# User-Centric VR-Based Single-Family House Interior Design System

by

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**ABSTRACT**

The vital role of interior design is gradually being realized due to its frequent interaction with the occupant and significant influence on building performance regarding living experience and indoor environmental effects. However, the current practice of interior design is inefficient and usually fails to satisfy occupant expectations, given that a universal data management process has yet to be established in the interior design industry that is comparable to those of other fields of architectural design. Thus, a significant amount of paperwork is still necessary in the home design process for communication among the client, designer, and builder. However, communication failure is common among occupants and designers, regarding the actual requirements, preferences, and design concepts of home design, due to their diverse levels of understanding and expertise. Therefore, this research proposes a virtual reality and building information modelling (VR–BIM)-based interior design framework aiming to incorporate BIM into the interior design profession and implement UCD more efficiently and effectively. A prototype system is also developed to enable data communication between the BIM software and VR platform as well as verify the proposed methodology. In this research, the tasks of interior finish material selection and lighting design are studied and improved with the introduction of two novel approaches. These two approaches function as the "brain" of the system to assist the user in making better design decisions based on the embedded rules acquired from design guides and previous research. Also, several multi-criteria decision-making methods and an optimization algorithm are implemented to facilitate the rule-application process. The results from case studies conducted in this research indicate that the proposed framework can improve the data management of interior design, and it is capable of assisting the user in designing a living

environment that is based on their actual requirements without the need of any significant experience or background in interior design.

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# CHAPTER 1 INTRODUCTION

## 1.1 Background and Motivation

There is consensus throughout the architecture and design industry that communication and data management are the two major categories where problems resulting in error and inefficiency throughout the working process occur. The deficiencies in communication have an impact on several aspects of the industry. For example, the overall design process can be compared to a relay race, where every participant (or discipline) must wait for its turn to take hold of the baton and run with it. However, the various disciplines (e.g., architects, mechanical engineers, home designers, consultants) involved in the project are confronted with difficulty in understanding one another accurately due to their distinct backgrounds. Thus, the baton, or the information of the building project, is dropped, or lost, which leads to an inefficient, time-consuming, and even costly design process. On the other hand, the current design evaluation process should focus more on the end-user opinion, given that current architectural design is a product of complex computation carried out by various building performance simulation and analysis software programs in terms of structure, energy efficiency, and environmental effect, of which the traditional approach, expert knowledge, cannot encompass. However, the application of end-user involvement in the early design stage is still under development, and the architects and designers are still "guessing" the end-user living behaviour and preferences based on personal experience.

When it comes to data management perspective, the issues primarily exist in the various levels of building a data model from incompatible software tools of various disciplines and the lack of an integrated information model. As exemplified by the current interior design profession, a significant amount of paperwork must still be completed in order to record the design concept and decisions made by designers and clients. However, this method of data management also results in a high risk of information loss and unclear instructions for personnel involved in the construction phase.

These two problems result in a situation where, as presented in Figure 1-1, the effort put forth during a building's lifecycle increases with the progress of the building project. Also, not addressing these issues consumes more effort compared to the scenario of frontloading the effort and knowledge that would normally occur at later lifecycle phases given that the previous situation possesses a high risk of miscommunication and rework, which is time-consuming and inefficient.

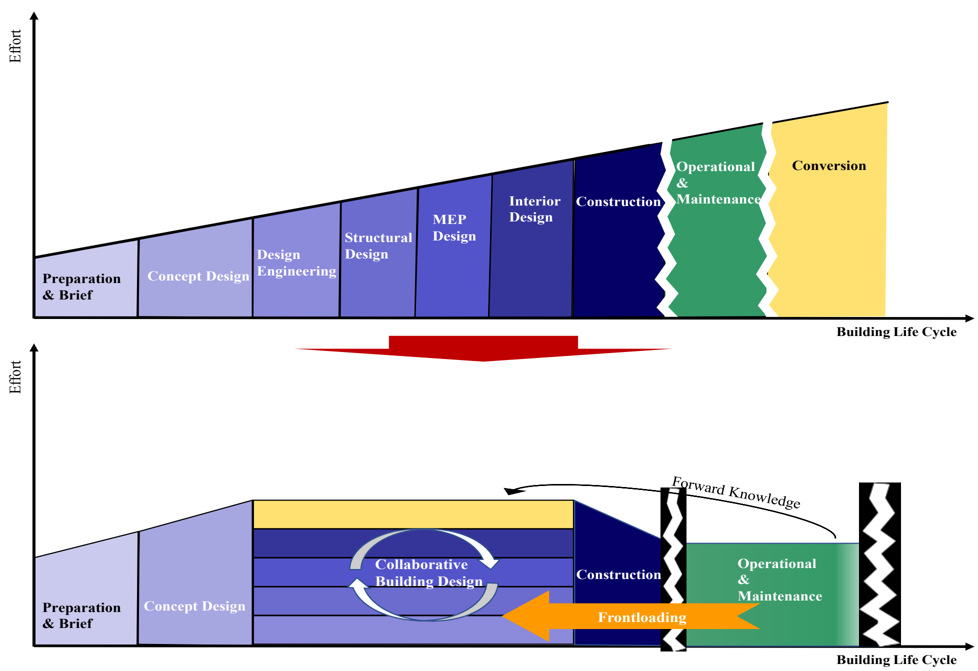



**Figure 1-1 Effort distribution during building lifecycle, adapted from Bullinger et al. (2010)**

To tackle the communication and data management issues, the architecture, engineering, and construction (AEC) industry has adopted a combination of process and concept that supports 3D, dynamic, real-time building modelling during the building lifecycle. One of the most popular representatives of this is Building Information Modelling (BIM), which is intelligent and capable of sharing information regarding the building project across several software platforms. Compared to the traditional method, BIM provides an efficient data management and communication platform, which allows for bi-directional data exchange, data format integration, and model visualization to support collaborative design among various disciplines. In recent years, the rate of BIM adoption and usage has steadily increased in both the North American and European architecture and design industry. Most practitioners believe BIM can help reduce cost and time consumption as well as greenhouse gas emission for the entire building lifecycle.

However, the interior design discipline currently plays only a small role in this approach compared to other disciplines. Interior design is an essential part of residential buildings in that suitable design promotes a healthy and high-quality living environment for residents. When performing interior design, home designers must consider many factors, such as environmental analysis, daylighting analysis, occupant preference, and building code. Although the majority of this information can be easily retrieved from BIM models or BIM-based external simulation tools based on the work of other disciplines, the implementation of BIM is rarely discussed in interior design practice or education. In current practice, potential homeowners usually visit show homes in order to view design options and determine their preferences; on this basis, the home designer determines interior design according to the identified personal preferences of the occupants as well as the functional requirements and proposes the results to the occupant in the form of a rendered 3D model and images. However, home designers at times still make educated guesses in the interior finishing selection process due to a lack of clarity about occupant preferences and the diversity of interior finishing products available. Such guesswork can lead to deviations from the occupant’s expectations, thereby triggering the need for design changes. For this reason, typically several rounds of reviews by the occupant and subsequent design changes are required before the final design can be reached. In addition, poor data management during the traditional interior design phase usually occurs, which leads to the home design decision being incompatible with the design from other disciplines (e.g., mechanical design or structural design) and often mistakes or discrepancies go unnoticed until the construction stage. As a result, continuous design modification and rework occur because of the lack of collaborative work between interior design and other disciplines.

In this regard, the BIM process and Virtual Reality (VR) technology have been demonstrated to offer an efficient platform for communication and data management through real-time visualization and a uniform data format. Specifically, VR technology can ease the communication between occupants and designer, given that it can offer a real-scale virtual space to assist the occupants in accurately interpreting and understanding the building information and providing useful feedback. Thus, the present research proposes an innovative methodology to implement a user-centered design (UCD) method in the interior design process through the application of BIM and VR technology. In this thesis, an intelligent system incorporating several multi-criteria decision-making methods and optimization algorithms is developed to address the semi-automatic interior design problem and facilitate user involvement.

## 1.2 Research Scope

Although interior design consists of many components, such as space layout, furniture design, finish selection, and lighting design, this research focuses on finish material decision-making and interior lighting design, since finish material selection and interior lighting design contribute to the visual effect, occupant preference, and the sustainability of interior design options to a significant degree. As such, it is easier to measure these influences under various finish material selections or lighting designs compared to the measurement of other interior design component. It should also be mentioned that the interior design study of commercial buildings is excluded from this research, as there is a significant difference between the interior design of residential buildings and that of commercial building in terms of the diversity of end-user profile, functionality fulfillment, structural integrity, and design constraints. The terms “end-user”, “occupant”, and “homeowner” in this research all refer to the person who uses or occupies the building and is not necessarily the person who owns the building; as such, they are not considered to be experts in architecture or design but rather to have knowledge and opinions about the performance of various facilities in the home in relation to their own priorities and goals.

### 1.3 Objective

The methodology presented in this research is designed to enhance data exchange and management and end-user involvement in residential building interior design in order to promote collaborative design among all participants in a building project and provide the end-user with a home design well aligned with their personal preferences.

The objective of this proposed framework is built upon the following **hypotheses**:

1. Implementing BIM in home design facilitates data sharing among all participants of a building project and promotes a collaborative design.
2. The end-user can have a more streamlined interior design experience and achieve a home design better aligned with their personal preferences if the proposed system can eliminate redundant information and help them to make informed decisions.

To verify these hypotheses, several sub-objectives are encompassed in this research:

1. Develop a system that provides a VR space for end-users to easily explore the potential interior design options and allows the accurate and timely data exchange between VR model and BIM model.
2. Identify the independent tasks involved in interior design and define the information flow of each task.
3. Investigate the influencing factors and conventional methods for each interior design task and develop a system encoded with this knowledge in order to facilitate the interior design process.

### 1.4 Thesis Organization

This thesis consists of five chapters. Chapter 1 introduces the background and motivation of this research and then illustrates the primary purpose and hypothesis of the proposed methodology.

Chapter 2 (**Literature Review**) covers relevant literature topics, including interior design for lighting and finish material selection, architecture design management, UCD in the architecture industry, human-machine interaction in building design, and VR in the AEC industry.

Chapter 3 (**Methodology**) introduces the general methodology used in this research, which primarily involves three processes: (1) VR–BIM-based interior design system development, (2) finish material selection approach introduction and implementation, and (3) recommender system construction for interior lighting design. The first process is conducted for building a fundamental working environment to support the implementation and verification of the following two interior design methods or frameworks.

Chapter 4 (**Implementation**) describes the implementation of the proposed framework and the prototype system through two case studies in terms of interior finish material selection and home lighting design for a kitchen. The primary objective of this chapter is to illustrate the feasibility of proposed framework regarding (1) data exchange and management among several platforms; (2) interactive particle swarm optimization-based approach for interior finish material selection; (3) knowledge-based interior lighting recommender system. Also, this chapter investigates the adoption of proposed VR–BIM-based interior design application in interior design for the common user according to the feedback of user experience.

Chapter 5 (**Conclusions**) includes a general conclusion of the research work and provides final discussion and recommendations for future work.

# CHAPTER 2 LITERATURE REVIEW

## 2.1 Interior Finishing Design

Today, the vital role of interior design as a discipline which connects homes, their occupants, and the surrounding community is gradually becoming recognized in the homebuilding industry. Many practitioners within the interior design profession begin by focusing on aspects of interior design such as human health and well-being and environmental sustainability (Bonda & Sosnowchick, 2006).

### 2.1.1 Residential Lighting Design

Lighting design is an important piece of the interior design puzzle. It plays a significant role not only in how the homeowner experiences a space, but also influences the building performance in terms of efficient energy use and building sustainability. Thus, many studies devoted to this area attempt to investigate the potential effects of indoor lighting on several factors and then develop a systematic method to optimize the lighting design.

It can be argued that a better understanding of a homeowner's beliefs about, preferences toward, and knowledge of lighting systems would improve the design to meet occupant needs, as the homeowner's attitude toward the lighting in their home will greatly affect their domestic behaviour (Veitch et al., 1993). Some previous studies argue that the indoor illuminance environment has a strong correlation with human psychological behaviour. For instance, Daurat et al. (1993) found that subjects report a more optimistic mood under 2,000 lux than under 300 lux. Belcher & Kluczny (1987) discovered that women exhibit a strongly negative shift in mood under the "bright" illuminance setting and a near neutral shift under the "dim" illuminance setting, whereas men have the opposite response. This finding was also proven by Knez & Kers

(2000), and they also concluded that age and gender have a bi-directional influence on the illuminance level and the colour temperature.

Kasof (2002) verified the hypothesis that bulimic behaviour is positively correlated with the individual's preference for dimmer lighting. Moreover, the generally low level of indoor illuminance at night may lead to behavioural disinhibition for occupants, undermining self-regulatory control and adherence to one's dietary standards (Kasof, 2001). Similarly, an experiment conducted by Gifford (1988) also indicated that dimmer lighting reduces self-awareness in a solitary indoor situation. During the experiment, he asked female participants to describe themselves (in words) under various levels of illuminance. The results indicated that the participants, when exposed to dimmer lighting, wrote less self-disclosing responses and used fewer self-referential words than those participants who were exposed to brighter lighting. Also, the results of this study underscored the difference among individual preference for interior illuminance levels. In other words, some people prefer bright lighting whereas others prefer dimmer lighting.

Not only does the factor of personality influence lighting preference, but also the location preference. Kuller et al. (2006) conducted a study that investigates the systematic impact of interior lighting and colour on an occupant's mood in an indoor environment. A total of 988 participants from 4 countries were engaged in this study, and the results revealed that the indoor illuminance and colour temperature affect mood, and that the indoor illuminance and colour temperature have a more significant effect on people who live farther north of the equator compared to those who live near the equator.

The effects of indoor illuminance on other areas, such as energy consumption, environmental effect, and economic effectiveness, also need to be considered. So & Leung (1998) state that a satisfactory lighting design can be achieved by means of detailed considerations in terms of scientific knowledge analysis, practical experience, technical feasibility, and economic reality, which indicates that the design of lighting systems is essentially a multi-objective optimization problem. In this context, many optimization algorithms are adapted to optimize the layout, quantity, illuminance, colour temperature, and power of lighting system design. For example, Corcione & Fontana (2003) used the genetic algorithm (GA) to determine the lighting installation of a sports field in which the objective function is the product of a horizontal uniformity function and an illuminance function. Shikder et al. (2010) integrated a lighting simulation program with a GA-based search technique in order to identify optimal lighting positioning. Yoshizawa & Kanematsu (2010) employed GA to identify optimal lighting layouts in order to achieve optimal tradeoffs among luminance, illuminance, Unified Glare Rating (UGR) glare index, and installation cost. Cassol et al. (2011) proposed a generalized extremal optimization (GEO) algorithm to calculate the location and luminous power of the lighting sources to achieve the design objectives regarding prescribed illuminance level and energy savings. Madias et al. (2016) used the non-dominated sorting genetic algorithm II to optimize interior lighting so as to maximize the illuminance uniformity and minimize energy consumption. Santiago et al. (2017) used GA in a multi-objective optimization to design the layout of LED lamps for the purpose of controlled environmental agriculture. In this method, the authors divided the whole plant growing area into small grids and used 0 or 1 in “genetic chromosome” as optimization variables to represent the presence of a lamp at specific grid joint locations. However, the research mentioned above does not consider human preferences when conducting the lighting design optimization. In this regard, Villa & Labayrade (2011) developed psycho-visual functions by implementing statistical analysis of the psycho-visual test results in order to integrate the human visual preference into a multi-objective office illuminance design optimization. FernáNdez & Besuievsky (2012) presented a novel approach to optimizing the lighting fixture arrangement with optimal skylight installation shapes under the constraints of user specifications and building code. In order to satisfy the desired illuminance of each occupant in an office setting while minimizing the energy consumption, Tanaka et al. (2009) applied Adaptive Neighborhood Algorithm with Correlation Coefficient (ANA/CC) for lighting system control.

According to the literature reviewed above, we can conclude that the design of indoor lighting systems is an important and complex task. Given that several factors need to be considered during the lighting design, many studies view lighting design as a multi-objective optimization problem and solve it with various optimization algorithms. The objective functions for lighting design among these studies are similar in that most of the objective functions incorporate the requirement from the level of illuminance, uniformity, glare effect, energy consumption, and cost; however, few involve the end users or occupants into the optimization process. As indicated by the previous literature, the illuminance environment is proven to be associated with human health. On the other hand, the illuminance-level preference varies from person to person, and the emotional behaviour of those under severe illuminance levels correspond to a subjective brightness level—the level at which the user finds it too bright or dark—rather than specific illuminance level values. Thus, in the research presented in this thesis, the personal illuminance preference is included in the lighting design method.

### 2.1.2 Material Selection in Interior Design

Similar to the lighting design, material selection also plays a significant role in interior design. From a health perspective, the material selection possesses a more noticeable effect on occupant health than lighting design. In 1999, Jaakkola et al. (1999) investigated the impact of polyvinyl chloride (PVC) finish material and textile wall material (e.g., wallpaper) on the development of bronchial obstructions in young children. By conducting a matched pair case-control study among 3,754 newborns in Oslo, Norway, including two years of follow-up observation, the study found that the presence of PVC flooring and textile wall material is significantly associated with the risk of bronchial obstruction compared to the reference case of wood flooring and painted walls and ceiling. Also, a population-based incident case-control study was presented by Jaakkola et al. (2006) to assess the relations between the use of various interior finish materials and the risk of asthma in adults. The results of the study also suggest the use of plaster flooring or plastic wall materials for 12 months is a determinant for the onset of asthma. In addition to health, some researchers study building materials from the aspects of environment and economics. For instance, Akanmu el al. (2015) proposed a material selection support system under the BIM environment. The total cost and carbon emission for the materials during the building lifecycle are applied as two objective functions to be optimized and criteria such as cost, quality, transportation distance, and environmental effect are also considered. A harmony search algorithm is also used in their study to determine the material combination scenario with minimal cost and carbon emission.

It is clear that the topic of building material selection and evaluation has been studied thoroughly in recent decades. In light of increasing concerns regarding the environment and human health as well as the development of a variety of alternative materials, material selection is becoming an increasingly critical and challenging task for engineering design.

However, official guidelines for building material selection have yet to be developed, and it should instead be approached as a multi-criteria decision-making (MCDM) problem. Thus, various material decision-making frameworks and searching strategies have been proposed in recent years to assist designers and end-users in selecting the most suitable materials. In general, there are three primary methods for material selection (Ashby et al., 2004): (1) free searching strategy based on quantitative analysis, (2) expert questionnaire strategy, and (3) inductive reasoning and analogy strategy. In the architectural domain, the former two strategies are implemented more frequently. For instance, as early as the mid-1990s, Mahmoud et al. (1996) had developed an expert system for evaluation and selection of floor finish materials. This system follows a selection process as a quantitative-analysis-based free searching strategy, screening, ranking, and providing supporting information in order to assist the designer and end-user to choose the most appropriate floor material. Similarly, Castro-Lacouture et al. (2009) refined the free searching method and developed a mixed-integer optimization model to assist the decision maker in selecting the appropriate building material. In addition to the two mentioned above, there are numerous well-documented studies on the free searching method (Farjami & Mohamedali, 2017; González & García Navarro, 2004). The advantage of this method is that it offers a straightforward, efficient, and quick application with considerable flexibility. Nevertheless, it requires detailed, analyzable input data, entailing some subjective criteria, such as aesthetic satisfaction, which are difficult to estimate.

On the other hand, some studies have attempted to build on the knowledge-based approach or to implement the information technology approach to solve the material selection problem (Goel & Chen, 1996; Zhang et al., 2015). For instance, Zha (2005) proposed a web-based knowledge-intensive manufacturing consulting service system to help designers select materials for manufacturing on the basis of information collected from online sources. Rahman et al. (2012) employed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) in a knowledge-based decision-support system for roofing material selection in which the background knowledge was collected from domain experts and a literature review. In most knowledge-based strategies, it should be noted, the user is guided through a set of questions with a built-in knowledge model used to help the user select their desired material. However, since some demands from the user cannot be expressed explicitly, this kind of method is thus limited in practice.

Although a number of research studies have been directed toward material selection, the majority of these focus on the quantitative performance of material and fail to consider the individual user's subjective preferences. Most of the existing literature evaluates and selects materials for interior design from an engineering perspective. Criteria such as indoor air quality, environmental impact, and energy efficiency are the factors that are most frequently investigated (Niu & Burnett, 2001; Sim & Park, 2002; Farjami & Mohamedali, 2017), whereas the aesthetic preferences of homeowners are often neglected. Certainly, these quantitative performance indices, such as impacts on occupant health, environment, functional performance, and cost, are important in the interior material selection, but the result of interior design means more to the homeowner than a mere engineered product. The designer and researcher thus have to take subjective performance into account. As a result, the proposed interior material selection method seeks to implement the concept of UCD, which focuses on understanding and achieving end-user needs and requirements. Such a method can assist the user to express their needs more precisely and efficiently.

## 2.2 Architecture Design Management

The previous section illustrates the influence and the current research trend of interior design, which offers a comprehensive approach regarding the recent research on interior design from design and operation perspectives. This section outlines a method to understand how to improve the design from a management perspective.

Design management is a challenging task given that the product may be a result of socially-constructed phenomenon and decision making of which the end result can be inherently unpredictable (Kestle & London, 2002). The poor management of early design phases has proven to be the cause of document deficiency and rework (El. Reifi & Emmitt, 2013; Tilley, 2005). These issues influence building projects negatively in terms of being over budget or reducing productivity (Baldwin et al., 1999). The research by El. Reifi & Emmitt (2013) also demonstrated that issues related to the design brief (a written document for a design project at the early design stage) are responsible for approximately 30% of the rework.

Notably, most design problems are related to poor design information management (BEDC Report, 1987). This idea is also supported by Tenah (1986), who argues that a supervisor could not perform their duties efficiently without accurate, timely, and applicable information. Consequently, a significant amount of time and effort are wasted due to the information management process of the design phase (Flager et al., 2009).

The flow of information has a significant effect on all other resource flows and it is essential to improve its management methodology (Dave et al., 2010; Sacks et al., 2010). With more advanced and efficient information management, some of the unnecessary wasted time and effort could be reduced and put toward value-creating activities.

To solve the problem, Austin & Newton (1993) developed a data flow diagram-based design model to map information flows during building design. Steward's design structure matrix was used in their research to analyze the proposed design model in order to suggest the allocation of each interdependent task efficiently. Persson et al. (2009) investigated several AEC companies that implement predefined building components regarding their information management and identified the critical factors of information management during the building industrialization in order to achieve the potential efficiency benefit of industrialized building production. The results indicated that most of the surveyed companies have several areas for improvement in order to achieve optimal management of house design and manufacturing. The three tasks that must be prioritized in order to realize their goal include: (1) formally describing the relevant process; (2) explicitly depicting the product range; and (3) creating an appropriate information system strategy.

On the other hand, current construction projects have become increasingly complicated, requiring more detailed drawings for the project construction phase. However, Van Berlo & Natrop (2015) questioned whether the information presented by 2D drawings can encompass the necessary information for all construction phases; the result of their study indicated that most of the drawings are not specific enough for specialized tasks. A study by Love & Li (2000) noted that incomplete and incorrect information often caused rework during construction, which finally leads to a result of inactivity and inefficiency for several onsite tasks. In order to reduce the risk of rework, supervisors or other onsite staff have to transfer information between the construction site (paper-based) and their office computers/data management systems to make up for any lost information. As a result, some documentation of construction activities, meeting memos, and inspection records often have to be carried out more than once, because this type of documentation is paper-based and must then be inputted into digital format after the fact (Lofgren, 2007). This redundant communication leads to wasteful use of administrative resources. According to the research carried out by Samuelson (2003), the unsatisfactory performance in terms of the requirements for design information and communication behaviours explains the low productivity in the construction industry.

One of the primary tasks in the design phase is information exchange and communication among multiple project participants. Generally, there are two methods for communicating information for project design, synchronous communication and asynchronous communication. Synchronous communication represents a real-time information flow between two or more individuals (e.g., meetings, telephone conversations), while asynchronous communication refers to a remote flow of information, which is neither direct nor in real-time (e.g., emails, drawings, models). Currently, the use of Information Communication Technology (ICT) tools in the construction industry is increasing; ICT is a powerful tool for asynchronous communication, but can also be used in synchronous communication. Svalestuen et al. (2017) stated that the use of intranet as a project tool makes information available to the project team members immediately, thereby increasing the speed of the overall flow of information. Thus, several AEC companies have adopted ICT tools. One example is the prevalent practice of BIM. The implementation of BIM onsite facilitates communication between design and construction and also eases the difficulties in understanding the complex problems and solutions (Svalestuen et al., 2017). Also, BIM is a documentation alternative such that information generated from one device is stored in a database that is accessible by all team members. A system like KanBIM™ ensures that the process information and the product information can be traced throughout the project (Sacks et al., 2013).

In addition to information management, relation management of various tasks during the design phase is also a method involved in efficient building design. Kalsaas & Sacks (2011) emphasized that it is crucial to identify dependencies in the design process in order to manage them. Once recognized, some methods such as negotiations, mutual adjustment, and opinion-based communication can be applied to the various dependencies to facilitate the design process (Andersen, 2011). In the interior design profession, it is rare for the design sequence to be arranged from an information management perspective. Thus, a standard methodology to incorporate interior design information and process into the overall BIM process is essential.

### 2.3 Building Information Modelling in Interior Design

BIM is a combination of concept, methodology, and process that generates and manages the physical and functional characteristics of the building project in a digital format during the building lifecycle. The virtual model constructed through the implementation of the BIM technique can be used for the purpose of visualization, shop drawing generation, code reviews, estimating, construction sequencing, collision detection, failure analysis, and facilities management. The 2007-2008 annual report from the Cooperative Research Centre (CRC) for Construction Innovation reveals that the implementation of BIM could offer several benefits, including effective and efficient information management, better building design and production quality, controlled lifecycle costs and environmental effects, and reduction in project design and construction time (CRCC Innovation, 2008). Also, BIM provides a collaborative working platform for all project stakeholders and encourages the integration of multi-disciplinary knowledge, which significantly changes the traditional project workflow and the delivery method (Hardin, 2009). Thus, BIM has recently become one of the most promising research topics in the AEC industry (Azhar, 2011).

An international survey conducted by RIBA Enterprises (a knowledge management organization of the Royal Institute of British Architects) in 2016 indicated that Canada has a high adoption rate regarding BIM application and the most frequent usage is to provide 3D visualization of buildings (as presented in Figure 2-1 and Figure 2-2). Also, Figure 2-3 demonstrates the survey results published by Conject, a commercial project management software company, that the most optimized process for BIM in an AEC company is data sharing, followed by clash detection and design review. Thus, the data exchange and analysis involving BIM is valued most during practical application, and the accuracy and integrity of the geometrical and non-geometrical information in the BIM models is crucial.

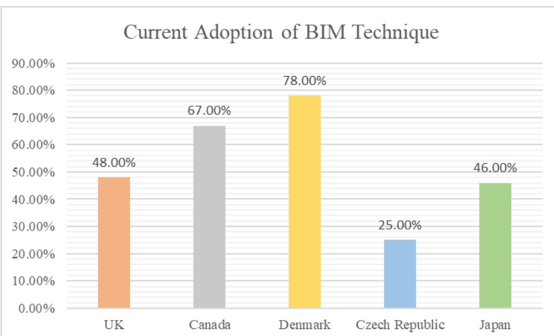



**Figure 2-1 Current adoption rate of BIM technique in five countries, source: National BIM Report (2016)**

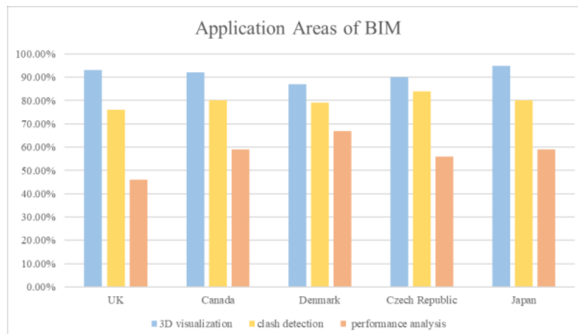



**Figure 2-2 Primary application area of BIM in AEC industry, source: National BIM Report (2016)**

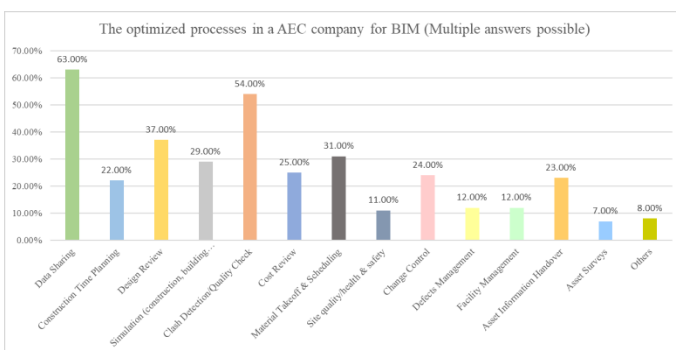



**Figure 2-3 Optimized process in an AEC company, source: BIM survey (2015)**

Although the development and adoption of BIM are widespread in the AEC industry, the interior design profession does not play a significant role. Notably, when it comes to the collaborative design between various aspects of the built environment, interior design is often excluded. It appears that the BIM concept or relevant BIM-based simulation and analysis tools are rarely discussed in the practice or education of interior design. A study by Floyd & Seidler (2010) indicated that more than 53% of interior designers have never used BIM in their work. However, the increasing demand for BIM in the interior design industry is gaining awareness and attention. The study results by Floyd and Seidler also stated that 85% of interior designers and educators believe that interior design education should include BIM in the future.

The current interior design profession has gradually transitioned from traditional one-dimensional subjective aesthetic art creation work into a user-centered and multi-criteria scientific, systematic design, which requires much more knowledge regarding building systems and building science relevant to indoor spaces. Thus, the building information regarding interior finishing should be incorporated into the BIM process as well as assist the interior designer and other members of the project team to make informed decisions.

Also, in current practice, the sequence for building design is usually as follows: architectural design, structural engineering design, mechanical engineering design (e.g., electrical and plumbing engineering), and interior design. To conduct an electrical and plumbing plan for the mechanical engineering design, some information from the interior design plan is required, such as the layout of the lighting system, sockets, cabinets, and toilets. However, this information is not available in the current mechanical engineering design stage. Thus, engineers must rely on guesswork regarding the homeowner's preferences, and the interior layout design is based on the engineer's personal experience. In this regard, the opportunity for the homeowner to customize their home is greatly reduced, which may lead to a less satisfying living experience. Therefore, the present research proposes the implementation of BIM into the interior design profession as well as the incorporation of interior design information in order to increase the integrity of the BIM model.

### 2.3 User-centered Design for Architecture Design

The current trend in the architecture industry reveals that buildings are becoming increasingly complicated, especially regarding the fact that buildings are increasingly turning into the analysis result of computer technology. In other words, traditional expert knowledge is becoming insufficient for evaluating building designs. Thus, the new method of evaluation for a building project will be carried out from an economic point of view, determining how well the building meets end-user expectations. In fact, several studies have also revealed that if buildings are not designed to meet occupant expectations, occupants may experience varying levels of discomfort and exhibit diverse living behaviour from that of the design's prediction (Gunay et al., 2013; Inkarojrit, 2005; Wymelenberg, 2012), which may ultimately result in a reduction in the efficiency of building performance, such as in the form of increased energy consumption (Dubois & Blomsterberg, 2011).

In this context, Thyssen et al. (2010) argued that failure to fully understand end-user requirements may lead to a high risk of either low fulfillment of client expectations or multiple design alternations during the project process, which ultimately results in increased cost and a negative attitude from the project participants. Thus, the question of how to facilitate end-user engagement during the building design and construction process is receiving increasing attention.

Traditionally, demographics, social impact assessment, and post-occupancy evaluation are key methods through which end-users are engaged in building projects. Builders analyze such information in the early building stage in order to understand the potential user and receive feedback (Burdge & Vanclay, 1996), or assess the quality and performance of design after the owner's occupancy to determine the degree to which the building has met owner expectations (Lackney & Zajfen, 2005). However, these methods demand substantial efforts to obtain the required analysis results, which makes design improvement less feasible. For this reason, there has been a considerable push in construction in recent years to move beyond this traditional approach and find new ways to involve users in design. Bullinger et al. (2010) suggested that design teams adopt UCD methods to improve the design of buildings around end-user needs, requirements, and preferences. A few previous studies integrated UCD methods into the design of buildings and found improvements in user satisfaction and building performance (Bullinger et al., 2010; Zahedi et al., 2011). Nugroho & Ferdiana (2014) improved the design of health status monitoring systems in residential facilities for elderly occupants by identifying end-user privacy preferences and gaining a better understanding of the nature of occupants' interactions with different interfaces. Hansen & Vanegas (2003) developed a web-based application to automate the design brief process and assist AEC firms in developing clear statements of user/client requirements, a tool which promotes client engagement throughout the project lifecycle. Kurokawa et al. (2017) used the concepts of actor-network theory to address the multiple-client engagement problem in a single building project. Their approach explores design from the perspective of client preference, thereby serving to inform the negotiation around specific design processes and helping to explain the degree of influence of various preferences on the outcome. Despite these advancements in research in this area, the current UCD process still lacks an effective approach to involve end-users, as the UCD concept is primarily implemented by consulting the user's needs rather than directly involving the user during the design process.

Thus, to enhance the user's involvement in interior design, an interactive material selection approach is necessary for providing the user with three-dimensional spatial awareness and an effortless design engagement experience.

## 2.4 Human-machine Interaction in Building Design

In the early design phase, most of the design problems are ill-defined, and the constraints surrounding the problem are not fully formulated. Thus, an interactive design tool can assist the designer in refining the design problem interactively, providing an intuitive representation (e.g., charts, figures, 3D models) to interact with, and demonstrating an interface that enables rapid design and exploration. In 1981, Liggett & Mitchell (1981) developed an interactive design tool based on a probability model to design the building floor plan layout. This tool can guide the design based on the probable "goodness" at each stage of progress and provide feedback to the designer with corresponding graphic representations. Tidd et al. (1992) created an interactive design tool to allow the designer to graphically interact with design parameters and behaviours. In 2002, Michalek & Papalambros (2002) developed an interactive optimization tool for building layout design, which views the layout design as an optimization problem of finding the best arrangement and size of a group of rectangular units (representing rooms). Three types of real-time interaction are incorporated in this tool. First, it allows the designer to define the problem while the changes are visually represented in the building model. Then, the user can guide the optimization process by modifying the design variables during the search. Given that the rooms are defined as one-dimensional rectangular spaces and constraints can be specified in advance, it can be posed as an efficient interactive exploratory tool able to reduce the overall duration of layout design. On the other hand, with the development of computer-aided design (CAD) tools, some studies have built their interactive design tools within that software environment. For example, Kharrufa et al. (1988) developed an architectural CAD tool allowing the designer to interact with spaces. Ku et al. (2011) developed a concept known as Building interactive Modelling (BiM), which is an interactive visualization building design tool able to take into consideration the end-user experience and expertise. This model allows users to virtually walk through and explore the proposed building and make comments on the design. The use of BiM encourages end-user involvement in the early design process. Heidari et al. (2014) developed a smart design system to facilitate the smart home design problem by involving the end-user at the early design phase. The smart design system provides interactive and responsive modelling to the user in which not only can the user walk through the proposed house, but also the house can respond to the user's activity and interaction. Moreover, according to the three-design-paradigms theory proposed by Oxman et al. (2011), this study implemented a task-based model allowing the user to walk through and evaluate the smart home design. Given that the present level of interactivity in VR models will continue to improve as a result of users performing activities, the user will then be able to provide more specific design reviews to help the designer refine the design based on user feedback. Also, Lee & Ha (2013) proposed a customer interactive building information modelling method (CIBIM) within the Revit environment to allow the end-user to modify the location of walls, floor, lighting, and furniture for an apartment design. The design components within the system are pre-embedded with rules to ensure they adhere to their contextual relationship. The analysis results gathered from a user experience survey revealed that the proposed parametric CIBIM design effectively performs in the area of design customization thereby reducing the burden on designers, engineers, and contractors.

Interactive design tool studies investigate the interaction between the building design and the user by providing the user with real-time visualization feedback when design changes occur (e.g., design objective, constraints, variables). This is an intuitive method to inform the designer or the user about the progress of the design.

### 2.5 Virtual Reality Application in AEC Industry

VR technology has been undergoing development since the 20th century and has also been studied and implemented in the architecture industry for collaborative visualization and construction improvement purposes. In the area of building design, VR implementation offers an opportunity to involve users with no architectural background in the design process. In this regard, the concept of UCD and support from VR technique implementation prompts the development of several human-machine interaction methods.

Compared to traditional design and communication, VR is excellent at providing scaled and spatial representations and 3D real-time interactive scenes. Due to the increasing complexity of current building design, it is difficult for a non-expert to understand such complicated dimensional and technical parameters in two-dimensional drawings or BIM. However, VR offers an exploratory experience by allowing users to enter the full scale (1:1) VR model and providing them with intuitional impressions. In this regard, VR is believed to offer an efficient communication platform during the building design process (Bouchlaghem et al., 2005).

There are two types of VR systems: (1) desktop VR system (PC-based); and (2) immersive VR system (Bouchlaghem et al., 1996). For the PC-based VR system, the user views and interacts with a computer monitor by mouse or keyboard. While in immersive VR (IVR), the design model is demonstrated through a head-mounted display unit and permits a higher degree of immersion to allow the users to feel totally integrated into the virtual space. The different degree of immersive presentation targets on different size of the group of reviewers. As exemplified by Castronovo et al. (2013), two VR systems are developed to study their level of immersion and user experience during the design review process. One of the systems is a fully-immersive five-wall CAVE environment, and the other is a semi-immersive three-screen demonstration system. The results indicated little variance in the overall highly-rated effectiveness of the two systems. Specifically, the fully-immersive system slightly outperformed the semi-immersive system in providing a higher sense of presence and compelling sense of movement through the model. Also, the results showed that a fully-immersive environment is more suitable for a group with a small number of reviewers, while the semi-immersive environment seems slightly more appropriate in conducting design review for a group with many reviewers.

The application of VR technology was adopted by the AEC industry toward the end of the1980s. In 1994, Campbell & Wells (1994) conducted a comparison between designs implemented using VR and the traditional method by graduate students in an architecture program and concluded that the application of VR technique is advantageous in various phases of the design process, although the deficiencies among software and hardware were evident at that time. Retik (1995) implemented a PC-based VR technology to share collaborative visual planning of the construction process, which allowed the user to visually monitor and interact with the simulated construction project. Furthermore, the research by Palmon et al. (2006) presented how people with disabilities could use VR technology for a pre-occupancy evaluation.

A survey proposed by Bouchlaghem et al. (1996) investigated the general conception from practitioners and the potential improvement for the application of the VR technique in the construction industry in the UK. The results indicated that the primary obstacles against the generalization of VR in the construction industry at the time of their study were twofold: first, people were unaware of the technique; and second, the cost of VR implementation at that time was significant. However, VR devices have become more affordable and accessible in recent years due to the rapid development of electrical devices.

Recently, an increasing number of studies have attempted to combine BIM and VR in order to develop an interactive simulation of an intelligent and responsive environment, given that most currently available BIM software focus on supporting the facility design process and not necessarily on supporting the design review process (Shiratuddin & Thabet, 2011). Although these techniques have been explored for several decades, the implementation of the VR–BIM technique in building industry practice has yet to be fully achieved. Johansson et al. (2014) presented a portable system for immersive BIM visualization as a natural and integrated part in the design process. This system is implemented as an Autodesk Revit Plugin and uses the Oculus Rift head-mounted display (HMD) together with a rendering engine to visualize and manage large and complex BIM models in real-time. Roupé et al. (2016) implemented a VR–BIM design tool in the construction of a new office building. They conducted a semi-structured interview to investigate if the virtual interface could resolve the current practice design issue by providing the participants a better understanding of building space and design. Both of these studies primarily applied the VR technique in the design review stage. On the other hand, with the development of VR technology, some studies have begun to explore the other potential applications for VR in the AEC industry rather than for demonstration and design review purposes. Given that a design can be easily changed and rendered in the VR environment, the designer can collect the occupancy information under various design settings, which will fundamentally change the method of data collection for predicting occupant behaviour. Niu et al. (2016) employed a VR-integrated approach based on the Design with Intent (DwI) concept in a pre-occupancy evaluation process for the lighting control system design in a residential building. By changing the design patterns of a lighting control system in the VR environment, the designer was able to determine whether a specific design may lead to a desired occupancy behaviour and thus deliver a more energy-efficient design. The results indicated that the integration of VR and DwI could reduce the energy consumption gap between the predicted and actual occupant behaviours. Thus, incorporating VR technology into the design process can significantly ease the communication between designer and homeowner as well as improve the building performance from various aspects.

## CHAPTER 3 METHODOLOGY

### 3.1 Overview

The primary goal of this research is to enhance data exchange and the realization of the UCD concept in interior design. To achieve this, a framework for an intelligent VR–BIM-based interior design system is introduced in this study, and a comprehensive methodology for the research is illustrated in Figure 3-1 below.

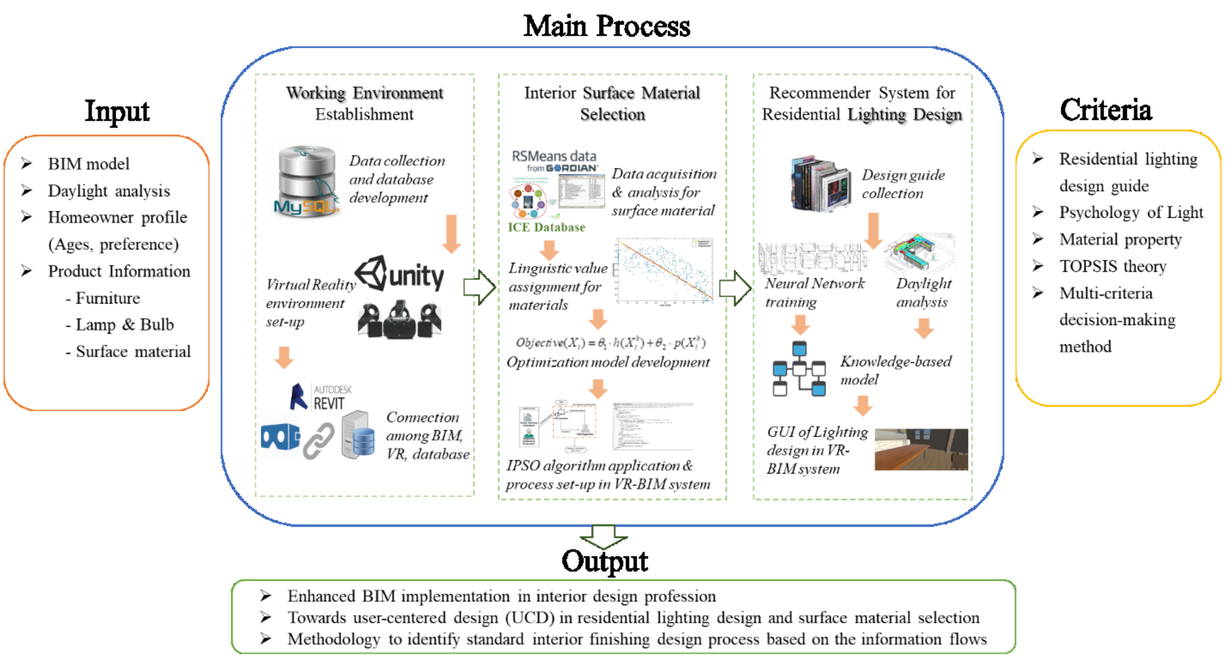



**Figure 3-1 General Methodology**

The research process consists of three main modules. Initially, a prototype VR–BIM-based interior design system is built in the first module as a basic working environment to enable the data sharing among several platforms such as a BIM software program (Revit), a game engine, a VR display device, and an SQL database. Visualization capability is also provided by the system to facilitate the two most mentioned problems in interior design, interior finish material selection and residential lighting design. The sequence of study for these two design activities is arranged based on the required information for each design task according to the literature review and market survey.

To facilitate each research stage, several inputs and criteria are identified in the methodology (Figure 3-1). Inputs are determined based on the required information for each research process, including architectural BIM model, daylight analysis by simulation tool, homeowner's information relevant to interior design decisions, and the property of interior finishing products for further selection. While criteria are used to set up the constraints of the proposed problem, such as residential lighting design guide, psychology, and material property, or support the problem-solving process, such as TOPSIS theory and other MCDM methods.

Furthermore, three outputs can be delivered from this research as follows:

- A more integral BIM model consisting of interior design information, which enhances BIM implementation in the interior design profession for data sharing and promotes a collaborative design.
- Two user-centric design methods applied to the finish material selection task and lighting design task, which optimizes the occupant interior design experience and delivers to users design results that accommodate the design constraints and user preferences.
- The arrangement of the research process sequence based on the information requirement of individual design tasks, which offers a new perspective regarding the sequencing of design activities in order to help the designer or homeowner to effectively and efficiently arrange the design sequence.

### 3.2 VR–BIM-based Work Environment Establishment

To involve homeowners at the early design stage as well as in the interior finishing decision-making process, a VR–BIM-based prototype system is presented in the first stage of this research to allow the homeowner to participate in the decision-making process for interior design under a VR environment and then integrate the information into a BIM model. In this system, the homeowner is provided with a to-scale virtual house model with arranged room layout, where the user can virtually walk through the house, design the lighting system, choose finish materials (e.g., wall paint, floor), and arrange furniture. Figure 3-2 presents the framework for the VR–BIM interior design system. As demonstrated, the building model with room layout arrangement and daylight analysis is the input of the system. The information from this model is stored in two locations based on the data functions. The geometric BIM model is exported as an FBX file and processed with 3ds Max software to protect the integrity of building material information. While the daylight analysis results (e.g., daylighting factor, average daylight illuminance per hour) and the room features information (e.g., room boundary and room type) are stored in a MySQL database. These two types of data will appear in the game engine (which will be outlined below) for model development, rendering, and space identification purposes.

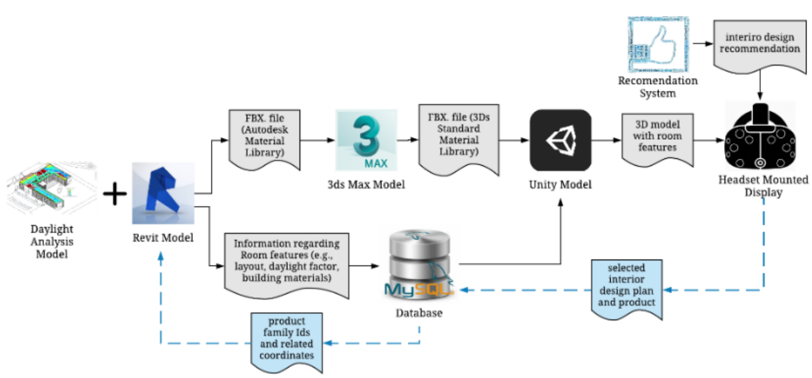



**Figure 3-2 Framework for proposed VR–BIM system**

Unity is implemented as the game engine in this research since it possesses the same compatibility in C# language as the Revit Plugin and MySQL database management system. The building model is displayed through a head-mounted display device, HTC Vive. Once the user completes the interior finishing decision-making process within the VR environment, the system records and saves all selected products into a MySQL database. Finally, a Revit Plugin is also developed in the system to monitor any real-time updates in the database, where it inserts or deletes the related interior design product model in the BIM house model once a new record is generated.

Compared to other VR architecture software on the market, such as Iris or Autodesk Live, the VR–BIM-based system developed in this research allows the user to autonomously design and select the interior finishing products and also stores all the information in the BIM model automatically. It acts as a foundation for all building design decision-making by providing a bi-directional data exchange and communication platform for all project participants. It incorporates interior design professionals into collaborative design and prevents information loss during the building design and construction process. Furthermore, an open database scheme is developed in this research which specifies the necessary attributes for common interior design tasks and allows for the future introduction of additional interior design products.

### 3.2.1 Database Development

Three databases are proposed in this research based on the variety of entities, including the interior design product database ($DB_3$), building feature database ($DB_2$) and product order database ($DB_3$). $DB_1$ stores all products (e.g., finish materials, furniture, and lighting fixtures) available for the homeowner to select for their home design. $DB_2$ stores all room boundaries and room types (e.g., kitchen, bathroom) as mentioned in the previous section. Furthermore, $DB_3$ database is to store the product ID ($id_{obj}$) and corresponding geometry information of materials and products (e.g., $xyz_{obj}$) that the user selects during the interior design process under VR environment. The proposed databases consist of 6 entities: 4 physical entities (i.e., finish materials, furniture, lighting fixtures, bulbs, rooms, walls) and 2 conceptual entities (i.e., daylight analysis, product orders. Every entity possesses multiple attributes). A brief description of the attributes associated with the 6 entities is outlined in Table 3-1.

**Table 3-1. Attribute variables stored in database**

| Entities | Attribute Definition | Variables |
|---|---|---|
| **Finish materials:** *Wall finishes* *Floor finishes* *Countertop* *Vanity finishes* *Cabinet finishes* *Kitchen island finishes* *Ceiling finishes* | Potential carbon dioxide emission of the finish material (kg-$CO_2$-e/ft$^2$) | $p_{i1}$ |
| | Embodied energy of the finish material (mg/ ft$^2$) | $p_{i2}$ |
| | Material cost (\$/ft$^2$) | $p_{i3}$ |
| | Labour cost for the installation of finish material (\$/ft$^2$) | $p_{i4}$ |
| | The finish material installation time (labour hr) | $p_{i6}$ |
| | Lifespan of the finish material (year) | $p_{i7}$ |
| | Moisture resistance of the finish material | $p_{i8}$ |
| | Maintainability of the finish material | $p_{i9}$ |
| | Lightness for lab colour space of the finish material | $L*$ |
| | Colour channel a for lab colour space of the finish material | $A*$ |
| | Colour channel b for lab colour space of the finish material | $B*$ |
| | Glossiness degree of the finish material | $G$ |
| | Metalicness degree of the finish material | $M$ |
| | 3D model in VR environment, stored as Blob. data type | $\text{mod}_{vr}$ |
| | 3D model in Autodesk Revit environment, also called family, stored as Blob data type | $\text{mod}_{bim}$ |
| **Furniture:** sofa, table, kitchen base | Height of furniture | $h_{obj}$ |
| | Width of furniture | $w_{obj}$ |

| | | |
|---|---|---|
| cabinet, kitchen upper cabinet, bed | Length of furniture | $l_{obj}$ |
| **Lighting fixtures** | Length of light: measured from the bottom of light fixture to top of arm or canopy (whichever is longest) | $h_l$ |
| | Diameter of light: measured from the outside edge of the fixture including glass shades | $d_l$ |
| | Finish of light fixture (e.g., bronze, chrome) | $Lf$ |
| | Light fixtures category (e.g., flush mounts, pendants, chandeliers) | $Lc$ |
| | Light fiuxtures style (e.g., traditional, modern ) | $Ls$ |
| | Shade colour of light fixture (e.g., white shade, clear shade) | $Lsc$ |
| | UL listed location for lighting: to distinguish if the light fixture can be used in dry, wet, or damp environment | $UL_l$ |
| | Maximum wattage for light fixture (W) | $LW_{\max}$ |
| | Light bulb base type | $B_{light}$ |
| **Bulbs** | Colour temperature of bulb | $CT_{bulb}$ |
| | Luminous flux of bulb (lumen) | $\Phi_s$ |
| | Wattage of bulb (W) | $w_b$ |
| | Bulb base | $B_{bulb}$ |
| **Daylight analysis** | Average daylight illuminance - 12:00 p.m (lux) | $E_{av-dl12}$ |
| | Daylight factor | $df$ |
| **Rooms** | Ceiling height: measured from the floor to the ceiling | $h_r$ |
| | Room type | $rt$ |
| | Room length | $l_r$ |
| | Room width | $w_r$ |
| | Room area | $A$ |
| | Average illuminance requirement for ambient lighting | $E_{rec-ambi}$ |
| | Average illuminance requirement for task lighting | $E_{rec-task}$ |
| | Room surface reflection | $Ref$ |

| | | |
|---|---|---|
| | Height of working area | $h_d$ |
| | Wall start point | $x_{wall-s}$ |
| | Wall endpoint | $x_{wall-e}$ |
| **Occupants** | Age of the oldest occupant | $o_{age}$ |
| **Product order** | Interior design product ID (unique for each material and product) | $id_{obj}$ |
| | Coordinates of object located *(x,y,z)* | $xyz_{obj}$ |
| | Rotation angle of product located, if applicable | $\theta$ |
| | Hosting element ID | $id_{host}$ |
| | Vectors $(\alpha_1, \alpha_2, \alpha_3)$ to indicate which faces of component to which the material is being applied | $xyz_{vec}$ |
| | ID of the component (e.g., wall, floor, countertop) for which the finish material is being changed | $id_{comp}$ |

The room boundary is defined by the surrounding walls. A room is represented as $R(h_r, x_1, x_2, x_3, ..., x_n)$, where $h_r$ is the ceiling height of the room and $x_1, x_2, x_3, ..., x_n$ represent the corner points of the room's floor. The corner points consist of the start points, $x_{wall-s}$, and the endpoints, $x_{wall-e}$, of every surrounding wall, with which an invisible polygon can be generated in the VR environment. Once the user enters the polygon in the VR environment, the system can detect the room type ( $rt$ ) and offer corresponding design information (e.g., recommended illuminance requirement for ambient lighting, $E_{rec-ambi}$). Also, "Hosting element ID" ($id_{host}$) of a product order refers to the components (e.g., wall, ceiling) to which the selected product is attached. When the system feeds the interior design selection by the user back to the BIM model through inserting the corresponding product model, $\mathrm{mod}_{bim}$ (also referred to as "family" in

Autodesk Revit), into the BIM model, it is sometimes necessary to specify $id_{host}$ in Revit. For instance, when placing a light fixture, the host ceiling or host wall must be indicated. Thus, $id_{host}$ is a necessary attribute for the "product order" entity, and the number is predefined by the BIM model.

Figure 3-3 presents the entity-relationship (ER) diagram of the proposed database developed through the MySQL relational database management system (DBMS). However, due to the various input requirements for finish materials, furniture, and light fixtures for $DB_3$ (product order database), the structure of $DB_3$ differs from that of the traditional relational database. An entity-attribute-value model is applied in order to avoid a sparse database structure and to increase the space efficiency. Each time a record is created in $DB_3$, the "Warehouse" entity table, as can be seen in Figure 3-3, automatically generates a new corresponding record. The specific product order attributes that are relevant to each product category (e.g., "coordinates" ($xyz_{obj}$) for furniture; "hosting element ID" ($id_{host}$) for light fixtures) are stored in the "Attribute" table. The "Product Order" table (value table) links the product and its attributes and stores the attribute values. In addition, the attribute product ID, $id_{obj}$, in the "Warehouse" table is coded following the classification rule of OmniClass Table23, which is a well-known classification system in the construction industry and provides a standardized basis for classifying information generated and used by AEC companies in North America.

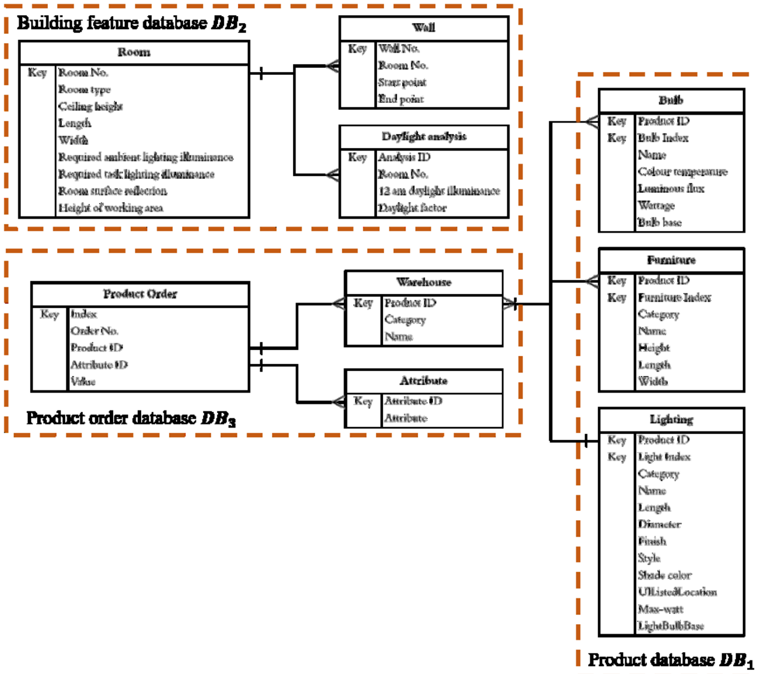



**Figure 3-3 ER database diagram**

### 3.2.2 User Interface within Virtual Reality Environment

Once an architectural design of a house is completed and transferred from Revit to VR platform, the homeowner can explore the house model and make the interior design decisions. Therefore, to assist in this process, a menu demonstrating all available interior products is constructed under VR environment and connected with the product information database. Figure 3-4 presents a graphic user interface (GUI) of the developed product menu. This menu extracts all information in $DB_1$ and divides it into various categories, such as wall paint and flooring, according to conventional home improvement retail websites. To reduce the searching burden for users, this menu offers a filter function (as noted under the Category and Sub-Category headings in Figure 3-4) to remove the unwanted products using specific requirement inputs.

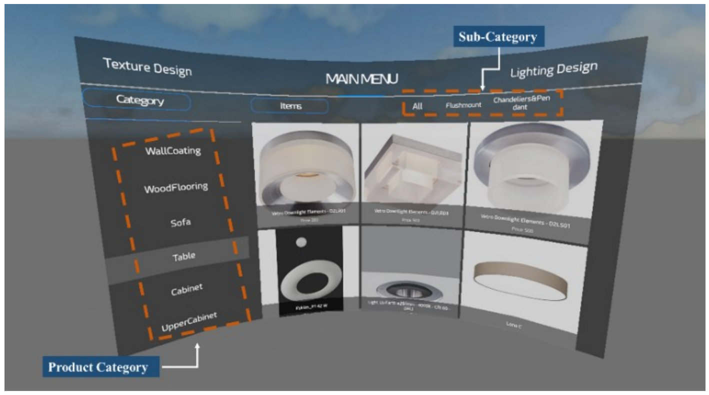



**Figure 3-4 Product information menu in VR environment**

Once the homeowner determines their desired product, a 3-D product model, $\text{mod}_{vr}$, will be retrieved from the database and will appear on the screen waiting to be placed in the appropriate location in the VR environment. Generally, there are two mechanisms for interior design modifications in this system, finish material change and furniture and light fixture layout. Figure 3-5 presents a data flow diagram that outlines the mechanism of finish material change. This process is initiated by the user through a signal that is sent out from the VR device controller. The signal contains messages including the component ID, $id_{comp}$, (e.g., walls, ceiling) of which the user would like to make material changes, the selected face of finishes (represented by vector $xyz_{vec}$) as there are usually multiple faces for a building component, and the product ID, $id_p$, of the selected material with which users would like to apply. The component information will be recorded in $DB_3$, while the material product information, such as lab colour, glossiness, metallicness ($L^*, A^*, B^*, G, M$), and material texture (stored as images), will be retrieved from $DB_1$ and sent to the VR environment for demonstration. Afterward, the system will also record the applied material product ID, $id_{obj}$, into $DB_3$.

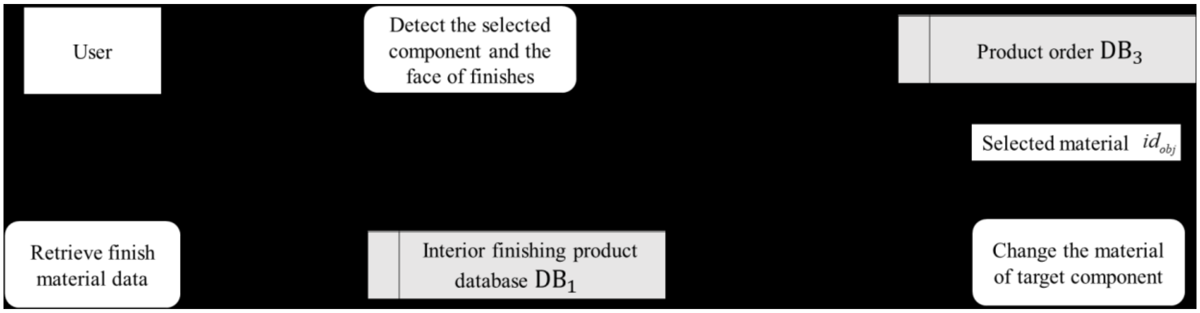



**Figure 3-5 Data flow diagram for conducting finish material changes**

On the other hand, product information retrieval from $DB_1$, which is then inputted to the VR platform, followed by recording the selected product ID ($id_{obj}$) and placing location ($xyz_{obj}$) in $DB_3$ are also necessary steps for the mechanism of furniture and light fixture layout, which is presented in Figure 3-6. In addition, two logic rules—collision detection and item-location relationship—are hard-coded in this system to facilitate the interior product selection process.

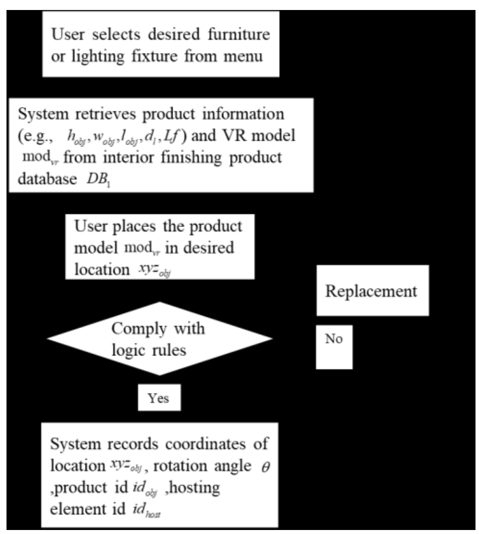



**Figure 3-6 Data flow diagram for conducting furniture and light fixture layout**

The collision detection rule allows the system to detect any possible object collision during the product placing process (e.g., the sofa has a collision with the wall as indicated in Figure 3-7), and thereby forbids the user from placing a product in such location and also requests a replacement. This rule is performed by assigning a bounding box to all objects (referred to as

"Box collider" in Unity) and checking if there is any overlap between these bounding boxes. As illustrated in Figure 3-8, object *A* and object *B,* two objects in the VR house model, are surrounded by bounding boxes, $box_A$ and $box_B$, respectively. Each box is defined by their minimum and maximum coordinates in x, y, and z directions (e.g., $A_{x-\min}, B_{y-\max}$). Then, if the minimum and maximum coordinates comply with all the following conditions, the boxes are detected as overlapping:

(1) $A_{x-\min} < B_{x-\max}$ and $A_{x-\max} > B_{x-\min}$;

(2) $A_{y-\min} < B_{y-\max}$ and $A_{y-\max} < B_{y-\min}$;

(3) $A_{z-\min} < B_{z-\max}$ and $A_{z-\max} < B_{z-\min}$.

Using the bounding boxes to identify object collisions eliminates the burden of CUP through the reduction of intensive computation for overlapping of complex shapes.

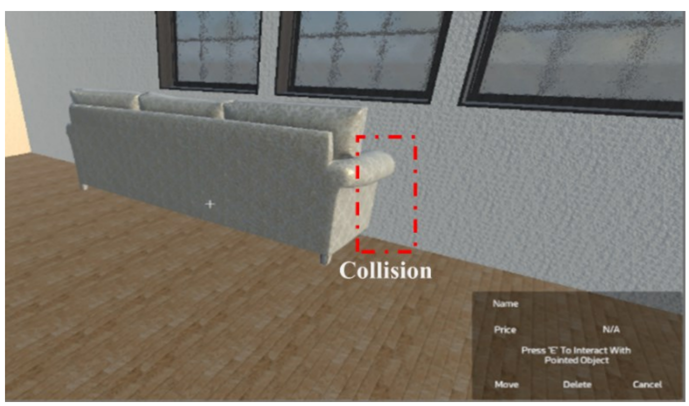



**Figure 3-7 Example of collision during object placement**

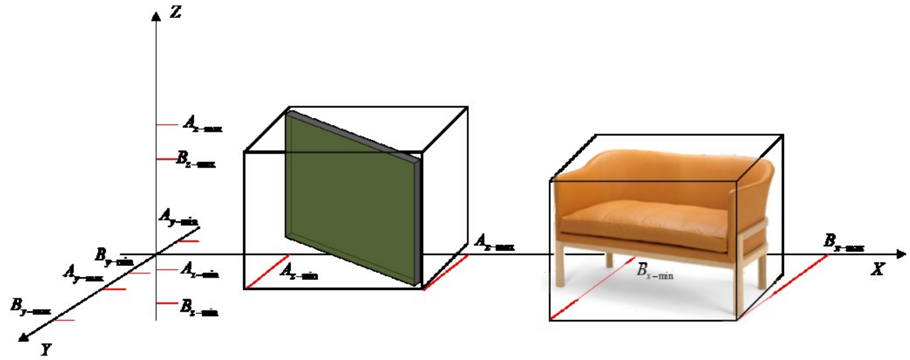



**Figure 3-8 Example of bounding boxes for building objects**

Furthermore, another logic rule, item-location relationship, implies that the interior items can only be placed in a location that conforms to human common sense. For instance, the user cannot place a ceiling lighting fixture on the floor or place a table on the wall. When the user mistakenly points the controller to an incompatible location to place an object, the object model will disappear in order to prevent this action. This function is achieved by categorizing the architectural building components (e.g., walls, floor, ceiling) into various groups and embedding the association between host elements and interior products or rooms and interior products by means of hard coding. For each product type, there are two pre-defined collections as the host element ID ( $id_{host}$ ) collection and the room type ( $rt$ ) collection, which are represented by $ID_{host-i}$ and $RT_i$ ( $i$ represents the corresponding category of interior design products) and contain all placing-allowable host elements and room spaces for interior products ( $id_{obj}$ ). During the product placement process, the system executes the procedure as indicated in Figure 3-9, where $id_{host-current}$ and $rt_{current}$ refer to the current host element and the room type in which the user would like to place the product.

**Data:** $id_{obj}, id_{host-current}, rt_{current}$
**begin**
  **Read:** $\mathbf{ID_{host-i}} = \{id_{host1}, \cdots, id_{host2}\}$, $\mathbf{RT_i} = \{rt_1, \cdots, rt_2\}$; **where** $i$ = product.category($id_{obj}$);
  **If** $(id_{host-current} \in \mathbf{ID_{host-i}})$ **and** $(rt_{current} \in \mathbf{RT_i})$ **then:**
    **Excute** placement
  **else:**
    **Hide** VR model $(id_{obj})$
  **end**
**end**

**Figure 3-9 Item-location relationship rule implementation**

Once the VR–BIM-based environment is established, the intelligent design method regarding finish material selection and home lighting design can be investigated in the next step. According to the information flow of the design process, the study of finish material selection is conducted prior to that of lighting design.

## 3.3 Interactive Particle Swarm Optimization Approach for Interior Finish Material Selection

The primary goal of the second research process is to design, develop, and test an innovative approach for interior finish material selection, which incorporates visual aesthetics and other conventional indices, such as carbon dioxide emission and embodied energy, into material evaluation criteria set.

Figure 3-10 demonstrates the detailed methodology of this research process. To begin, the information of available material for various types of interior finishes and their performance indices are investigated and collected through literature review and market research. Also, an SQL database is developed to store this data, thereby facilitating data management and easing data extraction in the following steps.

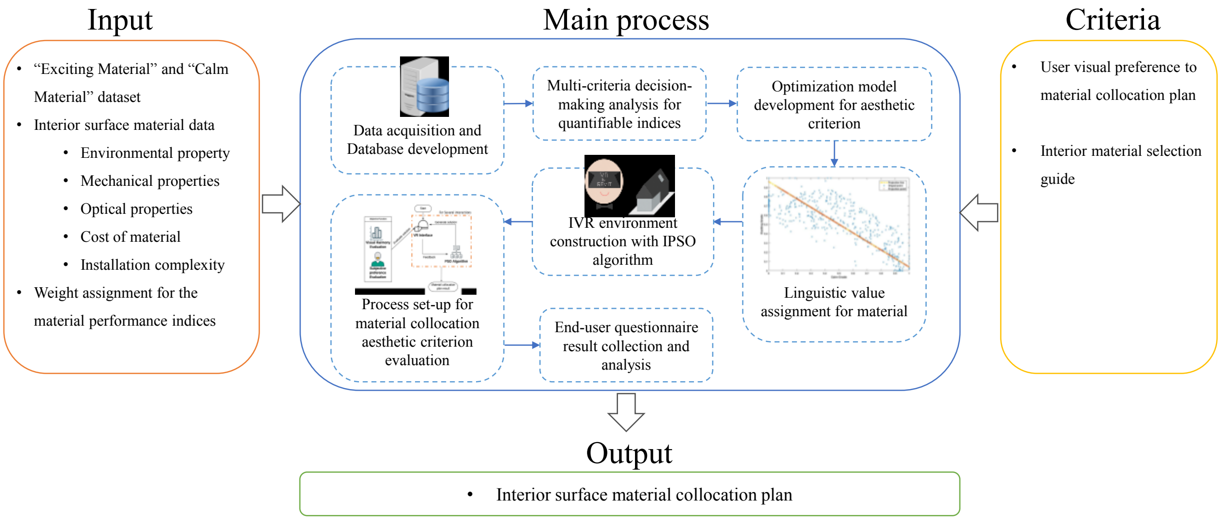



**Figure 3-10 Methodology for interior finish material decision-making approach**

In the proposed approach, material selection is carried out in two successive steps, material type selection and material product selection, which arises from the reasons that: (1) most of the available quantifiable performance data for interior material are given at the detail level of material type, rather than specific material product; (2) aesthetics of specific material products is a non-quantifiable evaluation criterion varying from person to person, and thus cannot be measured in terms of an objective numeric value. For this reason, the proposed approach uses a multi-criteria decision-making method to determine material type and then employs an optimization model for the selection of specific material products. Specifically, material type is selected by analyzing quantifiable performance indices, while the material product of each finish is determined from a visual aesthetics perspective. Also, the evaluation of aesthetics in material product selection takes all interior finish materials in one room as a study object (referred to as material collocation), which maintains the universal interior design principle of thinking holistically. Quantifiable material performance indices in material type selection mainly consist of three types as embodied energy and footprint, cost, and physical properties. Material type selection is formulated as an MCDM problem and is solved by means of Analytic Hierarchy

Process (AHP). In AHP, weights are assigned to all performance indices, with the overall performance of a given material evaluated using Equation 3-1:

$$P_i = \sum w_k \cdot p_{ik} \quad (3\text{-}1)$$

where:

$P_i$ refers to the overall performance of material *i*;

$w_k$ represents the normalized weight for performance *k*;

$p_{ik}$ indicates the scaled value for material *i* on performance *k*.

During material type selection, an overall performance score is calculated for each alternative material type. A radar chart is also drawn to aid the user's understanding of the benefits and drawbacks of each material type (Mosley & Mayer, 1999). It offers users more freedom to select material type compared to merely being given a final numeric score for each material type. During material product selection, the aesthetics criterion as a non-quantifiable performance index is investigated as an optimization problem. According to Ou et al. (2004), human preference and visual harmony both influence the measurement of aesthetics. In this context, an objective function measuring user preference and degree of visual harmony is developed to evaluate the aesthetics criterion of interior finish material selection. The visual harmony degree of material collocation is calculated by the dissimilarity of linguistic value distribution of currently estimated material collocation and a referenced material collocation, which could be a material collocation example (e.g., images, real cases) for which the user determines a high degree of visual harmony. To calculate the distance, every potential material needs to be assigned a linguistic value, where the linguistic value of each finish in a room can plot a distribution diagram. Meanwhile, user preference is directly measured by users assigning ratings within an IVR environment. It should be noted that a prototype system is built within an IVR environment, which offers a platform (referred to as "VR interface" in Figure 3-11) for users to visually evaluate material optical properties in a clear and realistic manner.

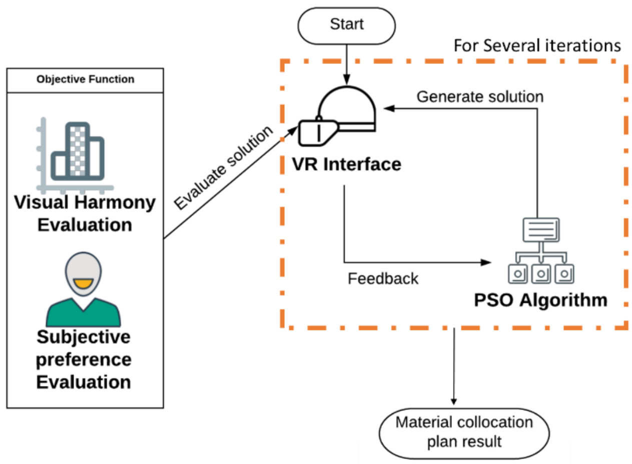



**Figure 3-11 Optimization of material collocation selection based on IPSO**

To obtain optimal material collocation, an interactive particle swarm optimization (IPSO) algorithm is employed in this research. The search process depicted in Figure 3-11 comprehensively illustrates the general process of how this method finds optimal material collocation in a human-machine interactive manner. When searching begins, the potential finish material collocation plans are generated, rendered, and demonstrated in IVR environment. The user can then fully explore the virtual properties of material and feedback their degree of preference to the presented material collocation. Meanwhile, the system calculates the visual harmony score of the given material collocation based on the previous description. The sum of these two scores is fed back to IPSO algorithm as an overall objective value. Then, IPSO algorithm updates and generates a new material collocation based on the feedback, and also sends it to the "VR interface" for the next iteration. The iteration processes continue until IPSO reaches its termination criteria, such as completing the specified number of iterations.

### 3.3.1 Material Type Selection: Multi-criteria Decision Making

To determine material types of each finish in a given room, three categories of quantifiable material evaluation criteria are used, including environmental factor, cost and time factor, and operation factor. The selection of material performance indices in the present study is based on the literature review conducted by Isakov (2016) as well as current market research. Isakov reviewed 33 material studies and material reports in order to identify the conventional evaluation criteria either developed in various building material selection tools or referenced in material reports reviewed. Figure 3-12 presents corresponding frequency of use for each evaluation criterion among the 33 material studies and material reports reviewed.

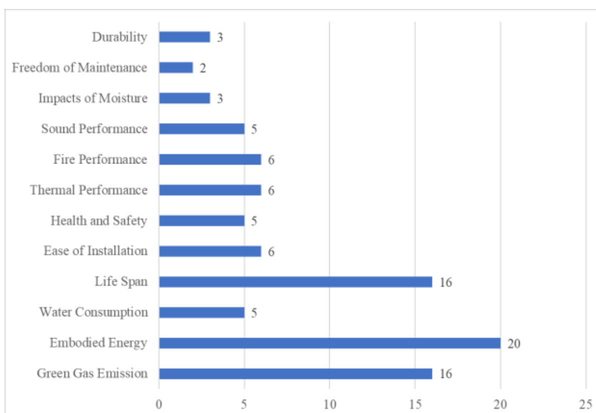



**Figure 3-12 Use frequency of material evaluation criteria, adapted from Isakov (2016)**

As illustrated in Figure 3-12, environmental indices—such as global warming potential (referred to as carbon dioxide emission potential) and embodied energy—and lifespan are the most widely used criteria in evaluating building materials. Furthermore, based on the current market research on the most heavily-weighted material performance indices for end-users, other performance indices, including material cost, labour cost, installation time, moisture resistance, and maintenance requirements, are also incorporated into the quantifiable evaluation indices developed and employed in the present research. The quantifiable evaluation indices are outlined in Table 3-2.

**Table 3-2. Quantifiable material evaluation indices**

| Factor | Criterion |
|---|---|
| **Environmental Impact** | Global Warming Potential (kg-$CO_2$-e/ft$^2$) |
| | Embodied Energy (MJ/ft$^2$) |
| **Cost/time Consumption** | Material Cost ($/ft$^2$) |
| | Labour Cost ($/ft$^2$) |
| | Installation Time (Labour hr) |
| **Operation Effect** | Lifespan (yr) |
| | Moisture Resistance |
| | Freedom from Maintenance |

The performance data of each material is collected from multiple sources, such as previous literature (e.g., Isakov, 2016), RSMeans cost data (Edmonton, Canada, 2017), ICE database (embodied energy and carbon data), and a survey of industry professionals. Several material types are selected for each finish as candidates based on their high probability of use in interior design. Each material type is assessed based on eight evaluation criteria, and the importance weights of each criterion are assigned by consultants and experts using AHP, which is one of the most popular technologies for multi-criteria decision-making, and is easy to use for determining weight coefficients using pairwise comparisons (Velasquez & Hester, 2013). A sample weight coefficient is provided in Table 3-3. Subsequently, a proper material type can be determined, which can deliver an overall performance score for each material type under each finish. Furthermore, a radar chart for each finish with various available material types is plotted in this approach as exemplified by the wall materials in Figure 3-13. Theoretically, the material type with the most significant enclosed area within one radar chart should be selected, as it has the best overall performance considering all evaluation indices.

**Table 3-3. Sample weight coefficient for material evaluation criteria**

| | Environment | | Cost/time | | | Operation | | |
|---|---|---|---|---|---|---|---|---|
| **Material** | Global Warming Potential | Embodied Energy | Material | Labour | Install Time | Life-span | Moisture Resistance | Freedom from Maintenance |
| Importance | 0.12 | 0.28 | 0.15 | 0.09 | 0.06 | 0.12 | 0.12 | 0.06 |

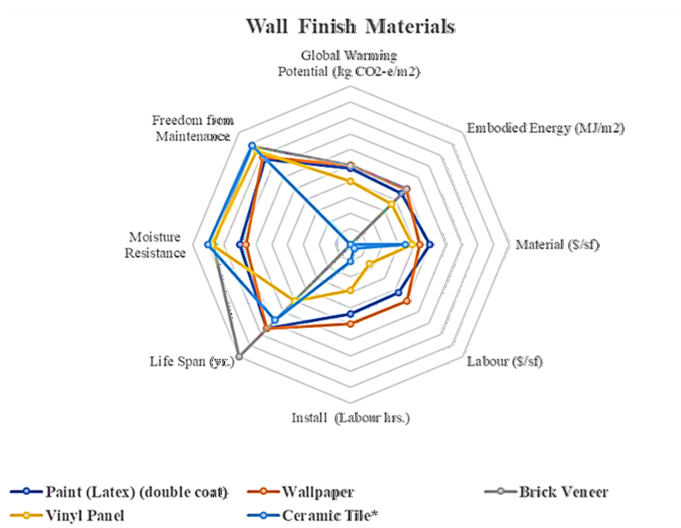
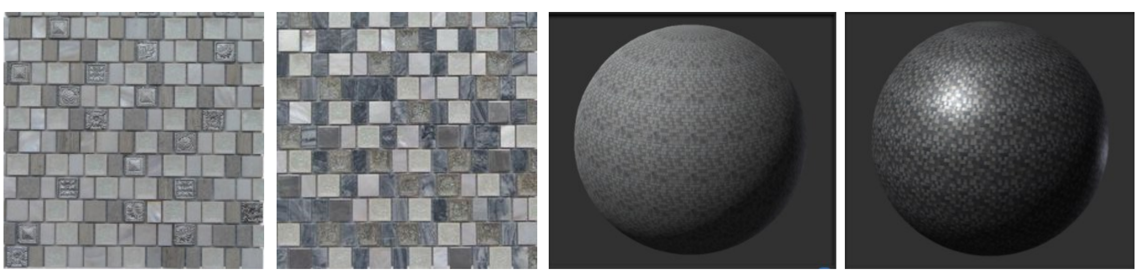



**Figure 3-13 Radar chart of wall finish material type selection**

### 3.3.2 Material Product Selection: Aesthetic Evaluation of Material Collocation

In reality, when the homeowner evaluates the aesthetics of material collocation, not only is colour, but other attributes such as glossiness and metallicness are taken into consideration. The variety of these attributes may be a result of material processing methods or material components. For instance, materials of similar colour but different glossiness and metallicness values could evoke different perceptions and feelings. For example, Figure 3-14a and Figure 3-14b represent the base colours of two materials. Their average LAB colour space values are similar: (55.4, −0.5, −0.8) and (57.3, −0.5, −0.8), respectively. However, when we modify their glossiness and metallicness values (modify material A to metallicness = 0 and glossiness = 0.217, as indicated in Figure 3-14c, and modify material B to metallicness = 0.327 and glossiness = 0.559, as indicated in Figure 3-14d), they are no longer visually similar. Notably, in this research, five parameters are used to describe the appearance of one material: lightness of the colour (L*), colour position on the spectrum between red/magenta and green (A*), colour position on the spectrum between yellow and blue (B*), glossiness, and metallicness. Thus L*A*B* represents the LAB colour space, which is similar to the RGB colour system, but captures the human perception of the world in a more accurate way than does the RGB colour space. Thus, during the interior material selection phase, the designer should help the homeowner to precisely identify the material appearance so as to be able to deliver them the desired interior design effect in the finished product.



(a) (b) (c) (d)

**Figure 3-14 Comparison of two materials before and after the modification of metallicness and glossiness**

To facilitate the homeowner involvement in design decisions and incorporate their preferences in interior finish material product selection, this research proposes an objective-oriented interactive optimization method, which assists the homeowner and designer in more clearly defining interior design problems and exploring more alternative interior material collocations. In a given room, each material design solution consists of multiple materials (N), and every material is determined by the five parameters (i.e., $L^*$, $A^*$, $B^*$, glossiness, metalness). As a result, there are decision variables, provided that the material product selection is seen as an optimization problem in order to maximize the satisfaction level of homeowners with respect to the material collocation of the room. As inferred from Ou et al. (2004), visual harmony and preference are two concepts that measure the aesthetic effect of material collocation. Hence, an objective function (Equation 3-2) which consists of two parts is formulated for this optimization problem in the proposed approach. One part, $h(X_i^k)$, measures the degree of visual harmony of the material collocation, while the other, $p(X_i^k)$, measures the preference level of homeowner to the material collocation $X_i^k$.

$$Objective(X_i) = \theta_1 \cdot h(X_i^k) + \theta_2 \cdot p(X_i^k) \tag{3-2}$$

where:

$X_i^k$ represents the $i^{th}$ material collocation solution;

$i$ and $k$ represent the particle index and the iteration number of IPSO, respectively;

$\theta_1$ and $\theta_2$ denote the weighting factors assigning importance to the sub-objectives.

In the section that follows, the development of these two sub-objective functions is discussed in detail.

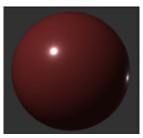
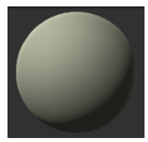
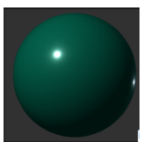
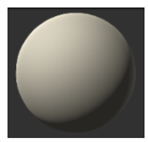
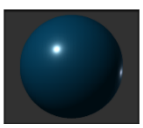
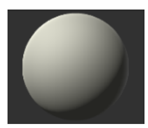
*3.3.2.1 Visual harmony measurement*

In everyday language, we often use emotional terms and adjectives, such as “soft”, “cold”, and “calm”, to describe optical characteristics of materials, underscoring the powerful mental impression colour exerts in human perception. It evokes an array of psychological associations (Wastiels et al. 2007) and can be evaluated in terms of pleasure-related language, as well as be applied in visual harmony evaluation (Shen et al. 1996). Thus, a pleasure-related linguistic feature described by a linguistic-based image scale, as introduced by Shen et al. (1996), is used in this research to represent the mental impression of material and to quantitatively evaluate the visual harmony degree of the material collocation. The visual harmony degree of a material collocation is calculated by the dissimilarity of the material linguistic value distribution from the reference value distribution. A comprehensive procedure for generating material linguistic value distribution is illustrated in Figure 3-15.


**Figure 3-15 Procedures for material linguistic-based image scale construction**

First, two material sets, EXCITING material and CALM material in this example, are constructed to represent opposing linguistic meanings representing contrast in a one-dimensional coordinate system. These sets consist of materials evoking completely exciting or calm impressions, respectively. It should be noted that each pair of EXCITING and CALM material sets is extracted from one material type only (e.g., wood), as it is problematic to compare mental impressions from different kinds of materials. The EXCITING material set herein represents the material impression of interesting or stimulating emotions, while the CALM material set represents soothing, serene, and comfortable sentiments. An example of EXCITING and CALM sets for wall painting materials is demonstrated in Table 3-4. As shown in the table, the appearance of a given material is defined with respect to five parameters, and each material corresponds with one exciting/calm-related linguistic value assigned using the method illustrated in Figure 3-16.

**Table 3-4. Examples of EXCITING and CALM material set**

| EXCITING material | CIV LAB value | Glossiness | Metallic-ness | CALM material | CIV LAB value | Glossiness | Metallic-ness |
|---|---|---|---|---|---|---|---|
|  | 31.70/ 38.67/ 23.44 | 0.75 | 0.13 |  | 80.42/ −7.80/ 14.67 | 0.09 | 0 |
|  | 44.90/ −36.09/ 7.33 | 0.86 | 0 |  | 95.56/ −1.10/ 12.06 | 0.05 | 0 |
|  | 31.59/ −5.20/ −28.01 | 0.70 | 0 |  | 96.70/ −1.87/ 8.53 | 0.22 | 0 |

The EXCITING/CALM degree for the remainder of the materials can be estimated based on their distances from these two material sets. The respective distance calculation equations are given as Equation 3-3 and Equation 3-4 below.

$$IDC(m_i, C) = \min\{\|m_i - c_j\|, c_j \in C\} \tag{3-3}$$

$$IDE(m_i, E) = \min\{\|m_i - e_k\|, e_k \in E\} \tag{3-4}$$

where:

*IDC* represents the material's distance from pre-defined CALM set $C$;

$IDE$ indicates the material's distance from EXCITING set $E$;

$m_i$ represents the analyzed material;

$c_j$ and $e_k$ refer to the nearest "calm material" and "exciting material" to material $m_i$, respectively.

The average distances between the remaining materials and the CALM set and EXCITING set are calculated following Equation 3-5 and Equation 3-6, respectively.

$$AvgD(M,C) = \sum_{m_i \in M} IDC(m_i, C) / N_m \tag{3-5}$$

$$AvgD(M,E) = \sum_{m_i \in M} IDE(m_i, E) / N_m \tag{3-6}$$

where $M$ represents the set of all materials excluding sets *C* and *E*, and $N_m$ represents the number of all materials excluding sets *C* and *E*.

Based on each material's distance to the CALM set and EXCITING set and the average distances, the material's Exciting degree and Calm degree (represented by *IEG* and *ICG*, respectively) can be calculated using Equation 3-7 to Equation 3-10. Furthermore, a two-dimensional feature space diagram can be plotted as illustrated in Figure 3-16. As only one numeric number is allowed to represent the linguistic meaning in the proposed method, a two-dimensional coordinate system is projected onto the one-dimensional coordinate system (also called 1D image scale) following the procedure developed by Shen et al. (1996). The projection line demonstrated in Figure 3-17 represents the desired one-dimensional image scale passing through a point (0.5,0.5), while the normalized distance between the projection point and the point (0.5,0.5) defines the coordinates of original point in the one-dimensional linguistic-based image scale. The sign (positive or negative) of the value reflects the mental impression bias of material toward either “exciting” or “calm”.

For instance, 1 represents a completely “exciting” impression, while −1 represents a completely “calm” impression.

$$\tilde{\ } \qquad ) = 1 - \frac{IDC(m_i, C)}{AvgD(M, C) + AvgD(M, E)} \tag{3-7}$$

$$ICG(m_i, C) = \begin{cases} \tilde{\ } \qquad \tilde{\ } \qquad [0,1] \\ 1, \tilde{\ } \qquad C) > 0 \\ 0, \tilde{\ } \qquad C) < 0 \end{cases} \tag{3-8}$$

$$\tilde{\ } \qquad ) = 1 - \frac{IDE(m_i, E)}{AvgD(M, C) + AvgD(M, E)} \tag{3-9}$$

$$IEG(m_i, E) = \begin{cases} \tilde{\ } \qquad \tilde{\ } \qquad 0,1] \\ 1, \tilde{\ } \qquad ) > 0 \\ 0, \tilde{\ } \qquad ) < 0 \end{cases} \tag{3-10}$$

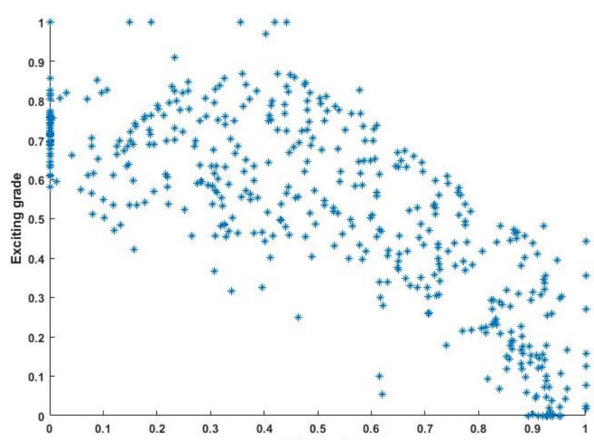


**Figure 3-16 Two-dimensional exciting/calm-related feature space diagram**

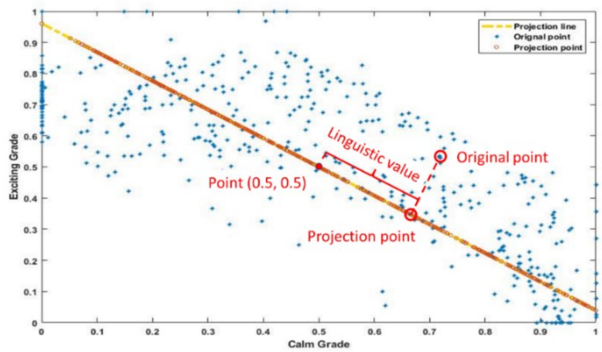



**Figure 3-17 One-dimensional image scale coordinate system**

For every material collocation, there are approximately $N$ finish material decisions, and thus $N$ material linguistic values, from which a material linguistic distribution (referred to as $MLD$) can be generated, as exemplified in Figure 3-18 below. The $x$-axis and $y$-axis of Figure 3-18 represent the interior finish index and material linguistic value, respectively.

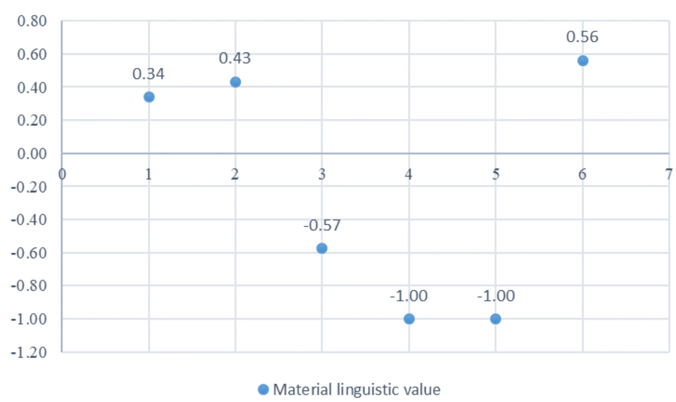



**Figure 3-18 Material linguistic value distribution**

The degree of visual harmony is calculated by comparing the $MLD_r$ of the analyzed solution with the $MLD_r$ of a reference material collocation. The reference could be a material collocation in a form as pictures and digital models that a homeowner finds to be visually harmonious. In the proposed method, rather than calculating the pairwise distance between $MLD_r$ and $MLD_c$, Hausdorff Distance (Equation 3-11) is used to estimate the dissimilarity between the material linguistic distributions of reference material collocation and the material collocation being analyzed. Furthermore, Equation 3-12 is used to normalize the dissimilarity value to a value falling within the range [0,1], while the minimal and maximal of dissimilarity are set to 0 and 2, respectively.

$$Dissimilarity(MLD_r, MLD_c) = \max_{mlv_r \in MLD_r} \min_{mlv_c \in MLD_c} \|mlv_r - mlv_c\| \qquad (3\text{-}11)$$

where:

$mlv_r$ represents a linguistic value of the reference material collocation;

$mlv_c$ represents a linguistic value of the material collocation being analyzed.

$$h(X_i^k) = 1 - Normalized(Dissimilarity) \qquad (3\text{-}12)$$

where:

$h(X_i^k)$ represents the degree of visual harmony of the current solution.

*3.3.2.2 Material collocation preference measurement*

The preference measurement of the objective function is used to evaluate the preference degree of homeowner to the material collocation. Preference degree is a highly subjective standard, and as such is difficult to express in a parametric formula. Thus, human judgment is incorporated in this research by directly scoring material collocations rather than developing a mathematic equation. For instance, the user can use the numbers −1, 0, and 1 to represent their various attitudes toward the current material collocation as “unacceptable”, “acceptable” and “like”, respectively. However, obtaining a satisfactory result by means of IPSO usually necessitates many iterations and is tedious and time-consuming. Therefore, this research implements distance-based objective function value prediction to estimate the preference scores to material collocations in certain iterations. A detailed description of the implementation step is provided in the following section.

### 3.3.3 IPSO-based approach for material product selection

In the material product selection, we take the interior finish material selection as an optimization problem and attempt to solve it using a small-population-based IPSO algorithm. Normally, the primary goal of an optimization approach is to define a mathematical fitness function. However, the preference degree of homeowner to a given material collocation typically arises from a combination of cultural, societal, educational, and psychological factors. As such it is non-commensurable and thus cannot be defined by means of a quantitative equation. For this reason, an interactive optimization is used in this research to address the problem without explicitly defining a cost function for homeowner aesthetic preference.

Interactive optimization is a method of evolutionary computation that uses human evaluation as objective function to optimize search results, and it has been widely implemented in many industries. For instance, Máder et al. (2005) proposed an IPSO and used it in the design of temperature profile. Unlike traditional interactive evolutionary computations, their IPSO method only asked the user to decide the best solution in this iteration and the best solution until now instead of ranking all potential solutions.

Implementation of interactive optimization entails that the parametric objective function is replaced by human judgment and knowledge in order to evaluate every potential solution during the optimization process. In other words, the homeowner directly marks potential material collocations and visually determines the preferred collocation so as to assist the search algorithm in efficiently determining the optimal material collocation plan.

*3.3.3.1 Interactive particle swarm optimization*

Particle swarm optimization (PSO) is a stochastic optimization technique introduced by Eberhart and Kennedy in 1995 and inspired by swarm intelligence and evolutionary computation. A typical PSO algorithm is initialized with a population of random potential solutions (also referred to as particles), where the particles (or referred to as solutions) keep moving forward to the particle with the highest objective value (referred as $gbest$). However, it is not possible to define a mathematic objective function by which to evaluate the objective value of every solution during evaluation of aesthetics-related criteria, as mentioned above. Thus, IPSO is implemented in this step of the method by replacing the parametric objective function with the user scoring value. The main difference between IPSO and traditional PSO, it should be noted, inheres in the objective function evaluation step.

The reason for selecting IPSO rather than other interactive evolutionary computation algorithms is that PSO has a more robust information sharing mechanism than do other evolutionary algorithms. For some evolutionary algorithms (such as genetic algorithm), the communication only occurs among the particles generated within one iteration, whereas the particles in PSO not only share information with others in the same generation but also receive information from the previous generation (the underlying mechanism) (Máder et al., 2005). Also, PSO is more efficient for optimization problems with simple variable-scopes compared to genetic algorithms (Hassan et al., 2005). Thus, IPSO is implemented in this research to search for the optimal interior finish material collocations.

#### *3.3.3.2 Assumption*

In order to implement the user's personal preference score to evaluate the material collocation, several assumptions need to be specified here:

- The best solution for material collocation is an area rather than a single point. Thus, multi-optimal solutions might exist in this case.
- Similar to the mechanism of human emotional impression to colours, humans also have associated feelings with different material appearances. For example, people are aware of the characteristics of material (e.g., hard or soft, cold or warm) even upon the first glimpse of a material.
- The materials with similar optical property possess similar pleasure-related linguistic meaning. For instance, the materials with low reflective glossiness and saturation colour seem more "calm" than the materials with high reflective glossiness and saturation colour. However, the material with the same linguistic meaning may not necessarily have similar visual characteristics, which is derived from the theory of "colour-similarity-coherence" mentioned by Shen et al. (1996).
- The difference in visual characteristics of materials can be measured by the linear distance of the five parameters ($L^*$, $A^*$, $B^*$ for colour, glossiness, metallicness).

#### *3.3.3.3 Procedure of small-population-based IPSO algorithm*

Usually, a large population size and generation number are required for the PSO approach to find the optimal material collocation. However, in this research, where the user scoring replaces the parametric objective function to evaluate material collocations, it is not feasible to follow the traditional approach, as the user is likely to lose interest or become distracted after intensive interaction with the system and thus unable to assign scores accurately. The human fatigue problem is common to all human-machine interaction systems and needs to be addressed. In order to balance the negative effects resulting from the human fatigue factor and small population size, a modified small population-based PSO algorithm proposed by Zhang et al. (2012) and a predictive function requiring less human interaction are adopted in the current optimization model.

The small population-based PSO uses three operations—mutation operation, DE-acceleration algorithm, and migration operation—to enhance the diversity of the small population and accelerate the convergence of the operation process as well as keep the crowding diversity of the swarm from causing it to fall short of the desired diversity level (Zhang et al., 2012). Specifically, mutation operation determines the moving guides for each particle; DE-acceleration algorithm prompts to update itself in the case that the optimal result sees no significant improvement after several generations; and migration operation regenerates a new particle when the diversity of swarm is lower than the limit value, thereby preventing the solution from becoming trapped at a local optimal position. Furthermore, a Euclidean distance-based approach is used to prompt the convergence of optimization. It measures the distance of the current material collocation from the user historical rating solutions and predicts the unscored solutions in order to generate more populations without the need for additional user interactions.

The pseudocode in Appendix A from Algorithm 1 to Algorithm 4 illustrates the detailed implementation of IPSO algorithm to solve the material collocation problem. It is of note that a time-decreasing inertia weight from 0.9 to 0.4 is specified here (Equation 3-13), as the large inertia weight at the beginning helps with finding the good seeds (initial solutions), while the small inertia weight later in the implementation facilitates fine search (Shi & Eberhart, 2000).

$$w = w^{\min} + k \cdot (w^{\max} - w^{\min}) / i^{\max} \tag{3-13}$$

where:

$w^{\min}$ represents the minimal inertia weight;

$w^{\max}$ represents the maximal inertia weight;

$i^{\max}$ represents the total number of iterations;

$k$ represents the current iteration index.

To begin, five material collocations, $X_i$, are initialized randomly. Every material collocation consists of $5N$ decision variables: $x_{i,n,j}^{k}$, where $i$ represents the index of particles; $n$ represents the index of interior finishes (e.g., floor, wall, ceiling, countertop); and $j$ represents the indices of material visual characteristics (e.g., $L^*$, $A^*$, $B^*$ for LAB colour space, glossiness, and metallicness). To begin with the first iteration, all particles are set as the $pbest$. Then, the homeowner is prompted to give a preference score to the five material collocations. The solution with the highest objective value (preference objective value $p(X_i^k)$ plus visual harmony objective value $h(X_i^k)$) is regarded as the current $gbest$. Then, the second iteration begins. The velocities and positions of every particle are updated according to the equations indicated in lines 12 and 13 of Algorithm 1 of Appendix A. All solutions are then evaluated again to identify the new current $pbest$ and $gbest$.

The implementation of the three operations described earlier is introduced beginning with the second iteration. For instance, as to the matter of increasing the diversity of particles in a small population, this method allows mutation operation to be executed under randomness (as indicated in Algorithm 2 in Appendix A). The mutation operation acts on the selection of a particle's moving guides, represented as $pbest$ and $gbest$, which influences the velocity of the particles. We can observe from Algorithm 2 that there is a possibility that the $pbest$ of a given particle is also its $pbest$ or another particle's $pbest$, or that its $gbest$ is also the $gbest$ or another particle's $pbest$. Also, DE-acceleration (illustrated in Algorithm 3 of Appendix A) is executed when the optimal solution's objective values for the latest iterations fail to see significant improvement, while the migration operation (Algorithm 4) is initiated when the swarm's crowding diversity is less than the desired value ($\phi$). In the interest of brevity, other parameters involved during this optimization are not discussed in detail here. The interested reader may refer to Zhang et al. (2012).

In addition, a distance-based method is applied after the third iteration to predict what scores the user will assign, and can thereby increase the overall iteration number and reduce the need for human-machine interactions in this process. The predicted preference scores for new solutions are calculated using Equation 3-14 based on the proportion of distance to all user scoring solutions positions. Here, $p(X_i^k)$ is the user preference score of material collocation $X_i^k$, while $d_n$ represents the distance between an unmarked material collocation, $X_n^k$, and that of user scoring material collocation $X_i^k$. This method predicts the preference scores of solutions in the next 20 iterations (i.e., the 4th to 24th iterations), and then the user is prompted to assign scores for the material collocations in the 25th iteration, the results of which will be used in the predictive function method in subsequent iterations (i.e., the 26th to 76th) for the purpose of modifying the direction of the solutions' evolution in the following iterations. The total number of iterations is approximately 180. The sequence of preference evaluations based on user scoring or predictive function method is outlined in Table 3-5. It should be clarified that this predictive method operates under the hypothesis that the user has basically the same degree of preference for similar material collocations.

$$p^*(X_n^k) = \frac{\sum (d_n \cdot p(X_i^k))}{\sum d_n} \tag{3-14}$$

**Table 3-5. Sequence of predictive function implementation**

| Iteration No. | Evaluator |
|---|---|
| **1** | Human |
| **2** | Human |
| **3** | Human |
| **4 - 24** | Predictive Function |
| **25** | Human |
| **26 - 76** | Predictive Function |
| **77** | Human |
| **78 - 178** | Predictive Function |
| **179** | Human |

Finally, three interior finish material collocations with the highest objective values during 180 iterations are selected as the optimal solutions and are recommended to the homeowner. Recommending three collocations instead of one serves to minimize the effect in which the visual harmony objective plays too significant a role in the material collocation selection process. Given that the user preference score only has three classes (unacceptable, acceptable, like), multiple material collocations may have the same preference score and thus would only be distinguishable based on the visual harmony score. In addition, since the positions of particles, or material collocation solutions, generated during the optimization process may not be linkable to an actual material in the database, the computer will search the nearest available point (based on

Euclidean distance) for each generated particle, acting as the new particle value in order to implement this IPSO method more practically.

### 3.4 Recommender System for Residential Lighting Design

The third phase in the present research is to streamline the interior lighting design process by proposing a knowledge-based recommender system which is able to suggest suitable interior lighting design and lighting products based on lighting design guides, occupant preferences (i.e., the ag), and building features (e.g., room type, dimensions).

Typically, recommender systems can be categorized into three groups: collaborative, content-based, and knowledge-based. The knowledge-based recommender system relies on the explicit description of user-preferred items for recommendations, rather than on historical data as is the case for the other two systems (Aggarwal, 2016). Since interior design is an uncommon activity for occupants and thus little historical data will be available, a knowledge-based recommender system is employed in this research.

Figure 3-19 presents the framework of the proposed recommender system. As illustrated in the figure, to begin, the Revit model of the house and its daylight analysis are inputted into the proposed system. The geometric model will be rendered and demonstrated within a VR environment, while rich building information (e.g., room type, dimensions, and building material) will be retrieved from the given BIM model and the daylight analysis results will be fed as input to the knowledge-based model.

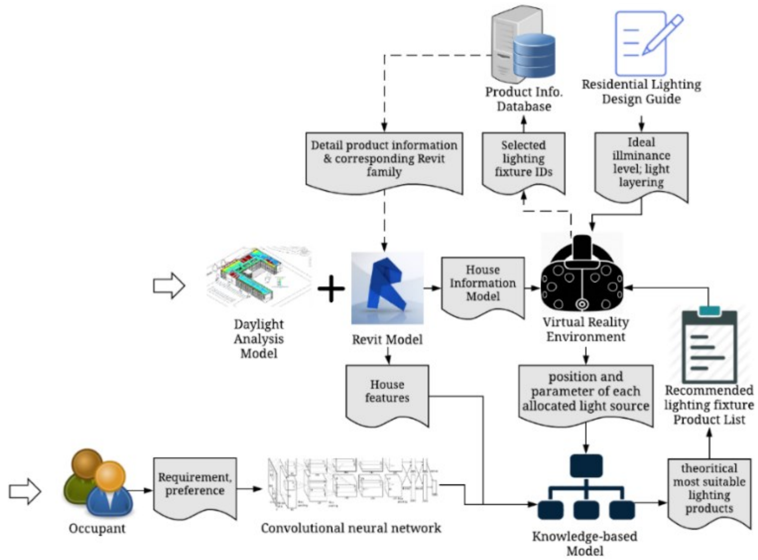



**Figure 3-19 Lighting design recommender system framework**

The knowledge-based model herein refers to domain-specific knowledge rules, which are provided by an expert in the area and some authoritative design guides. The model takes two forms to recommend lighting design and fixtures: (1) suggesting lighting setup in various scenarios; (2) and implementing domain-specific constraints on light fixture attributes. For example, when room type is “Bathroom”, light fixtures for vanity lighting will be suggested to be about 300 lx illuminance, mounted symmetrically on both sides of the vanity and roughly at the user’s eye level. Also, the UL Listed Location of light fixture should not include “Dry Locations”. As a further example, when it comes to “Living room”, the ambient lighting design is conducted first, and the knowledge-based model can propose several light source layout plans based on the ceiling height and area of the living room. Moreover, given that the lighting colour temperature for a living room should be near 2,700 K, the attribute value of “Bulb Colour Temperature” for bulbs used for creating ambient lighting should be set as 2,700.

Occupant requirements and preferences are also used as inputs to the proposed system in the form of text and images. Text information includes attributes of finishing products with respect to factors, such as functionality and affordability, which are directly related to the user experience. Examples of such text information include "the ceiling fan can be controlled remotely", and "the light fixture price should not exceed $200". Image information, which includes the visual attributes of a product, is analyzed by a pre-trained Convolutional Neural Network (CNN) model in order to identify user-desired product features (e.g., category, texture, and shape) based on the image content.

Once the knowledge-based model receives data from the daylight analysis, the BIM model, and user requirements, it generates proper designs regarding the brightness, colour temperature, and position of light sources under each lighting layer of each room. The occupants can then evaluate the lighting design via VR environment and modify the design directly such as increasing/decreasing the illuminance level, changing the colour temperature, and inserting/removing the light source. After the lighting design review, the lighting parameters and the position of each light source are determined and sent to the knowledge-based model again as parts of target product features.

With all of the target product features from the knowledge-based model, CNN (processed user requirement), and user requirements, a multi-criteria decision analysis method, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), is used to measure the similarity between available products in the product database and the specified target product. A list of the most similar products is then recommended to the user. After the user selects one of the recommended products, the system will retrieve the detailed product information along with a product model and insert it into the BIM model.

It should be noted that this research concentrates on the allocation and selection of interior lighting products. Also, decision making regarding the selection of interior light fixtures in this research not only depends on occupant preferences, but also must comply with the design requirements given in the design standards. Consequently, developing recommendation criteria and similarity metrics that assist occupants in exploring available options is crucial for the proposed system.

In addition, to validate the feasibility of the proposed framework, a recommender system for ceiling lights is developed. Lighting simulation and optimization have been studied in other research, such as Shikder et al. (2010) and Cassol et al. (2011), and it is outside the scope of the present research. A detailed explanation of the system development is presented in the following subsections.

### 3.4.1 Convolutional Neural Network Training

In this research, AlexNet (Krizhevsky et al., 2012) is used as the primary CNN model and is fine-tuned to match the product classes within a commercial software package, MATLAB. AlexNet is the first well-known CNN, which won the ILSVRC2012 classification task by classifying 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into 1,000 different classes (Krizhevsky et al., 2012). AlexNet contains eight layers, including five convolutional and three fully-connected, as indicated in Figure 3-20.

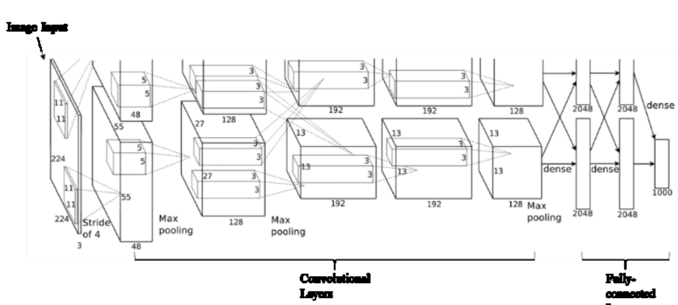


**Figure 3-20 AlexNet architecture, source: Krizhevsky et al. (2017)**

In order to train the CNN model for the purpose of image classification, various types of ceiling lighting photographs are collected and then annotated by category, finish colour, shade colour, and shape. Fourteen classes of light fixtures are chosen to train the neural network. The light fixture classes and related images are presented in Figure 3-21, where the caption under each photograph is the tag describing the light fixture. Each fixture class contains between 250 and 300 images.


**Figure 3-21 Fourteen classes of ceiling light fixtures and example images from homedepot.ca, houzz.com, and LampsPlus.com**

During the fine-tuning phase, the last fully-connected layer is removed and replaced with the output layers (14-class classifier). A small learning rate (0.001) is used to fine-tune the weights of the previous layers by continuing the backend propagation. Since the target image dataset includes ceiling light products, the method through which the convolutional layers extract the image features and distinguish them into various categories varies from its original task of classifying the natural images in ImageNet. The replaced output layers are constructed with one fully-connected layer, one Softmax layer, and one "ClassificationOutput" layer. The Softmax function (see Equation 3-15) is applied in the Softmax layer in order to compute the probability scores for every candidate class. Then, the CNN classifier outputs the class with the highest score as the predicted result. In the last layer, a cross entropy error (Equation 3-16) is assigned to evaluate the quality of the neural network, which is commonly used in the classification problem.

$$P(c_r|x,\theta) = \frac{P(c_r|x,\theta)P(c_r)}{\sum_{j=1}^{k} P(x,\theta|c_j)P(c_j)} = \frac{\exp(a_r(x,\theta))}{\sum_{j=1}^{k}\exp(a_j(x,\theta))} \tag{3-15}$$

$$E(\theta) = -\sum_{i=1}^{n}\sum_{j=1}^{k} t_{ij} \ln y_j(x_i,\theta) \tag{3-16}$$

where $P(c_r|x,\theta)$ denotes the conditional probability (i.e., the class prior probability) of the sample given class; $r,\theta$ represents the parameter vector; $t_{i,j}$ indicates that the $i^{\text{th}}$ sample belongs to the $j^{\text{th}}$ class; and $y_j(x_i,\theta)$ represents the output for sample *i*.

In the training process, the image dataset is divided into a training dataset and a test dataset with a ratio of 7:3. A gradient descent algorithm is used to update each layer's weights and biases in order to minimize the error function by moving toward the negative gradient of the loss function in small increments. The training progress is demonstrated in Figure 3-22, of which the result indicates the classification accuracy to be 84.75% for the testing data. By checking the error point, it is discovered that most of the errors occur during the prediction of shade colour. This determination is not easily arrived at from the images provided alone—even for humans—since the brightness and contrast of the images can have a significant influence on image recognition.

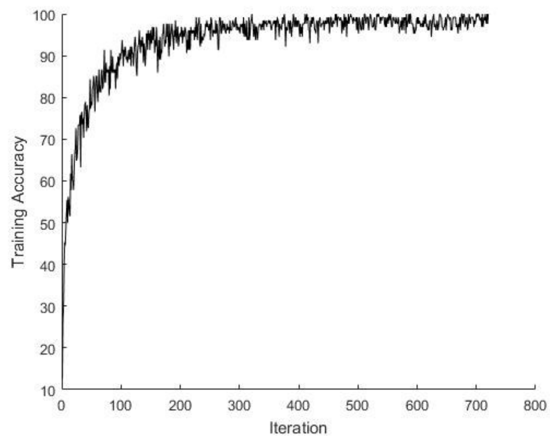



**Figure 3-22 CNN training progress**

### 3.4.2 Domain-Specific Rule Collection for Lighting Design

To develop a knowledge-based recommender system, domain-specific rules are required to match the user requirements or attributes to item attributes. The domain-specific rules for lighting design in this research can be categorized into two primary types based on the nature of their application: (1) *light source design rules or procedures* to identify the lighting layout with determined lighting parameters; (2) *lighting fixture selection rules* to generate optimal product features under various scenarios.

Prior to describing the goal implementation, it is necessary to define several concepts that are often mentioned in residential lighting design. Lighting serves multiple functions in interior design such as illumination and decoration. Based on their various functions, lighting fixtures are usually categorized into four lighting layers: decorative lighting, accent lighting, task lighting, and ambient/general lighting. Decorative lighting refers to the fact that the fixture itself or the light it generates is a focal point in the space and its primary role is visual appearance. Accent lighting is the type of lighting used to highlight specific objects or architectural features within an environment. Task lighting is typically used for performing work-related activities, such as reading, cooking, or shaving. Ambient/general lighting is the softest and most basic lighting that fills the room with a comfortable level of illuminance. Successful lighting design should effectively blend these four layers of lighting and allow the occupants to fully explore the functionality of the space. The importance ratings for lighting layers vary from room to room. Thus, it is necessary to code the rule, which outlines how to set up these four lighting layers and how these four layers interact with one another, in the rule-based model. For instance, a guide regarding the recommended illuminance level, $E_{av}$, for various lighting layers in a room is applied in this research and is illustrated in Figure 3-23 below, which is adapted from Japan's recommended illuminance levels published by Panasonic, an electronics company. The recommended illuminance for ambient lighting ($E_{rec-ambi}$) and task lighting ($E_{rec-task}$) for multiple types of rooms is indicated in this chart, but the other two layers are excluded given that decorative lighting and accent lighting are typically used to draw attention, and the illuminance parameter of these types of lighting greatly depends on the object which they highlight. Here it should be noted that the recommended illuminance level listed in Figure 3-24 is for young adults. If an elderly occupant (over 60 years of age) is living in the building, it is necessary to add three times more illuminance to the original level (Kunduraci, 2017).

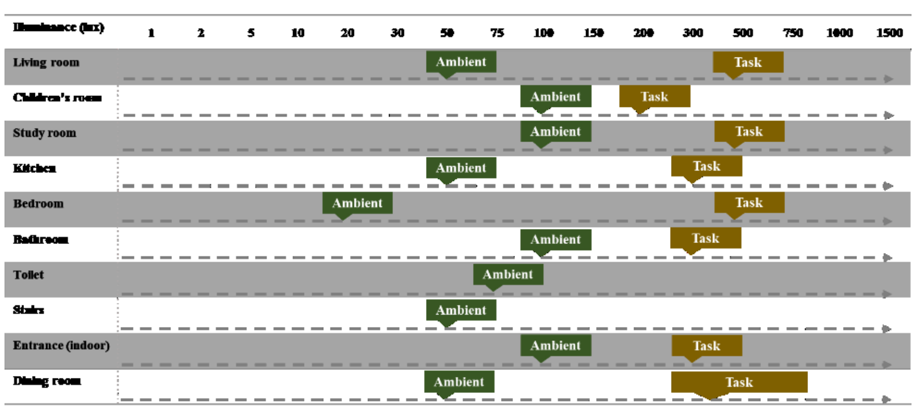



**Figure 3-23 Recommended illuminance level for various rooms**

Moreover, the daylight analysis result is also one of the most important components required by the knowledge-based model in order to deliver a proper lighting design. A survey of previous literature review found that most occupants prefer daylighting compared to artificial lighting. Also, optimal use of daylight could certainly reduce electricity consumption and improve the energy efficiency of a building. Hence, determining how to incorporate the daylight analysis results into residential lighting design for the proposed system is one of the problems this research aims to solve. In the case of this research, the daylight analysis results from Ecotect can deliver several daylight metrics, such as daylight factor ($df$) and day autonomy, to assist the homeowner and designer to optimize and communicate the quantity and quality of daylight within a space.

A daylight factor in architectural engineering is the ratio of the illuminance level within a house to the illuminance level outside the house, which is defined by Equation 3-17. According to the reference, the ideal daylight factor for everyday indoor activity in a room should range between 2% to 5%. If the daylight factor for a room is less than 2%, it is considered an inferior daylight environment.

Daylight factor: $$df = \frac{E_i}{E_o} \times 100\% \qquad (3\text{-}17)$$

where:

$E_i$ indicates the indoor illuminance at a point caused by daylight;

$E_o$ represents the simultaneous outdoor illuminance from an unobstructed hemisphere under an overcast sky condition.

On the other hand, the daylight autonomy is the ratio of working hours when the indoor illuminance is within the reasonable range and satisfied by daylight only, which is measured by comparing daylight illuminance on a working plane to the minimum requirement over time. Typically, the daylight analysis deems an illuminance level less than 100 lux as an insufficient daylight level, and an illuminance level greater than 2,000 lux as the upper threshold.

Also, the hourly change of average indoor illuminance by the combined lighting (sunlight and artificial lighting) needs to be plotted as illustrated in Figure 3-24. The yellow area is contributed by sunlight, while artificial lighting comprises the blue area. This illuminance contour is a reference for lighting designers for environmental analysis and can be used in the knowledge-based model to minimize the demand regarding artificial lighting installation. This figure can be generated given the recommended illuminance and the hourly daylight analysis results for each room from Ecotect (an example is presented in Figure 3-25).

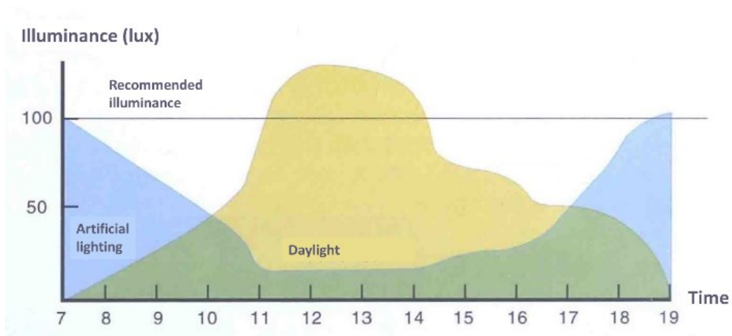



**Figure 3-24 Average hourly illuminance level**

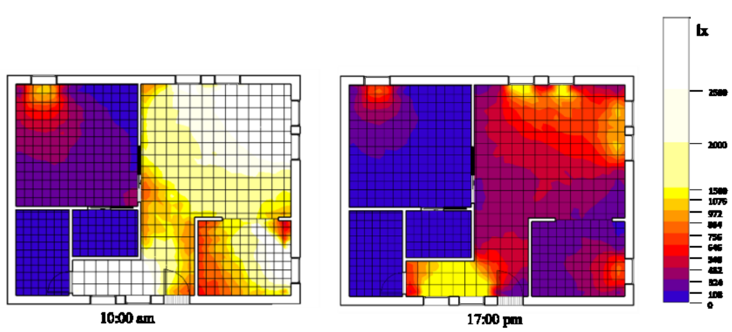


**Figure 3-25 Results of daylight analysis at 10:00 a.m. and 17:00 p.m.**

Considering the following factors: (1) recommended illuminance level for various lighting layers, (2) occupant's age, and (3) daylight analysis results, the system can estimate the required artificial lighting illuminance following Equations 3-18 to 3-21 below.

$$e_1 = \begin{cases} 1.0, df \geq 0.02 \\ 1.2, df < 0.02 \end{cases} \tag{3-18}$$

$$e_2 = \begin{cases} 1.0, o_{age} \leq 60 \\ 2.0, o_{age} > 60 \end{cases} \tag{3-19}$$

$$e_3 = \begin{cases} 1.0, E_{av-dl12} \geq 100 \\ 1.2, E_{av-dl12} < 100 \end{cases} \tag{3-20}$$

$$E_{av} = e_1 \times e_2 \times e_3 \times E_{rec} \tag{3-21}$$

where:

$e_1$ represents the coefficient considering daylight factor;

$e_2$ represents the coefficient of occupant age;

$e_3$ is the coefficient of average indoor daylight illuminance at approximately 12:00 p.m.

With the required illuminance of artificial lighting from previous steps, Equation 3-22 is then used to calculate the number of light sources.

$$N = \frac{E_{av} A}{\Phi_s U K} \tag{3-22}$$

where:

$E_{av}$ represents the required average illuminance level for this room;

$A$ denotes the area of the horizontal working plane;

$K$ represents the room surface maintenance factor, which is the proportion of the illuminance provided by a lighting installation in a room after a set time compared with that which occurred when the room had no artificial lighting installed. Its value can be determined by referring to a lighting design standard chart;

$\Phi_s$ represents the lighting design lumens per light source, which can be roughly determined from the manual of popular light fixtures and user's light fixture preference;

$U$ indicates the utilization factor that refers to the proportion of the luminous flux emitted by the light source that reaches the working plane.

In fact, the utilization factor $U$ in Equation 3-22 is affected by the following factors: room proportions, room reflectance (e.g., the reflectance of ceiling, floor, wall), spacing height ratio, light output ratio of luminaire, and flux distribution of luminaire. Thus, it is necessary to input all relevant information into the knowledge-based model in advance.

Furthermore, the uniformity of lighting distribution must also be taken into account when allocating the light source with defined illuminance parameters, especially for the ambient lighting layer. To perform the light source layout for the ambient lighting layer, the ceiling needs to be divided into an $M \times N$ grid with a 2-in width as presented in Figure 3-26. The yellow points of the grid intersections represent the potential locations of luminaires and the calculation points for illumination uniformity checking, which is analyzed through the point-by-point method by calculating the illuminance intensity ($E$) at each point (Hwa-Soo et al., 2014). The illumination intensity at each calculation point is delivered from Equation 3-23, where $I_i$

indicates the illuminance intensity at $\theta_i$ direction; $r_i$ represents the distance from light source to the calculation point; and $\theta_i$ represents the incidence angle that can be estimated by distance $r_i$ and the horizontal distance of light source from the calculation point as indicated in Figure 3-27. The illumination uniformity checking is carried out to minimize the deviance of illuminance intensity ($E$) at each calculation point under various luminaire arrangements. It is to note that the work plane in Figure 3-27 is an imaginary horizontal plane situated at the standard working height within an interior space. During the illuminance design and daylight analysis, most of the calculations and measurements are performed to the points on this plane. In the United States, the general height of the working plane is 30″.

$$E = \sum \frac{I_i}{r_i^2} \times \cos\theta_i \qquad (3\text{-}23)$$

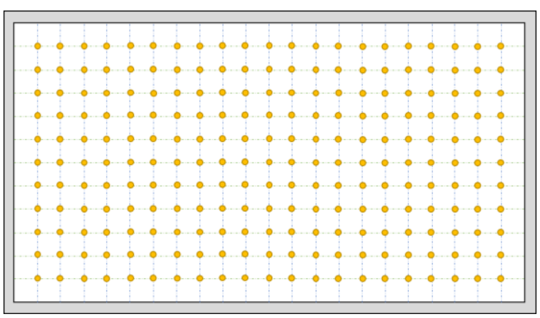


**Figure 3-26 Potential luminaire points and calculation points**

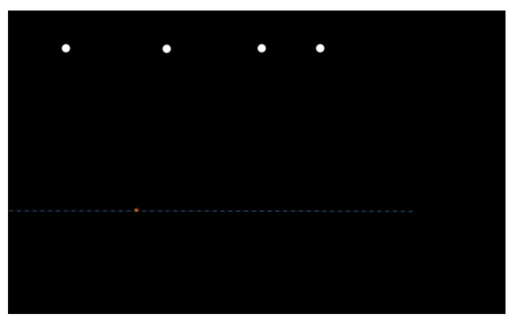


**Figure 3-27 Point-by-point method, source: Hwa-Soo et al. (2014)**

Finally, with the illuminance parameter and location of each light source determined from previous analysis, the rule-based system can apply the rules regarding light fixture product selection that are usually considered by the residential lighting designer. These rules, as per the example in Table 3-6, include light fixture height constraints, suggested light fixture width, suggested lighting colour temperature, suggested lighting brightness, lighting UL Listed

Location, and luminous efficacy. Most of the rules are formalized in consideration of the function of the given room.

**Table 3-6. Sample rules for determining target product features**

| | Entry | Living room | Kitchen | Dining room | Bedroom | Bathroom |
|---|---|---|---|---|---|---|
| Height (ft) | $h_r - 7$ | $h_r - 7$ | $h_r - 6$ | $h_r \leq 8$, $h_r$- 7;<br>$h_r > 8$, 0.75× $h_r$- 5 | $h_r - 7$ | $h_r - 8$ |
| Width (in) | $\frac{l_r + w_r}{12}$ | $\frac{l_r + w_r}{12}$ | $\frac{l_r + w_r}{12}$ | Depends on dining table size | $\frac{l_r + w_r}{12}$ | $\frac{l_r + w_r}{12}$ |
| UL Listed Location | Dry | Dry | Dry | Dry | Dry | Damp |
| Colour Temp. (K) | 2700 | 2700 | 4100 | 2700 | 2700 | 6000 |
| Luminous efficacy | If $\frac{\Phi_s}{w_b} \geq 60$, it is an energy-saving bulb | | | | | |

*Note:* $h_r$= *ceiling height;* $l_r$= *room length;* $w_r$ = *room width;* $w$= *watt of electricity power usage*

### 3.4.3 Object Similarity Metric

Once the proposed system has recognized the target product features from the previous steps, it compares the target item with product items from the product database by calculating the similarity distances of the specified attributes, a procedure referred to as TOPSIS method. Since it is feasible to generate a theoretically ideal lighting fixture given the design constraints and user preferences, and since the comparison of attribute values is meaningless for most lighting fixture attributes (e.g., length, categories), the TOPSIS method is used here instead of AHP to conduct the lighting fixture selection. It is worth noting that the product attributes are grouped into two categories, either symmetric attributes or asymmetric attributes. In the case of asymmetric attributes, the difference between two attribute variables does not affect the similarity measurement unless it falls within a certain specified range. For instance, when the price of item $d$ is less than or equal to the target price, the similarity measurement of this attribute is 1, regardless of the degree of difference between the two attribute variables. In contrast, the degree of similarity between two symmetric attributes depends entirely on the absolute difference between them. The calculation for the product similarity distance is expressed as Equation 3-24.

$$Similarity(t,d)=\sum_{n}^{i=1} w_i\left(1-\frac{|t_i-d_i|}{\max_i-\min_i}+I(t_i,d_i)\times\alpha_i\times\frac{|t_i-d_i|}{\max_i-\min_i}\right) \tag{3-24}$$

where $t_i$ and $d_i$ denote attribute $i$ for target item $t$ and item $d$, respectively, in the product database; $\max_i$ and $\min_i$ represent the maximum and minimum values of attribute $i$, respectively; $n$ denotes the number of attributes of a product; $w_i$ indicates the weighting factor for each attribute; $I(t_i,d_i)$ represents a binary function to determine whether $d_i$ is less or equal to $t_i$; and $a_i$ denotes the reward factor for asymmetric attributes.

When measuring the similarity of symmetric attributes, $a_i$ is set to 0, whereas, for asymmetric attributes, $a_i$ is greater than 0. More specifically, provided that the attribute similarity increases in proportion to the distance between a stored item and the target item, the value of $a_i$ is greater than 1. If the value of $a_i$ is equal to 1, then the recommender system counts whether the stored item's attribute value reaches the target value, regardless of the variance between them.

As soon as the similarity between the target item and stored items is calculated, a list of items similar to the targeted item is obtained. It should be noted that the results may lack diversity due to the nature of similarity measurement, resulting in the user being unsatisfied with the top-ranked results. In order to provide a variety of options within a reasonable range, a practical approach called "bounded greedy selection strategy" is used in this research. In the interest of brevity, the procedure is not explained in detail herein; however, a detailed explanation can be found in a study by Aggarwal (2016).

# CHAPTER 4 IMPLEMENTATION

To test the feasibility of the proposed methodology, a prototype system is developed utilizing several platforms: (1) MySQL database management system, (2) Autodesk Revit (BIM software), (3) Unity 3D (game engine), and (4) a set of VR head-mounted display devices, HTC Vive. This system provides a data exchange and immersive virtual reality (IVR) environment to facilitate the interior finish material selection and indoor lighting design solutions.

The prototype system runs on a computer with the following technical specifications: Intel® Core™ i7-7820 processor, NVIDIA GeForce® GTX 1080, and 16 GB RAM. Also, two case studies regarding interior finish material selection and home lighting design applied using the prototype system are conducted in this chapter in order to study the usability and efficiency of the proposed methods.

A building model of a two-storey wood-structure single-family house is used in this research for the case study. The designs regarding architectural and structural engineering as well as the room layout have been completed for this building. Figure 4-1 and Figure 4-2 demonstrate the 3D drawings and the floor plans of this house.

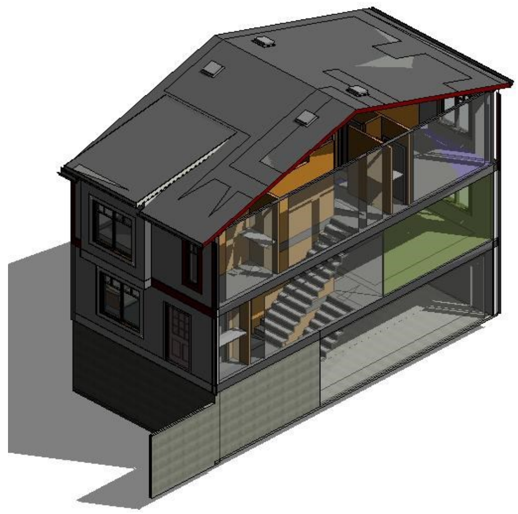
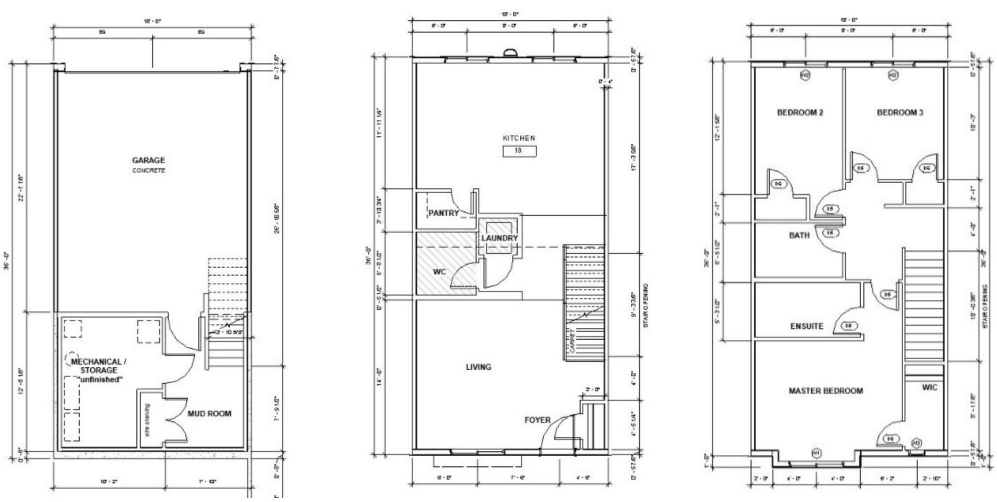


**Figure 4-1 Case study house model in Revit**




(a) Basement (b) Main floor (c) Second floor

**Figure 4-2 Floorplans**

## 4.1 Preparatory Work: Building Information Model Integration into VR–BIM-Based Interior Design System

To implement the VR–BIM interior design system, the designer must first perform a daylight analysis with a Revit built-in tool, Ecotect. This analysis provides the user a comprehensive understanding regarding the amount of sunlight emitted into the interior of the case study house and assists the homeowner and designer in creating comfortable and beautiful indoor spaces by selecting appropriate interior finishing products. LEED 2009 IEQc8 opt1 setting in Ecotect is applied as the criteria for daylight analysis in the case study. The simulation results are indicated in Figure 4-3 below. It should be noted that the basement is not included in the daylight analysis in this case study; and the results of the presented analysis are applied to interior finishing product selection which primarily focuses on the main and second floor. According to the results, 83% of the rooms satisfy the illuminance requirement at 9:30 a.m., and at 3:00 p.m. 90% of the rooms satisfy the illuminance requirement with the help of artificial lighting. Also, the hallway on the main floor and the bathroom in the second bedroom require additional assessment due to insufficient lighting level.

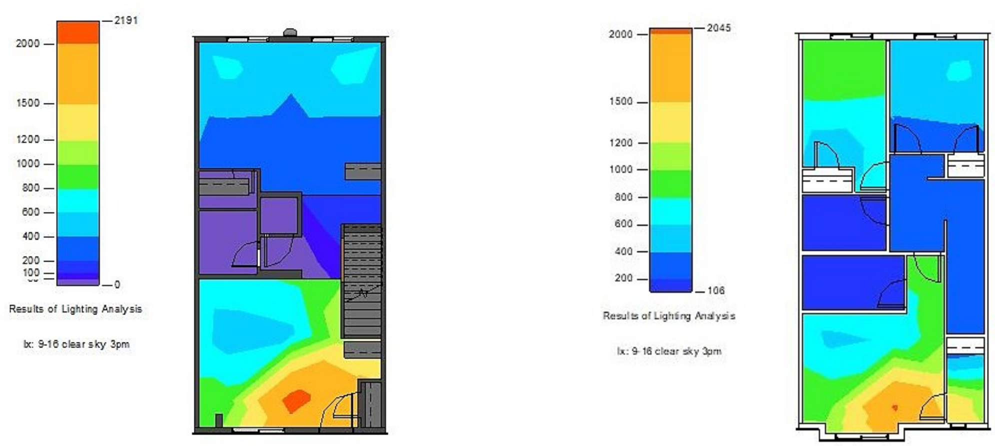
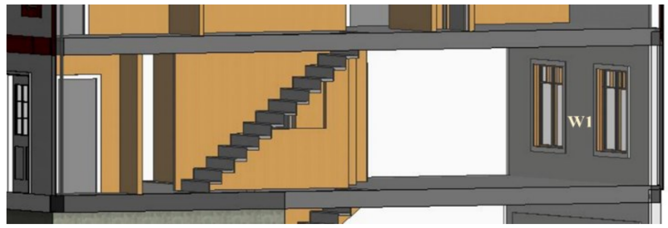


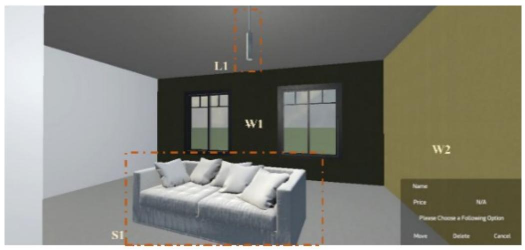

**Figure 4-3 Daylight analysis results from Ecotect**

The designer can then export the model and room feature information into Unity and the database, respectively, and the model is rendered in the Unity game engine as demonstrated in Figure 4-4. The system uses the first-person character to perform interior product selection process, which enables the homeowner to simulate the daily activities in their home and select the interior finishing products that best complement their behaviours. As the primary purpose of this step is to validate the feasibility of information exchange among several platforms, only three tasks are conducted in this experiment: (1) changing the colour of one wall; (2) allocating a sofa; and (3) allocating a lighting fixture. If all decisions made in the VR environment can be reflected in the BIM model, the data exchange function of the developed system is valid.

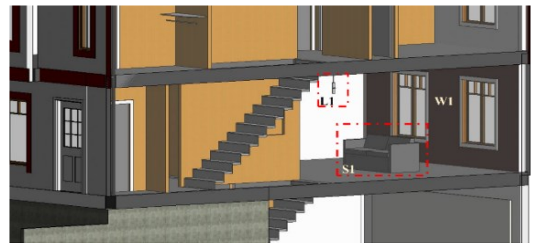
Figure 4-4 compares the VR model and BIM model during the homeowner's interior finishing decision-making process. As indicated in the figures, the proposed system can accurately and timely update the BIM model according to modifications the user makes in the VR environment, which proves that the VR–BIM-based interior design system supports the data exchange between the VR user interface and the BIM software (Revit). Thus, it will no longer be necessary for interior designers to export or re-draw the architectural model to perform the pre-design environmental analysis in this case as BIM software is incorporated in the interior design profession. Also, other participants of the building project can extract the desired information without unnecessary wasted time and effort. The integrity of interior design information in BIM also facilitates the building facilities management during the building operation phase.




(a) BIM model before interior finishing product decision-making process




(b) VR model after interior finishing product decision-making process




(c) BIM model after interior finishing product decision-making process

**Figure 4-4 Experiment results in VR interface and BIM software**

## 4.2 Case Study Ⅰ: Interior Finish Material Selection

### 4.2.1 Overview

Proper material selection for interiors is critical, and should provide significant benefits regarding environmental, economic, and social aspects (Castro-Lacouture et al., 2009). To verify the feasibility of the interactive particle swarm optimization (IPSO)-based interior finish material selection approach, the kitchen on the main floor of the case study house is set as the experiment environment. The area of the kitchen is approximately 223.41 $ft^2$ and the floor plan of the kitchen is illustrated in Figure 4-5 below. During the material collocation decision-making process, the layout of the kitchen remains fixed, but the finish materials of wall, floor, ceiling, countertop, cabinet and backsplash are continually updated according to the embedded IPSO algorithm. Also, the room illuminance setting in the IVR environment is to mimic the actual daylight which reflects the material's appearance.

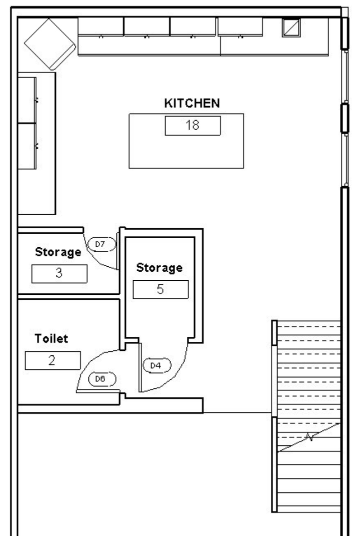



**Figure 4-5 Kitchen floor plan**

Twenty-five participants from the University of Alberta were involved in this experiment, which includes 20 students and 5 staff. The age of participants ranges from 23 to 50 years. Most of the participants are unfamiliar with interior finish material selection basics or interior design knowledge.

Initially, the participants are asked to select one kitchen design case that appeals to them from among several images and the selected scene is set as the reference for visual harmony evaluation in the IPSO method. Then, step 1 of material type decision making begins. Participants determine the importance weight of the various material criteria through the AHP method based on their knowledge or follow the default setting as indicated in Table 3-3 presented in Subsection 3.3.1. Then, a radar chart listing the overall performance indicators for materials can be generated by the multi-criteria decision-making method, by which participants are able to determine their desired material types for all finishes. Based on the material type decisions made in step 1, the corresponding data regarding material visual characters (e.g., material texture, LAB value, glossiness, and metallicness) will be uploaded into the game engine.

The average LAB colour value for each material is obtained by reducing the material texture image into pixels using the Bicubic method with the MATLAB image processing tool. Also, the glossiness and metallic value are assigned to materials based on the experienced knowledge of material physical properties from game rendering designers and interior designers. The values of glossiness and metallicness for materials with different processing methods and composites follow the uniform distribution within a specified range.

As step 2 begins, the participant enters the immersive virtual environment through HTC Vive headset and begins the material collocation selection as presented in Figure 4-6. The participant inputs their preference score for the current scene in a popup rating request window as presented in Figure 4-7. Once the user inputs the score for the current material collocation plan, the system records all information (i.e., the preference score giving by user, the parameter of material collocation), and updates the material collocation for the next generation. The average marking time for each user is around 40 times. Upon completion of the interactive material collocation selection, the participants are asked to fill out a questionnaire and provide some comments about their experience.

**Figure 4-6 Participant using the prototype system with HTC Vive**

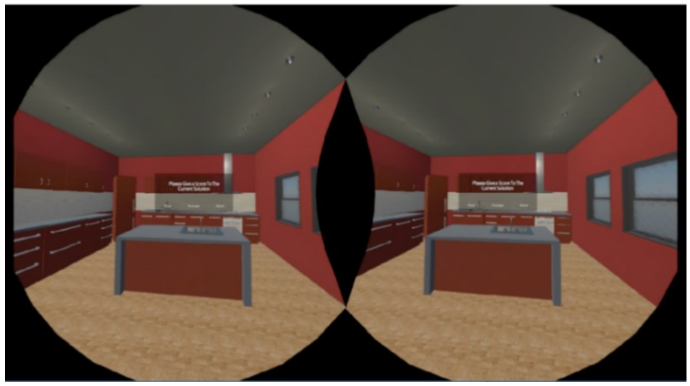


**Figure 4-7 GUI of prototype system under IVR environment**

### 4.2.2 Case Study I Experiment Results

The resulting analysis of the interior material selection process and questionnaire indicates that the method proposed in this chapter improves the efficiency of interior finish materials selection by homeowner, and the final recommendation of the material collocation from system represents the aesthetic preference of user in most cases. Also, the majority of the participants agree that the kitchen model in IVR environment can accurately represent the real-life scenario and provide them with a more detailed impression than two-dimensional images regarding how the various finish materials interact. Additionally, participants agree that this method allows them to explore some innovative interior finish material collocation plans which they had never thought of before.

It is also found that the average duration for the interactive material selection is approximately ten minutes, which is acceptable for most of participants. Figure 4-8 plots the objective value of *gbest* in every iteration for one example experiment. As we can see, the convergence behaviour reveals that there is a significant improvement regarding the user satisfaction and harmony score of the resulting plan compared to the initial one. In other words, it means the optimization process is efficient and the proposed method can gradually lead the participant toward their desire design in a effective way. Furthermore, Figure 4-9 demonstrates an example of the evolution process during the interactive material collocation selection, and the participant stated that the resulting plan could represent what he desired in mind.

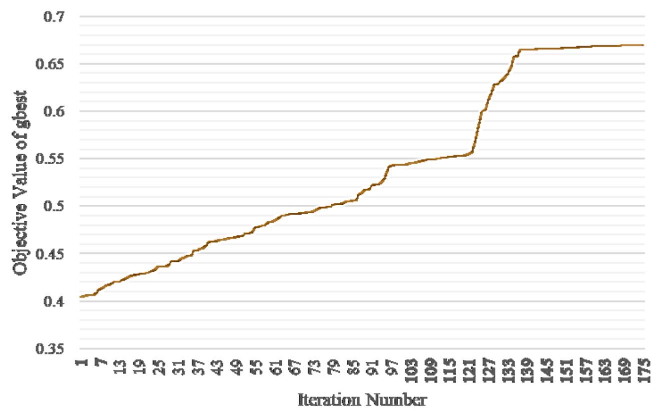



**Figure 4-8 Convergence process of Interactive PSO**


**Figure 4-9 Evolutionary process of material collocation plan within developed system**

### 4.2.3 Discussion for Case Study I

Generally, the proposed approach for finish material selection is able to assist homeowners in selecting their desired interior finish materials effectively, as demonstrated in the case study. However, the prototype system is limited in the following respects. (1) Data regarding material environmental, cost, and operation performances is a mean value for each material type (e.g., wood, marble). It cannot precisely describe the material's actual performance in practice, as one type of material may possess different properties according to its various sub-types, colour, pattern, origins, production mode, and so on. (2) The prediction function for interactive PSO used in this chapter is a distance-based method to predict the unrated material collocation plan. This method is based on the hypothesis that the user has a similar preference for similar material collocation plans. However, this hypothesis may be incorrect in some cases since human preference is a highly subjective criterion, which cannot be measured linearly. Thus, more studies regarding the relation between material visual characteristics and human preference need to be carried out in the future.

## 4.3 Case Study II: Home Lighting Design

### 4.3.1 Overview

In this case study, the system embedded with the knowledge-based recommender is used for a kitchen lighting design. To begin, the user enters the VR interface, and the system can detect the room type ($rt$) of the user's current location where the lighting design will be carried out. Then, the system analyzes the BIM model, daylight environment (e.g., $E_{av-dl12}$ and $df$), and identifies the room features, such as room type ($rt$), height ($h_r$), width ($w_r$), area ($A$), spacing to height ratio ( $\sqrt{A}/(h_r - h_d)$ ), finish material reflectance ( $ref$ ), and furniture location ( $xyz_{obj}$ ). The kitchen lighting design procedure coded in the recommender system is outlined in Figure 4-10.

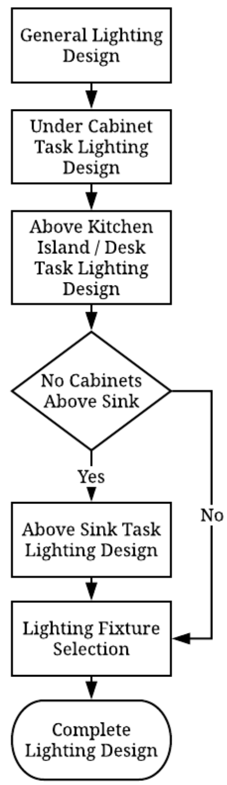



**Figure 4-10 Lighting design procedure for kitchen**

Accordingly, the knowledge-based model then proposes the lighting design specific to each lighting layer and demonstrates it within the VR interface. Figure 4-11 presents an example of the VR interface when the system demonstrates the ambient lighting layer design for a kitchen. The menu control marked with a yellow dashed frame indicates the required lighting layers in the current room. Their arrangement sequence (from left to right) represents the recommended design sequence, or in other words, the order of importance (more important to less important) in terms of multiple lighting layers design. If the user is satisfied with the proposed lighting design of the current layer, they can move to the next layer design and continue to view the lighting effect of the previous layer. Otherwise, they can "shut down" the current lighting layer design (click the “Hide” button outlined by the red dashed frame) and create a new design for the current layer based on their preferences. After all proposed lighting layer designs are reviewed and modified by the user, the remaining light source is the final lighting design decision for this kitchen. The user can save this design into the database by clicking the “Finish” button.


**Figure 4-11 VR interface of lighting design**

Once the lighting allocation and illuminance parameters are determined, the user is prompted by the system to choose the light fixtures for all light sources. The product selection procedure begins with loading the user’s preferred lighting image. The image will be new to the system, such as an image downloaded from the Internet or a photograph newly captured, and as such it will not have an existing tag in the database. For the item image, the system predicts the class to which it belongs. As presented in Figure 4-12, the selected item is classified correctly as “Flush Mount/Bronze Finish/White Shade”. Furnished with the illuminance parameter requirement, room attributes, and the user preferences (e.g., the design style and budget need to be explicitly specified), the knowledge model converts this information into corresponding product attributes. Following this, the system can conduct the recommendation analysis and retrieve similar items from the product database. The two results listed in Figure 4-12 represent the recommendation results for light fixture and bulb. Under the constraint of bulb base type and power, the light fixture results are generated. Once the user has selected their preferred light fixture, the recommendation of the bulb is performed. Finally, the system retrieves the Revit family model of the selected items from the database and inserts the component models into the BIM model as indicated in Figure 4-12.

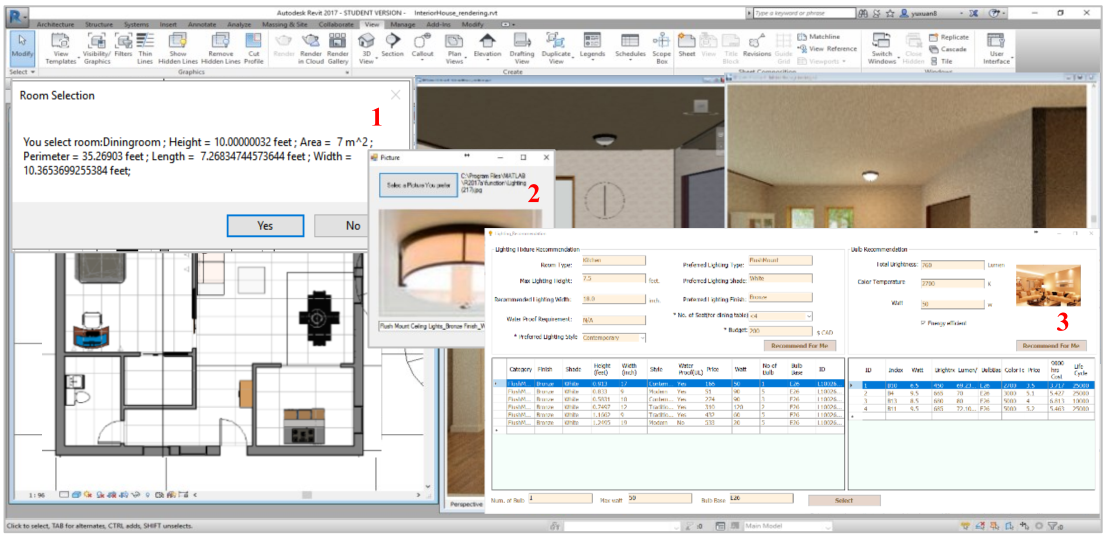



**Figure 4-12 GUI of lighting fixture recommended**

### 4.3.2 Case Study II Experiment Results

To test the performance of this prototype system, several participants who have never used this system before are recruited and divided into two groups. The first group is instructed to use this system to create lighting designs for five various residential kitchens. Those in the second group only observe the product selection interface (simulating an online shopping interface) to complete the same task. The purpose of this arrangement is to ensure that the two groups being compared have the same dataset. The initial test results indicate that the average duration of the lighting design process for one kitchen using the proposed system is approximately 5 minutes, whereas the traditional method takes approximately 10 minutes or more to achieve the same result.

# CHAPTER 5 CONCLUSIONS

## 5.1 Summary

Building information modelling (BIM) and Virtual Reality (VR) have been implemented to facilitate the communication and data sharing between different parties in many engineering fields of building projects. In this context, the incorporation of BIM and VR into the interior design field is becoming increasingly necessary in light of the increasing importance of informed decision making in the interior design profession, which is based on quantified data from the work of other disciplines (e.g., environmental analysis, structural analysis, MEP design). Also, since home design has more frequent interactions with occupant behaviour compared to other building design components, a high level of user contribution is necessary through the investigation of occupant attitudes and preferences toward home design. Therefore, a framework for a VR–BIM-based interior design system applied with two novel user-centric interior design methods is proposed in this research to facilitate end-user involvement in the interior design process. The framework is validated through the implementation of interior finish material selection and lighting design tasks in a prototype system.

The prototype VR–BIM interior design system developed in module 1 of the research consists of four primary components: BIM software, a VR environment, a rule-based system, and a database. Initially, interconnections between BIM software, VR environment, and database are built to ensure the feasibility and accuracy of data exchange of interior design for BIM. A user without any architectural background can effortlessly explore the building information and modify interior finishing products under the VR environment. With actual product information stored in the database, the interior design decision made by the user is more practical and more accessible for later construction. Also, the proposed rule-based system helps the average user to contribute to design decisions related to the selection of interior finishes and interior lighting fixtures in conformity to their preferences.

In module 2, the study of material selection for interior finishes is conducted. First, multiple material evaluation criteria are selected according to the literature review and market research results. Given the consideration of UCD, the human aesthetic preference is incorporated into the material-performance-measurement matrix. Thus, two types of performance criteria are identified in this research, quantifiable criteria and non-quantifiable criteria. The quantifiable performance criteria, including carbon dioxide emission, function performance, and costs, are analyzed by a multi-criteria decision-making technique, AHP, to determine the type of material. While non-quantifiable criteria, (in this study, human aesthetic preference), is evaluated by a small-population-size interactive particle swarm optimization algorithm (IPSO) in order to select the specific material product regarding colour, texture, and processing method. To allow the user to fully explore the optical properties of materials, this finish material selection process is programmed and executed within an IVR environment. The method is also tested by several participants with the developed VR–BIM-based system, and the results indicate this approach can assist common users in the selection of the proper finish materials and IPSO algorithm effectively and efficiently evolves the material collocation plan toward user desires.

Furthermore, a knowledge-based recommender system for lighting design and lighting fixture selection is constructed in module 3 to assist the occupant in addressing the UCD problem even without substantial lighting system knowledge. First, the influence on human physiological and psychological health under various interior lighting environments as well as some lighting design guidelines are investigated and transferred into the knowledge-based model in a quantitative way for determining the indoor illuminance setting and positions. Also, a convolutional neural network (CNN) is successfully trained and applied in order to identify the user's preferences regarding lighting fixtures and bulbs as well as to transfer the desired product features to the knowledge-based model. All attributes of lighting design and selection are evaluated by means of the TOPSIS method. Finally, a lighting fixture layout plan and recommendation list of products are demonstrated to the user. This prototype system for residential lighting design is developed under the VR–BIM-based system and an Autodesk Revit plugin based on the proposed framework for the proof of concept, on which a case study is also performed and demonstrates that the developed recommender system can recommend a proper design to the user in an efficient manner.

In conclusion, the methodology and prototype system proposed in this research lays the groundwork for the development of an intelligent VR–BIM-based design tool capable of enhancing the concept of UCD and data management efficiency in the interior design profession.

## 5.2 Research Contributions

The primary contributions from this research are summarized as follows.

Academic contributions:

(1) A VR–BIM-based interior design framework is proposed to promote the implementation of BIM in the interior design profession by providing a platform for the designer and user to interpret and understand the building model accurately, as well as modify the design under VR environment, and it also benefits from the automatic data synchronization between VR model and BIM model. The framework facilitates the data sharing between interior design and participants from other disciplines and promotes the concept of

collaborative design in building design and construction projects, which reduces the risk of inefficient building design and possible rework.

(2) A user-centered interior design methodology is introduced to view the occupant as the object of investigation when performing the task of home design. It increases the efficiency of user involvement during the interior design and offers the occupant a more comfortable living experience due to their preferences having been more accurately interpreted and accommodated.

(3) An optimization model and knowledge-based recommender system are built with the application of an IPSO algorithm and several multi-criteria decision-making methods respectively, such as TOPSIS, to solve the material selection and lighting design problem for interior design. It provides an innovative method by which for designers and occupants to carry out interior design by modelling it as a quantifiable problem rather than by intuition only.

Industrial contributions:

(1) A prototype system is developed in this research to verify the proposed framework and methodology. This system applies to all residential buildings, and it can provide an immersive virtual reality (IVR) building walk-through experience in a short timeframe. The product information database connected with the system provides the specific description of interior finishing product alternatives, which not only assists the user to make informed decisions but also minimizes the possibly disappointing variance between the design plan and the actual scenario.

(2) Two case studies are used to test the prototype system, and the results confirm that it offers a user-friendly interface and satisfying user experience for most of the participants,

and it can assist the occupant to efficiently make a proper decision regarding material selection and indoor lighting design.

## 5.2 Limitations and Future Research

In order to improve the performance of the proposed methodology and prototype system, the following directions can be pursued in the future:

(1) The presented methodology and protocol system apply only to a single-user scenario. To enhance the applicability of the system, future study should investigate how to accommodate conflicting results in a multi-user scenario (e.g., differing opinions between two occupants toward the design of the living room.

(2) As commercial building are significantly different from residential buildings in terms of design constraints and the diversity of end-users, the development of an intelligent interior design tool for commercial buildings is another interesting avenue of future work.

(3) In this research, we assume that a given user's interior design preference are consistent. However, the perception of project participants could be affected by different times of day, weather conditions, or mood. Thus, more experimentation and study are required to address this issue from a psychological perspective.

(4) The current VR–BIM-based interior design prototype system is developed under the Revit software environment and VR GUI, and the virtual building and product models are required to be stored locally. To make this framework more robust and compatible with other BIM software and ensure all data is accessible despite user locations, a cloud-based BIM database (e.g., BIM server) will be incorporated in future work.

(5) A rule-based system is coded with design guides, decision-making methods, and optimization algorithms in order to function as an intelligent agent of this interior design

system. However, most of the knowledge is embedded into the system by hard-coding. Hence, machine learning technology (e.g., pattern recognition, data mining) requires further investigation in order to pursue a system's active learning and enhance the intelligence of the proposed design system.

(6) The recommender system for interior lighting design in Chapter 5 is limited to the consideration of illuminance level, uniformity, and colour temperature for lighting design parameters, which ignores the effect of glare. More analysis for lighting glare rating by the Unified Glare Rating (UGR) tabular method will be included in the future.

(7) The indoor finish material decision-making process in Chapter 4 does not contain sufficient performance data for every specific material regarding the quantifiable evaluation criteria such as carbon dioxide emission or embodied energy. Further investigation needs to be conducted for a more accurate material selection.

(8) This research focuses only on the lighting design and finish material selection in home design, many other areas, such as furniture layout and kitchen cabinet design, can be investigated in the future to enhance the integrity of the presented framework.

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# APPENDIX A: PSEUDOCODE OF SMALL POPULATION-BASED IPSO ALGORITHM

**Algorithm 1:** IPSO Algorithm

**Data**: $w^{\min} = 0.4$, $w^{\max} = 0.9$, $c_1 = c_2 = 2$, $\mathrm{MLD}_r = \{l_{r1}, \cdots, l_{r6}\}$, $p_{\mathrm{mut}} = 0.12$, $g_{\mathrm{mut}} = 0.15$

**Initialization**: Initial swarm with random position and velocity vectors: $X_i \in \mathbb{R}^{n \times j}$, and $V_i \in \mathbb{R}^{n \times j}$;

**begin**

    **for** *Each solution* $i = 1 : N_p$ **do**

        Set $pbest_i = X_i^1$;

        **Evaluate** Objectives;

    **end for**

    $gbest = \max_{pbest_i}\{Objective(pbest_i)\}$;

    **for** *irritation* $k = 2 : k^{\max}$ **do**

        $w = w^{\min} + k(w^{\max} - w^{\min})/i^{\max}$;

        **for** *each solution* $i = 1 : N_p$, *each element* $n = 1 : N_n$, *each parameter* $j = 1 : N_j$ **do**

            Run **Mutation Operation –Algorithm 2**;

            $v_{i,j,n}^{k} = w \cdot v_{i,j,n}^{k-1} + c_1 \cdot rand() \cdot (\tilde{g}best_n - x_{i,j,n}^{k}) + c_1 \cdot rand() \cdot (\tilde{p}best_{i,n} - x_{i,j,n}^{k})$;

            $x_{i,j,n}^{k+1} = x_{i,j,n}^{k} + v_{i,j,n}^{k}$;

        **end for**

        **for** *Each solution* $i = 1 : N_p$ **do**

            **Evaluate** Objectives;

            $pbest_i^k = \max_{X_i^k}\{Objective(X_i^k)\}$;

        **end for**

        $gbest^k = \max_{pbest_i^k}\{Objective(pbest_i^k)\}$;

        **while** $avg(\Delta Objectives(gbest)) < 0.05$ **do**

            Run **DE-acceleration Operation –Algorithm 3**;

        **end while**

        Run **Migration Operation –Algorithm 4**;

    **end for**

**end**

**Algorithm 2: Mutation Operation**

Generate $r = randbetween(1, N_p)$, $u = randbetween(1, N_p)$;
$r \neq i$, $u \neq i$;
**If** $rand() < g_{mut}$ **then**
$\tilde{g}best^k_{n,j}(i) = gbest^k_{n,j}$
**else**
$\tilde{g}best^k_{n,j}(i) = pbest^k_{r,n,j}$
**end**
**If** $rand() < p_{mut}$ **then**
$\tilde{p}best^k_{n,j}(i) = pbest^k_{n,j}$
**else**
$\tilde{p}best^k_{n,j}(i) = pbest^k_{r,n,j}$
**end**

**Algorithm 3: DE-acceleration Operation**

$N_{p,acc} = 4$, $N_p = 5$, $m^{\max}_{acc} = 3$, $r = randbetween(1, N_p)$, $u = randbetween(1, N_p)$, $R_{\text{acc}} = 0.1$, $F_{\text{acc}} = 0.1$
$r \neq u$
**for** *each solution* $i = 1 : N_{p,acc}$, *each element* $n = 1 : N_n$, *each parameter* $j = 1 : N_j$ **do**
  **If** $rand() < R_{acc}$ **then**
  $\tilde{x}^0_{i,n,j} = gbest^k_{n,j} + F_{acc} \cdot (pbest^k_{r,n,j} - pbest^k_{u,n,j})$
  **else**
  $\tilde{x}^0_{i,n,j} = gbest^k_{n,j}$
  **end**
**end for**
**for** $m = 1 : m^{\max}_{acc}$ **do**
  **for** *each solution* $i = 1 : N_{p,acc}$, *each element* $n = 1 : N_n$, *each parameter* $j = 1 : N_j$ **do**
    $r_1 = randbetween(1, N_{p,acc})$, $r_2 = randbetween(1, N_{p,acc})$
    $r_1 \neq r_2$
    **If** $rand() < R_{acc}$ **then**
    $\tilde{x}^{m+1}_{i,n,j} = \tilde{x}^m_{i,n,j} + F_{acc} \cdot (\tilde{x}^m_{r_1,n,j} - \tilde{x}^m_{r_2,n,j})$
    **else**
    $\tilde{x}^{m+1}_{i,n,j} = \tilde{x}^m_{i,n,j}$
    **end**
  **end for**
  **Evaluate** Objectives $(\tilde{X}_i)$
  **If** Objectives($\tilde{X}^{m+1}_i$)> Objectives($\tilde{X}^m_i$) Then
  $\tilde{X}^{m+1}_i = \tilde{X}^{m+1}_i$
  **else**
  $\tilde{X}^{m+1}_i = \tilde{X}^m_i$
  **end**
  **If** Objectives($\tilde{X}^{m+1}_i$)> Objectives($gbest^k$) Then
  $gbest^k = \tilde{X}^{m+1}_i$
  **end**
**end for**

**Algorithm 4: Migration Operation**

$\sigma_m = 0.2, \phi = 0.75, r_1, r_2, r_3 = rand();$

$r \neq u$

**for** *each solution* $i = 1 : N_{p,acc},$ *each element* $n = 1 : N_n,$ *each parameter* $j = 1 : N_j$ **do**

  **If** $x^k_{i,n,j} > gbest^k_{n,j}$ **then**

  $d^k_{i,n,j} = \frac{x^k_{i,n,j} - gbest^k_{n,j}}{\max(x^k_{i,n,j}) - gbest^k_{n,j}}$

  **else**

  $d^k_{i,n,j} = \frac{gbest^k_{n,j} - x^k_{i,n,j}}{gbest^k_{n,j} - \max(x^k_{i,n,j})}$

  **end**

  **If** $d^k_{i,n,j} < \sigma_m$ **then**

  $\eta(x^k_{i,n,j}) = 1$

  **else**

  $\eta(x^k_{i,n,j}) = 0$

  **end**

  $\delta\rho = \frac{\eta(x^k_{i,n,j})}{(N_p \cdot N_n \cdot N_j)}$

  $t\rho = t\rho + \delta\rho$

**end for**

**If** $t\rho < \phi$ **then**

$\beta = (x^{\max}_{n,j} - gbest_{n,j})/(x^{\max}_{n,j} - x^{\min}_{n,j})$

Create a new solution:

  **If** $rand() < \beta$ **then**

  New $x^k_{i,n,j} = gbest_{n,j} + rand() \cdot (\max(x^k_{n,j}) - gbest_{n,j});$

  **else**

  New $x^k_{i,n,j} = \min(x^k_{n,j}) + rand() \cdot (gbest_{n,j} - \min(x^k_{n,j}));$

  **end**

**end**