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Prediction of Human Restorative Experience for Human-Centered Residential Architecture Design: A Non-Immersive VR–DOE-Based Machine Learning Method

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Abstract

Nowadays, the topic of restorative experience in built environments has attracted more attention because of the increasing stress levels in modern society. Researchers have sought to identify the architectural features that influence a person's perceived restorative experience to achieve human-centered architectural designs. However, the relevant design knowledge is unsystematically scattered, making it difficult for designers to interpret information and make informed decisions in practice. This paper explores the feasibility of machine learning in capturing the restorative quality of design alternatives, thereby providing decision support for proactive architectural design analysis. To deal with feature selection and the uncertainty associated with affective modeling, a framework is introduced that integrates design of experiments and machine learning methods. The human restorative experience is assessed within non-immersive VR environments using self-reported psychometric scales. Consequently, general regression neural network is revealed as superior to other machine learning methods in forecasting the restorative experience.

Keywords: Human-centered design; Restorative experience; Prediction model; Machine Learning; Virtual Reality; Design of Experiment; Residential design; Built environment.

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1 Introduction

Currently intrinsic to our daily lives, stress has been identified as a critical health issue that impacts multiple spheres of our society. For example, it entails expressive costs for healthcare systems, thus significantly affecting the economy [1]. The socio-urban context of extended periods of time spent indoors and increased urban densification has led researchers to investigate the expressive impacts of built environments on our mental well-being and to explore how design can help mitigate urban stress [2]. Previous studies have found that poorly designed buildings can negatively impact a person's psychological state by causing stress, anxiety, depression, and even violent behavior [3–5]. Greater focus has been placed on the affective experience elicited by architectural design attributes within the domain of human-centered architectural design. Specifically, the restorative potential of built environments, i.e., the capability to reduce mental fatigue, improve productivity, and relieve stress, has attracted considerable interest in recent years [6]. There is widespread agreement that particular design attributes of built environments can influence our mental resilience or foster restorative experiences [7,8]. However, the relevant knowledge to support experience-focused architectural design is scattered across several disciplines, such as architecture, psychology, and sociology. In addition, the information available in the early design stages is often vague, incomplete, and inconsistent [9,10]. Moreover, analytical models and tools to facilitate the decision-making process in the early stages of the design of built environments focused on emotional wellness are still scarce. Under this circumstance, the designer is compelled to judge vaguely and subjectively the experience-related quality of the design alternatives. Therefore, how to reduce the uncertainty and subjective bias of human assessment while increasing efficiency in identifying the optimal design alternative regarding the quality of experience criteria has been an area of great interest among researchers. Among researchers in design domains, there is a common belief that measuring the user experience of a product is the foremost step in improving such experience [9]. If the complex nonlinear relationship between design attributes and quality of experience can be established using mathematical methods, then it is possible to identify the design alternative with the highest quality of affective experience while eliminating the influence of subjective assessment [9]. Specifically, if we could construct prediction models that can be applied to forecast restorative experience values for each design alternative, the alternatives could be ranked by their restorative potential and thus the designer could detect faults, conduct further improvements, and make the appropriate decision on the design alternative, resulting in a more objective and efficient evaluation and development process in the early design stages.

In the field of architectural design, attempts to use machine learning to predict building performance in aspects such as environmental comfort have been made along with the development of information and communication technology. It is believed that the convergence between design and machine learning can address multifactor problems by finding connections between variables (i.e., input, internal, and output variables) without explicit knowledge on the physical behavior of the system [11,12]. Therefore, to evaluate the restorative quality of design alternatives in support of the decision-making process for the design of built environments focused on emotional wellness, this research aimed to develop machine learning models to predict individual restorative experiences using design attributes. Evidently, success in obtaining a reliable machine learning model depends heavily on the choice of input variables and the available dataset [13]. The restorative experience addressed in this study can only be measured with people's feedback; conducting such experiments on a large scale is usually time-consuming and expensive in terms of the massive effort required for participant recruitment and data collection [14]. An optimization of data collection for training machine learning models is necessary to maintain the quality of the dataset and eliminate the number of experiments conducted for data generation. Though several studies have associated the effect of design attributes on restorative quality of built environment, few discussions on the interaction effect of design attributes (i.e., the effect of one independent variable on an outcome depends on the state of another independent variable) are present in the literature. What's more, earlier studies have demonstrated different prediction performances among various machine learning models [15–19]. These performance differences emphasize the impact of the problem context and provide a strong reason to test several techniques for developing machine learning models.

In this regard, this study develops an integrated framework using non-immersive virtual reality (VR) and design of experiment (DOE) to leverage machine learning techniques in predicting the restorative quality of the built environment. The proposed method is intended to optimize the data collection process and address the complexity and uncertainty in modeling the human affective experience. The predictive performance of multiple machine learning models is compared for further prediction model selection to support the decision-making in human-centered architectural design. This approach could greatly help designers and decision makers improve the efficiency of design, selection, and successive iteration processes by using a genetic algorithm that employs specialized knowledge [20]. In addition, this study sought to identify the interaction effect of design attributes on the perceived restorative experience in the built environment, minimizing bias in estimating model parameters [21].

While a great number of studies related to restorative design have been conducted in the area of institutional construction [22–24], there have been few empirical investigations into residential design, despite the fact that emotional support and relaxation are major functions of the home environment [25]. As such, the focus of the present study is on residential buildings. Meanwhile, a generic kitchen model is used as a pilot study in our research since its essential functional elements (e.g., storage unit, stove, and oven) are generally the same among different households regardless of occupant differences in cultural background or personal preference. Thus, further investigation is needed on the affective needs for other building types. In addition, although this study aimed to quantify and represent the restorative experience of built environments using a single value, it cannot guarantee the superiority of a design. The quantitative value obtained by a predictive model is intended to be an indicator with the potential to evaluate the relative strength of a design alternative.

The remainder of the present paper is organized as follows. Firstly, the literature pertaining to qualitative and quantitative research on affective design and machine learning methods for affective experience modeling to clarify the point of departure. Secondly, the research methodology and scope are proposed and described in Section 3. A detailed discussion on the non-immersive VR-DOE-based method for data collection is illustrated in Section 4. Section 5 presents the data analysis and machine learning models for restorative experience modeling. Section 6 discusses the experimental findings and the predictive modeling results. Finally, Section 7 concludes by highlighting the applicability and limitations of these research findings.

2 Literature Review

2.1 Affective Design in Built Environment

Affective design usually focuses on the emotional and mental communication between the user and the products [26]. For decades, efforts have been made to understand the correlation between built environments and corresponding human affective experience and utilize such correlation as a foundation for human-centered building improvement in architectural domains [27,28]. According to Vischer's environmental comfort model (see Figure 1), psychological comfort is the highest level in the hierarchy for achieving occupant satisfaction, and it refers to a sense of belonging, ownership, and control over an environment in which stress also plays a critical role [29,30].

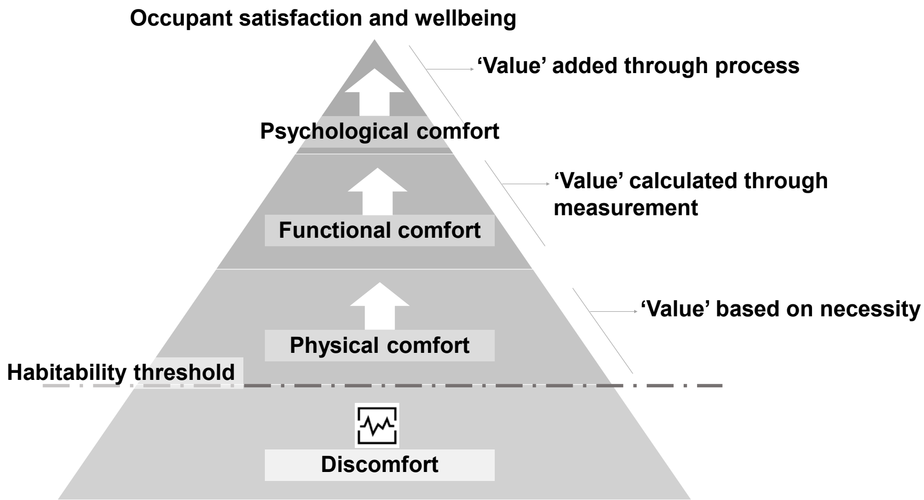


Figure 1. Habitability pyramid (source: Vischer [30])

There is consensus among scholars that specific characteristics of architectural environments could help people in reducing anxiety and recovering from cognitive fatigue and stress, thus increasing the overall satisfaction level attributable to built environments. Previous studies showed that design attributes, such as interior colors, views (through windows), lighting, and layout of the room, can serve as significant predictors in assessing the satisfaction level in healthcare facilities [22,23,31–33]. Various design elements in birthing centers, such as shapes and angles of walls, ceilings, and fixtures, were also found to be associated with women's affective experience and birth outcomes [34]. The golden ratio design principle was also found to affect a person's emotional response in an eye-tracking-based experiment [35]. The above-mentioned findings, equally, provide concrete evidence for designers optimizing affective design. For instance, decorative fountains have been increasingly used in healthcare facilities, as they can serve as positive distractions that reduce patients' stress levels [36]. Many hospital designs integrate gardens or modify the traditional waiting area in terms of the general layout, color scheme, or furniture in order to improve the mood, the physiological state, and the overall occupant satisfaction level.

Even though the qualitative evidence can provide designers with referable case studies and additional information, it is imperative that the designers have extensive experience and domain knowledge for interpreting the research findings and integrating credible research evidence in support of implementing relevant approaches in the design process. In this regard, many scholars have been attempting to quantitatively measure the effect of architectural design attributes on human experience. Ergan et al. conducted a crowdsourcing-based experiment to examine occupants' emotional reactions to various design attributes, such as window design, ceiling height, color, and space layout; in the experiment, the participants were asked to select their preferred space in a pair of bipolar scales and rate the preferred space with a semantic value [37]. To measure the human experience in a more objective manner, Ergan et al. also incorporated body area sensor networks (i.e., EEG, GSR, and PPG) to evaluate people's experience related to stress and anxiety under predefined different design scenarios [38]. Likewise, Martinez-Soto et al. used eye-tracking data to investigate people's reaction toward environment with different restorative potential. Gao and Zhang adopted the measure of physical measurement (i.e., skin conductance) and psychological scale to identify the patient's experience toward design characteristics.

Overall, these studies have clearly indicated the quantitative relationship between architectural design attribute and human experience. Nevertheless, compared to other building design frameworks such as LEED and Living Building Challenge (LBC), affective design still lacks clear analytical models and tools for practical application in current practice. Many experiments in the context of affective design were usually conducted through a one-factor-at-a-time (OFAT) method-based experiment design or by simultaneously altering multiple design attributes. This poses a challenge in interpreting the independent or interactive effects of the variable (i.e., design attribute) of primary interest. Thus, in this study, a machine learning method trained by data collected using fractional factorial experiment design is used to model the relationship between restorative experience and design attributes to predict the restorative quality of design alternatives in support of the early design process.

2.2 Prediction Models for Affective Design

Models are frequently referred to as efficient media for synthesizing and communicating knowledge during the design process. A model could be regarded as an abstraction used to explain concepts and their relationships, which are too complex to be otherwise illustrated; for example, the affective experience of architectural designs in this case [39].

In design domains, numerous attempts have been made to model the relationship between design attributes and the user's affective experience using machine learning methods [40]. These models can be generally categorized as multiple linear regression, artificial neural networks (ANNs), support vector machines (SVMs), and fuzzy inference systems (FISs) [19]. Specifically, multiple linear regression is widely used in the domain of affective modeling because of its easy implementation and interpretation [41]. Lanzotti and Tarantino applied logistic regression (i.e., a variant of linear regression) to predict users' perceived quality toward the interior design of trains [41]. Park et al. utilized linear regression models to model the user affective experience of mobile phones, which showed satisfactory performance in terms of goodness of fit [42]. However, this modeling was performed under the assumption that design attributes are linear with respect to a user's affective experience [19]. Thus, the uncertainty and bias in questionnaire data are typically neglected in the regression model. Compared with linear regressions, ANN models have been shown to be more capable of handling the nonlinear nature of human perception phenomena. Many neural networks have been adopted to depict the nonlinear relationship between user affective experience and product features for affective designs such as designs for motorcycle helmets, paddle tennis rackets, mobile phones, and office chairs [19,43,44]. For instance, a radial basis function was introduced by Chen et al. [45] to evaluate the cultural influence on affective experience. This function attempts to model data uncertainty by simulating the bell-shaped distribution in fuzzy-based systems. Similarly, Ling et al. [18] incorporated a wavelet function-based ANN to perform an affective design for mobile phones. Although ANNs can capture the nonlinearity between affective experience and the related design attributes, the unexplained behavior of the network, labeled the "black-box," reduces trust in the solutions [46]. In this regard, support vector regression (SVR), an extension of the SVM, is suggested as an alternative method for mapping the nonlinearity of feature space. The SVM is a popular machine learning tool, first identified by Vapnik, who observed its excellent performance in solving sparse and noisy data that usually exist in real-world problems such as pattern recognition [43]. In the design domain, SVR has been successfully adopted in predicting user affective responses based on product attributes [44,45]. Yang and Shieh [44] employed SVR to develop a model for predicting consumer affective responses to product forms. Fan et al. [45] proposed an SVR approach to model the relationship between design attributes and customers' affective responses.

Interestingly, Chan et al. [19] reviewed the literature that reports on the use of ANNs and SVR for affective modeling and found that SVR models perform better overall compared with neural network models. Moreover, taking advantage of its interpretability with which the developed model can be interpreted, verified, and improved by human experts, FIS, also known as a fuzzy rule-based model, was introduced by Lai et al. [46] in mobile phone design to handle the nonlinearity and fuzziness of human affective experience [50]. Similarly, this fuzzy rule-based modeling approach was also adopted in designing cars and office chairs [20,47,48].

In summary, this section provides a brief discussion of the general machine learning methods used to determine the relationship between human affective experience and design attributes. Even though many studies address the customer's affective needs for product designs, the relevant research in built environment design remains limited. Therefore, this study aims to assess the feasibility of using typical machine learning models (i.e., linear regression, ANN, SVM, and FIS) in predicting human affective experience of built environment.

3 Research Methodology

The primary objective of this study is to develop data-driven prediction models to evaluate restorative quality of design alternatives in support of the decision-making process for human-centered architectural design. To achieve this goal, a careful feature selection and data collection is necessary to deliver meaningful predictive modeling results. Accordingly, the present study proposes an integrated VR-DOE-based machine learning method to predict the restorative experience of the built environment. The data collection optimization was performed using the DOE method so that the input variable and data were properly selected to provide the most unbiased and precise results commensurate with the desired expenditure of time and effort. The use of DOE method also enables one to identify the output variation caused by the effect of the interaction among factors, providing researchers with a better understanding of the relationship between the restorative quality and the design attributes of the built environment, as well as explains more about the variability in the dependent variable [21]. Here, fractional factorial design was the DOE method used for experiment design, as it makes it possible to obtain a reasonable amount of training data through a fewer experiments number and screen the effect of each factor. Meanwhile, linear regression and three other machine learning modeling methods (artificial neural network, support vector regression, and fuzzy inference system) are employed to develop models to predict the restorative quality of a space, given its particular design attributes, and a comparative analysis of the performance of each predictive model is then conducted. In addition, this study incorporates relevant psychometric scales to scientifically measure the human-perceived restorativeness in virtual reality simulated environments, in order to maximize the utility of predictive models.

The steps of the research methodology are presented in Figure 2. The first and foremost step is to perform a comprehensive review of the available literature on architecture and psychology to identify the architectural design attributes that potentially influence the restorative- or stress-related human experiences (see section 4.1). The second step is to design and perform experiments, to investigate human responses related to restorative experiences under various combinations of design attributes, and collect data. A two-level fractional factorial design is employed to generate various combinations of design attributes for the experiments (see section 4.2), wherein the setting of each experimental run is generated in the form of a 360-degree panorama (i.e., VR image-based models) using Autodesk Revit®. This allows a careful yet effortless evaluation of the design model using any mobile or VR device (see section 4.3). These VR image-based design models are then used in the experiment to assess the restorativeness of the built environment. Additionally, a questionnaire is developed using psychometric scales (i.e., perceived restorativeness scale and restoration-supportive built environment scale), based on the previously reported studies on perceived restorativeness (see section 4.4) [49–51]. Once the questionnaire and the VR panorama-based models for each experimental run are prepared and examined through a pilot test, the online experiment is launched through emails and social media platforms to collect data (see section 4.5). The collected data are subsequently preprocessed, and the corresponding results are analyzed for statistical significance (see section 5.1 and 5.2). Once the input features are selected, multiple machine learning models are used to predict the restorative qualities of the built environment using design attributes (see section 5.3). Finally, a regression performance analysis of the developed predictive models is performed to identify the most appropriate models that can forecast the overall restorative quality of a built environment with several design alternatives.

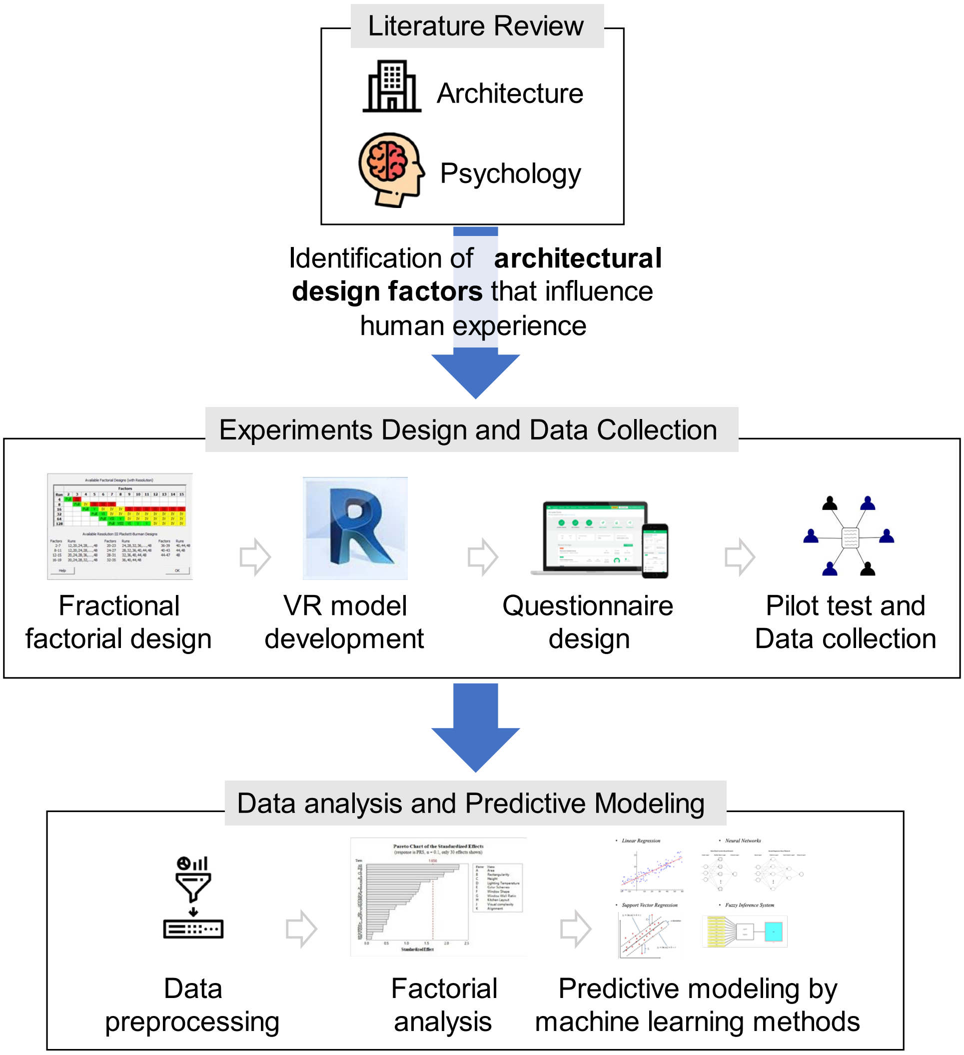


Figure 2 Research methodology

4 Experiments Design and Data Collection for Human Restorative Experience

4.1 Architectural Design Attributes

Many architectural design attributes have been found to be related to human-perceived restorativeness in the built environment [22,37]. It is generally believed that design attributes that support fascination, curiosity, or involuntary attention can be credited for enhancing recovery from mental fatigue [34]. Table 1 lists the eight architectural design attributes commonly related in the literature to restorativeness- and stress-related experiences.

Table 1. Architectural design attributes associated with human restorativeness- and stress-related experience in the literature

Architectural design attributes	References
Exposure to nature and indoor plant	[52–57]
Presence/absence, dimensions, shapes of windows	[23,58–63]
Openness/Spaciousness of spaces	[64–68]
Lighting	[69–72]
Finish color scheme	[73–80]
Visual complexity	[1,81–83]
Space layout	[33,37,84–87]
Spatial alignment	[37,88,89]

Window Designs and Access to Natural Elements

Access to natural elements and the presence of windows are the components most frequently discussed in the study of human restorative experience in built environments. Research suggests that increased exposure to bright light effectively reduces depression and improves the mood of occupant-users, even for people hospitalized with severe depression [55–57]. In this context, windows in built environment settings have been of great interest among scholars. Pati et al. indicated that the presence of windows has a positive impact on stress reduction, while Nejati supported that a window enhances the perceived quality of the overall experience of a physical environment [23,61]. Moreover, Lowenhaupt Collins pointed out that the perceived quality of a window's view is intimately related to the window's dimension and shape [62]. Generally, higher occupant satisfaction and visual comfort are associated with higher window-to-wall ratio (i.e., 30%) than with a lower window-to-wall ratio (i.e., 15%), as showed in Taehoona et al.[63].

Spaciousness of Spaces

The perceived spaciousness of an interior space has been correlated with a reduction in the feeling of stress and anxiety. Previous studies indicate that ceiling height, aspect ratio, and square footage are the main attributes that determine how people experience a space. That is, the larger the horizontal areas and the higher the ceiling height, the more spaciousness people perceive and, ultimately, the more comfortable they feel in the environment [64,66–68].

Lighting

Lighting has been considered a potential source of fascination to restore attention and promote the use of unintentional attention by augmenting one's perception of the environment [69]. Both the illuminance level and the correlated color temperature have been associated with attention restoration through the perception of brightness and the quality of color environments [72]. According to Manav, the color temperature of 4000k was preferred to 2700K for the perception of comfort and spaciousness, while an illumination level of 2000 lx was preferred to 500 lx for impressions of comfort, spaciousness, brightness perception, and color saturation [72].

Color Scheme

The choice of colors in architectural design plays a significant role in the process of attention restoration for individuals, as it is associated with one's feeling of serenity or agitation, which in turn impacts one's stress level [77–79]. Generally, warm color schemes involving shades of orange, yellow, and brown help people increase their awareness, whereas cold color schemes, including shades of green, blue, and grey, help people focus on visual and mental tasks [80].

Visual Complexity

Visual complexity is associated with visual attention and comfort with regard to the assumption that design attributes that enable one to capture involuntary attention can facilitate mentally restorative processes. The amount of detail in visual stimuli affects a person's ability to be effortlessly attentive [83]. In studies on visual perception [1], people have shown a preference for designs with greater visual complexity.

Space Layout

The layout of space (i.e., symmetry of objects in the interior environment) has also been identified as an influential design attribute, altering environmental perceptions [37]. A symmetrical space layout increases the perceived quality of the environment and affects occupant satisfaction [33]. Enquist and Arak found that people appreciate greater symmetry and that symmetrical patterns hold an almost universal appeal for humans [86,87].

Spatial Alignment

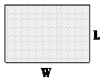
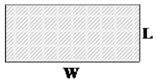
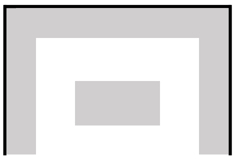
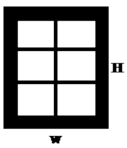
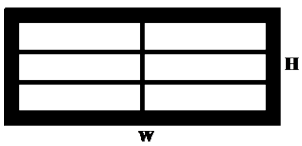
Spatial alignment allows the brain to identify similarities and differences among elements, which effectively draws visual attention to one important region by enhancing that region's visual saliency [89]. Based on their human experience and a built environment-related experiment, Ergan et al. concluded that people associate the experience of pleasure and aesthetics with the presence of spatial alignment and show greater preference for aligned spaces [37].

Based on the literature review and given the context of this study, the following 10 design attributes that are typical of architectural design elements in residential environments were selected and investigated in this study: 1) room size, 2) rectangularity of room shape, 3) ceiling height, 4) light temperature, 5) visual complexity, 6) room layout symmetry, 7) window-to-wall ratio, 8) window aspect ratio, 9) finish color scheme, and 10) space alignment.

4.2 Experiments Design

Statistical experimental design is frequently performed in experiment planning, as it allows appropriate data to be collected and analyzed in order to deliver valid and objective conclusions. The present study endeavored to establish a 'balanced' dataset that comprehensively represents all sample populations for predictive model development so that the model can characterize the relationship based on the data rather than merely 'memorizing' the training data of over- or under-represented populations [90]. To obtain uniformly distributed data over the investigated attributes and reduce the total number of experiments (design alternatives) required, the fractional factorial design approach was employed in this study to develop a balanced dataset. Specifically, two levels were assigned to each design attribute, as presented in Table 2. It should be noted that the space-A and space-B in the table are only meant to illustrate the different values of design attributes. The experiment aimed to gather response data from people regarding the extent of their perceived restorativeness in a setting that combines various interior design attributes. Compared to randomized controlled trial design, factorial design allows the researcher to comprehensively evaluate the influence of multiple attributes and detect interaction effects among these attributes [91]. However, for a study with many independent variables, full factorial design can lead to an excessive number of experimental runs and data, i.e., in this study, 1,024 experimental runs are required for full factorial design. In this context, fractional factorial design is considered a cost-efficient experiment design because it requires fewer experimental runs while maintaining the same level of statistical power [92]. In this study, the restorative quality of each design alternative (experimental run) was evaluated by the participants, and a greater number of experimental runs would significantly affect the respondent's cognitive burden and the relative costs associated with data collection. Thus, in this study, a $1/2^5$ factorial experiment design was conducted to examine the effect of the 10 aforementioned architectural design attributes at a two-level resulting in 32 experimental runs, which supports the selection of input features for further predictive modeling [93]. Table 3 presents the 32 experimental runs (design alternatives) of this study, as generated by the Minitab statistics software. Each run represents a combinatorial design alternative modeled later using Revit and evaluated in the later experiment.

Table 2. List of attributes and their levels with two unlabeled design alternatives in the experiment

Design attributes	Space-A	Space-B
Room size	110 ft^2	210 ft^2
Rectangularity of room shape	 Square	 Narrow Rectangle
Ceiling height	Slightly low	Slightly high
Light temperature	 Warm-white	 Daylight
Visual complexity	 Moderately low	 Moderately high
Room layout symmetry	 Asymmetric	 Symmetric
Window-to-wall ratio	Slightly low	Moderately high
Window aspect ratio	 Verical	 Horizontal

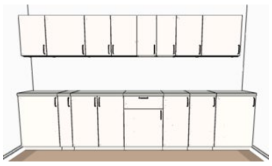
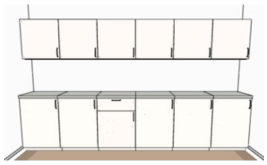
Finish color scheme	 Clean-White	 Modern Rustic
Spatial alignment	 Unaligned	 Aligned

Table 3. Experimental runs of design alternatives selected by fractional factorial design

Run	Attributes									
	Room size	Rectangularity of room shape	Ceiling height	Light temperature	Finish color scheme	Window aspect ratio	Window to wall ratio	Room layout symmetry	Visual complexity	Space alignment
1	210 ft^2	Narrow rectangle	Low	Daylight	Modern rustic	Horizontal	Low	Symmetric	High	Unaligned
2	110 ft^2	Square	Low	Warm-white	Modern rustic	Vertical	Low	Asymmetric	High	Unaligned
3	110 ft^2	Narrow rectangle	High	Daylight	Modern rustic	Horizontal	Low	Asymmetric	High	Aligned
4	210 ft^2	Square	High	Warm-white	Clean-white	Vertical	High	Asymmetric	Low	Unaligned
5	110 ft^2	Narrow rectangle	High	Warm-white	Clean-white	Vertical	High	Asymmetric	High	Aligned
6	110 ft^2	Narrow rectangle	High	Warm-white	Modern rustic	Vertical	Low	Symmetric	Low	Unaligned
7	210 ft^2	Narrow rectangle	High	Warm-white	Clean-white	Horizontal	Low	Symmetric	Low	Aligned
8	110 ft^2	Square	High	Daylight	Clean-white	Vertical	Low	Asymmetric	Low	Aligned
9	110 ft^2	Square	High	Warm-white	Modern rustic	Horizontal	High	Asymmetric	Low	Aligned
10	110 ft^2	Square	Low	Warm-white	Clean-white	Vertical	High	Symmetric	Low	Aligned
11	110 ft^2	Narrow rectangle	Low	Warm-white	Modern rustic	Horizontal	High	Symmetric	High	Aligned
12	110 ft^2	Narrow rectangle	Low	Warm-white	Clean-white	Horizontal	Low	Asymmetric	Low	Unaligned
13	110 ft^2	Narrow rectangle	Low	Daylight	Clean-white	Vertical	Low	Symmetric	High	Aligned
14	110 ft^2	Narrow rectangle	High	Daylight	Clean-white	Horizontal	High	Symmetric	Low	Unaligned
15	210 ft^2	Square	High	Daylight	Modern rustic	Horizontal	Low	Asymmetric	Low	Unaligned
16	210 ft^2	Square	Low	Daylight	Modern rustic	Vertical	High	Asymmetric	High	Aligned
17	210 ft^2	Square	Low	Daylight	Clean-white	Vertical	Low	Symmetric	Low	Unaligned
18	110 ft^2	Square	Low	Daylight	Modern rustic	Horizontal	Low	Symmetric	Low	Aligned
19	210 ft^2	Narrow rectangle	High	Daylight	Modern rustic	Vertical	High	Symmetric	Low	Aligned
20	110 ft^2	Square	High	Warm-white	Clean-white	Horizontal	Low	Symmetric	High	Unaligned
21	110 ft^2	Narrow rectangle	Low	Daylight	Modern rustic	Vertical	High	Asymmetric	Low	Unaligned
22	210 ft^2	Narrow rectangle	High	Warm-white	Modern rustic	Horizontal	High	Asymmetric	High	Unaligned

23	210 ft^2	Square	Low	Warm-white	Clean-white	Horizontal	Low	Asymmetric	High	Aligned
24	210 ft^2	Square	High	Daylight	Clean-white	Horizontal	High	Symmetric	High	Aligned
25	110 ft^2	Square	High	Daylight	Modern rustic	Vertical	High	Symmetric	High	Unaligned
26	210 ft^2	Narrow rectangle	High	Daylight	Clean-white	Vertical	Low	Asymmetric	High	Unaligned
27	210 ft^2	Square	High	Warm-white	Modern rustic	Vertical	Low	Symmetric	High	Aligned
28	210 ft^2	Narrow rectangle	Low	Daylight	Clean-white	Horizontal	High	Asymmetric	Low	Aligned
29	210 ft^2	Narrow rectangle	Low	Warm-white	Modern rustic	Vertical	Low	Asymmetric	Low	Aligned
30	210 ft^2	Square	Low	Warm-white	Modern rustic	Horizontal	High	Symmetric	Low	Unaligned
31	110 ft^2	Square	Low	Daylight	Clean-white	Horizontal	High	Asymmetric	High	Unaligned
32	210 ft^2	Narrow rectangle	Low	Warm-white	Clean-white	Vertical	High	Symmetric	High	Unaligned

4.3 Virtual Reality Model Generation

It would be impractical to provide 32 real room settings with defined design attributes for the purpose of the experiment. Thus, following the DOE results, each experimental run (design alternative) was represented in a VR-based 360-degree panoramic model (see Figure 3). The basic geometry, structure, and design setting of the virtual environment and objects (e.g., cabinet, countertop, sink, light fixture) were configured in a building information model in Revit (2019). Autodesk Cloud Rendering was then used to render the design into high-resolution stereo panoramas that could be shared via a website URL. Participants could then use either a smartphone with cardboard VR viewer or a desktop to access the VR panorama.

A number of studies have demonstrated that there is not a significant difference in terms of occupant perception between physical spaces and well-designed VR environments [63,94–97]. Moreover, using VR models rather than static images to represent design configurations allows for a continuous stream of congruent stimuli that deliver a vivid illusion of reality to the participant. This has to do with the concept of "presence," the subjective feeling of "being in a virtual environment," which determines the effectiveness of a VR simulation. On the other hand, to ensure adequate visual fidelity among various VR display platforms (e.g., smartphone-based VR and desktop-VR paradigms), the devices used in the experiment (VR display type and resolution configurations) were recorded. Although the interaction fidelity and immersion level provided by the two display systems used are different, their influence on emotional elicitation may not be significant [98–103]. Meanwhile, an assumption was made in this study that a satisfactory sense of presence provided by the VR model can ensure sufficient emotional stimulation of participants, since the emotional elicitation effect is strongly associated with the feeling of presence in a VR platform [104]. Therefore, multiple questions adopted from Heydarian et al. [105] assessing the realism of the VR environment compared to the physical world were included in the questionnaire in order to verify the validity of the developed VR model.

Figure 3 Screenshots of VR models for experimental runs

4.4 Design of Questionnaire

During the experiment, participants were expected to assess the restorative quality of a room setting and describe their relevant experience by filling out a questionnaire, which consisted of two parts: a) background questions and b) restorative experience measurement.

4.4.1 Background Questions

Prior to the questions measuring one's restorative experience, the questionnaire asked for demographic information, including age, gender, and education level, and past experiences with architectural design, virtual reality models, and built environments as settings for restorative experiences. The additional background questions regarding past experiences with architectural design, virtual reality models, and built environments were intended to examine the influence of these experiences on the interpretation of results pertaining to perceived restorativeness. Moreover, the Ishihara color blindness test was added as a core module in the demographic information portion of the questionnaire to identify and eliminate the potential influence of participants with color blindness.

4.4.2 Restorative Experience Measurement

To measure the human-perceived restorativeness of the built environment in a reliable and quantifiable manner [106], two self-reported restorativeness scales—the Perceived Restorativeness Scale (PRS) by Hartig et al. [49,51] and the Built Environment Restoration Support Scale (BERS) by Fischl and Garling [107]—were incorporated in this study as part of the questionnaire. Self-reported restoration experience assessment, as an explicit measure, has been widely used in studies on environmental restorativeness to quantify individual's psychological reactions [50,106,108]. Specifically, the selected self-reported scale, PRS, is one of the most widely used measures addressing the extent to which certain environmental settings have restorative qualities, and its validity has been proven by sufficient psychometric analysis in terms of content, construct, convergent, discriminant, and criterion-related validity [50,106]. This scale has been credited for its generalizability and sensibility in identifying differences in perceived restorativeness in a given environment on the part of participants of various ages, health levels, and nationalities. However, PRS is rarely used for indoor environments. In comparison, the BERS was explicitly proposed to assess the restorative quality of the built environment but rarely examined in previous studies. Since limited attempts have been made to examine the validity of the BERS, it was included in the questionnaire only as a supplemental measure to the PRS.

In the PRS measurement, perceived restorativeness is assessed using four dimensions, namely, the feelings of "being away," "fascination," "coherence," and "compatibility," based on Kaplan and Kaplan's Attention Restoration Theory [109,110]. Given this paper's focus, the interested reader can refer to the cited references [51,111] for a detailed description of each restorativeness dimension. The PRS measurement developed by Hartig et al. [49,51] uses either 26 or 16 items. This study adapted the 16-item method to make it more suitable for use in research contexts where the evaluated scenario comprises indoor built environments [51]. As a result, 17 seven-point Likert-scale questions (see Table 4) were proposed in the questionnaire to measure the participants' perceived restorativeness. Moreover, to measure restorative experience in a standardized, plausible, and relevant context, emotion-provoking methods that put participants under psychological stress before exposure to configured environmental settings have been commonly used in previous studies to ease the restoration effect measurement [22,112]. Thus, a scenario description adapted from Lindal and Hartig [65] was provided to participants before moving on to the restorativeness measurement for the contextual stimuli control: *Imagine it is* *afternoon. You are walking home from work alone. You are mentally exhausted from intense concentration at work, and you appreciate having a chance to stroll and recover*. The purpose of this affective description was to specify a condition of directed attention fatigue and to emphasize for participants the range of variation in compatibility due to factors other than a change in the physical environment [65].

It is noteworthy that the developed questionnaire was reviewed by six researchers in the field of architectural design and ergonomics before being sent to prospective respondents. These researchers were asked to provide feedback on the visual noticeability of the design attributes as the visual stimulus component of the environmental settings, as well as on the validity of each questionnaire item in terms of wording, format, content, and clarity. Based on the researchers' feedback, the VR models and questionnaire were modified and finalized.

Table 4. Measurement items in questionnaire

Dimensions		Questionnaire Items
Perceived Restorativeness Scale (PRS)	Being Away	Spending time here gives me a break from my day-to-day routine.
		Being here helps me to relax my focus on getting things done.
	Fascination	This place is fascinating.
		This place draws my attention without any effort on my part.
		My attention is drawn to many interesting features in this space.
		I want to get to know this place better.
		There is much to explore and discover in this space.
	Coherence	There is too much going on in this space.
		This is a confusing place.
		There is a great deal of distraction in this space.
		It is chaotic in here.
	Compatibility	This space fits my character.
		I can do things I enjoy in this space.
		Sometimes even a small space can feel like a whole world of its own.
		It can seem like it is enough room to become completely engaged in this space and not concern yourself with anything beyond its walls.
		It is easy to see how things are organized in this space.
		I could find ways to enjoy myself in a place like this.

Built Environment Restoration Support Scale (BERS)	Recall one of those times when you worked hard on a project that required intense and prolonged effort. Remember how it felt. You probably reached a point where you could tell that your ability to work effectively had started to decline and that you needed a break. You needed to do something during the break to restore your ability to work effectively on the project. Put yourself in that mindset now, and then please rate your satisfaction level toward the presented design as a setting in which to take a break and restore your ability to work effectively.

4.5 Participant Recruitment and Data Collection

Data collection was conducted via the Internet. Participants received an invitation letter through e-mail that contained a link to the online questionnaire. Participants were invited to complete the experiment voluntarily, and could withdraw at any time. A total of 32 VR models (one for each experimental run) were assessed in this study. Figure 4 shows the procedure for a single experimental session. After the introduction and background information section, participants were given 2 min to read a paragraph of affective text (i.e., stimulus material for eliciting stressful feelings) as stated in Section 4.4.2 [22,112]. Then, a 3-min non-immersive VR experience of the configured design was provided, where the exposure duration was determined in reference to previous lab-based human affective-related experiments [38,113–116]. Afterward, participants were asked to evaluate their perceived restorativeness experience by answering the next section of the questionnaire. An access link was made available in every question so that the participant could re-visit the VR environment as needed to reduce memory load and improve the accuracy of the affective judgment. Each experimental session took approximately 13-20 minutes on average to complete.

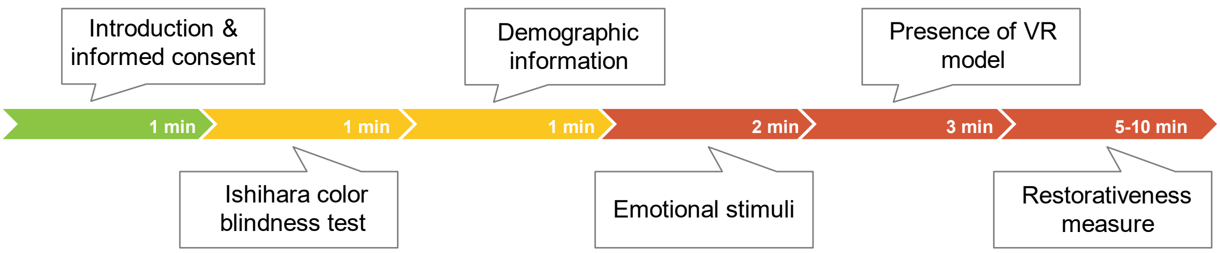


Figure 4 Overview of a single experimental session

5 Data Analysis and Prediction

Once the responses were collected through the experiments, data preprocessing and analysis were then performed to identify the meaningful input features for the development of prediction models. In this study, five machine-learning models, namely, linear regression, radial basis function neural network (RBFNN), general regression neural network (GRNN), SVR, and FIS, were developed to predict the human restorative experience toward the built environment. Their predictive performance was also compared using performance metrics for further model selection.

5.1 Data Pre-Processing

Data preprocessing aimed to clear responses that did not meet certain criteria, such as incomplete responses, responses that were given too quickly ("speeder" responses), inconsistent responses, and outlier responses [117,118]. Specifically, to ensure the credibility of the experimental results, four indices—(a) total response time, (b) response patterns (i.e., *LongString*), (c) Mahalanobis distance, and (d) Cronbach's alpha—were calculated based on the response data, and data cleaning was performed accordingly. For example, the speeder and inattentiveness responses can be easily identified through the respondents' response times and patterns. The response time measures the total time needed by the respondent to complete the questionnaire. A much shorter response time indicates that the respondent may be speeding through questions and paying little attention to providing an assessment. The response pattern is analyzed to identify respondents' careless responses (for example, a respondent who consistently provides the same answer). Following the method proposed by Johnson [119], an index termed *LongString* was used to compute the maximum number of items with identical consecutive response on a single page [117–119]. As for the outlier responses, the Mahalanobis distance, denoted as *MD* in Equation 1, was computed for each response for the same design alternative, measuring the multivariable distance between each response vector and the mean of the sample vector, which indicates the individual responses outside the distribution. Moreover, with respect to the internal consistency of the measures, Cronbach's alpha (see Equation 2) was estimated to reflect the extent to which the question was inter-correlated in measuring the participants' perceived restorative experience. In alignment with previous works, a of at least 0.7 was also used in this study to indicate adequate internal consistency of responses [120].

$$MD^2 = (r - \hat{r})^T \cdot C^{-1} \cdot (r - \hat{r}) \qquad (1)$$

where r is the vector of the response; $\hat{\mu}$ is the vector of mean value; and C is the covariance matrix of these two variables' vectors.

$$\alpha = \frac{n}{n-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_x^2}\right) \quad (2)$$

where n is the number of responses; σ_i^2 is the variance of questionnaire item i; and σ_x^2 is the total variance of the questionnaire.

5.2 Factorial Analysis

To detect which architectural design attributes and which interactions between attributes influence one's perceived restorativeness to the greatest extent, an analysis of variance (ANOVA) was performed on the remaining dataset (i.e., after data pre-processing) using Minitab 18 statistical software. The main effect of a design attribute was measured by the corresponding change in the output, i.e., the restorative experience associated with the change made at the level of that design attribute averaged over other design attributes. The interaction effect (i.e., two-way interaction between variables A and B) is defined as the average difference between the main effect by A at the high level of B and the effect of A at a low level of B. Note that the significance of a design attribute or its effect on restorative experience is determined by its p-value [121].

5.3 Predictive Modeling for Restorative Experience

As reported in previous studies, prediction models developed using machine-learning methods may show different prediction performances under various problem contexts [16–20]. To explore the capability of machine-learning models in affective modeling for built environments, linear regression and three other typical machine-learning methods (ANN, SVR, and FIS) were tested to develop the prediction models for human restorative experience. These three machine learning models were adapted from a comprehensive literature review conducted by Chan et al. [19] that examined 94 research publications and summarized the machine-learning methods used to model the relationship between the affective quality of a product and its design attributes. Among the machine-learning methods discussed in the study by Chan et al., we focused on models with a lower variance capable of characterizing the relationship from a small dataset in order to mitigate the risk of overfitting (considering that it is impractical to conduct such data collection experiments on a large scale, given the associated cost and effort). As a result, three machine-learning methods were selected due to their generic applicability and their ability to handle noisy and nonlinear small datasets, as proven in previous studies [19].

The inputs to the machine-learning models included the selected variables identified as statistically significant based on the factorial analysis in the previous step, while the output was the numeric measurement of the reported restorative experience. To begin, the dataset was divided into a training set and a validation set. The overall dataset was divided into training and testing sets based on the principle that the size of the dataset for machine learning should be roughly ten times the degrees of freedom in the model, which means approximately 100 sample points are needed for a 10-variable model. Although we would like to have kept as many samples as possible in the training dataset to provide more features for training, an inordinately small testing set may have resulted in unacceptably high variance in the performance assessment results. Thus, 100 responses (83%) were used for training and 20 responses (17%) for testing. Due to the limited sample sizes, k-fold cross-validation was applied to the training set to mitigate the risk of overfitting and to enhance the model fitting and generalization. The training set was initially used to identify the optimal model parameter with 5-fold cross-validation. The parameter setting achieving good performance in minimizing the averaged 5-fold cross-validation error for both the training set and the testing set was determined to be the optimal solution. Subsequently, the parameters obtained were adapted in order to train/fine-tune a model using the entire training set (i.e., 100 responses). Accordingly, the trained models were evaluated on the validation set (i.e., 20 responses), and performance metrics of RMSE and R^2 were used to evaluate the predictive performance of the models. All design and training of the machine-learning models was performed in MATLAB 2020b. It should be noted that the optimal parameters of each method were determined based on the best prediction performance via grid search in the parameter space after multiple trial-and-error tests. The following subsections describe the process of developing the machine-learning models.

5.3.1 Linear Regression Model

Linear regression model (see Equation 3) predicts the output, i.e., perceived restorativeness in the built environment, as a weighted sum of the input features. Each weight ω_i of the input features in the model can be determined by the least-squares method as well as maximum likelihood estimation. To maximize the precision of predictors in a model, insignificant variables were eliminated in a stepwise manner during the regression process. A threshold of 0.1 regarding the variables' statistical significance (i.e., p-value < 0.1) was applied during the linear regression to avoid an underspecified regression model, in accordance with the limitation of the sample size and the subjective nature of self-reported surveys. All individual factors and the lower terms of interaction factors with significant effects were included in the linear model to present the model hierarchy.

$$Y = f(x) = \sum_{i=1}^{n} \omega_i x \qquad (3)$$

5.3.2 ANN Model

To choose a neural network architecture, multiple factors are considered, such as a simple model architect, strong capability for nonlinear fitting, generalization for new data, and tolerance for small sample size and high noise by human subjectivity in an affective design. Inspired by previous studies and data characteristics [122–127], the radial basis function neural network (RBFNN) and the general regression neural network (GRNN) were used in this study because of their ability to achieve global optimization with strong robustness and fault tolerance [124]. At times, it should be noted, they have even demonstrated better accuracy and training speed than other neural networks with simple architecture, e.g., multilayer perceptron networks [128,129]. Figure 5 shows their respective architectures.

The RBFNN is a three-layer feedforward network that uses radial basis function as its activation function. The output of this result can then be expressed as a scalar function of input vectors, as shown in Equation 4. Here, $\varphi(x, x_c)$ denotes the radial basis function whose output depends on the Euclidean distance to the center x_c. To calculate the center of the radial, the Gaussian function (see Equation 5) was used on each hidden unit as the transfer function. The value coming out of the hidden layer (i.e., radial basic layer) is multiplied by a weight associated with the node and passed to the output layer. Then, the output layer accumulates up the weighted values and presents this sum as the network's output.

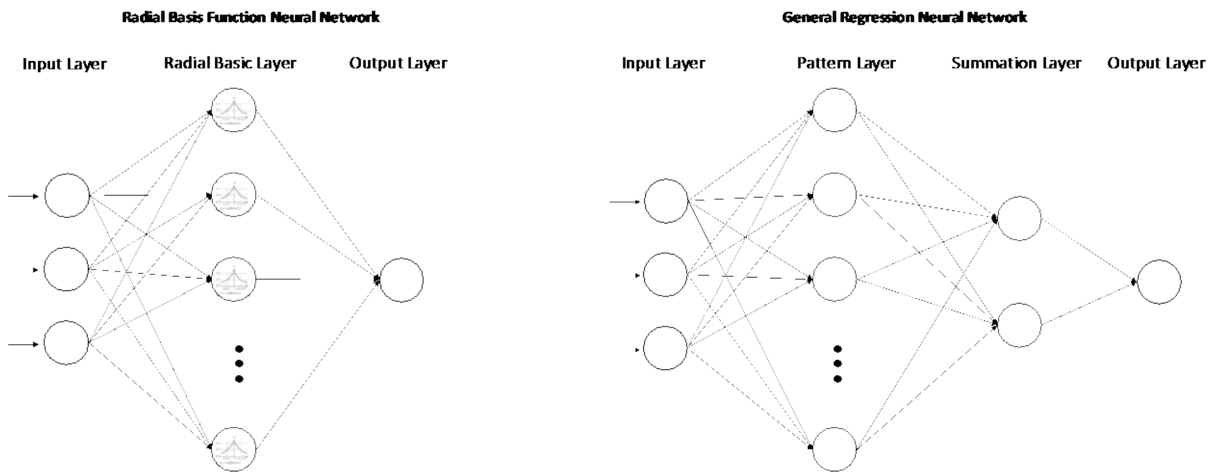


Figure 5 Architectures of the RBFNN and the GRNN

$$Y = f(x) = \sum_{j=1}^{m} w_j \varphi_j(x, x_c) \qquad (4)$$

$$\varphi(x, x_c) = \exp\left(-\frac{\|x - x_c\|^2}{2\sigma^2}\right) \qquad (5)$$

where x_c is the center vector; w_j is the connection weight from the hidden unit to the output unit; σ is the width of the Gaussian function; and $\|x - x_c\|$ represents the distance input to the center of the basis function.

The GRNN is a variation to the radial basis neural networks and consists of four parts: the input layer, the pattern layer, the summation layer, and the output layer. This model is known for its ability to achieve global optimization with strong robustness and fault tolerance. The mathematic representation of the GRNN can be seen into Equation 6, where w_k is the activation weight of the pattern layer node k and $K(x, x_k)$ is the radial basis function kernel.

$$f(x) = \frac{\sum w_k K(x, x_k)}{\sum K(x, x_k)} \qquad (6)$$

During the network design and training process, the smoothing factor of the kernel functions to train these two neural networks was set at 0.3 as a trade-off between the model generalizability and the fast-changing function.

5.3.3 SVR Model

Support vector regression applies a line referred to as *hyperplane* to descript the trend of the data. Rather than minimizing the error between the observed and predicted values, SVR aims to fit the best line within a threshold value so that as many samples as possible can be included to enhance model reliability. To obtain the SVR model, the regression process can be formed as the optimization problem outlined in Equation 7 [130].

$$Minimize\colon \frac{1}{2}\|\omega\|^2 \qquad (7)$$

$$subject\ to \begin{cases} y_i - \omega_i \cdot \phi(\mathrm{x}) - b_i \leq \varepsilon \\ \omega_i \cdot \phi(\mathrm{x}) + b_i - y_i \leq \varepsilon \\ i = 1,2, \ldots l \end{cases}$$

where y_i is the observed output; weighted vector ω_i and bias b_i are the parameters for the prediction of an observed data; and ε is the epsilon margin that serves as a threshold for the difference between the prediction and the observed outputs.

The performance of the SVR model depends heavily on its parameters, such as the kernel function parameter, the regulation parameter, and the width of the epsilon-insensitive band. It is necessary to optimize the training parameters for better generalization performance and to eliminate the overfitting problem, given the limited sample size [131]. During the training process, SVR employed a Gaussian function as the kernel function and the sequential minimal optimization algorithm (SMO) to find the optimal solution. The best performance was found when the Kernel scale was 2.154 and Edsilon was 0.535.

5.3.4 FIS Model

To obtain a fuzzy inference system from the data, the foremost step is to divide the data space into fuzzy clusters. Following Park and Han's instruction, this study employed the fuzzy subtractive clustering algorithm (FSC), an unsupervised algorithm, to identify potential clusters among the input data [20]. The FSC can automatically estimate a fair number of clusters based on the density (potential) of data points in a space where a cluster center is one of the clustered data [132,133]. Consequently, 10 rules (10 clusters) were generated based on the optimal combination of fuzzy clustering parameters. The local model of each rule was then expressed using the Takagi–Sugeno–Kang (TSK) model in a mathematical manner. The regression parameters of the local models were further determined by the linear least-squares estimation technique and represented as outlined in Equation 8.

$$For\ x \in C_k, THEN\ Y_{PR} = a_0 + \sum_{j=1}^{M} a_j x_j \tag{8}$$

where x_j is the j^{th} dimension of data point; M is the overall dimension of design elements (i.e., equal to 10 in this case); and a_0 are the regression parameters; C_k refers to the k^{th} cluster.

5.3.5 Assessment of Prediction Performance

The accuracy of the predictive result is reflected in the prediction error; thus, measuring and analyzing the magnitude of the prediction error is of great significance in terms of demonstrating the accuracy of the prediction result [134]. Root mean square error (RMSE) is a standard metric that expresses the average deviation between the predicted value and the observed value, and it is commonly used to compare the performance of machine-learning regression models [44,124]. However, it is difficult to ascertain the quality of a predictive model by merely looking at a singular value of RMSE. For instance, an RMSE value of 0.4 alone does not intuitively indicate whether or not a model performs well in predicting restorative quality. This shortcoming can be addressed with the use of another performance indicator, R-squared (R^2), which gives the percentage of output variance that can be explained by the independent variables in the model

[135]. Compared to RMSE, R^2 is more informative in indicating the model prediction performance, where an R^2 value of 0.8 means that the evaluated model explains 80% of the variation within the data, regardless of the ranges and distributions of the ground truth values [135]. Therefore, in the present study, both RMSE and R^2 were used to assess the goodness-of-fit of the prediction models, where a high R^2 value and a low RMSE in all possible regression methods is considered to be indicative of a better fit in modeling the relationship between perceived restorativeness and architectural design attributes.

In addition, the scatterplots of the observed data against the predicted data were further employed to illustrate the distribution pattern of the prediction error, (i.e., a constant variance of error across the various levels of the dependent variable). In other words, the scatterplots of observed vs. predicted PRS scores in our study revealed whether the predictive model could perform equivalently in predicting various levels of dependent variables. For instance, the scatterplots of observed vs. predicted PRS scores in our study revealed whether the predictive model could perform equivalently in predicting various design settings with different PRS scores [136].

6 Results and Discussion

A summary of the main findings from the experiment together with analytical results regarding predictive modeling are provided in the section.

6.1 Demographic Characteristics

A total of 144 participants took part in the experiment, and 120 responses (data points) were used for further data analysis and prediction model development after data cleaning has been carried out to remove any incomplete or unqualified responses. Data reliability was tested with Cronbach alpha and the result of 0.824 suggests a good internal consistency of survey responses, which means the online questionnaire results are able to reliably measure a person's perceived restorative experience under specific interior design settings. The distribution of the participants in terms of demographic characteristics (age, gender, and education level) is outlined in Table 5. Participants were queried as to their background knowledge and relevant experience with respect to interior design, and only 4.2% of participants stated they do not have any experience or knowledge of interior design. Moreover, more than 50% of participants had interior design experience or were familiar with the basic principle. In terms of virtual reality models, 70.8% of participants stated they have prior experience with VR techniques and gave the VR model a score of 5.43 out of 7 (SD=0.72) in terms of its sense of presence, indicating that the virtual model is an adequate representation of the physical environment for the purpose of measuring user experience [137]. During the experiment, no significant differences were found for age, gender, and level of education, which suggests the demographic variables did not influence the responses in the present study. However, the attitude of a respondent with respect to whether or not the kitchen is a relaxed place in the home was found to be significantly associated with the result of the respondent's response for restorativeness measure (p-value = 0.03). This finding is consistent with previous research findings that a person's previous experience or their environment-related attitude would influence their perception of the environment [138,139].

Table 5. Demographic information of participants

		Number of participants	Proportion
Gender	Female	34	28.33%
	Male	86	71.67%
Age range	18–24	4	3.33%
	25–34	70	58.33%
	35–44	27	22.50%
	45–54	14	11.67%
	55–64	5	4.17%
Education level	Some college training but no degree	13	10.83%
	High school degree or equivalent (e.g., GED)	5	4.17%
	Bachelor's degree	66	55.00%
	Graduate degree	36	30.00%

6.2 Factorial Analysis of Design Attributes

The Pareto chart in Figure 6 summarizes the top 20 input variables with significant main and interaction effects according to the results of the factorial analysis. The bars for each variable represent the absolute values of standardized effects of design attributes and their interactions on human-perceived restorative experience as measured by PRS and BRES. The reference line of 1.982 is plotted to indicate the 95% significance level, meaning that if a bar crosses the reference line, this indicates that the variable is determined as being influential to the output change at a statistical significance level of 0.05 (p-value < 0.05). Therefore, at the protected significance level (i.e., 95% significance level), the main effects of window aspect ratio, room size, and light temperature were significantly influential to restorative experience results measured by both PRS and BERS, revealing the strong relationship between the design feature and human-perceived restorativeness in environments. However, finish color scheme and ceiling height contribute a statistically significant difference to the result of PRS score, but fail the significance hypothesis test for the BRES measure, which may be explained by the expression of BRES leading the participant to focus more on assessing the feeling of "being away" and "fascination" in environments while neglecting the concept of "coherence." Similarly, the difference in interaction effect of Rectangularity × Room layout symmetry according to PRS and BERS measures could also be explained the same way. The significant interaction effect of Rectangularity × Room layout symmetry was evident in terms of the output of "coherence" feeling in PRS measure (p-value < 0.05); in contrast, the same interaction effect failed the hypothesis test for the BERS measure. For this reason, PRS is used as the only target output in the data analysis that follows.

In terms of interaction effects, the six two-way interaction effects of Rectangularity × Room layout symmetry; Ceiling height × Window-to-wall ratio; Room size × Finish color scheme; Rectangularity × Light temperature; Room size × Visual complexity; and Light temperature × Window aspect ratio were identified as contributing to the results of PRS measure in the present study. Three examples of interaction effects with the most significant standardized effect are plotted in Figure 7, illustrating the mean PRS score versus two levels of design attributes under different settings of other variables. As shown in Figure 7a, if the ceiling height of a room is low, a low window-to-wall ratio (indicated by the black dashed line) is associated with a higher score of PRS and restorative experience, whereas in the scenario in which a room has a high ceiling, the participant found the high window-to-wall ratio offers a more restorative experience according to the PRS score. Likewise, in a rectangular kitchen, as depicted as the red line in Figure 7Figure 7c, the participant found the asymmetrical layout could provide them a more restorative experience in comparison to a symmetrical layout, although the symmetry of a space is usually positively associated with higher perceived restorativeness in environments as shown in the case of square-shape kitchen space. Moreover, looking at Figure 7b, it is apparent that the room size has a significant influence on a person's perceived restorativeness under a modern rustic color setting. In contrast, the PRS score appeared to be less affected by room size when the color scheme is clean-white.

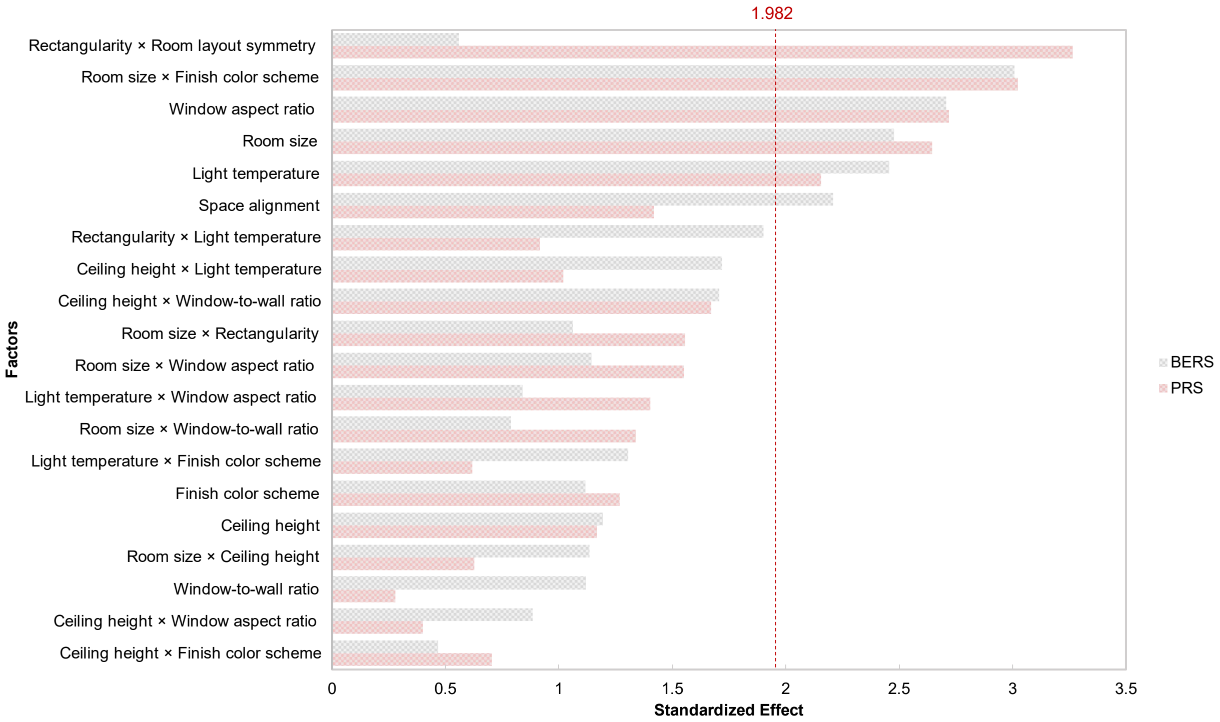


Figure 6 Pareto chart of the standardized effects for responses using PRS and BERS scales

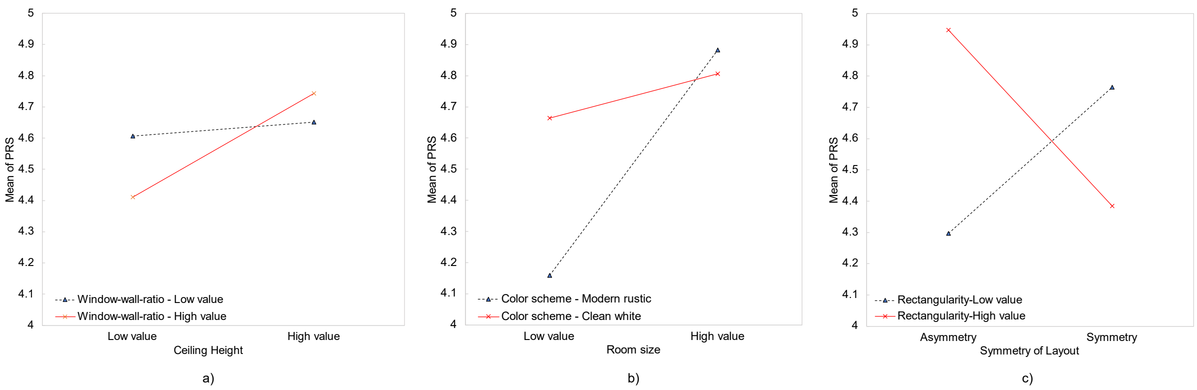


Figure 7 Plots for interaction effects of (a) Ceiling height × Window-wall ratio, (b) Room size × Finish color scheme, and (c) Room layout symmetry × Rectangularity

6.3 Comparison of Predictive Modeling Results

Multiple machine learning methods were applied using the response data to build the prediction model. As suggested by the factorial analysis results in Section 4.2 (i.e., that all design attributes should be incorporated into the linear model according to the significance level of effects and the model hierarchy), a total of ten design attributes—(1) room size, (2) rectangularity of room shape, (3) ceiling height, (4) light temperature, (5) visual complexity, (6) room layout symmetry, (7) window-to-wall ratio, (8) window aspect ratio, (9) finish color scheme, and (10) space alignment—were set as the dependent variable inputs for the other machine learning methods. Moreover, the extent to which the participant believes a kitchen is a relaxed place is also included as a context input variable to assess the perceived restorative quality in environments during modeling as their significant correlation was argued by other scholars and supported by the result of the factor analysis in the present study. Meanwhile, as has already been noted in the factorial analysis (i.e., Section 6.2), the description used to measure BERS might cause the participant to focus more on the "being away" and "fascination" aspects while assessing the restorativeness of the environments. The PRS score was used as the only target output for the predictive modeling. It should also be noted that PRS was more thoroughly examined for construct validity and generalizability compared to BERS. Also, PRS has more scale items to rate than BERS, which reduces the risk of internal inconsistency [106].

As a result, a total number of five predictive models were developed, of which the machine learning methods used to develop the models include linear regression, neural networks (i.e., GRNN and RBFNN), support vector regression (SVR), and fuzzy inference system (FIS). The comparison of their prediction performance using training and testing sets is shown in Table 6. It is apparent that three artificial intelligence methods, i.e., SVR, neural network, and FIS, all have better predictive performance than the linear regression. The R-squared value of linear regression indicates that this model is capable of explaining only 36.00% of the variation in human-perceived restorative experience in the validation set. However, some scholars have argued that the interpretation of R-squared value varies depending on the research area. Any study involving an attempt to predict human behavior, such as in psychology, typically tends to yield lower R-squared values in comparison to engineering problems due to the non-linearity of human nature, as previously discussed herein [140,141]. Additionally, to obtain more in-depth insight into the performance of GRNN, RBFNN, FIS, and SVR models, their respective best model structures and fitness plots were used to compare the prediction performance. Among the four prediction models, the GRNN and RBFNN neural networks have similar statistical performance in terms of low RMSE scores and high R-squared values. Comparing GRNN and RBFNN, the performance of the former is only slightly better. This result is consistent with the experiment conducted by Chen et al. [124], which studies the human emotional response to various aircraft cockpit designs. Moreover, since GRNN is a single-pass associative memory feedforward neural network, its computation time for training is relatively shorter than that of other artificial neural networks.

Figure 8 further demonstrates the scatterplots of observed data against predicted data using each of the four artificial intelligence models. The *x*-axis is the predicted PRS score by predictive model and the *y*-axis is the observed value. Therefore, the closeness of data points to the regressed diagonal line indicates the goodness-of-fit of the models. The plots for GRNN, RBFNN, and FIS (see Figure 8a, 8b, 8c) are quite similar in terms of the slope of goodness-of-fit as well as the data pattern, and their predicted values are relatively close to the corresponding observed PRS values in comparison to those predicted by the SVR model (see Figure 8d). While assessing the performance of models for their applicability in predicting the target output, it should be noted that both the average error of regression and the distribution or the pattern of prediction error should be taken into consideration. From these scatterplots, the residual distribution can be observed by measuring the distance from the data points to the diagonal line. Ideally, the distribution should be symmetrical around the diagonal line, indicating reliable standard errors of regression coefficients. However, as shown in the support vector regression scatterplot (Figure 7d), the distribution of data points indicates that the SVR model has relatively poor performance when predicting the cases with various PRS values, as these data points can be seen to be crowding below the diagonal line when PRS < 4 and gathering above the line when PRS > 4. Overall, GRNN, RBFNN, and FIS models perform reasonably well in predicting the PRS score of a room based on the design attributes when compared to linear regression and SVR models. The results also suggest that the GRNN model is superior to RBFNN and FIS in terms of PRS score forecasting among the validation datasets.

Table 6. Performance values of machine learning methods

Machine learning method		RMSE		R-squared	
		Train	Test	Train	Test
Linear regression		0.4025	0.5214	60.91%	36.00%
SVR		0.3742	0.3289	69.70%	73.19%
Neural networks	RBFNN	0.2676	0.2631	83.14%	82.85%
	GRNN	0.2670	0.2532	83.21%	84.11%
FIS		0.2819	0.2922	81.29%	78.85%

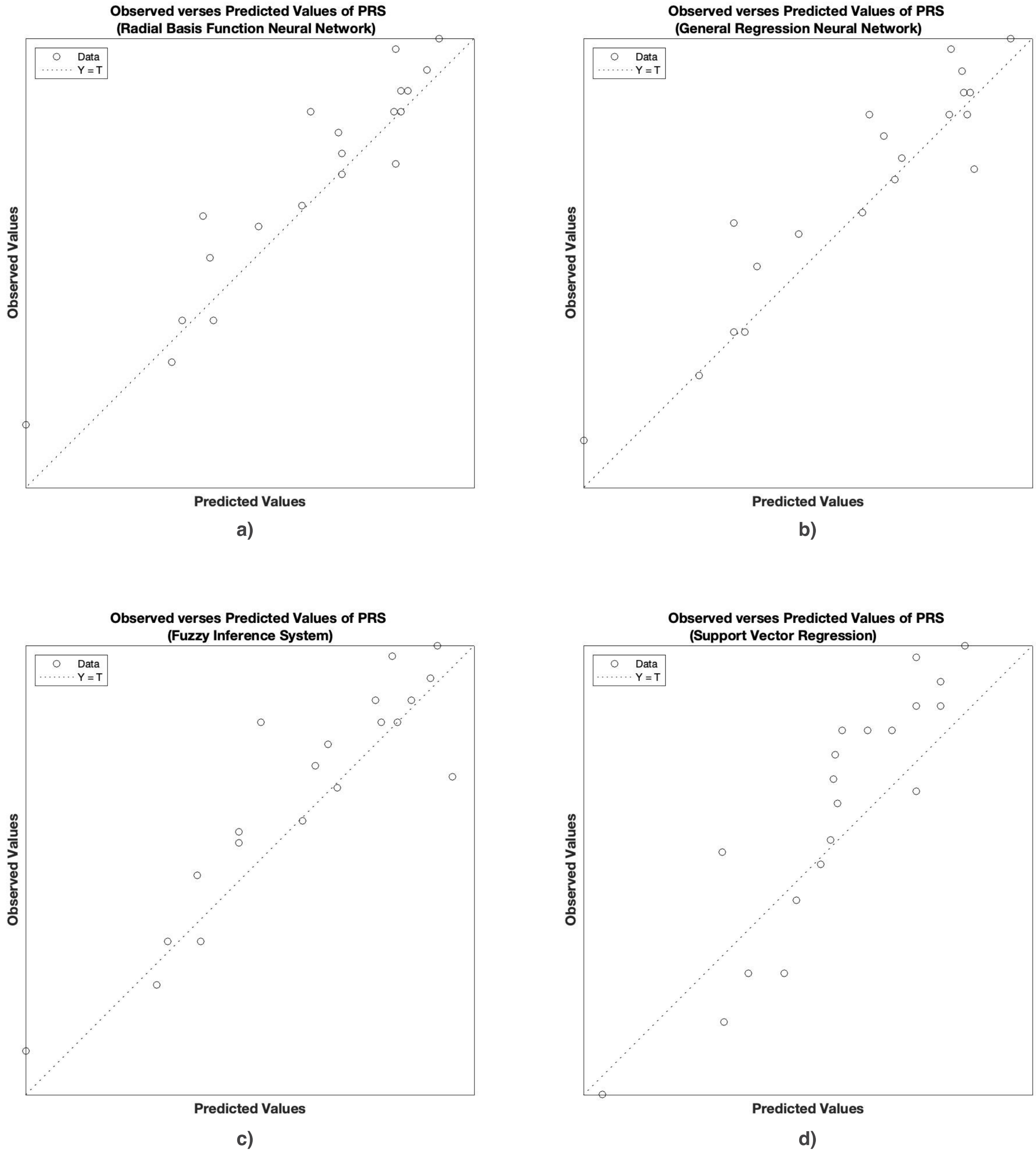


Figure 8. PRS values observed and predicted by four machine learning models

7 Conclusions and Future Work

The affective experience of occupant-users is vital for the perceived usability of residential buildings and should be considered in the early design phases. Although many studies have attempted to identify the architectural design attributes that most influence the human affective experience, the fragmented and ambiguous nature of the relevant information makes its use in human-centered architectural designs challenging. This study aimed to construct prediction models that could be applied to forecast values of experiential quality for each residential design alternative in order for the design practitioner to easily capture the affective quality of the design and further improve user satisfaction with the design, regardless of the designer's experience, skills, and subjective opinion. Such prediction models lay a foundation for developing analytical models and tools to facilitate the decision-making process at the early stages of design to ensure an emotional wellness-focused built environment. It should be noted that conventional machine learning methods for affective design usually require large datasets for feature selection and to ensure the delivery of meaningful results. This can be time-consuming and expensive for studies with human subject. This work thus contributes to the body of knowledge on human–building interaction by introducing a non-immersive VR-DOE-based machine learning method that optimizes the data collection process and addresses the inherent complexity and uncertainty in modeling the affective experience.

In this study, VR technologies were employed not only to produce a controllable and valid experimental environment, but also to demonstrate various combinations of design attributes and environment settings. This study also employed fractional factorial design for highly efficient experiment planning and screening for significant factors. The results show that an interior's spaciousness and color scheme were the most noticeable and influential attributes in the human restorative experience, consistent with the findings from previous studies. In addition, significant interaction effects were identified for Ceiling height × Window-to-wall ratio, Room size × Finish color scheme, and Room layout symmetry × Rectangularity of room shape, which had often been overlooked in previous studies. Moreover, five machine learning models were proposed to represent the restorative experience in the built environment and compared in terms of their prediction performance. The results suggest that the GRNN model was superior in describing the nonlinear relationship between design attributes and human affective experience in comparison to the predictive models developed using the other four machine learning methods, i.e., linear regression, fuzzy inference system, support vector regression, and RBFNN. Taken together, these findings add to the rapidly expanding field of human-centered environmental design and form a basis for the future development of a decision support system for designers in wellness-focused architectural design (considering that the relevant knowledge is scattered across several disciplines).

Despite its valuable contributions, this study was subject to several limitations. First, the participants recruited were mostly characterized as highly educated and young, which may influence the generalizability of the results. Second, the factors related to personal subjective experience, such as cultural differences or preference bias toward specific design settings, should also be included in future studies to enhance the quality of affective modeling. Third, the feasibility of using human physiological responses, such as electrocardiogram (ECG), electroencephalogram (EEG), skin conductance (SC), or blood oxygen to measure human affective response toward environmental stimuli have been explored by many researchers [2,22,38,113,115,142]. Although the causal quantitative relationship between biosensing data and the perceived restorativeness is still under investigation and inconclusive [2,115], it is still believed that the use of objective human physiological response measures in combination with self-reported restorativeness scales in future research would be of great help in eliminating the potential biases in self-report assessments and better understanding the complex interaction between built environment and human experience [143]. Likewise, further validation using actual residential design scenarios should also be carried out, whereby the restorative quality of design, evaluated using predictive models, could be analyzed based on the feedback provided by professional architects to improve the ecological validity of the predictive model. In addition, an assumption was made during the experiment that a satisfying sense of presence provided by VR models could promise sufficient emotional stimulus received by participants; to improve the accuracy of prediction results from the non-immersive VR-based method, further improvement of incorporating the variable of VR display platforms into analysis should be also investigated in future work. Overall, insights gained from further research are also expected to contribute to the early stages of projects by providing designers with more scientific feedback on their designs.

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