

Analysis of the Coupling Effects of Built and Environmental Factors on Researchers' Psychological Satisfaction with University Research Spaces Based on the Sparse Identification of Nonlinear Dynamics (SINDy) Algorithm

Hanyu Zhou, Junqi Li, Wenchang Wang and Changan Liu *

School of Architecture and Urban Planning, Shandong Jianzhu University, Jinan 250101, China

* Correspondence: liuchangan@sdjzu.edu.cn

How To Cite: Zhou, H.; Li, J.; Wang, W.; et al. Analysis of the Coupling Effects of Built and Environmental Factors on Researchers' Psychological Satisfaction with University Research Spaces Based on the Sparse Identification of Nonlinear Dynamics (SINDy) Algorithm. *Urban and Building Science* 2026, 2(3), 7. <https://doi.org/10.53941/ubs.2026.100021>

Received: 13 April 2026

Revised: 28 June 2026

Accepted: 1 July 2026

Published: 30 July 2026

Abstract: High levels of occupational stress are common among university researchers, creating increasingly stringent requirements for indoor environmental quality (IEQ). However, existing evaluation models tend to be built for conventional office or residential environments and typically assume linear relationships, making them insufficient for capturing the nonlinear coupling effects among multiple environmental variables. Previous evaluation models struggle to capture the nonlinear coupling relationships among multiple environmental factors, failing to establish a comprehensive psychological satisfaction evaluation model for university research spaces. This study focuses on the psychological health of university researchers and, taking the Shandong region as a case study, investigates how the built factors and environmental factors of research spaces (e.g., lighting, noise, layout form) influence researchers' psychological states. A combined weighting method based on Principal Component Analysis and the Analytic Hierarchy Process (PCA-AHP) was employed to extract seven key environmental factors. A total of 1347 subjective and objective datasets were collected under 18 experimental conditions. The present study innovatively introduces the Sparse Identification of Nonlinear Dynamics (SINDy) algorithm from nonlinear dynamical systems theory to establish a psychological satisfaction evaluation model capable of capturing the coupling effects among multiple environmental factors. The results indicate that participants' prior emotional states significantly affect psychological perception and evaluation. Significant coupling effects were observed between indoor temperature and per capita area, as well as between temperature and distance from the window (dist_window); with increasing temperature, the positive contributions of per capita area and dist_window to psychological satisfaction are attenuated. This study reveals the coupled relationships among multiple environmental factors in research spaces, which regulate users' psychological states and behavioral patterns, thereby alleviating negative emotions stemming from occupational stress.

Keywords: psychological satisfaction evaluation; sparse identification of nonlinear dynamic systems; scientific research space; environmental psychology; indoor environmental quality



1. Introduction

People spend the majority of their daily lives indoors [1], and numerous studies have reported close relationships between indoor environmental conditions and occupants' comfort, health, and productivity [2–5]. In university research environments, the quality of the indoor environment plays a critical role in both research performance and quality of life. However, the IEQ of contemporary university research spaces faces several significant challenges. As research activities become increasingly intensive, occupants exhibit greater environmental sensitivity and more refined environmental expectations than those typically observed in conventional office settings. University researchers now demand higher levels of indoor environmental quality, requiring more precise and sophisticated environmental conditions. Nevertheless, there remains a lack of clear quantitative understanding regarding how multiple physical environmental factors interact and jointly influence psychological satisfaction. Improving the environmental quality of research spaces is therefore essential for supporting academic research activities, highlighting the urgent need for a comprehensive psychological satisfaction evaluation model tailored to university research environments.

In recent years, the continuous growth in the population of students and faculty in Chinese universities has intensified the mismatch between increasing space demand and limited educational facilities, placing substantial pressure on existing campus infrastructure. Under such circumstances, campus construction and renovation projects tend to prioritize overall planning, spatial layout, and outdoor landscapes, while insufficient attention is devoted to the systematic optimization of indoor environmental conditions within buildings [6]. This tendency is also evident in Shandong Province. Shandong is located in northern China and is characterized by hot, humid summers and cold, dry winters. The province was selected as the study area because its higher education system is well developed and research activities are highly concentrated, making it representative of regional universities in China. In this region, university research spaces typically take the built form of independent research buildings or academic work zones within mixed-use blocks, encompass typologies such as individual studies, team studios, and open-plan workstations, and are generally characterized by flexible partitions and the permeation of social and collaborative areas.

Considering the unique characteristics of university research spaces and the challenges they currently face, existing studies exhibit the following three major limitations:

- (1) Insufficient research on comfort in university research environments. Existing studies on overall comfort predominantly focus on general building types such as office buildings and teaching facilities. For example, Weerasinghe et al. [7] found in office settings that occupants' primary comfort concerns are closely associated with thermal conditions and air quality. More recently, Sadick et al. [5] investigated the relationship between teachers' satisfaction with indoor environmental quality and their well-being, demonstrating that ventilation and thermal comfort are significant determinants of physical well-being. However, their study was limited to primary and secondary school teachers and did not address university researchers, a representative knowledge-working population characterized by prolonged sedentary work and high cognitive demands. Although Da Yang et al. [8] conducted research within a university context, their work focused on classroom environments and developed an evaluation model based on four dimensions: thermal comfort, visual comfort, acoustic comfort, and indoor air quality. Typical research environments, such as research laboratories and graduate student offices, were not considered. While these studies provide valuable insights into comfort assessment in specific settings, they do not adequately reflect the distinctive characteristics of university research spaces, including prolonged sitting, sustained concentration, and shared-space occupancy.
- (2) Insufficient investigation of the coupling relationships among factors influencing comfort. Previous studies on overall comfort have generally considered three categories of variables: physical factors, non-physical factors, and subjective factors. Early research primarily focused on the relationships between physical environmental parameters and subjective perceptions, examining how variables such as acoustics, lighting, thermal conditions, and air quality affect comfort [9]. Beyond physical parameters, increasing attention has also been directed toward social and individual factors. Studies have shown that occupant density [10], job characteristics [11], office type [12], and individual behavioral patterns [13] can all influence environmental perceptions. Cheung et al. [14] reported that overall indoor comfort is associated with factors such as privacy, indoor cleanliness, available space, furniture adequacy, and occupants' ability to control environmental conditions. Similarly, Rafaela Bortolini et al. [15] argued that comprehensive comfort assessments should encompass three interacting dimensions: physical environmental factors, building characteristics, and occupant control. As a result, research perspectives have gradually evolved from single-parameter analyses toward more integrated and systematic approaches. However, most existing studies remain limited to correlation analyses and have not established predictive "environment–psychology" models. Current evaluation

frameworks are therefore unable to effectively characterize the nonlinear coupling effects among multiple environmental factors or support the development of effective prediction–intervention systems.

- (3) Insufficient application of data-driven comfort modeling approaches. In constructing predictive models of comprehensive comfort for university researchers, multidimensional indicators (physical, social, and personal) and complex nonlinear interactions between environmental conditions and psychological perception must be considered. Developing interpretable “white-box” models is therefore crucial. Traditional steady-state models (e.g., PMV-PPD), although physically interpretable, are insufficient for capturing dynamic changes and individual differences. Consequently, data-driven predictive models have become the dominant approach in this field, aiming to uncover latent patterns from high-dimensional data.

Existing studies generally follow two main pathways. The first focuses on improving predictive accuracy by employing algorithms such as Random Forests (RF), Gradient Boosting Decision Trees (GBDT), Support Vector Machines (SVM), and neural networks, which have achieved notable success in thermal comfort and behavioral prediction studies [16]. The second pathway emphasizes model interpretability. On one hand, some studies introduce fuzzy logic systems, mapping environmental parameters to comfort evaluations through human-interpretable “IF-THEN” rules, thereby balancing accuracy and transparency. On the other hand, many studies apply post hoc interpretation techniques, such as SHAP (SHapley Additive Explanations), to “black-box” models in order to quantify feature contributions and enhance transparency [17].

Nevertheless, fuzzy logic systems rely heavily on expert knowledge and are limited in their ability to automatically discover complex interactions from data, while SHAP and similar techniques provide only static feature importance and cannot reveal how factors dynamically couple and evolve. Moreover, most existing models do not yield explicit dynamical relationships and predominantly focus on energy use, adaptive behaviors, or thermal perception, rather than on dynamic coupling between multiple environmental factors and psychological satisfaction.

To overcome these limitations, this study introduces the Sparse Identification of Nonlinear Dynamics (SINDy) algorithm. The principal advantage of this approach lies in its ability to extract interpretable dynamical equations from time-series or spatial data. By employing sparse regression to identify a small number of key terms governing system behavior, SINDy can automatically derive concise, explicit equations that describe system evolution, thereby preserving model transparency while effectively capturing multifactor coupling mechanisms.

This study addresses the global issue of elevated occupational stress and increasing mental health risks among researchers, with a specific focus on university research personnel in China. The climatic conditions, campus development patterns, and stage of educational infrastructure construction in Shandong are all highly representative. Therefore, the findings can provide empirical evidence for optimizing research-space environments in regions with similar latitudes, climatic characteristics, and cultural contexts worldwide. The objective of this research is to establish a quantitative relationship model between environmental parameters of university research spaces and researchers’ psychological health indicators in Shandong universities, thereby elucidating the mechanisms through which built factors and environmental factors influence psychological states. Based on the SINDy algorithm, an “environment-psychology” predictive model is developed to further examine evaluation indicators for university research spaces and characterize nonlinear coupling effects among multiple factors, ultimately constructing a psychological satisfaction evaluation model for such spaces. The model incorporates non-physical and subjective factors, such as per capita area, and integrates objective environmental parameters with subjective psychological satisfaction to form a more realistic nonlinear coupling evaluation framework.

2. Research Methods

Research spaces in some universities in Shandong exhibit significant common characteristics in functional layout, facility configuration, and usage scenarios. Based on this, the author constructed a standardized model reflecting the commonalities of regional university research spaces through inductive refinement, providing a unified research framework for subsequent experiments.

In the screening of environmental factors and determination of quantitative indicators, the study employed a combined PCA-AHP approach: First, the Analytic Hierarchy Process (AHP) is employed to hierarchically and structurally decompose the built factors (e.g., temperature, illuminance) and environmental factors (e.g., occupant density, distance to window) of research spaces. Drawing on the practical experience of researchers and spatial design experts, this approach preliminarily established the logical relationships between factors, effectively mitigating the limitations of singular subjective judgments. Subsequently, principal component analysis (PCA) was applied to perform covariance matrix analysis on environmental factor data. This process reduced dimensionality while eliminating secondary environmental parameters with minimal correlation to researchers’ psychological perceptions. Through this process, relatively significant physical and non-physical environmental

factors were identified. The results integrated experts' experiential understanding of research settings while maintaining data-driven objectivity, thereby establishing corresponding quantitative indices for each factor.

Building upon this foundation, the study created 18 distinct environmental condition combinations. Subjective and objective data were collected from respondents, and the SINDy algorithm was employed to construct an “environment-psychology” predictive model. This culminated in the development of a psychological satisfaction evaluation model for university research spaces. The workflow is illustrated in Figure 1.

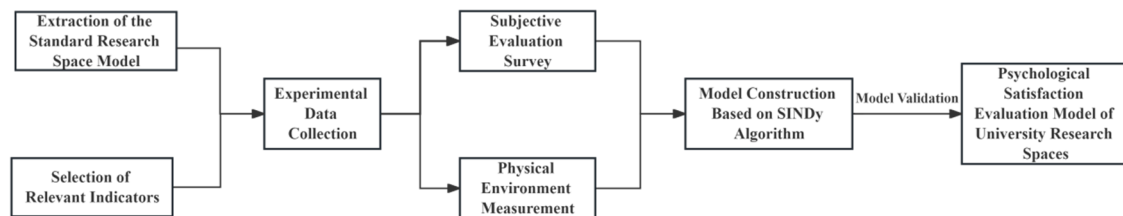


Figure 1. Flowchart of the proposed SINDy-based methodology for constructing a psychological satisfaction evaluation model in university research spaces.

2.1. Extraction of the Standard Research Space Model

The research site was selected at Shandong Jianzhu University in Jinan, Shandong Province, focusing mainly on academic buildings constructed earlier. The survey covered eight architecture research buildings and a total of 69 research spaces. Detailed survey findings and summarized information are provided in the Supplementary Materials (Supplementary Files S1 and S3). The results indicated that conventional research spaces within these architecture research building are primarily rectangular, with a depth of approximately 7–9 m and a bay of 4–5 m, length-width ratio of about 2:1 and an average area ranging between 35 and 40 square meters.

2.2. Selection of Relevant Indicators

To enhance the objectivity of ranking the importance of spatial environmental factors, the PCA-AHP method was adopted to calculate combined weights for the environmental factors of research spaces. The process included the following steps [18]:

- (1) Establishing the evaluation indicator system. Based on spatial feature factors proposed by Ergon [19] and the parameters of sound, light, thermal, and air quality, a three-level evaluation system of “The target level-the element level-the index level” was constructed (Table 1).
- (2) Combining PCA and AHP for weighting. A new judgment matrix was constructed using the upper triangular elements of the group decision matrix. After logarithmic transformation, the covariance matrix was calculated, and principal components were extracted and normalized using PCA. The PCA results were then used to guide the AHP weighting process, ensuring that the final weights of the evaluation indicators were more reasonable [20].
- (3) Determining combined weights (Table 1). The PCA-AHP weighting results indicated that indoor physical environment, spatial guidance, interior atmosphere, layout form, space scale and per capita area, and indoor–outdoor interaction were assigned weights of 0.4180, 0.0526, 0.0363, 0.1233, 0.2027, and 0.1671, respectively.

Table 1. Construction of evaluation index system and combined weight analysis results based on AHP and AHP-PCA for scientific research space environment.

Primary Indicators	AHP Weight	AHP-PCA Weight	Second-Level Indicators	AHP Total Weight	Weight Ranking	AHP-PCA Global Weights	Weight Ranking
A1 Indoor Physical Environment	0.4118	0.4180	A11 Lighting Environment	0.0858	5	0.0941	3
			A12 Acoustic Environment	0.0639	7	0.0722	6
			A13 Thermal Environment	0.1669	1	0.1693	1
			A14 Air Quality	0.0952	3	0.0824	4
A2 Guiding	0.0470	0.0526	A21 Visual Guidance Indoors	0.0280	12	0.0406	9
			A22 Room Location Easy to Find/Accessible	0.0190	15	0.0120	17
A3 Interior Ambience	0.0442	0.0363	A31 Interior Primary Color	0.0240	14	0.0217	14
			A32 Furniture Material	0.0079	19	0.0065	19
			A33 Openness to the Outside	0.0123	18	0.0080	18
			A41 functional Partition	0.0352	9	0.0459	8
A4 Interior Layout	0.1055	0.1233	A42 Symmetrical Furniture Arrangement	0.0164	17	0.0183	16
			A43 Furniture Outlines	0.0178	16	0.0186	15
			A44 Flexible Space Layout	0.0361	8	0.0406	10

Table 1. Cont.

Primary Indicators	AHP Weight	AHP-PCA Weight	Second-Level Indicators	AHP Total Weight	Weight Ranking	AHP-PCA Global Weights	Weight Ranking
A5 Space Scale and Usable Area	0.2011	0.2027	A51 Ceiling Height	0.0293	10	0.0296	11
			A52 Room Shape	0.0290	11	0.0292	12
			A53 Per Capita Indoor Area	0.1428	2	0.1439	2
A6 Interior-Exterior Interaction	0.1904	0.1671	A61 Window Size	0.0245	13	0.0242	13
			A62 Dist_window	0.0786	6	0.0771	5
			A63 Window Angle Relationship	0.0873	4	0.0658	7

Among them, the indoor physical environment was the most significant factor, followed by space scale and per capita area. After global weighting, seven indicators with weights above 5% were identified: thermal environment, per capita area, lighting environment, air quality, dist_window, acoustic environment, and visual relationship with the window. Together, these seven factors accounted for 70.5% of the total weight and were therefore selected as the key experimental variables.

2.3. Experimental Data Collection

To rationally define the range of physical environmental levels, the study referred to the method of Qi Wu [21] and divided the satisfaction thresholds at 33.3% and 66.6% into three levels. An orthogonal experimental design with three levels was adopted (Table 2).

Table 2. Quantitative indicator classification of physical environmental factors and three-level orthogonal experimental design for scientific research space.

No.	Indicator Name	Quantitative Index	Ambient Level		
			A (I)	B (II)	C (III)
1	Indoor Thermal Environment	Temperature (°C)	22 °C to 25.5 °C	21 °C to 22 °C; 25.5 °C to 27 °C	<21 °C; >27 °C
2	Indoor Acoustic Environment	Sound Pressure Level (dB)	<57.5 dB	57.5 dB to 67 dB	>67 dB
3	Indoor Lighting Environment	Illumination of Working Plane (lux)	>260 lux	50 lux to 260 lux	<50 lux
4	Indoor Air Quality	Carbon Dioxide Concentration (ppm)	850 ppm	850 ppm to 1200 ppm	>1200 ppm
5	Indoor-outdoor Natural Environment	Angle of View Relative to Window	Facing the Window	Side-facing Window	Back to Window
6	Interface	Work Surface Illuminance	0~2 m	2~5.5 m	Over 5.5 m
7	Per Capita Indoor Area	Number of People/Area	Over 10 m ² /person	5–10 m ² /person	Below 5 m ² /person

2.3.1. Subjective Evaluation Survey

The subjective questionnaire consisted of three sections: (1) background information of participants; (2) data on their psychological health; and (3) satisfaction ratings for environmental factors and comprehensive comfort.

In the first section, based on literature review, the major background variables affecting researchers' mental health were identified. A background survey was designed referencing the SF-36 Health Survey and the Social Support Questionnaire to collect demographic and contextual information of the participants.

In the second section, determination of participants' psychological health status. To comprehensively assess participants' emotional states, the circumplex model (Figure 2) comprises four poles (the endpoints of the x–y axes) representing extreme emotional states, spanning from low to high arousal and from negative to positive valence [22,23]. The circular structure as a whole encompasses eight distinct emotional states. This model has been applied in several studies on comfort evaluation [24,25] and is also one of the most widely used and extensively validated measurement approaches in emotion psychology research [26].

In the third section, participants rated the key environmental factors—indoor physical environment, per capita area, and indoor–outdoor interface—along with comprehensive satisfaction, using a seven-point Likert scale [27] (Figure 2) ranging from −3 to +3, where higher scores indicated higher subjective comfort.

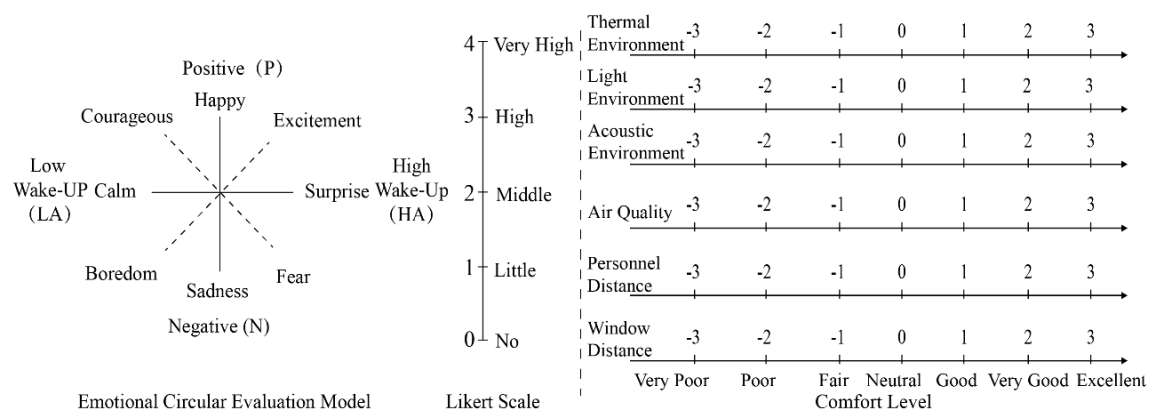


Figure 2. Subjective evaluation survey tool for researchers based on circumplex model of affect and multi-dimensional environmental satisfaction scale.

2.3.2. Physical Environment Measurement

The experiment was conducted in a research laboratory within the Architecture Department building. The room measured 4.26 m in width, 8.66 m in depth, and 3.5 m in height. The walls were painted white, the floor was covered with 60 × 60 cm white marble tiles, and three incandescent lamps provided basic illumination. A wall-mounted air conditioner (input power 1565 W, cooling capacity 5150 W) controlled indoor temperature.

A sliding window (900 mm sill height, 2500 mm width, 1750 mm height) maintained typical indoor humidity around 45%, and local air velocity below 0.1 m/s. Distributed sensors were deployed near workstations to capture accurate measurements of temperature, humidity, sound pressure level, illuminance, and CO₂ dioxide concentration using instruments such as HOBO U12-012, HT2000, and AS804B noise level.

2.4. Experimental Procedure Design

The target population of this study consisted of long-term users of university research spaces. Participants were required to meet the following inclusion criteria: (1) enrollment as a master's or doctoral student; (2) a minimum daily occupancy of 6 h in research offices or laboratories; and (3) good physical health to ensure normal perception and evaluation of environmental stimuli. Written informed consent was obtained from all participants. A copy of the consent form is provided in Supplementary File S2.

The required sample size was estimated before the experiment based on the study design. A total of 18 experimental conditions were established. Using a medium effect size ($f = 0.25$), a statistical power of 80%, and a significance level of $\alpha = 0.05$, the minimum required sample size was calculated using G*Power software and determined to be no less than 269 participants. In addition, based on sample-size recommendations from comparable studies on psychological responses to indoor environments, the final sample size of 336 participants was considered sufficient to detect moderate environment–psychology associations.

Considering the natural gender composition of engineering research teams in universities within Shandong Province, a total of 336 volunteers (203 males and 133 females) were ultimately recruited for the experiment, resulting in a male-to-female ratio of approximately 1.53:1. To ensure high-quality responses, all participants were instructed to obtain adequate rest during the 24 h preceding the experiment and to refrain from strenuous physical activity, alcohol consumption, and caffeine intake.

Each experimental session lasted 115 min. The first 30 min were for adaptation to the environmental conditions (thermal, acoustic, and lighting). During the experiment, temperature and CO₂ dioxide concentration were held stable, while lighting level, position, and noise were varied stepwise. After the 30-min adaptation, participants completed a 15-min questionnaire, followed by two more rounds of adjusted environmental settings (each with 20-min adaptation and 15-min feedback phases) [28] (Figure 3).



Figure 3. Site layout, equipment deployment, and three-stage operational workflow for the subjective experiment. (a) Test site photograph; (b) experimental workflow design.

3. Results and Analysis

After data screening, questionnaires that were incomplete or contained obvious logical inconsistencies were excluded. Examples of such inconsistencies included participants reporting comfort or high comfort under a sound pressure level of 70 dB. Ultimately, 1347 valid observations were retained for analysis. The distribution of valid samples across different environmental conditions is presented in Table 3.

Table 3. Statistical distribution of valid subjective questionnaire samples collected under varying gradients of spatial physical environmental factors.

Category	Category A (I)	Number of Records	Category B (II)	Number of Records	Category C (III)	Number of Records
Dist window	0~2 m	339	2~5.5 m	402	Over 5.5 m	606
Window Viewing Angle	-45°~45°	410	45°~90°	528	Above 90°	409
Per Capita Usable Area	≥10 m ² /person	478	5~10 m ² /person	542	Below 5 m ² /person	327
Temperature	22 °C to 25.5 °C	225	21 °C to 22 °C; 25.5 °C to 27 °C	293	<21 °C; >27 °C	829
CO ₂ Concentration	<850 ppm	416	850 to 1200 ppm	504	>1200 ppm	427
Sound Pressure Level	<57.5 dB	836	57.5 dB to 67 dB	255	>67 dB	256
Illumination of working Plane	>260 lux	342	50 lux to 260 lux	689	<50 lux	316

3.1. Relationship between Prior Emotional States and Comfort Scores

To further examine whether participants' prior emotional states affected their psychological perception ratings, partial correlation analysis was performed between emotional states and environmental evaluation scores. The results (Figure 4) revealed distinct differences between positive emotions (e.g., happiness, excitement, calmness, courage) and negative emotions (e.g., sadness, boredom, fear, surprise). Positive emotions showed a generally positive correlation with comfort ratings, while negative emotions were negatively correlated. This indicates that an individual's prior emotional state indeed influences the perception of environmental quality: participants in a positive mood tended to assign higher satisfaction scores, whereas those in a negative mood rated the same environment lower. In other words, as emotional well-being declines, individuals' tolerance for environmental stressors decreases accordingly.

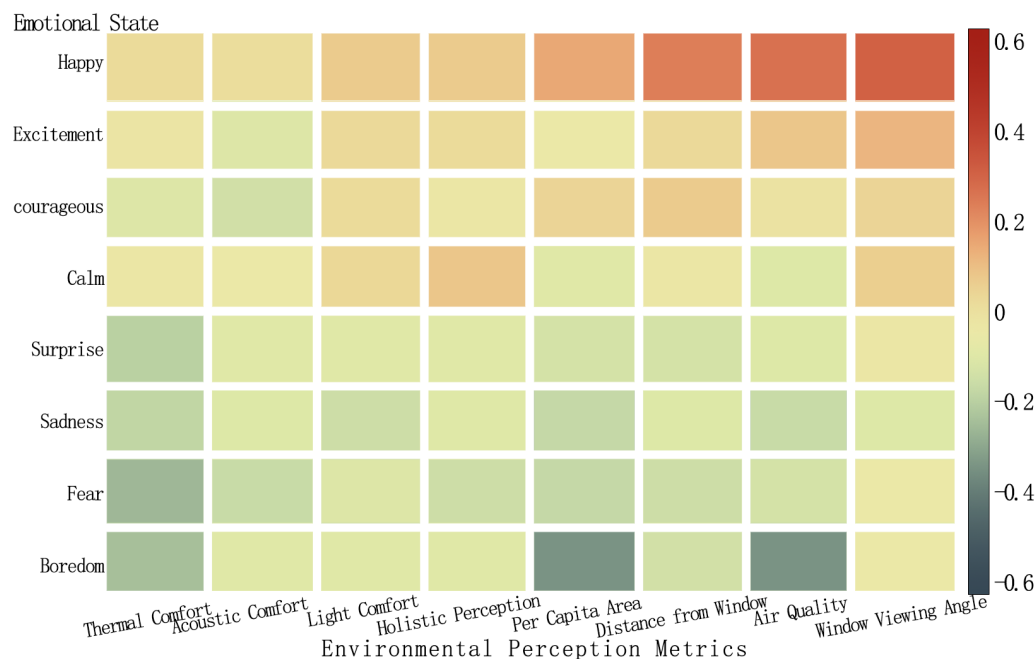


Figure 4. Heatmap of partial correlation analysis between researchers' emotional states and multi-dimensional spatial environment perception indicators (Controlling for Environmental Parameters).

3.2. Construction of the SINDy Model

In previous research, many evaluation models have often adopted linear assumptions to simplify computation. However, in actual research environments, built factors and environmental factors such as temperature and illuminance do not exhibit simple linear relationships with psychological satisfaction; instead, they involve complex nonlinear coupling effects. The Sparse Identification of Nonlinear Dynamics (SINDy) algorithm, as a well-established technique in nonlinear dynamic systems [29], is capable of accurately identifying key influential terms from large datasets while eliminating redundant information [30], making it highly suitable for addressing such nonlinear problems.

Based on the principles of the SINDy algorithm described above, the experimentally collected data were analyzed, screened, and fitted, ultimately constructing a model for evaluating psychological satisfaction in university research spaces.

(1) Function Library Selection

In practice, the specific form of nonlinear model expression remains unknown. The coefficients describing the relationship between an individual's psychological satisfaction and various factors—such as illuminance, temperature, CO₂ concentration, sound pressure level, window viewing angle, and dist_window—are also unknown. Considering the complexity of the variables selected for the experiment, this study selected a nonlinear function library comprising first- to third-order polynomial functions and first- and second-order trigonometric functions.

(2) Simulation Results

Due to seasonal constraints and laboratory limitations, the final actual control ranges were: temperature 14.5–23.6 °C, sound pressure level 33.6–74 dB, work surface illuminance 3.9–800 lux, CO₂ concentration 123–1780 ppm,

and per-person usable area 2.5–38 m² per person. The dist_window ranged from 0.6 to 7.6 m, with viewing angles set at 0°, 90°, and 180°.

To validate the model, the experiment selected 90% (1212 sets) of the 1347 datasets to construct an evaluation model using the SINDy algorithm. While avoiding overfitting, all function combinations within the library were tested sequentially. A concise model expression achieving over 85% accuracy was identified as a combination of a second-order polynomial function and a first-order trigonometric function. The model and fitting results are as follows:

(a) Functional Model (all environmental variables > 0):

$$Y = (0.1022 \cdot X_{\text{area}} + 0.4068 \cdot X_{\text{dis}} - 0.09604 \cdot X_{\text{sou}} + 0.2679 \cdot X_{\text{tem}} - 0.005808 \cdot X_{\text{area}} \cdot X_{\text{tem}} - 0.03788 \cdot X_{\text{dis}} \cdot X_{\text{tem}} - 0.03615 \cdot X_{\text{dis}} \cdot \cos(X_{\text{dis}}) - 0.04522 \cdot X_{\text{dis}} \cdot \sin(X_{\text{dis}}) + 0.04387 \cdot X_{\text{dis}}^2) / 0.8$$

Note: Per capita area (X_{area}), dist_window (X_{dis}), sound pressure level (X_{sou}), work area temperature (X_{tem}), Y represents psychological satisfaction evaluation score. The model accuracy is 86.09%.

(b) Simulation scenario shown in Figure 5:

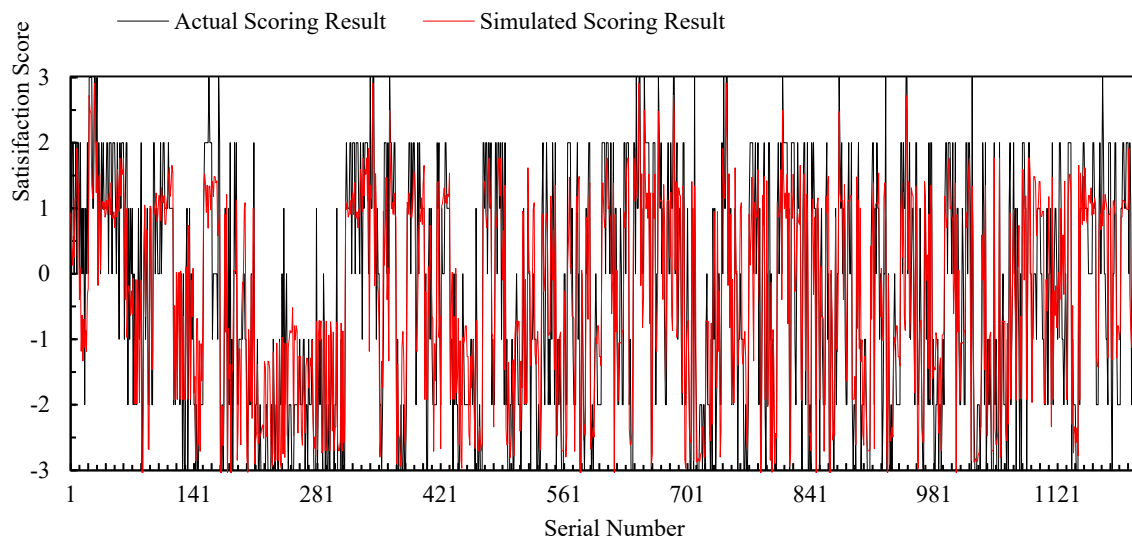


Figure 5. Comparison between the psychological satisfaction fitting results of the SINDy evaluation model and actual scores on the training dataset.

The raw experimental data, including subjective/objective measurements, actual scoring result, and SINDy simulated scoring result, are available in Supplementary File S3.

The remaining 10% (135 datasets) were substituted into the SINDy evaluation formula for calculation. The predicted results and actual scores are shown in Figure 6:

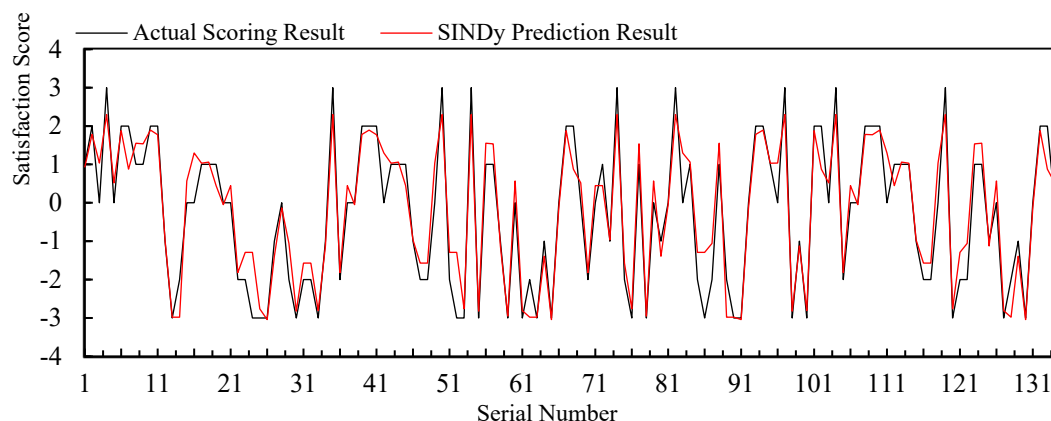


Figure 6. Validation comparison between predicted psychological satisfaction scores of the SINDy evaluation model and actual scores on the test dataset.

To further validate the accuracy of the SINDy algorithm fitting, this paper selected evaluation models related to psychological satisfaction in office buildings developed by several international scholars (Table 4). After substituting the collected 135 experimental data points, the comparison results are as follows:

Table 4. Psychological satisfaction evaluation models for office buildings in previous studies.

Author	Literature Model Type	Model Explanation
1	$S = 0.42 \times S_T + 0.09 \times S_{IAQ} + 0.28 \times S_A$ $S_T = (0.021 \times T^2 - 0.919 \times T + 10.225) \times 100\%$ $S_{IAQ} = [0.28 \ln(CO_2) - 1.68] \times 100\%$ $S_V = [0.0389 \times SPL - 1.9652] \times 100\%$	0%: Better than average performance 20%: Average performance 30%: Below average
2	$S = 0.30 \times S_T + 0.36 \times S_{IAQ} + 0.16 \times S_V + 0.18 \times S_A$ $S_T = 95 \times e^{-0.03353 \times PMV^4 - 0.2179 \times PMV^2}$ $S_A = 100 - 2 \times (\text{Actual SPL} - \text{Design SPL})$ $S_V = -176.16 x^2 + 738.4X - 690.29$, where $X = \{\ln(\ln(I))\}$ $S_{IAQ} = 100 - P_{DIAQ}$ $P_{DIAQ} = 395 \times \exp(-15.15 C_{CO_2}^{-0.25})$	80~100 points: Very good 60~80 points: Good 40~60: Moderate 20~40: Low 0~20: Very Low
3	$S = 0.075 + 0.316 \times S_T + 0.118 \times S_{IAQ} + 0.171 \times S_V + 0.224 \times S_A$ $S_T = -0.0063 \times T^2 + 0.287 \times T - 2.934$ $S_A = -0.0230 \times SPL + 1.382$ $S_V = -5 \times 10^{-7} \times I^2 + 0.0011 \times I - 0.106$ $S_{IAQ} = -0.0002 \times CO_2 + 0.244$	$S > 0$, Satisfactory $S < 0$, Unsatisfactory

Note: S—Psychological satisfaction; S_T —Thermal comfort satisfaction; S_A —Acoustic comfort satisfaction; S_V —Visual comfort satisfaction; S_{IAQ} —Indoor air quality satisfaction; SPL—Sound pressure level at the measurement point (dB); T—Ambient temperature at the measurement point (°C); CO_2 —Carbon dioxide concentration at the measurement point (ppm); I—Illuminance at the measurement surface (lux).

K.W. Mui [31] Scholar (Author 1) adopted the dissatisfaction formula, which categorizes dissatisfaction scores roughly from −3 to 3:3 points (0–5%), 2 points (6–10%), 1 point (11–20%), 0 points (21–30%), −1 point (31–55%), −2 points (56–80%), −3 (81–100%). M. Ncube [32] Scholar (Author 2) employs a percentage-based system with environmental quality rated on a 5-point scale. Scores from 0 to 100 are mapped to the −3 to 3 range. The mapped composite score is calculated as “original score $\times 0.06 - 3$ ”. In the original score range, 0 corresponds to −3 and 100 corresponds to 3. Scholar B. Cao [33] (Author 3) employed a linear combination without explicit boundaries, where the value range depends on multiple sub-items. Based on practical conditions, assuming a temperature range of 0–30 °C, sound pressure level 30–75 dB, illuminance 0–1200 lux, and CO_2 concentration 300–2000 ppm. The resulting S composite range is −0.7 to 0.5. Mapping this range to −3 to 3 yields the post-mapping composite score: “(original score + 0.7) $\times 5 - 3$ ”.

Model Accuracy Comparison (Figure 7):

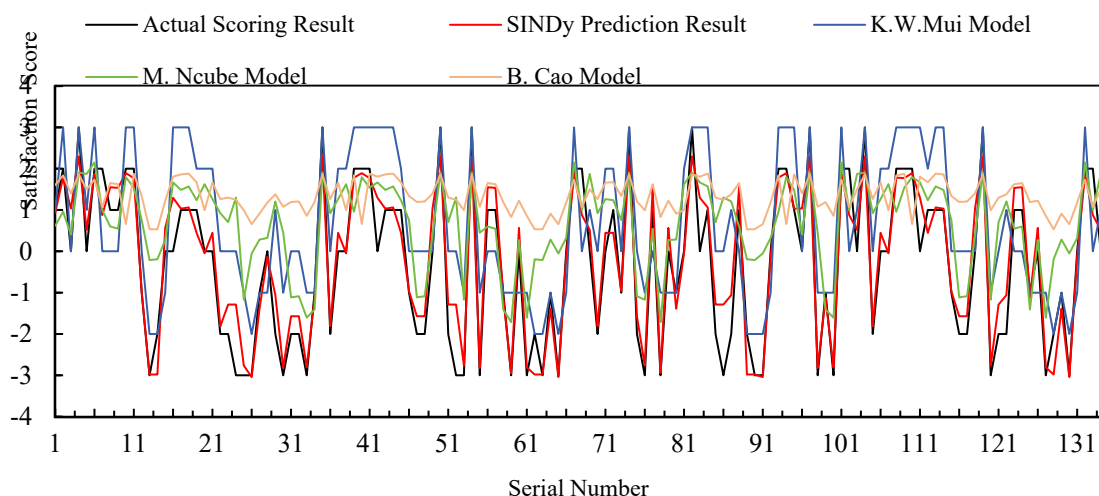


Figure 7. Comparative analysis of psychological satisfaction prediction accuracy among the SINDy evaluation model and existing models by K.W. Mui, M. Ncube, and B. Cao.

Comparing the MSE values of the four models (Table 5) reveals that the SINDy model exhibits the lowest MSE, closely aligning with actual scoring patterns and demonstrating superior fit compared to the other three models. This indicates that the predictive model constructed using the SINDy algorithm better captures real-world scoring dynamics, effectively reflecting various trend shifts and peak values.

Table 5. Comparison of Mean Squared Error (MSE) between the SINDy model and existing mainstream models in predicting psychological satisfaction in university research spaces.

Model Name	MSE
SINDy Model	0.3518
K.W. Mui Model	2.6286
M. Ncube Model	3.0081
B. Cao Model	5.7478

3.3. Model Analysis and Comparison

The SINDy model effectively captures both linear (e.g., $0.1022 \cdot X_{\text{area}}$) and nonlinear interaction terms (e.g., $-0.005808 \cdot X_{\text{area}} \cdot X_{\text{tem}}$, $X_{\text{(dis)}}^2$), demonstrating that psychological satisfaction is influenced by multifactorial synergy rather than independent effects.

The illuminance variable and window viewing angle variable were excluded from the model. After conducting multicollinearity analysis, the VIF values for all three variables were found to be less than 3 (Table 6). Therefore, in this experiment, no multicollinearity issues exist among “illuminance at the work surface”, “window viewing angle” and “dist_window”.

Table 6. Multicollinearity diagnostic results of environmental predictor variables in the psychological satisfaction evaluation model based on Variance Inflation Factor (VIF).

Model	Unstandardized Coefficient		Standardized Coefficient	t	Significance	Collinearity Statistics	
	B	Standard Error	Beta			Tolerance	VIF
(Constant)	−0.498	0.279		−1.783	0.075		
Illuminance at Work Surface	0.003	0.001	0.283	5.322	0.000	0.891	1.122
Dist_window	−0.047	0.040	−0.059	−1.180	0.239	0.996	1.004
Window Angle	−0.004	0.001	−0.155	−2.921	0.004	0.894	1.118

(Note: The dependent variable is the comprehensive environmental comfort score).

“Work surface illuminance” was excluded by the SINDy algorithm. This may be attributed to participants completing electronic questionnaires, which potentially mitigated the negative impact of lower work surface illuminance. “Window viewing angle” and “CO₂ concentration” may have been less perceptible participants. The interaction effects of model variables are presented as follows (Table 7):

Table 7. Coefficients and practical interpretations of main effects, interaction terms, and nonlinear terms of environmental factors in the psychological satisfaction evaluation model for research spaces.

Variable	Main Effect	Interaction/Nonlinear Term	Practical Significance
Per Capita Area X_{area}	+0.1022	Interaction with indoor temperature	As temperature increases, the marginal benefit of per capita area may decrease
Dist_window X_{dis}	+0.4068	Trigonometric function + quadratic term	Due to the influence of quadratic terms and trigonometric functions, there may exist an optimal distance
Sound Pressure Level X_{sou}	0.0960	None	For every 1 dB(A) increase, satisfaction decreases 0.09604 points
Indoor Temperature X_{tem}	+0.2679	Interaction with per capita area and dist_window	Higher temperatures may enhance satisfaction, but this must be coordinated with spatial layout considerations

Based on main effects and interactions, sound pressure level inversely correlates with psychological satisfaction: each 1 dB increase reduces satisfaction by 0.0960 points. Both per capita area and dist_window interact with indoor temperature, with negative interaction coefficients, indicating that these variables jointly mitigate each other’s effects within the model.

(1) Per capita area and indoor temperature:

The main effect of per capita area is 0.1022, indicating that for every 1 m²/person increase in per capita area, psychological satisfaction increases by 0.1022 points. The main effect of indoor temperature is 0.2679, indicating that for every 1 °C increase, psychological satisfaction increases by 0.2679 points. The interaction term between the two is $-0.005808 \times X_{\text{area}} \times X_{\text{tem}}$. This indicates that when both factors act together, an increase in one weakens the positive contribution of the other to comfort. In short, as temperature increases, the positive contribution of per capita area to psychological satisfaction diminishes. To further explore their mutually inhibitory relationship, Figure 8 illustrates their combined effect on psychological satisfaction scores when the dist_window is 1.2 m and sound pressure level is 35 dB:

To clarify the relationship, extracting the common factors from all terms containing X_{area} and X_{tem} (assuming $X_{\text{dis}} = 1.2$ m) yields:

$$Y = X_{\text{tem}} \times (0.2222444 - 0.005808 X_{\text{area}}) + 0.1022 X_{\text{area}} + \dots$$

The expression reveals:

- Within the temperature range of 13–24 °C during winter, occupants' satisfaction with indoor thermal comfort shows a positive correlation with psychological satisfaction; the higher the thermal comfort score, the higher the psychological satisfaction score.
- Since X_{area} remains below 38 m²/person in this model, both $0.2222444 - 0.005808 X_{\text{area}}$ and $0.1022 X_{\text{area}}$ remain positive. Within the 0–38 m²/person, indoor per capita area positively correlates with psychological satisfaction.
- The positive correlation between X_{tem} and psychological satisfaction is inhibited by X_{area} . As X_{area} increases, the coefficient of X_{tem} decreases, reducing its contribution to psychological satisfaction scores.

(2) Indoor Temperature and dist_window:

The main effect of dist_window is 0.4068, indicating that for every 1 m increase in dist_window, psychological satisfaction increases by 0.4068 points. The main effect of indoor temperature is 0.2679, indicating that for every 1 °C increase in temperature, psychological satisfaction increases by 0.2679 points. The interaction term between the two is $-0.03788 \times X_{\text{dis}} \times X_{\text{tem}}$. This indicates that when both factors act together, an increase in one weakens the positive contribution of the other to comfort. In short, as temperature rises, the positive contribution of window distance to psychological satisfaction diminishes.

In the SINDy equation, dist_window is the most complex variable form, comprising linear, trigonometric, and quadratic terms. Variables interacting with it are sound pressure level and indoor temperature. Assuming a constant per capita floor area of 5 m²/person and sound pressure levels categorized as quiet (35 dB), the combined effects of indoor temperature and dist_window on psychological satisfaction are illustrated in Figure 9.

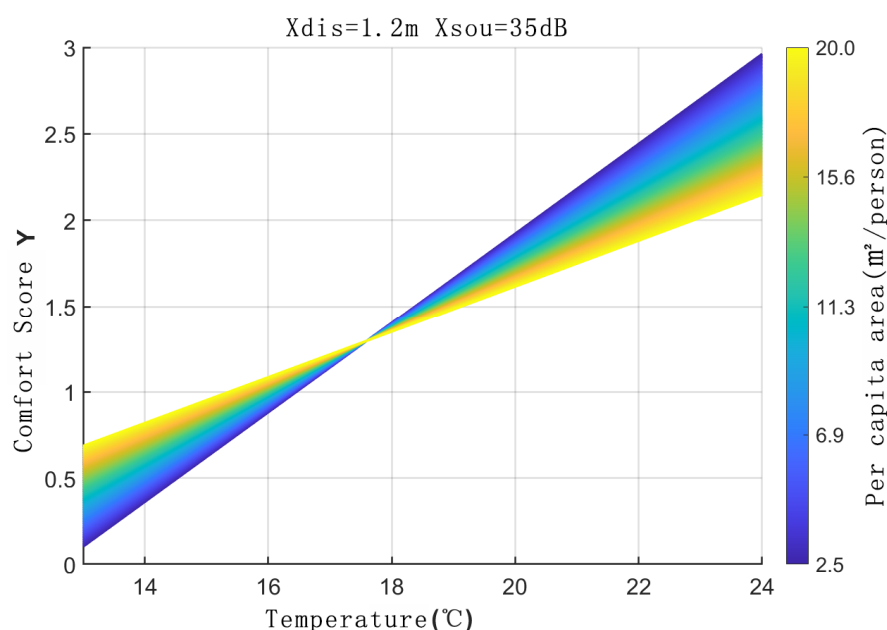


Figure 8. Analysis of the interaction effect between per capita usable area and indoor temperature on researchers' psychological satisfaction under fixed environmental conditions.

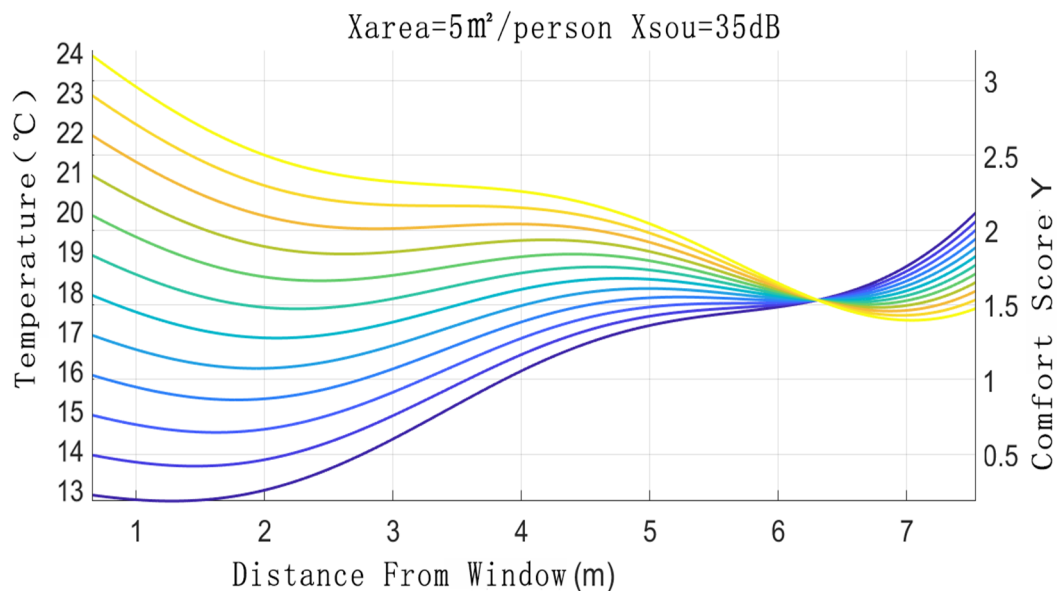


Figure 9. Nonlinear relationship between distance to window and researchers' psychological satisfaction under different indoor temperatures and fixed per capita area.

To clarify the relationship between these variables, common factors were extracted from all expressions containing X_{dis} and X_{tem} terms (assuming $X_{sou} = 35$ dB and $X_{area} = 5$ m²/person), yielding:

$$Y = X_{dis}\{0.4068 + 0.20098X_{tem} - 0.03615 \times \cos(X_{dis}) - 0.04522 \times \sin(X_{dis})\} + X_{dis}^2 + \dots$$

Based on the graph and formula, the following can be observed:

- (i) The relationship between dist_window and psychological satisfaction follows a quadratic function with trigonometric components, not a simple linear change. The perceived quality of workstation proximity to windows is influenced by temperature.
- (ii) During winter, in colder conditions (13–18 °C), dist_window positively correlates with psychological satisfaction—greater distance yields higher comfort.
- (iii) In winter, under more comfortable temperatures (19–23 °C), the relationship between dist_window and psychological satisfaction is negatively correlated—closer proximity yields greater comfort.

In summary, this study yielded the following major findings. First, participants' pre-existing emotional states significantly moderated their perceptions of environmental quality. Positive emotions (e.g., happiness and calmness) were positively correlated with satisfaction ratings across all environmental dimensions, whereas negative emotions (e.g., sadness and fear) were negatively correlated with satisfaction ratings. This finding indicates that occupants exhibit a substantially lower tolerance for environmental deficiencies when experiencing negative emotional states. Second, the nonlinear explicit model developed using the Sparse Identification of Nonlinear Dynamics (SINDy) algorithm outperformed conventional linear models, achieving an accuracy of 86.09% and an MSE of 0.3518. The model effectively identified multiplicative coupling effects and nonlinear optimal ranges among environmental factors. Third, four key factors were identified: floor area per person, distance from the window, sound pressure level, and workspace temperature. A significant inhibitory interaction was observed between temperature and floor area per person (interaction coefficient: $-0.005808 \times X_{area} \times X_{tem}$), indicating that the positive contribution of floor area per person to satisfaction diminished as temperature increased. Fourth, a similar inhibitory interaction was identified between temperature and distance from the window. Moreover, the effect of window distance on satisfaction followed a combined quadratic ($0.04387 \times X_{dis}^2$) and trigonometric functional pattern ($-0.03615 \times X_{dis} \times \cos(X_{dis})$, $-0.04522 \times X_{dis} \times \sin(X_{dis})$). Under low-temperature conditions (13–18 °C), locations farther from windows were associated with higher comfort levels due to the “cold-wall effect”. In contrast, under thermally acceptable conditions (19–23 °C), locations closer to windows were associated with higher comfort levels.

4. Discussion

Existing comfort evaluations predominantly target general building categories such as office buildings and lack multi-factor coupled psychological satisfaction evaluation models tailored to university research spaces. To

address this gap, the present study investigated 69 research spaces across eight architecture research building at Shandong Jianzhu University. The AHP-PCA method was applied to determine factor weights, and a comprehensive psychological satisfaction evaluation model for university research spaces was established using the SINDy algorithm.

The proposed model suggests that maintaining comfort in research spaces depends on the coordinated coupling of three levels of factors: Core built factors (e.g., temperature and illuminance), environmental factors (e.g., floor area per person and distance from the window), and psychological mediating and moderating factors (e.g., emotional state and psychological satisfaction). The interactions among these three levels can be summarized as follows. An increase in floor area per person suppresses the positive contribution of temperature to comfort. The influence of distance from the window exhibits a nonlinear pattern characterized by the superposition of quadratic and trigonometric functions, suggesting the existence of an optimal distance zone that balances daylight availability, the cold-wall effect, and privacy requirements. In addition, negative emotional states significantly reduce occupants' tolerance thresholds for environmental discomfort, indicating that emotional state moderates the strength of the relationship between physical environmental conditions and psychological satisfaction.

The model demonstrates that comfort maintenance in university research spaces is governed by nonlinear interactions among multiple factors rather than by the attainment of individual environmental standards alone. Reconsidering previous studies from this perspective reveals that traditional evaluation models often lack sufficient accuracy when applied to university research environments. For example, widely used multiple linear regression models generally assume that the effects of temperature, illuminance, noise, and other environmental variables are independent and constant. Furthermore, they do not incorporate spatial moderating variables such as floor area per person and distance from the window. Consequently, when applied to university research spaces characterized by substantial variations in spatial scale, these models fail to capture satisfaction variations arising from multi-factor coupling effects. Similarly, some models focusing exclusively on thermal comfort, such as those developed by Chin-to-Cheung et al. [14], can accurately predict responses to individual physical environmental factors but neglect the moderating effect of emotional state on discomfort thresholds. As a result, they cannot adequately explain why students with different psychological states may provide substantially different comfort ratings under identical physical environmental conditions. R. Bortolini et al. [15] employed Bayesian networks to characterize probabilistic dependencies among variables in university classrooms and recognized the importance of multi-factor interactions. However, their model remained limited to statistical associations and did not identify deterministic pathways through which environmental factors influence satisfaction via spatial characteristics and psychological states. These findings indicate that satisfaction in research spaces is not determined by the simple accumulation of environmental factors but is jointly governed by nonlinear interactions among key variables. Furthermore, compared with previous psychological satisfaction prediction models, such as the deep-transfer-learning model developed by Yanfei Gao et al., which achieved an accuracy of 57.04% [34], the SINDy-based model achieved an accuracy of 86.09%, demonstrating superior capability in capturing complex nonlinear relationships and providing a closer fit to actual psychological satisfaction data.

Among the multiple factors investigated, floor area per person, distance from the window, sound pressure level, and workspace temperature were ultimately identified as the most influential variables affecting overall comfort in research spaces. The evaluation equation established using these four key factors effectively quantifies the relationship between psychological satisfaction and its primary determinants. This finding is consistent with previous studies [35], further confirming that factors such as floor area per person and temperature play central roles in overall psychological satisfaction evaluation. More importantly, the present study demonstrates that substantial interaction effects exist among these variables.

- (1) A significant interaction effect was identified between temperature and floor area per person in determining overall comfort in research spaces. The increase in floor area per person weakened the positive effect of indoor temperature on comfort. This phenomenon may be explained by two mechanisms. First, the perceived spaciousness of an indoor environment may influence occupants' thermal perception, suggesting that larger and more open spaces reduce the perceived intensity of thermal conditions. Second, larger indoor spaces require greater thermal energy to achieve the same temperature increase. Since occupants themselves act as heat sources, larger floor areas per person may require higher ambient temperatures to maintain thermal comfort equilibrium.
- (2) An interaction was also identified between indoor temperature and distance from the window. The effect of distance from the window followed a combined quadratic and trigonometric pattern, resulting in a shifting optimal solution. Two possible explanations may account for this phenomenon. (a) Due to the cold-wall effect, occupants seated near windows are more sensitive to low temperatures and therefore require greater thermal compensation to achieve the same comfort level; (b) Colder air tends to accumulate near window

areas because of downward cold-air movement, resulting in lower temperatures around the feet and increasing the temperature required to maintain thermal comfort.

The results indicate that as participants' emotional states become more negative, their tolerance of the environment decreases accordingly. This suggests that preference data based on subjective voting may contain certain biases. Moreover, researchers' emotional states may interact with the spatial environment, altering the effective values of physical factors and thereby influencing comprehensive psychological satisfaction. Future investigations could incorporate the effects of user behavioral choices to more comprehensively elucidate the complex mechanisms linking building physical environments and psychological responses. Although the identification of emotional state as a moderating variable is conceptually informative, the current dataset is insufficient to quantify its effect magnitude. Future studies may integrate physiological sensor data (e.g., heart rate variability) with real-time emotional self-reports to enhance explanatory power.

The significance of this study lies in three aspects. Theoretically, it proposes a nonlinear evaluation framework integrating physical parameters and psychological perception, promoting a shift from static to dynamic modeling in building environmental evaluation. Methodologically, it validates the applicability of the SINDy algorithm for multivariable coupling analysis in building environments, providing a new tool for complex system modeling. Practically, the identified interaction effects (e.g., coupling between temperature and per capita area) can directly inform research space design: under limited space conditions, priority should be given to precise thermal control rather than merely increasing per capita area. Additionally, the nonlinear optimization formulation for *dist_window* offers quantitative guidance for daylighting and view design.

This study also has certain limitations. The experiment was confined to a single case study, which inherently limits the direct generalizability of the results. Although the proposed model effectively explores relationships between multiple factors and psychological satisfaction in university research contexts, future research could enhance applicability by incorporating additional contextual variables, such as geographic region, season, and activity patterns. Expanding to multi-case studies would further validate the model's applicability and accuracy across diverse and complex environments, enabling broader application to psychological satisfaction evaluation in university research spaces. Furthermore, only seven environmental variables were considered, which does not fully characterize research space environments. Future studies could incorporate additional variables, such as humidity, air velocity, and other indoor air quality indicators (e.g., formaldehyde concentration), to more comprehensively reflect real environmental conditions and enhance model reliability.

5. Conclusions

This study develops a nonlinear predictive model of psychological satisfaction in university research spaces by integrating objective physical parameters with subjective psychological perception. The key innovation lies in the application of the SINDy sparse identification algorithm, which effectively addresses the challenge of quantitatively characterizing complex coupling effects among multiple environmental factors. Research space comfort is not a simple additive outcome of individual environmental factors, but is jointly governed by significant nonlinear interactions—such as inhibitory coupling effects—among core factors including temperature, per capita area, and *dist_window*.

The proposed data-driven coupling model demonstrates higher predictive accuracy (86.09%) than traditional approaches, providing a more reliable quantitative tool for understanding dynamic “environment-psychology” relationships. This research contributes to the development of more scientific and precise design standards for research environments, enabling optimization of indoor environmental quality at the source. It also offers a basis for developing dynamic environmental control systems to achieve personalized and adaptive workplace optimization.

The evaluation model developed in this study exhibits a certain degree of generalizability and is primarily applicable to university research environments and research personnel. In terms of environmental settings, the model is suitable for a wide range of university research spaces, including faculty offices, graduate student offices, and similar workspaces. The key built factors identified by the model, such as temperature, illuminance, and noise, together with their coupling mechanisms, provide broadly applicable references for the design and evaluation of university research environments.

The identified interaction effects, such as the coupling relationship between temperature and floor area per person, can directly inform research-space design strategies. Within limited floor areas, priority should be given to improving temperature control accuracy rather than simply increasing floor area per occupant. Furthermore, the nonlinear optimization relationship associated with distance from the window provides quantitative guidance for daylighting and view-oriented design. During cold seasons (indoor temperature <18 °C), workstations should preferably be located away from exterior walls and windows to minimize the cold-wall effect. During transitional

seasons or in adequately heated indoor environments (19–23 °C), seating near windows may be encouraged to maximize access to natural daylight and outdoor views. The trigonometric component of the model further suggests that the optimal window distance is not monotonic. Therefore, a flexible distance range of approximately 2–4 m is recommended, with adjustments based on local climatic conditions. Given the significant influence of pre-existing emotional states on environmental evaluations, restorative features such as indoor greenery, quiet retreat areas, and adaptive lighting systems could be integrated into research environments. These interventions may help alleviate negative emotions, reduce perceptual bias toward environmental conditions, and indirectly enhance overall psychological satisfaction.

The data-driven nonlinear multifactor coupling model exhibits strong extensibility. Additional relevant factors—such as humidity and air quality—can be incorporated according to specific application scenarios and practical conditions, and large-scale validation can be conducted across different climate zones and types of universities to assess generalizability. Future research may integrate a broader range of variables to expand the model's applicability and practical value, thereby deepening and broadening analytical insights and providing more comprehensive guidance for the design and utilization of university research spaces.

Supplementary Materials

The additional data and information can be downloaded at: <https://media.scilit.com/articles/others/2607300929083619/UBS-26040101-SM.zip>. File S1: Research Status on Design Parameters for Standard Models of Scientific Research Spaces in Universities (including text, tables, and figures) (PDF). File S2: Informed consent form for participants (PDF). File S3: Experimental subjective/objective measurement data, actual scoring result, and SINDy simulated scoring result (Excel).

Author Contributions

H.Z.: writing the original draft, conceptualization, manuscript review and editing, funding acquisition, resources, supervision and formal analysis; J.L.: writing the original draft, manuscript review and editing, investigation, data curation and conceptualization; W.W.: writing the original draft, data curation, investigation, formal analysis; C.L.: resources, supervision. All authors have read and agreed to the published version of the manuscript.

Funding

This work was financially supported by Natural Science Foundation of Shandong Province (No. ZR2023QE340); Shandong Provincial Humanities and Social Sciences Research Project (General Program) named Research on Dynamic Weighting Evaluation Models for Indoor comfort in Buildings—A Case Study of Educational Buildings in Regions with Hot Summers and Cold Winters.

Institutional Review Board Statement

Ethical review and approval were waived for this study due to the anonymous questionnaire design and the study involving no medical or biological interventions on human subjects. Informed consent was obtained from all participants.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT to strengthen and polish the article's expression and to remove some overly specialized expressions. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Nomenclature

AHP	Analytic Hierarchy Process
CO ₂	Carbon Dioxide
dB	Decibel
dist_window	Distance from the window (m)
GBDT	Gradient Boosting Decision Tree
IEQ	Indoor Environmental Quality
lux	Unit of illuminance
MSE	Mean Squared Error
PCA	Principal Component Analysis
PD _{IAQ}	Percentage Dissatisfied with Indoor Air Quality
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
ppm	Parts per million
RF	Random Forest
S	Psychological satisfaction
S _A	Acoustic comfort satisfaction
SF-36	36-Item Short Form Health Survey
SHAP	SHapley Additive Explanations
S _{IAQ}	Indoor air quality satisfaction
SINDy	Sparse Identification of Nonlinear Dynamics
SPL	Sound pressure level (dB)
S _T	Thermal comfort satisfaction
S _V	Visual comfort satisfaction
SVM	Support Vector Machine
VIF	Variance Inflation Factor
X _{area}	Per capita usable area (m ² /person)
X _{dis}	Distance from the window (m)—variable in the model
X _{sou}	Sound pressure level (dB)—variable in the model
X _{tem}	Indoor temperature (°C)—variable in the model
Y	Psychological satisfaction evaluation score

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