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A Knowledge-Based Human-Computer Interaction System for the Building Design Evaluation Using Artificial Neural Network

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Abstract

In recent years, human factors in cooperative computation have been studied increasingly, since various application contexts are complicated and highly related to the knowledge of subject-matter experts such as health care, military, and artistic designing. Due to the difficulty of knowledge elicitation and representation, human computation always faces the challenge of human-computer interaction issues. In this regard, this paper presents a human-computer interaction system based on subject knowledge to assess the influence of architecture on urban environments. Human computation is significant in generating reasonable and effective grades based on both subjective feelings and objective indicators, avoiding subjectivity and discreteness in traditional expert reviews. The artificial neural network algorithm takes part in kernel modeling to represent the comprehensive expert knowledge and calculate scores based on objective indicators. To evaluate the usability and effectiveness of the presented methodology, a dataset including 22 accomplished projects was applied and validated. The mean absolute error of the validation data was 5.53, which shows that the presented model can achieve a high accuracy. Based on the established model, two new architectural projects in the research area were evaluated and studied. The evaluated scores tallied 68 and 73, authentically reflecting the performance of the design schemes.

Keywords

Human-Computer Interaction System, Building Design Evaluation, Human Computation, Knowledge Elicitation, Artificial Neural Networks

1. Introduction

One fundamental objective of sustainable development is avoiding the degradation of the natural environment [1, 2]. Since the 1990s, the "green building" movement has been a universal action toward energy crises and global sustainability requirements [3]. In addition, the important impacts of buildings on the environment are always caused by decisions made in the early design stages [4]. However,

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architecture design is a very complex system with strong subjectivity and discreteness. For the same project, the design output from different architects may be quite different. Globally, the most accepted approach for architectural scheme evaluation is an expert review. Based on their own experience and knowledge, experts have different priorities, agendas, and understandings of a project. Only relying on the expert review, the assessment results are always subject to doubts about objectivity and reliability. Therefore, it is necessary to evaluate projects at the design stage with a more stable and reliable method, in lockstep with maximizing the role and effectiveness of expert knowledge. Since the comprehensive evaluation of building design requires the representation of a large amount of subject knowledge and calculation of heterogeneous data, it is an efficient method to utilize human processing in tandem with powerful computing capacity, which is known as human computation.

Having grown rapidly in both industry and academia, human computation systems have been purposefully introduced to solve complicated problems in various subject contexts. Computers are fast, objective, and accurate with powerful abilities of storage and computing, while humans are creative, ratiocinative, and general with social consciousness. The human, as a computational element, participates in the design and analysis of information processing systems [5], through which the intelligence of humans and the capability of computers are fully applied. With the knowledge elicitation process, subject matter professionals can input their judgments to the human computation system, and they are represented as a knowledge database. It should be noticed that the human-computer interaction (HCI) design during this process should be taken seriously, because most subject-matter experts cannot understand the fundamental principle of the human computation system. An appropriate method of HCI should retrieve subject knowledge from professionals as accurately as possible. Furthermore, the interaction between knowledge and objective indicators is also an HCI research issue. Considering the evaluation of building design is a typical nonlinear calculation and recent research apply machine learning to enhance the HCI system, artificial neural network (ANN) can take part in the kernel modeling in the system. In this regard, ANN has been widely used in many scientific research fields and performed outstanding expression ability in complex mapping. With the suitable configuration, ANN modeling can discover the potential and complicated relationship between a subjective assessment and objective indicators, thus implementing the HCI between them.

Accordingly, this paper intends to introduce human computation in a new method to evaluate the influence of building design on the environment aspect. By studying the evaluation factors and knowledge elicitation of experts, the basic logical structure of the evaluation system is established. Human computation can play a significant role in the building evaluation to generate reasonable and effective grades based on both subjective feelings and objective indicators. ANN technology is used to establish the calculation model between the objective data of the building scheme and the subjective evaluation scores of experts. Then, this evaluation methodology was analyzed and verified by actual cases. If the construction scheme is optimized at the architectural design stage, the investment and consumption of technology, materials, and equipment can be effectively reduced. Likewise, it is expected that this study can improve the design scheme, stimulating the development of cities and the natural environment in a more sustainable way. The primary contributions of this paper are listed as follows:

- Utilize human computation into an evaluation system by using the objective data of the building scheme and subjective evaluation of experts.
- Provide a more stable and reliable evaluation methodology of architectural schemes on the environment aspect, maximizing the role and effectiveness of expert knowledge and improving the sustainability of the urban environment.
- ANN is employed as an HCI method to represent comprehensive expert knowledge and calculate scores based on objective indicators in architectural schemes.

The rest of this paper is organized as follows. In Section 2, the related work is presented; in Section 3, the methodology of the evaluation method based on HCI is introduced, while Section 4 provides the experiment of a natural landscape protection area with 22 projects to verify the accuracy and validity of this method, and Section 5 wraps up this paper with the conclusion.

2. Related Work

Architectural criticism and building performance evaluation are the main ways to evaluate the quality of buildings, both of which have made great contributions to the development of sustainable architecture design. Analysis, evaluation, and the issuance of judgments are the main functions of architectural critics [6]. Recently, the most popular building performance evaluation has been green building rating tools (GBRTs), as they provide design guidelines and predetermination of evaluation criteria [7]. Based mainly on advanced technological solutions [8], GBRTs have been criticized [9] for ignoring the human dimension and connection between humans and nature [10]. Current environmentally sustainable design approaches narrowly focus on the thermal efficiency of the building envelope [11], suggesting evidence-based approaches [12] and lacking social criteria [13]. Thus, a more complete and sustainable evaluation method for buildings is needed.

With strong subjectivity and discreteness, architecture design is a very complex system, and advanced techniques need to be introduced in the evaluation system. Human computation is an interdisciplinary field, and Von Ahn [14] was the first to define it as “a paradigm for utilizing human processing power to solve problems that computers cannot yet solve.” Now, it has been used wildly in various subjects and has improved the cooperation between human beings and computing systems. Al-Subaihin and Al-Khalifa [15] used human computation to establish an implementation and evaluation system for sentiment analysis of Arabic. More accurate schematized maps will be made from pictures when human computation and machine clustering are combined for image processing [16]. Wojcik et al. [17] use survey data and human computation to improve the tracking of flu contagion. Another popular research topic of human computation is automated driving with researchers applying probability theory and risk prediction methods to generate cooperative action for the sake of driving safety [18, 19].

Human computation technique allows subject-matter experts to work with high computing capacity, and thus it can achieve satisfactory performance on building design evaluation. However, the methodology of HCI between the knowledge of experts and specific computer systems is a critical research question. Based on fuzzy logic theory and HCI, Sha et al. [20] designed an online psychological consultation system to utilize professional knowledge and help users improve emotion management. Gong et al. [21] proposed a novel emotion control system based on HCI and the Internet of Things to establish an emotional model. Moreover, some researchers focused on enhancing decision support between humans and computers in complex scenarios by applying HCI, such as intelligent aircraft control [22] and 3D spatial orientation [23]. Along with the development of machine learning, numerous studies have combined various supervised learning with HCI to achieve better HCI quality. Al-Ma'aitah et al. [24] presented an application dependable interaction module based on computer vision and HCI, which applied a deep belief network to analyze user behaviors. Gesture recognition is another common research topic in HCI, with Fu et al. [25] having developed an intelligent system based on an ANN to assist hearing-impaired users with smoother communication. Furthermore, Wang and Yan [26] proposed a methodology to capture arm movements based on fuzzy control theory and modified genetic algorithm to improve HCI in virtual reality.

Nowadays, ANN is one of the spotlighted topics of machine learning, which has attracted more researchers in a variety of domains, including both academic and industrial contexts. ANN is discussed and introduced in many other subjects and performs well in complex systems [27, 28], such as the forecast of rainfall intensity for tropical climate [29], and the Dead Sea water levels’ analysis [30]. Based on the ANN model, the building reliability performance can be assessed more accurately and scientifically [31]. Leveraging the outperformance of computer technology, the assessment of green buildings can thus be improved [32], and the disturbance of subjective matters can be reduced with satisfaction [33]. It has also been used in construction waste management evaluation models [34], predicting the effect of nighttime ventilation [35], predicting indoor air quality [36], and selecting the optimal equipment model in smart house systems [37].

That said, considering the evaluation of building design is a complicated task that involves quantized data, knowledge from subject professionals, and a nonlinear assessment mechanism, there is little research focusing on comprehensive measurement. Furthermore, the research of human computation application warrants more exploration on the methodology of HCI. Therefore, this study proposes a new evaluation methodology to reflect the extent of utilization and harmony between buildings and nature, combined with the outperformance of human computation and HCI.

3. Methodology

Considering the evaluation of building design comprehensively is a knowledge-based task, which indicates that subject-matter experts should be involved in the methodology. Moreover, objective indicators reflect many significant features and should be utilized. As a result, the assessment system for building design work can be treated as a human computation framework and the major task is to identify calculation. Traditionally, the calculation of an assessment system is represented by applying a weighted summation, while the weight is assigned by the analytical hierarchy process or multiple linear regression by training. These common approaches can provide linear computation and generate weighted average scores for building projects which require evaluation. However, the linear calculation has a critical weakness in the assessment system, because some extreme defects in the building design can decrease the overall score even more than its share. That means the distribution of weights is asymmetric in the scoring range. Recently, ANN shows high performance and is regarded as a general machine learning approach in various research areas, especially expert systems. It can be trained to represent very complicated nonlinear mapping and process fuzzy knowledge from subject-matter experts.

Since ANN modeling is supervised learning which requires high-quality training data, this study presents an efficient HCI system based on the principle of psychometrics. This system can incorporate the opinions on building design from subject-matter experts, and implement knowledge elicitation which highly affects the accuracy of the human computation system. By using the high-quality training data generated by subject-matter experts, the proposed ANN model can work accurately and efficiently.

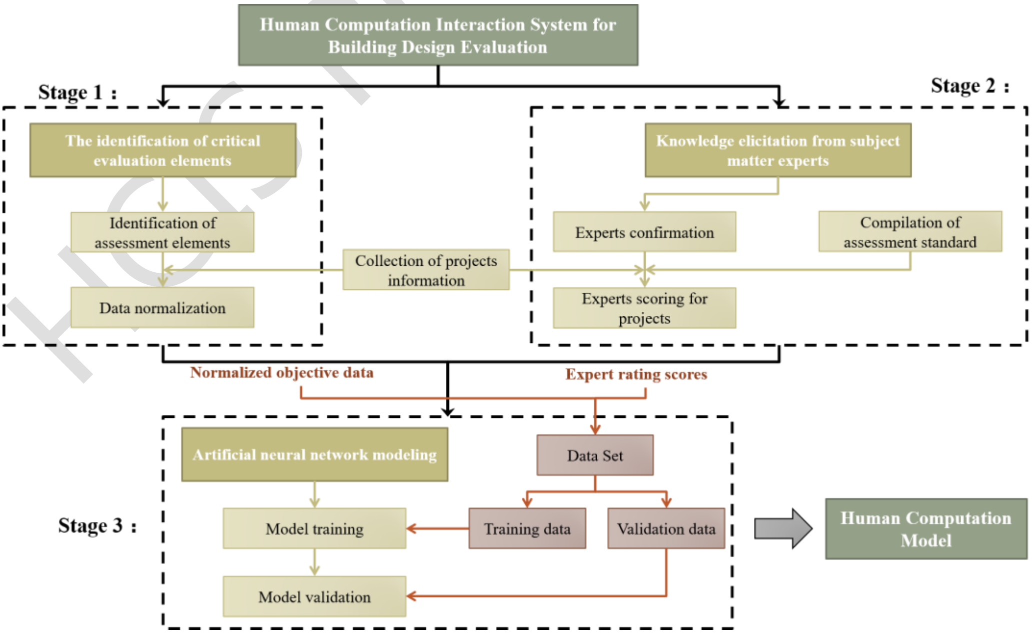


Fig. 1. Research process.

To establish the assessment methodology of a building's influence on the natural environment, three major procedures are decided to be presented as follows: (1) The identification of critical evaluation elements; (2) knowledge elicitation from subject-matter experts through the HCI system; and (3) ANN modeling. The assessment needs to be straightforward and easy to understand, so it is designed as a scoring model. The inputs are the data of the project scheme, and the output is its score. The higher the score, the more appropriate the design for the given site and surrounding environment. Fig. 1 shows the process of this research in detail.

3.1 Evaluation Factors

To determine relevant and comprehensive evaluation factors, we collected information from experts' comments, previously published studies, and 14 international evaluation standards for green buildings. Based on the collected valuable references, 13 factors were chosen as preliminary results. Then, six of them were excluded, since their frequency of occurrence in references was lower than 15%, or they could not be expressed by objective data. The final seven evaluation factors were water, wind, light, land utilization, ecological value, architectural space, and view of landscape.

Discussed and deliberated by experts, all seven factors were chosen as the component elements according to 1–3 objective scheme data. The selected data can directly reflect the expression of the evaluation factors in the design scheme. All the elements and their correlation to features are presented in Table 1.

Table 1. Correlation between evaluation features and elements

Evaluation features	Element	Correlation
Ecological value	Green area ratio;	Positive
	The variety of greening types;	Positive
	Changing number of species	Negative
Land utilization	Plot ratio;	Negative
	Building density;	Negative
	The average changed amount of site elevation;	Negative
	The volume of earthwork per site area	Negative
Light	Window-to-wall ratio;	Positive
	The number of window forms;	Positive
	The area of light blind-zone	Negative
Wind	The area of façade facing prevailing wind direction in winter;	Negative
	The ratio of effective ventilation area & building area;	Positive
Water	Amount of wetland variation	Negative
Architectural space	Area of transitional spaces & balcony	Positive
	Height of building;	Negative
	The ratio of outdoor atrium area to building floor area	Positive
View of landscape	Building orientation;	Positive
	The distance to the main landscape	Positive

Ecological value

To assess the features of the ecological value of a project, three elements were taken into consideration: the green area ratio (GAR), the variety of greening types, and the changing number of species. The minimum GAR of a site is stipulated by the government to promote the accessibility of green spaces, ecological function, better liveability, and climate adaptation in the urban environment [38]. A positive correlation exists between GAR and the evaluation features. The variety of greening types refers to roof, vertical, and ground greening. It has been confirmed in practice that vertical and roof greening not only benefits the aesthetic and landscape quantity of urban areas but also performs well in reducing building energy consumption. In 43% of cities in Germany, roof greening receives financial incentives from the government [39]. The more types of greening that are designed in a project, the more it achieves ecological value. Since the site selection and construction of the project should not have an impact on the habitat of precious plants and animals, changing the number of species is taken into consideration.

Land utilization

The assessment elements of this feature are the plot ratio, building density, the average change in site elevation, and volume of earthwork per site area. The plot ratio (total floor area divided by the specified area of land) and building density (percentage of land area that has been developed) clearly determine the concentration of buildings in a given geographic land. The high values of these two elements suggest that the land's utility has been maximized to the fullest. However, this may cause other problems to the surroundings, such as overcrowding, increased traffic, and an increase in pollution. Therefore, the value of these elements should be controlled in an appropriate range. The other two elements reflect the level of land exploitation. The design of site elevation should be conducive to drainage and possibly minimize the amount of earthwork. The large construction of land modification projects may incur large recovery costs for ground surface damage, water loss, and soil erosion.

Lighting

Three elements were chosen as the component of the light feature. The first was the window-to-wall ratio, which is the measure of the percentage area determined by dividing the building's total glaze area by its exterior envelope wall area. The window area is related to the natural environment in terms of access to daylight, ventilation, and view. The second element was the number of window forms, which is decided by the position and styling of windows. The consideration of this element reflects the indoor daylight quality and lighting effects. The last was the light blind zone, which is the area that cannot be shined by sunlight throughout the year. Sunlight blockage may be harmful to nature and residents; thus, the value of this element should be as low as possible. The data can be calculated by sunlight simulation software.

Wind

For the feature of wind, the elements were decided as the area of façade facing the prevailing wind direction in winter, and the ratio of effective ventilation and building areas. Since the prevailing wind direction has a great influence on building energy savings, in this assessment system, the smaller the area of the façade facing the prevailing wind direction in winter is, the better the design of a particular project will be. An adequate opening window area ensures adequate ventilation of the building. Therefore, a higher ratio of effective ventilation and building areas means that the building will obtain better ventilation. By improving the thermal comfort level, natural ventilation can benefit the indoor environment [40], which is an efficient strategy to reduce the energy consumption of buildings [41].

Architectural space

Three elements were chosen as the components of this feature. The first was the area of transitional spaces and balconies. The transitional space allows people to embrace nature, which further explains why the relationship between architecture, nature, and space should not be an estranged one but a connection. Therefore, it is expected that the larger the area of transitional spaces and balcony, the more harmonious with nature the building becomes. The second element was the building height. The confirmation of building height depends on many factors, such as the height of the natural landscape nearby, the height of other buildings in the vicinity, and the distances to those buildings. The ratio of outdoor atrium area to building floor area was the third element. Previous studies have shown that atrium geometry, atrium shape and roof structure influence various aspects of the physical environment, such as daytime lighting, acoustics, natural ventilation, and the thermal environment [42].

View of landscape

The visible landscape is believed to affect human beings in many ways, including aesthetic appreciation, health, and wellbeing [43]. Usually, orientation is determined by the combination of two main factors of sunlight and ventilation. Considering the requirements of ventilation and sunlight comprehensively, the best orientation or range of the best appropriate orientation in a particular region can be obtained. One is scored to the building orientation within a 15° deviation of the best orientation, and 0.8 is scored to that within a 30° deviation. The distance to the main landscape is the second element of this evaluation feature. We believe that the greater the distance to the main landscape is, the less adverse the effects will be.

3.2 Calculation Formula Establishment

Most parameters of architectural design can be directly acquired by objective measurement and with one value, such as the plot ratio and amount of wetland variation. To calculate these parameters, a simple and straightforward method is to standardize data and convert them to indices. It is extremely helpful to compare the same parameter in different projects and remove dimensions for further calculation in the assessment framework. The Z-score is a very common data standardization approach in statistics and data mining that relies on the mean value and standard deviation. The Z-score calculation can be expressed mathematically as follows:

$$Z_i = \frac{x_i - \bar{X}}{S_X} \tag{1}$$

where x_i is the *i*-th value of dataset X; $\bar{X}$ is the mean value of dataset X; and S_X is the standard deviation of dataset X.

With the calculation of the Z-score function, data can be standardized to a dataset with a mean value equal to zero and a standard deviation equal to one. However, in architectural design assessments, the number of projects is usually small in a specific study area. Moreover, since the architectural features are varied, the value distribution of some parameters could be very uneven. As a result, the Z-scores of these parameters were highly dispersed and could not reflect the data tendency. Therefore, this study revised the Z-score calculation by replacing the mean value with the median, with the revised formula being expressed mathematically as follows:

$$Z_i = \frac{x_i - X_{median}}{S_X} \tag{2}$$

where x_i is the *i*-th value of dataset X; X_{median} is the median value of dataset X; and S_X is the standard deviation of dataset X.

The next procedure of index calculation is to determine the boundary and normalize the data to the index range from 0 to 100. The calculation can be expressed mathematically as follows:

$$Z_{max} = \frac{X_{max} - X_{median}}{S_X} \tag{3}$$

$$Z_{min} = \frac{X_{min} - X_{median}}{S_X} \tag{4}$$

$$Z_{scope} = \max(|Z_{min}|, |Z_{max}|) \tag{5}$$

$$Index_i = \frac{\pm Z_i}{Z_{scope}} \times 50 + 50 \tag{6}$$

where x_i is the i-th value of dataset X; X_{median} is the median value of dataset X; and S_X is the standard deviation of dataset X.

Specifically, considering that some parameters are positively correlated with the assessment while the others are negatively correlated, the proposed calculation method includes the plus-minus sign in the equation. If a parameter is negatively correlated, a negative sign is applied; therefore, the index is always positively correlated with the assessment.

3.3 Knowledge Elicitation

Calculated by objective data, the score of each factor still needs to be tested and corrected, since their distribution needs to conform to the actual situation and reflect common cognition. Although traditional expert reviews have drawbacks, the experiment and knowledge of experts are valuable, and this study decided to use them to correct the calculated scores. The chosen experts should satisfy two of the five following conditions given as: (i) the architect possesses basic knowledge of the particular area of evaluated projects; (ii) the architect has finished projects in the particular area with positive public recognition; (iii) the architect is well-known for solving contradictions between nature and buildings; (iv) the professor studies the relationship between architecture and the environment; and (v) the architect, as a major designer, has won national or higher architecture awards. If the area has special natural features, the advice of other experts, such as ecologists and geologists, is also needed. The number of experts needs to be 10% of the evaluated projects and at least 10 persons. A sufficient number of experts will ensure that there are enough valid scores. Since the invalid score will be removed, less effective data will affect the accuracy of the final evaluation system.

Two types of basic information were offered to experts for evaluation. One was the information on the evaluated area, and the other was the information on each finished project, which is detailed in Table 2. Every project was evaluated based on this information. At the same time, all the chosen experts will evaluate and decide on a score for every project based on the same assessment standard, which is shown in Table 3. Since the data of projects are standardized and normalized on a scale from 0 to 100, experts need to assign a score on a scale of 1 to 100 for better correspondence. Each project is scored accordingly and divided into five levels of awful (0–20), bad (21–40), natural (41–60), good (61–80), and excellent (81–100). Then, the collated scores and objective data were used for data training through computer technology, and the corresponding relationship between the objective project data and subjective scores were obtained.

Table 2. List of basic information for evaluation

Basic information	Contents	Details
Information of the evaluated area	Geographic information of area; Introduction & distribution map of the main natural resources & landscapes in the area; Project distribution map	
Information of each finished project	Main design & construction data; Live-action effect pictures; Main technical drawings; Analysis diagram & design description	Master plan, floor plans, sections, elevations, & landscape layout

3.4 Modelling

Since the different evaluation features have extremely complicated internal relations and ambiguous expert knowledge, it is difficult to represent the overall rating score based on evaluation features in a linear model. This research employs ANNs and error backpropagation (BP) algorithms to model, and calculates the overall rating score of the design in a natural environment consideration. Compared to traditional multiple linear regression or support vector machine methods, ANNs can represent nonlinear relationships through unstructured data. Given that the knowledge from single subject-matter experts is always vague and interdependent, it is highly appropriate to apply ANNs in such systems.

Table 3. Assessment standard and scoring tables

	Assessment standard (the extent possible)				
Ecological value	a. Protects the original ecological characteristics and selects locally adapted plant species; b. Appropriate greening forms with diversity & efficacy; c. Considers to reduce whole life impacts from pollution				
Land utilization	a. Has adverse effects on forest, farmland, water, & wetland; b. Damage or affect the original landform; c. Reasonable & effective use of land, no overexploitation or waste				
Light	a. Design rooms with natural lighting as many as possible; b. Generates light pollution that affects the surrounding buildings or natural environment				
Wind	a. The main orientation of the building is effectively designed to avoid the prevailing wind direction in winter; b. Design rooms with natural ventilation as many as possible				
Water	a. Damage or pollute the surrounding wetland, coastal landscape, & water resource; b. Design a low-impact development water system effective & appropriate; c. Prevents soil erosion in the process of construction & operation				
Architectural space	a. Design shapes & forms of architecture with the consideration of the status quo of the surrounding environment; b. Design an appropriate masterplan layout with effective setback distance between the surrounding environment & existing buildings; c. Respect the characteristics of the surrounding environment to enhance contact with nature; d. The building height is appropriate without damaging the skyline & natural topography				
View of landscape	a. Disturbs the opportunities & rights of the public to enjoy natural resources; b. Blocks the visual view of surrounding buildings in the direction of the main landscape				
Score	0–20	21–40	40–60	61–80	81–100

Evaluation features defined in the previous sections can be fed into this layer as input, and they are weighted and transferred to the hidden layers. The hidden layer usually includes different sublayers and nodes depending on the training data, and the output layer will output the overall rating score. The BP algorithm can learn the mapping relationships between evaluation features and rating scores generated by experts in the training dataset, and adjust the weight vectors between different layers by applying a gradient descent algorithm. The loss function can be the mean square error (MSE), which is expressed mathematically as follows:

$$loss = \frac{1}{N}\sum_{y\in D}(y - y_p)^2 \tag{7}$$

where y is the true value in the training dataset and y_p is the calculated value of the current model.

To introduce nonlinear factors to the ANN, the rectified linear unit (ReLU) function was selected as the activation function, which is expressed mathematically as follows:

$$f(x) = \max(0, w^T x + b) \tag{8}$$

It has no saturation region, so there is no problem of gradient disappearance in ReLU. In addition, its unilateral inhibition mechanism is consistent with the neurobiological mechanisms, which allows it to boast a faster convergence rate than traditional sigmoid and $tanh$ functions.

4. Case Study

To verify the feasibility of the evaluation method, projects in the Xuejiadao area were selected as the research sample. Xuejiadao is located on the west coast of Jiaozhou Bay, Qingdao, China. This area is a part of the city with a relatively independent natural environment. As a natural landscape protection area, a higher respect for nature is required for its construction projects.

Xuejiadao is a long peninsula extending from northeast to southwest, connected to the land in the central area. The east, south, and north orientations are surrounded by the sea with winding coastlines. There are mainly six hills in the territory of the peninsula, and the highest is YanTai Mountain at 174.8 m above sea level. There are no large rivers or lakes on the territory, only the Dingjia River with a total length of less than 5 km and the Dingjia River Reservoir within the region, which is a seasonal river. The annual average temperature in Xuejiadao is 12.2°C, -1.7°C in January, and 27.3°C in August. The recorded lowest temperature was -16.2°C (January 3, 1976), and the highest was 37.4°C (July 8, 1964). The annual average precipitation numbers 794.9 mm, with a maximum of 1,458.3 mm in 1964 and a minimum of 481.4 mm in 1977. Precipitation is mainly concentrated from June to September, accounting for 71.4% of the annual precipitation.

4.1 Dataset Acquirement

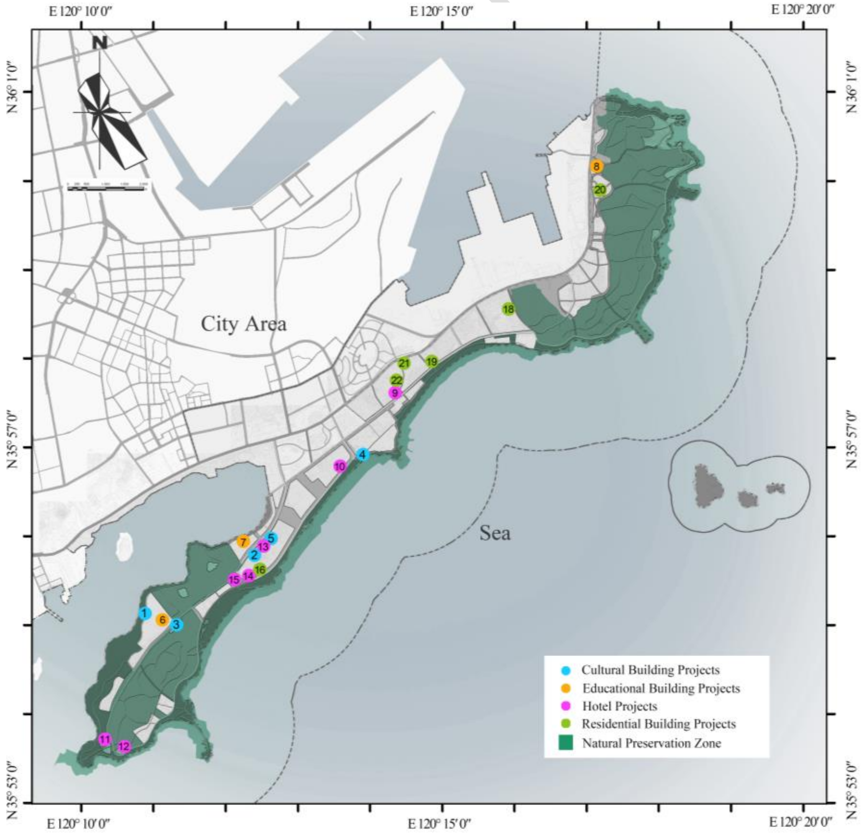


Fig. 2. Geographic coordinate information of the research area and distribution of projects.

To establish the evaluation model, data, and information on 20 projects located in the research area was collected, such as five cultural building projects, three educational building projects, seven hotel projects, and five residential building projects. The north and south of the research area marked the natural preservation zone, and thus the distribution of projects is mainly decided by the geographical features of the research area. These four types of projects are the main building types of this area, with the distribution shown in Fig. 2. All of the projects' information was collected from architectural design institutes and property developers. The names of the projects were requested to remain anonymous.

Most of the projects consisted of a group of buildings with more than 20,000 m^2 in total site area. Only three residential projects contained buildings with heights over 50 meters, while the others were less than 30 m. The GARs of the four projects were lower than 35%, and two of these were up to 70%. The general information of these 22 projects is shown in Table 4.

Table 4. List of basic information for evaluation

Project types	Amount	Height	Site area	Green area ratio
Educational building	3	<24 m (all)	>50,000 m^2 (all)	30%–40%
Hotel	7	<24 m (6)	<10,000 m^2 (2)	<35% (1), >70% (1)
		>30 m (1)	25,000–55,000 m^2 (others)	45%–50% (others)
Cultural building	5	<24 m (all)	>100,000 m^2 (1)	<20% (1), >70% (1)
			<35,000 m^2 (4)	45%–50% (others)
Residential building	5	<30 m (2)	>100,000 m^2 (3)	<35% (1)
		>60 m (3)	<30,000 m^2 (4)	35%–50% (others)

For knowledge elicitation, the project information was offered to 10 experts for assessment. These 10 experts include four associate professors or professors with over 15 years of teaching and practical design experience and six architects with over 20 years of practical project experience. All the experts boast extensive experience with different architecture types, finished projects in Qingdao, and know the basic knowledge of the research area. Each project was scored on a scale of 1 to 100 according to Table 3.

Table 5. Objective score information of the assessment elements

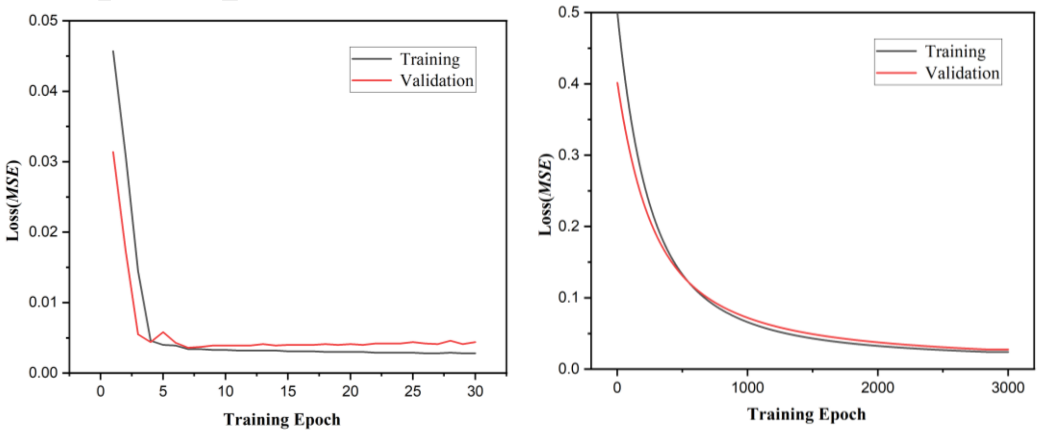
Elements	Min	Median	Max	Std
Green area ratio	21.24	50	100	18.83
The variety of greening types	50	50	100	18.54
Plot ratio	0	50	52.63	14.17
Building density	0	50	58.89	13.05
Average changed amount of site elevation	0	50	60.13	15.11
Volume of earthwork per site area	0	50	54.52	11.56
Window-to-wall ratio	6.89	50	100	27.75
Number of window forms	50	50	100	19.85
The area of light blind zone	50	50	100	13.79
Area of facade facing prevailing wind direction in winter	0	50	54.31	11.73
Ratio of effective ventilation & building areas	32.26	50	100	16.72
Amount of wetland variation	7.95	50	100	18.75
Area of transitional spaces and balcony	46.02	50	100	13.45
Building height	0	50	56.70	16.92
Ratio of outdoor atrium area to building floor area	50	50	100	11.58
Building orientation	0	50	50	24.94
Distance to main landscape	8.24	50	100	33.00

Seventeen assessment elements of the objective data of each project were calculated with the calculation formula denoted in 3.2, and the basic information is summarized in Table 5. With these expert scores, there were 200 instances of data. Among them, 20% were randomly selected for validation, and the others constituted the training of ANNs.

4.2 Modeling and Results

With the training data acquired from the previous work, there are 200 instances passing the examination to implement modeling. Table 5 describes the important information of the dataset. The dataset is split to training and validation data, and each of them includes 160 and 40 instances. According to Occam's razor policy, the machine learning model should be kept concise under the premise of data representation. Considering that the relationship between objective indicators and comprehensive evaluation scores is complicated, this study established a fully connected ANN with three hidden layers, and the number of neural nodes of each hidden layer was 64, 32, and 16. Multiple setups of ANN have been experimented with, and this four-layer model achieves the best performance considering both accuracy and efficiency. In order to avoid the vanishing gradient issue in the training process, the ReLu function was selected as the activation in each neural node. For the purpose of validating the applicability and outperformance of ANN, a traditional calculation method is also deployed as a baseline, which is multiple linear regression (MLR). MLR randomly initialized the weight vector in the polynomial and then optimizes the loss function by applying the stochastic gradient descent (SGD) algorithm based on training data. This research employed Python and Keras in TensorFlow to implement ANN modeling and MLR training. This approach allowed scientific researchers to establish multilayer models to rapidly conduct both classification and regression. The modeling platform is based on TensorFlow 2.5.0, which is deployed with macOS featuring a 3.4 GHz CPU and 24 GB memory.

By training only 30 epochs of data, the proposed ANN method was convergent and reached the smallest loss according to the loss function of MSE. The smallest mean absolute error (MAE) of the training data was 4.34, while the validation data was 5.53 in the centesimal system, which showed a high accuracy of the evaluation score regression. Moreover, the training history indicated that there was no obvious overfitting in the training process, with the generalization ability of the trained model being satisfied. Fig. 3(a) shows the MAE variance in the training process of ANN modeling. As a baseline method, the MLR method can also achieve convergence after 6,000 epochs with the same training data, and the MAE variance is shown in Fig. 3(b). MSE was also selected as the loss function in MLR modeling, and the SGD algorithm was implemented. The learning rate was set to 0.001 and batch size to 16. The MAE of the same validation data for the MLR method was 10.61, which is much higher than that for ANN. This verified that ANN modeling can achieve a higher accuracy compared to the traditional MLR method.



(a) (b)

Fig. 3. MAE training variance: (a) ANN and (b) MLR.

4.3 Model Application and Discussion

Based on the established evaluation model of the research area, information on two more projects was collected to verify the accuracy and validity, and these two projects are under construction. The objective data for assessment elements are presented in Table 6. All objective data were input into the established evaluation model, obtaining a score of 68 and 73 for projects A and B, respectively.

Table 6. Objective data for the assessment elements of new projects

Elements	Project A (Cultural building)		Project B (Residential building)	
	Data	Index	Data	Index
Green area ratio	0.1	6.90	0.3	35.59
The variety of greening types	3	100	1	50
Plot ratio	0.79	45	1.76	19.47
Building density	0.39	18.12	0.23	44.97
Average changed amount of site elevation (m)	1.8	51.90	14	0
Volume of earthwork per site area (m^3)	3.83	43.37	3	45.92
Window-to-wall ratio	0.52	73.93	0.22	18.06
Number of window forms	2	75	1	50
The area of light blind zone (m^2)	1021	43.28	2,826.6	31.40
Area of facade facing prevailing wind direction in winter (m^2)	2,164.32	52.14	0	54.31
Ratio of effective ventilation & building areas	0.067	61.29	0.058	46.77
Amount of wetland variation (m^2)	0	50	0	50
Area of transitional spaces and balcony (m^2)	2,065.5	50.56	13,687.66	81.90
Building height (m)	23	49.33	50	32.18
Ratio of outdoor atrium area to building floor area	0.07	52.48	0	50
Building orientation	1	50	1	50
Distance to the main landscape (m)	50	11.76	900	100

The scores for these two projects are meaningful and reasonable. It can be seen from the master plan of Project A (Fig. 4) that the outdoor activity space was mainly paved with rigid material. The GAR of project A was only 10%, lower than the average for the whole research area, which is one of the main reasons for its low score. Another reason is that it was too close to the main scenic spot, only 50 m from the beach. This would have negative effects on the surroundings during construction, and the view of the landscape would be overshadowed.

The plot ratio of Project B was 1.76, which is high and reduces the evaluation score. The section of Project B is shown in Fig. 5. The construction of this project was made complicated by a subway maintenance depot underground. The average change in site elevation was up to 14 m, which is the main reason for the reduced score. However, compared to other projects, this project is far from the main scenic spot and has a high area of transitional spaces and balconies, promoting the final evaluation score.

Compared to the traditional method of expert review, this HCI system for building design evaluation is fairer and stabler. The number of experts is limited in the evaluation of each building project; thus, the opinion of each expert will have a great impact on the evaluation of the project. Moreover, experts may be completely different for different project evaluations, and the experience and cognition of experts might be quite opposite, because of which the evaluation standards are difficult to be unified. This HCI system for the building design evaluation has trained a large number of project and expert data in the process of model establishment, effectively learning and using expert knowledge. The established model is stable with the evaluation criteria being uniform.

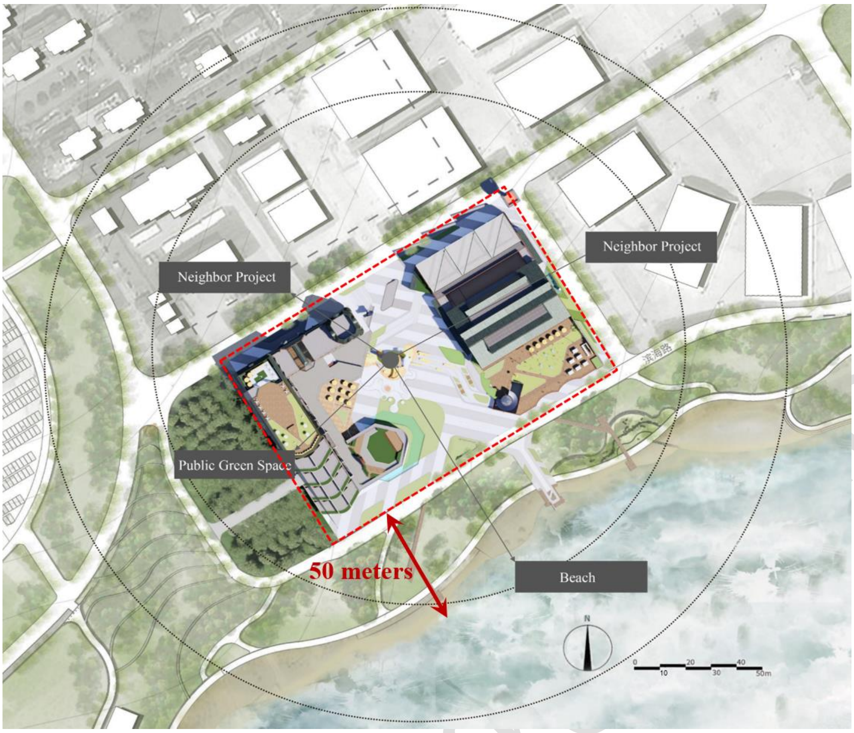


Fig. 4. The master plan of Project A.

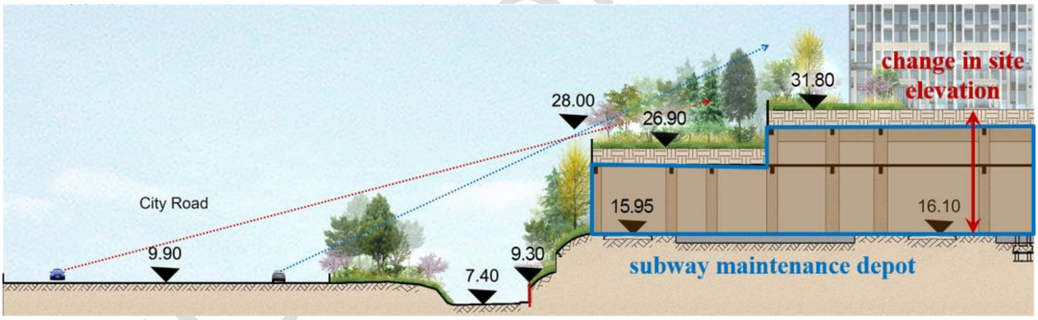


Fig. 5. The section of Project B.

5. Conclusion

Current building rating tools performed poorly in explaining whether buildings are designed to be harmonious with the surrounding environment or harmful to the surrounding landscape and natural topography. In addition, the building design assessment is complicated and highly related to the knowledge of subject-matter experts. This paper presents a HCI system based on the ANN to assess the influence of the building design on the environment domain, while human computation was introduced in this evaluation system with scoring by experts. Seven evaluation factors and 17 elements were decided by document searching, reviewing, and expert consultation. The 17 objective assessment data of the building scheme were calculated and normalized into scores using the formulas. Then, ANN technology was used to establish the calculation model between the objective scores of the building data and the subjective evaluation scores of experts. To analyze and verify the evaluation methodology, information on 20 actual cases in the Xuejiadao area was collected. With the datasets including 160 training data and 40 validation data, the proposed ANN was convergent and reached the smallest loss by training 30 epochs of data. The smallest MAE of the validation data numbered 5.53, meaning that the average difference between the score calculated by the model and the expert score was 5.53. In addition, the accuracy and validity of this evaluation methodology were verified by two new projects in the research area. This assessment method can effectively simulate the scoring thoughts of experts, showing a high accuracy and stability.

This study offers a fair and stable assessment methodology, combining humans as a computational element in the design and analysis of information processing systems. In order to establish an effective interaction between subject-matter experts and high-performance computation capacity, and HCI system is designed and implemented. To some extent, this assessment method is more stable, reliable and objective than the traditional expert review, and more comprehensive and humanized with social criteria than green building rating tools. It is expected that this study can improve the building design assessment and stimulate the optimization of the building scheme at the design stage, which can effectively reduce the investment and consumption of technology, materials, and equipment. In addition, this study offers a fair and stable assessment methodology, providing guidance and a basis for design improvement on natural considerations. Architects may use this assessment method to test their design schemes and modify them in time, allowing them to effectively reduce the times and cost of expert review and shorten the design period.

This evaluation method has high requirements for the selection of experts. For the human computation system, the preferences of experts are reflected in the accuracy and validity of the evaluation model. Thus, for future studies, expert evaluation scales and standards should be designed and compiled to minimize the subjective impact. Also, evaluation elements can be further studied and added to the evaluation model, allowing the evaluation system to be more accurate and comprehensive. In addition, the feasibility and accuracy of this evaluation system in other natural and urban environments can be verified.

Author’s Contributions

Conceptualization, WG. Investigation and methodology, GZ, SM, WG. Writing of the original draft, DZ. Writing of review & editing, SM. Formal analysis, DZ, XW. Data curation, DZ, YL. Supervision, XW. Visualization, DZ. Software, GZ.

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Competing Interests

The authors declare that they have no competing interests.

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