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# Architectural Reply for Smart Building Design Concepts Based on Artificial Intelligence Simulation Models and Digital Twins

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**Abstract:** Artificial Intelligence (AI) simulation models and digital twins (DT) are used in designing and treating the activities, layout, and functions for the new generation of buildings to enhance user experience and optimize building performance. These models use data about a building's use, configuration, functions, and environment to simulate different design options and predict their effects on house function efficiency, comfort, and safety. On the one hand, AI algorithms are used to analyze this data and find patterns and trends that can guide the design process. On the other hand, DTs are digital recreations of actual structures that can replicate building performance in real time. These models would evaluate alternative design options, the performance of the building, and ways to improve user comfort and building efficiency. This study examined the important role of intelligent building design aspects, such as activities using multi-layout and the creation of particular functions based on AI simulation models, in developing DT-based smart building systems. The empirical data came from a study of architecture and engineering firms throughout the globe using a CSAQ (computer-administered, self-completed survey). For this purpose, the study employed structural equation modeling (SEM) to examine the hypotheses and build the relationship model. The research verifies the relevance of AI-based simulation models supporting the creation of intelligent building design features (activities, layout, functionalities), enabling the construction of DT-based smart building systems. Furthermore, this study highlights the need for further exploration of AI-based simulation models' role and integration with DT in smart building design.

**Keywords:** smart building design; artificial intelligence; AI simulations models; digital twins

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## 1. Introduction

People's tastes and lifestyles have shifted over the past decade thanks to technological developments; these shifts should be considered while creating and organizing cities. Now more than ever, it's crucial to build mobile houses with more openness and robust interconnections between parts [1]. Adaptive, responsive, dynamic, adaptable, and resilient are all used to describe this design style [2]. Smart buildings are the product of technological advancement; they are designed to be flexible, accommodating, and suitable for various purposes. Smart houses are designed to meet the needs of their residents in terms of efficiency, security, and comfort [3]. Therefore, arranging activities in living areas to meet residents' needs and create more comfortable living spaces is one of the most crucial factors in smart building design [4]. Smart technology aims to improve internal space efficiency by incorporating new ideas and placing a focus on the needs of inhabitants. However, some studies on smart buildings prioritize technology implementation over other aspects of living and space [5]. Despite efforts by academia and industry to introduce ambient intelligence into homes on a small scale, the general concept of smart buildings is not yet widely adopted in practice [6]. Understanding what factors contribute to customer satisfaction can assist designers and engineers in creating products that meet users' needs and preferences. Evaluating individuals' preferences in smart home design can also provide insight into the factors that affect their comfort with this technology [7]. However, there is no assurance that sophisticated features will be embraced and used even if they are made available. As a result, they do not automatically result in a better quality of life [8,9]. Radha [1] set out to learn how cutting-edge technology might improve the adaptability of indoor areas, particularly in smart buildings, and how this could lead to better utilization of the indoor regions in Sulaymaniyah. They polled to determine what residents valued most in a home's design. Then they used that data to modify innovative home plans to be more competitive in the Sulaymaniyah real estate market.

Smart buildings integrate intelligence, business operations, control, materials, and construction as a whole system, stressing adaptability rather than a reaction to fulfill building development goals, such as energy and efficiency, longevity, comfort, and satisfaction. These systems may alter, and the smart building can respond over time because it can get and interpret more information from various sources [10]. Comfort, safety, security, design, and long-term sustainability are all part of what makes a building smart [11].

The term Artificial Intelligence (AI) is commonly used to describe computer systems that can accomplish jobs traditionally done by people and even transcend human intellect by displaying traits including perception, reasoning, interaction, and learning. These systems don't require reprogramming to learn and apply new information to previously unanticipated situations [12]. To maximize the effectiveness of building management and operations, an increasing number of smart buildings are adopting Artificial Intelligence technology [11]. A high percentage of the energy produced is used in buildings, but AI can reduce that drastically with improved automation, control, and dependability. Moreover, these technologies may be employed to make buildings safer and more comfortable places to live. Panchalingham and Chan's [11] review of smart building research includes a wide range of important AI topics, including expert systems, fuzzy logic, genetic algorithms, machine learning, machine vision, natural language processing, neural networks, and pattern recognition. The study concluded that researchers in the field should have paid more attention to deep learning and natural language processing than to issues like machine learning, neural networks, and pattern recognition.

As technology, especially the Internet of Things (IoT), continues to evolve, the idea of utilizing AI in constructing smart buildings is becoming increasingly widespread. These structures include information collecting, intelligent sensing, and responsible decision-making [13], all with an eye on the complex interactions between humans, machines, and the environment. Smart buildings, fully automated constructions that extensively use IoT devices are becoming increasingly common. The industry is increasingly moving toward simulating such smart buildings in virtual environments. Many other meanings for digital twin have been offered, not simply in the context of smart buildings. According to one source [14], a digital twin is a set of data structures that define an object's physical characteristics from the molecular to the geometric levels. Another definition is a probabilistic simulation of an as-built vehicle or system that incorporates several physical mechanisms and scales [15]. Finally, it is an operationally responsive and future-looking representation of the relevant physical asset or system. These descriptions agree that a digital twin is a static representation of a system's physical structure and a dynamic representation of its state and evolution across time, comprised of data from sensors and actuators. In the context of smart buildings, this encompasses not just the building's structural and functional design but also the building's evolution through time and sensor data.

The development of a modern infrastructure and the incorporation of advanced control systems, data processing, and AI have led to the rise of smart building. Owners, managers, and tenants benefit from the enhanced efficiency, lower operating and maintenance costs, lower energy usage, and higher levels of comfort and safety that smart buildings provide [11]. However, examining the market's current status reveals that there is still room for improvement in the adoption of smart houses in the housing sector, partly owing to a need for more research on the real advantages of smart homes for different categories of users. The degree to which people adopt smart homes relies on how effectively it meets their needs and preferences [1]. Most recent studies have zeroed in on just a few key technological advancements in the field of smart building design. There needs to be an exploration of how these technologies change the dynamics of the environments in which people live, work, and play. Therefore, there should be well-defined standards for determining how incorporating smart technology would modify the configurations of a building's interiors to their respective roles and activities. Therefore, this research aims to evaluate the significance of user activities, spatial layout and functions of buildings, and AI simulation models in the smart building design process while creating DT-based smart building systems.

The following is the structure of this study: The second section provides context for the use of architectural design concepts in the development of smart buildings, discusses the role of Artificial Intelligence (AI) in architectural design, demonstrates how AI has been helpful in the development of smart building designs and introduces the DT-based smart building system framework. In the third section, we dive deep into our methodology, covering everything from our choice of research questions to how we arrived at our hypotheses, measured our results, and evaluated our structural model. There is a discussion of the theoretical contributions, limits, and directions for further research in section four. Finally, the paper ends with the conclusions.

## 2. Theoretical Background

### *2.1. Architectural Design Concept in the Creation of Smart Buildings*

Song et al. [16] claim that architecture is distinctive among the arts because it requires a delicate balancing act between form, stability, and use. Designing a building is a difficult task requiring ingenuity and years of practice. Therefore, AI in this area should be concerned with something other than discovering a unique solution inside a predetermined search space, but instead with researching design criteria and alternative solutions. This is because the design criteria must be determined at the conceptual stage. In addition, many decisions on design details involve balancing several different, sometimes subjective, measures. While numerical formulations of problems are helpful, inconsistent assessment criteria make it hard to establish design goals [17,18]. Lê et al. [19,20] outline the foundations of smart buildings as follows: adaptability (the ability to learn, predict, and satisfy the needs of users and the stress from the external environment); multi-functionality (the ability to allow the performance of more than one function in a building); interactivity (the ability to enable the interaction among users); and efficiency.

#### 2.1.1. Smart Interior Design

Digital materials, decorations, electronics, and sensors are only some of the creative and technological aspects that make up smart interior design. Its roots are in the time-honored practice of creating aesthetically pleasing living spaces. Using digital technology such as IP networks and mobile applications, this strategy prioritizes integrating features like ventilation, lighting, temperature management, alarms, occupancy control, and social interaction to offer a comfortable, productive, and healthy living environment for inhabitants [21]. When a building has smart interior design, the architecture becomes a data source for monitoring and assessing the structure's operation. For instance, the smart interior design system may identify and report any malfunctions in the building's machinery, allowing the occupants to feel safe and secure. This data helps streamline operations, monitor in-process progress, and cut overhead. Smart interior design may be understood as the process by which a building's spaces are designed to maximize its adaptability to various uses and functions [22,23].

These methods increase a building's flexibility by expanding the variety of functions performed within its walls. New buildings could be built without them, but the area would have to be more significant to provide the same functionality, convenience, and aesthetics [3]. Intelligent interior design discovers the most successful ways to create an attractive, comfortable, joyful, and productive atmosphere while offering efficient, adaptable, and cost-effective solutions to satisfy the changing and complicated expectations of occupants. Interior design technology also allows buildings to better serve their users by adapting to their preferences and enhancing their functionality, occupant comfort, energy efficiency, and cost-effectiveness. To provide clients with a wide range of customizable alternatives, designers can use smart internal design strategies to craft adaptable and intelligent design solutions. [24].

Smart Building Model Activities

Time-re-organizing activities involve rearranging and scheduling time more effectively and efficiently. This may entail making a calendar or to-do list, establishing priorities, assigning work, and stopping pointless pursuits. Since a house is an activity system, it must be able to adapt to its occupants' evolving needs and desires [1].

Location re-organizing activity refers to the rearranging and improving of the utilization of available physical space. The actions aimed at restructuring the locations have the goals of improving user comfort, producing a place that is both more functional and visually beautiful, and maximizing efficiency. It is conceivable to create new immersive virtual worlds at a scale that will allow our brains to wander freely across many platforms, even though the necessary infrastructure and technology still need to be built [1].

Performing fixed-time activities involve those things such as cleaning, lighting, heating and cooling, etc. Within a home, it refers to accomplishing household tasks within a predetermined time range or deadline or following a predetermined plan for finishing duties and activities [25].

Performing activities in a determined location refers to the carrying out of house activities and tasks in a specific house space according to the action or any change in user activity [26]. This can include working from a rearranged house space for different activities and functions, conducting activities or rest in a particular location, or carrying out specific tasks or activities that can only be done in certain conditions and spaces. It ensures that the action is done in a comfortable environment and that the required conditions and comfort are available.

Multitasking activities refer to the ability to perform multiple tasks or activities simultaneously. Examples of multitasking include talking on the phone while cooking, watching TV while relaxing, or sending an email during a family discussion [27].

Smart Building Model Layout

The time use of space describes how people use and divide their time across various living places or surroundings. The system will look at how residents interact, use other rooms or outside spaces, and respond to alterations in how people interact with space over time [28].

Changing the shape of the space involves altering a room by including or deriving from current home features, creating a new zone, or even repurposing an entire space. There are several ways to change the geometry of an area, such as by adding or removing rooms or walls, rearranging furniture, or other fixtures, or using various materials or finishes. In the future, it is hoped that architectural design will more fully take advantage of our developing understanding of the human senses and how they interact with one another, as frequently changing a space's design aims to increase its usefulness, boost efficiency, or produce a more aesthetically pleasing setting [29].

The change of use of spaces occurs through repurposing or modifying a place for a different function than initially intended [30]. This can involve changing a bedroom into a living room, dividing an ample space into two or three usable rooms, or turning a living room into a gathering place. Frequently changing how space is used aims to utilize available resources better and respond to changing demands and needs. Social, economic, and cultural changes may also be the cause of changing how areas are used. For instance, a shift in how people work and live might affect how places are used, such as reversing the usage of social and private spaces.

An area without physical borders is a space not defined or bordered by physical structures, referring to spaces with no physical boundaries. After removing locked walls, these areas become open functioning rooms and can even be virtual places. However, objects like walls, fences, or virtual space restrictions outline regions with actual bounds. These borders may denote house activity zones, provide privacy, or delineate a particular house zone. Physically borderless areas can have both beneficial and harmful effects. Many people can benefit from them, giving them a feeling of openness and freedom [31].

The change of size of a space refers to space size that can be changed using two different architectural forms, such as the integration form, where many areas are unified into an ample space. Alternatively, there is the derivation form, where a large space can be divided into specific small rooms [32]. This is achieved by using light, movable internal walls.

Smart Building Model Functions

User behavior may be understood in terms of the physical adjustments people need to make to incorporate smart technology into their everyday lives [33] or the influence of people's demographics and character traits on their attitudes toward smart homes [34]. Predicting how people will operate in such spaces requires taking into account not just the operational and space usage features of the structure, but also the culture of the residents [35]. Occupant presence, activity in space, and the effectiveness of environmental controls on those factors all impact other people's actions in the building.

The term area with physical constraints [1] describes public and private settings using intelligent physical boundaries.

Adaptable areas grow or shrink to accommodate new functions, and the form evolves to accommodate new subsystems [1].

Users' perspectives and the sorts of needs that smart buildings should strive to answer are both subject to change [36], as are the elements (such as users' knowledge and trust) that influence the acceptance and adoption of smart houses, as well as their intentions to utilize such dwellings [37].

Rearranging components (i.e., relocating pieces, transforming the room into an area inside/outside) also improves the layout's performance [1].

### *2.2. Artificial Intelligence Methods in Architectural Design*

Parametric linkages, self-organizing processes, and algorithms are some of the computational methods used to create architectural designs with little human input [18]. Artificial Intelligence (AI) may be used to improve the design and presentation of buildings by identifying trends in existing design data. Generating 2D and 3D architectural designs, categorizing architectural styles and building types, recognizing architectural drawings and spaces, and synthesizing indoor scenes are just some of the many uses for deep learning algorithms, like GANs and VAEs, in the architectural design and visualization industry. GANs have most significantly impacted the automated creation of architectural elements such as building masses, floor plans, interior designs, and facades [38]. The use of deep learning algorithms to generate building floor plans is a topic of ongoing study. The Archi-GAN model is one implementation of GANs that employs a trained model with an image dataset to create architectural designs [39]. The House-GAN technique [40] is another case in point; it employs a graph-constrained GAN to produce house plans. Wu et al. [41] presented a method that uses an encoder-decoder network to create home blueprints from a given perimeter. The approach employs a convolutional neural network (CNN) to position a living room in the floor plan and then uses two more deep neural networks to build the remaining rooms iteratively. As an alternative to employing GCNs and CNNs, a new method dubbed "Graph2Plan" has been proposed for designing floor plans that consider the user's preferred format. With this technique, we can look at constraints, such as where rooms may be placed, in the program. As a result, several researchers have been looking at deep learning approaches like GANs, ResNET, CNNs, and fully convolutional networks

(FCNs) to accurately transform rasterized photos into vectorized architectural floor plans of any complexity [4,42].

As Sutherland [43] presents, parametric relationships and algorithms allow the initial design to change in response to the user's intervention with its parameters, yielding results that the creator might not have anticipated. As mentioned by Dunn, parametric design allows for the assignment of values or expressions to organize and manage the definitions of elements and groupings of characteristics [44]. As Davis [45] pointed out, parametric design also results in new interactions and connections between all design aspects, as the geometry of a design adapts to the values of its parameters. Like a system of equations, when one portion is changed, all the others respond accordingly, often by automatically adjusting parameters or associated values. Yet, the time investment needed to create parametric scripts is a significant downside of this design approach. Due to this cost, generative algorithms, which completely leverage the computer's analytical power to overcome human limits [46], have been increasingly prominent in modern techniques. To facilitate the generation of novel, high-performance, efficient, creative, and aesthetically pleasing architectural items, Moreno-De-Luca and Carrillo [47] compiled the most widely used multi-objective optimization techniques in structural and architectural design, as not only an optimization model but also as an integral part of a design methodology. They suggested a unified optimization and morphogenetic process considering structural, bioclimatic, green building, acoustic, and lighting design factors. By using this technique, improved performance and considerable cost savings may be achieved in the final designed solution. In contrast to the objective assessment criteria used by standard genetic algorithms, which are identified and then automatically applied to finding the best solution, the subjective criteria used by interactive techniques are incorporated into the design process. This method has become increasingly popular due to developments in user-friendly design environments, graphical user interfaces, parametric variables' availability, skills display, and feedback on performance [48].

### *2.3. AI-Based Simulations for Designing Smart Buildings*

With the help of AI technology, smart buildings, and control systems may be better designed from the start, leading to improved performance. As Hang et al. [49] demonstrated, artificial neural networks (ANNs) offer considerable benefits over conventional methods and may be used in intelligent building system design and operation. Nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, and managing imprecise and fuzzy input are only some of ANN's many capabilities in information processing. According to this paper's findings, expert systems that automatically inspect plans for fire prevention and make hourly and short-term predictions have been developed using ANN technology. Moreover, indoor temperature is reflected in the long-term electrical energy consumption, and cold-hot loads are anticipated to enhance the efficiency of the air conditioning system.

Dibowski et al. [50] offered a novel automated approach when constructing complex BAS systems. This approach considered the system's composition, device selection, and interoperability to guarantee that all system components are compatible. Given that much of the existing literature on AI and automation in this subject is concerned with the performance of the automation systems rather than how to design them efficiently, this study makes a substantial addition to the design side of building automation systems. This research also confirmed that practical design solutions might be generated automatically in a reasonable time (several to tens of minutes). However, as computing power advances, this time frame may shrink.

An automated technique for the design of wireless automation systems in smart buildings was developed by Ploennigs et al. [51]. Despite their rising popularity, wireless systems can only be set up correctly when too much emphasis is placed on trial-and-error configuration methods. Therefore, the research looked at a comprehensive tool ecosystem that helps engineers create reliable systems more quickly. Design productivity could be increased by providing extensive tool support and automating operations like device composition, deployment, and performance analysis. Because of this, there were significant enhancements to device compatibility and signal strength within buildings. According to Hang et al. [49], practical designs for building automation systems can be generated automatically in a short time (several to tens of minutes). Future improvements in computational power can further reduce these design times, enhancing the efficiency of the design process.

Artificial neural networks (ANN) were shown to be well suited for fault and failure tolerance tasks, as noted by Dibowski et al. [50]. ANNs are known for their powerful information processing properties. They have potential in various areas, including fire safety engineering and temperature and load prediction, which might be explored in future studies.

When creating new designs, as et al. [52] presented a deep learning-based approach. The process entails teaching neural networks to examine graph representations of current designs, extract relevant subgraphs, and then combine those subgraphs to generate novel methods. They also investigated the possibility of using generative adversarial networks to create unknown patterns.

Further study of the use of AI technologies in the service of efficient office and common space was called for by Ewert et al. [53]. Data from Internet of Things (IoT) sensors that track foot traffic and room occupancy in real-time are used to determine the most efficient ways to put a space to use. This technology may also generate adaptable leasing models that maximize space use by combining current supply and demand data.

### 2.4. DT-Based Smart Building System Framework

Predictive maintenance [4,54], increased resource efficiency [55], enhanced occupant comfort [56], optimized design option analysis [57], and closed-loop design [55] are all possible because of a building's DT. Because DT identifies problems and potential improvements throughout the building's operational period, it may be used to guide future building designs [56]. Technologies such as 3D CAD modeling, WSNs, machine learning algorithms [57], and data analytics help make DT a reality. A smart building is defined by its parts, its purpose, and the results it produces, according to a study by Jia et al. [58]. Equipment, appliances, sensors, control infrastructure, and new technologies that are integral to the technical operation of a building are all included. Health, comfort, productivity, and energy efficiency [59] are just a few of the results that benefit the environment, society, and the economy that may be attributed to the intelligent and practical design of a building.

With the help of ifcOWL for the building's infrastructure, SSN (semantic sensor network), and SOSA (sensor, observation, sample, and actuator) for describing IoT devices, a TripleStore can be built for a smart building's DT that is independent of traditional industrial tools. When topological data is needed, established additional ontologies such as BOT (building ontology topology) for the building's topological representation can be used to facilitate searching [60].

A summary of the literature involving AI-based simulations in architectural design of smart buildings and a DT-based smart building system is presented in Table 1.

**Table 1.** Summary of the literature involving AI-based simulations in architectural design of smart buildings to generate DT-based smart building system.

| No | Title | Reference |
|---|---|---|
| 1 | Application of Artificial Neural Network in Intelligent Building | [49] |
| 2 | Automated Design of Building Automation Systems | [50] |
| 3 | Holistic Design of Wireless Building Automation Systems | [51] |
| 4 | Advantages of Surrogate Models for Architectural Design Optimization | [61] |
| 5 | An Evolutionary Approach for 3D Architectural Space Layout Design Exploration | [62] |
| 6 | Graph-Based Representation of Design Properties in Creating Building Floorplans | [63] |

**Table 1.** *Cont.*

| No | Title | Reference |
|---|---|---|
| 7 | Artificial Intelligence in Architecture: Generating Conceptual Design via Deep Learning | [52] |
| 8 | Artificial Intelligence and Machines: A Curse or Blessing for Corporate Real Estate? | [53] |
| 9 | Design Automation for Smart Building Systems | [58] |
| 10 | An IoT-Based Automation System for Older Homes: A Use Case for Lighting System | [59] |
| 11 | Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0 | [54] |
| 12 | Digital Twin Service Towards Smart Manufacturing | [55] |
| 13 | Deep Convolutional Priors for Indoor Scene Synthesis, ACM Transactions on Graphics | [64] |
| 14 | Architectural Drawings Recognition and Generation through Machine Learning | [65] |
| 15 | FloorNet: A Unified Framework for Floorplan Reconstruction from 3D Scan | [66] |
| 16 | Customization and Generation of Floor Plans Based on Graph Transformations | [67] |
| 17 | DuLa-Net: A Dual-Projection Network for Estimating Room Layouts from a Single RGB Panorama | [68] |
| 18 | Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings | [56] |
| 19 | Architectural Layout Design through Deep Learning And Agent-Based Modeling: A Hybrid Approach | [69] |
| 20 | A Digital-Twin-Assisted Fault Diagnosis Using Deep Transfer Learning | [57] |
| 21 | Archigan: Artificial Intelligence X Architecture | [70] |
| 22 | A Reference Architecture for Smart Building Digital Twin | [60] |
| 23 | Inference of Drawing Elements and Space Usage On Architectural Drawings Using Semantic Segmentation | [71] |
| 24 | House Style Recognition Using Deep Convolutional Neural Network | [72] |
| 25 | Artificial Intelligence Applied to Conceptual Design. A Review of Its Use in Architecture | [18] |
| 26 | Generative Design of Decorative Architectural Parts | [73] |
| 27 | Generative Architectural and Urban Design Method Through Artificial Neural Network | [74] |
| 28 | A Bibliometric Review on Artificial Intelligence for Smart Buildings | [13] |
| 29 | A State-Of-The-Art Review on Artificial Intelligence for Smart Buildings | [11] |
| 30 | Self-Sparse Generative Adversarial Network for Autonomous Early-Stage Design of Architectural Sketches | [75] |
| 31 | Generating Synthetic Space Allocation Probability Layouts Based on Trained Conditional-GANs | [76] |

## 3. Research Methodology

The overview of the research methodology involving theoretical and practical level approach is depicted in Figure 1.

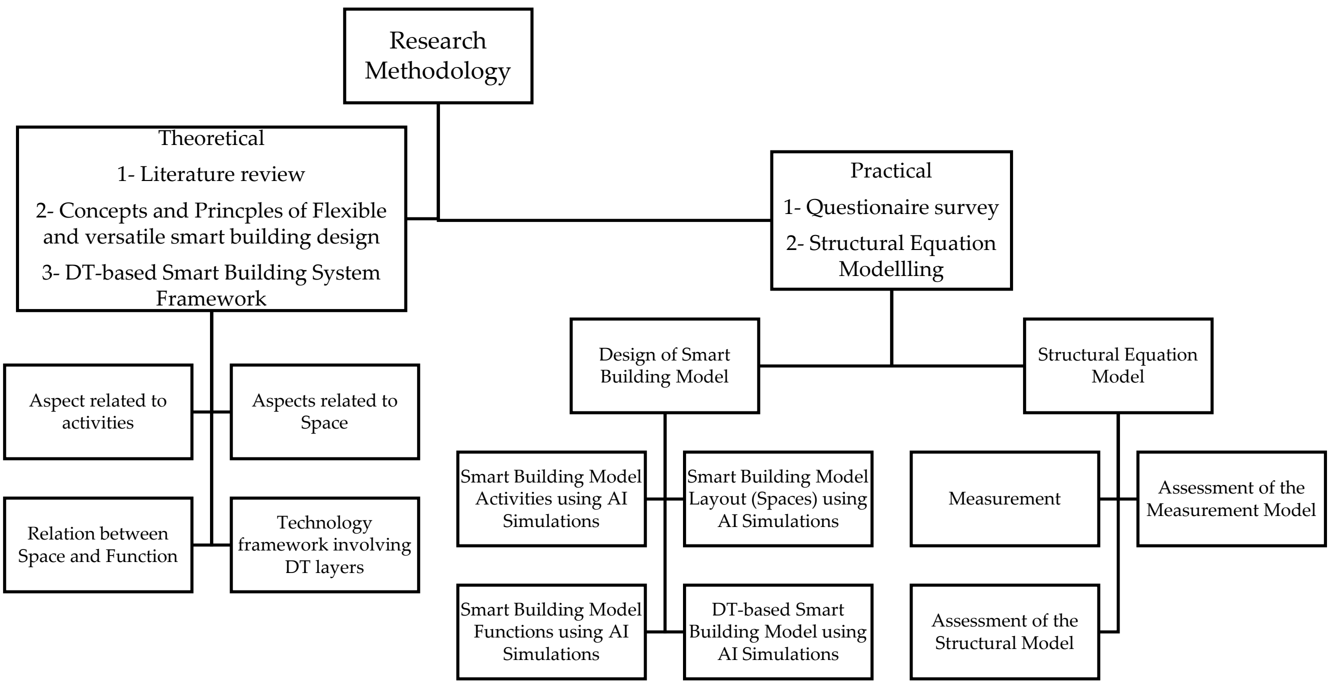


**Figure 1.** Research methodology.

### 3.1. SEM Model and Hypotheses Development

The review of the literature presented in Section 2 indicates that there are significant relationships between smart building model activities, layout, functions, AI-based simulation models, and DT-based smart building systems integrated with AI simulation models. Figure 2 illustrates how smart building model activities, layout, functions, and AI-based simulation models are related to DT-based smart building systems integrated with AI simulation models. The orientations and theoretical underpinnings of the connections between the construct measures and the latent variables are described. This motivates the following conjectures:

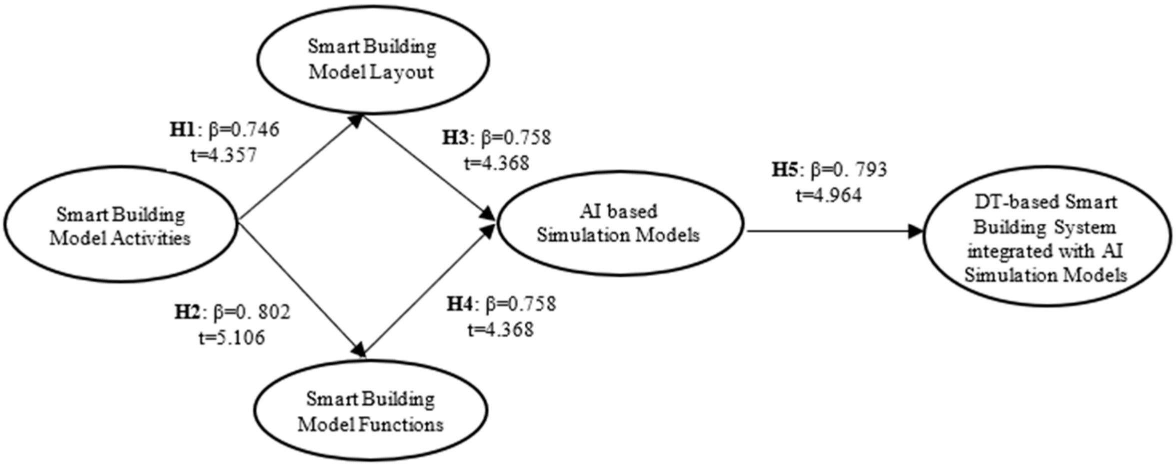


**Figure 2.** Hypothesized SEM model.

**H1.** *Creating smart building model activities facilitates the generation of smart building model layout.*

**H2.** *Creating smart building model activities enables initiation of smart building model functions.*

**H3.** *Utilizing smart building model layout helps the development of AI-based simulation models.*

**H4.** *Employing smart building model functions supports the development of AI-based simulation models.*

**H5.** *Facilitating AI-based simulation models empowers the generation of a DT-based smart building system.*

### 3.2. Data Collection

The chosen approach is a survey questionnaire sent out to companies in the fields of architectural design, information technology, and digital strategy consulting (known as "Digitaliz"). One hundred seventy-five worldwide organizations were contacted and made aware of the study's goals through various means of communication. On a scale from 1 (strongly disagree) to 5 (completely agree), the respondents were asked to assess their level of agreement with each statement (strongly agree). Companies' point-of-contact for the questionnaire survey were either the top management or senior management, therefore it was anticipated that their level of expertise would yield reliable results. Out of a total of 125 respondents, 26 were design managers, 23 were design coordinators, 20 were IT managers, 24 were digitalization consultants, and 7 were academics.

There were 25 questions in the questionnaire, all of which pertained to the survey's primary focus area (the "Design of the Smart Building Model") as seen in Appendix A. The basis for the indicator classification is the smart interior design and spatial flexibility of inner space involving a multi-use plan, mobility, divisibility, multi-functionality that create the relationships between model activities, model layout, and model functions. Each question in the survey was designed to gauge respondents' awareness of how using smart building model activities, layout, and functions encourage the growth of AI-based simulation models, which in turn enable the construction of DT-based smart building systems. Respondent demographics are displayed in Table 2.

**Table 2.** Distribution of respondents according to company type, role, company size, and region.

| **Company Type** | Digitalization Consultants: 24% | Design Managers: 26% | Design Coordinators: 23% | IT Manager: 20% | Academic: 7% |
|---|---|---|---|---|---|
| **Role** | Digital twin: 3%<br>Digitalization: 10%<br>BIM: 6%<br>Software development: 4% | BIM: 17%<br>Digital twin: 9% | BIM: 16%<br>Digital twin: 7% | Digitalization: 12%<br>Software development: 8% | PhD student: 7% |
| **Company Size** | | | | | |
| Small (32%)_ | 7% | 8% | 8% | 5% | 4% |
| Medium (35%)_ | 8% | 9% | 9% | 5% | 4% |
| Large (33%)_ | 7% | 9% | 8% | 4% | 5% |
| **Operating Region** | | | | | |
| Scandinavia (35%)_ | 6% | 8% | 8% | 7% | 6% |
| Europe (42%)_ | 8% | 10% | 10% | 8% | 6% |
| N. America (13%)_ | 2% | 4% | 4% | 2% | 1% |
| Middle East (10%) | 1% | 3% | 3% | 2% | 1% |

### *3.3. Measurement*

Multiple items were used to create a measurement of the variables, which increases trust in their reliability and validity. All of the items were of a perceptual nature and graded on a five-point Likert scale. Table 3 details the instruments used to evaluate each independent variable.

**Table 3.** Measurement model evaluation.

| **Scale Items** | **Item** | **Mean** | **SD** | **Loadings** | **AVE** | **CR** | **α** |
|---|---|---|---|---|---|---|---|
| **Design of Smart Building Model** | | | | | | | |
| *Smart Building Model Activities* | *SBMA* | | | | | | |
| Time-re-organizing activity | *SBMA1* | 3.745 | 0.715 | 0.728 | | | |
| Location re-organizing activity | *SBMA2* | 3.815 | 0.775 | 0.759 | | | |
| Performing fixed time activities | *SBMA3* | 3.810 | 0.746 | 0.752 | 0,751 | 0.825 | 0.740 |
| Performing activities in a fixed location | *SBMA4* | 3.790 | 0.724 | 0.746 | | | |
| Multitasking activities | *SBMA5* | 3.825 | 0.778 | 0.766 | | | |
| *Smart Building Model Layout* | SBML | | | | | | |
| Time use of space | SBML1 | 3.765 | 0.735 | 0.748 | | | |
| Change shape of space | SBML2 | 3.835 | 0.795 | 0.779 | | | |
| Change use of spaces | SBML3 | 3.820 | 0.766 | 0.772 | 0.762 | 0.835 | 0.750 |
| An area of without physical borders | SBML4 | 3.810 | 0.744 | 0.766 | | | |
| Change size of space | SBML | 3.845 | 0.798 | 0.786 | | | |
| *Smart Building Model Functions* | SBMF | | | | | | |
| Understanding the behaviors of consumers | SBMF1 | 3.805 | 0.775 | 0.748 | | | |
| Area with physical limitations | SBMF2 | 3.875 | 0.835 | 0.779 | | | |
| Change of functions | SBMF3 | 3.860 | 0.806 | 0.772 | 0.813 | 0.875 | 0.770 |
| Change of users | SBMF4 | 3.850 | 0.784 | 0.766 | | | |
| Elements rearrange | SBMF5 | 3.885 | 0.838 | 0.786 | | | |
| *AI-based Simulation Models* | AISM | | | | | | |
| High level constraints and inputs by the designer | AISM1 | 4.105 | 0.815 | 0.788 | | | |
| Hierarchical Agent-based modelling (rule-based method) | AISM2 | 4.175 | 0.875 | 0.809 | | | |
| Data-driven method (cGAN) | AISM3 | 4.210 | 0.915 | 0.848 | 0.852 | 0.895 | 0.810 |
| Post-processing by the designer | AISM4 | 4.250 | 0.824 | 0.806 | | | |
| Training and evaluation of cGAN | AISM5 | 4.405 | 0.868 | 0.846 | | | |

**Table 3.** *Cont.*

| Scale Items | Item | Mean | SD | Loadings | AVE | CR | α |
|---|---|---|---|---|---|---|---|
| *DT-based Smart Building System using AI Simulation Models* | DTSBS-AISM | | | | | | |
| Building the TripleStore for RDF data (IFCowl, SSN, SOSA, BOT) | DTSBS-AISM1 | 4.105 | 0.815 | 0.788 | | | |
| Data enrichment and consistency | DTSBS-AISM2 | 4.175 | 0.875 | 0.809 | | | |
| Data flow program generation | DTSB/S-AISM3 | 4.210 | 0.915 | 0.848 | 0.891 | 0.935 | 0.830 |
| System at run time | DTSBS-AISM4 | 4.250 | 0.824 | 0.806 | | | |
| Applications | DTSBS-AISM5 | 4.445 | 0.908 | 0.886 | | | |

Note: AVE = average variance extracted; CR = composite reliability; α = Cronbach alpha.

### 3.4. Assessment of the Measurement Model

Data were analyzed using variance-based structural equation modeling by SmartPLS 4.0 PLS path modeling. First, the construct reliability, convergent validity, discriminant validity, and standardized factor loadings of the latent variables in the model were examined to evaluate the measurement model's quality [77]. The convergent validity of the measured constructs in PLS-SEM may be assessed using two different tests: (i), a composite reliability (CR) score and Cronbach's alpha for the constructs; and (ii) the average variance retrieved (AVE). A construct's variation from its indicators is measured using AVE about the degree of measurement error.

The composite reliability (CR) for construct $\xi_j$ is defined as follows [78]:

$$\rho_{c\xi j} = \frac{\left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2}{\left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2 + \theta_{jk}} \tag{1}$$

where:

$K_j$ is the number of indicators of construct $\xi_j$;
$\lambda_{jk}$ are factor loadings;
$\theta_{jk}$ is the error variance of the $k$th indicator ($k$ = 1,..., $K_j$) of construct $\xi_j$.

$$\theta_{jk} = \sum_{k=1}^{K_j} 1 - \lambda_{jk}^2 \tag{2}$$

The average variance extracted (AVE) for construct $\xi j$ is defined as follows [78]:

$$AVE\xi_j = \frac{\sum_{k=1}^{K_j} \lambda_{jk}^2}{\left(\sum_{k=1}^{K_j} \lambda_{jk}^2\right) + \theta_{jk}} \tag{3}$$

where:

$K_j$ is the number of indicators of construct $\xi_j$;
$\lambda_{jk}$ are factor loadings;
$\theta_{jk}$ is the error variance of the $k$th indicator ($k$ = 1,..., $K_j$) of construct $\xi_j$.

When the measurement model was analyzed, it was discovered that all the constructs had appropriate internal reliability, as shown in Table 3, where the composite reliability (CR) value of each construct is more significant than 0.70 (between 0.825 and 0.935). Additionally, all the model's constructs have AVE values greater than 0.5 (between 0.751 and 0.891), indicating that their convergent validity is sufficient. Next, the discriminant validity of the constructs was evaluated by computing the square root value of the AVE for each construct. The findings demonstrate that all absolute root values are more significant than the correlation values with all other constructs, which supports Table 4′s assertion that all constructs have sufficient discriminant validity. The measurement model exhibits the necessary robustness to assess the link between the components.

**Table 4.** Constructs intercorrelations and discriminant validity.

| Latent Construct | Smart Building Model Activities | Smart Building Model Layout | Smart Building Model Functions | AI-Based Simulation Models | DT-Based Smart Building System Using AI Simulation Models |
|---|---|---|---|---|---|
| Smart Building Model Activities | 0.891 | | | | |
| Smart Building Model Layout | 0.676 | 0.901 | | | |
| Smart Building Model Functions | 0.687 | 0.701 | 0.924 | | |
| AI-based Simulation Models | 0.691 | 0.711 | 0.736 | 0.946 | |
| DT-based Smart Building System using AI Simulation Models | 0.706 | 0.731 | 0.752 | 0.789 | 0.957 |

### *3.5. Assessment of the Structural Model*

The $R^2$ values of the dependent constructs, the values of the path coefficients, and the model's goodness-of-fit (GoF) value were employed as the three criteria to evaluate the validity of the structural model [77,79]. The model's $R^2$ value demonstrates that exogenous smart building model activities, smart building model layout, and smart building model functions collectively accounted for 67.27% of the variance in AI-based simulation models, enabling the generation of DT-based smart building systems using AI simulation models. Additionally, the findings demonstrate a positive correlation between smart building model activities and smart building model layout (=0.746, $p = 0.05$), as well as a positive correlation between smart building model functions and AI-based simulation models (=0.802, $p = 0.01$) and smart building model layout and smart building model functions. As a result, Table 5 shows a positive correlation between DT-based smart building systems and AI-based simulation models (=0.849, $p = 0.01$). The model's GoF value is 0.38, indicating a significant model fit. This shows that the model is suitable and remarkably reliable.

**Table 5.** Results of PLS analysis constructs intercorrelations and discriminant validity.

| Structural Paths in the Model | Sign | PLS Path Co-Efficient | t-Statistic | Inference |
|---|---|---|---|---|
| H1: Smart Building Model Activities → Smart Building Model Layout | + | $\beta = 0.746$ ** | 4.357 | Supported |
| H2: Smart Building Model Activities → Smart Building Model Functions | + | $\beta = 0.758$ ** | 4.368 | Supported |
| H3: Smart Building Model Layout → AI-based Simulation Models | + | $\beta = 0.802$ *** | 4.606 | Supported |
| H4: Smart Building Model Functions → AI-based Simulation Models | + | $\beta = 0.826$ *** | 4.964 | Supported |
| H5: AI-based Simulation Models → DT-based Smart Building System | + | $\beta = 0.849$ *** | 5.256 | Supported |

** $p < 0.05$, *** $p < 0.01$.

## 4. Discussion

To create a DT-based smart building system, this study provides a hypothesized model that is tested to determine the role that AI-based/simulation models have in the architectural design of smart buildings. The results are in line with the literature [11], which suggests that there are practical ways in which AI may improve the creation of simulation models by simplifying model structure and functionality to produce DT-based smart building systems. Similar circumstances or arrangements can be found in many different buildings and automating the setup of these settings can save time and money. AI has also been shown to enhance automation system performance through better design, including enhanced signal transfer and fewer device compatibility difficulties. Designers need AI-assisted tools to provide sophisticated results quickly as smart buildings become more complex and consumer demands rise.

The results support the literature's findings [52] that a deep neural network technique utilizing graphs to construct conceptual ideas demonstrated how different functional performance criteria, or goal functions, were used to combine found building blocks and produce original designs. Investigating AI is a fascinating undertaking that may close the computational resource gap for early architecture projects and address more general demands of the architectural profession, such as design analysis and development.

The results of this study are consistent with the literature [38], which indicates that applications that produce mechanical architectural structures, such as creating floor plans, coming up with original concepts, and synthesizing indoor scenes, frequently use deep learning models that generate new designs, such as GANs and VAEs.

The results are consistent with the literature [66] and show that a deep learning framework was created for determining 3D room layouts from a single panoramic image by utilizing a unique network design with two encoder-decoder branches to analyze features from two different perspectives of the input image, specifically the necessary rectangular panorama-view and the perspective ceiling-view.

The results are in line with the literature [67], which states that the automatic generation of rectangular floor plans was achieved based on existing legacy floor plans with the capability for further improvement and customization. This is achieved by deriving a dual graph from the provided input file specifying a floor plan and automatically reproducing different floor plans by maintaining the connectivity of the original intent. Alternatively, this can be achieved by using transformation rules to manipulate spatial relations among rooms, and to create improved floor plans conforming to specific requirements.

The results are consistent with the literature [76], showing that trained conditional GANs trained on this dataset successfully produced synthetic space allocation probability layouts. The five pre-established topological and geometrical benchmarks assess the trained model's output designs.

The results are consistent with the literature [71], which states that architectural design automation technology was created using AI. Additionally, that deep learning was used to learn, identify, and infer the architectural elements and space compositions portrayed in architectural drawings.

The results support the literature's findings [73] that an autonomous design approach for architectural shape sketches was developed by using a new self-sparse generative adversarial network (self-sparse GAN), outpacing the problems of traditional design methods' time commitment and excessive reliance on human aesthetic knowledge.

The results align with the literature [74], which shows that architects may produce architectural designs by learning from examples using a tailored artificial neural network tuned for creating 3D shapes.

The results of this study are consistent with the literature [60], which suggests that reference architecture, created for developing and operating a DT, might offer a comprehensive perspective for an intelligent building (including structural/static and temporal/dynamic data). The software architecture may solve the issue of segregated BIM data, which also provides a thorough understanding of a smart building. An essential component of the DT of the smart building is this data. The data allows it to incorporate data from actual Internet of Things devices and digital simulation tools into building management or intelligent control systems.

The results are consistent with the literature [80], which suggests that DT may be utilized to virtualize the design idea further. The DT process would use the trial data from the design concept prototype to fine-tune the model's parameters, then use the improved model to predict performance during use before revising the design. Numerous processes (model improvement and forecasting) are involved in this process throughout the design phase without adding any new information [81].

The conclusions are in line with the literature [82–84], which suggests that creating a DT of a building that is integrated with AI simulations would improve the creation of asset management requirements throughout the design phase.

*Limitations and Future Study*

Minor drawbacks of the study include the small sample size, the few parameters examined, and the small number of surveyed places. The study emphasizes the requirement for further investigation into the function of AI-based simulation models and their incorporation with DT in intelligent building design. A reference model (architecture) for creating innovative building design concepts based on AI simulation models coupled with a DT might be built as a viable methodology for future research. This reference model (architecture), which includes a common vocabulary, reusable designs, and industry best practices, could make it easier to develop various applications. It also involves the frame of reference, interoperability, mergers, acquisitions, outsourcing, benchmarking, and regulatory compliance.

## 5. Conclusions

Smart building design concepts utilize AI simulation models and DT to enhance the user experience and optimize building performance. The models use information about building usage, patterning layout and functions, and environmental factors to simulate different design options and predict their impact on building efficiency, comfort, and safety. AI algorithms analyze this data to identify patterns and trends that can inform the design process. Meanwhile, DT are digital representations of actual structures that can replicate building performance in real time. These models can assess various design options, detect potential issues, and enhance building functions and user comfort. This study presented the crucial role of smart building design aspects involving activities, layout, and function based on AI simulation models for developing DT-based smart building systems. The SEM method has been used to test the hypotheses and develop the skill model to examine the reliability, validity, and contribution of the AI simulation models integrated with DT. The findings of the SEM analysis showed complete consistency with the existing literature that AI can streamline the process of creating simulation models and generating DT-based smart building systems.

This research suggests that smart buildings design aspects involving activities, layout, and functions based on AI simulation models for developing DT-based smart building systems should be based on users' changing desires and expectations by using appropriate technology solutions (DT, IoT etc.), as technology has become an integral part of users' lives. In order to improve buildings' efficiency and maintain users' comfort, and safety, we recommend to reducing fixed spaces in the environment and increasing adaptive operations to avoid the need for future renovations or building work for potential extensions.

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## Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| ANN | Artificial Neural Networks |
| AVE | Average Variance Extracted |
| BOT | Building Ontology Topology |
| CSAQ | Computer Administered Self-completed Survey |
| CNN | Convolutional Neural Network |
| CR | Composite Reliability |
| DT | Digital Twins |
| DTSBS | DT-based Smart Building System using AI Simulation Models |
| FCN | Fully Convolutional Network |
| GAN | Generative Adversarial Network |
| GNF | Graph Convolutional Network |
| GoF | Goodness-of-fit |
| ifcOWL | Industry Foundation Classes Web Ontology Language |
| IoT | Internet of Things |
| ResNet | Residual Network |
| RDF | Resource Description Framework |
| SBMA | Smart Building Model Activities |
| SBMF | Smart Building Model Functions |
| SBML | Smart Building Model Layout |
| AISM | AI-based Simulation Models |
| SEM | Structural Equation Modeling |
| SOSA | Sensor, Observation, Sample, and Actuator |
| SSN | Semantic Sensor Network |
| VAE | Variational Autoencoders |

## Appendix A

Questionnaire Survey

Your profession:

Your main technological area of expertise:

The number of years you have been working in mentioned field:

The company's name:

The company size (0–50 Employees—Small, 50–250 Employees—Medium, >250 Employees—Large):

From what country are you mainly operating?

"To what extent do you agree with the following items describing your organization's view on Design of the Smart Building Model? (1 = strongly disagree; 5 = strongly agree)."

| | | **Likert Scale Values** | | | | |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** |
| **No** | **Questions** | **Strongly Disagree** | **Disagree** | **Neutral** | **Agree** | **Strongly Agree** |
| | *Smart Building Model Activities* | | | | | |
| 1 | Time-re-organizing activity facilitates the generation of model layout and functions | | | | | |
| 2 | Location re-organizing activity facilitates the generation of model layout and functions | | | | | |
| 3 | Performing fixed time activities facilitates the generation of model layout and functions | | | | | |

| | | Likert Scale Values | | | | |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** |
| **No** | **Questions** | **Strongly Disagree** | **Disagree** | **Neutral** | **Agree** | **Strongly Agree** |
| 4 | Performing activities in a fixed location facilitate the generation of model layout and functions | | | | | |
| 5 | Multitasking activities facilitate the generation of model layout and functions | | | | | |
| | *Smart Building Model Layout* | | | | | |
| 6 | Time use of space helps the development of AI-based Simulation Models | | | | | |
| 7 | Change shape of space helps the development of AI-based Simulation Models | | | | | |
| 8 | Change use of spaces helps the development of AI-based Simulation Models | | | | | |
| 9 | An area of without physical borders helps the development of AI-based Simulation Models | | | | | |
| 10 | Change size of space helps the development of AI-based Simulation Models | | | | | |
| | *Smart Building Model Functions* | | | | | |
| 11 | Understanding the behaviors of consumers supports the development of AI-based simulation models | | | | | |
| 12 | Area with physical limitations support the development of AI-based simulation models | | | | | |
| 13 | Change of functions support the development of AI-based simulation models | | | | | |
| 14 | Change of users support the development of AI-based simulation models | | | | | |
| 15 | Elements rearrange support the development of AI-based simulation models | | | | | |
| | *AI-based Simulation Models* | | | | | |
| 16 | High level constraints and inputs by the designer empower the generation of DT-based Smart Building System | | | | | |
| 17 | Hierarchical Agent-based Modelling (rule-based method) empowers the generation of DT-based Smart Building System | | | | | |
| 18 | Data-driven Method (cGAN) empowers the generation of DT-based Smart Building System | | | | | |
| 19 | Post-processing by the designer empowers the generation of DT-based Smart Building System | | | | | |
| 20 | Training and evaluation of cGAN empowers the generation of DT-based Smart Building System | | | | | |
| | *DT-based Smart Building System using AI Simulation Models* | | | | | |
| 21 | Building the TripleStore for RDF data (IFCowl, SSN, SOSA, BOT) empowers the generation of DT-based Smart Building System | | | | | |
| 22 | Data enrichment and consistency empowers the generation of DT-based Smart Building System | | | | | |

| | | Likert Scale Values | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| No | Questions | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| 23 | Data flow program generation empowers the generation of DT-based Smart Building System | | | | | |
| 24 | System at run time empowers the generation of DT-based Smart Building System | | | | | |
| 25 | Applications empowers the generation of DT-based Smart Building System | | | | | |

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