International Journal of Sociologies and Anthropologies Science Reviews
Volume 5 Issue 3: May-June 2025: ISSN 2985-2730
Website: **https://so07.tci-thaijo.org/index.php/IJSASR/index**

The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments

Chen Chen[1], Yang Xing[2] and Yu-pei Kuo[3]
[1]Guangdong Literary & Art Vocational College, Mainland China
[2]School of Arts and Design, Huizhou University, Mainland China
[1;2]Chinese International College, Dhurakij Pundit University, Thailand
[3]Cross College Elite Tech Program, National Kaohsiung University of Science and Technology, Taiwan
[1]E-mail: aniya513cc@gmail.com, ORCID ID: https://orcid.org/0009-0005-9303-6989
[2]E-mail: yangxing0418@aliyun.com, ORCID ID: https://orcid.org/0000-0002-0350-4269
[3]E-mail: yupeikuo@nkust.edu.tw, ORCID ID: https://orcid.org/0009-0001-9706-9893
Received 03/04/2025 Revised 22/04/2025 Accepted 20/05/2025

Abstract

Background and Aim: The psychological mechanisms of human-space interaction are critical for understanding how environmental elements influence human emotions, cognition, and behavior. Previous examinations have investigated the impact of physical space on psychological well-being, but there has been little consideration of the dynamic, real-time adaptation of virtual environments based on individual emotional reactions. The aim is to investigate the effects of artificial intelligence (AI)-enabled spatial experiments on emotional regulation and stress reduction.

Materials and Methods: During this experiment, 500 volunteers were exposed to various virtual locations, including an urban setting, a forest, and a tranquil beach. Participants' emotional reactions were evaluated using biometric sensors and virtual reality (VR). The AI system utilized machine learning (ML) methods, such as the Red Panda Optimization Finetuned Intelligent Random Forest (RPO-IntelliRF), to monitor physiological reactions, including heart rate and skin conductivity, and dynamically adapt the virtual environment accordingly. If stress indicators were detected, the environment was adjusted to a more relaxing setting.

Results: The impact of these real-time modifications was assessed by analyzing changes in emotional state and physiological markers before and after interaction. The findings demonstrated a significant reduction in stress levels when the RPO-IntelliRF method intervened. Furthermore, the model achieved 89% accuracy, 80% precision, 81% recall, and an 87% F1 score in detecting and responding to stress-related indicators. Compared to static environments, participants reported greater relaxation and improved emotional well-being.

Conclusion: These results highlight the potential of AI-enabled spatial experiments for real-time environmental modifications, offering valuable insights into the psychological dynamics of human-space interaction and its implications for mental health enhancement.

Keywords: Psychological Mechanisms; Virtual Environment; Human Emotions; Red Panda Optimization Finetuned Intelligent Random Forest (RPO-IntelliRF)

Introduction

The field of environmental psychology conducts its inquiries to understand human-space interactions because these connections produce both emotional reactions and cognitive workings, and behavioral responses. The interaction of individuals with physical infrastructure and virtual systems has consequences on both how they relate to others and their efficiency levels and overall quality of life (Zheng et al., 2023). Spatial experiment functions as a new research design method, incorporating psychological analytical methods to develop user-centered designs for architecture and urban planning (Gerli et al., 2022).

Space exploration embeds environmental indications into human psychology as one of the essential psychological elements between people and outer space. Various environmental elements, including lighting, spatial arrangement, sensory richness, and biophilic layout, impact stress levels and concentration periods as well as overall well-being (Kühn & Gallinat, 2024). The assistants can modify these factors through controlled virtual environments that use AI-based simulation to detect changes in heart rate and eye-tracking actions, and intellectual activity. AI assists in designing perfect human-tailored settings for universities and medical structures, along with smart cities (Alvari et al., 2024). Virtual spatial testing enables AI-empowered customized environment exposure. Such learning models transform spaces through user-selected actions combined with their emotional state. Broadly speaking, AI technologies in urban

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: **https://doi.org/10.60027/ijsasr.2025.7341**

areas, through pattern projection, help users access spaces better, and intelligent workplaces modify their lighting levels as a method to keep users focused. Spatio-technical solutions that integrate AI strive to become health-based and adaptive while offering enhanced comfort and usefulness to users (Maroju & Bhattacharya, 2025).

In addition, while AI can enhance human perceptive and environmental design capacity, it should not replace it, as it only enhances the comprehension of human-space interaction (Chen & Ibrahim, 2023). A combination of conventional psychological concepts of spatial cognition and experience with spatial experiments enabled by AI can lead to the development of a comprehensive approach to spatial cognition and experience (Takac et al., 2023). The aim is to explore the effects of AI-enabled spatial experiments on emotional regulation and stress reduction.

The structural framework of the research is listed as follows: A list of literature reviews was provided in Section 2. The method is explained in Section 3. The results and discussion section is contained in Section 4. Section 5 provides the conclusion.

Objectives

1. Examine how AI-powered virtual worlds affect people's emotional states.
2. Describe how artificial intelligence (AI) might be used to improve human-space interactions and promote wellbeing.
3. Assess the accuracy and reliability of machine learning models, such as the Red Panda Optimization Finetuned Intelligent Random Forest (RPO-IntelliRF), in detecting and responding to stress-related indicators.

Literature review

The numerous variations in emotional intelligence (EI) within the context of AI integration were examined in Subramani and Manoharan (2024), which demonstrated the significance of EI in several fields. A smooth integration that promoted the emotional and intellectual aspects of medical care while acknowledging the possible challenges and advantages between AI and EI. A theoretical assessment of the present application of AI in the area of mental wellness was provided in Atias and Atias (2024). They examined the legal, therapeutic, and technological aspects of the proper application of AI in mental wellness treatment. A regulatory structure was required for all AI systems used in mental health care, and additional investigation was needed to assess the risks and dependability of the systems.

A stress identification strategy that integrates a metaheuristic fuzzy inference system-based learning (fMFiS-L) with emotion identification methods was that were examined by Rezaee et al (2022). The result achieved favorable results in emotion classification, through achieving an accuracy rate of 92%. The analysis of stress identification using devices with sensors coupled to deep learning (DL)-based techniques appeared in Hamatta et al (2022). An Enhanced Convolutional Neural Network-Long short-term memory (ECNN-LSTM) detected all input data with full accuracy to anticipate human emotional states between calm and stressed.

A sophisticated AI educational application with IoT capabilities utilized emotional intelligence to support ASD children as described by Vanaja and Arockia (2023). The system allowed students to express learning content during educational activities by delivering audio rhymes as part of their diverse learning material. The general usage and effectiveness of AI apps for treating anxiety and depressive signs were explored by Pavlopoulos et al (2024). Large language models (LLMs) within AI applications showed significant potential, according to research findings, because they delivered personalized therapy access easily while supporting standard mental health therapy methods.

The incorporation of modern AI technologies, such as emotion recognition and adaptive learning systems, to improve the acquisition of second languages was examined in Shi (2024). Research findings have shown that AI technologies used in learning can enhance emotional control and storage capacity among students. The utilization of AI technology to optimize Recurrent Neural Network (RNN) was investigated in conjunction with an assessment of psychological elements influencing tennis-training

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

approaches by Du et al (2025). Achievements in this exploration demonstrate better results than previous studies, indicating the success of psychological control enabled by artificial intelligence-enhanced RNNs.

Conceptual Framework

Methodology

The Spatial Experiment Dataset, powered by AI, provides environmental factors as well as spatial measurement points with sensor data that are suitable for artificial intelligence experiments. Biometric sensors operated with VR helped measure physiological responses via multiple data cleaning protocols that standardized the results using Z-score normalization. The machine learning application in RPO-IntelliRF measured stress indicators to activate modifications in simulated spaces that helped users manage their stress.

1. Data collection

The AI-Enabled Spatial Experiment Dataset on Kaggle contains spatial data for AI-driven experiments, featuring sensor readings, environmental parameters, and spatial coordinates. It supports research in robotics, smart environments, and spatial analytics. The dataset is useful for AI modeling, spatial reasoning, and real-world simulations, providing structured data for experimentation and machine learning applications.

Source:https://www.kaggle.com/datasets/ziya07/ai-enabled-spatial-experiment-dataset/data.

2. Data cleaning

Data cleaning describes the capability of detecting and fixing mistakes, inconsistencies, and inaccuracies in raw data before analysis. It involves several procedures dealing with missing numbers, eliminating duplicates, fixing outliers, and formatting the data consistently. Additionally, data cleaning includes numerical data, standardizing variables, and encoding categorical data to ensure the dataset is appropriate.

3. Z-score normalization

The use of Z-score enables the standardization of data from the AI spatial experiment, which ensures unbiased comparison of emotion and stress effects. Standard deviation (SD) normalization constitutes the basic method animals use to turn input measurements into standardized units having a mean value of zero and a unit standard deviation. The analysis calculates the standard deviation together with the average value for each feature. The normalization process for every feature uses the mean and standard deviation calculated in Equation (1).

$$CapZ = (W - mean(W)/std(W) \quad (1)$$

Where $std(W)$indicates an SD of feature W and mea the mean of feature W. The benefit is that it lessens the impact of outliers on the information.

4. RPO-IntelliRF

The RPO-IntelliRF is an innovative method for AI-enabled spatial experiments on stress management and emotional control. This technique integrates an IntelliRF model with the RPO algorithm that was developed based on the red panda's adaptive foraging behaviour for developing stress-related experiments that achieve better categorization and forecasting accuracy.

RPO-IntelliRF's dynamic hyperparameter optimization makes it possible for the Random Forest model to select and make decisions in real-time. Biometric signal monitoring in spatial experiments is processed in immersive VR settings and other behavioral reactions, which include reactions to various AI-generated stresses and relaxation stimuli. The RPO fine-tunes feature weights based on the most significant factors that affect emotional regulation evaluation. The stress and emotional reactions in different spatial situations, such as controlled laboratory conditions, interactive VR, and urban green areas, are analyzed to offer individualized AI-driven solutions. RPO combined with IntelliRF offers a strong, practical, and flexible model to which future exploration in stress reduction, mental health, and AI-based treatment can be developed.

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

International Journal of Sociologies and Anthropologies Science Reviews
Volume 5 Issue 3: May-June 2025: ISSN 2985-2730
Website: https://so07.tci-thaijo.org/index.php/IJSASR/index

4.1 IntelliRF

An IntelliRF model is capable of evaluating a wide range of human reactions to environmental settings. It reveals trends in behavioral patterns, emotions, and mental operations by fusing AI with geographical data, offering insights into the spatial impacts of psychological reactions and decision-making.

The random forest method does not overfit and has a better tolerance for noise and outliers. It also has a greater categorization accuracy. The result indicates that the accuracy of random forest categorization varies.

Since Iterative Dichotomiser 3 (ID3) and Classification and Regression Trees (CART) are integrated with the random forest method, node splitting optimization is taken into account for both techniques. The node splitting equation displays the Gini index and information gain achieved when characteristics are used for dividing the sample set C, as shown in Equations (2-5).

$$Gain(C,b) = Ent(C) - \sum_{u=1}^{U} \frac{|C^u|}{|C|} Ent(C^u) \quad (2)$$

$$Gini(C,b) = \sum_{u=1}^{U} \frac{|C^u|}{C} Gini(C^u) \quad (3)$$

Where C^u denotes that the u branch node includes all of the instances in the C with a value of b^u on the feature b.

$$Ent(C) = -\sum_{l=1}^{|z|} o_l log_2 o_l \quad (4)$$

$$Gini(C) = \sum_{l=1 l' \neq l}^{|z|} olol' = 1 - \sum_{l=1}^{|z|} ol^2 \quad (5)$$

The adaptive parameter selection (APS) procedure and the combination node splitting calculations are as follows in Equation (6) because the intent of node splitting should be to increase the integrity of the data set in the following divisions.

$$G = \min_{\alpha,\beta \in Q} E\{C,b\} = \alpha Gini(C,b) - \beta Gain(C,b) \begin{cases} \alpha + \beta = 1 \\ 0 \leq \alpha,\beta \leq 1 \end{cases} \quad (6)$$

Where,

$Alpha\alpha, \beta$- Weight coefficient of feature splitting.

Where$G$ has a low value. The most effective combination of parameters is obtained by using the APS technique. To enhance the categorization impact, ID3 and CART are both the best node segmentation standards.

Performance is evaluated using the categorization error rate and accuracy rate. Equation (7) defines the categorization error rate for sample C.

$$F(e,C) = \frac{1}{n} \sum_{j=1}^{n} JJ\left(e\left(w_j\right) \neq z_j\right) \quad (7)$$

Equation (8) provides the accuracy rate.

$$acc(e;C) \frac{1}{n} \sum_{j=1}^{n} JJ\left(e\left(w_j\right) = z_j\right) = 1 - F(e;C) \quad (8)$$

4.2 RPO

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

International Journal of Sociologies and Anthropologies Science Reviews
Volume 5 Issue 3: May-June 2025: ISSN 2985-2730
Website: https://so07.tci-thaijo.org/index.php/IJSASR/index

RPO improves the calculation of human behavior in a variety of spatial situations, resulting in better-designed interactions that influence psychological results. Through effective management of elements like lighting, interactivity, and space arrangement, RPO can reveal trends that support mental and emotional health, resulting in improved designs for human-space interaction.

This section discusses utilizing the Red Panda Optimization (RPO) to optimize emotional regulation and stress reductionuctionS_d, N_d, D_d *and* O_d parameters. A recently developed nature-inspired optimization method, RPO, draws inspiration from red panda foraging behavior to optimize strategies for managing stress and regulating emotions effectively. It was created to deal with challenging emotional regulation and stress reduction problems. Managing emotions and reducing stress are combined in RPO. To achieve the ideal emotional balance, it employs adaptive coping strategies that explore a range of emotional responses while focusing on positive regulation techniques. The method uses psychological resources efficiently, promoting resilience and reducing emotional exhaustion. It is effective in managing stress on a large scale, as it requires minimal cognitive effort compared to certain other regulation techniques. The fundamental design principle of RPO is based on the two key aspects of emotional well-being: mindful self-awareness and restorative relaxation.

(a)The stepwise procedure of RPO

To determine the optimal emotional regulation strategy under RPO, a sequential procedure is defined. To improve stress reduction and improve emotional stability, S_d, N_d, D_d, *and* O_d characteristics, RPO distributes the coping mechanisms evenly. Figure 1 shows the flowchart that corresponds to the ideal solution that is improved by RPO.

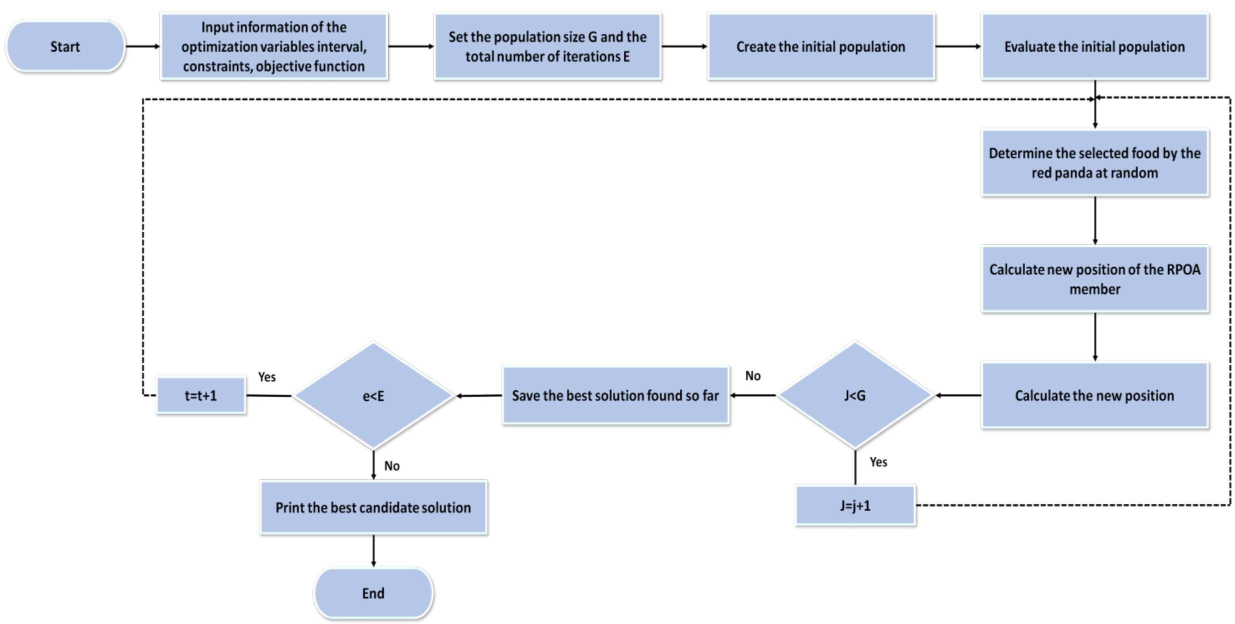

Figure 1 Flowchart of RPO
Note: Constructed by the researcher

(b) Initialization

A population-centered meta-heuristic strategy based on emotion regulation is the suggested RPO approach. The matrix is used to represent the emotion regulation strategies. The suggested values for the continuous variable related to stress reduction are included in every column of the suggested matrix, and each row represents an individual strategy for optimizing emotional responses and reducing stress levels described in Equation (9).

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

$$y = \begin{bmatrix} y_1 \\ \vdots \\ y_j \\ \vdots \\ y_G \end{bmatrix}_{G\times 1} = \begin{bmatrix} y(P_1) \\ \vdots \\ y(P_j) \\ \vdots \\ y(P_G) \end{bmatrix}_{G\times 1} \quad (9)$$

Where,
y_j-Outcome of tthejth individual's emotion regulation response, and
y-Values of the stress reduction vector.
(c) Random generation

Determine the emotional regulation and stress regulation variables, then generate them randomly. The ideal selection of stress reduction techniques is determined by their effectiveness in managing emotional responses under stress.

(d) Fitness function assessment

The initialization process generates an initial emotional state. To improve the fitness function in the emotional regulation and stress regulation parameters$S_d, N_d, D_d,$ and O_d, the fitness function evaluates key parameters related to coping mechanisms and psychological resilience. This can be expressed by Equation (10).

$$fitness\ function = optimizing\ (S_d, N_d, D_d, O_d) \quad (10)$$

Exploration phase for the approach of red pandas while foraging

Red pandas exhibit strong emotional regulation and stress reduction abilities, which allow them to adapt and remain calm in various situations. The matched red panda will navigate to a chosen location based on a sense of comfort and emotional balance, ensuring a stress-free experience in its environment, as shown in Equation (11).

$$Q_j = \{P_u \mid C \in \{1,2,\ldots,G\}\ and\ S_u < S_j\} \cap \{P_{best}\} \quad (11)$$

Where, P_{best}indicates the optimal emotional regulation based on the objective function, and $Q_j$indicates the collection of suggested stress reduction strategies for j^{th}individual.

(f) Exploitation phase for enhancing S_d, N_d, D_d, O_d

The value of the emotional regulation function improves the stress reduction location; Equations (12&13) are used to calculate the modified emotion regulation's location.

$$P_j^{y1}: o_{j,i}^{y1} = p_{j,i} + t.(S_d - a.p_{j,i}) \quad (12)$$

$$P_j = \begin{cases} P_j^{y1}, y_j^{y1} < y_j; \\ P_j, else \end{cases} \quad (13)$$

Where,
P_j^{Y1}-New emotional regulation strategy that is dependent on the initial stress management phase,
y_j^{y1}–stress reduction value,
$T_{j,i}$-j^{th}coping technique,
T_j–Emotional regulation method for the j^{th}individual,

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

$p_{j,i}^{y1}$-i^{th}coping technique.

The capacity of individuals to regulate their emotions and manage stress determines its progression in the second stage of the RPO. Individuals often engage in relaxation techniques to reduce stress. The individual's previous emotional state is adjusted based on adaptive coping techniques by Equations (14&15) if their stress level is decreased.

$$N_d = p_{j,i} + \frac{O_d + t.(vf_i - xf_i)}{e} \tag{14}$$

$$D_d = \begin{cases} P_j^{y2}, y_i^{y2} < y_j \\ P_j, \ else \end{cases} \tag{15}$$

Where,
P_j^{y2}- The individual's emotional state is influenced by the second stage of the RPO,
$p_{j,i}^{y2}$–Regulation intensity of i^{th}stage,
t-Arbitraryemotional resilience factor,
y_j^{y2}–Overall stress reduction value.
(g) Termination Condition

The RPO's output provides the most effective stress reduction approach, which repeatedly performs until $Y = Y + 1$ is achieved.

Results

The experiment setup was performed in the programming language of Python 3.10.1 and is used to implement the suggested RPO-IntelliRF method on a Windows 11 laptop with an Intel i7 core CPU and 8GB of RAM. This section provides an in-depth explanation of the experimental outcomes. The proposed strategy was assessed, and its effectiveness was determined using the following indicators: accuracy, F1-score, precision, and recall. Furthermore, a comparative investigation will be conducted with other existing approaches, including the Bagging ensemble learning model (Tao et al., 2022). Table 1 displays the comparison of classifiers: performance evaluation results.

Table 1 Numerical values of comparison result between proposed and conventional techniques

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Bagging ensemble learning model	74.2 %	68.7 %	77.4 %	70.9 %
RPO-IntelliRF [Proposed]	89 %	80 %	81 %	87 %

1. Confusion matrix

A confusion matrix for Psychological Mechanisms of Human-Space Interaction in AI-enabled spatial experiments would categorize predictions and actual outcomes in human-space interaction training. It could compare expected vs. observed psychological responses (e.g., stress, comfort) to AI-designed spaces. Categories might include True Positive (accurate prediction), False Positive (unexpected response), False Negative (missed reaction), and True Negative (correct non-response). These AI-enabled spatial experiments on emotional regulation and stress reduction provide valuable insights into optimizing environments for well-being by refining predictive models and improving the accuracy of psychological response assessments. Figure 2 shows the outcome of the confusion matrix.

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

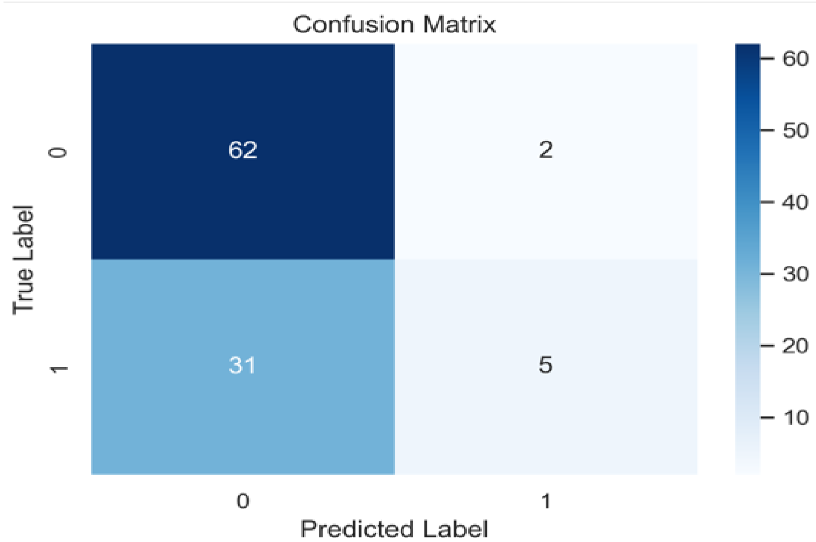

Figure 2 The outcome of the Confusion matrix
Note: Constructed by the researcher

2. ROC Curve
The ROC curve for Psychological Mechanisms of Human-Space Interaction in AI-enabled spatial experiments illustrates the model's ability to distinguish between psychological responses in different spatial conditions. With an AUC of 0.72, the model demonstrates moderate predictive performance, indicating reasonable discrimination between positive and negative psychological outcomes in AI-driven spatial experiments, though with the possibility for improvement. Figure 3 illustrates the ROC curve.

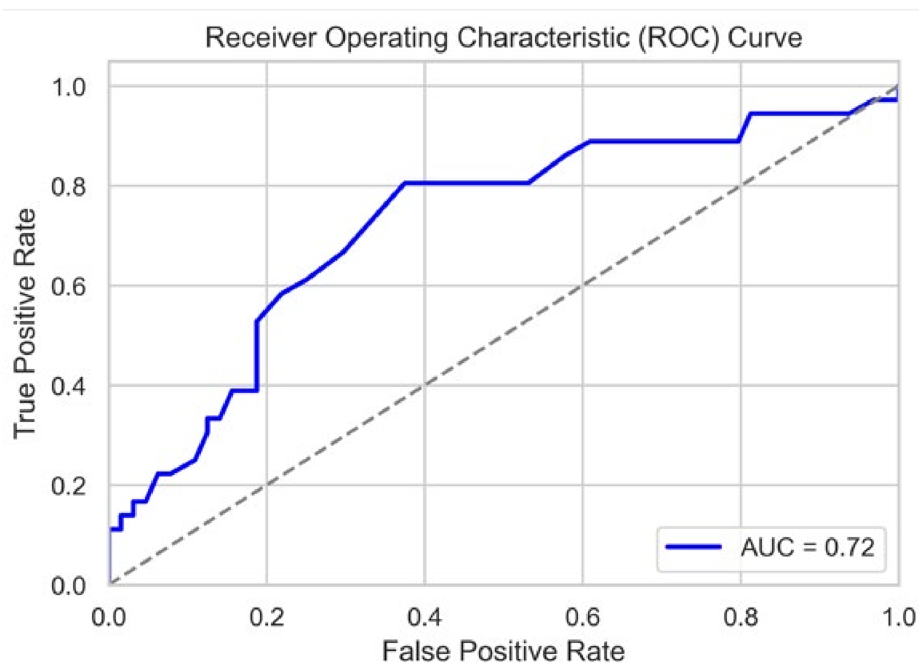

Figure 3 illustrates the ROC curve.
Note: Constructed by the researcher

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

3. Distribution of Virtual Environments

The distribution of virtual environments in AI-enabled spatial experiments categorizes participants across different settings: Urban (196 participants), Forest (165 participants), and Beach (139 participants). By exposing individuals to these varied environments, researchers analyze psychological mechanisms in human-space interactions, assessing behavioral, cognitive, and emotional responses. These AI-enabled spatial experiments facilitate the education of emotional regulation and stress reduction by examining how different environments influence psychological well-being. Controlled allocation ensures comparative insights into spatial perception, engagement, and decision-making across diverse digital contexts. Figure 4 shows the Distribution of Virtual Environments.

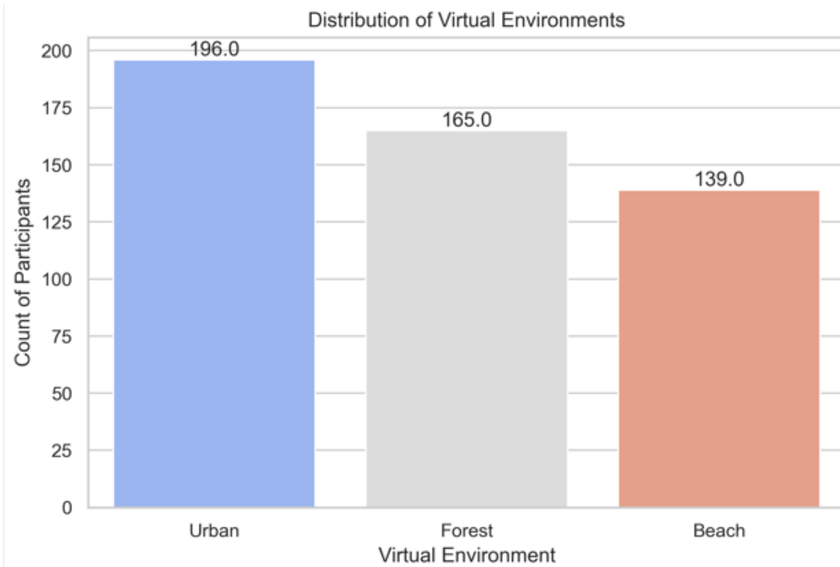

Figure 4 The Result of Distribution of Virtual Environments
Note: Constructed by the researcher

4. Accuracy

Enabled spatial experiments on emotional regulation and stress reduction with AI-driven accuracy, rigorous data validation, controlled environments, and precise measurement of human responses, enhancing reliability in understanding psychological mechanisms in human-space interaction. The RPO-IntelliRF model achieved 89% accuracy, outperforming the Bagging ensemble learning model, which had 74.2% accuracy. This demonstrates highlighting RPO-IntelliRF as the superior method for enhanced predictive performance and classification accuracy.

5. Precision

The AI-driven spatial experiments enabled the analysis of psychological mechanisms in human-space interactions, enhancing precision in environmental design, emotional regulation, stress reduction, cognitive responses, and adaptive architecture for optimized user experience and well-being. The result compares a Bagging ensemble learning model and RPO-IntelliRF for precision. RPO-IntelliRF achieves 80% precision, outperforming the Bagging model's 68.7%. This suggests that RPO-IntelliRF is a more effective method for improving classification precision in the given context.

6. Recall

AI applications in spatial experiments evaluate psychological factors that influence human-space interactions between cognition, perception, and behavior, which leads to optimized environmental design. The experimental design allows spatial modifications that manage emotions and decrease stress while boosting well-being and operational effectiveness, and flexible teamwork between humans and AI. The RPO-IntelliRF model demonstrates superior recall performance compared to Bagging ensemble learning

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

because it reaches 81% recall while Bagging ensemble learning stops at 77.4%. RPO-IntelliRF demonstrates higher competence in recognizing relevant instances, which proves it is an effective approach to enhance classification precision and decrease false negative occurrences.

7. F1-Score

AI technology conducts spatial tests that examine human relationships with space to educate emotional management and stress reduction. Evaluation through F1-scores in these tests gives quantitative measures of emotional responses to enable better AI-controlled spatial design for human-centered adaptable environments. The RPO-IntelliRF model, an advanced Bagging ensemble learning model approach, outperforms the standard method with an F1-score of 87%, compared to 70.9% for traditional bagging. This demonstrates its superior predictive accuracy and effectiveness in classification tasks. Figure 5 displays the Performance Evaluation Results.

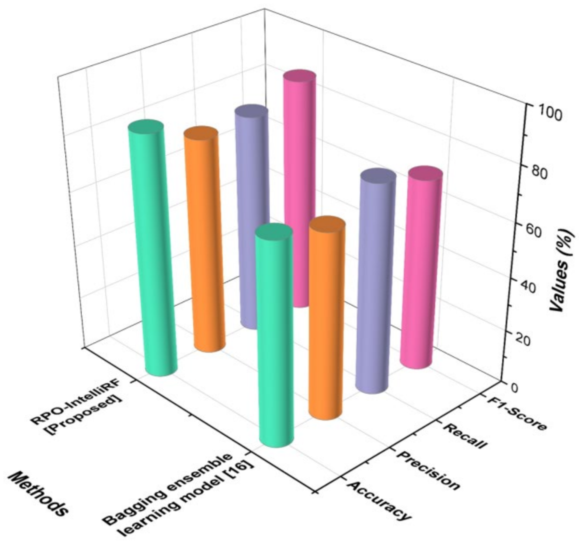

Figure 5 Performance Evaluation of suggested RPO-IntelliRF model and prior studies
Note: Constructed by the researcher

Discussion

AI-enabled spatial experiments analyze human-space interaction mechanisms to decrease stress and control emotions through behavioral, emotional and cognitive recognition of real-world and virtual space environments. The complexity of AI-enabled spatial experiments regarding emotional regulation and stress reduction poses difficulties for bagging ensemble learning models since it interacts with human emotions that are highly variable along with subjective responses and environmental conditions. When it comes to detecting complex links between artificial intelligence-driven stimuli and psychological effects the model falls short which decreases its interpretability capabilities. The implementation of bagging models depends on massive datasets of high quality, which could remain unfeasible in psychological studies. The ability to properly generalize through diverse populations, along with sticking to particular emotional patterns, reduces its utilization effectiveness. To overcome this, the RPO-IntelliRF system can optimize their models by selecting the best features and improving decision trees that result in better generalization in experiments involving spatial AI and psychological exploration. The method reduces overfitting while adjusting to emotional changes and delivers dependable stress regulation prediction outcomes for various human groups.

Conclusion

The platform uses AI technology to run spatial tests that control emotions through biometric detectors and virtual reality systems. The Spatial Experiment Dataset from Kaggle uses AI technology to store sensor

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

readings with environmental parameters along with spatial coordinates for AI experiments. The analysis followed data cleaning, resulting in Z-score normalization, which made data point's equivalent. The RPO-IntelliRF activated modifications in the virtual environment parameters. AI-based adaptable spaces succeeded in lowering stress, according to the research outcomes, thus demonstrating their strength in enhancing emotional well-being. The Psychological Mechanisms of Human-Space Interaction in AI-Enabled Spatial Experiments evaluated RPO-IntelliRF, as it reached high performance through 89% accuracy, 80% precision, 81% recall and 87% F1-score. AI-driven spatial analysis tool sets show their ability to detect human psychological responses through spatial analysis within these results. The emotional understanding of spatial environments remains uncertain in present-day AI models because it engages in primitive patterns of emotional analysis. Limited generalizability, ethical issues, expensive expenses, reliance on technology, individual differences, threats to data privacy, and possible unforeseen psychological impacts. Advancements in AI-driven simulations, multimodal sensing, and personalized spatial adaptation can enhance human-space interactions, improving urban planning and smart environments.

Recommendation

Based on the findings of this study, several recommendations can be made to enhance the application of AI-enabled spatial experiments in emotional regulation and stress reduction:

1. Enhancing AI Emotional Understanding:

Current AI models are based on basic emotional analysis. Future research should incorporate advanced affective computing approaches, such as deep learning-based emotion recognition, to enhance AI's ability to interpret complicated human emotions and behavioral reactions.

2. Ethical and Privacy Considerations:

Given concerns over data privacy and ethical issues, AI-enabled spatial experiments must comply with strict ethical guidelines. Researchers and developers should ensure transparency, informed consent, and data anonymization to mitigate risks related to personal data collection.

3. Increasing Generalizability:

The study's findings should be validated across diverse populations and settings to improve the generalizability of AI-driven spatial adaptation. Future experiments should consider cultural, demographic, and psychological differences in emotional responses to spatial environments.

4. Reducing Implementation Costs:

The high cost of biometric sensors, VR systems, and AI infrastructure may restrict broader adoption. Researchers and developers should explore cost-effective alternatives, such as mobile-based emotion tracking and cloud-based AI models, to improve accessibility and scalability.

5. Advancements in AI-Driven Spatial Adaptation:

Further advancements in AI-driven optimizations, multimodal sensing, and personalized spatial modifications should be developed. To enhance the adaptability of virtual environments real-time EEG monitoring, gaze tracking, and voice emotion detection should be incorporated.

6. Application in Real-World Scenarios:

Smart cities, workplace environment, healthcare facilities requires AI-based spatial adaptation which should be integrated into real-world applications. In future it should be explored that how AI can adapt and optimize spatial designs to enhance well-being, productivity, and mental health.

By solving these issues, AI-enabled spatial studies can become more successful, ethical, and generally applicable, propelling human-space interaction research forward and boosting emotional well-being in a variety of settings.

References

Alvari, G., Vallefuoco, E., Cristofolini, M., Salvadori, E., Dianti, M., Moltani, A., Castello, D. D., Venuti, P., & Furlanello, C. (2024). *Exploring physiological responses in virtual reality-based*

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: https://doi.org/10.60027/ijsasr.2025.7341

interventions for autism spectrum disorder: A data-driven investigation. arXiv preprint arXiv:2404.07159. https://doi.org/10.48550/arXiv.2404.07159

Atias, V., & Atias, K. (2024, October). Methods and applications of artificial intelligence in mental health care. In *2024 International Conference Automatics and Informatics (ICAI)* (pp. 614–620). IEEE. https://doi.org/10.1109/ICAI63388.2024.10851672

Chen, X., & Ibrahim, Z. (2023). A comprehensive study of emotional responses in AI-enhanced interactive installation art. *Sustainability, 15*(22), 15830. https://doi.org/10.3390/su152215830

Du, Y., Xia, Y., Wang, L., Zhang, T., & Ju, L. (2024). The influence of psychological change factors of tennis training strategy using optimized recurrent neural network and artificial intelligence. *Heliyon, 10*(13), e33273. https://doi.org/10.1016/j.heliyon.2024.e33273

Gerli, P., Clement, J., Esposito, G., Mora, L., & Crutzen, N. (2022). The hidden power of emotions: How psychological factors influence skill development in smart technology adoption. *Technological Forecasting and Social Change, 180*, 121721. https://doi.org/10.1016/j.techfore.2022.121721

Hamatta, H. S., Banerjee, K., Anandaram, H., ShabbirAlam, M., Deva Durai, C. A., Parvathi Devi, B., Palivela, H., Rajagopal, R., & Yeshitla, A. (2022). Genetic algorithm-based human mental stress detection and alerting in Internet of Things. *Computational Intelligence and Neuroscience, 2022*(1), 4086213. https://doi.org/10.1155/2022/4086213

Kühn, S., & Gallinat, J. (2024). Environmental neuroscience unravels the pathway from the physical environment to mental health. *Nature Mental Health, 2*(3), 263–269. https://doi.org/10.1038/s44220-023-00137-6

Maroju, P. K., & Bhattacharya, P. (2025). Understanding emotional intelligence: The heart of human-centered technology. In *Humanizing Technology With Emotional Intelligence* (pp. 1–18). IGI Global. https://doi.org/10.4018/979-8-3693-7011-7.ch001

Pavlopoulos, A., Rachiotis, T., & Maglogiannis, I. (2024). An overview of tools and technologies for anxiety and depression management using AI. *Applied Sciences, 14*(19), 9068. https://doi.org/10.3390/app14199068

Rezaee, K., Yang, X., Khosravi, M. R., Zhang, R., Lin, W., & Jeon, G. (2022). Fusion-based learning for stress recognition in smart home: An IoMT framework. *Building and Environment, 216*, 108988. https://doi.org/10.1016/j.buildenv.2022.108988

Shi, L. (2025). The integration of advanced AI-enabled emotion detection and adaptive learning systems for improved emotional regulation. *Journal of Educational Computing Research, 63*(1), 173–201. https://doi.org/10.1177/07356331241296890

Subramani, K., & Manoharan, G. (2024, June). Humanizing the role of artificial intelligence in revolutionizing emotional intelligence. In *2024 3rd International Conference on Computational Modelling, Simulation and Optimization (ICCMSO)* (pp. 237–242). IEEE. https://doi.org/10.1109/ICCMSO61761.2024.00056

Takac, M., Collett, J., Conduit, R., & De Foe, A. (2023). A cognitive model for emotional regulation in virtual reality exposure. *Virtual Reality, 27*(1), 159–172. https://doi.org/10.1007/s10055-021-00531-4

Tao, K., Huang, Y., Shen, Y., & Sun, L. (2022). Automated stress recognition using supervised learning classifiers by interactive virtual reality scenes. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 30*, 2060–2066. https://doi.org/10.1109/TNSRE.2022.3192571

Vanaja, D. S., & Arockia Raj, J. (2025). AI-enhanced IoT tool for emotional and social development in children with autism. *International Journal of High Speed Electronics and Systems, 2540148*. https://doi.org/10.1142/S0129156425401482

Zheng, L., Zhao, Y., Duan, R., Yang, W., Wang, Z., & Su, J. (2023). The influence path of community green exposure index on activity behavior under multi-dimensional spatial perception. *Frontiers in Public Health, 11*, 1243838. https://doi.org/10.3389/fpubh.2023.1243838

Citation
Chen, C., Yang, X., & Yu-pei , K. (2025). The Psychological Mechanisms of Human-Space Interaction: AI-Enabled Spatial Experiments. International Journal of Sociologies and Anthropologies Science Reviews, 5 (3), 807-818; DOI: **https://doi.org/10.60027/ijsasr.2025.7341**