*	0.77			
	2-*D*	0.78			
Communication and cooperation	3-*A*	0.89	0.92	0.82	0.73
	3-*B*	0.87			
	3-*C*	0.94			
	3-*D*	0.88			

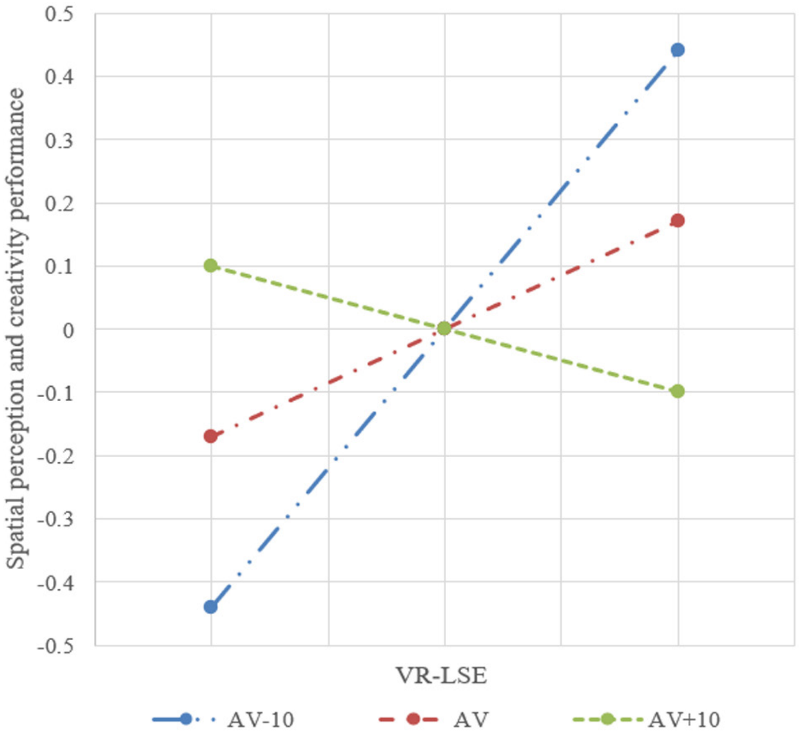

Fig. 3. VR-LSE, promoting regulation and orientation, and spatial perception and creativity performance

According to Figure 3, the relationship between spatial perception and creativity performance is significantly influenced by the level of promotion of regulation and orientation. Under minimal regulatory and orientational influence, the impact of VR-LSE was found to have a negative correlation with spatial perception and creativity performance; however, this relationship varied across different contexts. Under a high degree of regulatory promotion and orientation, the impact of VR-LSE is positively correlated with spatial perception and creativity performance. However, it is important to note that this relationship varied across different contexts. Overall the degree of regulatory promotion and orientation acts as moderating variables that can significantly impact the relationship between VR-LSE and spatial perception and creativity performance. This moderating effect varied across different contexts. Therefore, it is important to consider the level of regulatory promotion orientation when conducting VR-based landscape education.

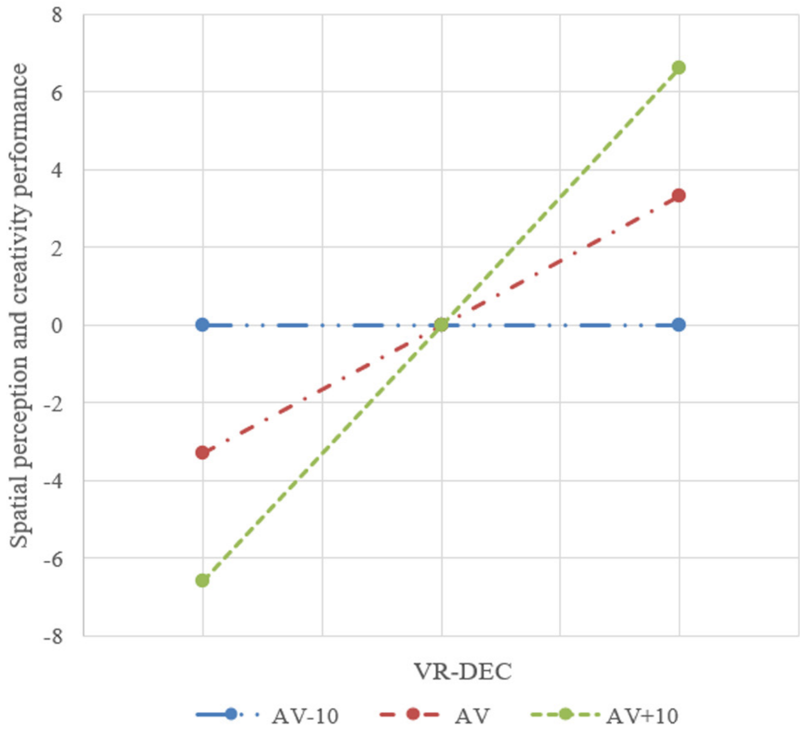

Fig. 4. VR-DEC, promoting regulation and orientation, and spatial perception and creativity performance

According to Figure 4, individuals with a low degree of regulation and orientation showed a negative relationship between the increase of VR-DEC and the decrease of spatial perception and creativity performance. This trend became more pronounced in different contexts. Individuals with a moderate level of regulatory focus and orientation showed no sensitivity to VR-DEC, resulting in no effect or spatial perception and creativity. However, for individuals with a high level of promoting regulation and orientation the increase in VR-DEC was positively correlated with improved performance in spatial perception and creativity. This trend became more pronounced in various contexts. Based on this data, it can be concluded that the relationship between VR-DEC and spatial perception and creativity performance is largely moderated by the degree of regulatory promotion and orientation. This relationship varies in different contexts and is influenced by varying degrees of regulatory promotion and orientation. So, when carrying out VR-based landscape education, it is crucial to consider the extent to which regulation and orientation are promoted among students in order to predict their spatial perception and creativity performance.

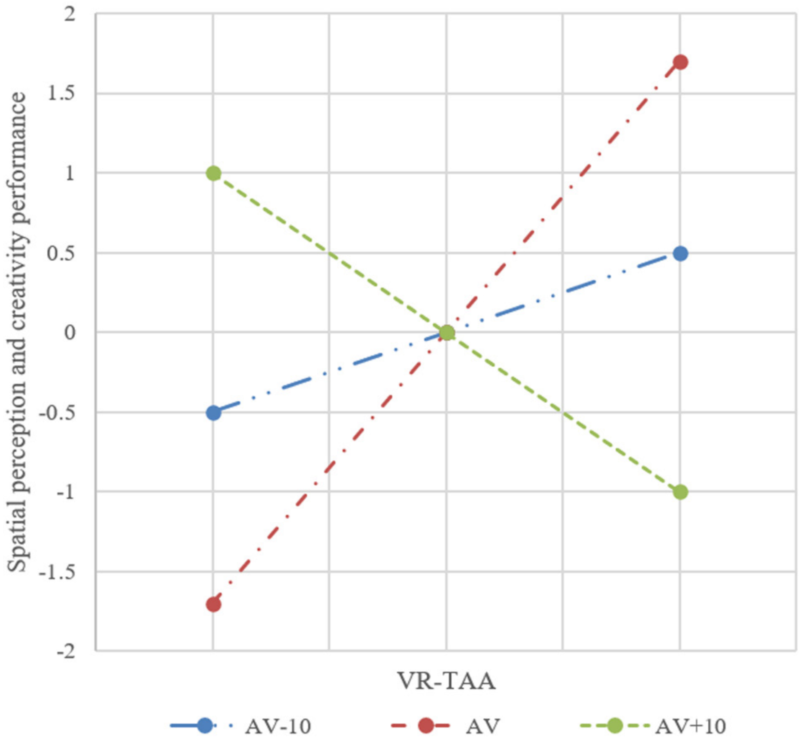

Fig. 5. VR-TAA, promoting regulation and orientation, and spatial perception and creativity performance

According to Figure 5, individuals with a low degree of regulation and orientation showed a negative correlation between spatial perception and creativity performance as VR-TAA increased in two contexts. However, this relationship turned into a positive correlation in the AV + 10 context. Individuals with a moderate level of regulatory promotion and orientation showed no sensitivity to the impact of VR-TAA, and there was no correlation between VR-TAA and spatial perception or creativity performance. However, individuals with a high level of regulatory promotion and orientation exhibited a positive correlation between VR-TAA and spatial perception as well as creativity performance in two scenarios. Interestingly, this relationship turned negative in the AV + 10 scenario. Overall, the relationship between VR-TAA and spatial perception and creativity performance is largely influenced by the level of promotion of regulation and orientation. This relationship exhibits contrasting trends in different contexts and under varying degrees of promotion of regulation and orientation. This suggests that when providing VR-based landscape education, it is important to take into account how changes in students' spatial perception and creativity performance are affected by their level of promoting regulation and orientation.

5 CONCLUSION

This paper investigates the influence of VR-based landscape education on the spatial perception and creativity of students studying environmental design. Through experimentation and data analysis, the role of VR in landscape education was determined. The discussion focused on how VR can effectively enhance students' spatial perception and creativity. The entropy weight method was adopted to determine the objective weights of each metric for evaluating the spatial perception and creativity of environmental design students. Additionally, a TOPSIS method based on comprehensive weight assignment was used to evaluate the spatial perception and creativity of the students. Then, the specific influence mechanism of landscape education on students' competencies was investigated, and the corresponding hypothesis model was constructed and empirically verified using structural equation modeling.

Through reliability and validity analyses, the VR-based landscape education was proven to be reliable and valid. The hypothesis model was then tested using SEM to verify the relationship between VR-based landscape education and students' spatial perception and creativity. Next, the data from different contexts were analyzed in detail, taking into consideration the variables of the degree of promoting regulation and orientation. It was found that this variable has a significant influence on students' spatial perception and creative performance.

Research findings from this paper demonstrate that VR-based landscape education has a significant impact on the spatial perception and creativity of students studying environmental design. Specifically, VR can be used as an effective tool in landscape education to help students enhance their spatial perception and creativity. This paper provides solid theoretical support and empirical evidence for VR-based landscape education. It emphasizes the importance and necessity of integrating VR technology in landscape education.

6 REFERENCES

[1] Y. Kuang, Q. Wang, and J. Jiang, "Analysis and conclusion: Children's safety education games based on VR," in *International Conference on Computer Science and Education*, Singapore, 2022, pp. 585–596. https://doi.org/10.1007/978-981-99-2446-2_53

[2] G. Asiksoy, "Effects of virtual lab experiences on students' achievement and perceptions of learning physics," *International Journal of Online and Biomedical Engineering*, vol. 19, no. 11, pp. 31–41, 2023. https://doi.org/10.3991/ijoe.v19i11.39049

[3] D. Purbohadi, S. Afriani, N. Rachmanio, and A. Dewi, "Developing medical virtual teaching assistant based on speech recognition technology," *International Journal of Online and Biomedical Engineering*, vol. 17, no. 4, pp. 107–120, 2021. https://doi.org/10.3991/ijoe.v17i04.21343

[4] Suyanta, I. Wiludjeng, Jumadi, S. R. D. Astuti, A. R. P. Sari, I. Md Isa, R. Jafaar, and Rahadian, "Virtual laboratory-based game application: The quality and its effects towards students' motivation and self-regulated learning," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 18, pp. 114–132, 2022. https://doi.org/10.3991/ijim.v16i18.32875

[5] B. Kurniawan, R. P. Shrestha, I. K. Astina, N. Hadi, L. Y. Irawan, E. Kurniawati, and A. Wiradimadja, "Developing a virtual nature laboratory of faculty social science (LAV-FIS) to assists field-based learning during pandemic: A need analysis review," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 7, pp. 22–37, 2022. https://doi.org/10.3991/ijim.v16i07.28481

[6] C. Kustandi, D. N. Fadhillah, R. Situmorang, D. S. Prawiladilaga, and S. Hartati, "VR use in online learning for higher education in Indonesia," *International Journal of Interactive Mobile Technologies*, vol. 14, no. 1, pp. 31–47, 2020. https://doi.org/10.3991/ijim.v14i01.11337

[7] M. M. Wielfrid, M. S. Iza, and G. B. Tra, "Information extraction model to improve learning game metadata indexing," *Ingénierie des Systèmes d'Information*, vol. 25, no. 1, pp. 11–19, 2020. https://doi.org/10.18280/isi.250102

[8] F. Sukmawati, E. B. Santosa, and T. Rejekiningsih, "Design of virtual reality zoos through Internet of Things (IoT) for student learning about wild animals," *Revue d'Intelligence Artificielle*, vol. 37, no. 2, pp. 483–492, 2023. https://doi.org/10.18280/ria.370225

[9] Rukayah, J. Daryanto, I. R. W. Atmojo, R. Ardiansyah, D. Y. Saputri, M. Salimi, "Augmented reality media development in STEAM learning in elementary schools," *Ingénierie des Systèmes d'Information*, vol. 27, no. 3, pp. 463–471, 2022. https://doi.org/10.18280/isi.270313

[10] M. Bhatia, P. Manani, A. Garg, S. Bhatia, and R. Adlakha, "Mapping mindset about gamification: Teaching learning perspective in UAE education system and Indian education system," *Revue d'Intelligence Artificielle*, vol. 37, no. 1, pp. 47–52, 2023. https://doi.org/10.18280/ria.370107

[11] Y. V. Tsekhmister, T. Konovalova, B. Y. Tsekhmister, A. Agrawal, and D. Ghosh, "Evaluation of virtual reality technology and online teaching system for medical students in Ukraine during COVID-19 pandemic," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 23, pp. 127–139, 2021. https://doi.org/10.3991/ijet.v16i23.26099

[12] A. A. Eldokhny and A. M. Drwish, "Effectiveness of augmented reality in online distance learning at the time of the COVID-19 pandemic," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 9, pp. 198–218, 2021. https://doi.org/10.3991/ijet.v16i09.17895

[13] V. Laciok, A. Bernatik, and M. Lesnak, "Experimental implementation of new technology into the area of teaching occupational safety for industry 4.0," *International Journal of Safety and Security Engineering*, vol. 10, no. 3, pp. 403–407, 2020. https://doi.org/10.18280/ijsse.100313

[14] A. Kumar, A. K. J. Saudagar, M. AlKhathami, B. Alsamani, M. H. A. Hasanat, M. B. Khan, A. Kumar, and K. U. Singh, "AIAVRT: 5.0 transformation in medical education with next generation AI- 3D animation and VR integrated computer graphics imagery," *Traitement du Signal*, vol. 39, no. 5, pp. 1823–1832, 2022. https://doi.org/10.18280/ts.390542

[15] O. Zhukova, V. Mandragelia, T. Alieksieienko, A. Semenenko, and E. Skibina, "Digital technologies for introducing gamification into the education system in the context of the development of industry 4.0," *Ingénierie des Systèmes d'Information*, vol. 28, no. 1, pp. 141–147, 2023. https://doi.org/10.18280/isi.280114

[16] M. Carrión, M. Santórum, M. Pérez, and J. Aguilar, "A participatory methodology for the design of serious games in the educational environment," in *2017 Congreso Internacional de Innovacion y Tendencias en Ingenieria (CONIITI)*, Bogota, Colombia, 2017, pp. 1–6. https://doi.org/10.1109/CONIITI.2017.8273363

[17] M. Shalan and S. Reda, "CloudV: A cloud-based educational digital design environment," in *2017 IEEE International Conference on Microelectronic Systems Education (MSE)*, Lake Louise, AB, Canada, 2017, pp. 39–42. https://doi.org/10.1109/MSE.2017.7945081

[18] C. D'Apice, C. Grieco, L. Liscio, and R. Piscopo, "Design of an educational adventure game to teach computer security in the working environment," in *DMS*, 2015, pp. 179–185. https://doi.org/10.18293/DMS2015-002

[19] K. Skripkin, "How environment influences on organizational design of educational institution: New analytical instruments," in *CEUR Workshop Proceedings*, Moscow, 2016, pp. 482–493.

[20] N. M. Papachristos, I. Vrellis, A. Natsis, and T. A. Mikropoulos, "The role of environment design in an educational multi-user virtual environment," *British Journal of Educational Technology*, vol. 45, no. 4, pp. 636–646, 2014. https://doi.org/10.1111/bjet.12056

7 AUTHORS

Yu Xiao received the Bachelor's degree from Shanghai for Science and Technology University, P.R. China. Now, she studies in College of Communication and Art Design of University of Shanghai for Science and Technology. Her research interest include urban and rural planning and design, architectural and environmental design and theory (E-mail: 213513027@usst.edu.cn; ORCID: https://orcid.org/0009-0002-6790-1260).

Yong Wang holds a Master's degree from Tsinghua University, China. He is currently working at the College of Communication and Art Design of University of Shanghai for Science and Technology, and his research interests include urban and rural space design, tourism planning and design and industrial planning, architectural and environmental design and theory, visual design and communication (E-mail: wy1505@163.com; ORCID: https://orcid.org/0009-0001-7528-762X).

Fangzhi Guo holds a Doctor of engineering degree from Tianjin University, China. She is currently working at the College of Communication and Art Design of University of Shanghai for Science and Technology, where her research interests include big data and urban planning, rural space renovation, industrial heritage update (E-mail: guoguofang@usst.edu.cn; ORCID: https://orcid.org/0009-0003-4399-5618).