A Knowledge-based Framework for Human-Centered Residential Built Environment Design

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

In

Civil (Cross-disciplinary)

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ABSTRACT

The considerable amount of time typically spent at home in contemporary society underscores the importance of understanding the interaction between occupants and built environments and implementing this knowledge into design practice to ensure occupant satisfaction and adequate building performance. In recent decades, the concept of human-centered design, which optimizes the environment around the occupant's capability and preferences/requirements rather than forcing the user to change their behavior to accommodate the design, has been attracting increasing interest within building domain. However, due to the overwhelming volume of information, the dynamic nature of the decision-making context, and the multi-disciplinary knowledge (and multi-disciplinary stakeholders) involved in design knowledge management, the current practice of residential design tends to fall short of supporting well-informed decisions for creating an occupant-focused built environment. In this regard, this research aims to optimize the knowledge management of residential design in terms of knowledge explicitation, knowledge acquisition, knowledge representation, and knowledge communication in order to leverage knowledge in support of consistent and effective design decision-making, thereby maximizing design quality and improving occupant satisfaction. To accomplish this, the following four objectives targeting the optimization of the knowledge management process are pursued: (1) Develop a machine learning-based framework using the virtual reality and design-of-experiments techniques to model the implicit relationship between human perceived experience and building design attributes, where the proposed data-driven predictive model is used to evaluate the affective quality of design alternatives based on their specific design settings. (2) Develop a residential design knowledge-based decision support system to capture knowledge of occupant requirements and their associated impacts on design criteria in order to tail design specifications for specific occupant groups and support a rational resource

allocation among specific design criteria. (This knowledge-based system aims to equips novice design practitioners with appropriate design knowledge and assist them in making user-centered design decisions consistently.) (3) Develop a domain ontology to formally represent the knowledge of human-centered residential design in a machine-readable format in order to promote knowledge reuse and sharing among design professionals and in computer-aided design systems, where the developed ontology is included in the knowledge-based decision support system as the knowledge resource input. (4) Develop an integrated framework for collaborative decision-making in residential design to anticipate and address potential design conflicts between stakeholders and to aid in developing consensus design solutions. The virtual reality technique is integrated with group decision-making models to eliminate barriers to knowledge communication and to the consensus-building process. Overall, this research optimizes knowledge management in residential built environment design, thereby enhancing the intelligent decision-making process and delivering a built environment that meets occupant expectations.

PREFACE

This thesis is the original work of the author, Yuxuan Zhang. This thesis is organized according to the guidelines for paper-based theses. Five journal papers related to this thesis have been published or are under review for publication as listed below.

1. Zhang, Y., Liu, H., Kang, S.-C., and Al-Hussein, M. (2020). "Virtual reality applications for the built environment: Research trends and opportunities." Automation in Construction, 118, 103311.
2. Zhang, Y., Xiao. B., Al-Hussein, M., and Li, X. (2022) "Prediction of Human Restorative Experience for Human-Centered Architectural Designs: An VR-DOE based Machine Learning Method." Automation in Construction.
3. Zhang, Y., Chen. Y., and Li, X., "An Integrated Framework of Knowledge-Based Decision Support System for User-Centered Residential Design." Expert Systems with Applications (under review)
4. Zhang, Y., Al-Hussein, M., and Li, X., "Ontology for User-Centered Design in Residential Built Environment." Journal of Building Engineering (under review)
5. Zhang, Y., Xiao. B., and Li, X. "An Integrated Framework for VR-Based Collaborative Design Support System for Consensus-Building in Built Environment Design." Automation in Construction (under review)

The research described in this thesis has received the following research ethics approvals from the University of Alberta's Research Ethics Board:

1. Project Name: Home Design for Wellness: Assessing Human Perceived Restorativeness in Architectural Spaces, No. Pro00102035

2. Project Name: An Integrated Framework for Virtual Reality-Based Decision Support System for Consensus Reaching in Residential Design, No. Pro00119069

ACKNOWLEDGMENTS

First and foremost, I would like to express my sincere gratitude to my supervisor, Dr. Mohamed Al-Hussein and Dr. Xinming Li, for their immense support, inspiration, visionary guidance, and great patience throughout my studies. It has been an honour to conduct my PhD research project under the supervision of two amazing professors. Without their trust and generous support, I would never be standing where I am now.

Also, I would like to express my thanks to Jonathan Tomalty and Kristin Berg for editing my thesis and for their valuable suggestions on my publications. I would also extend deep thanks to my dear colleagues and friends, Karen, Regina, Beda, Yuan, Hexu, Walt, Shuai, Bo, and Jason, for being so supportive throughout this time. The delightful chats and interactions with you made my PhD journey much more enjoyable.

Especially, my deepest gratitude is given to my parents, Qiujiao and Quanshan, as well as to my families, who have been an immense support behind me and have helped me through the lowest points in my life. My husband, Shunyi, is also very much appreciated for his kind and continuous company during this phase of my life.

Again, the last word goes to Aric, my baby boy, who is the light of my life and gives me the extra strength and motivation to pursue my dream. This thesis is dedicated to him.

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LIST OF ABBREVIATIONS

3D	Three-dimensional
AEC	Architecture, engineering, and construction
AHP	Analytic hierarchy process
ANN	Artificial neural network
AR	Augmented reality
BERS	Built environment restoration support scale
BIM	Building information modeling
BPS	Building performance simulation
DSS	Decision support system
EEG	Electroencephalogram
FIS	Fuzzy inference system
FSC	Fuzzy subtractive clustering
GRNN	General regression neural network
GSR	Galvanic skin response
HCD	Human-centered design
HoQ	House of quality
ICT	Information and communication technology
IR	Intermediate representations
IT	Information technology
LBC	Living building challenge
KBS	Knowledge-based system
KBDSS	Knowledge-based decision support system
KM	Knowledge management
MCDM	Multicriteria decision-making
MURB	Multi-unit residential buildings
OFAT	One-factor-at-a-time
PCA	Principal component analysis
PPG	Photoplethysmography
PRS	Perceived restorativeness scale
PSO	Particle swarm optimization
QFD	Quality function deployment
RBFNN	Radial basis function network

RC	Rated contrast
SMO	Sequential minimal optimization
SVM	Support vector machine
SVR	Support vector regression
TFN	Triangular fuzzy number
TSK	Takagi–sugeno–kang
UCD	User-centered design
VR	Virtual reality

Chapter 1: INTRODUCTION

1.1 Background and Motivation

The design of a building's interior space has a significant impact on occupants' wellness and productivity (Eberhard, 2009; Heydarian et al., 2017; Salleh, 2008; Sullivan & Chang, 2011). With the extensive time that people spend indoors, understanding the interaction between occupants and built environments, and then implementing this knowledge into built environment design, have the potential to improve both user satisfaction and building performance (Ergan et al., 2018; Heydarian et al., 2017). Specifically, accurately and thoroughly identifying user requirements in the early design phase can significantly increase user satisfaction by offering an accessible living experience while also decreasing costs by reducing the likelihood of rework, budget overruns, and even litigation issues. In this regard, human-centered design (HCD), which places the user at the core of the design process and optimizes the environment around the user's capabilities and needs rather than forcing the user to conform their behavior to the design, has been noted in a number of recent studies as a way of supporting a human-centered environment and enhancing overall user satisfaction (Harte et al., 2017).

In the area of building design, HCD is regarded as a knowledge-intensive process involving stakeholders from different disciplinary backgrounds. In this context, built environment design can be defined as a series of complex and multidimensional decisions requiring knowledge from various disciplines such as architecture, engineering, environmental psychology, behavioral science, and even sociology (Chou & Ngo, 2016; Cimini et al., 2015; Dong et al., 2018; Ellsworth-Krebs et al., 2019; Ergan et al., 2018; Hoisington et al., 2019; Lee & Park, 2011; Wang, 2021). These disciplines bring different information and different perspectives for addressing challenges in the design of the built environment, where decision-makers are frequently confronted with an abundance of information and design options, such as the selection of façade designs (Heydarian et al., 2017) or the collocation of finishing products (Zhang et al., 2019). During design, this information and these design configurations, in turn, are encountered within the evolving context of social development and technological innovation (Lee & Ha, 2013; Wang et al., 2017). For instance, four-member households were the most common household size in Korea back in 1985, representing 25.3% of all households; while in 2019, one-member households became the most prevalent type in Korea, representing 36.9% of all households (Statistics Korea). This trend in the evolution of the household structure has been taken into consideration in apartment design in recent years as a way of preventing unnecessary remodelling by homebuyers and associated waste-generation and pollution (Lee & Ha, 2013). Similarly, when making decisions concerning the design of the built environment, it is necessary to also acknowledge the changing context of knowledge acquisition and application, such as changes in demographic characteristics, lifestyle paradigms, climate, and the emergence of building technologies, equipment, and materials.

Such a complex, knowledge-intensive process makes it difficult for design practitioners (e.g., homebuyers, designers) to make informed decisions in built environment design, and inexperienced decision-makers often struggle to accurately depict and comprehend all facets of design requirements and translate them into specific design solutions (McLoone et al., 2010). Likewise, due to the knowledge gap in human–building interaction and residential design, designers sometimes resort to making educated guesses about occupant capability and needs (Ielegems et al., 2016), resulting in deviations from the occupant's expectations and subsequently triggering design modifications and rework. In this regard, the client typically defers to the designer’s knowledge and experience with specific types of projects (Haddad, 2014). However, even skilled designers are not always capable of retaining all relevant details, and must seek information from external sources. They routinely navigate the design rules, reconcile inconsistencies, and fill in gaps using common sense, though unaware of the complexity of their own mental processes during design development (Heylighen & Neuckermans, 2000). In such cases, the various modalities of architectural and design knowledge may not be fully utilized in practice, and the consistency of design decision quality, cannot be guaranteed (Gunda, 2008).

On the other hand, the widespread implementation in architecture and construction of information and communication technologies (ICT), such as building information modelling (BIM), virtual reality (VR), and text mining among social media data, has provided building stakeholders with significant advantages in terms of information accessibility and exchange in building design and construction (Lu et al., 2015; Shin et al., 2008). At the same time, though, the emergence of this unconventional data and information makes knowledge search and acquisition in the design phase a time-consuming task. Identifying useful information from ICT applications can be a challenge for design practitioners, and the applicability of the knowledge available to the project at hand is not always intuitive (Huber, 2018; Wu et al., 2012). While data mining and knowledge discovery techniques are widely used in various domains to help extract useful information from data, there are relatively few studies dealing specifically with knowledge management for decision-making in built environment design (Piramuthu, 2005). These problems and challenges in the current practice of human-centered built environment design underscore the pressing need to leverage design knowledge from a variety of domains and data sources in support of consistent and effective design decision-making, and thereby improve the design quality in careful consideration of occupant preferences and demands.

1.1.1 Human-Centered Design in Built Environment

Human-centered design (HCD), also referred to in the relevant ISO standards as "usability engineering", is a design philosophy that places the user at the center of the design process and improves the usability of a system by emphasizing human factor knowledge and appropriate techniques (Harte et al., 2017; ISO 9241-210, 2019). The 2010 international standard ISO 9241-210, it should be noted, uses the terms HCD and user-centered design (UCD) interchangeably (Harte et al., 2017).

Over the past two decades, numerous attempts have been made within the building construction field to more accurately and explicitly define user requirements so that a more comfortable built environment can be achieved. For instance, Vischer proposed an environmental comfort model to categorize occupant requirements in built environments (Vischer, 2008b). In this model, three environmental comfort factors—namely, physical comfort, functional comfort, and psychological comfort—were proposed to describe the different human–building interactions and their impacts on human experience. Specifically, physical comfort represents a perception of well-being, functional comfort measures the extent to which the occupant can perform the desired activities in the space, and psychological comfort in the environment refers to affective and emotional needs, such as a sense of belonging, ownership, and control over the environment (Vischer, 2008a, 2008b). Likewise, Ellsworth-Krebs et al. (2019) identified factors—i.e., thermal comfort, tactile comfort, physiological comfort, odor and fresh air, mental well-being, companionship and contributory comfort, relaxation, control, visual comfort, acoustic comfort and familiarity—to extend the definition of home comfort beyond merely thermal and physical characterization (Ellsworth-Krebs et al., 2019). These frameworks provide a solid foundation for human-centered residential built environment design with regard to its root nature of requirement engineering that seeks to explore and document the requirements and the extent to which they are being fulfilled by the design throughout the lifecycle of the building.

Meanwhile, many researchers have noted the significance of knowledge and decision models developed in the context of human-centered residential design, which can play a critical role in improving design decision-making in consideration of users' preferences and demands (Wang et al., 2017). For instance, Afifi et al. (2014) modelled the fall risk associated with staircase architectural design elements as the basis for recommending best practices for fulfilling the safety needs of older adults. (Afifi et al., 2014). Heydarian et al. (2017) proposed a data-driven model to optimize the design around the occupant's behavior based on data collected on occupants' lighting preferences. Moreover, Lee & Park (2011) suggested that cross-cultural adaptation should be emphasized in residential design to improve the user experience of the built environment based on an in-depth survey on the interrelationships between cultural differences and residential design.

However, what is lacking is a consensus knowledge framework that could be referred to in human-centered residential design. The design practitioner is thus required to have extensive experience and domain knowledge in order to effectively interpret research findings and integrate credible research evidence to support the implementation of relevant approaches in the design process due to the scattered and fragmented nature of HCD knowledge in the residential environment. In this regard, a knowledge-based framework that supports ready retrieval, reuse, and sharing of knowledge to support decision-making in human-centered residential design has yet to be explored.

1.1.2 Knowledge Management

Knowledge can be defined as the concepts, skills, experiences, and vision that provide a framework for creating, evaluating, and using information and knowledge management is concerned with the explicit and systematic management of necessary knowledge and its associated processes of creation, collection, organization, communication, application, and exploitation (Apuvra & Singh, 2011). Processing and integrating information from a variety of sources is the primary goal of knowledge management (Gao et al., 2018).

In the context of architecture, engineering, and construction (AEC), much of the knowledge is experience-based and fragmented among a wide range of disciplines (Woo et al., 2004). Despite the use of explicit knowledge, i.e., codified knowledge that is easily articulated, written down, and formally transmittable in documents, the sharing of tacit knowledge that is embedded in personal experiences and perceptions among project stakeholders remains a challenge (Koskinen et al., 2003; Woo et al., 2004). In building design, for instance, only a minor portion of user needs derives from explicit knowledge that can be easily expressed and documented in checklists, guidelines, and regulations. Rather, most user needs and preferences, such as sensory needs and the desired affective experience of the built environment, are subjective, implicit, and much more difficult to ascertain or express (Ergan et al., 2019; Ielegems et al., 2016), and this remains a concern because implicit user needs have been widely identified as critical factors in making buildings more enjoyable and attractive for users (Ielegems et al., 2016). Design professionals may thus face a formidable barrier in understanding user requirements and effectively translating them into their designs, leading them to rely on their experience, professional intuition, and/or other forms of tacit knowledge to successfully complete design tasks (Woo et al., 2004). Due to the uniqueness and complexity of building projects, it is impossible to directly replicate best practices from the past (Ni et al., 2022). Currently, design practitioners still serve as the primary carriers of tacit knowledge in general practice. Thus, in the design of built environments, a knowledge framework for the management and application of both explicit and tacit knowledge is required to facilitate knowledge utilization and provide greater insight into the knowledge creation process.

According to the theory of knowledge creation (Nonaka & Takeuchi, 1995), the key to knowledge management lies in the mobilization of tacit knowledge and its conversion into explicit knowledge, which represents the knowledge externalization process in the socialization, externalization, combination, and internalization (SECI) model. During this process, tacit knowledge can be converted into explicit knowledge through conceptualization, visualization, metaphor, and analogy with the assistance of a variety of techniques. For instance, numerous researchers have highlighted expert systems and artificial intelligence (AI) as examples of the positive impact of information and communication technology (ICT) on the externalization and transfer of knowledge (Venkitachalam & Busch, 2012).

In recent years, the effective use of knowledge management technologies is a consideration that has been garnering increasing attention within the AEC domain, as it is seen as a promising strategy for continuous improvement of building projects based on lessons learned (Kamara et al., 2002; Rezgui et al., 2010). These knowledge management-related studies have generally focused on translating personal knowledge into explicit information that can be effectively stored and reused to fill knowledge gaps across the building's lifecycle, such as construction equipment selection (El-Tourkey et al., 2022), building material selection (Rahman et al., 2012), healthcare building evaluation (Guerrero et al., 2022), energy efficiency retrofit (Medal et al., 2021), and budget estimation for building restoration (Wang et al., 2008), to name a few. The prevalence of knowledge-based systems underscores the great potential of information techniques to advance knowledge in the design process and to leverage knowledge in addressing the design problem at hand (Verhagen et al., 2012). As such, it is reasonable to expect that the optimization of knowledge management in built environment design will improve the knowledge intensive decision-making process and thereby improve the quality of design outcomes. In this research, then, several information technologies, including machine learning, virtual prototyping (i.e., VR), quality deployment function (QFD), decision-making models, and ontology, are adopted to establish a systematic knowledge-based framework for optimizing the knowledge management process in built environment design.

1.2 Research Objectives

The research presented herein is built upon the following hypothesis:

"*The application of information techniques and analytical decision models for human-centered residential built environment design can aid in acquiring, structuring, and explicitizing the design requirements and knowledge in a schematic representation so that they are easily understandable and accessible by design practitioners, thereby enhancing the efficiency and quality of design and improving occupants' satisfaction with the built environment.*"

This research is predicated on the fact that the current practice of knowledge management and decision-making in built environment design cannot provide adequate design support in the context of multi-disciplinary knowledge and information overload to support effective human-centered design of the built environment. To address this gap, four research questions aimed at optimizing the knowledge management of decision-making processes in human-centered residential built environment design are explored in this study:

(1) How can affective human experience knowledge be explicitly modelled for human-centered residential design?

(2) How can design specifications be tailored to the particular needs of the occupants?

(3) How can human-centered residential design knowledge be formally represented?

(4) How can multiple stakeholders collaborate to make well-informed residential design decisions?

To answer these questions, the following objectives (see Figure 1-1) are pursued in this research:

1. Develop a VR- and design-of-experiments (DOE)-based framework for characterizing the relationship between human affective experience and building design attributes to predict the restorative quality of design with data-driven machine-learning models.
2. Develop a knowledge-based decision support system (KBDSS) for residential design to capture diverse occupants' needs and tailor the design specifications to specific occupant clusters in order to support rational resource allocation and maximize occupant satisfaction.
3. Develop a domain ontology to formally represent the knowledge of human–building interactions and built environment in a machine-readable format to promote knowledge reuse and sharing among design professionals and computer-aided design systems.
4. Develop an integrated framework for collaborative decision-making in built environment design that eliminates communication barriers in the negotiation process and potential design conflicts toward consensus design solutions.

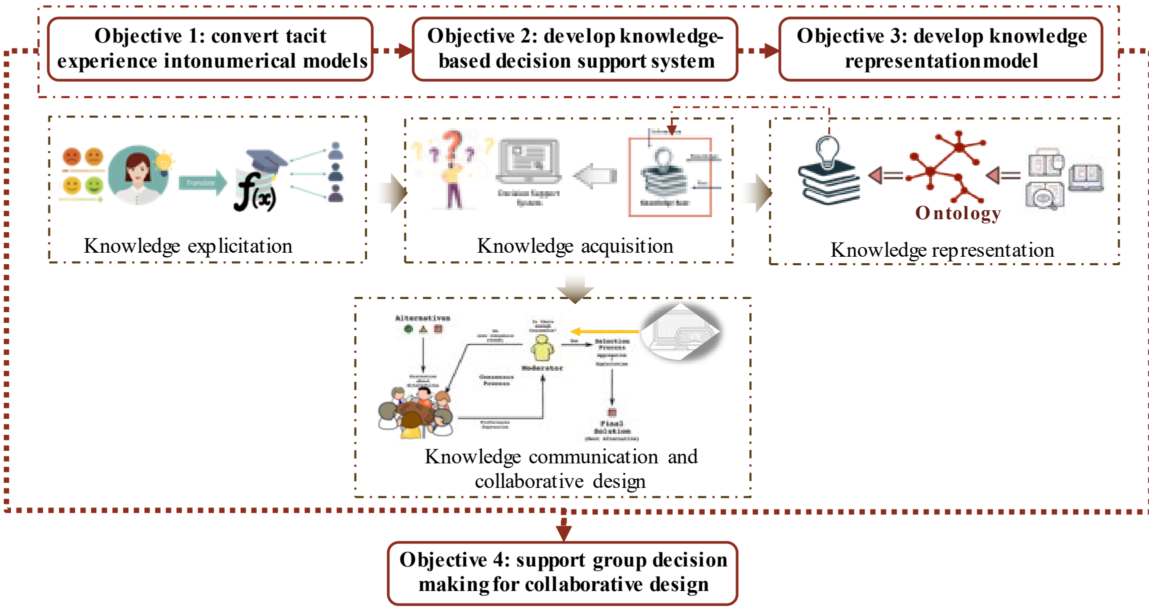


Figure 1-1 Research objectives

These four objectives focus on improving the human-centered residential design decision-making by optimizing the various phases of knowledge management. Specifically, Objectives 1 and 2 focus on explicitizing and capturing knowledge related to the design requirements and their interrelations with built environment design settings. In Objective 1, the tacit experience of the built environment is explicitly associated with specific design settings and expressed in numerical models that can be stored and shared in documents. In Objective 2, a matrix based KBDSS is proposed to facilitate knowledge search and acquisition in residential design decision-making, where the results of Objective 1 are included in the knowledge base. Moreover, Objective 3 optimizes the knowledge storage component of the KBDSS developed in Objective 2 so that the developed knowledge representation can be reused and shared in a standard and machine-learnable format. Finally, Objective 4 improves the process of knowledge communication and group decision-making in built environment design, where the knowledge acquired in Objectives 1 and 2 can be incorporated as supplemental information for further decision support.

1.3 Thesis Organization

This thesis consists of eight chapters. Chapter 1 presents the background and motivation of this research and briefly introduces human-centered design and knowledge management in the building domain. The hypothesis, research questions, and objectives of this research are also outlined in this chapter.

Chapter 2 presents a VR-DOE-based framework to explore the feasibility of machine-learning models in describing the implicit relationship between occupants' affective experience (i.e., perceived restorativeness in environments) and built environment settings, thereby providing decision support for proactive architectural design analysis. This framework incorporates VR and DOE techniques to provide a controllable and validated experimental setting that enables the efficient and cost-effective collection of human experience data and balanced learning datasets. Furthermore, the performance (in terms of prediction of restorative quality) of the five selected machine-learning models—i.e., general regression neural network (GRNN), radial basis function neural network (RBFNN), support vector regression (SVR), and fuzzy inference system (FIS)—is compared and analyzed.

Chapter 3 introduces an integrated KBDSS framework to equip novice design practitioners with appropriate design knowledge and assist them in making user-centered design decisions consistently. The proposed framework uses the quality function deployment approach, decision support analysis, and fuzzy set theory to comprehensively capture occupant requirements, translate them into quantifiable design specifications, and prioritize the design specifications based on specific user characteristics, thereby enabling design decisions that improve satisfaction among a larger crowd. To illustrate the efficacy of such a decision support framework, a residential kitchen design case study is presented with the support of the developed KBDSS prototype.

Chapter 4 proposes a domain ontology to formally represent the user-centered residential design knowledge in support of the effective use of knowledge-based systems. This ontology is developed based on the knowledge acquired from the literature review (encompassing research reports, building codes and regulations, design cases, and the findings of term extraction from social media data). It comprises seven core concepts—occupant-user, residential design, activity, physical comfort, psychological comfort, constraint, and usability performance—as well as the relations, properties, and axioms that define them, providing a formalized and standardized vocabulary for human-centered residential design. This work is expected to promote knowledge reuse and sharing among stakeholders and computer systems.

Chapter 5 presents the integration of multi-user VR platforms and consensus models to facilitate knowledge comprehension and design conflicts in group decision-making as part of built environment design. A collaborative design support system is developed to provide a powerful visualization and consensus-based negotiation process by which for stakeholders to communicate their preferences and generate consensus design solutions that consider all decision-makers' opinions in an iterative, interactive manner.

Finally, the conclusions and research contributions are summarized in Chapter 6, in addition to a discussion of the study limitations and future research directions.

Chapter 2: PREDICTION OF HUMAN RESTORATIVE EXPERIENCE FOR HUMAN-CENTERED RESIDENTIAL ARCHITECTURE DESIGN[1]

2.1 Introduction

Currently intrinsic to our daily lives, stress has been identified as a critical health issue that affects multiple spheres of our society. For example, it entails high costs for healthcare systems, thus significantly affecting the economy (Taylor, 2006). The socio-urban context of extended periods of time spent indoors and increased urban densification has led researchers to investigate the significant impacts of built environments on our mental well-being and to explore how design can help mitigate urban stress (Zou & Ergan, 2019). Previous studies have found that poorly designed buildings can negatively affect a person's psychological state by causing stress, anxiety, depression, and even violent behaviour (Eberhard, 2009; Salleh, 2008; Sullivan & Chang, 2011). 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 (Yin et al., 2018). There is widespread agreement that particular design attributes of built environments can influence our mental resilience or foster restorative experiences (Huisman et al., 2012; Weber & Trojan, 2018). 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

[1] A version of this chapter has been published in Automation in Construction, as follows: Zhang, Y., Xiao. B., Al-Hussein, M., and Li, X. (2022) "Prediction of Human Restorative Experience for Human-Centered Architectural Designs: An VR-DOE based Machine Learning Method." Automation in Construction. https://doi.org/10.1016/j.autcon.2022.104189.

in the early design stage is often vague, incomplete, and inconsistent (Rezaee et al., 2015; Zhang et al., 2017). 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 (Zhang et al., 2017). 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 (Zhang et al., 2017). 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 stage.

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 behaviour of the system (Kim & Cho, 2000; Solomatine et al., 2008). 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 (Buragohain & Mahanta, 2008). 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 (Patel et al., 2003). 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 (Chan et al., 2020; Delen et al., 2007; Diego-Mas & Alcaide-Marzal, 2016; Ling et al., 2014; Moro et al., 2014). 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 modelling 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 (Park & Han, 2004). 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 (Lavrakas, 2008).

While a great number of studies related to restorative design have been conducted in the area of institutional construction (Gao & Zhang, 2020; Gulwadi, 2006; Nejati et al., 2016), there have been few empirical investigations into residential design, despite the fact that emotional support and relaxation are major functions of the home environment (Ellsworth-Krebs et al., 2019). 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 chapter is organized as follows. First, the literature pertaining to qualitative and quantitative research on affective design and machine-learning methods for affective experience modelling to clarify the point of departure. Second, the research methods and scope are described in Section 2.3. A detailed discussion on the non-immersive VR-DOE-based method for data collection is illustrated in Section 2.4. Section 2.5 presents the data analysis and machine-learning models for restorative experience modelling. Section 2.6 discusses the experimental findings and the predictive modelling results. Finally, Section 2.7 concludes by highlighting the applicability and limitations of these research findings.

2.2 Literature Review

2.2.1 Affective Design in Built Environment

Affective design usually focuses on the emotional and mental communication between the user and the products (Ng et al., 2012). For decades, efforts have been made to understand the correlation between built environments and corresponding human affective experience and utilize this correlation as a foundation for human-centered building improvement in architectural domains (Heydarian et al., 2017; Kim et al., 2017). According to Vischer's environmental comfort model (see Figure 2-), 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 (Vischer, 2007, 2008a).

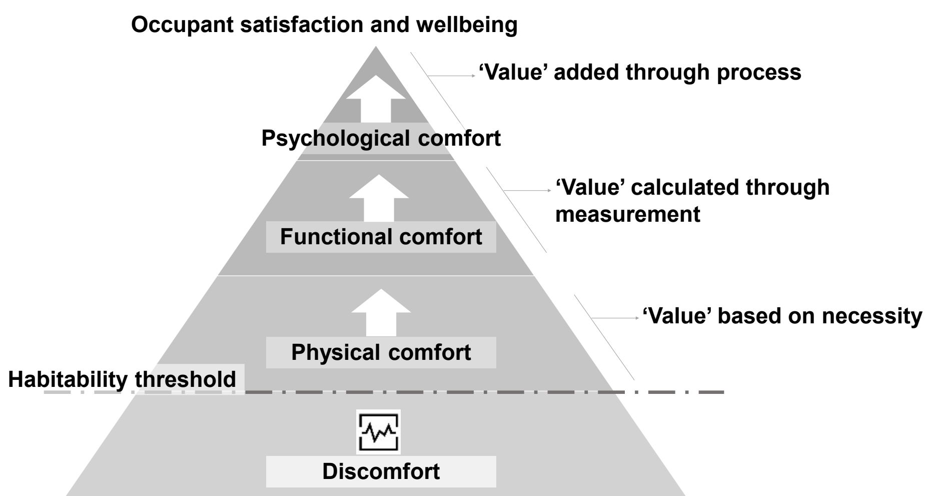


Figure 2-1. Habitability pyramid (source: Vischer, 2007).

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 colours, views (through windows), lighting, and layout of the room, can serve as significant predictors in assessing the satisfaction level in healthcare facilities (Chamilothori et al., 2019; Gao & Zhang, 2020; Harris et al., 2002; Nejati et al., 2016; Schweitzer et al., 2004). 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 (Kopec, 2017). The golden ratio design principle was also found to affect a person's emotional response in an eye-tracking-based experiment (Tuszyńska-Bogucka et al., 2020). 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 (Shah & Gharbia, 1999). Many hospital designs integrate gardens or modify the traditional waiting area in terms of the general layout, colour 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. (2018) conducted a crowdsourcing-based experiment to examine occupants' emotional reactions to various design attributes, such as window design, ceiling height, colour, 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. To measure the human experience in a more objective manner, Ergan et al. (2019) 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. 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 (Gao & Zhang, 2020).

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.

2.2.2 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 (Teixeira et al., 2012).

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 (Barnes & Lillford, 2007). These models can be generally categorized as multiple linear regression, artificial neural networks (ANNs), support vector machines (SVMs), and fuzzy inference systems (FISs) (Chan et al., 2020). Specifically, multiple linear regression is widely used in the domain of affective modelling because of its easy implementation and interpretation (Lanzotti & Tarantino, 2008). Lanzotti and Tarantino applied logistic regression (i.e., a variant of linear regression) to predict users' perceived quality toward the interior design of trains (Lanzotti & Tarantino, 2008). Park et al. used linear regression models to model the user affective experience of mobile phones, which showed satisfactory performance in terms of goodness of fit (Park et al., 2013). However, this modelling was performed under the assumption that design attributes are linear with respect to a user's affective experience (Chan et al., 2020). 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 (Chan et al., 2020; Fan et al., 2014; Yang & Shieh, 2010). For instance, a radial basis function was introduced by Chen et al. (2021) 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. (2014) 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 behaviour of the network, labelled the "black-box," reduces trust in the solutions. 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 (Burges, 1998). In the design domain, SVR has been successfully adopted in predicting user affective responses based on product attributes (Fan et al., 2014; Yang & Shieh, 2010). Yang and Shieh (2010) employed SVR to develop a model for predicting consumer affective responses to product forms. Fan et al. (2014) proposed an SVR approach to model the relationship between design attributes and customers' affective responses.

Interestingly, Chan et al. (2020) reviewed the literature that reports on the use of ANNs and SVR for affective modelling 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. (2006) in mobile phone design to handle the nonlinearity and fuzziness of human affective experience. Similarly, this fuzzy rule-based modelling approach was also adopted in designing cars and office chairs (Lin et al., 2007; Park & Han, 2004; Sutono et al., 2016).

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.

2.3 Research Methods

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 modelling 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 (Lavrakas, 2008). 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 modelling 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 research methods are illustrated in Figure 2-2. 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 2.4.1). 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 2.4.2), 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 2.4.3). 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 2.4.4) (Hartig et al., 1996; Hartig, Kaiser, et al., 1997; Hartig, Korpela, et al., 1997). 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 2.4.5). The collected data are subsequently preprocessed, and the corresponding results are analyzed for statistical significance (see Sections 3.5.1 and 3.5.2). 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 2.5.3). 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.

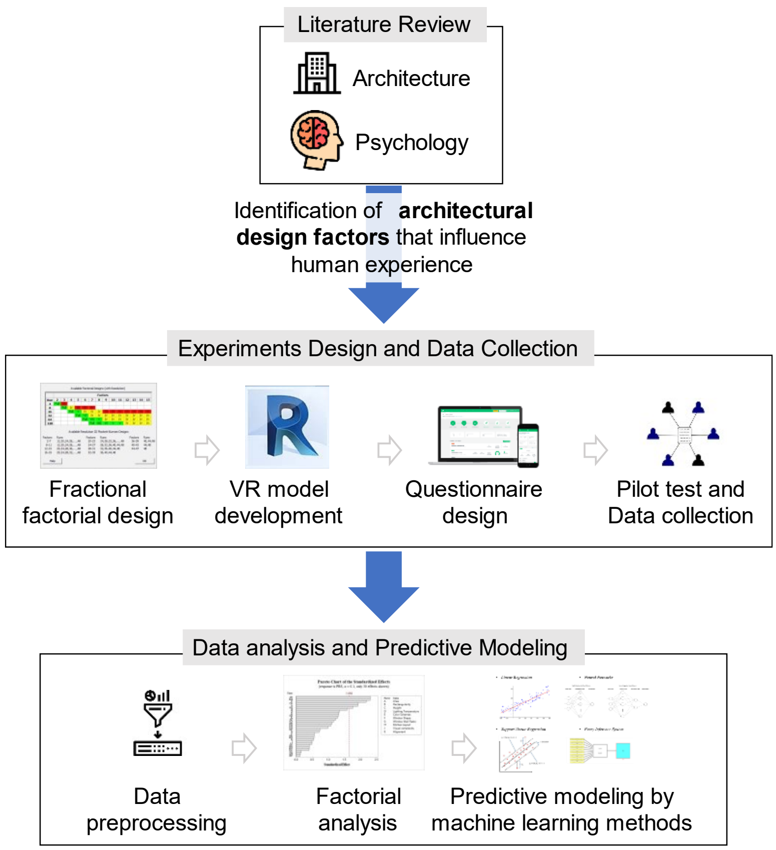


Figure 2-2. Research methods.

2.4 Experiments Design and Data Collection for Human Restorative Experience

2.4.1 Architectural Design Attributes

Many architectural design attributes have been found to be related to human-perceived restorativeness in the built environment (Ergan et al., 2018; Gao & Zhang, 2020). It is generally believed that design attributes that support fascination, curiosity, or involuntary attention can be credited for enhancing recovery from mental fatigue (Kopec, 2017). Table 2-1 lists the eight architectural design attributes commonly related in the literature to restorativeness- and stress-related experiences.

Table 2-1. Architectural design attributes associated with human restorativeness- and stress-related experience in the literature

Architectural design attributes	References
Exposure to nature and indoor plant	Bagot et al. (2015), Burnard & Kutnar (2015), Hartig & Evans (1993), Hipp et al. (2016), Iwata et al. (1997), Wells & Evans (2003)
Presence/absence, dimensions, shapes of windows	Collins (1976), Evensen et al. (2015), Hong et al. (2019), Nejati et al. (2016), Ozdemir (2010), Pati et al. (2008), Pohl (2011)
Openness/Spaciousness of spaces	Evans (2003), Lindal & Hartig (2013), Sadalla & Oxley (1984), Vartanian et al. (2015), Winchip et al. (1989)
Lighting	Beute & de Kort (2014), Manav (2007), Nikunen et al. (2014), Nikunen & Korpela (2009)
Finishing colour scheme	Hall (1990), Hidayetoglu et al. (2012), Lamb et al. (2010), Macrae (2005), Meerwein et al. (2007), Michaelis (2011), Pile (1997), Rubert et al. (2007)
Visual complexity	Cassarino & Setti (2016), Jang et al. (2018), Orth & Wirtz (2014), Taylor (2006)
Space layout	Enquist & Arak (1994), Ergan et al. (2018), Finlay et al. (2010), Lindal & Hartig (2015), Oliva & Torralba (2001), Schweitzer et al.(2004)
Spatial alignment	Ergan et al. (2018), Gentner (1983), Michal & Lustig (2014)

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 occupants, even for people hospitalized with severe depression (Hartig & Evans, 1993; Iwata et al., 1997; Wells & Evans, 2003). 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 (Nejati et al., 2016; Pati et al., 2008). Moreover, Lowenhaupt Collins pointed out that the perceived quality of a window's view is intimately related to the window's dimension and shape (Pohl, 2011). 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 Hong et al. (2019).

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 (Evans, 2003; Sadalla & Oxley, 1984; Vartanian et al., 2015; Winchip et al., 1989).

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 (Nikunen et al., 2014). Both the illuminance level and the correlated colour temperature have been associated with attention restoration through the perception of brightness and the quality of colour environments (Manav, 2007). According to Manav, the colour 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 colour saturation (Manav, 2007).

Colour Scheme

The choice of colours 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 affects one's stress level (Hall, 1990; Macrae, 2005; Pile, 1997). Generally, warm colour schemes involving shades of orange, yellow, and brown help people increase their awareness, whereas cold colour schemes, including shades of green, blue, and grey, help people focus on visual and mental tasks (Hidayetoglu et al., 2012).

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 (Jang et al., 2018). In studies on visual perception (Taylor, 2006), 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 (Ergan et al., 2018). A symmetrical space layout increases the perceived quality of the environment and affects occupant satisfaction (Schweitzer et al., 2004). Enquist and Arak found that people appreciate greater symmetry and that symmetrical patterns hold an almost universal appeal for humans (Enquist & Arak, 1994; Lindal & Hartig, 2015).

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 (Michal & Lustig, 2014). 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 (Ergan et al., 2018).

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) finishing colour scheme, and (10) space alignment.

2.4.2 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 validated 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 (Vabalas et al., 2019). 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 2-2. 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 (Baker et al., 2017). 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 (Collins et al., 2009). 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 modelling (Antony, 2003). Table 2-3 presents the 32 experimental runs (design alternatives) of this study, as generated by the Minitab statistics software. Each run represents a combinatorial design alternative modelled later using Revit and evaluated in the later experiment.

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

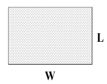
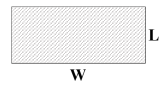
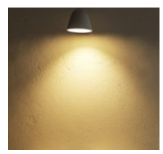
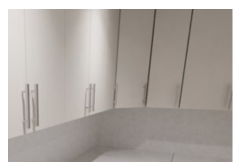
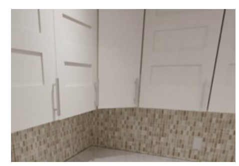
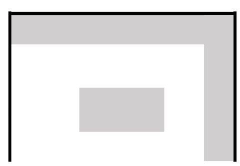
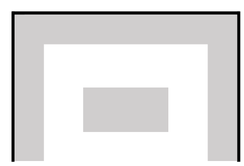
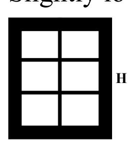
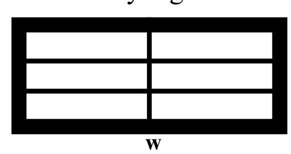
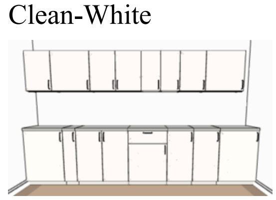
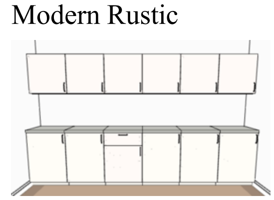
Design attributes	Space-A	Space-B
Room size	110 ft^2	210 ft^2
Rectangularity of room shape	 Square	 Narrow Rectangle
Ceiling height	Slightly low	Slightly high
Light temperature	 Warm-white	 Daylight
Visual complexity	 Moderately low	 Moderately high
Room layout symmetry	 Asymmetric	 Symmetric
Window-to-wall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

Table 2-3. Experimental runs of design alternatives selected by fractional factorial design

Run	Attributes									
	Room size	Rectangularity of room shape	Ceiling height	Light temperature	Finishing colour 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

2.4.3 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 2-3). 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 (Calogiuri et al., 2018; Heydarian et al., 2015; Hong et al., 2019; Iachini et al., 2016; Zhang et al., 2020). 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 (Baños et al., 2004; Roettl & Terlutter, 2018; Srivastava et al., 2019; Terlutter et al., 2016; Voigt-Antons et al., 2020; Wilson Christopher J. & Soranzo Alessandro, 2015). 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 (Riva et al., 2007). Therefore, multiple questions adopted from Heydarian et al. (2015) 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 2-3. Screenshots of VR models for experimental runs.

2.4.4 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.

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 colour 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 colour blindness.

Restorative Experience Measurement

To measure the human-perceived restorativeness of the built environment in a reliable and quantifiable manner (Han, 2018), two self-reported restorativeness scales—the Perceived Restorativeness Scale (PRS) by Hartig et al. (1997) and the Built Environment Restoration Support Scale (BERS) by Fischl and Garling (2008)—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 (Han, 2018; Hartig et al., 1996; Pasini et al., 2014). 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 (Han, 2018; Hartig et al., 1996). 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 (Herzog et al., 2003; Katz, 1991). Given this chapter's focus, the interested reader can refer to the cited references (Hartig et al., 1997; Hartig & Staats, 2003) for a detailed description of each restorativeness dimension. The PRS measurement developed by Hartig et al. (Hartig et al., 1997; Hartig et al., 1997) 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 scenarios are indoor built environments (Hartig et al., 1997). As a result, 17 seven-point Likert-scale questions (see Table 2-4) 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 (Gao & Zhang, 2020; Ulrich et al., 1991). Thus, a scenario description adapted from Lindal and Hartig (2013) 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 (Lindal & Hartig, 2013).

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 2-4. 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.

2.4.5 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 2-4 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 (Gao & Zhang, 2020; Ulrich et al., 1991). 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 (Abujelala et al., 2021; Chen et al., 2018; Ergan et al., 2019; Shemesh et al., 2016, 2017). 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.

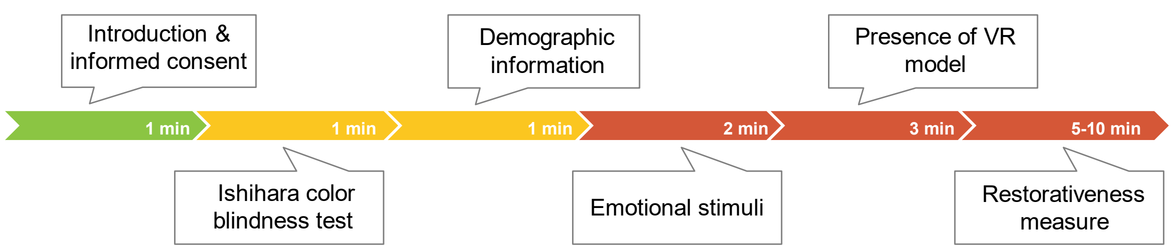


Figure 2-4. Overview of a single experimental session.

2.5 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.

2.5.1 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 (Curran, 2016; Meade & Craig, 2012). 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 (Johnson, 2005), an index termed *LongString* was used to compute the maximum number of items with identical consecutive response on a single page (Curran, 2016; Johnson, 2005; Meade & Craig, 2012). As for the outlier responses, the Mahalanobis distance, denoted as *MD* in Equation 2-1, 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 2-2) 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 (Tsang et al., 2017).

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

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.

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

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.

2.5.2 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 (Tauxe et al., 2006).

2.5.3 Predictive Modelling for Restorative Experience

As reported in previous studies, prediction models developed using machine-learning methods may show different prediction performances under various problem contexts. To explore the capability of machine-learning models in affective modelling 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. (2020) 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 (Chan et al., 2020).

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.

Linear Regression Model

Linear regression model (see Equation 2-3) 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.

$$Y = f(x) = \sum_{i=1}^{n} \omega_i x \tag{2-3}$$

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 (Chen & Yan, 2008; Chen et al., 2008; Chen et al., 2021b; Lin, 2013; Tian et al., 2014; Wang et al., 2020), 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 (Chen et al., 2021b). 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 (Izonin et al., 2021; Wu et al., 2012). Figure 2- 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 2-4. 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 2-5) 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.

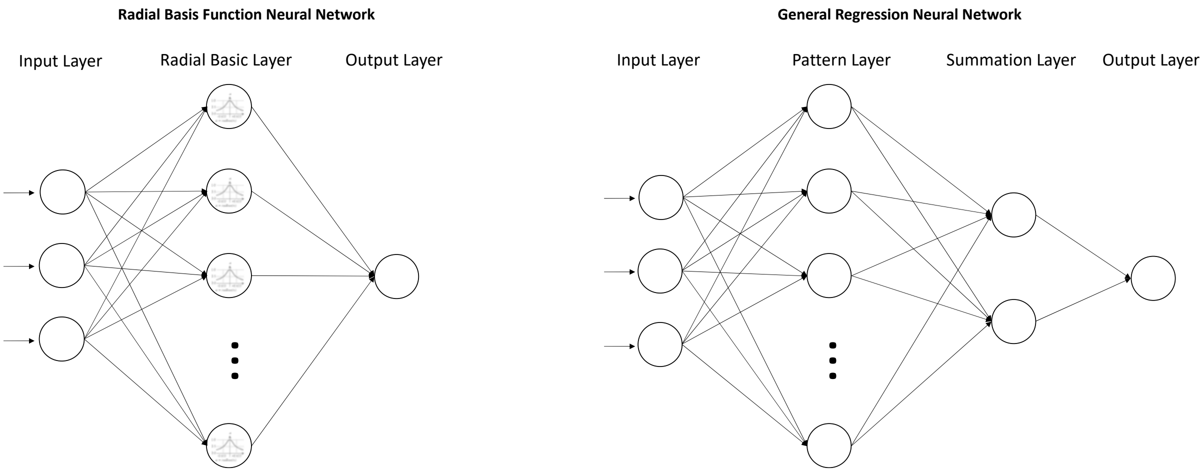


Figure 2-5. Architectures of the RBFNN and the GRNN.

$$Y = f(x) = \sum_{j=1}^{m} w_j \varphi_j(x, x_c) \tag{2-4}$$

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

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 2-6, where w_k is the activation weight of the pattern layer node k and $K(x, x_k)$ is the radial basis function kernel.

$$f(x) = \frac{\sum w_k K(x, x_k)}{\sum K(x, x_k)} \tag{2-6}$$

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.

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 2-7 (Vapnik, 1995).

$$Minimize: \frac{1}{2}\|\omega\|^2 \tag{2-7}$$

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

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 (Platt, 1999). 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.

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 (Park & Han, 2004). 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 (Bataineh et al., 2011; Chiu, 1994). 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 2-8.

$$For\ x \in C_k, THEN\ Y_{PR} = a_0 + \sum_{j=1}^{M} a_j x_j \tag{2-8}$$

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.

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 (Botchkarev, 2018). 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 (Chen et al., 2021b; Yang & Shieh, 2010). 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 (Chicco et al., 2021). 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 (Chicco et al., 2021). 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 modelling 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 (Piñeiro et al., 2008).

2.6 Results and Discussion

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

2.6.1 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 2-5. 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 (Heydarian et al., 2015). 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 (Gunnarsson et al., 2017; Hartig, 2017).

Table 2-5. 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%

2.6.2 Factorial Analysis of Design Attributes

The Pareto chart in Figure 2- 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, finishing colour 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 × Finishing colour 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 2-, illustrating the mean PRS score versus two levels of design attributes under different settings of other variables. As shown in Figure 2-a, 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 2-c, 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 2-b, it is apparent that the room size has a significant influence on a person's perceived restorativeness under a modern rustic colour setting. In contrast, the PRS score appeared to be less affected by room size when the colour scheme is clean-white.

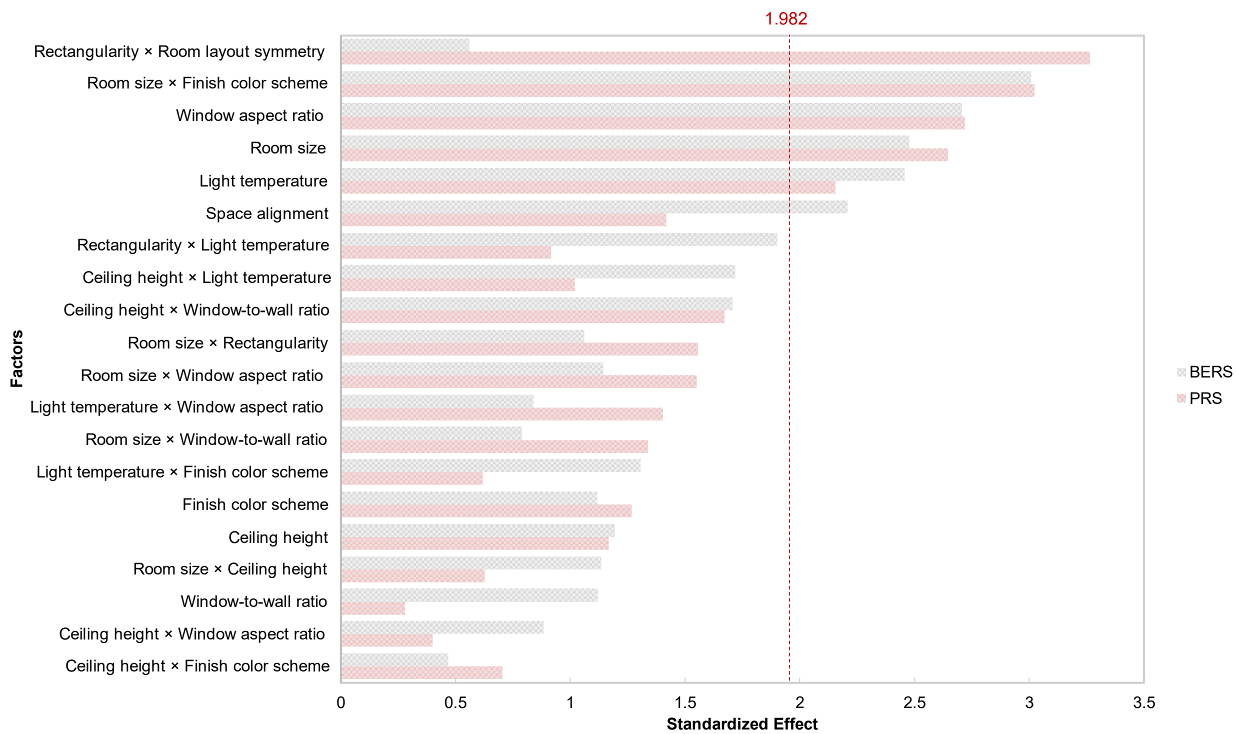


Figure 2-6. Pareto chart of the standardized effects for responses using PRS and BERS scales.

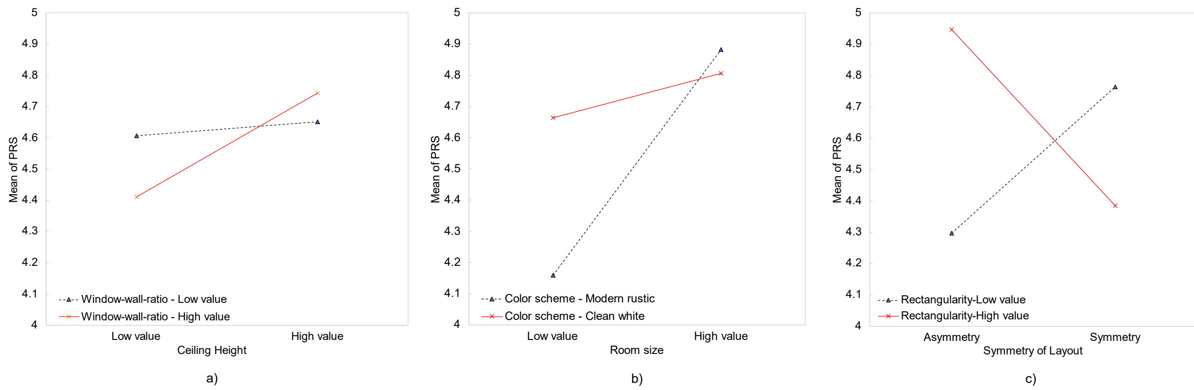


Figure 2-7. Plots for interaction effects of (a) Ceiling height × Window-wall ratio, (b) Room size × Finishing colour scheme, and (c) Room layout symmetry × Rectangularity.

2.6.3 Comparison of Predictive Modelling 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 2.4.2 (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) finishing colour 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 modelling 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 2.6.2), 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 modelling. 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 (Han, 2018).

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 2-6. 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 behaviour, 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 (Chin, 2010; Hair et al., 2011). 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. (2021b), 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 2- 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 2-a, 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 2-d). 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 2-8d), 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 2-6. 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%

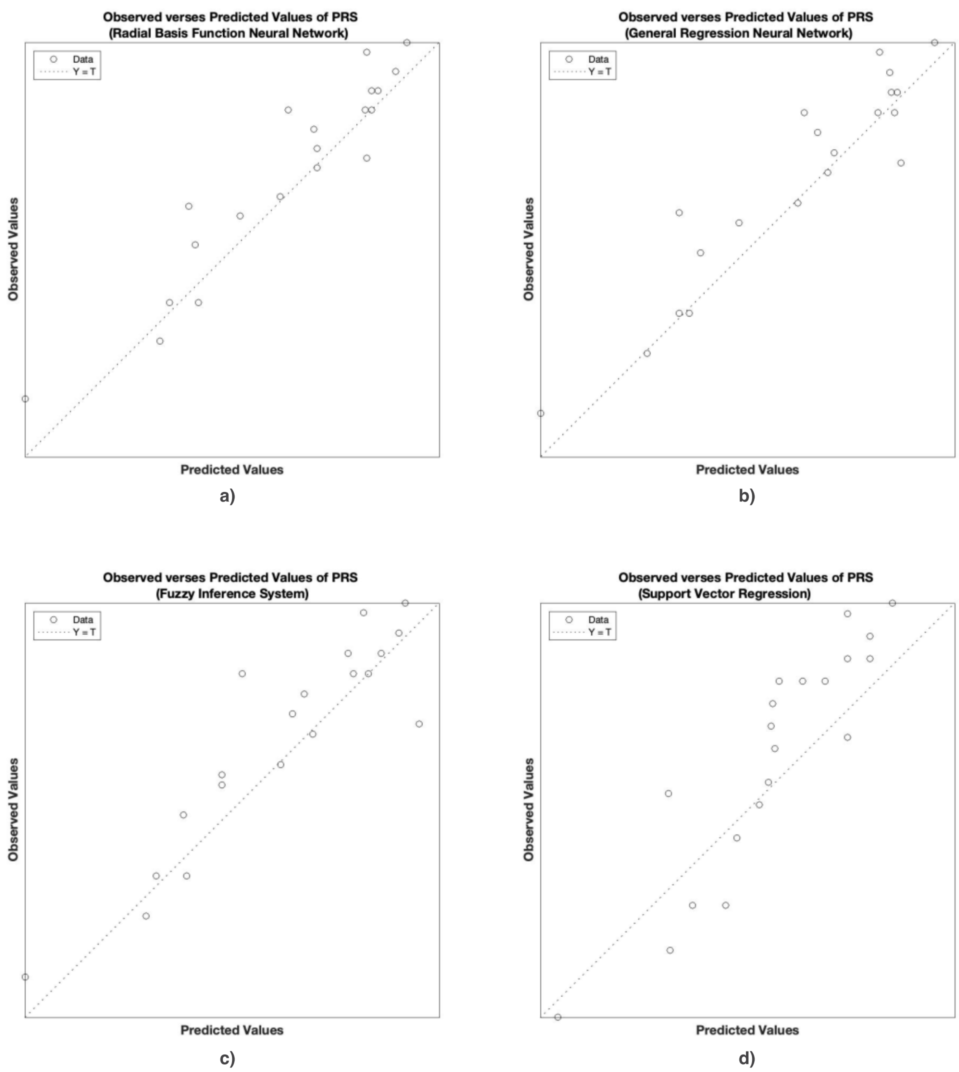


Figure 2-8. PRS values observed and predicted by four machine-learning models.

2.7 Conclusions and Future Work

The affective experience of occupants 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 modelling the affective experience.

In this study, VR technologies were employed not only to produce a controllable and validated 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 colour 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 × Finishing colour 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 modelling. 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 (Abujelala et al., 2021; Ergan et al., 2019; Gao & Zhang, 2020; Ke et al., 2021; Shemesh et al., 2016; Zou & Ergan, 2019). Although the causal quantitative relationship between biosensing data and the perceived restorativeness is still under investigation and inconclusive (Abujelala et al., 2021; Zou & Ergan, 2019), 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 (Bratman et al., 2012). 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.

Chapter 3: KNOWLEDGE-BASED DECISION SUPPORT SYSTEM FOR USER-CENTERED RESIDENTIAL DESIGN[2]

3.1 Introduction

Built environments markedly affect people's productivity and well-being (Ellsworth-Krebs et al., 2019; Ergan et al., 2019). Due to the extended durations that people spend indoors, user-centered design (UCD) has been increasingly considered a necessity in providing occupants with a comfortable living experience and realizing successful projects in architectural development (Abras et al., 2004; Heydarian et al., 2017). The home space, as a center of activities ranging from work and hobbies to leisure and any other activities related to human physiological needs, is where people spend much of their lives (Andargie et al., 2019). Thus, its definition extends beyond a "roof over one's head" (Ellsworth-Krebs et al., 2019). User requirements for the residential environment have been increasing and diversifying in keeping with economic and demographic changes in recent decades and the rapid growth of the interior design service market globally.

However, due to the vast body of knowledge regarding residential design with respect to architecture, technology, art, physics, and even psychology, many modalities of architectural and design knowledge are not fully utilized in practice, which results in an inadequate consideration of requirements and rough estimation during the early design stage (Ielegems et al., 2016). Moreover, limitations in the user experience and quality of information mean the user may fail to describe their actual needs (Kuo et al., 2009). Therefore, novice designers are regularly confronted with

[2] A version of this chapter has been submitted to Expert Systems with Applications.

knowledge dissymmetry and challenges in assessing the performance of design alternatives with regard to their capability of satisfying user requirements. This deficiency in knowledge management in residential design results in inefficient design selection, poor user satisfaction, and even the recurrence of mistakes on similar projects.

To date, knowledge-based analytical models and decision support systems (DSSs) have attracted a lot of attention in academia and industry; however, few studies have proposed knowledge-based systems (KBSs) for residential design (Lee et al., 2008). The proposed systems typically emphasize the cost factor in design decisions and generally lack the ability to identify the most appropriate design by considering the numerous user requirements pertaining to UCD. Moreover, far too little attention has been given to adequately studying the potential user of the built environment at the initial stage of building design, such as who they are and what they need. This lack of attention may lead to incorrect assumptions in the design decision made and design developed (Martin et al., 2012). This highlights a need, with respect to decision making, in current residential design regarding comprehensively explicating user requirements and determining the most appropriated design. This can be accomplished by synthesizing and analyzing a multitude of design criteria to adequately fulfill user requirements.

In an effort to fill this research gap, this study proposes an integrated framework of a knowledge-based decision support system (KBDSS) to optimize the decision-making process in user-centered residential design at an early stage. In this framework, a requirement conversion tool, quality function deployment (QFD), is adopted with DSS and fuzzy set theory to translate the user requirement into quantifiable design specifications (design criteria) to form design decision-making into a multicriteria decision-making (MCDM) problem. Meanwhile, the proposed framework uses the Kano model and clustering techniques to segment the user group and, thus, precisely assess to what degree user satisfaction is affected by particular design criteria (Atlason et al., 2018). Therefore, the proposed framework can help the design practitioner to consider how much resources to reasonably devote to improving a specific design criterion. Notably, decision makers in residential design, including novice design practitioners and homebuyers with less design experience, are potential users of this knowledge-based decision support tool.

3.2 Related Work

3.2.1 UCD for Built Environment

UCD is a design philosophy that puts the user at the core of the design process. In the domain of the built environment, Vischer (2011) proposed that buildings should be designed to support the activities of the occupants. In this theory, the occupant (user) is regarded as an active agent and consumer whose relationship with the built environment is dynamic and interactive (Ruohomäki et al., 2015). This theory roughly matches an essential aspect of built environment design that focuses on resolving the functional and aesthetic requirements into a coherent whole by assembling the desired properties of specific design elements.

Recognizing the influence of human–building interactions on occupants with regard to enhanced wellness and productivity (Ergan et al., 2018), several attempts have been made to adapt UCD methods in building design to achieve higher user satisfaction (Heydarian et al., 2017; Zhang et al., 2019). For instance, Heydarian et al. (2017) incorporated user preference data for evaluating design alternatives with the objective of meeting end-user lighting preferences while reducing lighting-related energy consumption in buildings. Nugroho and Ferdiana improved the design of residential facilities by identifying the privacy preferences of occupants and elucidating relationships between occupants and different design alternatives (Kurnianingsih et al., 2014). Likewise, to improve the work environment around people's needs, requirements, and preferences, Doshi and Clay (2017) adopted an empathetic, visual, and human-centered method to engage the user in analyzing the existing space for improvements in redesign.

Overall, these studies partially indicate the typical activities for UCD, such as (1) explicitly understanding users (e.g., user personas) and the use scenario, (2) specifying the user requirement, (3) proposing design solutions, and (4) evaluating the design solutions against user requirements (Wallach & Scholz, 2012). However, the diversity of user needs and how to incorporate each user's requirements in building design remain largely unresolved in practice (Afacan & Demirkan, 2010). Buildings are nowadays generally designed following codes and standards that are often based on generalizations with large margins of errors rather than being fitted to occupant behaviours and preferences (Heydarian et al., 2017). Accordingly, a systematic methodology for addressing the diverse user requirements and providing analytical models to assess the potential user satisfaction with the design alternatives is necessary for practical application in UCD.

3.2.2 Knowledge-Based Decision Making in Building Domain

Architecture, engineering, and construction (AEC) is a knowledge-intensive industry, where much of the knowledge is experience-based and fragmented among a wide range of disciplines (Woo et al., 2004). Along with the rapid advancement of building technology and materials development, it is challenging for designers and engineers to make rational decisions in the face of a seemingly endless source of data and information (Kazak & van Hoof, 2018). Accordingly, researchers suggested that the use of KBDSS could help decision makers integrate all design elements and explore their potential consequences in a given analysis (Hwang et al., 2018; Kazak & van Hoof, 2018; Nielsen et al., 2016). Technically, KBDSS is an integration of an expert and decision-support system, which consists of (1) a knowledge base containing expert knowledge for a particular problem domain, (2) an inference engine for generating inferences over the knowledge base, (3) an interactive user interface, and (4) a decision-support shell for helping decision makers compile useful information and data for effective decision making (Chung et al., 2016; Hwang et al., 2018). Owing to its superior flexibility and adaptability in accommodating changes in accordance with the problem context, KBDSS has been widely used to tackle a variety of tasks (Hwang et al., 2018). For instance, Hwang et al. (2018) developed a KBDSS for prefabricated prefinished volumetric construction (KBDSS-PPVC) to facilitate decision-making for PPVC implementation. Nasser et al. incorporated a KBS to support the implementation of six lean sigma principles applied to enhance the quality management performance for a healthcare environment (Al Khamisi et al., 2019). Likewise, KBDSS can address other decision-making problems across multiple stages of the building lifecycle, such as construction equipment selection (El-Tourkey et al., 2022), building material selection (Rahman et al., 2012), healthcare building evaluation (Guerrero et al., 2022), energy efficiency retrofit (Medal et al., 2021), and budget estimation for building restoration (Wang et al., 2008).

Particularly, for handling requirement-engineering-related problems, (Singhaputtangkul et al., 2013) proposed an integrated framework of KBDSS for the selection of building envelope materials. The QFD method was incorporated with a knowledge-based system to address common issues identified in the decision-making stage, such as an inadequate consideration of requirements and the lack of efficiency and consistency during decision making. This work provides valuable insight into the decision support method for requirement-oriented design for our study because there is a lack of instructional methodology in support of a knowledge-based decision making in current user-centered built environment design.

3.3 Proposed Integrative Method

To understand the priorities of user requirements and match the appropriate design solution with the user characteristics and preferences in a formalized and specific manner, an integrated QFD-based framework for developing a KBDSS in a user-centered residential design is proposed, as illustrated in Figure 3-1. In accordance with the HoQ architecture, this framework mainly consists of five phases, namely, (a) defining and collecting users' requirements; (b) prioritizing user requirements per user clustering; (c) translating user requirements into design specifications and solutions; (d) identifying the relationship between design specifications and user requirements; and (e) establishing priority of design specifications for user clusters, along with a knowledge base system that stores relevant design knowledge. Meanwhile, three knowledge base modules, that is, KB-S, KB-R, and KB-U, are developed to support knowledge management in the decision-making process.

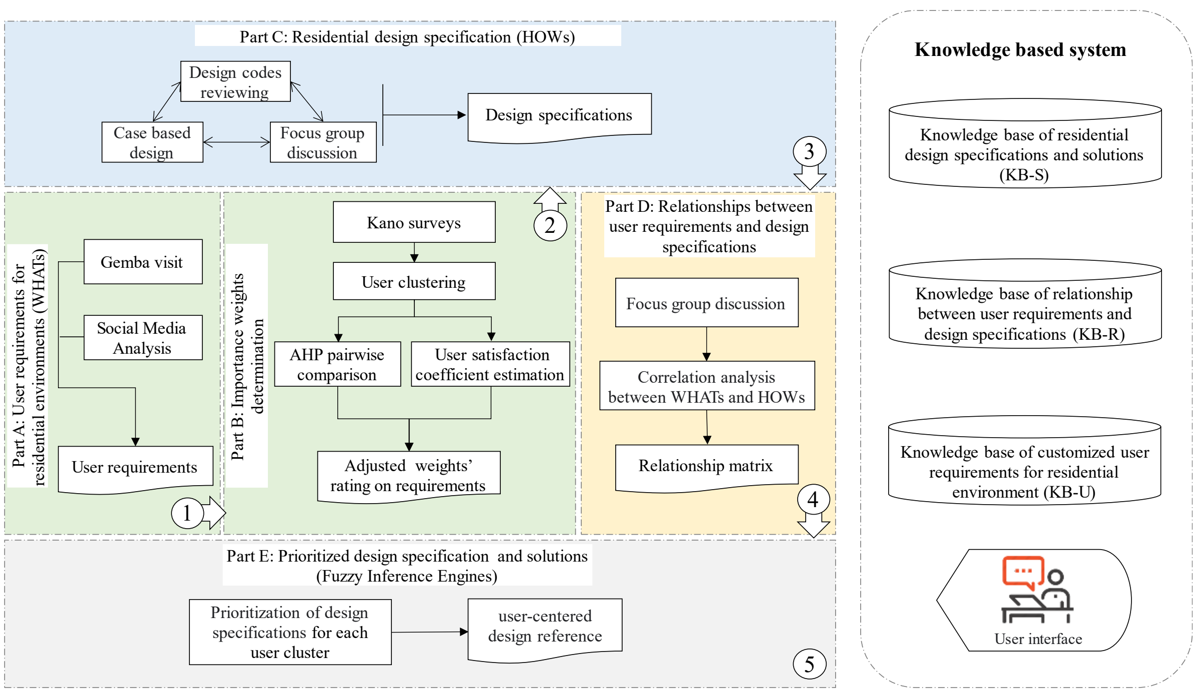


Figure 3-1. QFD-based framework for development of knowledge-based decision support system

3.3.1 Knowledge Base for User-Centered Residential Design

Multiple levels of knowledge, that is, "know-what" and "know-how," are usually needed in the decision-making process. From the knowledge base structure in (Singhaputtangkul et al., 2013), three knowledge base modules are proposed to store the information regarding user requirements (KB-U), design specifications (KB-S), and their correlations (KB-R), which reveal how user requirements could be met by the design specifications. Notably, "know-why" knowledge is also implemented in the knowledge base so that the system can provide the principles and mechanisms underlying the collected user requirements and design specifications for decision justification. For instance, for each identified design specification, detailed information is provided in terms of the application context, possible effect, and expected performance of the criteria as a decision guide. The data for the user centered residential design was mostly acquired from the Gemba visit, semi-structured interviews, and social media, as discussed in the following section.

3.3.2 Part A: Occupant requirements identification for residential environments (WHATs)

In the present study, data from Gemba walk and social media analysis are used to identifying user requirements and enhance the coverage and completeness of knowledge (Chin et al., 2019).

Gemba Visit

Many existing studies have indicated that implicit or hidden requirements are more pertinent to users than explicit requirements and correspond to higher satisfaction levels (Chin et al., 2019). During the Gemba walk, the researcher observes how the occupant uses and interacts with the space and measures important dimensions for residential design, such as the area, layout, heights of working stations, and illuminance level, for further analysis. An interview should later be conducted with the primary user of the space to explore their subjective opinion of the current design. The information from the Gemba step provides essential insight into the user requirements, and it is useful for interpreting the user's voice for further analysis.

Social Media Analysis

To optimize user requirement collection, information from social media platforms is adopted as the main resource to determine the actual needs of users with low time expenditure (Lai et al., 2006). In the present study, the information related to users' requirements was extracted by keyword querying among multiple popular social media platforms for sharing ideas on home design, decor, and improvement. The researchers went through the posts individually to extract the information (i.e., sentences) related to specific residential design requirements. Special attention was given to the negative feedback on their current design. The querying process was stopped when a number of similar user requirement items was repeatedly identified in the search result, with new information only being occasionally obtained.

Once the information on user requirements is collected, an affinity diagram method can be adopted to externalize the tacit knowledge underlying the raw information and cluster it into individual requirement items (Awasthi & Chauhan, 2012). Notably, query information should be screened more than once to identify the actual user needs behind the statement and maximally explore potential need items.

3.3.3 Part B: Importance Weights Determination per User Clustering

By generating a list of user requirement for residential design, a prioritization is performed, as illustrated in Figure 3-2. Generally, the relative weight for requirement prioritization ($w_{adj.ur}$) is determined by two factors: the opinions from the expert (w_{ur}) and the user groups ($k_{adj.}$). This enables the DSS to adopt the knowledge from residential design professionals, who identify essential and urgent requirements for a specific user group and incorporate the user's preference to enhance their overall satisfaction (Kang et al., 2018).

Further, user clustering is first performed based on the different satisfaction attitudes toward requirement fulfillment to segment the users and better tailor the user's preference and features, enhancing their overall satisfaction. Requirement priority, rather than conventional demographic data, is used to segment user groups because (1) demographic information is sometimes too vague to give the designer insights into what the user wants or values, and (2) people's lifestyle changes over generations in keeping with the development of information technology. From the increase in smart appliance usage to gender fluidity, demographic data are simply not enough to identify users with similar needs. Thus, the Kano model is adopted in this study to denote the individual user's preference for each requirement item and user segmentation purposes.

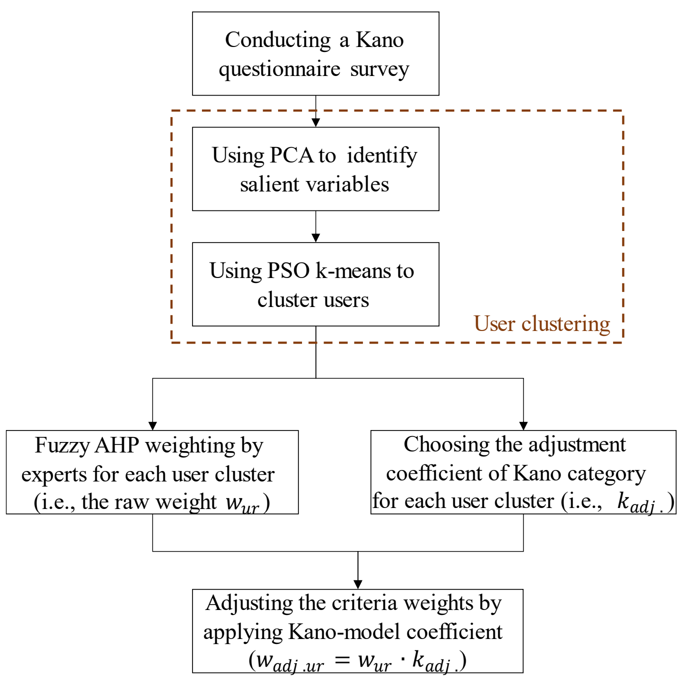


Figure 3-2. Prioritization of user requirements

Kano Survey Design

The Kano model measures and classifies the user satisfaction level considering how well different design attributes (requirements) could satisfy user needs (Kano et al., 1984). To perform an effective user segmentation for depicting user personas, a Kano-model-based questionnaire is designed to measure people's preferences toward different user requirements in residential design. The first part of the questionnaire contains general background information about the respondents, such as their family structure, physical ability, and typical usage scenario. The second is in the form of pair questions to collect satisfaction differences per user requirement items: one question is formulated in a positive manner (i.e., functional), whereas the other is formulated in a negative manner (i.e., dysfunctional), as shown in the example in Figure 3-3. Because the data gathered from respondents are used as training data for user clustering, Cronbach's alpha is used to test the reliability of the survey; a value greater than 0.7 denotes that the data can be used for further clustering analysis.

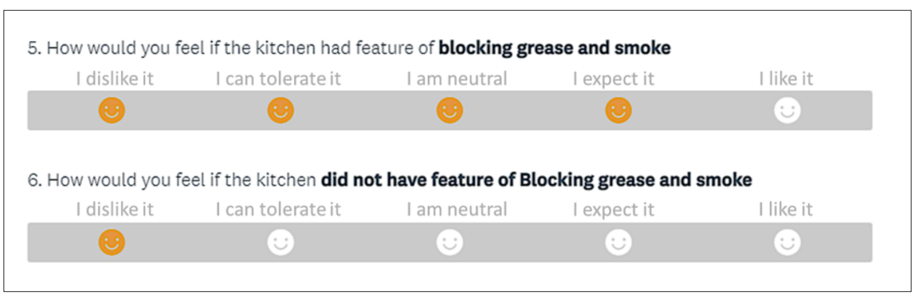


Figure 3-3. Example of the Kano questionnaire in the case study.

Representative User Requirements Identification

Due to the large number of user requirement items regarding Kano quality (i.e., functional and dysfunctional units of user requirements) and the limited response samples, principal component analysis (PCA) is applied to the Kano survey responses to achieve a better user clustering analysis result (Alsayat & El-Sayed, 2016). In the present study, PCA is performed to identify the representative user requirement items that account for most of the variance for performing further clustering analysis. Accordingly, trivial user requirement items, for which the accumulated correlation (i.e., factor loading) for all components is less than 0.5, are removed sequentially, according to the rotated component matrix (Kuo et al., 2012)

User clustering

After salient user requirement items are identified, user segmentation can then be performed by grouping users with similar requirement priorities. A particle swarm optimization (PSO) clustering algorithm is adopted in the proposed framework to find groups of users with similar preference (Van Der Merwe & Engelbrecht, 2003). This algorithm reduces the effect of initial conditions (i.e., the number of clusters) and delivers more accurate clustering results than traditional K-means method. In the PSO-based clustering analysis, the final cluster number is determined by the trial-and-error optimization results and expert judgment of the sample distributions within the clusters. The user personas can then be developed in accordance with the particular preference toward the requirement denoted by the Kano attributes and specified typical user characteristics summarized from survey data (Tu et al., 2010).

Relative weight calculation for prioritizing user requirements

For each user cluster, the relative weights of the user requirements are calculated from the original criteria weights (w_{ur}) generated by the pairwise comparison among user requirements and the adjustment coefficient ($k_{adj.}$), which is assigned based on its Kano quality, as outlined in

Equation 3-1 (Kang et al., 2018). The calculation of these two indices is presented in detail in the following sections.

$$w_{adj.ur} = \frac{w_{ur} \cdot k_i}{\sum_{i=1}^{n} w_{ur} \cdot k_i} \quad (3-1)$$

where $w_{adj.}$ is the final adjusted weight for the user requirement, w_{ur} is the raw relative weight estimated from the AHP matrix, and k_i is the adjustment coefficient according to its Kano quality classification.

a) Relative Weight Estimated by Fuzzy AHP

In obtaining the opinion of residential design professionals on the prioritization of user requirements, the expert is required to compare the relative importance of user requirements for a given user persona, which is represented in a fuzzy pairwise comparison matrix. To generate a collective decision form a group of experts, the geometric mean method (see Equation 3-2) is used to accumulate the individual's pairwise comparison matrix of user requirements (Chen et al., 2007). Then, a logarithmic fuzzy preference programming (LFPP)-based method (Wang & Chin, 2011) is adopted to address the fuzzy AHP priority of the user requirements. This method formulates the fuzzy weight derivation as a logarithmic nonlinear programming problem, generating a unique optimal crisp priority vector for fuzzy pairwise comparison matrices. It has been proven to address the significant drawbacks in previous fuzzy AHP prioritization, such as producing a conflicted priority result of a fuzzy pairwise comparison matrix or leading to distinct conclusions (Wang & Chin, 2011). By solving the nonlinear priority optimization model (Equations 3-3 and 3-4) proposed in the LFPP-based method, the relative weight of user requirements can be calculated based on the collective pairwise comparison matrix (Wang & Chin, 2011).

$$l_{ij} = \left(\prod_{k=1}^{K} l_{ijk}\right)^{\frac{1}{k}}, m_{ij} = \left(\prod_{k=1}^{K} m_{ijk}\right)^{\frac{1}{k}}, u_{ij} = \left(\prod_{k=1}^{K} u_{ijk}\right)^{\frac{1}{k}} \quad (3-2)$$

$$Minimize\ F = (1-\lambda)^2 + M \cdot \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \left(\delta_{ij}^2 + \eta_{ij}^2\right) \quad (3-3)$$

$$Subject\ to \begin{cases} x_i - x_j - \lambda \ln\left(\dfrac{m_{ij}}{l_{ij}}\right) + \delta_{ij} \geq \ln l_{ij}, i = 1, \dots, n-1; j = i+1, \dots, n \\ -x_i + x_j - \lambda \ln\left(\dfrac{u_{ij}}{m_{ij}}\right) + \eta_{ij} \geq -\ln u_{ij}, i = 1, \dots, n-1; j = i+1, \dots, n \\ \lambda, x_i \geq 0, i = 1, \dots, n \\ \delta_{ij}, \eta_{ij} \geq 0, i = 1, \dots, n-1; j = i+1, \dots, n \end{cases}$$

$$w_{ur_i} = \frac{\exp(x_i^*)}{\sum_{j=1}^{n} \exp\left(x_j^*\right)}, i = 1, \dots, n \quad (3-4)$$

where triple (l_{ij}, m_{ij}, u_{ij}) represents the expert's judgement of the fuzzy relative importance of ith over jth user requirements, K is the number of expert, λ is the minimum membership degree to which the priority vector satisfies each fuzzy pairwise comparison, δ_{ij} and η_{ij} are non-negative deviation variables that are introduced to prevent λ from taking a negative value, M is a specified sufficiently large constant, and x_i^* (i = 1..., n) is the optimal solution to this model.

b) Adjustment Coefficient Estimation by the Kano Model

On the other hand, the user satisfaction factor is considered in determining the priority of a user requirement by including an adjustment coefficient (i.e., k_i in Equation 3-1). This coefficient is assigned based on the Kano attribute of the user requirements. These are determined based on the Kano questionnaire response as outlined in Figure 3-4, and the categories include "attractive requirement (AR)," "one-dimensional requirement (OR)," "must-be requirement (MR)," "indifferent requirement (IR)," "reverse requirement (RR)," and "questionable requirement (QR)." This evaluation table is adopted from Pouliot's model, which slightly differs from the standard Kano evaluation tables. This evaluation table considers uncertainty factors: someone may have not fully understood the questionnaire, and the proposed requirement may be the opposite of what they want. When conflicted responses are obtained in the Kano questionnaire (i.e., "like" and "like" for both functional and dysfunctional questions), such user requirements would be classified as QR, which needs to be examined carefully by the researcher.

Because the Kano attributes of user requirements are determined on a group basis, the satisfaction and dissatisfaction indexes (SI and DI in Equations 3-5 and 3-6) are introduced by estimating the distribution of Kano attributes in each category for a given requirement to address the variance within one cluster (Berger et al., 1993). According to the value distributions in Table 3-1, the indexes of SI and DI together determine the collective Kano attributes of the given user requirement (Avikal et al., 2020).

Dysfunctional (requirement not fulfilled)

Functional (requirement not fulfilled)	**Like it**	**Expect it**	**Does not matter (Neutral)**	**Tolerable**	**Dislike**
Like it	QR	AR	AR	AR	OR
Expect it	RR	QR	IR	IR	MR
Does not matter (Neutral)	RR	IR	IR	IR	MR
Tolerable	RR	IR	IR	QR	MR
Dislike	RR	RR	RR	RR	QR

Notes: **AR**: attractive requirement, **OR**:one-dimensional requirement, **MR**: must-be requirement, **IR**: indifference requirement, **RR**: reversal requirement, and **QR**: questionable requirement.

Figure 3-4. Categorization of Kano attributes on user requirement.

In the proposed DSS, attention is primarily given to MR, followed by AR, OR, and lastly, IR; thus, their adjustment coefficients for user requirement prioritizations could be set as 6, 4, 2, and 1, respectively (Chen & Chuang, 2008).

$$SI = \frac{AR + OR}{AR + OR + IR + MR} \tag{3-5}$$

$$DI = \frac{MR + OR}{(AR + OR + IR + MR)(-1)} \tag{3-6}$$

Table 3-1. Collective Kano attribute of user requirement based on SI and DI index

SI Value / DI Value	[0, 0.5]	[0.5, 1]
[−0.5, 0]	IR	AR
[−1, −0.5]	MR	OR

3.3.4 Part C: Residential Design Specification Development (HOWs)

The next step in HoQ, after analyzing the user requirements, focuses on residential design specifications. This step aims to develop a decomposition that comprehensively outlines all relative design specifications for fulfilling user requirements in residential design. These design specifications could be engineering and/or ergonomic characteristics (walkway width, for example), referring to the parameter that the residential designer can actually control and make decisions on. Typically, they are qualitatively or quantitively measurable so that designers can determine whether the user's needs are fulfilled. The list of residential design specifications could be generated through brainstorming among design experts on the research team after a comprehensive literature review on design guidelines, articles, and previous design cases. Specifically, the team would refer to each user requirement and translate it into a list of design specifications from a technical perspective (Marsot, 2005). These design specifications should be grouped according to the design elements, such as the layout and light designs, which can be efficiently edited and updated for knowledge management (Singhaputtangkul et al., 2013).

In addition, the intercorrelations between design specifications should be recognized (using Table 3-2) to highlight the potential conflicts and tradeoffs at the early design phase, thus eliminating the risk of rework or design changes (Bouchereau & Rowlands, 2015). For instance, the "walkway width" in the kitchen design may be slightly negatively related to the design specification of "working surface area" due to the overall space limitation. Thus, the corresponding grid space between these two design specifications should be marked as "Weak+ve."

To estimate the effect of the intercorrelations on the relative importance of the design specifications, a distance-based method proposed by Iqbal et al. (2016) is adopted to calculate the correlation magnitude (see Equations 3-7 to 3-12). This method translates the correlation strength of each design specification item into a distance index N_j'. A value of N_j' closer to 0 implies that this design specification is strongly correlated with other items, whereas a value closer to 0.5 implies that this design specification may be independent of other design specifications or that there are both negative and positive correlations associated with this design specification. According to Iqbal et al. (2016), Equation 3-13 is used to re-evaluate the importance of design specifications, given the original relative weights delivered from the user requirement prioritization and the normalized distance by roof matrix correlations.

Table 3-2. Linguistics–symbolic–numeric scale for pairwise intercorrelations between design specifications

Linguistic	Numeric scale
Strong synergies +ve	0.9
Weak synergies +ve	0.3
Weak opposites –ve	−0.3
Strong opposites –ve	−0.9

$$R_j' = \left[r_{i,j}'\right]_{n,1} = \begin{cases} 1, i = j \\ -1 \leq r_{i,j} \leq 1, i \neq j \end{cases} \quad (3-7)$$

$$Z_j' = \left[z_{i,j}'\right]_{n,1}, z_{i,j} = 1; \forall i \quad (3-8)$$

$$E_j' = \left[e_{i,j}'\right]_{n,1} = \begin{cases} 1, i = j \\ -1, i \neq j \end{cases} \quad (3-9)$$

$$d_j'\left(R_j', Z_j'\right) = \sum_{i=1}^{n} \left|r_{i,j}' - z_{i,j}'\right| \quad (3-10)$$

$$d_j'\left(E_j', Z_j'\right) = \sum_{i=1}^{n} \left|e_{i,j}' - z_{i,j}'\right| \quad (3-11)$$

$$N_j'\left(R_j', Z_j', E_j'\right) = \frac{d_j'\left(R_j', Z_j'\right)}{d_j'\left(E_j', Z_j'\right)} = \frac{\sum_{i=1}^{n}\left|r_{i,j}' - z_{i,j}'\right|}{\sum_{i=1}^{n}\left|e_{i,j}' - z_{i,j}'\right|}, 0 \leq N_j'\left(R_j', Z_j', E_j'\right) \leq 1 \quad (3-12)$$

$$W_j^c = W_j \cdot \left(1 - N_j'\right) \quad (3-13)$$

where R_j' is a given matrix of pairwise correlations, $r_{i,j}'$ represents the correlation between design specifications i and j, Z_j' is the ideal column vector of correlations in which the correlation index $z_{i,j}'$ always equals one, and E_j' is the column vector for the most undesirable situation in which any given design specification j is negatively correlated (-1) with the others. $N_j'(R_j', Z_j', E_j')$ refers to the Manhattan distance ratio of a given column vector between the extreme column vector E_j' and the ideal column vector Z_j'.

3.3.5 Part D: Relationships Between Occupant Requirements and Design Specification

After the occupant requirements and design specifications are determined, a relationship matrix defining the correlation between the user requirements and design specifications is then established. Figure 3-5 illustrates the fuzzy linguistic scales (i.e., triangular fuzzy number sets, TFNs) incorporated in the proposed method for determining the association between user requirements and design specifications. Notably, the number of linguistic scales in the term set determines the granularity of uncertainty modelled by the linguistic descriptor. Typically, the more knowledge is available, the more granularity, according to Bonissone & Decker (1986). This method incorporates a five-term linguistic set, given the experience level of design experts.

Similar to the previous group decision process in FAHP (Section 3.3.4), the degree of correlation between occupant requirement and design specification is obtained by aggregating multiple design experts' decisions using geometric mean algorithm. In addition, the requirement–characteristics correlation matrix should be examined to ensure that each user requirement corresponds to at least one design specification, and each requirement is expected to have a significant correlation (i.e., "assigned linguistic term" as "High influence") with a design characteristic.

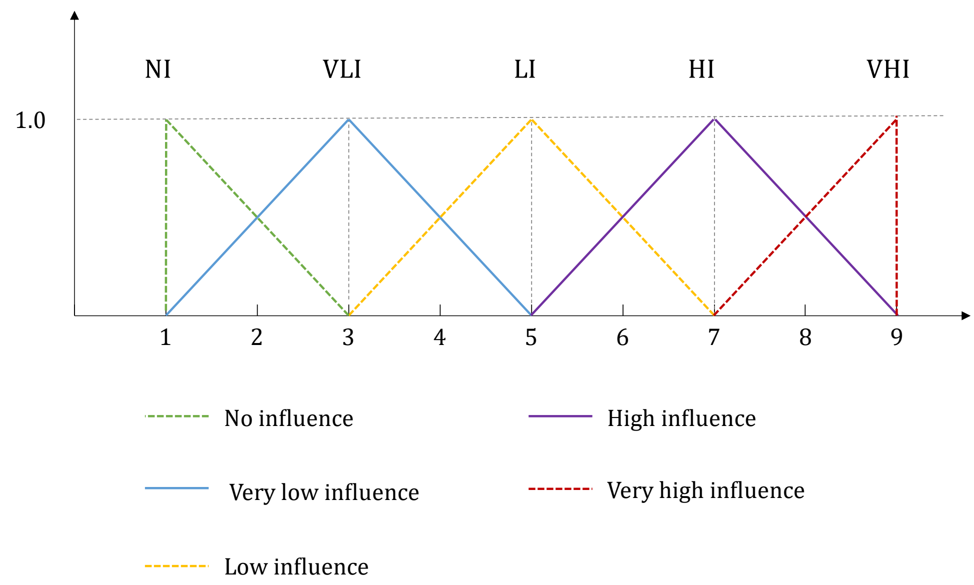


Figure 3-5. Fuzzy number sets.

3.3.6 Part E: Prioritization of Design Specifications

To prioritize the design specifications per user cluster, the absolute importance of design specifications is computed by integrating both the adjusted relative weight of user requirements, correlation matrix between user requirements and design specifications, and interrelation index among design specifications.

The mathematical formula is given in Equations 3-14 and 3-15 by following the fuzzy set ranking method proposed by Yager (1981). This method is based on the idea of associating the fuzzy number with a scalar value $Y_{i,j}$ calculated through Equation 3-14, where a, b, and c represent the lower, medium, and upper values or fuzzy numbers set (i.e., TFNs) in the correlation matrix, respectively (Bevilacqua et al., 2006). By obtaining the fuzzy set ranking, the prioritization of the design specification can then be drawn up using Equation 3-15, which generally multiplies the relative importance of user requirements w_{ur_i} and the ranking index of the fuzzy relationship matrix ($Y_{i,j}$), as well as the adjustment coefficient by design specification correlations. Once the ranking of design specifications is completed, design alternatives can then be assessed and compared with the weight of each specification item.

$$Y_{i,j} = \frac{a_{i,j} + 2b_{i,j} + c_{i,j}}{4} \quad (3-14)$$

$$w_j = \frac{\left(1 - N'_j\right) \sum_{i=1}^{n} (Y_{i,j} \cdot w_{ur_i})}{\sum_{j=1}^{m} ((1 - N'_j) \sum_{i=1}^{n} (Y_{i,j} \cdot w_{ur_i}))} \quad (3-15)$$

where i and j refer to the i th of n user requirement and the j th of m design specifications, respectively.

3.4 Illustrative Example for Kitchen Design

In this section, a case study of KBDSS for kitchen design in a multiunit residential building (MURB) is adopted to illustrate the application of the proposed methodology. The choice of MURB kitchen design relies on the following considerations. First, the kitchen is usually regarded as the center of home, and its diverse roles require this space to simultaneously fulfill both comfort and functional requirements in (Maguire et al., 2014). Further, residential design in MURBs is more challenging than in single-family buildings due to their compartmentalized interior space, building height, and control options for occupants, resulting in a relatively low satisfaction among MURB occupants (Fonberg & Schellenberg, 2019). Therefore, fulfilling occupants' requirements under such a high-constraint design environment remains a challenge during decision making in the early residential design stage.

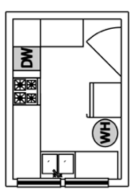
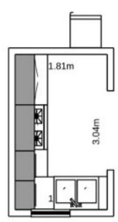
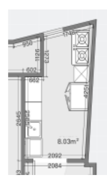
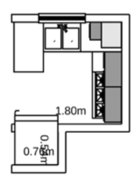
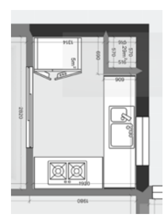
3.4.1 Development of KBDSS for MURB Kitchen Design

Following the proposed QFD-based method, this section presents a detailed description of how the KBDSS is developed for MURB kitchen design.

Step 1: Collect user's requirements for MURB kitchen design

Six MURB kitchens from three cities in China were visited to acquire a basic understanding of how occupants interact with kitchen environments and what kind of requirements may be reported. Table 3-3 summarizes the property type and household information of the visited kitchen.

Table 3-3. Information summary of the visited kitchen.

	Kitchen 1	Kitchen 2	Kitchen 3	Kitchen 4	Kitchen 5	Kitchen 6
Household	Married family with children	Married family with children	Married family with children	Married family without children	Married family with children	Married family with children
Frequency of usage	Everyday	Everyday	Everyday	Once or twice a week	Everyday	Everyday
Area	5.76 m^3	4.66 m^3	8.03 m^3	4.81 m^3	4.76 m^3	5.97 m^3
Year of Built	2010	2019	2000	1998	2005	2016
Kitchen layout						

During the Gemba visit, most users specified problems related to cleaning, organization, and storage space. For instance, it was common to observe stuffs stacked on the floor due to the space limit. Further, it was found that the kitchen used by similar household types and family structures could have very different requirements priority due to their differences in lifestyles. Accordingly, a finer division of the kitchen design market may be necessary for allocating the limited design resources to personalization needs. After the Gemba visit, comprehensive information extraction was performed over an internet forum (i.e., "Zhi-Hu" and "Xiao-Hong-Shu"). The keywords “kitchen design,” “kitchen,” and “kitchen decoration” were used to query the relevant reviews and self-posted contents. To accurately obtain the information related to user requirements in kitchen design, design complaints and recommendations were underscored.

A total of 43 user requirements items for the MURB kitchen were identified in this case study, as presented in Figure 3-6. These were subsequently grouped into 11 categories using the affinity diagram method in a group discussion (Yang et al., 2021). For each category, a label is chosen to broadly describe all the contained requirement items, namely, (1) hygiene and health, (2) energy saving, (3) social connectivity, (4) preparation support, (5) illuminance, (6) smart home, (7) appliance usage, (8) maintenance, (9) ergonomics & accessibility, (10) storage & organization, and (10) aesthetics.

Hygiene and Health		Smart Home	
UR1	No bacteria breeding, mold and other problems	UR22	Remote control of equipment
UR2	Anti-insect	UR23	Assist with meal preparation
UR3	Blocking grease and smoke	UR24	Prompting healthier meal choices
UR4	No unpleasant odor	UR25	Learn user behavior and automatically adapt to their daily schedule
Energy Saving		Appliance Usage	
UR5	Efficient electricity usage	UR26	Access to garbage disposal
UR6	Water efficiency	UR27	Access to appliances with different power
UR7	Efficient appliance energy consumption	UR28	Multiple appliances can work at the same time
Storage & Organization		Maintenance	
UR8	Sufficient storage space	UR29	Maintenance with low effort
UR9	Well-organized cabinet, drawer, and pantry	UR30	Easy to clean
UR10	Easy to find what you need	UR31	Resistant to dirt and stains
UR11	Keep the countertops clear	Ergonomics & Accessibility	
UR12	Keep all items organized	UR32	Efficient workflow avoiding repetitive movement
UR13	Displaying collections without clutter	UR33	Ergonomic comfort
Social Connectivity		UR34	Easy access objects from high place and avoid bumping heads
UR14	Prompting Communication	UR35	Avoid bending and squatting during kitchen activities
UR15	Collaborative environment	UR36	Enough space for comfortable movement and operation
UR16	Shared dining and cooking space	UR37	Avoid slip and fall injury
Preparation Support		UR38	Wheelchair accessibility
UR17	Sufficient work surface	UR39	Easy control of lighting
UR18	Separation of dirty dishes from pod preparation	UR40	Easily operate kitchen appliances
UR19	Easy to clean large pots and pans	UR41	Smooth kitchen activities with reduced labor
Illuminance		Aesthetic	
UR20	Uniform lighting without glare	UR42	Simple, bright, and fresh
UR21	Bright operation area	UR43	Pleasant, relaxed, and comfortable

Figure 3-6. User requirements for the MURB kitchen.

Step 2: User clustering

A Kano survey on the collected user requirements was performed to understand the diversity of people's preference toward different user requirements items in a MURB kitchen. Thus, 178 responses collected from the Kano survey were used for further user clustering analysis after data cleaning on uncompleted and unqualified responses.

As a result, four user clusters were identified in this study, and their characteristics are outlined in Figure 3-7. The user characteristics for each cluster are summarized according to the participant's current kitchen design attributes and their attitudes toward different requirement items (based on

Kano survey). As representative users, this can help experts quickly determine the common needs and behaviours of a group and, thus, the importance of design specifications.

Group	Characteristics
Group 1	High requirement for kitchen design
Group 1	High demand for comfort and functionality of use
Group 1	Interested in high-tech products
Group 1	Kitchen area of 8-12 sqm
Group 1	Like to invite friends over
Group 1	Cooking time is usually long, 40% use the kitchen more than an hour per time
Group 1	75% with electrical scales
Group 2	Users want a small, well-equipped kitchen
Group 2	Users want a kitchen environment that is pleasant, relaxing, and restful
Group 2	Users want to interact with others while cooking
Group 2	Users are concerned about the layout and ergonomic comfort of the kitchen
Group 2	Users are very concerned about the grease problem in the kitchen
Group 2	Kitchen area of 4–8 sqm
Group 2	Highest kitchen use frequency compared to other groups
Group 2	Users are relatively traditional and do not have a strong preference for high-tech products
Group 2	Users want the kitchen to have social functions
Group 2	Users like to invite friends to their homes for dining
Group 2	40% have no electric oven, while the average is 20%
Group 2	30% entertain once per week
Group 3	Only request the most basic, simple, and practical functions, such as kitchen appliances that are easy to operate, well-ventilated kitchen, adequate storage space, and neatly placed items.”
Group 3	Users do not require ergonomic and technical features
Group 3	Only 28% of users find social function necessary
Group 3	Water quality is valued
Group 3	Users have a lower frequency of grocery visit than that in other groups
Group 3	Users with the lowest kitchen use frequency.
Group 3	Cooking time is usually short
Group 3	42.9% of users with coffee machine
Group 3	71.4% of users without slow cooker
Group 4	Users value ergonomic comfort in kitchen design
Group 4	Kitchen cleanliness and practicality are important to users
Group 4	Users are attracted to high-tech products in the kitchen but do not consider them necessary
Group 4	Kitchen size is larger than 4 sqm
Group 4	It is likely to have elderly users at home
Group 4	Users may have accessibility requirements

Figure 3-7. Personas of four user clusters.

Step 3: Prioritize user requirements for each user cluster

After identifying the user requirement items and the user cluster, four experts with experience ranging between three and five years in residential design were asked to judge the relative importance of user requirement items using an AHP-based questionnaire. The expert was first asked to go through a description of user personas, as shown in each box of Figure 3-7. They were then instructed to select the more important user requirement items in a pairwise comparison and indicate the relative importance level. Following the method introduced in Section a), the relative weight of the user requirement in each group could thus be computed.

Meanwhile, according to the Kano model of each cluster, the adjusts were assigned as multipliers to the relative weight of each user requirement. Consequently, the absolute importance of the user requirement for each cluster was determined. The result showed that the most valued requirements for Group 1 include “bright operation area” and “odd-free”, “blocking grease and smoke” and “bright operation area” for Group 2, “bright operation area” and “sufficient work surface” for Group 3, and “blocking grease and smoke” and “electricity saving” for Group 4.

Step 4: MURB kitchen design specifications

From a comprehensive literature review of the design guidelines and existing design cases, 101 design specifications capable of systematically fulfilling the user requirements were summarized as outlined in Figure 3-8. These design specifications were divided into 13 categories based on the associated conventional kitchen design elements. In addition, their potential interaction effects were evaluated.

Index		Item
DS1	Control	Under cabinet lighting can be switched in backsplash
DS2		Main ceiling lighting is switched where it is easily accessed by those entrances
DS3		The light should be operated from more than one entrance
DS4		The height of switch is around arm bowl
DS5		Light control for adaptive compensation
DS6	Vertical layout	Lower level of wall cabinet is within Ergonomic Zone 3
DS7		Accessible height of cabinet door is within Ergonomic Zone 3
DS8		Height of microwave or oven is within Ergonomic Zone 1&2
DS9		Vertical clearance above preparation area
DS10		Ergonomic countertop surface heigh
DS11		Ergonomic cooktop surface heigh
DS12		Vertical clearance above cooking top
DS13		Adjustable countertop/cooktop height
DS14	Interaction with other building	Sufficient width of doorway
DS15		Clear openings of doorways
DS16		Clear floor space for maneuvering
DS17		Sink is under the window if possible
DS18		Appropriated distance between cook range and gas duct
DS19		Opening floor plan
DS20		Closing floor plan
DS21		Sink is right next to dishwasher
DS22		Semi-open kitchen
DS23	Landing Area	Microwave landing area
DS24		Refrigerator landing area
DS25		Oven landing area
DS26		Cooking landing area
DS27		Sink landing area
DS28		Preparation area
DS29	Working zone layout	The sum of all three sides of the triangle should be between 13–26’
DS30		No single leg of the triangle measuring less than 4 feet nor more than 9’
DS31		No work triangle leg may intersect an island/peninsula or other obstacle by more than 12”
DS32		If a kitchen has only one sink, locate it adjacent to or across from the cooking surface and refrigerator.
DS33		A full-height, full-depth, tall obstacle should not separate two primary work centers
DS34	Clearance	Distance between island/cabinet should be more than 30”
DS35		Sufficient walkway width for operation
DS36		Toe clearance should extend 17"minimum beneath the element
DS37		Toe kicks are generally 3½” high and 3” deep
DS38		Sufficient space between countertop/table edge to any wall or obstruction behind the seating area
DS39	Cabinet design	Ergonomic hob design
DS40		Corner cabinet equipped with functional storage device
DS41		Material is heat resistance
DS42		Material is stability, less prone to warping and fading
DS43		Material with durability, susceptible to scratches and dents
DS44		Material is moisture resistance
DS45		Maximize pullout storage
DS46		Sufficient height for appliance storage
DS47		Functional built-in specialty organizers or drawers
DS48		Sufficient accessible storage footage
DS49		Fitted dimension with built-in appliance
DS50		Sufficient storage at sink area

Index		Item
DS51		The size of kitchen island should be more than 32*48”
DS52		The height of dining area of kitchen island should be more than 36-45”
DS53		The height of cooking and cleaning should be more than 32-36”
DS54		Cabinet is equipped with electric lifting or moving pulling baskets
DS55	Countertop design	Countertop with clipped or round corners rather than sharp
DS56		Material with repairability
DS57		Material with Heat resistance
DS58		Material is High density
DS59		Material is Nontoxic
DS60		Sufficient countertop frontage
DS61		With water retaining strip
DS62		Material is Resistance to wear
DS63	Appliance	Equip with waste disposal
DS64		Energy efficient appliances
DS65		Water purifier equipped
DS66		Range with high airflow
DS67		Range with high exhaust hood capture efficiency (shape)
DS68		Meet with air pressure requirement （260-450）
DS69		Loosen grease Filter of range
DS70		Easily uninstalled Oil box of range
DS71		Appliances equipped with sensors
DS72		Appliance could connect to internet
DS73	Sink and faucet	Sufficient depth for tall cookware
DS74		Large sink bowl
DS75		Functional division
DS76		Shallow sink depth for ergonomic comfort
DS77		Solid surface sink with countertop
DS78		Space for dish drainer
DS79		Low flow faucets
DS80		Faucet is pullable
DS81		Faucet with high neck taps allow room to fill kettle or saucepan
DS82	Receptacles	Sufficient quantity of receptacles around preparation area
DS83		Consequent receptacle outlet is required every 2’ if possible
DS84		Refrigerators and microwave ovens require separate circuits.
DS85		Total quantity of receptacles should be more than 7-8
DS86		Separate circuit is recommended for dishwashers, but not required.
DS87	Lighting	Light should be 1 m higher above cooktop
DS88		Task lighting is required (under cabinet & above the sink)
DS89		Energy efficient light bulb
DS90		Illuminance of food prep. area>750 lux
DS91		Illuminance of dining area > 50-150 lux
DS92		Overall lighting illuminance > 450-750 lux
DS93		Lighting temperature for ambient lighting 2500k
DS94		Working area lighting temperature approximately 5000k
DS95	Finishing	Lighter color flooring
DS96		Dark countertop
DS97		Rough surface floor tile
DS98		Satisfaction combination of finishing
DS99		Material of Moisture resistance of Backsplash
DS100		Material of Heat resistance of Ceiling
DS101		Material of Moisture resistance of Ceiling

Figure 3-8. Design specification items.

Step 5: Determine the importance of design specifications based on *relationship matrix*

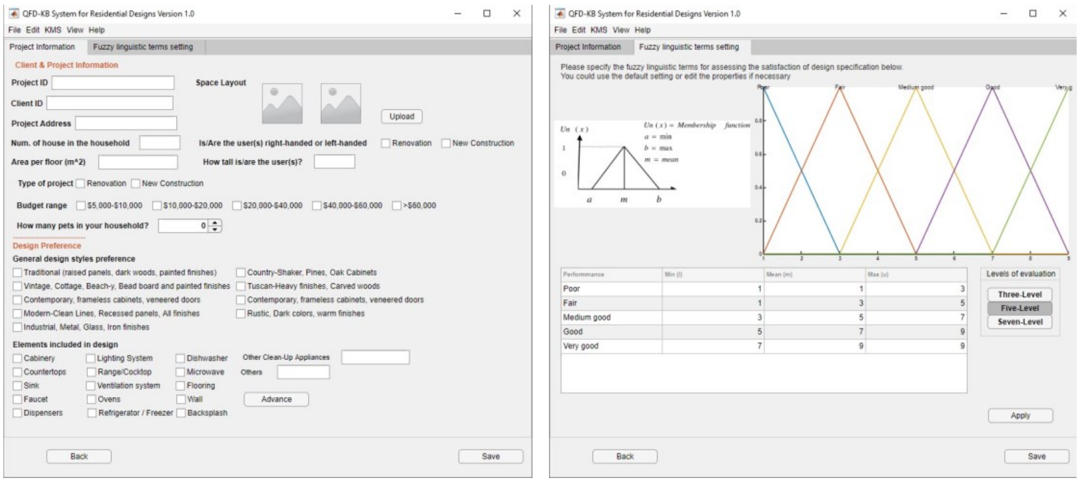
The effect of design specifications on user requirements was then assessed in a relationship matrix based on consensus among the design experts. By solving the fuzzy relationship matrix, the relative weight of the kitchen design specification could be computed for each cluster. According to the result, Group 2 showed relatively more interest in smart appliances; thus, the design specifications of “appliances equipped with sensors” (DS71) and “appliance could connect to internet” (DS72) obtained higher relative weights during the analysis. Likewise, Group 3 was tagged with a “pragmatist” user persona, where the focus was on the most essential functions of kitchen design. Accordingly, the design specification on the cooking landing area and sink landing area had higher priority.

Step 6: Develop knowledge-based kitchen design decision support system

Following the above steps, a knowledge-based decision support prototype system was developed to evaluate potential user satisfaction with design alternatives.

With this system, the decision maker was first required to enter the basic information of the kitchen design project, as shown in the actual screenshots in Figure 3-9a, and to define the linguistic evaluation scale to be used in assessing the fulfillment level of the design specification (see Figure 3-9b) using a three-level (poor, moderate, and good) or five-level (poor, fair, medium good, good, and very good) linguistic evaluation scale. A finer granularity of linguistic terms (i.e., seven-level linguistic scale) should be used if the decision maker has more knowledge regarding the kitchen design specifications and less uncertainty regarding the performance evaluation to be made.

After the preparation setup, the system entered the ‘Quick Design’ module. This module had the decision maker go through the personas of each user group (see Figure 3-10a) to determine which user personas appropriately describe the potential user of the kitchen. Four user personas were outlined in this case study: Group 1 – demanding user, Group 2 – technology lover and high demand on ergonomic comfort, Group 3 – practical user emphasizing the functionality of kitchen, and Group 4 – user with the most essential needs.



a b

Figure 3-9. GUI of preparation setup for project information and linguistic evaluation scale.

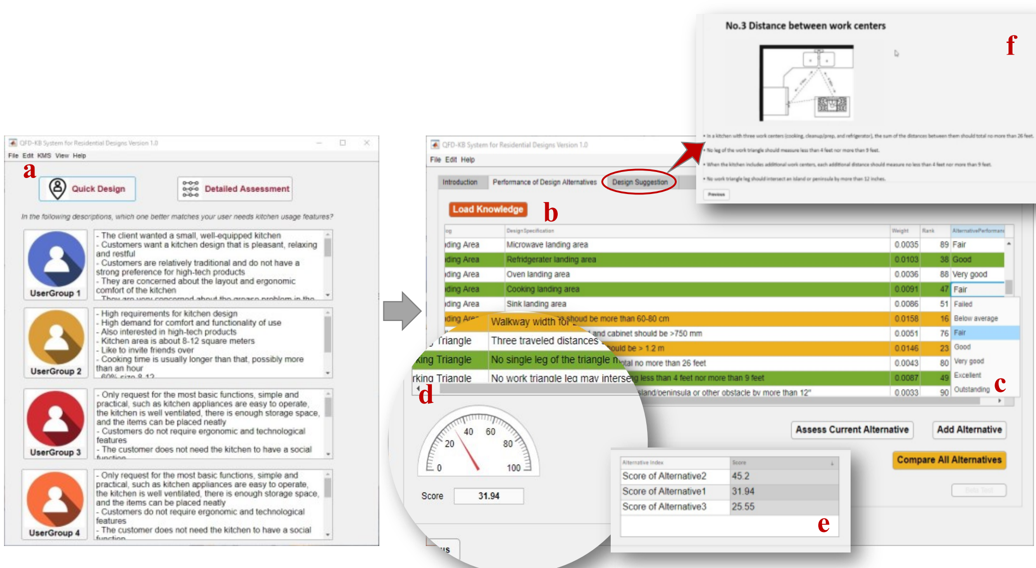


Figure 3-10. GUI of KBDSS for user-centered designs assessment.

Depending on the user group, the system retrieved the relevant information on design specifications from the knowledge base (see Figure 3-10b). Because KBDSS was also expected to help decision makers understand kitchen design and assess the effect of implementing a design, the top-50 design specifications ranked in the order of importance were marked in green, and those ranked in the top 20 were marked in yellow to highlight the design specification with greater effect on user satisfaction. The decision maker then rated the performance satisfaction of users with the design alternatives considering the fulfillment level in the design specification items, in the form of the fuzzy linguistic term, as shown in the list (see Figure 3-10c). The final score of each design alternative was individually shown in the left corner of the gauge (see Figure 3-10d), and a comparison among the design alternatives was demonstrated in table of Figure 3-10e. By obtaining the performance of design alternatives in the form of numeric scores, the decision maker could determine the optimal design alternative in a straightforward manner. Notably, all evaluations with regard to design specification criteria (i.e., the rating of design criteria for each alternative) were recorded and stored in a database that could be used for further analysis.

Further, if the decision maker had any uncertainty regarding the design criteria during the evaluation process, they could always refer to the "Design Suggestion" module (see Figure 3-12a) to access the related knowledge. This knowledge included the design guideline and specification for each design criterion, allowing the decision maker to measure the performance parameters of kitchen design, as shown in Figure 3-10f.

3.4.2 Validation and Result Analysis

To validate the performance of this KBDSS, the design evaluation results from the decision support tool and those analyzed by senior design experts in an experiment were compared.

Experimental validation

Four MURB kitchen design alternatives (see Figure 3-11) proposed by three prominent real-estate developers in China were chosen as the experimental subjects. Generally, the room areas in these kitchen designs are approximately four to six square meters, and their target housing market position as well as their unit construction cost are similar. The designs were proposed by the developers based on their understanding of the users' kitchen requirements, and all designs had been adopted as universal design plans in actual building projects. Thus, it is interesting to investigate how these designs could be assessed within different user groups. Moreover, a sensitivity analysis could also be conducted using the evaluation results to determine the effect of changing the weight of design criteria on the ranking of design alternatives for different user groups.

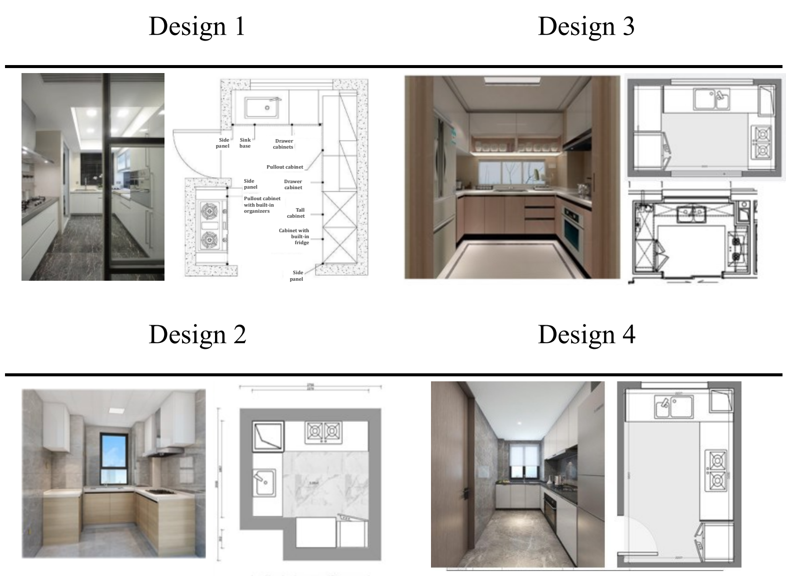


Figure 3-11. Design alternatives

During the experimental validation, the research team acted as a junior decision maker to rate the performance satisfaction with the four kitchen designs for each user group. Utilizing the quantitative tool in the knowledge base for criteria assessment, few conflicts were found among the team's performance assessment of the design criteria. Thus, the team's opinions (i.e., fuzzy number sets) were aggregated through the average-value technique. Notably, the kitchen design specification included during the design evaluation should be associated with the existing design elements, and there is no need to exhaustively go through all design specifications.

Meanwhile, the four senior design experts introduced earlier were invited to assess the appropriateness of the design alternatives in a pairwise comparison (i.e., AHP method) and rank the preferred design alternatives for each user group based on their background. Therefore, the ranking of design alternatives generated from the DSS could be analyzed along with the ranking result provided by experts.

Result analysis and discussion

Table 3-4 lists the evaluation of design alternatives conducted with the proposed KBDSS, and Table 3-5 presents the ranking of design alternatives among various user groups suggested by the design expert through a pairwise comparison method. The most appropriate designs for user groups using the knowledge-based decision support tool are Design 3 for Group 1, Design 4 for Group 2, Design 3 for Group 3, and Design 3 for Group 4.

Overall, the KBDSS ranking results agree with the rankings recommended by the design experts, which suggests that the proposed KBDSS could successfully use the collected knowledge and relevant analytical models to support the decision maker in making sound judgments. From a sensitivity analysis point of view, the rankings of design alternatives (see Table 3-4) suggests that the different weights assigned to the design specification under different user group settings result in changes in the final ranking of design alternatives. Groups 1 and 3 have the most similar weight distributions among the design specifications, and the same rankings results are obtained in these two user group settings. This indicates that the ranking of the sensitivity analysis is in good agreement when considering closeness (Yazdani et al., 2017). Notably, Design 3 and 2 generally have the most stable ranking positions (the best and the worst options) under various user group settings. Thus, the decision maker could be very confident that Design 3 fulfills the design requirement for universal users, whereas Design 2 may likely fail in providing a satisfactory kitchen space, considering changes in the current user requirement.

Table 3-4. Rankings of design alternatives for user groups determined by the knowledge-based decision support system.

Alternatives	Group 1		Group 2		Group 3		Group 4	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Design 1	61.61%	3	60.70%	3	60.75%	3	62.70%	2
Design 2	53.30%	4	52.78%	4	54.01%	4	53.74%	4
Design 3	**65.20%**	**1**	63.92%	2	**65.27%**	**1**	**65.25%**	**1**
Design 4	63.64%	2	**64.00%**	**1**	64.26%	2	62.51%	3

Table 3-5. Ranking of design alternatives through pairwise comparison.

Alternatives	Group 1		Group 2		Group 3		Group 4	
	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank
Design 1	0.15	3	0.11	3	0.11	3	0.25	2
Design 2	0.06	4	0.06	4	0.06	4	0.08	4
Design 3	**0.58**	**1**	0.27	2	**0.55**	**1**	**0.43**	**1**
Design 4	0.21	2	**0.56**	**1**	0.29	2	0.24	3

In addition, feedback from the decision makers on the design of the KBDSS was sought. The team members recognized the value of the developed KBDSS in helping laymen with little background knowledge better understand the manifold selection criteria to be considered in the selection of design alternatives and the rationale behind the assessment of design requirements. Thus, with the aid of this DSS, the decision maker can make a rational decision in a more effective and straightforward manner.

3.5 Conclusion

A novel and systematic KBDSS methodology is proposed in this study to facilitate decision-making for user-centered residential design. This proposed system improves the efficiency, quality, and consistency of UCD decisions by providing less experienced design practitioners with specific knowledge about decision problems and assisting them in consistently assessing the quality of design alternatives.

In this proposed framework, the Kano model is incorporated with clustering technologies to facilitate user segmentation and enable design decisions that provide a higher degree of satisfaction among a wider audience. The incorporation of a fuzzy inference engine in QFD implementation addresses the uncertainty and subjectivity problem in the design selection and assessment process to enhance the consistency of the decisions. To illustrate the proposed framework and test the validity of the KBDSS, a case study of MURB kitchen design is demonstrated along with the application of the developed prototype system.

The results showed that the proposed KBDSS can provide a consistent assessment of the design performance while mitigating the identified challenges in UCD, such as the inadequate consideration of user requirements and the failed translation of user requirements into design specifications. Using the proposed KBDSS, complex design assessment tasks for user centered residential design can be simplified—from the overall design to the detailed evaluation of individual design specification. Moreover, the proposed KBDSS can help design practitioners understand the rationale behind the performance of design specifications and their effects on overall design quality. The research findings can contribute to a better understanding of design decisions for the built environment and represent a further step towards developing a systematic and scientific methodology for user-oriented built environment design.

Despite its contributions, this study has several limitations. First, due to the limited data collection in the case study, our personas of kitchen users were not exhaustive. In addition, considering the changing environment, the dynamics of user needs should be featured in future studies and conflicting opinions among group members should be addressed. Further, this research is limited to the residential environment. An extended application to other building types is highly recommended for a future study to establish a robust KBDSS for UCD in built environments.

Chapter 4: ONTOLOGY-BASED KNOWLEDGE MANAGEMENT FOR HUMAN-CENTERED RESIDENTIAL DESIGN[3]

4.1 Introduction

Built environments have significant impacts on our physical and psychological wellness, work and learning performance, social behavior, and many other building-related behaviors (Du et al., 2018). With the extended amount of time that people spend indoors, user-centered design (UCD), which optimizes the environment around occupants' capabilities and preferences/requirements rather than forcing the user to adapt to the design, has been strongly recommended for built environments to facilitate a comfortable living experience and provide greater user satisfaction with the building project. In practice, an effective user-oriented design is expected to satisfy a desired set of requirements, even if they are not explicitly specified by the current user but could be inferred from existing documentation and previous experience. This necessitates the participation of relevant expert stakeholders to comprehensively identify design requirements, users' capabilities, and methods for evaluating design decisions following specific design objectives (Hagedorn et al., 2016).

However, the extensive multi-disciplinary knowledge involved in built environment design makes it incredibly difficult for stakeholders to retain all necessary details and collaborate their knowledge in each decision-making process. The stakeholders frequently acquire information from external sources, such as documentation, drawings, models, information systems, or other professionals. Such collaboration and knowledge exchange between entities (humans, documentation, or

[3] A version of this chapter has been submitted to Journal of Building Engineering.

machines) reveals a strong motivation to improve the efficiency of knowledge sharing and reuse while eliminating the misunderstandings and missing data (Hagedorn et al., 2016). In accordance with existing studies, knowledge reuse in the design domain, such as providing design recommendations or case-based reasoning among existing design cases, can significantly reduce product development time and cost, with designers streamlining the design process if they have easy access to all necessary design information (Sarder, 2006). In recent decades, attempts have been made in assisting designers in pursuing informed decision by providing necessary information, storing design objectives, and predicting the performance of alternative solutions (Afacan & Demirkan, 2011; Guerrero et al., 2022; Singhaputtangkul et al., 2013). For instance, Afifi et al. (2014) proposed a decision model to analyze the falling risk associated with the architectural design of staircase elements in order to recommend best practices for creating elderly-friendly designs (Afifi et al., 2014). Heydarian et al. (2017), likewise, developed a data-driven model to optimize the designs around the occupant's behaviour related with lighting preference (Heydarian et al., 2017). These studies recognized that the effectiveness of information and knowledge support substantially influences the quality and creativity of the design process and its outcomes.

However, despite the presence of numerous studies on generating and capturing design rationale to address complex built environment design challenges, the knowledge share and exchange still remain inconvenient and inefficient in current design practice, particularly when addressing the diverse requirements of occupants and the huge collection of design alternatives. Moreover, the context of built environment design is constantly evolving in accordance with social development. The variation caused by different lifestyle paradigms, climate change, demographic change, and the development of building technologies is also expected to be reflected in decision-making of built environment design for fulfilling the evolving demands of occupants (Lee & Ha, 2013). In this regard, a knowledge-based system that provides formalized design knowledge with flexible data schema is expected to provide up-to-date knowledge for relevant decision support and eliminate the ambiguous language among various stakeholders for enhancing the quality of user-focused residential design (Guo & Goh, 2017; Xing et al., 2019).

The development of ontology is typically regarded as the initial step in developing knowledge-based systems. As one of the emerging semantic web technologies, ontology has been widely used to represent knowledge across a variety of domains, and thereby providing a common understanding of information structure and domain knowledge for further intelligent-based decision support (Asim et al., 2018; Gao et al., 2018; Liu et al., 2016; Shue et al., 2009). Generally, ontology is defined as "an explicit specification of a shared conceptualization." It formally represents knowledge by defining the categorization (taxonomies), properties, and axioms (limitations) of relevant concepts and establishing the logical relations between concepts in a particular domain, enabling information integration, retrieval, and reuse in a machine-readable format (Zhong et al., 2019). In recent decades, numerous ontologies have been proposed in the domain of architecture and building to represent the dispersed knowledge of numerous disciplines, such as the ontologies for building environmental monitoring (Zhong et al., 2018), active fall protection system design (Guo & Goh, 2017), building and infrastructure construction (El-Diraby, 2013; El-Gohary & El-Diraby, 2010), concrete bridge rehabilitation (Wu et al., 2021), and the ontologies describing occupant behaviour in buildings (Hong et al., 2015; Putra et al., 2021). These applications of ontology technology denote its important role in representing and reusing knowledge semantically. Putra et al. (2021) also suggested that ontology is helpful in information integration, since it is more flexible and extensible in knowledge representation compared with conventional data schemas, making them better options to store knowledge that requires timely maintenance and updates. As a formal and explicit specification of a shared conception of domain knowledge, domain ontology is thus an essential component for knowledge-based systems in user-centered residential design.

To the author's knowledge, however, no ontology has yet been developed to comprehensively describe the knowledge of user-oriented residential environment design. To fulfill this research gap, this chapter proposes a domain ontology, being called UCRD-Onto, to describe the knowledge of human–building interactions and the domain of residential design. This proposed ontology is expected to capture the user-centered residential design knowledge from multiple disciplines and store the domain knowledge in a formalized and explicit format, allowing relevant knowledge to be efficiently shared and exchanged between different stakeholders and generating a machine-understandable vocabulary for the development of intelligent design support systems.

4.2 Methodology

Concerning the application domain and context of UCRD-Onto, an ontology development methodology (see Figure 4-1) is proposed in this study combining METHONTOLOGY and Ontology 101, the two most matured and widely used ontology development approaches (Guo & Goh, 2017; Xing et al., 2019). The proposed methodology enables the building of domain ontology from scratch and independent the development process from the uses of ontology so that the developed ontology is not limited by its application systems (Guo & Goh, 2017). In this study, ontology development could be illustrated in nine steps and divided into three stages: specification, ontology development, and evaluation. A detailed discussion regarding the user-centered residential design ontology development is presented in the following steps.

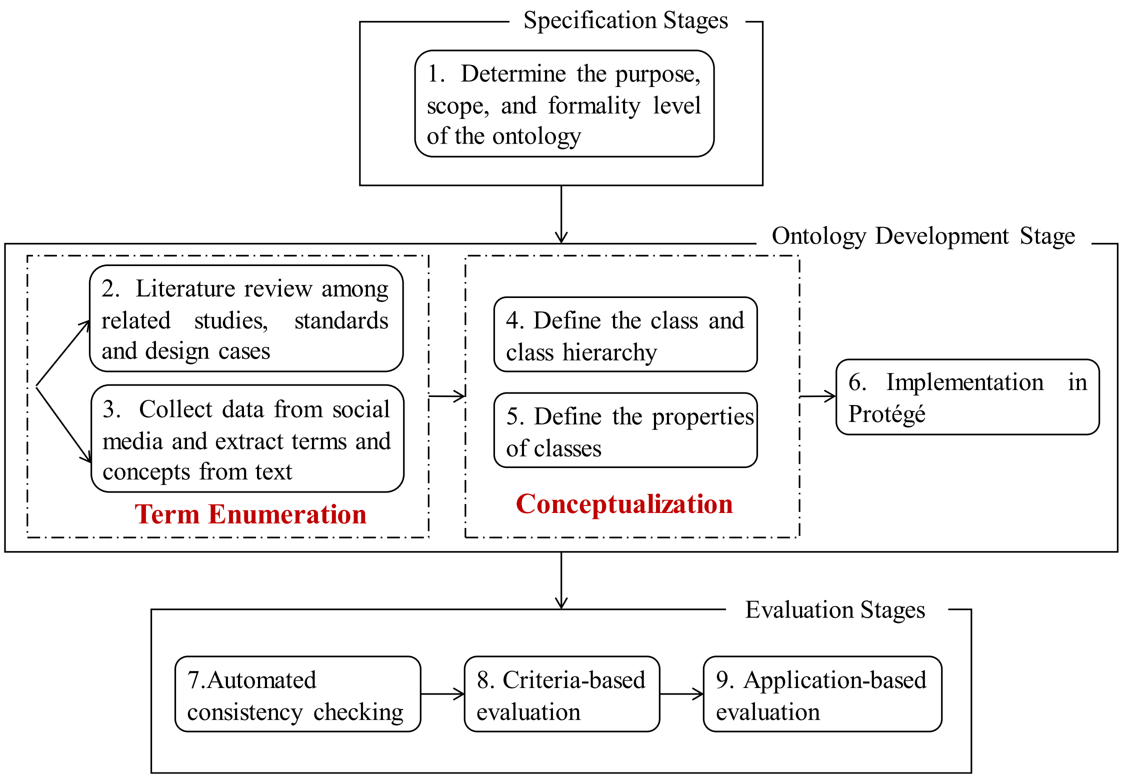


Figure 4-2. Development process of HCRD-Onto.

Step 1 Determine the purpose, scope, and formality level of the ontology

Prior to the ontology development, it is necessary to determine the purpose, scope, level of formality, and intended users of the domain ontology to be developed. Thus, a list of basic and competency questions is established in Step 1 to help identify the domain and scope of ontology. These questions include, but are not limited to:

Q1: What is the purpose of this ontology?

A1: To formally represent the knowledge of residential design, along with the occupants' needs and design constraints, across a variety of contexts.

Q2: What type of built environment will be covered in this study?

A2: Residential buildings.

Q3: What is the domain of ontology?

A3: This ontology comprises the basic concepts of residential design, as well as their interrelationships, the requirements in support of indoor activities, intended physical feelings, and psychological experience. It does not include the design of the building's construction (i.e., the envelope of buildings).

Q4: Who is the user of the developed ontology?

A4: Decision makers of residential designs, such as the designer or the homeowner

Q5: What information should be captured in the ontology?

A5: The information includes (1) the design settings for residential environments, such as design elements and their properties, space configurations, and design options; (2) the requirements toward residential environments concerning occupant's behaviour and experience; (3) the relationship between the requirements and the design settings; (4) the information related to design standards and building codes.

By answering these questions, an ontology design specification could thus be generated, serving as a guideline for the overall ontology development process. Generally, this ontology aims to inform design decision-makers on the design elements and the requirements to be considered for a user-centered residential design, as well as appropriate design options concerning their different characteristics. This ontology encompasses numerous stakeholder perspectives, such as those of occupants, architects, structural engineers, psychologists, and even health or human factors practitioners.

Step 2 Term enumeration from literature review

By having the ontology's scope and objectives, the next step is to enumerate terms in the ontology by acquiring knowledge from the domain of interest. In this case, the main knowledge source in this stage includes research on human–building interaction, residential design, environmental comfort, residential design cases, and design standards and regulations. Knowledge acquisition from multiple sources can help the developed ontology become more relevant, representative, and comprehensive. Specifically, relevant terms and concepts retrieved through literature review on research reports, to some extent, represent the formal language of design knowledge communicated within the general academic community. In addition, the documentation of design cases reveals how design practitioners process different design requirements and how they communicate the knowledge of residential environments with other stakeholders. By reviewing this documentation, a number of important terms of UCRD-Onto could be derived. In addition, standards and technical manuals focus on residential building design are also referred as complementary resources for knowledge acquisition. These standards include residential building code GB 50368-2005, national code for design of the residential interior decoration JGJ367-2015; fundamental parameters for kitchens and related equipment in housing GB/T 11228-2008; kitchen and bathroom planning guidelines with access standards by national kitchen and bath association; accessible and usable buildings and facilities ICC/ANSI a117. 1. These codes and standards specify the essential requirement for residential design, representing structured expert knowledge and industry norms in the domain.

Step 3 Term extraction from social media data

To satisfy the informational needs of design practitioners with different professional levels, it is also necessary to emphasize the viewpoint of layman users with little design knowledge in UCRD-Onto. Researchers suggested that social media data, as a form of passive crowdsourcing, could advance abstract idea-collection on public opinions and perceptions (Wan et al., 2021). The user-generated content shared on the social media platform and the conversations among people online may represent a voice of the public in a more accurate manner, since this content is usually created without initiation, stimulation, or moderation (Browarnik & Maimon, 2015). Compared with conventional knowledge acquisition methods that explicit concepts and relations from small and structural information sources (e.g., reports and standards), ontology learning from social media content instead tackles the massive heterogeneous data online from which manually building ontology is highly labor-intensive and time-consuming. To enable knowledge acquisition from social media data, a co-occurrence-network-based analysis method (see Figure 4-2) for domain term extraction is adapted in this step following the existing research on natural language processing (NLP) (Asim et al., 2018). The statistical co-occurrence analysis locates the term units that occur together in pursuit of extracting related terms with high frequency and finding the implicit associations between various terms and concepts.

To begin with, data collection is performed through web content scraping from specific social media platforms and online communities where people popularly share their home design ideas. User-generated posts on Xiaohongshu (a Chinese social media) and Houzz (an American online community) are chosen as the term extraction source in this study because of the unique target community of design, architecture, and home improvement of these two platforms, and their adequate active users for analyzable data in Chines and English language respectively. According to the literature review findings (Step 2), the information and knowledge related to residential design are usually divided based on the functional rooms, such as kitchen, bathroom, living room, concerning their different functions and attributes. Thus, the keywords related to different rooms (e.g., “bathroom,” “bathroom design,” or “shower design” for bathroom design knowledge) are used to query the relevant contents. Once the corpus data is collected, text pre-processing is subsequently performed following conventional NLP pre-processing techniques, i.e., (1) breaking the raw text into the list of words (Tokenization), (2) normalizing words into their basic or root form (Stemming), (3) reducing the word to its lemma (Lemmatization), and (4) finally removing the stop words. It should be noted that the middle two NLP procedures (i.e., text stemming and text lemmatization) are only applied in English language processing. NLP toolkits in Python, including NLTK (Natural Language Toolkit) Library and Jieba (a Chinese word segmentation tool), are used for English and Chinese language pre-processing, respectively. Likewise, the user-generated posts online usually consist of internet slang and emoji; thus, an adapted stop word list containing these slang and unusual characters is used to filler out the stop word in text pre-processing.

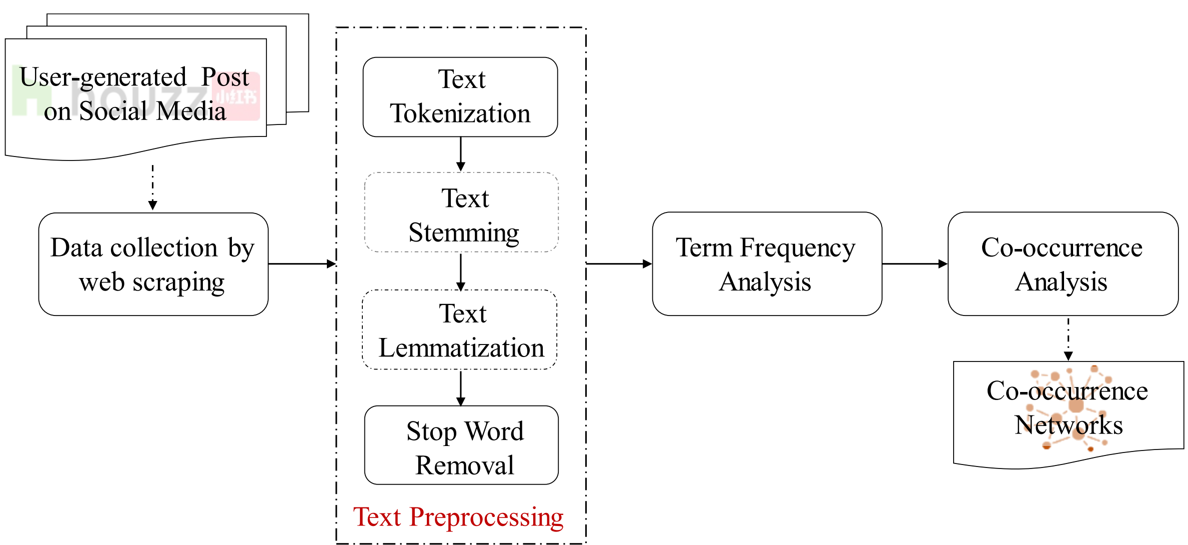
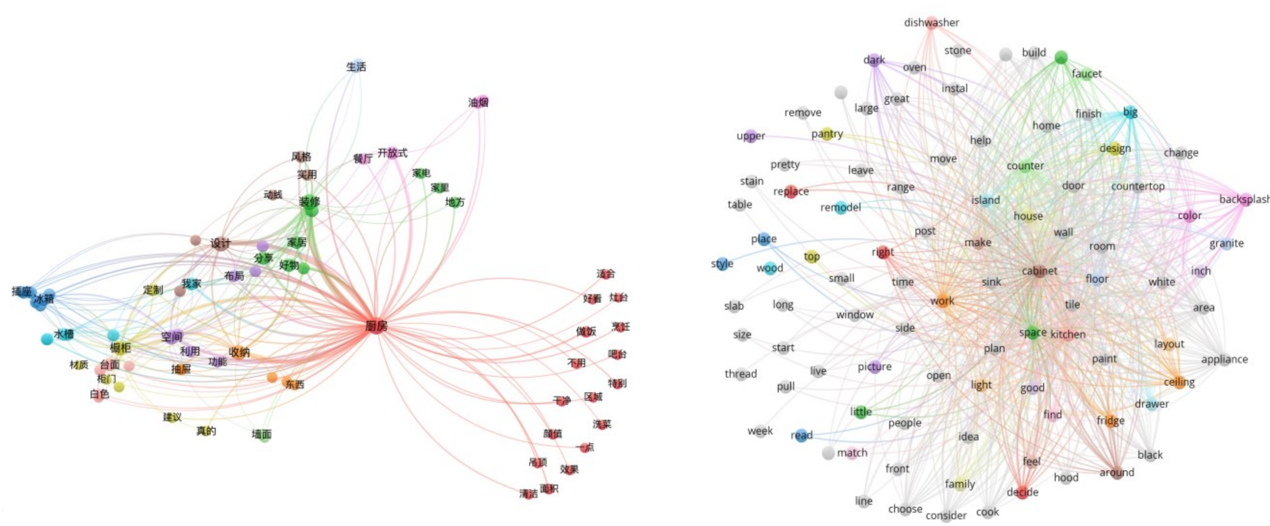


Figure 4-2. Co-occurrence networks development from social media data.

By far, the user-generated text of each post is converted into a list of terms. Based on that, the frequency of terms and the set of collocates of which terms with significant frequency appear in the same context are to be calculated and presented in a matrix manner. To efficiently capture the domain terms and concepts from the co-occurrence analysis, visualization of the co-occurrence network is generated where the dimension of node represents the frequency of the term, and the thickness of the line reflects the affinity of terms. Figure 4-3 shows an example of co-occurrence networks generated from kitchen design posts in Chinese social media (Xiaohongshu) and English online community (Houzz) respective, where each co-occurrence network is created from more than 1000 corpus (posts). The terms with higher frequency and centrality (i.e., larger nodes with many connections) may be chosen in UCRD-Onto to represent how people online describe this type of design knowledge (e.g., cabinet, floor, light, appliance, window, pantry). Besides, the collocates of terms with close affinity jointly form a cluster of relevant terms, which is helpful in concept extraction from a linguistic or textual perspective (Browarnik & Maimon, 2015). For instance, activities, such as storage, cooking, cleaning, and food preparation, are the most frequent terms when people discuss the kitchen design, according to the Chinese co-occurrence network (Figure 4-3a).



a) Chinese Co-occurrence Network

b) English Co-occurrence Network

Figure 4-3. Example of co-occurrence network on kitchen design.

Step 4 and 5 Concept definition and conceptualization

By enumerating domain terms and extracting residential design-related concepts in previous steps, this section aims to develop a concept hierarchy (taxonomy) of UCRD-Onto and define the properties of concept classes. These two steps are closely intertwined and usually performed in a reciprocating manner (Natalya F. Noy & McGuinness, 2001). In this study, a top-down taxonomy development approach is adopted to construct the concept hierarchy and determine the properties and relations among these concepts. Specifically, the researchers define the most general concept in UCRD-Onto and subsequent specialization of the concept. Then, for each concept, a set of intermediates representations that describe the data structure used by a compiler is built, which includes concept dictionaries containing all the domain concepts and instances of such concepts, tables of binary relations, attribute tables for each concept and instance in the concept dictionary, and the logical axioms tables. Note that these concepts, relations, and axioms are determined through a consensus-based discussion among the research team on the analysis of literature review and co-occurrence results.

Step 6 Implementation in Protégé

Following the intermediate representations, the taxonomy along with defined concepts and relations are coded by OWL language using Protégé 5.0 platform, a JAVA-based ontology editing tool with an open architecture. The defined concepts, properties, and relations referred are classes, data properties, and object properties in Protégé, respectively, represented by subject-property-object triplet expressions (Xing et al., 2019). In addition to its mature applications across various domains, the extensible architecture of Protégé platform also enables ontology developers to access a set of open-source API to customize their knowledge base system to have it integrated with other applications effortlessly (Shue et al., 2009).

Step7-9 Ontology Evaluation

Upon completing the UCRD-Onto development, a careful evaluation is performed to determine whether this ontology is appropriate to represent the domain knowledge of occupant-oriented residential design and its relevant applications. in accordance with the difference of ontologies and their application domains, several proper and formal evaluation criteria and methodologies have been proposed to measure the quality of ontology design, such as the 'gold standard,' data-driven, criterion-based, application-based, and application-based evaluations (Delir Haghighi et al., 2013). In this study, several factors are taken into account to determine the suitable evaluation approaches in considering the limitation of each approach and the objective of the developed ontology: (1) there is no benchmark ontology or standard measurement tool that could be referred for standard evaluation; and (2) this ontology evaluation is more focused on the correctness, clarity, and applicability of the developed ontology since this is the first domain ontology in the occupant-oriented residential environment area, which is expected to be expanded and evolved in future studies. Therefore, three ontology evaluation approaches, i.e., automated consistency checking, criterion-based evaluation, and application-based evaluation method, are adopted to assess the quality of UCRD-Onto.

First, the automated consistency checking (Step 7) is implemented using the description logic reasoner, Pellet, a third-party plug-in embedded in Protégé. It checks for lexical and syntax errors, identifies contradictory facts, and aids in bug diagnosis and resolution. Along with the incremental ontology coding process (adding new concepts and modifying old ones), the automated consistency checking will iteratively review the updated ontology to ensure completeness, consistency, and non-redundancy in the defined ontology.

Next, the content and design of UCRD-Onto will be manually evaluated using the criterion-based approach with a set of predefined criteria (Step 8). Following the existing literature, various criteria are available for ontology evaluation, as the example in Table 4-1. In considering the objectives of UCRD and its application domains, five criteria proposed by past studies (Delir Haghighi et al., 2013; El-Gohary & El-Diraby, 2010; Guo & Goh, 2017; Xing et al., 2019; Yu et al., 2005), i.e., clarity, extendibility, correctness, completeness, and coverage, are adapted to evaluate the content of UCRD-Onto. With the selected criteria, focus group discussion among expert participants with knowledge background in information technologies, building design, and human factors are considered the main form of conducting criterion-based evaluation in this study. A detailed discussion regarding the ontology evaluation criteria, along with the analysis results, is presented in Section 4.4.

Table 4-1. Example list of common ontology evaluation criteria.

	Xing et al. (2019)	Guo and Goh (2017)	Delir Haghighi et al. (2013)	El-Gohary and El-Diraby (2010)	Yu et al. (2005)
Clarity	✓	✓	✓		✓
Consistency	✓		✓	✓	✓
Extendibility	✓	✓	✓		✓
Correctness	✓		✓	✓	✓
Completeness	✓	✓	✓		✓
Coverage		✓	✓	✓	✓
Conciseness	✓		✓		✓
Minimal encoding bias					✓
Minimal ontological commitments			✓		✓

Ease of Use	✓

In the last step, an application-based evaluation is conducted to evaluate the capability of ontology by (1) deploying UCRD-Onto to describe the content of residential design cases and (2) performing the task of knowledge acquisition in an information system (Step 9). The prototype information system is developed based on UCRD-Onto with the support of an ontology API JENA, aiming to provide appropriate information support for design decision makings. By examining the application results, the competency of UCRD-Onto in knowledge description for residential design and human–building interactions could thus be demonstrated.

4.3 HCRD-Ontology

This section provides a comprehensive discussion of the concepts and definitions, semantic relations, and relevant attributes of UCRD-Onto, which were developed by following the steps outlined in the methodology section.

4.3.1 A Meta Ontology Model

As shown in Figure 4-4, a meta ontology model is first proposed as the generic knowledge hierarchy of UCRD-Onto. Four kinds of generic concepts are included to synthesize the knowledge hierarchy of user-centered residential design: (1) the requirement concept refers to the user needs in a residential setting, which are broadly categorized by three environment comfort factors, namely psychological comfort, physical comfort, and activity intended in accordance with the "environmental comfort" theory model (Vischer, 2008a); (2) the design concept represents residential design solutions, consisted with building element, space element, and placement; (3) the context concept represents the constraints or situations in which the proposed requirement is configured and determined, describing the design constraints from three perspectives, i.e., the design standard and regulatory, the constraints existing in the project, and the environmental aspect;

and (4) measurement concept represents the assessment of design quality. Following this meta model, the subsequent paragraphs present a detailed definition of concepts and relations in UCRD-Onto.

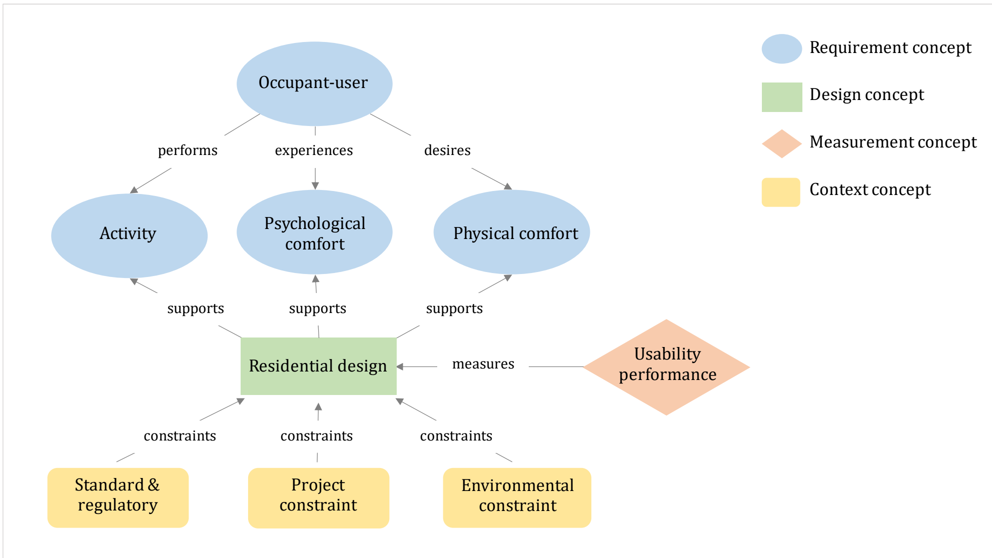


Figure 4-4. Meta ontology model.

4.3.2 **Concept Taxonomies and Definition**

Occupant-User

Occupant-user refers to the resident who intends to use or live in the space. It could be a single individual or the individuals in a household. Pertaining to ISO 9241-210 standard and the user-centered building design framework proposed by Attaianese and Duca (2012), identifying user profiling along with the specified use context is one of the critical processes in user-centered design (Heimgärtner, 2020). Thus, *occupant-user* is a primary concept in UCRD-Onto, containing relevant characteristics that might be associated with their requirements or preference in residential design.

User and *persona* are two subclasses of *occupant-user* in UCRD-Onto, representing the physical individuals and the archetypical users for which the residential environment is designed. *User* concept is usually featured by the attributes of demographic data, cultural background, and preference that influence how people interact with built environments. Besides, the health status information of users, such as impairments and specific disabilities, could be included in the analysis of accessibility requirements, so that residential design can provide such users with more appropriate environmental settings. On the other hand, the *persona* refers to the user analysis model in conventional UCD that helps the design practitioner understand the target users. Similar to *user* concept, *persona* is also defined by demographic information, physical and cognitive abilities, behaviour characteristics, and user personalities (Attaianese & Duca, 2012; Salminen et al., 2020), whereas the characteristics and design goals of *personas* are generated and defined through user clustering and segmentation on a larger group of users.

Residential Design

Residential design refers to the design solutions and configuration of interior spaces that is defined by building enclosure from the external environment in a residential built context. It is the most intimate space where our health, physical, and psychical is affectable. Generally, the design for residential interior space consists of components such as spatial plans, furniture, finishes, equipment, lighting, heating, and so on; thereby a hierarchy of design elements concepts (see Figure 4-5) categorizing these components to describe the design solutions in UCRD-Onto is illustrated below.

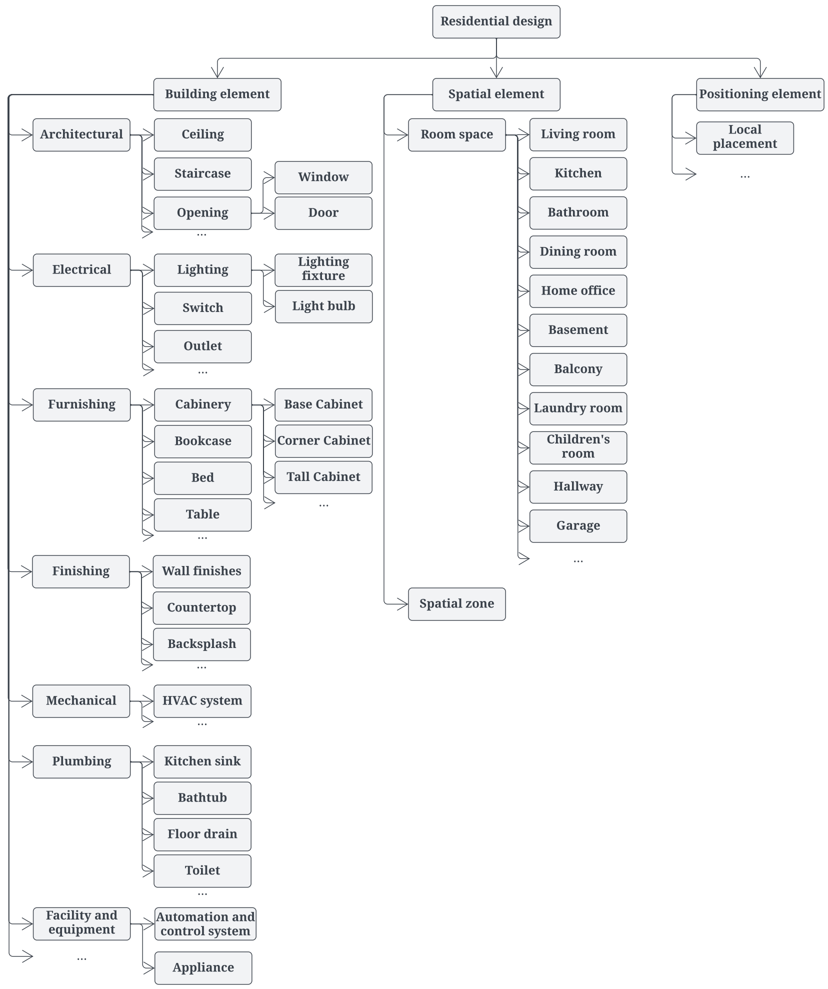


Figure 4-5. Taxonomy of residential design.

Building Element

In the context of UCRD-Onto, *building elements* is a general concept for physically existing and tangible components in a residential building system. The hierarchy of this concept is derived from Omni classification system, which is compatible with BIM software (e.g., Revit) and can be comprehended by the majority of design practitioners (Afsari & Eastman, 2016). According to the Omni classification system, the major components of *building elements* include *architectural*, *finishing*, *furnishing*, *mechanical*, *electrical*, *plumbing*, and *residential facility and equipment* as outlined in Figure 4-5. Note that the definitions of these concepts also adhere to the Industry Foundation Classes (IFC) schema, an open standard representing data related to building and construction. For instance, the *electrical* in HCRD-Onto defines the concepts of cabled systems with power supply and data transmission and the electrical devices and light fixtures connected by cabling and the protection of electrical devices.

Spatial Element

Spatial element is the generalization of all spatial elements that describe a space or spatial zones. In this definition, the *room* represents a hierarchical decomposition of spatial elements, describing an area or volume bounded actually or theoretically. Particularly, a room in the residential building is usually associated with certain functions, such as kitchen, living room, and bathroom, as listed in the taxonomy. On the other hand, the other sub-concept of special element, *spatial zone*, denotes the functional areas in a building, such as thermal zone and lighting zone, which is a non-hierarchical decomposition and may overlap with the existing subdivisions of indoor space.

Placement Element

The concept of *placement element* under *residential design* defines how the building design elements are arranged and located. Following the definition of IFC scheme, its component, *local placement*, can describes the relative position of building design elements in relation to the position of the other ones. This concept could be also used to represent the coordinate position of building design elements following the predefined coordinate system of building projects.

Activity

Activity refers to the event or task that occupants wish to perform for a purpose in an interior space. This concept is defined by the functional comfort factor in the environmental comfort model

(Vischer, 2008a) that assesses the availability of environment to support users in accomplishing desired tasks. In UCRD-Onto, the activity focuses on the routine self-care and domestic tasks expected to be performed by occupants in residential environment settings.

To comprehensively list all activities instance in the residential environment, the activity classification in the ATUS survey (i.e., a national survey studying the time use pattern of people) is referred to synthesize the relevant sub-concepts in *activity* (Fisher et al., 2018), as illustrated in Figure 4-6. Each activity could be subdivided into several sub-activities or actions for detailed requirement analysis. This detailed division also assists in depicting the interrelationship among requirement concepts among activity, physical comfort, and psychological comfort. For instance, *household activity* with certain amount of labour may be frequently associated with some instances of *physical comfort,* and the activities of *socializing & relaxing & leisure* may also fulfill requirements in *psychological comfort*.

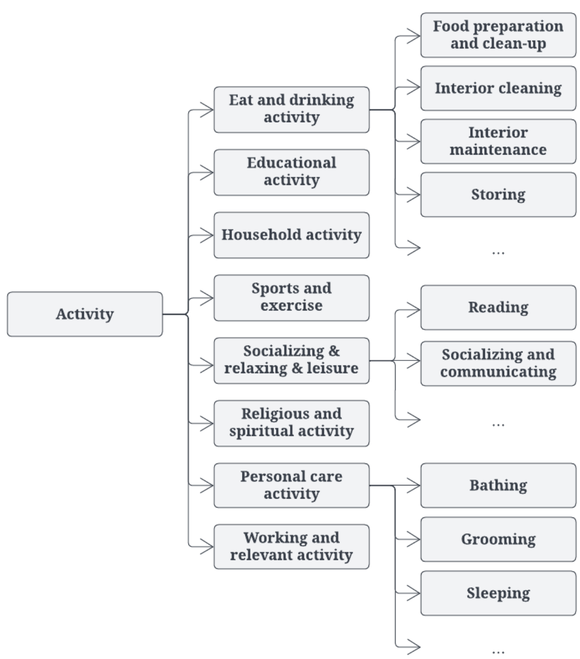


Figure 4-6. Taxonomy of activity.

Physical Comfort

Physical comfort is pertaining to bodily sensations and represents the desired experience of well-being in environmental conditions. This kind of comfort refers to the basic human needs, and is mostly specified by standards (e.g., EN-ISO 7730: 2005 and ASHRAE55-2013) which can be efficiently measured using quantitative metrics (Chen et al., 2019; Vischer, 2008a). In the context of home environments, physical comfort is defined by the perspectives of indoor air quality, thermal comfort, auditoria comfort, thermal comfort, and visual comfort, as illustrated in Figure 4-7 and introduced below.

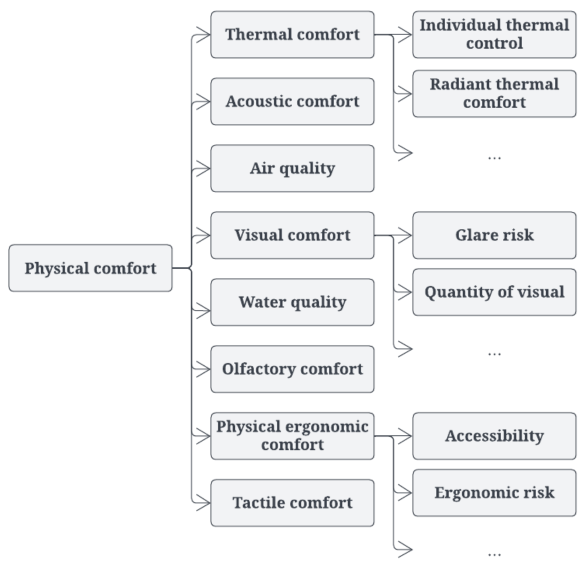


Figure 4-7. Taxonomy of physical comfort.

a) Indoor Air Quality

Indoor air quality for environmental physical comfort refers to the sensation and perception of the indoor air quality and smell, describing how good or bad the air in the indoor environment is with respect to pollution or contamination by pollutants (Adeleke & Moodley, 2015; Putra et al., 2021).

The quantity of CO2, CO, PM10, O3, NO2, relative humidity, and air velocity are usually referred to characterize indoor air quality in built environments (Chen et al., 2019).

b) Acoustic Comfort

Acoustic comfort describes the physical needs of human hearing perception to indoor noise level, against the intruding environmental noise. Such comfort results from a balance of acoustic conditions instead of the absence of all noise (Esfandiari et al., 2017); thereby, the requirement for acoustic comfort is specified by both the sound level and the room acoustics in a specific room context. Moreover, the acoustic criteria from WELL standard, such as sound pressure level, reverberation time, and sound masking, are adopted to characterize *acoustic comfort* in UCRD-Onto (Chen et al., 2019).

c) Ergonomic Comfort

Ergonomic comfort describes the physical body-related wellness, which assesses the environment with regard to its ability in injury prevention and task efficiency enhancement. Three major components, i.e., *work efficiency*, *accessibility*, and *ergonomic risk*, are included to characterize the concept of ergonomic comfort in built environment. Among these sub-concept, *work efficiency* defines the desired task and workload to be accomplished with minimal cost (e.g., time or resource) in such environmental context, *accessibility* describes the environment's capacity for occupants to access, use, and exit buildings or building elements on equal terms with other individuals, regardless of disability, age, or gender (ISO, 2011), and *ergonomic risk* refers to the potential risk of musculoskeletal disorders that are caused by certain design settings. Costa et al. (2012) suggested that the requirement for ergonomic comfort should be associated with the task and activity performed by the occupants. For example, the requirement of efficient workflow, accessibility, and lower workload pressure has been heavily emphasized for ergonomic comfort in kitchen and meal-preparation-related activities (Pinto et al., 2000).

It is to note that, sometimes, there is a blurry boundary between the comfort needs among physical, functional, and psychological. For instance, the requirement for ergonomic comfort could be either categorized into the physical comfort, or functional comfort (activity) since this kind of comfort both intends to prevent the user from injury (i.e., basic needs of safety) and support the productivity of related activity (i.e., functional efficiency).

d) Thermal Comfort

Thermal comfort represents a desired condition where people feel satisfied with the thermal environment based on subjective evaluation, i.e., not feeling either too hot or too cold (Lu et al., 2019). It is a personal experience dependent on a great number of criteria and can be different from one person to another within the same space. Even though thermal sensitivity is affected by the factors of age, gender, activity, and cultural habit, the basic principles underneath thermal comfort are largely universal. Specifically, the thermal environment can be characterized through a set of factors, including indoor air temperature and humidity, surrounding surface temperatures, indoor air velocity, activity level, incident radiation, and clothing level of the occupant (Hong et al., 2015), which are thus incorporated as the property of *thermal comfort* in UCRD-Onto.

e) Visual Comfort

Visual comfort describes the preferred subjective reaction to the quantity and quality of light within environments at a given time (Sarode & Shirsath, 2014). It is a subjective condition of visual well-being induced by certain visual environment settings. Generally, the visual quality of space can be determined by factors including: the sources and quality of light, the distribution of light within the space, and the human perception (i.e., physiology of the human eye). In the context of residential environments, the requirements of visual comfort for artificial lighting settings are usually specified with the functional intention of supporting specific activities and atmosphere rendering. Several index properties, such as luminance contrast ration, unified glare rating, and illuminance, are adopted from a visual comfort review to characterize *visual comfort* in our ontology (Carlucci et al., 2015).

f) Tactile Comfort

Tactile comfort describes the skin's sensational comfort based on the mechanical contact of the fabric with the skin (Taieb et al., 2010). Although few studies on tactile comfort were observed in the field of environmental comfort-related study, Ellsworth-Krebs found in their survey that many occupants indicated their needs toward the tactile experience provided by the furniture as being pleasing to the touch (Ellsworth-Krebs et al., 2019). Thus, this kind of comfort is included in UCRD-Onto for completeness purposes.

Psychological Comfort

Psychological comfort refers to the desired wellness state that is archived by filling psychological, mental, affective, and feeling-related needs with passive environmental support. According to the definition by Leal (1986), psychological comfort is a positive feeling free of extreme tension or pain, a sense of relaxation, self-esteem awareness, and an accepting attitude toward others. As for residential environments, the psychological expectation is usually associated with terms such as companionship and attachment, relaxation, and sense of control, relaxation (Ellsworth-Krebs et al., 2019). However, in compared with the studies on physical comfort, the requirement for psychological wellness is rarely explicitly mentioned in the relevant literatures.

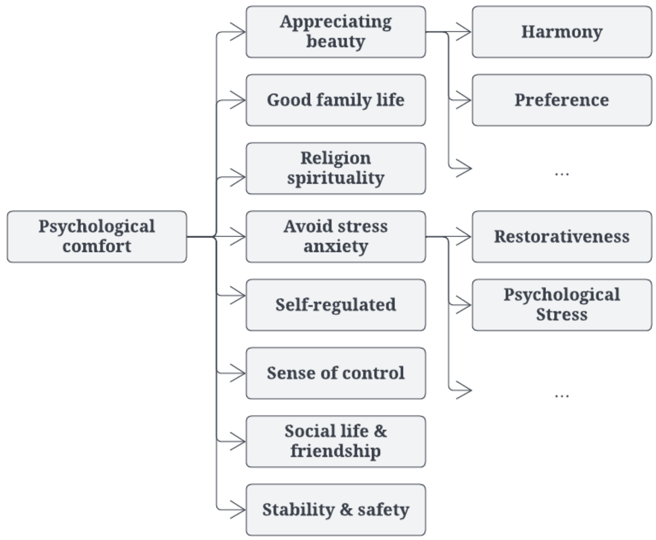


Figure 4-8. Taxonomy of psychological comfort.

This study adopted the taxonomy of human psychological motives in Talevich et al. (2017) to synthesizes the components under psychological comfort concept in UCRD-Onto (see Figure 4-8) (Talevich et al., 2017). For instance, *social life and friendship* is used to describe the intended feelings of attachment and companionship, expecting an affective experience bond with a particular group or scenario. In the context of the dwelling scenario, an ideal experience is mostly depicted to be shared and has features that enable householders to accommodate guests. *Feeling of relaxation*, on the other hand, is associated with a pleasant emotional state of low tension and being absent of stress, anxiety, or fear (Ellsworth-Krebs et al., 2019). The perceived restorativeness in environments is an instance of such affective experience that denotes the mental recovery process from mental fatigue (Kals & Müller, 2012; Kaplan & Kaplan, 1989; Kopec, 2017). Moreover, the desire for *appreciating beauty* also plays an essential role in built environment design in addition to the affective needs of relaxation, accompany, and social support. This experience is a psychological process in which the attention is attracted to the object, while all other objects, events, and everyday concerns are suppressed (Marković, 2012). Theoretically, the perception of aesthetics in built environment is usually associated with the principles of harmony, proportion, style, balance, and variety (Alfakhri et al., 2018).

Constraints

A constraint in the HCRD-Onto is something that limits or controls how the residential environment could be designed. It is imposed on design solutions and restricts the range of design solutions that can be configured and adopted. The taxonomy of design constraints in the present ontology is adopted from the category in Niemeijer (2011), of which the constraints is divided into legal constraints, environmental constraint, and project constraint based on their different imposing sources.

a) Standards and Regulatory Frameworks

The concept of *standards and regulatory frameworks* represents the legal constraints specified in relevant laws, regulations, and building codes that should be adhered by the design solutions. These constraints commonly focus on safety and security protection, hazard elimination, and accessibility compliance. Examples of standard and regulatory constraints for residential design include the code for the design of residential interior decoration JGJ367-2015, the design code for residential buildings GB 50096-2011, the code for fire prevention in the design of interior decoration of buildings GB 50222-2017, and residential building code GB 50368-2005.

b) Environmental Constraints

Environmental constraints represent environmental conditions or impacts that must be considered when performing the residential design. For instance, the designs of residential environments should concern the regional climate characteristics and the resilience of climate change as well as the environmental impacts of decisions in consequent energy consumption, carbon emissions, and air pollution (Dili et al., 2010; Tian et al., 2018; Zhang et al., 2019).

c) Project Constraints

Project constraints restrict factors related to the building project, such as the resource allocation of time, budget, workforce, and the space and layout limitations caused by architectural and structural designs. Besides, due to the property of materials and the feasibility of interior construction methods, the technical constraint is also included as a component of project constraints. These project limitations can influence how the user requirement is fulfilled and how built environments could be designed in practice.

Usability Performance

Typically, design decisions are based on achieving a balance between multiple objectives, and sometimes a well-designed residential environment may still fall short of achieving certain requirements to a level of complete satisfaction. To understand the limitations of implemented design solutions, the measure concept, *usability performance,* is incorporated in UCRD-Onto to assess the usability performance of residential design solutions and provide a more comprehensive picture of UCD in residential environments. This concept is used to evaluate the built environment based on the expected performances and fulfillment levels for specific user requirements (i.e., intended activity support, psychological comfort supports, and physical comfort supports) after a residential design solution has been implemented. For instance, WELL Building Standard is an instance of *usability performance*, which assesses the building performance based on its impact on human health and well-being (International WELL Building Institute, 2015).

4.3.3 Semantic Relations

Semantic relations, as an essential part of ontology, describe the meaningful association between concepts. The linkages of concepts enrich their definitions and refine their context in knowledge interpretation (El-Diraby & Osman, 2011) improving ontology's expressiveness and linguistic aspects. It is believed that ontology can embed some tacit knowledge of concepts in their relationship with other concepts (El-Diraby, 2013). In UCRD-Onto, the semantic relation can be categorized into three types as discussed below:

1) Hyponymy (is–a) relations: this taxonomic relation defines the category or type of a concept. It is associated with two varieties of variances: (1) representing additional means for describing types and categories, or (2) defining a concept's category or type by excluding it from a certain domain, such as <is_similar_to> and <is_disjoint>, respectively. The UCRD recognizes the following is–a relations examples: Base Cabinet for Sink Base <is_a> a Base Cabinet, and Base Cabinet <is_disjoint> with a Wall Cabinet.
2) Meronymy (whole–part) relations: this relationship illustrates the connection between a concept and its constituent element. For example, in UCRD-Onto, Cabinet <has_part> Cabinet Frame. It is related to its reverse relation <part_of>.
3) Descriptive relation: this relationship explains the essence and behavioural context of concept. The primary descriptive relations in UCRD-Onto include the attributive relation, the contingency relation, the conformance relation, and the requirement relation.
    a. attributive relation identifies the characteristics of concepts, and it is typically highlighted by generic verb phrases containing 'has. As an example, in UCRD-Onto would be Building_Element <hasPlacement>Local_Placement.
    b. contingency relation describes cause-and-effect relationships with causative verbs like "support, namely, <supportActivity>, <supportExperience>, <supportFeeling>, which are inverse of <isSupportedBy>, <isStimulatedBy>, and <isInfluencedBy>, respectively. For example, Space_Element <supportFeeling> of Physical Comfort.

c. conformance relation represents a constraining relationship between concepts. As an example, Standard&Regulatory <constraints> Placement_Element.
d. requirement relation establishes a connection between the condition or capacity that must be met or possessed by the residential design and the occupant. This is accomplished through verbs like <perform>, <experience>, and <desire>.

4.3.4 Property

The concept alone cannot provide sufficient information to achieve the purpose of the UCRD-Onto. Thus, following the definition of taxonomy and relations, the properties of concept (attributes) are described to locate the necessary information of ontology. This property definition is helpful for the residential design specification and reasoning because the involved design elements and requirements are usually characterized by multiple properties (El-Gohary & El-Diraby, 2010; Guo & Goh, 2017), such as the dimensions and luminance level for lighting fixtures, the riser height and stair length for staircases, and the duration and intent for activity-related requirements. Besides, it also enhances the efficiency of knowledge management by providing more information for the semantic search of relevant entities via their properties (El-Gohary & El-Diraby, 2010). Different data types could be taken to represent property values, such as integer, float, string, and Boolean types.

Figure 4-9 outlines some examples of properties attached to the concepts in UCRD-Onto. These properties are retrieved through previous literature reviews on human–building interaction studies and design standards, which may be essential for design configurations and may have an impact on human experience. It is to note that all subclasses of a concept inherit the property of the concept. For instance, all properties of *room*, such as area, height, length, and width, will be inherited by all subclasses of *room*, including *kitchen*, *living room*, and *bathroom*. Thus, a property should be attached to the most general concept that has that property (Natalya F. Noy & McGuinness, 2001).

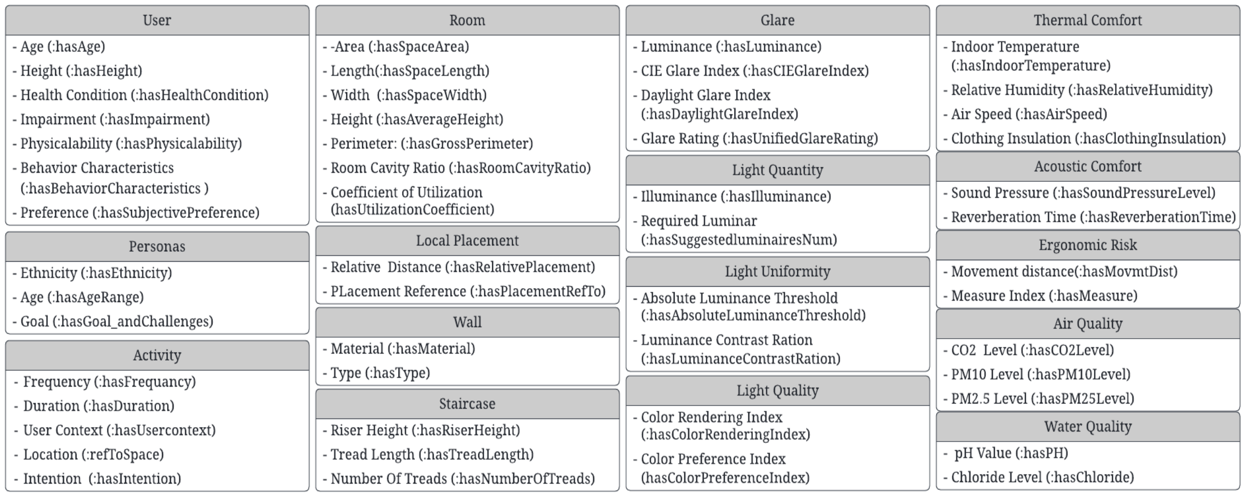


Figure 4-3. Examples of concept properties.

4.3.5 Axioms

Each ontology has three major components: taxonomy, relations, and axioms. Axioms specify the logical rules and formal assertions used to define the semantic context of concepts and relations in the domain, thereby limiting how they can be interpreted (El-Diraby, 2013; El-Gohary & El-Diraby, 2010; Guo & Goh, 2017). The axiom can define the meaning, scope, and even criteria of concepts and relations via formal logical expressions in natural language and first-order logic (FOL). Such specification allows to infer and deduce information from ontology. To facilitate this, several domain axioms are formulated in UCRD-Onto, as shown in the examples below.

- Example 1: A kitchen is defined as a room supporting the activities of food preparation, interior cleaning, and storage, $(\forall x, a1, a2, a3)$ ((Room (x) ^ supportActivity (x, a1, a2) ^ Food_Preparation_and_Clean-up (a1) ^ Interior_Cleaning (a2) ^ Storing (a3)) $\supset$ Kitchen (x)).

- Example 2: A design solution for kitchen space involves the design elements of ceiling and ceiling finishes, flooring finishes, wall finishes, backsplash, lighting, cabinet, countertop, sink, faucet, switch, layout, switch, outlet, and appliances of cooking equipment, ventilation equipment, refrigerator, waste deposal system, floor drain: (∀x, d1, d2, d3, d4, d5, d6, d7, d8, d9, d10, d11, d12, d13, d14, d15, d16, d17, d18, d19)(Kitchen (x) ⊃(hasDesignElement(x, d1, d2, d3, d4, d5, d6, d7, d8, d9, d10, d11, d12, d13, d14, d15, d16, d17, d18, d19) ^ Ceiling (d1) ^ Ceiling_Finishes (d2) ^ Flooring_Finishes (d3) ^ Wall_Finishes (d4) ^ Lighting (d5) ^ Backsplash (d6) ^ Countertop (d7) ^ Faucet (d8) ^ Kitchen_Sink (d9) ^ Kitchen_Cabinet (d10) ^ Wall_Storage (d11) ^ Floor_Drain (d12) ^ Waste_Disposal_Unit (d13) ^ Electrical_Outlet (d14) ^ Electrical_Switch (d15) ^ Cooking_Equipment (d16) ^ Cooking_Ventilation_Equipment (d17) ^ Refrigerators_And_Freezer (d18) ^ Door (d19))

4.3.6 Implementation

Protégé is a free, open-source ontology editor that allows developers to create and manage terminologies and ontologies in a visual manner. In this study, the concept, properties, and relations of UCRD-Onto defined in the intermediate's representations are respectively coded as classes, data properties, and object properties in Protégé 5.0. Figure 4-10 demonstrates a screenshot of the ontology developing process in Protégé, where the left part is the class taxonomy of the proposed UCRD-Onto (marked in red dashed box), the lower right half part (orange dashed box) is the class description that outlines the defined axioms of class using OWL syntax, and the upper right half part (blue dashed box) is the object property defining the relations among classes. By implementing the UCRD-Onto within Protégé, different aspects of design knowledge are linked into one semantic network, which lays the foundation of knowledge-based decision support systems for residential design.

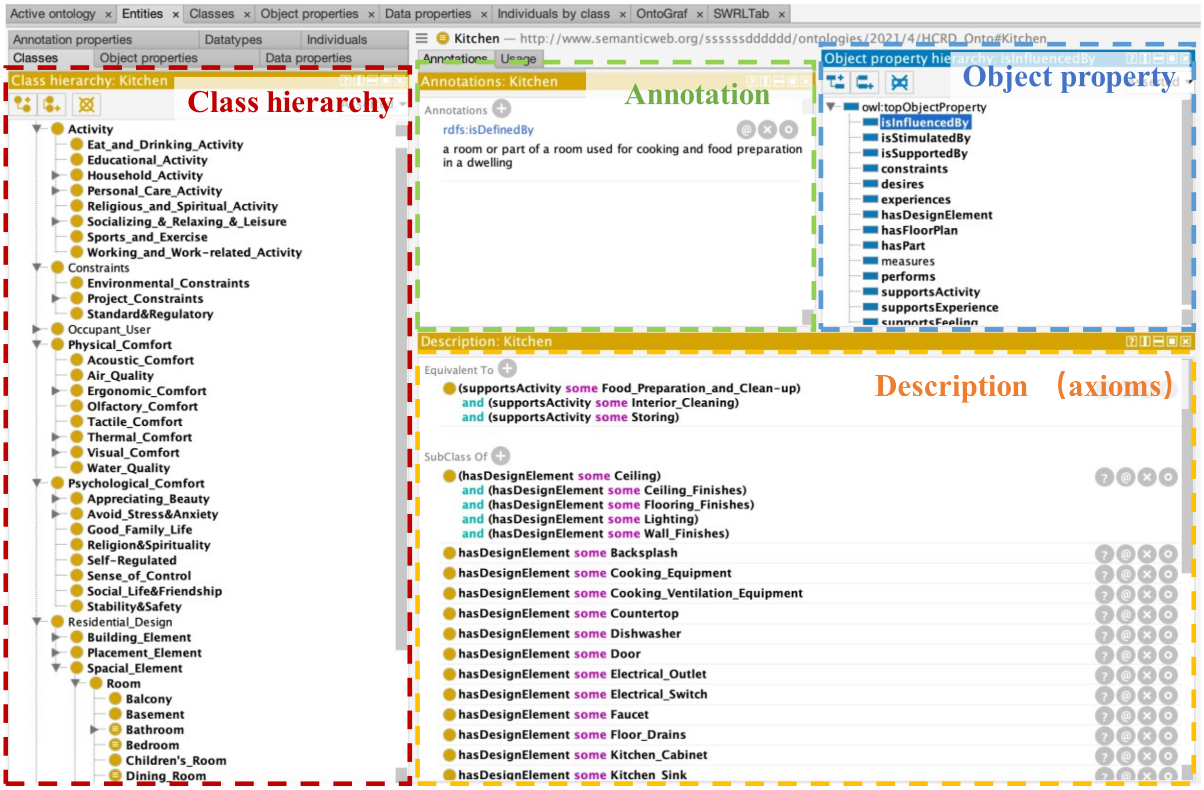


Figure 4-10. Screenshot of UCRD-Onto in Protégé.

4.4 Ontology Evaluation

This section provides an in-depth analysis of the ontology evaluation procedure and corresponding evaluation results. The performance of UCRD-Onto was evaluated using three ontology evaluation approaches: automated consistency checking, criterion-based evaluation, and application-based evaluation, as illustrated below.

4.4.1 Automated Consistency Checking

The UCRD-Onto was automatically checked for contradictory facts using a built-in description logic reasoner, Pellet, ensuring any conclusions by ontology applications are inferential and semantically consistent. By executing the reasoner, the hierarchies, domains, ranges, and conflicting disjoint assertions in the ontology are automatically examined, and the inconsistency, as well as the inferred classes and relations, are highlighted in red and displayed on the Protégé interface. This automated ontology evaluation tool greatly reduces manual checking efforts and delivers a meaningful, correct, and minimally redundant ontology (El-Gohary & El-Diraby, 2010). As a result, Pellet's consistency checking result was positive, and the inconsistencies observed during the ontology development process were addressed to ensure the ontology's application.

4.4.2 Criterion-based Evaluation

Criterion-based evaluation is mainly focused on verifying the content of an ontology. Considering the objectives and application domain of the UCRD-Onto, in addition to consistency criteria that were evaluated by the logic reasoner, the other five criteria, namely, clarity, correctness, completeness, coverage, and extendibility, were selected to conduct the ontology assessment. In this study, focus group discussion was considered the main form of conducting criterion-based evaluation since this evaluation requires expert judgment with respect to abstraction, classification, and coverage. The focus group consists of five individuals: four research team members with expertise in built environment design, information systems, and human factors, and one interior design practitioner with more than three years of project experience. On the basis of the proposed criterion, it was believed that these participants could evaluate the content and quality of UCRD-Onto with their knowledge and experience. A more detailed account of each criterion and its evaluation result is given in the following paragraph.

- Clarity: clarify criteria refers to whether an ontology can effectively communicate the intended meaning of defined concepts and whether definitions in the ontology are clearly specified without ambiguity. Following Gruber's (1995) definition, the specification for clarity could be elaborated as follows: (1) the concepts in ontology should be formally defined without subjectivity, (2) the ontology should be documented using natural language, and (3) the terms in ontology should express their intended meanings to conform to the knowledge comprehension of various social situations and computation requirements. In this study, the majority of ontology terms and their definitions in the present study were extracted directly from domain-related publications, design standards, and building codes, which were typically developed through consensus among field researchers, domain experts, or working groups appointed by building and housing development-related departments. Besides, for terms with synonyms defined in other documentation, the annotation "<rdfs:comment>" in protégé is included to denote the synonyms of given concepts.

- Correctness: The correctness criterion evaluates whether ontology represents the correct modelling of real-world concepts (Delir Haghighi et al., 2013). To support a practical application of UCRD-Onto in knowledge-based systems, the correctness of ontology has been the main focus of our evaluation. The participants were provided comprehensive documentation on the class definitions, relations, and relevant properties, along with the knowledge source related to the UCRD-Onto development. During the focus group discussion, the definition of classes and the reasons for the setup of the properties were also explained. By collecting and adapting the feedback from participants, the semantic correctness of ontology could be further verified. For instance, the class definition of *usability_performance* has been revised to include the concept of *post-occupancy_eevaluation* as well by adapting the comments from experts.

- Completeness: The completeness criterion refers to the coverage of information represented by the concepts and relation in UCRD-Onto over the domain knowledge of residential design and occupant requirements (Delir Haghighi et al., 2013). This criterion lays a basis for the knowledge-based system application to be developed in the next stage, concerning the ontology capability in knowledge sharing, transferring, and reuse. It should be noted that the proposed ontology mainly focuses on design elements closely related to human–building interactions and experience. Thus, the completeness of ontology was evaluated by going through the class hierarchy and the relations to determine whether the core concepts and attributes associated with human–building interaction and built environment design were included in the ontology. As well, the information collected from literature and design standards was used as a frame of reference to identify the incompleteness of ontology in terms of scope, exhaustiveness, and granularity (Guo & Goh, 2017).
- Extendibility: extendibility refers to the capability of ontology to extend further or to be applied to a specific application domain without changing its current definition (Delir Haghighi et al., 2013; Guo & Goh, 2017). According to the feedback from the focus group discussion, it is possible to extend UCRD-Onto to support knowledge-based residential decision-making involving other requirement considerations; and it is also feasible to extend the use of UCRD-Onto to other application domains (e.g., different building types) following the architecture of meta ontology model with certain modifications and extensions. Both of such extensions would not require changing well-defined concepts and relations in the UCRD-Onto. Thus, the extensibility of UCRD-Onto that enables the reuse and extension of the different parts of the ontology was verified.

In conclusion, the results of criterion-based evaluation indicated that the UCRD-Onto was correct, clear, extendable, and complete in terms of content, scope, exhaustiveness, and granularity. As for the consistency criterion, it was evaluated by Pellet objectively with good results. Based on the feedback from focus group discussion, this ontology is believed to possess all necessary and essential concepts for serving the objective of representing human-centered residential design-related knowledge in a formalized and reusable manner. However, the result of criterion-based evaluation is sometimes questioned for its subjective and qualitative measure since the evaluation is heavily relying on expert judgment. To address this limitation, an application-based evaluation is still necessary to further validate the competency of ontology.

4.4.3 Application-based Evaluation

To evaluate the capability of UCRD-Onto, an application-based evaluation was performed by applying the proposed ontology to an experimental residential design scenario. In accordance with conventional residential design procedures, the UCRD-Onto was initially used to describe the context of design cases and constraints using the terms, relations, and relevant properties of the developed ontology. Next, a prototype of an ontology-based knowledge system based on UCRD-Onto was developed to perform information retrieval for requirements specifications. In this application-based evaluation, the ontology was tested to represent and retrieve the design information for each room in the experimental residential design case, with the evaluation of the kitchen room design provided as an illustration. This evaluation assessed the competency of UCRD-Onto in terms of knowledge description and retrieval for residential design.

A **Kitchen** is to be designed for a *159 cm height* *elderly* **Personas** of [ergonomic design valuer]. The **Kitchen** is expected to <supportsActivity> **Activities** of [Cooking] [Storing food] [Kitchen and Food Clean-up] at a *frequency* of *everyday*, *once-a-week*, and *twice-a-week*, respectively.
To <supports> **Physical Comfort, Ergonoomic Risk** related requirements should be followed to eliminate *ergonomic risk*. To <supports> **Visual_Comfort,** the **Quantity of Visual** <isInfluencedBy> **Kitchen** space should be identified respectively. For **Psychological comfort**, the psychological feeling of **Avoid_Stress&Anxiety** [Biophilia-Restorative] is expected to be experienced by approaching a *level* of *satisfied score* in *Psychological Measure Scale* *Perceived Restorativeness Scale*; and reach a satisfied [Harmony] *score* for the requirement of **Appreciating_Beauty**.
This **Kitchen** is designed for a **Project** of an *apartment building* <inAccordanceWith> the **Envelop_Constraints**. This design should be performed under the constraints of **Standard&Regulatory** [*GB 50096-2011]* and *[JGJ 367-2015]*

Figure 4-11. Design Problem Description using UCRD-Onto.

Figure 4-11 demonstrates a description example of kitchen design scenario using UCRD-Onto. Following the description formatting in Guo & Goh [361], different typography was used to distinguish the concept class (e.g., ***kitchen***), the class properties (e.g., *frequency*), the class property value (e.g., *159 cm height elderly*), the relation (e.g., <supportsActivity>), and the instance (i.e., [ergonomic design valuer]). This description provides the basic information of occupant, and indicates the general needs on intended activities, preferred physical experience, and desired psychological comfort. In addition, the context of design problems, such as the building project type and the mandatory building codes, were also described through the terms and knowledge defined in UCRD-Onto.

On the other hand, an ontology-based knowledge retrieval prototyping system is developed in this chapter with the support of semantic web rule language (SWRL) and semantic query-enhanced web rule language (SQWRL) for requirements specification in residential design. Figure 4-12 outlines the overall system architecture, of which the essential components include the knowledge base modules, reasoning module, and user interface modules.

To begin with the knowledge base modules, the residential design-related knowledge, such as the instance of residential design elements with their attributes and the requirements to support certain activities or specific human experience, was converted into UCRD-Onto and SWRL rules by the Protégé platform, forming as the knowledge base in the developed system. Specifically, the requirements knowledge based on different contexts and its associated definitions (e.g., user characteristics or space configuration) were coded in the SWRLTab plug-ins of Protégé in a rule-based manner, as the examples outlined in Figure 4-13. In SWRL, the implication sign "->" connects antecedent and consequence, while the question mark "?" denotes the variables in each atom. When the antecedents are met (i.e., statement before "->"), the SWRL rules are then triggered, enabling context-driven inference and the storing of requirement-specific knowledge. To interact with that knowledge, the SPARQL query engine was incorporated into the system with the support of a SPARQL server tool, Apache Jena Fuseki, to enable the endpoint service so that the SPARQL query could be requested from other application platforms to retrieve the information in UCRD-Onto.

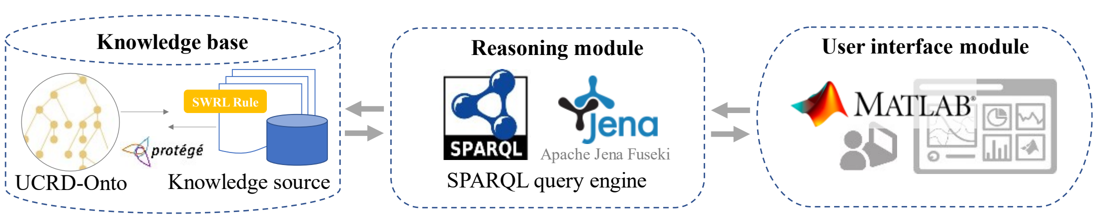


Figure 4-12. Architecture of ontology base design information system.

Define different kitchen sizes	
Rule 1-2	Small size kitchen (<150 ft.): Kitchen(?p) ^ucrd:hasArea(?p,?area) ^ swrlb:lessThan(?,150) -> ucrd: Small_Kitchen
Rule 1-3	Medium size kitchen (150-350 ft.): Kitchen(?p) ^ucrd:has Area(?p,?area) ^ swrlb:greaterThan(?,150) ^ swrlb:lessThan(?,350) -> ucrd: Medium_Kitchen(?p)
Rule 1-4	Large size kitchen (>350ft.): Kitchen(?p) ^ucrd:hasArea(?p,?area) ^ swrlb:greaterThan(?,350) -> ucrd: Large_Kitchen(?p)
Define the linkage between kitchen size and specific storing requirements	
Rule 2-1	Storing needs for the small kitchen: ucrd:Storing(?p) ^ ucrd:refersToSpace(?p,?rs) ^ swrlb:equal(?rs,"kitchen") ^ ucrd:hasAreaContext(?p,?ac) ^ swrlb:equal(?ac,"small kitchen") ^ ucrd:Small_Kitchen (?k) -> ucrd:isSupportedBy (?p,?k)
Rule 2-2	Storing needs for the medium kitchen: ucrd:Storing(?p) ^ ucrd:refersToSpace(?p,?rs) ^ swrlb:equal(?rs,"kitchen") ^ ucrd:hasAreaContext(?p,?ac) ^ swrlb:equal(?ac,"medium kitchen") ^ ucrd:Medium_Kitchen (?k) -> ucrd:isSupportedBy (?p,?k)
Rule 2-3	Storing needs for the large kitchen: ucrd:Storing(?p) ^ ucrd:refersToSpace(?p,?rs) ^ swrlb:equal(?rs,"kitchen") ^ ucrd:hasAreaContext(?p,?ac) ^ swrlb:equal(?ac,"large kitchen") ^ ucrd:Large_Kitchen (?k) -> ucrd:isSupportedBy (?p,?k)
Define the linkage between specific activities with elderly user	
Rule 3-1	ucrd:Activity(?p) ^ ucrd:hasUserContext (?p,?ur) ^ swrlb:contains(?ur, "elderly") ^ Personas(?k) ^ ucrd:hasAgeRange(?k,?age) ^ swrlb:equal(?age,">60") ->ucrd:performs(?k,?p)
Define index for lighting analysis	
Rule 4-1	Room cavity ratio: ucrd:Room(?s) ^ ucrd:hasSpaceLength(?s,?len) ^ ucrd:hasSpaceWidth(?s,?wd) ^ ucrd:Lighting(?ltng) ^ ucrd:hasPosition(?ltng, ?locp) ^ ucrd:LocalPosition(?locp)^ ucrd:hasPlacementRefTo(?locp,?fl) ^ ucrd:Floor(?fl) ^ ucrd:hasRelativePlacementZ(?locp,?rht) ^ swrlb:multiply(?x1,wd,len) ^ swrlb:add(?x2, wd,len) ^ swrlb:multiply(?x3,x2,rht) ^ swrlb:divide(?ri,x1,x3) -> ucrd:hasRoomCavityRatio(?s, ri)
Rule 4-2	Coefficient of utilization: ucrd:Room(?s) ^ ucrd:Ceiling_Finishes(?c) ^ ucrd:hasReflectance (?c,?rf1) ^ ucrd:Flooring_Finishes(?f) ^ ucrd:hasReflectance (?f,?rf2) ^ ucrd:Wall_Finishes(?w) ^ ucrd:hasReflectance (?w,?rf3) ^ ucrd:cuTable (?cu,?rf1,?rf2,?rf3)-> ucrd:hasUtilizationCoefficient(?s,?cu)
Rule 4-3	Required luminaires for kitchen visual needs: ucrd:Kitchen(?k)^ ucrd:hasArea(?k,?area)^ ucrd:hasUtilizationCoefficient(?s,?cu) ^ ucrd:Quantity_of_Visual(?q) ^ucrd:isInfluencedBy(?q,?k) ^ ucrd:hasUserContext(?q,?ur) ^ swrlb:contains(?ur,"elderly") ^ ucrd:Lighting(?ltng) ^ ucrd:haslumen(?ltng,?lm) ^ ucrd:hasLightLossFactor(?ltng,?llf) ^ swrlb:multiply(?x1,500,?area) ^ swrlb:multiply(?x2,?lm,?cu,?llf) ^ swrlb:divide(?n,?x1,?x2) -> ucrd:hasSuggestedluminairesNum(?q, ?n)

Figure 4-13. Example of SWRL rules.

The results from SPARQL queries are then saved in a text format and presented in the graphic user interface. In the shown study, a graphic user interface of the information retrieval system is developed using MATLAB App designer to help users identify residential design requirements, where the MATLAB built-in function "urlread" was used to execute the SPARQL queries with endpoint settings. As the example of querying results shown in Figure 4-14, regarding the query premises of the intended experience (e.g., intended activities of "storing" and "food preparation and clean"), user characterizes (e.g., "elderly" and "ergonomic design valuer"), and project settings (e.g., "condominium," "frame structure"), the requirements on specific design elements could be retrieved and listed with the explained intentions and suggestions using concepts and relations formalized by the UCRD-Onto. Designers can then refer to the retrieved information to make informed residential design decisions.

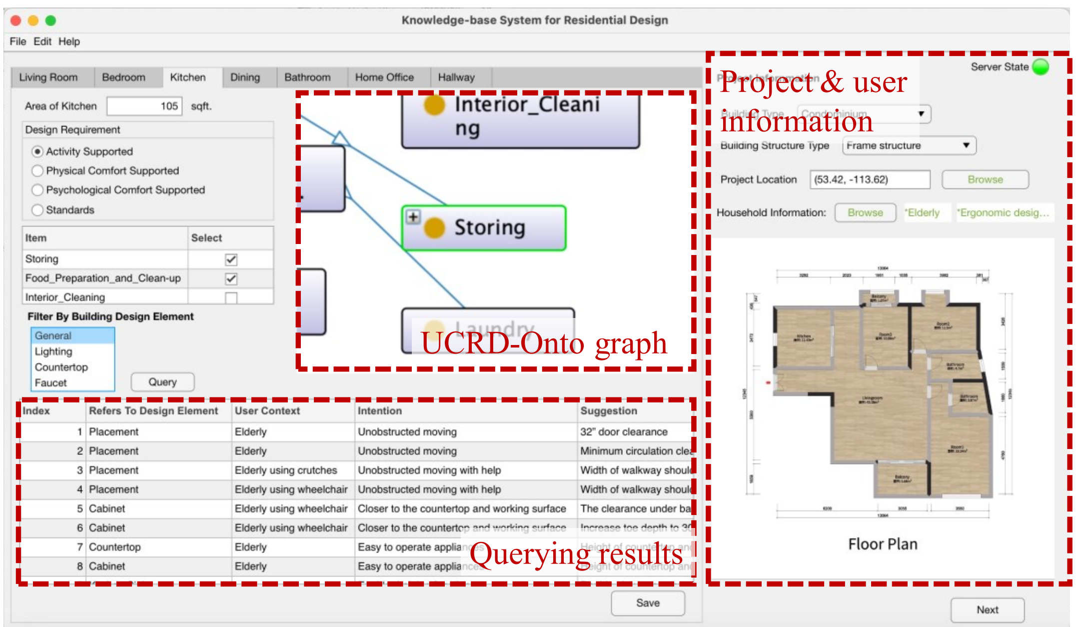


Figure 4-14. GUI screenshot of information retrieval system for residential design requirements.

In summary, the domain knowledge for residential design and requirement determination have been formalized and tested in describing design cases and querying design requirements based on the guideline of UCRD-Onto throughout this application-based evaluation. By having ontology components in describing design scenarios and relevant solutions, the coverage and feasibility of UCRD-Onto in knowledge representation are further validated in terms of systematically capturing key concepts and relationships. Furthermore, the successfully established semantic interactions between reasoning modules and knowledge base (i.e., the ontology) by SWRL rules and SPARQL queries demonstrated the consistent descriptions of domain knowledge in UCRD-Onto and confirmed the objective fulfillment of UCRD-Onto in knowledge-based system applications (Xing et al., 2019). As suggested by the findings of the application-based evaluation, the proposed ontology can be used to standardize the structure of user-centered residential design knowledge and hence facilitate knowledge retrieval and storage.

4.5 Conclusions

User-centered design for residential built environments has been regarded as a complex and information-intensive task involving multi-stakeholders and multi-disciplinary knowledge. Regarding the overwhelming volume of information and data concerning human–building interaction, a knowledge-based system that supports knowledge integration and semantic interoperability between stakeholders would be of great assistance in determining appropriate design requirements and developing solutions. Thus, this study denotes an initial effort to develop a domain ontology (UCRD-Onto) that focus on representing the knowledge of residential design and the relevant requirements associated with human preferences with regard to and experience of the built environment. Comprehensive literature was performed among relevant studies, regulations, standards, and existing cases to acquire comprehensive domain knowledge for ontology development. Besides, the social media data was also explored using NLP to extract consumer terms to incorporate the viewpoints of layman users in ontology learning. In this chapter, the framework of UCRD-Onto mainly consists of four parts, including requirement-related concept, design-related concept, context-related concept, and measurement-related concepts, which can be described by nine main classes as *occupant-user, activity, psychological comfort, physical comfort, residential design, standard & regulatory, project constraint, environmental constraint,* and *usability performance.* The proposed ontology was evaluated using automated consistency checking, criterion-based evaluation, and task-based evaluation in order to assess its ability to formally and explicitly represent the knowledge of user-centered residential design. As indicated in the evaluation results, the UCRD-Onto is consistent, correct, clarified, and comprehensive in capturing and describing relevant knowledge required in user-centered design for residential environments so that the knowledge could be shared and reused even by computer machines.

Overall, the proposed ontology sheds new light on the knowledge-based decision support for user-centered residential design. It provides a formal and shared vocabulary for the residential design domain, potentially dealing with coordination issues, inconsistencies, and communication between different entities (i.e., human and machines). Knowledge sharing and reuse among different parties and even computer applications can be promoted while the unnecessary misunderstanding caused by inconsistent terms and assumptions is eliminated. Moreover, UCRD-Onto also help facilitate the integration of residential design informatics systems to existing knowledge or information models in other domains. The development of UCRD-Onto, for instance, denotes a further step toward building information modelling (BIM) based computer-aided automatic built environment design by clearly describing the connections between design components and their associations with design factors (Yang et al., 2019).

Despite its contributions, this study was subject to several limitations. First, the proposed UCRD-Onto did not exhaustively acquire all knowledge of the residential design field since it is impossible to fully represent a domain of interest with a single ontology (Gruber, 1995; Guo & Goh, 2017). The ontology is heavily dependent on the reviewed documentation in this study. Besides, the current ontology is mainly for residential design; the future work of UCRD-Onto will be focused on extending other types of built environments, such as healthcare facilities and education buildings.

Moreover, many efforts in architectural engineering and computer science nowadays are being made to pursue the automation of architectural design (Akase & Okada, 2013; Sydora & Stroulia, 2020); thus, the identification and representation of design knowledge is the most fundamental and critical issue that must be addressed to achieve design computation (Aksamija & Grobler, 2007). In this regard, additional effort will be required to integrate the proposed ontology with BIM tools to enable a more automated built environment context identification in perusing an automatic intelligent built environment design.

Chapter 5: VR-BASED COLLABORATIVE DESIGN SUPPORT SYSTEM FOR CONSENSUS BUILDING IN BUILT ENVIRONMENT DESIGN[4]

5.1 Introduction

With the increasing amount of time people are spending indoors today, the design quality of the built environment has become an important factor in productivity and well-being (Ergan et al., 2018). In this context, an emerging trend in design practice in recent decades within the architecture, engineering, and construction (AEC) domain has been the intensive collaboration between multiple stakeholders with different disciplinary backgrounds and experience in the design of communities and spaces (Luck, 2018). Effective collaboration in design decision-making is thus widely seen as a necessity based on the assumption that decisions made by stakeholders with diverse expertise will be higher in quality than those made by homogeneous stakeholders, especially when multiple stakeholders' interests must be accommodated (Singhaputtangkul & Zhao, 2016). For instance, collaboration in the design of a shared space in the built environment (e.g., the hallway of hospital) results in high design quality in that the various stakeholders (e.g., patient groups, healthcare staff, architects, and engineers) exchange knowledge and jointly define the project goals in order to reach a generally satisfactory solution (Elf et al., 2015).

Within the domain traditional collective decision making—i.e., group decision-making (GDM)—negotiation and collaboration have long been recognized as time-consuming processes, this being attributable to an ill-defined decision-making process, information asymmetry, the diverse disciplinary backgrounds of the negotiating partners, and conflicting interests between stakeholders

[4] A version of this chapter has been submitted to Automation in Construction.

(Bhooshan, 2017; Xue et al., 2009). These factors may cause mood decay among decision-makers, provoking frustration and apathy and leading to low-quality project outcomes, dissatisfaction among users, project delays, and higher costs (Elf et al., 2015). As a means of improving the efficiency of design collaborations in the building construction domain, many efforts have been directed toward the development of virtual collaborative platforms that remove the barriers in communication and understanding between disciplines (Zhang et al., 2020). Specifically, as they undergo rapid development and become increasingly affordable, virtual reality (VR) technologies are now playing a significant role in addressing these issues in collaborative design. The immersive and interactive experiences provided by VR in visualizing and representing the design model can help fulfill the need for mutual trust and provide a foundation for common understanding and successful collaboration among stakeholders. However, most existing VR-based collaborative systems are limited to the functions of visualization and data synchronization. There is a lack of moderator support from the GDM mechanism to facilitate an efficient collaborative design and negotiation process that ultimately results in an acceptable built environment design.

As such, the consensus-based GDM method, which seeks reasonable agreement among all stakeholders in a given situation with respect to the various design alternatives and criteria, may be helpful as a means of building consensus and generating a satisfactory design solution (Wibowo & Deng, 2013). Although many theoretical models have been proposed for consensus-based GDM problems (Dong et al., 2018; Wu et al., 2018), there is little research applying such methods in building design collaboration (Singhaputtangkul & Zhao, 2016). In addition, little information is available concerning the application of consensus models integrated with VR as a decision support tool for collaborative design. To fill these gaps, this research proposes a VR-based collaborative design support system to help stakeholders develop acceptable design solutions with less time and effort compared to current practice. The proposed collaborative design support system not only helps to address the comprehension and communication challenges encountered in the negotiation process in current practice by offering robust visualization and user-friendly interfaces for built environment design, but also provides an iterative and dynamic decision-making process that yields consensus-based design solutions rooted in meaningful collaboration after multiple rounds of negotiation and modification.

The balance of this chapter is organized as follows. Section 5.2 reviews the literature pertaining to GDM methods and VR applications for design collaboration in AEC. In Section 5.3, the theoretical models adopted in this study to facilitate the consensus-based collaborative design process are presented. Next, in Section 5.4, a detailed illustration of the proposed collaborative design process featuring the VR-based collaborative design support system is presented, along with the system scheme. In Section 5.5, a test case applying the system is used to illustrate the manner in which a simple collaborative built-environment design problem is solved. Finally, Section 5.6 concludes by highlighting the research contributions and limitations.

5.2 Literature Review

5.2.1 GDM in Building Domains

Design decisions within the building construction domain usually involve the mutual understanding, participation, and input of multiple stakeholders spanning different disciplines. It is a cooperative process where team members come together to resolve issues and achieve a high-quality outcome. To improve the effectiveness of group decisions in the building sector, many computerized and IT-supported decision-making technologies have been proposed. For instance, Smith et al. (Russell-Smith et al., 2015) presented a decision support system to engage design team members from different disciplines in assessing the sustainability of building designs and making further design decisions accordingly. Garbett et al. (2021) used AR and BIM technologies to develop a collaborative design platform that enables multi-user visualization and collaboration for construction project management.

Moreover, Roupé et al. (2020) suggested that incorporating VR techniques in collaborative design systems facilitates interactive and collaborative design work with immediate feedback, thereby providing stakeholders with better understanding of, knowledge exchange with respect to, design problems. Similar collaborative design systems have also been proposed in the form of virtual design studios (Pektaş, 2015) and Internet-based collaboration systems (Xue et al., 2012). Underlying the development of these collaboration tools has been a recognition of the importance of providing stakeholders with a shared platform for real-time communication where stakeholders can access information, data, and knowledge without being constrained by geographic location (Du et al., 2018).

Negotiation (i.e., consensus-building), meanwhile, as a critical collaborative decision-making behaviour, is recognized as time-consuming due to stakeholders' multiple preferences, intentions, and pay-off threshold. To manage conflicting interests in collaborative decision-making, many consensus support methods have been developed to help reach an acceptable level of agreement. For example, Arroyo et al. (2016) adopted the method, choosing by advantages (CBA), to facilitate collective decision-making in sustainable building design. The method they proposed was found to facilitate consensus-building and yield a solution with higher satisfaction compared to conventional methods. Chen et al. (2021) proposed a negotiation-based system to guide the consensus-building process for construction-contractor selection in such a manner that the final decision would be mutually acceptable to expert stakeholders, arguing that such a negotiation support system can help decision-makers to efficiently and effectively pursue their interests throughout the negotiation process even amid conflicting goals. In addition, the assumption that stakeholders tend to withhold their opinion in order to avoid disagreement has also been identified as a major issue in collaborative decision-making that results in poor group decision outcomes (Singhaputtangkul & Zhao, 2016). Researchers have suggested in this regard that the application of consensus schemes may mitigate this problem by promoting an effective discussion process within the group and reducing divergence of opinions (Parreiras et al., 2012; Singhaputtangkul & Zhao, 2016). The consensus scheme has been adopted by researchers to facilitate GDM in building envelope design (Singhaputtangkul & Zhao, 2016) and project management (Elbarkouky & Fayek, 2011). In these studies, the consensus scheme was shown to aid decision-makers in openly discussing issues and addressing matters of conflicting interest during the decision-making process and in systematically reviewing and refining their design preferences to minimize divergent opinions among decision-makers.

Although negotiation and consensus support mechanisms have been widely studied within the building domain, consensus-building processes specifically within the context of collaborative built environment design have not been addressed in previous studies. Compared to construction management and engineering design, built environment design has a unique context with more diverse backgrounds in design and negotiation knowledge being represented among the stakeholders. This underscores the need for a more straightforward approach to facilitating the negotiation process, i.e., providing clear instruction to guide decision-makers toward a consensus state and more user-friendly human–computer interactions by which for decision-makers who are not from an architectural background to better understand and communicate design decisions.

5.2.2 VR for Design Collaboration

Effective collaboration among colleagues and other professionals in the early building design phases is crucial for the final project design and delivery. In this regard, the rapidly expanding body of knowledge on virtual collaborative design points to the growth of multi-user virtual environment research (Koutsabasis et al., 2012). VR has received considerable attention in the AEC industry in recent decades for its ability to provide multisensory 3D environments that immerse the user in a virtual world, thereby helping to fulfill the high demand for visual forms of communication supporting the design, engineering, and construction of the built environment (Kim et al., 2013). As an immersive and interactive design review medium, VR allows participants to feel as though they are physically present in the environment being represented virtually, giving them a sense of scale. It allows users to gain clear insight into the various design alternatives in the early design stage and to make informed decisions, effectively eliminating potential errors or conflicts and ultimately increasing the likelihood of end-user satisfaction (Kumar et al., 2011; Shameri et al., 2013). For this reason, VR-supported design studios that provide participants with dynamic spaces in which to engage in coordinated conjoined action, helping to offset the adverse effects of absence of collaborative local spaces, are becoming increasingly common (Zhang et al., 2020).

A virtual design studio can be defined as a computer-generated, avatar-based virtual environment in which members of the design team can be virtually present interacting in the same space as anthropomorphic avatars represented in 3D virtual environment while they are physically distant (Koutsabasis et al., 2012). Researchers have asserted that this kind of VR platform is effective in promoting social relationships among collaborators (Kohler et al., 2011). Beyond the effectiveness of VR in exposing rich details and eliminating design misunderstandings, the benefits that the co-presence of virtual avatars offers in terms of promoting creativity in architectural design have also been noted by many researchers (Issa, 2000; Uribe Larach & Cabra, 2010). For example, Uribe Larach and Cabra (2010) used a game engine to set up a virtual discussion space replicating a meeting room for problem solving. Their results suggested that using co-present avatars makes direct interaction between the design and the participant feasible, effectively engaging participants in co-creation. This collaboration within the avatar-based virtual space was also found to be conducive to generating creative solutions. This result is consistent with the findings of Kohler et al. (Kohler et al., 2011). It can thus be concluded that the co-presence offered in the VR environment strengthens the sense of collaboration among team members, especially in terms of social aspects such as dependencies, encouragement, and mutual learning, compared to other forms of remote collaboration.

However, the current VR-supported collaborative design system mostly emphasizes VR's visualization capability and providing a feeling of being present, whereas a systematic solution to leverage VR in group decision support to improve the efficiency and quality of collaborative design outcomes has yet to be explored. Thus, in the present research, a consensus-based group decision support method is integrated with VR design to facilitate collaborative design of the built environment.

5.3 Theoretical Consensus Model of GDM in Built Environment Design

A consensus-based theoretical model is proposed in this study to guide the consensus process of collaborative decision-making for built environment design. This consensus scheme is adapted and extended from the similarity- and proximity-based consensus model developed in Wu and Chiclana (2014) to enable its use in a multi-criterion decision making (MCDM) scenario as a way of arriving at a consensus solution with minimal preference adjustment. In the interest of completeness, the relevant definitions and representation formats used in the model are briefly described in the following subsections.

5.3.1 Preference relations

In a collaborative design decision-making problem, a set of decision-makers (stakeholders) $D = \{d_1, \dots, d_s\}$ need to determine their preferences (opinions) toward design elements $C = \{c_1, \dots, c_m\}$ for a set of design alternatives, $X = \{x_1, \dots, x_n\}$. As illustrated below, each preference decision can be represented in a fuzzy MCDM model.

Definition 1. G^h denotes a collection of fuzzy decision matrices given by stakeholder d^h, where there are n alternatives under consideration for m design elements. We define:

$$g^h = \begin{bmatrix} g_{11} & \cdots & g_{1m} \\ \vdots & \ddots & \vdots \\ g_{n1} & \cdots & g_{nm} \end{bmatrix} \qquad (5-1)$$

where $i = 1,2, \dots, n$ is the index of design alternative, $j = 1,2, \dots, m$ refers to the number of design elements, and, accordingly, g_{ij} represents the rating of alternative, i, against design element, j. If the rating, g_{ij}, is a set of triangular fuzzy numbers (TFNs), then it can be represented as $(\mathrm{g}_{ijl}, \mathrm{g}_{ijm}, \mathrm{g}_{iju})$.

This fuzzy MCDM model can be converted into a complementary preference relation among design alternatives using the method introduced in Lee (2005) for further consensus measurement.

Definition 2. A complementary preference relation, P, denotes a stakeholder's preferences on a set of alternatives, $X = \{x_1, \dots, x_n\}$. We define:

$$P = (p_{i,k})_{n \times n} \qquad (5-2)$$

$$p_{ik} + p_{ki} = 1 \qquad (5-3)$$

where $p_{ik} \in [0,1]$ denotes the stakeholder's degree of preference for design alternative i over design alternative j

Definition 3. We let $g_a = (g_{a_l}, g_{a_m}, g_{a_u})$ and $g_b = (g_{b_l}, g_{b_m}, g_{b_u})$ be two TFNs representing the stakeholder's preference attitudes toward design alternative a and b with regard to one particular design element. In preference relation, P, then, the membership function, $\mu_p(g_b, g_b)$, can represent the degree of preference of g_a over g_b. We define:

$$\mu_p(\mathrm{A}, \mathrm{B}) = \frac{1}{2}\left(\frac{(g_{a_l} - g_{b_u}) + 2(g_{a_m} - g_{b_m}) + (g_{a_u} - g_{b_l})}{2\|T\|} + 1\right) \qquad (5-4)$$

where

$$\|T\| = \begin{cases} \dfrac{(t_l^+ - t_u^-) + 2(t_m^+ - t_m^-) + (t_u^+ - t_l^-)}{2}, & if\ t_l^+ \geq t_u^- \\ \dfrac{(t_l^+ - t_u^-) + 2(t_m^+ - t_m^-) + (t_u^+ - t_l^-)}{2} + 2(t_u^- - t_l^+), & if\ t_l^+ < t_u^- \end{cases}$$

$$t_l^+ = max\{g_{a_l}, g_{b_l}\}, t_m^+ = max\{g_{a_m}, g_{b_m}\}, t_u^+ = max\{g_{a_u}, g_{b_u}\},$$

$$t_l^- = min\{g_{a_l}, g_{b_l}\}, t_m^- = min\{g_{a_m}, g_{b_m}\}, t_u^- = min\{g_{a_u}, g_{b_u}\}$$

Thus, the preference relation can be represented as $P = (\mu_p(g_a, g_b))_{n\times n}$.

5.3.2 Consensus model based on similarity and proximity measures

If we obtain the complimentary preference relation, P, for each stakeholder, a typical consensus process comprises the following steps (S):

S1. The moderator in GDM checks whether the level of consensus (agreement) among all stakeholders is sufficient.

S2. If the level of agreement is sufficient, the consensus process stops, and the aggregation process is carried out (proceed to step 4).

S2. If the level of consensus is not sufficient, the moderator gives recommendations to the stakeholders to help them refine their opinions toward a consensus solution.

S3. In consideration of these recommendations, the stakeholders change their preferences with respect to the design alternatives, and the next iteration of the consensus process begins (i.e., return to step 1).

S4. The aggregation and selection process is carried out by calculating the collective group preference, and a final solution to the problem is determined.

Wu and Chiclana (2014) proposed two kinds of measures, namely, similarity degree and the proximity degree, to reflect the level of agreement (consensus) among stakeholders with respect to feasible alternatives. Both measures convey the concept of similarity between stakeholders in a group; the former measures the relative similarity between pairs of stakeholders, while the latter quantifies how far each stakeholder is from the collective preference. Accordingly, the consensus model employed in the present study requires that the similarity and proximity measures be defined at four levels: (1) the design element level; (2) the design alternative level; (3) the pair of design alternatives level; and (4) the preference relation level. The consensus control processes and the minimum adjustment-based feedback mechanism must also be tailored to the context of multi-criterion GDM problems to ensure an optimal solution that maximizes proximity to stakeholders' original preferences.

Degree of similarity

Definition 4. We let g^h and g^l be two preference decision matrices provided by stakeholders d_h and d_l, respectively. Then, SE_{ij}^{hl} denotes the degree of preference similarity with respect to the alternatives x_i, given design element j (Wu & Chiclana, 2014). We define:

$$SE_{ij}^{hl} = 1 - d\left(g_{ij}^{h}, g_{ij}^{l}\right) \qquad (5-5)$$

where $d(g_{ij}^{h}, g_{ij}^{l})$ denotes a distance function measuring the normalized distance between g_{ij}^{h} and g_{ij}^{l}. Thus, the degree of similarity of stakeholder d_h with respect to design alternatives x_i against design element j relative to the other stakeholders in the group is calculated as:

$$SDE_{ij}^{h} = \frac{\sum_{l=1, l\neq h}^{m} SE_{ij}^{hl}}{m-1} \qquad (5-6)$$

where m refers to the number of stakeholders in the group.

Definition 5. We let $P^{h} = \left(p_{ik}^{h}\right)$ and $P^{l} = \left(p_{ik}^{l}\right)$ be two complementary preference relations with respect to a set of alternatives X provided by stakeholders d_h and d_l, respectively. Then, SD_{ik}^{hl} denotes the degree of similarity between stakeholders d_h and d_l with respect to the pair of alternatives (x_i, x_k). We define:

$$SD_{ik}^{hl} = 1 - \left(p_{ik}^{h} - p_{ik}^{l}\right) \qquad (5-7)$$

Definition 6. The degree of similarity of stakeholder d_h with respect to the pair of design alternatives (x_i, x_k) relative to the other stakeholders in the group is calculated as:

$$SPA_{ik}^{h} = \frac{\sum_{l=1, l\neq h}^{m} SD_{ik}^{hl}}{m-1} \qquad (5-8)$$

Definition 7. The degree of similarity with respect to design alternatives SA_{i}^{h} denotes the degree of similarity of a given stakeholder with respect to design alternative x_i relative to the other stakeholders in the group. We define:

$$SA_{i}^{h} = \frac{\sum_{k=1}^{n} SPA_{ik}^{h}}{n} \qquad (5-9)$$

Definition 8. The degree of similarity with respect to stakeholder preference SD^h denotes the degree of similarity of a given stakeholder with respect to the whole set of design alternatives X relative to the other stakeholders in the group. We define:

$$SD^h = \frac{\sum_{i=1}^{n} SA_i^h}{n} \qquad (5-10)$$

Accordingly, each stakeholder in a collaborative design decision-making scenario can be associated with a relative degree of importance, RSD^h, based on the degree of similarity determined as described above. We define:

$$RSD^h = \frac{SD^h}{\sum_{l=1}^{m} SD^l} \qquad (5-11)$$

Degree of proximity

The degree of proximity is a measure of the similarity between a given stakeholder's preference and the collective preference of all stakeholders in the group. To obtain collective stakeholder preferences, the degree of importance of the various stakeholders in the collaborative design decision-making process must first be considered. This importance is calculated by combining the relative degree of similarity and the associated degree of importance based on the stakeholders' characteristics. For instance, the preference from the primary users of the built environment being designed or the stakeholders with comparably expansive design knowledge and experience may be assigned more weight in preference aggregation (Wu & Chiclana, 2014).

Definition 9. W denotes the degree of importance of the different stakeholders in design decision-making as determined based on their relative degree of similarity, RSD, and associated importance degree AID based on their design experience, authority, or use priority of the space. We define:

$$w = \eta \cdot AID + (1 - \eta) \cdot RSD \qquad (5-12)$$

$$\sum AID^h = 1$$

where $\eta > 0.5$ indicates that the associated importance degree is given a higher weight than the relative similarity (i.e., RSD) in determining the stakeholder's degree of importance. Notably, for homogeneous collaborative design scenarios, the value, $\eta = 0$, applies.

Definition 10. Given a collection of preference decision matrices $G = \{g\}$ for a set of stakeholders $D = \{d^1, \dots, d^h\}$ in a group, g^c denotes the collective decision matrix with respect to design element, j, in design alternative i:

$$g_{ij}^c = \sum_{h=1}^{m} w^h \cdot g_{ij}^h \qquad (5-13)$$

Definition 11. Accordingly, the collective preference relation $P^c = (p_{ik}^c)_{n \times n}$ can be calculated as follows:

$$p_{ik}^c = w^1 \otimes p_{ik}^1 \oplus w^2 \otimes p_{ik}^2 \oplus \dots \oplus w^m \otimes p_{ik}^m \qquad (5-14)$$

where w^m is determined based on Equation (12) above.

Definition 12. We let g^h be decision matrices for design alternatives x_i provided by stakeholders d_h, and let g^c be the collective decision matrix aggregated based on the group of stakeholders' respective decisions. Then, PE_{ij}^h denotes the degree of proximity of stakeholders, d_h, with respect to design alternatives, x_i, given design element, j. We define:

$$PE_{ij}^h = 1 - d\left(g_{ij}^h, g_{ij}^c\right) \qquad (5-15)$$

Definition 13. Given the collective preference relation, P^c, and the complementary preference relation, P^h, on the part of stakeholder, d_h, PPA_i^h measures the degree of proximity of stakeholder, d_h, to the group with respect to the pair of design alternatives (x_i, x_k). We define:

$$PPA_{ik}^h = SD\left(p_{ik}^h, p_{ik}^c\right) \qquad (5-16)$$

Definition 14. The degree of proximity with respect to design alternatives, PA_i^h, refers to the degree of proximity of stakeholder, d_h, to the group with respect to design alternatives, x_i. We define:

$$PA_i^h = \frac{\sum_{k=1}^{n} PPA_{ik}^h}{n} \qquad (5-17)$$

Definition 15. The degree of proximity for stakeholder preference relation, PD^h, is the degree of proximity of stakeholder, d_h, to the group with respect to the set of design alternatives, X, which is calculated as:

$$PD^h = \frac{\sum_{i=1}^{n} PA_i^h}{n} \qquad (5-18)$$

All of the above measures, including those related to the degree of similarity, are defined for the scenario with complete preference relations.

Consensus control mechanism

The degree of similarity and degree of proximity measures having been defined, the degree of consensus among stakeholders must also be defined at four levels as noted above, namely, the design element level, the pair of design alternatives level, the design alternatives level, and the stakeholder preference relation level.

Definition 16. Consensus level on the design elements ($CLDE$) denotes the consensus level of stakeholder d_h with respect to design alternatives, i, given design element, j.

$$CLDE_{ij}^{h} = \psi \cdot SDE_{ij}^{h} + (1 - \psi) \cdot PE_{ij}^{h} \quad (5-19)$$

Definition 17. Consensus level on the pairs of design alternatives ($CLPDA$) denotes the level of consensus of stakeholder d_h with respect to the pair of design alternatives, i and k. We define:

$$CLPDA_{ik}^{h} = \psi \cdot SPA_{ik}^{h} + (1 - \psi) \cdot PPA_{ik}^{h} \quad (5-20)$$

Definition 18. Consensus level on the design alternatives (CLDA) denotes the level of consensus of stakeholder d_h with respect to design alternative, i. We define:

$$CLDA_{i}^{h} = \psi \cdot SA_{ik}^{h} + (1 - \psi) \cdot PA_{i}^{h} \quad (5-21)$$

Definition 19. Consensus level on the stakeholder preference relation (CL) denotes the level of consensus of stakeholder d_h with respect to design alternative, i. We define:

$$CL^{h} = \psi \cdot SD^{h} + (1 - \psi) \cdot PD^{h} \quad (5-22)$$

where $\psi \in [0,1]$ is a parameter that controls the weights of both the similarity and proximity criteria. To reach a consensus solution, CL should exceed the minimum satisfaction threshold, γ. It should be noted that the likelihood of reaching full agreement in collaborative design decisions is rather low, which means the threshold value of consensus $\gamma < 1$. In addition, in most cases, as long as consensus is achieved among more than half of the decision-makers, the design decision may be considered acceptable. Thus, the threshold value could be more specifically defined to be within the range of $\gamma \in [0.5,1)$.

Minimum adjustment cost feedback mechanism

The purpose of the feedback mechanism is to provide stakeholders who do not satisfy the degree of consensus criteria with easy-to-follow recommendations intended to result in a higher level of consensus for the final design decisions (Alonso et al., 2010). Conventional feedback mechanisms usually assume a fixed feedback parameter at the outset without considering the cost of stakeholder preference adjustment. To help maintain proximity to the original design preferences of stakeholders and minimize the need for adjustment, a minimum adjustment cost feedback mechanism is used in this study (Wu et al., 2018).

Generally, the feedback mechanism consists of two sub-modules: the first identifies the preference values that need to be modified, while the second generates recommendations with feedback parameters. In the first module, a two-stage process is used to identify any inconsistent stakeholders, d_h, and design alternatives, i, that are lower than the threshold value of consensus level, γ.

S1. Stakeholders who should modify their preferences are those whose preference relation consensus level is lower than the threshold value, γ, i.e.,

$$IND = \{h|CL^h < \gamma\} \tag{5-23}$$

S2. For the stakeholders identified in Step 1, their design alternatives with a consensus level $CLDA_i^h$ lower than the threshold, γ, should be considered as candidates to be changed, i.e.,

$$DALT = \left\{(h, i)\middle|h \in IND \wedge CLDA_i^h < \gamma\right\} \tag{5-24}$$

S3. Finally, the design elements to be reviewed are those with a consensus index $CLDE_{ij}^h$ under the threshold, γ, i.e.,

$$APS = \left\{(h, i, j)\middle|(h, i) \in DALT \wedge CLDE_{ij}^h < \gamma\right\} \tag{5-25}$$

The feedback mechanism then presents the inconsistent stakeholder with recommended preference values as previously identified in APS, which contains the new preference values will result in a higher degree of consensus.

Definition 20. For all $(h, i, j) \in APS$, the following recommendation is provided to the relevant stakeholders: "would you like to consider changing your degree of preference regarding design element j in design alternatives i to a value close to rt_{ij}^{h}." We define:

$$rt_{ij}^{h} = (1 - \delta) \cdot g_{ij}^{h} + \delta * g_{ij}^{c} \qquad (5 - 26)$$

where $\delta \in [0,1]$ denotes a feedback mechanism parameter to control the degree of acceptance of recommendations.

When $\delta = 1$, the original preference is completely replaced by the collective one, while $\delta = 0$ means the original preference is kept unchanged. Thus, the larger the feedback parameter δ is, the greater the adjustment the stakeholder is recommended to make will be. Therefore, selecting a boundary parameter (δ_{min}) is an important issue in collaborative design decision-making problems of this nature.

Following the optimal model of minimum adjustments established by Wu et al. (2018), the feedback mechanism parameter can be determined by solving the optimization below (Equation 5-27). This optimization model seeks to minimize the changes between the adjusted preference decision, $g_{i,j}^{h}$, and the original preference decision, $g_{i,j}^{h}$, in addressing inconsistent opinions with respect to design element, j, in design alternative, i, held by stakeholder, d_h, while ensuring that both the adjusted preference relation and the unchanged one can satisfy the minimum consensus requirement, γ.

$$min \sum_{i,\, j,\, h \in APS} \delta \left| g_{i,j}^{h} - g_{i,j}^{h'} \right| \qquad (5 - 27)$$

$$s.t. \begin{cases} CL(g^{h'}) \geq \gamma \\ CL(g^{s}) \geq \gamma \end{cases}$$

It should be noted that the recommendation, rt_{ij}^{h}, here is calculated into a set of fuzzy numbers. In keeping with the principle underlying the feedback mechanism that recommendations must be simple to understand and apply, the recommendation, rt_{ij}^{h}, should be presented to stakeholders in the same manner as their preference input (i.e., in linguistic form).

5.4 Integrated VR-based collaborative design system

In building design, VR techniques have been widely used for design collaboration because of the notable representativeness of the design element options in exposing rich details and eliminating design misunderstandings (Zhang et al., 2020). To leverage the advantages of VR in facilitating GDM, an integrated framework of a VR-based collaborative design system (see Figure 5-1) is proposed to assist decision-makers in reaching consensus and enhancing the efficiency of decision-making in built environment design.

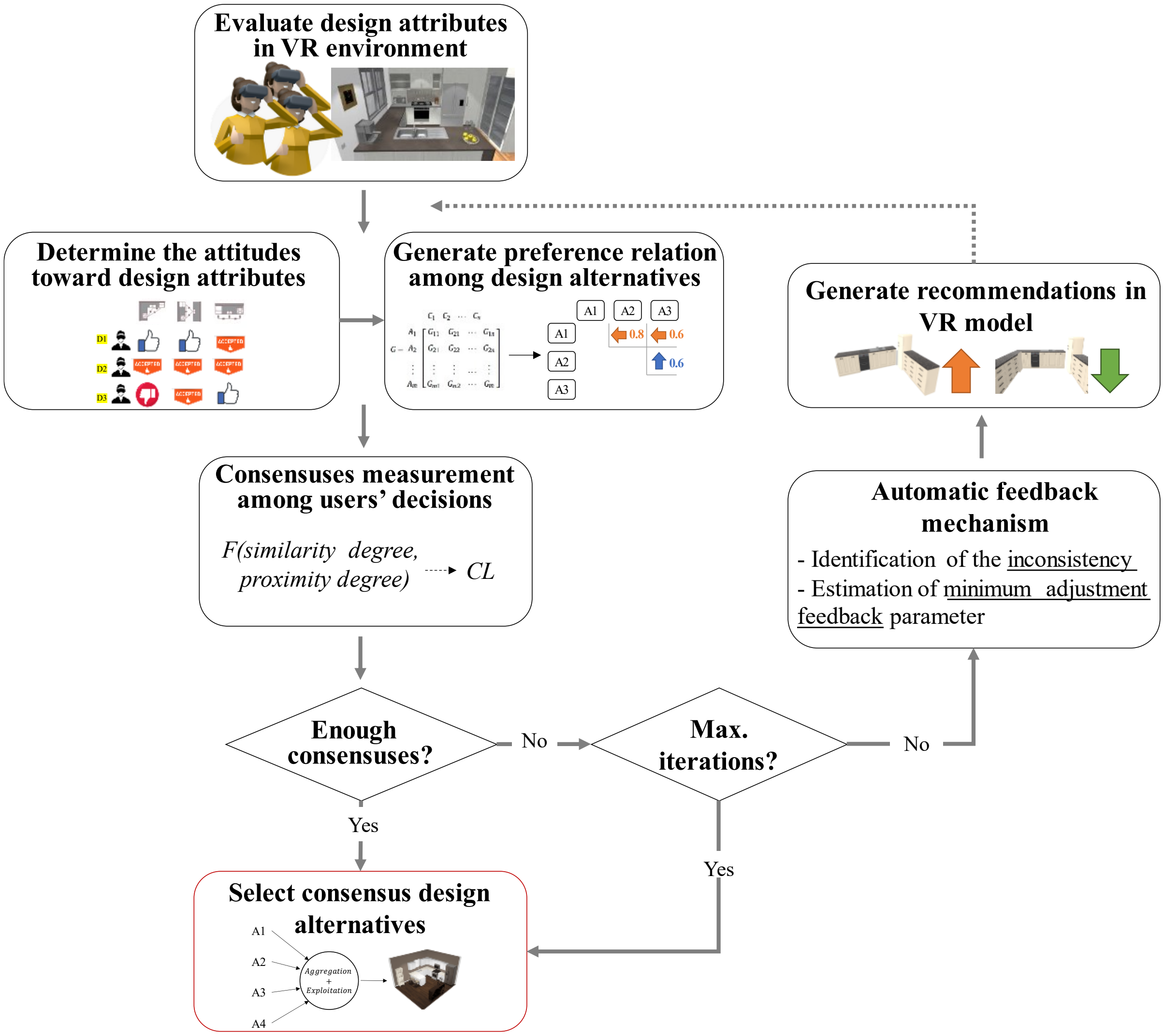


Figure 5-1. VR-based collaborative design system

5.4.1 GDM process with the proposed system

This VR-based collaborative design system is developed in accordance with the theoretical consensus model presented in Section 5.3.2. First, it allows users to comprehensively evaluate design element options in a VR environment. In contrast to the conventional catalogue selection or 2D drawing method, the VR-based interface provides users with 3D spatial awareness and an effortless design engagement experience, which are critical for built environment design. Moreover, users can rotate, tilt, and magnify a virtual product model from many angles within the VR platform. This institutive visualization and effortless maneuvering experience are also conducive to efficient communication among stakeholders and support the co-design experience.

For each design element option, stakeholders assign preference-related linguistic variables, such as 'Like,' 'Dislike,' and 'Acceptable,' to denote their preference. These linguistic variables can be converted into TFNs, and a fuzzy decision matrix of design alternatives (i.e., fuzzy MCDM model) with all combinations of design element options can be generated for each stakeholder. Then, using the preference relation membership introduced in Section 5.3.1, a complementary preference relation is generated for each stakeholder, outlining their relative preferences toward each pair of design alternatives.

Converting a fuzzy MCDM model into a complementary preference relation, rather than having the stakeholder make pairwise comparisons directly, is preferable as a way of (1) eliminating the workload associated with exhaustively assessing a great number of design alternatives with diverse combinations of design element options, and (2) allowing the decision-maker to examine each design element in a more detailed manner and consistently express their preference. It should be noted that, in this study, the degree of preference toward a given design alternative is assumed to be a weighted sum of the preference degree of design elements. This relative importance of design elements can be pre-determined by stakeholders based on personal experience. For instance, when there are three design elements, e.g., layout, style, and fixture selection, the stakeholder may determine their relative importance in influencing the final quality of a given design to be 30%, 30%, and 40%.

By generating the preference relation, along with the fuzzy decision matrices, the system can then estimate the current consensus status by calculating each stakeholder's degrees of similarity and proximity relative to the group's preference. If the level of consensus among the stakeholders satisfies the predefined threshold, the system will designate a "soft consensus" status and proceed to the aggregation and selection phases. Meanwhile, with the associated importance weights of stakeholders with regard to their knowledge background or space usage frequency having been established, the collective overall preference values of design alternatives can be calculated using Equations (6-12) and (6-14). For a homogeneous GDM scenario in which the stakeholders share roughly the same design knowledge and space usage patterns, the impact of the associated degree of importance is considered negligible. Accordingly, the ranking of design alternatives can be obtained from this collective pairwise preference decision matrix, and the optimum consensus solution can be selected accordingly.

On the other hand, stakeholders whose consensus level is lower than the minimum threshold are designated by the system as "inconsistent decision-makers" who may need to change their opinions/decisions in order for a consensus design solution to be reached. In such cases, the automatic feedback mechanism explores the extent to which inconsistent stakeholders need to modify their preferences in order for their consensus levels to satisfy the consensus threshold boundary at a minimal preference adjustment. By solving the minimum adjustment optimization model presented in Section 0, feedback mechanism parameters can be determined, and detailed recommendations can be generated accordingly for the given stakeholder(s).

In a typical GDM situation, these recommendations are presented in a text form, such as "*You should provide a preference value for design element [D1] in design alternative [No. 1] near (0.168, 0.418, 0.668).*" Obviously, this form of feedback is not sufficiently detailed and persuasive to communicate the pros and cons of design element options in such a way as to motivate stakeholders to refine their opinions toward the consensus, especially for stakeholders who do not have a background in architecture and thus may have limited spatial comprehension and may have difficulty fully understanding conventional architectural terms. In this regard, the proposed system leverages VR's ability to demonstrate different combinations of design element options when there are inconsistent design alternatives. Meanwhile, relevant design knowledge of the various design element options is provided to stakeholders in the VR interface. The system allows the stakeholder to re-evaluate the different design element options under the top three inconsistent design alternatives ranked based on the value of the consensus level on the design alternatives. This visualization-based system allows stakeholders to have a clearer view of the design decision-making process by indicating the inconsistency, negotiation progress, and influence of the adjusted preference on the overall design.

During consensus analysis, the system calculates the difference between the recommended preference and the stakeholder's original preference using Equation (6-28). If the recommended preference is lower than the original preference, the system will direct the individual to lower their preference for this design element option; otherwise, the system will recommend to the given stakeholder that they raise their preference level. Once the stakeholder accepts the recommendation or makes other adjustments, the system will re-assign the preference matrices following the recommended value:

$$diff = \frac{(r_l - g_r) + (r_m - g_m) + (r_u - g_u)}{3} \qquad (5-28)$$

where r and g represent the recommended preference and the original preference with respect to the particular design element.

The system then repeats the previous steps, i.e., converting preference decision matrices into preference relations, calculating the current consensus level, and examining whether the consensus state satisfies the predefined requirement. It should also be noted that, if the predefined maximum number of iterations is reached or the stakeholder consensus levels are updated so that they fall within the tolerance value following two iterations (e.g., the difference of consensus degree between two iterations is less than 0.01), the consensus-based GDM process will be stopped to ensure GDM efficiency.

5.4.2 System Scheme

To support the collaborative decision-making process for built environment design as presented above, this study proposes a VR-based collaborative design prototype system. The system is programmed and fully implemented using a tech stack with game development engines, software development kits (SDKs) for specific VR hardware, and database tools. Given that there are various different functions and tasks to be performed, the system is designed in the form of a series of modules: (1) a visual interface (VR module), (2) a computation and analysis (computing) module, and (3) a data storage module. This structure makes it relatively straightforward to upgrade the system in a targeted manner by applying changes only to a particular module as needed. Figure 2 illustrates the schema underlying the VR-based collaborative design system and the interactions among modules.

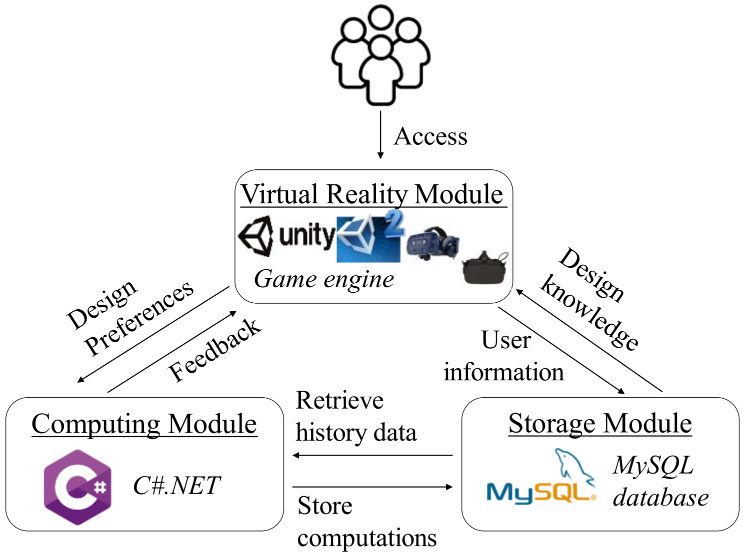


Figure 5-2. Schema underlying the VR-based collaborative design system

VR module

The VR module is the starting point for implementation of the proposed system, as this module governs stakeholder access to the system. This module is developed within a game engine (i.e., Unity, which is also used in the application example presented below), with the support of OpenVR SDK to enable the interactions and maneuvering by VR hardware. This module collects the stakeholders' preferences with respect to the design element options and design alternatives and feeds back the recommendations generated by the consensus model. Stakeholders can even review relevant information related to the design development, such as daylight perception, as in the example shown in Figure 5-3, which is also discussed in previous studies (Keshavarzi et al., 2021; Zhang et al., 2019). All of the information obtained by the system can be subsequently retrieved from the storage module.

Figure 5-3. Example of daylight condition simulation in a VR environment.

To enable a multiple-user VR experience for timely GDM, a networking application programming interface (API), i.e., Photon, is incorporated to support networking. The stakeholders are represented in the cloud-based collaborative space in easily distinguishable colour-coded avatars and can communicate through voice chat.

Computing module

The computing module is the 'brain' of the VR-based collaborative design system, guiding the overall collective decision-making process. After obtaining the preference-related data collected in the VR interface, the computing module then calculates the consensus measures, analyzes the current consensus statistics, and generates the recommendations that are presented to stakeholders at the end of each consensus iteration. This computing module is implemented using the C# language, since C# is the primary language used by both the Unity and the MySQL server that works as a database server in this study. For each consensus iteration, the computations and recommendations are stored, along with the preferences expressed by the stakeholders, in a database; as such, the computing module must be able to communicate with the storage module. Once all the computations have been carried out, the information concerning the consensus progress is sent to the stakeholders, and, if necessary, stakeholders are prompted by the system to initiate a new consensus iteration. In other words, this module automates most of the tasks typically executed by the moderator in traditional GDM.

Storage module

The storage module is developed (using the MySQL database) to store, retrieve, and manage all of the information produced by the system (and that the other two modules will need during the consensus-based decision-making process). Moreover, relevant design knowledge is also stored in the database to support informed design decision-making. In this way, the decision-maker can easily explore product information and refer to previous cases to ensure evidence-based built environment design. Data are stored in a relational database, as illustrated in the simplified entity relation in Figure 5-4.

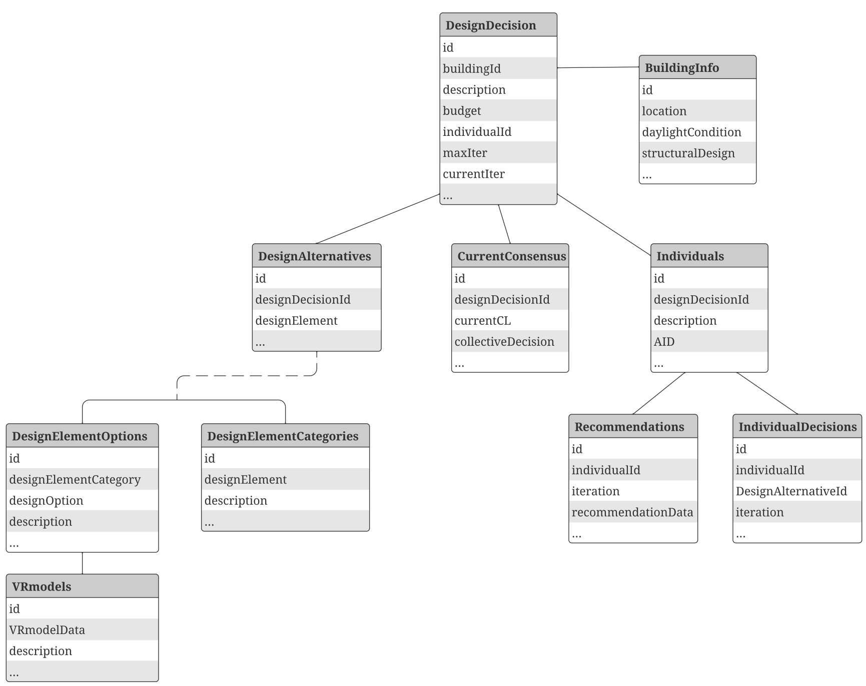


Figure 5-4. Main entity relation in the storage module database.

5.5 Test Case Application

This section presents a test case example of applying the VR-based collaborative design system to solve a simple collaborative decision-making problem for built environment design. The aim here is to assist a group of stakeholders in determining the optimum kitchen design from a set of alternatives based on their preferences. The design alternatives are generated through an exhaustive combination of various design element options. The kitchen design alternatives in this example are defined in terms of four design elements: layout (3 options), design style (3 options), cabinet colour style (4 options), and flooring material (2 options). Given that there are multiple options available for each design element as shown in Table 5-1, 72 different design alternatives, each a unique combination of design element options, can be obtained.

Table 5-1. Design elements options

D1: Layout	D2: Design Style	D3: Cabinet Colour Style	D4: Flooring Material
Galley kitchens (GK)	Traditional (TDS)	White (WC)	Ceramic Tile (CF)
L-shaped kitchens (LK)	Contemporary (CS)	Grey (GC)	Timber (TF)
U-shaped kitchen (UK)	Transitional (TS)	Brown (BC)	
		Beige (BEC)	

In the case application, three participants, referred to as stakeholders (d^1, d^2, d^3) were invited to engage in a collaborative design task. Each participant wore a head-mounted VR display device, two of them being Oculus Quest 2 headsets and the other an HTC Vive Pro headset. The headsets were linked to a computer with the following technical specifications: Intel(R) Core i7-11700KF processor, NVIDIA GeForce RTX 3080. During the test case, the participants were asked to indicate their degree of preference of various design element options using a linguistic scale, i.e., 'Like', 'Acceptable', and 'Dislike', and these were then converted into TFNs in the system as (0.5, 0.75, (1), (0.25, 0.5, 0.75), and (0, 0.25, 0.5), respectively [416]. For simplicity, a 3-level granularity fuzzy term set was used to represent the different levels of satisfaction with the various design element options. As proposed by Bonissone and Decker (1986), participants were presented with three different linguistic scales to choose from (based on their design knowledge and experience) for expressing their preferences: a 5-level scale, a 7-level scale, and a 9-level scale. In this case, stakeholders d^2 and d^3 had more design experience than stakeholder d^1, and it was assumed that d^2, as the primary user of this space, would spend a longer time in this designed space than the other stakeholders; thus, the associated importance degrees were objectively assigned to these three stakeholders as $AID^1 = 0.15, AID^2 = 0.5, AID^3 = 0.35$ by the researcher for illustration purpose. In addition, the importance of the design element in affecting the design alternative selection was homogenously assigned for the three stakeholders as [0.3, 0.3, 0.2, 0.2] for the four design elements. For the consensus-based decision-making model, this test case assumed the following parameters to control the process: similarity–proximity parameter, $\psi = 0.5$, importance parameter $\eta = 0.5$, and consensus threshold $\lambda = 0.9$.

In the section below, the perspective of stakeholder d^1 is taken in describing how the stakeholders performed a collaborative kitchen design with the guidance of the VR-based collaborative design system; the procedure was similar for the other participants.

5.5.1 Collective kitchen design: First round

Once stakeholder d^1 had logged in to the system, they were required to indicate preferences for various design element options after reviewing the basic room information and design guidelines, as illustrated in Figure 5-5.

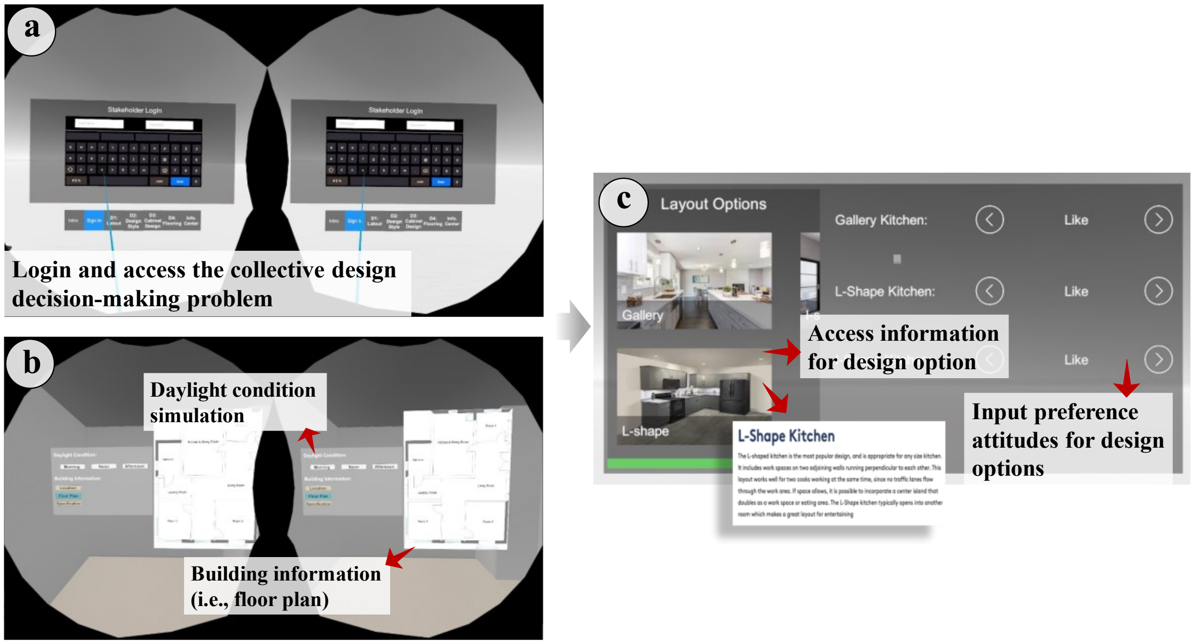


Figure 5-5. GUIs of the system when stakeholders log in and give preference to design element options

The preference decision matrix for stakeholder d^1—and the same applies to the other two stakeholders—is provided in the expression below, which can be expressed in the form of fuzzy MCDM models and converted into the complementary preference relation among the 72 design alternatives.

$$
\begin{array}{cc}
 & \begin{array}{cccc} \quad D1 \quad & \quad D2 \quad & \quad D3 \quad & \quad D4 \quad \end{array} \\
G^1 = & \begin{bmatrix}
\{GK,(0.5,0.75,1)\} & \{TDS,(0.5,0.75,1)\} & \{WC,(0.5,0.75,1)\} & \{CF,(0.5,0.75,1)\} \\
\{LK,(0,0.25,0.5)\} & \{CS,(0,0.25,0.5)\} & \{GC,(0,0.25,0.5)\} & \{TF,(0,0.25,0.5)\} \\
\{UK,(0,0.25,0.5)\} & \{TS,(0,0.25,0.5)\} & \{BC,(0.5,0.75,1)\} & \\
 & & \{BEC,(0,0.25,0.5)\} &
\end{bmatrix}
\end{array}
$$

$$
\begin{array}{cc}
 & \begin{array}{cccc} \quad D1 \quad & \quad D2 \quad & \quad D3 \quad & \quad D4 \quad \end{array} \\
G^2 = & \begin{bmatrix}
\{GK,(0,0.25,0.5)\} & \{TDS,(0,0.25,0.5)\} & \{WC,(0,0.25,0.5)\} & \{CF,(0.25,0.5,0.75)\} \\
\{LK,(0.25,0.5,0.75)\} & \{CS,(0,0.25,0.5)\} & \{GC,(0.25,0.5,0.75)\} & \{TF,(0,0.25,0.5)\} \\
\{UK,(0.5,0.75,1)\} & \{TS,(0.5,0.75,1)\} & \{BC,(0,0.25,0.5)\} & \\
 & & \{BEC,(0.5,0.75,1)\} &
\end{bmatrix}
\end{array}
$$

$$G^3 = \begin{array}{cccc} D1 & D2 & D3 & D4 \\ \left[\begin{array}{cccc} \{GK,(0,0.25,0.5)\} & \{TDS,(0,0.25,0.5)\} & \{WC,(0.25,0.5,0.75)\} & \{CF,(0.5,0.75,1)\} \\ \{LK,(0.5,0.75,1)\} & \{CS,(0.5,0.75,1)\} & \{GC,(0.25,0.5,0.75)\} & \{TF,(0,0.25,0.5)\} \\ \{UK,(0.5,0.75,1)\} & \{TS,(0.5,0.75,1)\} & \{BC,(0,0.25,0.5)\} & \\ & & \{BEC,(0.5,0.75,1)\} & \end{array}\right] \end{array}$$

Based on the preference relations, the computing module then estimated the consensus level for each stakeholder as $CL^1 = 0.88, CL^2 = 0.93, CL^3 = 0.92$. This consensus degree was returned to the individuals in the VR interface so that they could easily capture the current consensus status (see Figure 5-6a). As can be seen, stakeholder d^1 did not meet the consensus threshold requirement (i.e., $\lambda = 0.9$). Thus, the system's feedback mechanism designated stakeholder d^1 as inconsistent' and started proceeding to the step of generating recommendations. Before creating specific recommendations for stakeholder d^1, the computing module solved the minimum adjustment optimization models in order to obtain the feedback mechanism parameter. It was found that, when $\delta = 0.87$, the consensus degree of stakeholder d^1 would satisfy the threshold, i.e., 0.9, while minimizing the preference adjustment required of stakeholder d^1. (All stakeholders, it should be noted, were represented in a virtual conference room throughout this consensus state analysis stage.) Once the feedback had been generated (see Figure 5-6b) and recommended preferences toward specific design element options presented (e.g., “Would you LOWER the preference for [Gallery Kitchen] near to Accept?”), the stakeholders exchanged thoughts on particular design element options and re-assessed the related design information in the database (Figure 5-6c). Moreover, the system retrieved the design features of the “inconsistent” design alternatives identified (see Figure 5-6d), namely, design alternatives [No. 1], [No. 2], and [No. 5], for stakeholder d^1 and allowed the stakeholder to change the design options so they could re-evaluate them in the inconsistent design setting (i.e., [No. 1], [No. 2], or [No. 5], see Figure 5-7).

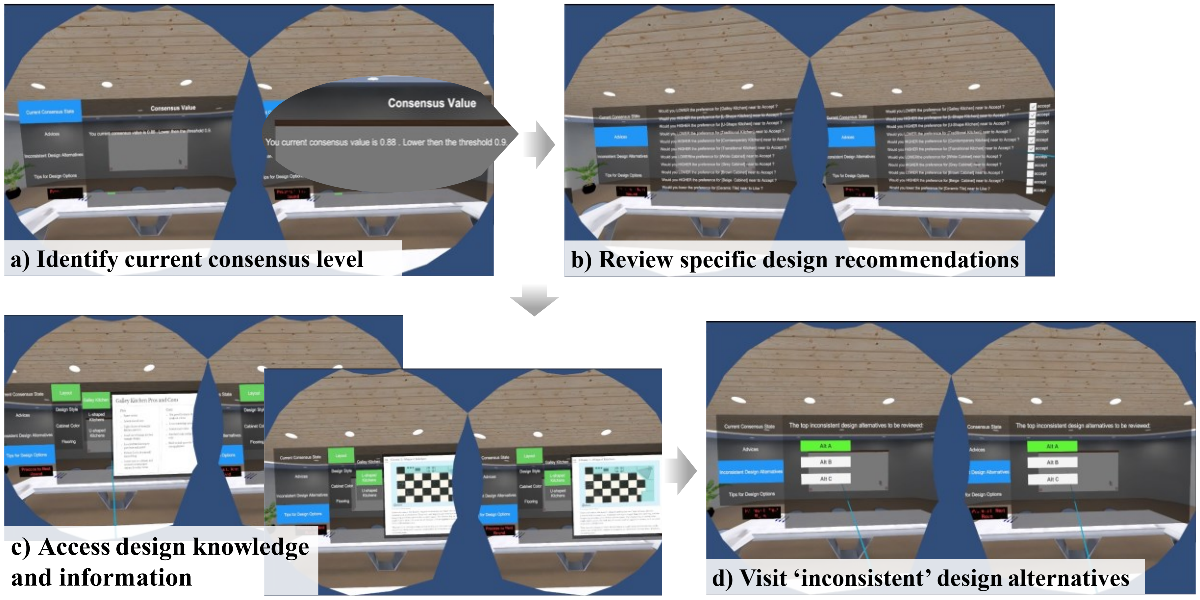
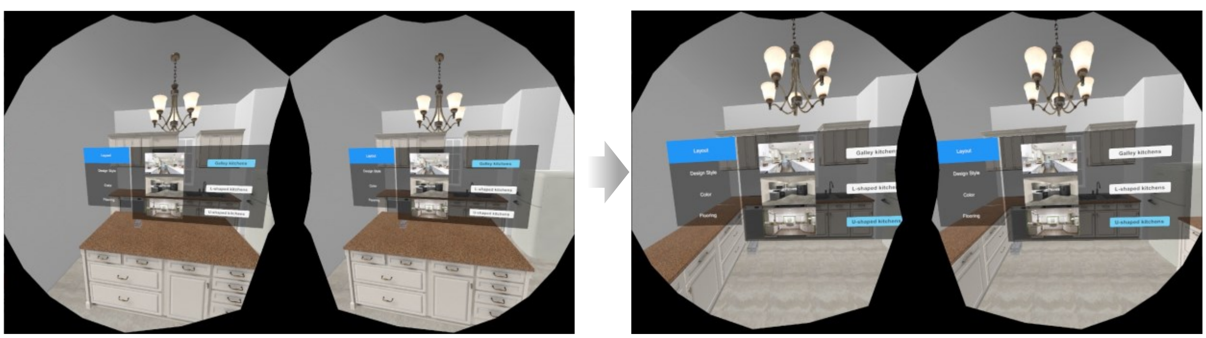
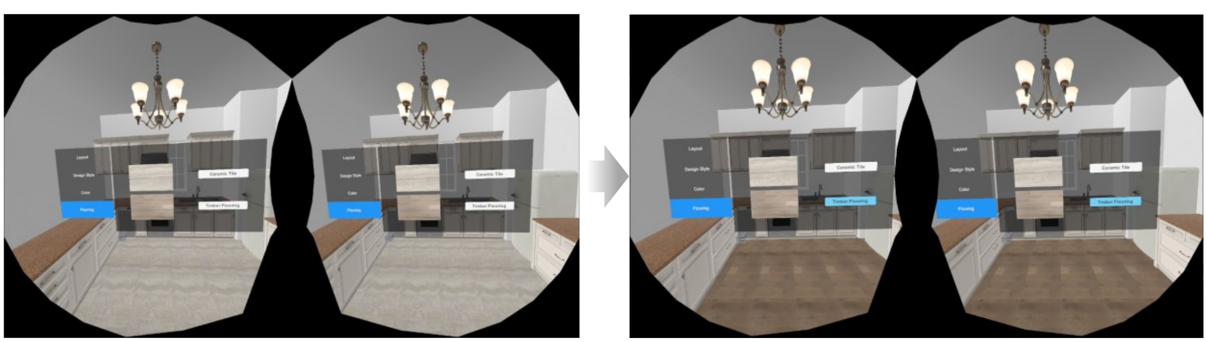


Figure 5-6. GUIs of the system during the consensus analysis and feedback mechanisms.



a) Change the design element D1 Layout from Galley to U-shaped



b) Change the design element D4 Flooring from Ceramic Tile to Timber

Figure 5-7. Re-evaluation of design element options in a VR environment.

5.5.2 Second collaborative design decision round

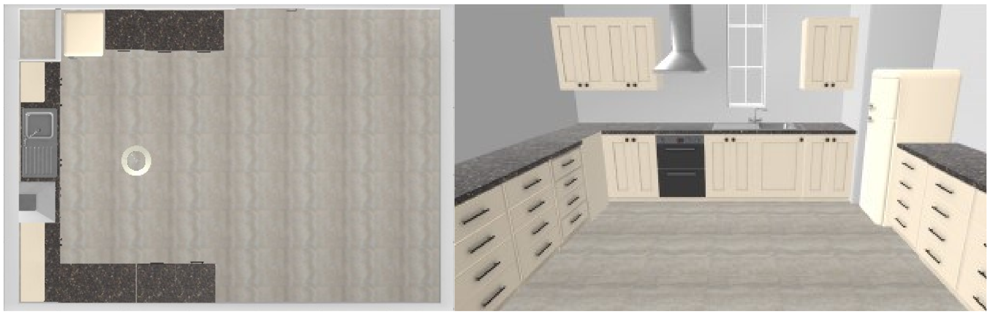
After reviewing the feedback, Stakeholder d^1 ultimately followed the recommendations for D1 and D2 while rejecting the recommendations for D3 and D4. Thus, in the new collaborative design round, the stakeholders' preference matrices for the four design elements were updated as follows:

$$
\begin{array}{c}
\begin{array}{cccc} \qquad D1 \qquad & \qquad D2 \qquad & \qquad D3 \qquad & \qquad D4 \qquad \end{array} \\
G^1 = \begin{bmatrix}
\{GK,(0.17,0.42,0.67)\} & \{TDS,(0.17,0.42,0.67)\} & \{WC,(0.5,0.75,1)\} & \{CF,(0.5,0.75,1)\} \\
\{LK,(0.24,0.49,0.74)\} & \{CS,(0.24,0.49,0.74)\} & \{GC,(0,0.25,0.5)\} & \{TF,(0,0.25,0.5)\} \\
\{UK,(0.33,0.58,0.83)\} & \{TS,(0.33,0.58,0.83)\} & \{BC,(0.5,0.75,1)\} & \\
 & & \{BEC,(0,0.25,0.5)\} &
\end{bmatrix}
\end{array}
$$

$$
\begin{array}{c}
\begin{array}{cccc} \qquad D1 \qquad & \qquad D2 \qquad & \qquad D3 \qquad & \qquad D4 \qquad \end{array} \\
G^2 = \begin{bmatrix}
\{GK,(0,0.25,0.5)\} & \{TDS,(0,0.25,0.5)\} & \{WC,(0,0.25,0.5)\} & \{CF,(0.25,0.5,0.75)\} \\
\{LK,(0.25,0.5,0.75)\} & \{CS,(0,0.25,0.5)\} & \{GC,(0.25,0.5,0.75)\} & \{TF,(0,0.25,0.5)\} \\
\{UK,(0.5,0.75,1)\} & \{TS,(0.5,0.75,1)\} & \{BC,(0,0.25,0.5)\} & \\
 & & \{BEC,(0.5,0.75,1)\} &
\end{bmatrix}
\end{array}
$$

$$
\begin{array}{c}
\begin{array}{cccc} \qquad D1 \qquad & \qquad D2 \qquad & \qquad D3 \qquad & \qquad D4 \qquad \end{array} \\
G^3 = \begin{bmatrix}
\{GK,(0,0.25,0.5)\} & \{TDS,(0,0.25,0.5)\} & \{WC,(0.25,0.5,0.75)\} & \{CF,(0.5,0.75,1)\} \\
\{LK,(0.5,0.75,1)\} & \{CS,(0.5,0.75,1)\} & \{GC,(0.25,0.5,0.75)\} & \{TF,(0,0.25,0.5)\} \\
\{IK,(0.5,0.75,1)\} & \{TS,(0.5,0.75,1)\} & \{BC,(0,0.25,0.5)\} & \\
 & & \{BEC,(0.5,0.75,1)\} &
\end{bmatrix}
\end{array}
$$

The computing module returned the following current consensus level values, each of them satisfying the minimum threshold: $CL^1 = 0.96, CL^2 = 0.96, CL^3 = 0.95$. As such, it can be concluded that the system successfully executed the selection and aggregation process. Design alternatives [No. 71], [No. 47], and [No. 72] were found to be the top three collaborative consensus design solutions considering all stakeholders' preferences, as shown in Figure 5-8.



a) Design Alternative 71

b) Design Alternative 47

c) Design Alternative 72

Figure 5-8. Collaborative design solutions generated by the system.

5.6 Conclusions and Future Work

This study proposes an integrated framework of a VR-based collaborative design support system to facilitate collective decision-making for built environment design. This is the first study integrating a consensus scheme with a VR platform to leverage visualization, communication, and

GDM methods to assist stakeholders in obtaining acceptable design solutions in the early design stage.

In the proposed framework, the consensus-building process is guided by both (1) the degree of similarity between every two stakeholders and (2) the degree of proximity between a stakeholder and the other stakeholders in the group. Furthermore, the system adopts a minimum adjustment feedback mechanism to generate personalized recommendations for inconsistent stakeholders that will assist them in satisfying the threshold value for group consensus while maximizing proximity between their original preferences and the consensus design choice during the negotiation process. This practice helps with achieving an acceptable compromise between group consensus and minimum preference adjustment. Meanwhile, the developed VR platform offers stakeholders a user-friendly collaborative environment that improves stakeholders' comprehension of spatial information and other related knowledge for better communication on collaborative-built environment design. Furthermore, with the support of the networking connection module, the collaborative VR platform also allows stakeholders to communicate their preferences without being physically present. This novel integration of the consensus model and VR technologies allows stakeholders to examine and clarify conflicting issues in collaborative design decision-making and to minimize disparity between stakeholders' preferences with relative ease.

From a practical perspective, the findings of this study contribute to achieving more effective collective decision-making among stakeholders in the design of shared spaces. From an academic perspective, this study expands the use of the consensus model in conjunction with VR techniques to cover decision-making issues in participatory-based built environment designs. In this way, this study contributes substantively to the body of knowledge on intelligent design collaboration in the virtual environment. However, this study is subject to the limitation that only one test case was conducted to illustrate the application and feasibility of the VR-based collaborative design support system. As such, future research should evaluate the effectiveness of this system with more actual built environment design cases, specifically in terms of the efficiency of the system in facilitating consensus-building, human–computer interaction, and user-friendliness. In addition, the current consensus model assumes that stakeholders provide a complete preference relation and the same linguistic term sets to describe their preference attitudes toward design element options. However, in actual practice, decision-makers with different backgrounds and knowledge may provide their preferences using different linguistic term sets or incomplete matrices. Therefore, further research is required to investigate the scenario with multi-granular linguistic term sets and with uncertainty regarding the information in the preference decision matrices.

Chapter 6: CONCLUSIONS

6.1 Research Summary

Understanding the interactions between occupants and built environments and implementing such knowledge into building design are strategies with high potential to improve user satisfaction and building performance in human-centered residential built environment design. However, the overwhelming volume of design information, the dynamic nature of decision-making, and the need to coordinate multi-disciplinary knowledge in design knowledge management pose significant obstacles to effective decision-making in human-centered residential design. To facilitate this knowledge-intensive HCD process, effective knowledge management can leverage design knowledge from multiple domains and data sources to support consistent and effective design decision-making for occupant-oriented built environment design. In this regard, this research proposes four integrated frameworks to optimize the knowledge management process—encompassing knowledge explicitization, knowledge acquisition, knowledge representation, and knowledge communication—in support of effective knowledge-based design decision-making, as described in the above chapters.

As described in Chapter 2, the first framework explores the feasibility of using machine learning to explicitly model the restorative quality of design alternatives, thereby providing decision support for proactive architectural design analysis. To achieve this goal, virtual reality (VR), design-of-experiments (DOE), and machine-learning models are incorporated in the framework to facilitate the collection of human experience data, design feature selection, and affective modelling, respectively. Specifically, upon comprehensively identifying the influential design attributes on human perceived restorativeness, VR is employed to enable a controllable and validated experimental environment for human–building experience data collection and to demonstrate various combinations of design attributes configured by the fractional factorial design. Four machine-learning models—GRNN, RBFNN, SVR, and FIS—are then used to develop models for predicting the restorative quality of a space based on human–building experience data collected from VR experiments. The results of this study indicate that the machine-learning model is capable of modelling the nonlinear relationship between design attributes and human affective experience; meanwhile, the GRNN model is found to outperform other machine-learning methods in predicting restorative experience.

In Chapter 3, an integrated QFD-based framework for developing the KBDSS of human-centered residential design is proposed as the second framework in this research. The purpose of this framework is to gain understanding of the priorities underlying user requirements and match the appropriate design solution with the user's characteristics and preferences in a formalized and specific manner. To begin with, Gemba visits and social media analysis are conducted to comprehensively collect the knowledge regarding user requirements in built environments. Then, the Kano model is incorporated with clustering technologies to facilitate user segmentation based on occupants' preferences with respect to particular requirements. Finally, using fuzzy analytic hierarchy process (AHP) analysis, a prioritized design specification for each user cluster can be generated based on the relative importance of occupant requirements in each user cluster and their associated correlations with design specifications. The prioritized design specifications can thus be regarded as a collection of indices for assessing the potential user satisfaction of various alternative design solutions. To illustrate the proposed framework and assess the validity of the KBDSS, a case study of a kitchen design for a multi-unit residential building (MURB) is presented, demonstrating the application of the developed prototype system. As suggested by the results of the case study, the proposed KBDSS can effectively use the collected knowledge and relevant analytical models to support the decision-maker in making sound judgments.

The third framework, described in Chapter 4, introduces the development of a domain ontology, UCRD-Onto, which formalizes user-centered residential design knowledge to support effective knowledge reuse and implementation in KBDSS. In this framework, Ontology 101 and METHODOLOGY are used to develop the ontology based on knowledge acquired from research reports, building codes and regulations, design cases, and the results of term extraction from social media data. This ontology covers the basic concepts involved in user-centered residential design, such as occupant, residential design, activity, physical comfort, psychological comfort, constraints, and usability performance, as well as the relations, properties, and axioms that define them. In addition, three ontology evaluation methods, i.e., automated consistency testing, criterion-based evaluation, and application evaluation, are adopted in this framework to assess the performance of ontology in terms of consistency and criteria, namely, clarity, correctness, completeness, coverage, and extendibility.

The aims of the fourth framework of this research, described in Chapter 5, is to propose a collaborative built-environment design system that can consider all decision-makers' opinions and guide a group of stakeholders toward consensus design solutions. In the proposed framework, VR technologies are incorporated with the group decision-making (GDM) consensus model to facilitate knowledge communication and the consensus-building process. Specifically, the multi-user VR platform offers stakeholders a user-friendly collaborative environment that improves stakeholders' comprehension of spatial information and other related knowledge for better communication in collaborative built-environment design, even when the stakeholders are not physically present together. The consensus models in this framework analyze the degree of similarity between every two stakeholders and the degree of proximity between a given stakeholder and the other stakeholders in the group in order to guide the negotiation process in an iterative, interactive manner. This proposed framework can aid stakeholders in reaching a decision that satisfies the threshold value for group consensus while remaining close to their original preferences during the negotiation process.

6.2 Research Contributions

This research proposes a framework that uses information techniques and analytical decision models to optimize knowledge management in human-centered residential built environment design decision-making. The primary contributions of this research, corresponding to the four frameworks described above, are summarized as follows:

(1) A data-driven prediction model is developed in this research to explicitize the restorative quality of residential design alternatives based on design attributes, allowing 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, expertise, and subjective opinion. This prediction model lays a foundation for developing analytical models and tools to facilitate the decision-making process at the early design stage to ensure a built environment that gives due consideration to the emotional wellness of occupants. In addition, this work contributes to the body of knowledge on human–building interactions by introducing a VR–DOE-based method that optimizes the process of collecting human–building experience-related data in order to provide a cost-effective and reliable dataset for affective modelling.

(2) A QFD-based KBDSS is developed to capture and manage knowledge related to occupant requirements and the associated design specifications. Using the proposed KBDSS, complex design assessment tasks for human-centered residential design can be simplified, from the overall design to the evaluation of specific quantifiable design criteria, thereby providing design practitioners with specific decision support and aiding in consistently and accurately assessing the quality of design alternatives. Meanwhile, this proposed system provides more refined design knowledge retrieval and implementation based on user segmentation, ensuring a higher degree of satisfaction among a wider crowd. The knowledge captured by this framework also helps design practitioners to better understand the factors governing the performance of particular design specifications and their effects on overall human-centered design (HCD) quality.

(3) A domain ontology, UCRD-Onto, is developed in this research that focuses on representing the knowledge of residential design, constraints, and the relevant requirements associated with human preferences with respect to and experience of the built environment. This ontology provides a formal and shared vocabulary for the residential design domain to promote the sharing and reuse of knowledge among different parties, and deals with coordination issues, inconsistencies, and communication between stakeholders with different disciplinary backgrounds. By incorporating social media data into the ontology learning process, the perspective of non-professional users is also emphasized in this ontology in order to facilitate the informational needs of design practitioners with varying levels of expertise.

(4) A VR-based collaborative design support system is developed in this research that facilitates negotiation and knowledge communication for collaborative decision-making in

built environment design. This is the first study integrating a consensus scheme with a VR platform to leverage visualization, communication, and GDM methods in order to assist stakeholders in arriving at acceptable design solutions in the early design stage. This work not only allows stakeholders to achieve more effective collective decision-making in the design of shared spaces; but also extends the applicability of the consensus model by incorporating VR techniques to cover decision-making issues in participatory-based built environment design.

6.3 Limitations and Future Research

Notwithstanding these contributions, there are opportunities for further work in this area as summarized below:

(1) More advanced data collection methods could be used to increase the quantity and quality of data for knowledge creation and acquisition. For instance, in the present research, the data on the implicit human experience of the built environment was collected using a self-reported psychometric scale. The incorporation of objective human physiological response measures, such as electrocardiogram (ECG), electroencephalogram (EEG), skin conductance (SC), or blood oxygen, in future research would be of great help in eliminating the potential biases in self-report assessments and in better understanding the complex interaction between the built environment and human experience. Moreover, factors related to human–building interactions, such as personality, cultural differences, and dynamic needs of occupants, should also be explored in future studies to provide more intelligent decision-support.

(2) Further validation of proposed frameworks and systems in actual residential design scenarios should also be undertaken, wherein the quality of HCD, measured using either predictive models or KBDSS in this research, could be analyzed based on architect feedback and post-occupancy evaluation. This validation would also assist in calibrating the proposed models, improving their ecological validity, i.e., the degree to which proposed models accurately reflect the relevant interactions in a real-world setting.

(3) The present research is limited to the residential built environment. An extended application to other building types, such as healthcare facilities, office buildings, and educational buildings is highly recommended as an avenue of future study as a way of establishing a robust knowledge management and decision support framework for HCD that is generically applicable to any built environment.

(4) The decision-making models developed in this research (i.e., fuzzy AHP in the second framework and the consensus model in the fourth framework) assume that decision-makers provide a complete judgment and the same linguistic term sets to describe their attitudes toward different decision alternatives. However, in actual practice, decision-makers with different backgrounds and knowledge may provide their judgments using different linguistic term sets or incomplete matrices. Therefore, further research is needed to investigate decision-making scenarios involving multi-granular linguistic term sets and with uncertainty regarding the information in the decision matrices.

(5) Notable assumptions in the development of the first and fourth frameworks (Chapters 2 and 5) are that (1) VR models can provide adequate representations of the physical environment, and (2) the sense of presence provided by VR models provides sufficient emotional and physical stimulus to participants. To improve the accuracy of the information and design

knowledge collected from VR-based methods, the VR display platform and configuration should also be incorporated as variables in the analysis in future work.

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