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# A Review of Artificial Intelligence Applications in Architectural Design: Energy-Saving Renovations and Adaptive Building Envelopes

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**Abstract:** This paper explores the applications and impacts of artificial intelligence (AI) in building envelopes and interior space design. The relevant literature was searched using databases such as Science Direct, Web of Science, Scopus, and CNKI, and 89 studies were selected for analysis based on the PRISMA protocol. This paper first analyzes the role of AI in transforming architectural design methods, particularly its different roles in the auxiliary, collaborative, and leading design processes. It then discusses AI's applications in the energy-efficient renovation of building envelopes, smart façade design for cold climate buildings, and thermal imaging detection. Furthermore, this paper summarizes AI-based interior space environment design methods, covering the current state of research, applications, impacts, and challenges both domestically and internationally. Finally, this paper looks ahead to the broad prospects for AI technology in the architecture and interior design fields while addressing the challenges related to the integration of personalized design and environmental sustainability concepts.

**Keywords:** artificial intelligence; architectural design; energy-saving renovations; building envelopes; adaptive architecture; sustainable building design

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## 1. Introduction

Since ancient times, humans have aspired to create technologies that mimic the functions of the brain. With the development of fields such as mathematical logic, physics, philosophy, and the rapid progress of computer technology, artificial intelligence (AI) has gradually moved from theory to practice. In 1956, John McCarthy first introduced the term "artificial intelligence" at the Dartmouth Conference, marking the birth of AI as an independent academic discipline [1].

Artificial intelligence is widely defined as the theory, methods, technologies, and applications aimed at simulating and extending human intelligence. After more than six decades of development, AI technology has continually advanced and is now widely applied across various fields, particularly in architectural design. AI has not only become an auxiliary tool in architectural design but has also gradually evolved into a collaborative partner with architects and may eventually become a leading force in design (Figure 1) [2,3].

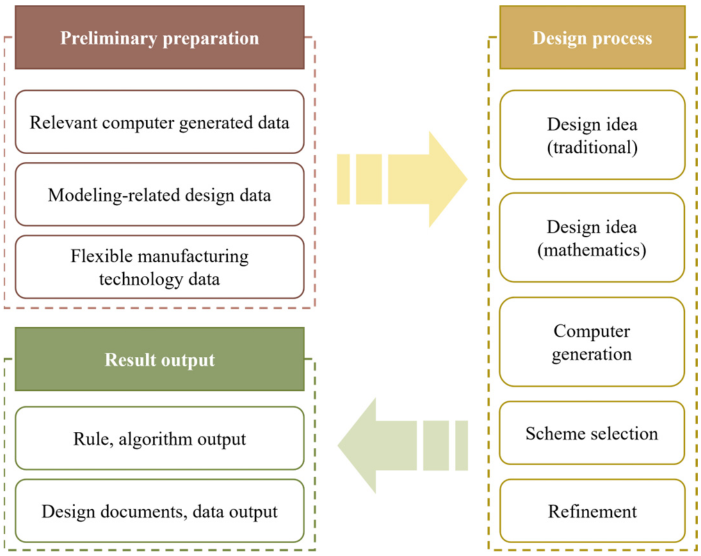


**Figure 1.** Computer-aided design process.

In architectural design, the primary uses of AI include classification, decision-making, and optimization. Through classification tasks, AI can identify and categorize different types of design elements, such as architectural styles and spatial layouts. Decision-making tasks involve recommending design solutions through algorithms, helping architects make the most appropriate design choices. Optimization tasks use intelligent algorithms to optimize architectural plans, such as the spatial layout and energy use, improving design efficiency and quality [4].

The application of AI is not limited to the design phase but extends across various stages of construction and operation. During the design process, AI can assist with style transfer, the automatic generation of building facades, and spatial optimization. In the construction and operation stages, AI can perform intelligent building simulations and optimizations through Building Information Modeling (BIM) [5].

In terms of usage, AI mainly relies on techniques such as deep learning, generative adversarial networks (GANs), expert systems, and optimization algorithms. For instance, deep learning can generate preliminary design plans in collaborative design, GANs are used for generating building facades, while expert systems assist architects in the decision-making process by providing recommendations and solutions.

As time has progressed, architectural design has become more complex, imposing higher demands on architects [6,7]. Powerful computing capabilities are the key to achieving complex designs. While the early computer-aided design did not reach the level of AI, it laid the foundation for AI applications in architectural design [8,9].

Architects such as Frank Gehry and Zaha Hadid used advanced software to explore nonlinear design [10] and simplified the design process through parametric methods [11]. The introduction of digital technology has brought a revolutionary change to architectural design. In the late 1960s, academia began exploring AI applications in design, with shape grammar providing new logical possibilities for architectural design [12,13]. In the early 1980s, a leap in computing power and increased funding fueled AI research, making expert systems and reasoning mechanisms a hot topic, which promoted their application in design [14].

Initially, AI assisted design through expert systems and case-based reasoning, simplifying design tasks (Figure 2). However, due to the high programming requirements, its application was limited. As technology advanced, AI became more widespread and accurate, supporting various types of projects and design conditions. Today, AI plays a role in all stages of architectural design, construction, and operation, including style transfer, automated generation, spatial optimization, and intelligent building simulation.

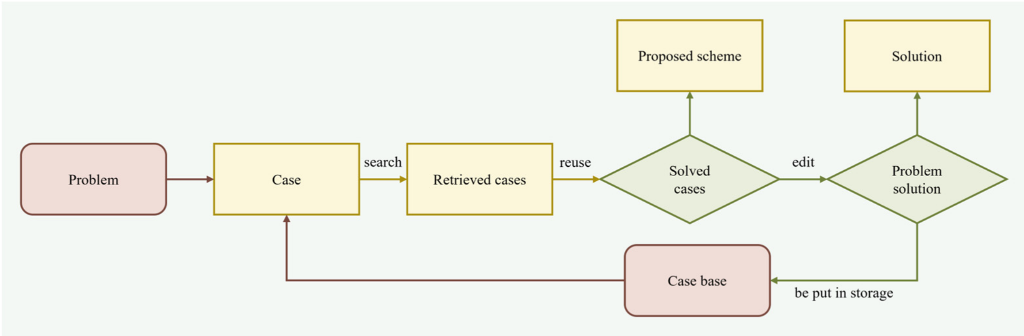


**Figure 2.** Case-based reasoning aided design process.

For example, through generative adversarial networks (GANs) and style transfer techniques, architects can quickly generate building facades [15]. AI is capable of learning design data, generating plans, optimizing layouts, and simulating building performance. However, the output of AI is still one way, lacking feedback, and primarily serves as an auxiliary tool for architects [16].

In the early 1980s, with increases in computing power and funding, AI research gained new momentum, and the development of expert systems and reasoning mechanisms promoted the growth of assisted design systems. Technological advancements enabled AI to evolve from basic automation to applications in swarm intelligence and neural networks, fundamentally transforming architectural design.

Since the revival of deep learning technology in 2006, deep neural networks and convolutional neural networks have been widely applied in AI collaboration within architectural design. This revival stemmed from the introduction of Deep Belief Networks (DBN) and Deep Autoencoders by Geoffrey Hinton and others, which solved the vanishing gradient problem in deep networks and laid the foundation for AI applications across various fields [17,18]. In the collaborative design phase, AI becomes a partner to architects [19], generating preliminary design schemes, which are then refined and optimized by architects to improve the design quality and innovation. For example, Sun Cheng used deep learning models to integrate design intentions; Zheng Hao and others demonstrated the application of GANs in human–AI collaborative design, indicating the broad potential of AI collaboration in architectural design [20]. In advance, the integration of metaverse and generative AI in participatory building design (PBD) represents a significant advancement in human-centric architecture, enabling the automated collection and analysis of user requirements through immersive virtual environments while bridging the gap between designers and end users through automated visualization and feedback mechanisms [21].

By integrating AI, a breakthrough came with the application of machine learning algorithms for calibrating building simulation models, enabling more accurate predictions of thermal behavior and energy consumption patterns. By visualizing thermal images with RGB, the system can now effectively analyze complex thermal behaviors, optimize envelope designs, and evaluate different material combinations simultaneously [22]. Recent studies have demonstrated that deep learning methods, particularly YOLOv7, can achieve high precision in detecting thermal anomalies in building envelopes, processing up to 141 frames per second$^2$ [23]. Recent research has demonstrated a new method for detecting thermal anomalies in building envelopes through an AI-driven prediction of thermal distributions from color images, employing pix2pix generative adversarial network (GAN) architecture. It effectively performed as a one-class classifier to identify regions with significant mismatches between the predicted and actual thermal distributions without requiring extensive labelled datasets, achieving reliable predictions with mean absolute errors of 0.5 degrees Celsius under optimal conditions [24].

AI is shifting from an auxiliary role in the field of architectural design to a dominant one. While current machine learning has not yet reached true intelligence, research is focused on causal reasoning. In the dominant stage, AI may mimic the thinking of architects and autonomously optimize designs through big data and evaluation systems, but it still cannot fully replace architects. Despite AI's roles in design and evaluation, achieving full dominance in design still requires further innovation and integration [25].

This paper conducts a systematic review of the application of AI technology in building envelope design, with a focus on its potential for energy-saving transformations and improving thermal comfort. This study identifies practical frameworks for applying existing technologies, aiming to bridge the gap between AI innovation and its real-world implementation in architectural design. Currently, even when conditions allow, the industry often lacks sufficient utilization of AI technology, especially in extreme climate regions. This paper encourages greater adoption and optimization of AI in these areas to ensure that existing technologies are more highly and effectively utilized, particularly in building envelope design, where they can significantly enhance energy efficiency. These findings aim to raise awareness among stakeholders about the transformative potential of AI in building envelopes and to drive further development and refinement of these technologies. This research not only contributes to academic discourse but also provides valuable insights for policymaking, professional practices, and future research, fostering the broader application of AI in addressing the challenges of sustainable building environments.

As shown in Figure 3, this study focuses on the application of artificial intelligence (AI) in the energy-saving renovation of building envelopes, exploring the background and demands of such renovations. This research includes multi-objective optimization design for energy-saving renovation of existing building envelopes and methods for optimizing renovation parameters. For example, integrating photovoltaic thermal (BIPV/T) systems with AI algorithms enhances insulation performance, reduces energy consumption, and increases economic feasibility. In the study by Javadijan et al., the use of NSGA-II optimization significantly improved energy, thermal, and economic performance while also providing environmental benefits, establishing it as a multifunctional green energy solution.

This study further identifies three key challenges in designing intelligent building envelopes for cold regions. First, there is a need for advanced AI frameworks to support adaptive building envelope designs that can respond to varying environmental conditions. Second, the use of thermal imaging technology for detecting building envelope issues requires further refinement, especially in cold climates where insulation and energy loss are critical. Lastly, the integration of AI into these designs must address the balance between a personalized, user-centric design and environmental sustainability. Moving forward, AI will need to bridge these challenges by advancing design methodologies and improving detection technologies.

In addition to optimizing building envelopes, this research also explores AI's role in interior design, particularly in enhancing indoor environmental perception. AI optimizes lighting, air quality, and temperature control, improving both user comfort and energy efficiency. However, future research must continue to innovate and address challenges to apply AI more effectively in creating sustainable, energy-efficient interior spaces.

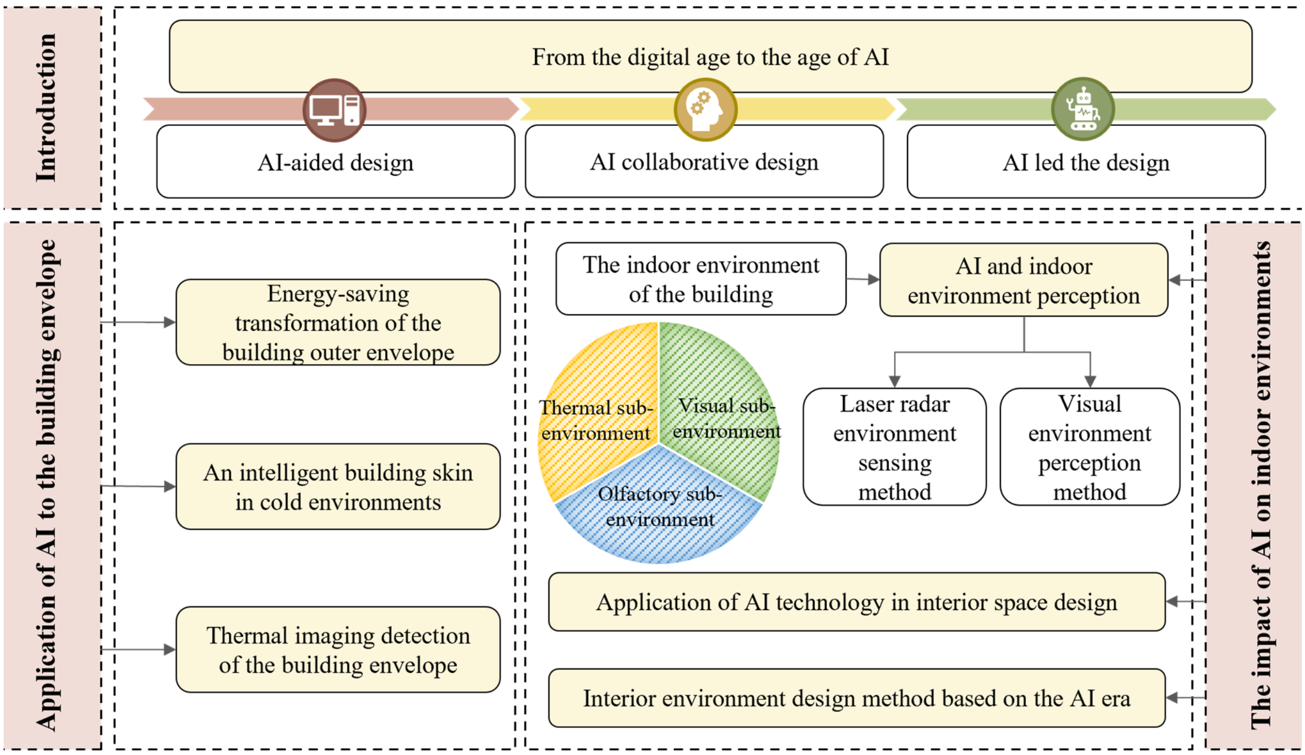


**Figure 3.** The research framework of this paper.

## 2. Methodology

This study conducted a review to explore the applications and impacts of artificial intelligence (AI) on architectural design, focusing specifically on building envelope design, interior environmental performance, and energy-saving transformations. This review examines research and review articles published over the past 15 years in two languages, English and Chinese, during a period marked by the increasing diversification of AI integration in architecture. Four primary academic databases—ScienceDirect, Web of Science, Scopus, and the China National Knowledge Network (CNKI)—were used to identify high-quality studies. The inclusion of CNKI ensured the representation of relevant Chinese research alongside international studies.

The systematic review followed the Preferred Reporting Items for Reviews and Meta-Analyses (PRISMA) protocol, encompassing stages such as defining the inclusion and exclusion criteria, shown as Figure 4. The search query was constructed based on keywords derived from the titles of relevant studies and divided into four categories, architectural design, energy-saving renovations, adaptive building envelopes, and artificial intelligence, as shown in Table 1. An initial search using terms like "artificial intelligence", "envelope structure", "indoor environment", "energy-saving transformation", and "smart skin" identified 529 articles: 52 from ScienceDirect, 212 from Web of Science, 197 from Scopus, and 68 from CNKI. After removing 171 duplicate articles, the dataset was reduced to 358 articles. Further filtering excluded studies unrelated to architectural design applications, such as those focusing on building equipment details, later utilization of AI in building maintenance, and the effects of AI on the development of society. This refinement prioritized the literature addressing AI-driven energy-saving design methods, narrowing the dataset to 207 articles.

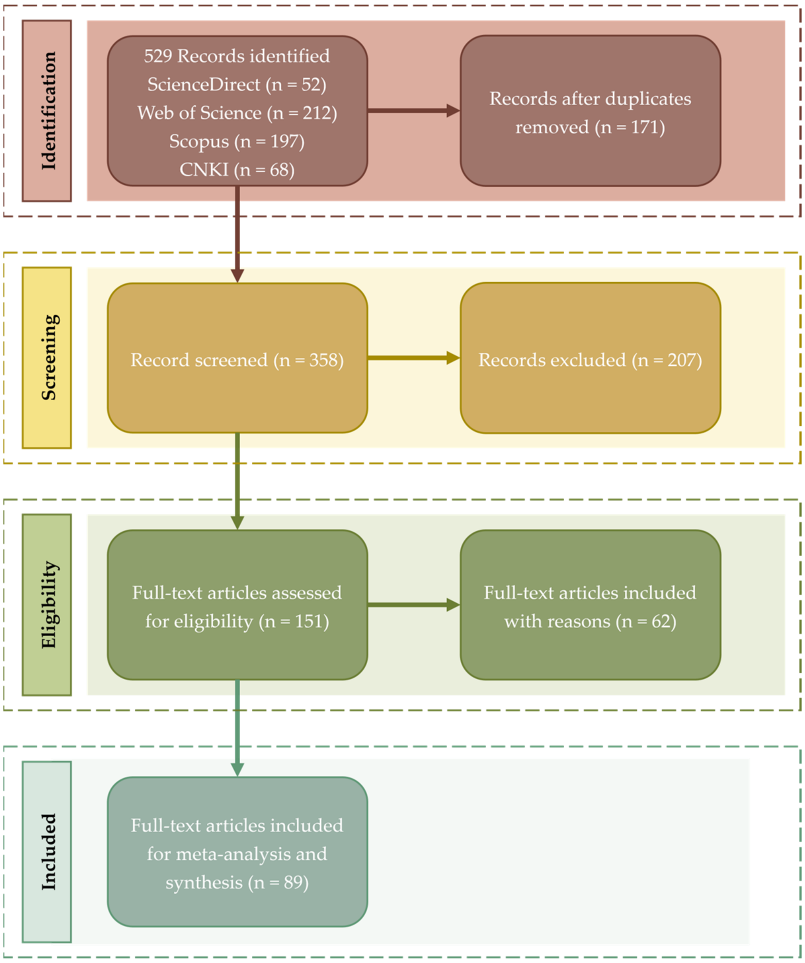


**Figure 4.** Meta-analysis.

**Table 1.** Search query.

| S/N | Search Category | Search Query |
|---|---|---|
| 1. | Architectural Design | "architectural design" OR "building design" OR "architecture engineering" OR "architectural innovations" |
| 2. | Energy-Saving Renovations | "energy-saving renovations" OR "energy-efficient buildings" OR "sustainable building renovations" OR "low-energy architecture" |
| 3. | Adaptive Building Envelopes | "adaptive building envelope" OR "dynamic building facades" OR "smart facades" OR "building envelope optimization" OR "kinetic façade" OR "dynamic facade systems" |
| 4. | Artificial Intelligence | "artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "AI applications in architecture" |
| 5. | Combined | 1 AND (2 OR 3) AND 4 |

To ensure the highest quality of analysis, an additional eligibility screen was conducted based on journal rankings, limiting the selection to Q1 and Q2 publications. This process excluded 62 articles, leaving 89 studies for the detailed examination. These selected articles were deeply analyzed and categorized, forming the foundation of this review paper.

The paper classification reveals that the research methods for the influence of AI on building envelope and interior environment design include field measurements and numerical simulations, and most of the papers use them simultaneously. Some studies focus solely on numerical simulations, such as energy-saving transformations, intelligent building skins in cold areas, and thermal imaging detection. This review also assessed the impact of AI on the indoor environment and discussed the indoor environment of buildings, AI and indoor environment perception, and indoor environment design methods based on the AI era, emphasizing its potential in improving building performance and indoor environment comfort [26].

## 3. Application of AI to Building Envelopes

The application of AI to building envelopes represents a significant advancement in architectural design, particularly in addressing energy efficiency and environmental adaptations. This section explores three key aspects: energy-saving renovations, intelligent building skin design for cold climates, and thermal imaging detection. These applications demonstrate how AI technologies are transforming traditional building envelope design and management, leading to more sustainable and efficient building solutions.

### *3.1. Energy-Saving Transformation of the Building Envelope*

China is striving to achieve a carbon peak by 2030 and carbon neutrality by 2060, which is a critical goal in its socio-economic development. The construction sector is the key sector responsible for about 40% of global energy consumption and up to one-quarter of global greenhouse gas emissions. According to the China Building Energy Consumption Research Report (2020), building energy consumption accounts for 21.7% of China's total energy consumption, with public buildings being particularly energy-intensive [27,28]. Energy-saving renovations of public buildings are thus essential.

In the practice of building energy-saving transformation, researchers have optimized the design of different insulation materials, external walls of different thicknesses, and building parameters through simulation analyses, energy consumption simulations, parameter sensitivity analyses, and other methods, effectively reducing energy consumption and improving indoor thermal comfort. For example, incorporating phase change materials in walls significantly improves thermal comfort and reduces the heating demand in indoor spaces. In addition, by taking measures such as window shading, changing glass types, and increasing enclosure materials, we carry out the energy-saving transformation of residential buildings and explore the investment payback period of different levels of transformation measures.

Building Information Modeling (BIM) technology [29] aids in predicting energy consumption, optimizing designs, and analyzing performance, helping architects identify key factors and propose renovations. However, the use of BIM to obtain performance data requires simulated parameter setting and calculation, which is inefficient in the design optimization of a large number of renovation schemes. Therefore, researchers have explored more efficient and intelligent ways to clarify the correlations between design parameters and building performance.

An artificial neural network (ANN) [30] is widely used in building energy consumption research to provide a decision basis. A multi-objective optimization method and genetic algorithm are used in building design optimization. The reference-point-based non-dominated sorting genetic algorithm (NSGA-III) can solve the problem of a traditional genetic algorithm in multi-objective optimization. Moreover, determining the probability of cross and variation behavior in genetic algorithm is crucial to analyze uncertainty.

Ding Zhikun et al. [31] proposed a multi-objective optimization method for the parameter design of an energy-saving renovation of an existing building envelope, utilizing EnergyPlus-based DesignBuilder software. This tool, with its real-time simulation and graphical interface, provides actionable data to bridge academic research and practical applications.

In the system of factors influencing building energy consumption, the envelope structure plays a decisive role [32]. Therefore, relevant research focuses on the U-value of external walls, roofs, and external windows, which are three design parameters closely related to energy consumption. After setting building and environmental parameters according to the actual requirements of the project, a simulation analysis is carried out to obtain building performance datasets under different design schemes. These serve two purposes: providing samples for training BP neural network prediction models to enhance accuracy and laying the groundwork for multi-objective optimization in energy-saving renovations.

Furthermore, BP neural network models are used to predict building performance, including normalization, ensuring fair treatment of input variables with varying dimensions and ranges. The BP neural network is propagated forward and back, and the weight and threshold are adjusted to obtain the ideal result.

In the process of model training, parameter optimization is the key to improve the prediction accuracy. The random search method automates hyperparameter selection, reducing the reliance on manual design [33]. In addition, evaluation indicators such as the coefficient of determination (R2), root mean square error (RMSE), and mean absolute error (MAE) are used to measure the prediction accuracy of the model to ensure that the model can accurately reflect the building performance.

In the stage of multi-objective optimization, the prediction model is based on the BP neural network. The random search method automates hyperparameter selection, reducing the reliance on manual design, which can hardly be expressed by traditional methods. At the same time, constraints on the design parameters ensure the feasibility of the solution. The NSGA-III algorithm improves diversity using reference points. Performance evaluation indicators such as the hypervolume (HV) are used to measure the convergence and diversity of algorithms and guide the optimization direction of algorithms [34].

The Monte Carlo method simulates random processes in a genetic algorithm to determine crossover and mutation probabilities, avoiding local optimality. The ideal point method deals with the Pareto optimal solution set by calculating the distance to the ideal point, balancing multi-objective optimization with practical applications.

In summary, through the simulation analysis of DesignBuilder software, the BP neural network prediction model, NSGA-III algorithm multi-objective optimization, Monte Carlo method and ideal point method, a comprehensive building performance optimization process was constructed to enhance the design efficiency and accuracy, supporting building energy conservation and sustainable development goals.

### *3.2. Intelligent Building Skins in Cold Areas*

Figure 5 shows the evolution of intelligent building skins, highlighting key developments from the 1960s to the present. It illustrates the progression from early explorations of dynamic urban spaces to the application of advanced design elements such as form, transmission, and control in modern architecture.

Since the 1960s, the intelligent development of building skins has undergone a significant evolution, gradually becoming a multidisciplinary research field focused on meeting the multiple green performance optimization needs of buildings.

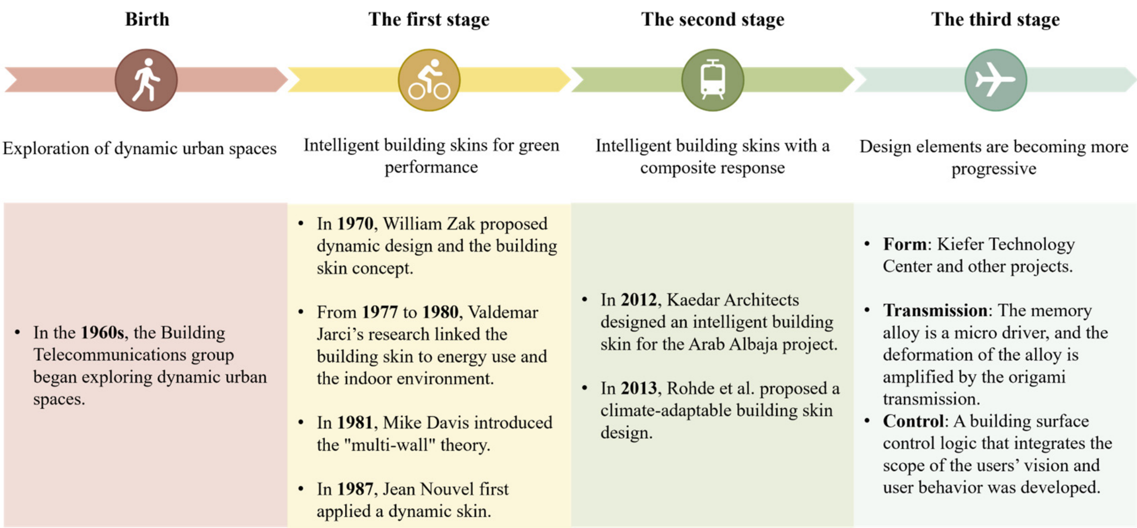


**Figure 5.** Some key nodes of the intelligent evolution of the building skin [35].

In the 1980s, Mike Davis proposed the "multi-wall" design theory to address energy issues without compromising the smooth aesthetics of curtain walls, creating climate-responsive building skins [36]. Jean Nouvel, in the Center for the Study of the Arab World project, used a complex system of mechanical diaphragms that automatically adjust sunlight entry and regulate indoor lighting [37].

In cold regions, buildings face the challenge of more extreme climatic conditions, which not only increase energy demands for indoor adjustments but also lead to an increase in energy consumption. Over the past decade, the heating area in northern China's cities and towns has increased significantly, and with it, the heating energy consumption, which accounts for a considerable proportion of building energy consumption. In response to this challenge, the Chinese government has introduced a series of green building standards [38], such as Green Building Evaluation Standards, Near-Zero Energy Building Technical Standards, and Healthy Building Evaluation Standards, to promote energy conservation and ecological urban development. As depicted in Figure 6, the history of the development of building energy efficiency standards in China shows a clear progression from initial energy-saving design standards in the 1980s to more comprehensive and stringent standards in recent years [35].

The building envelope in cold areas plays a crucial role in regulating material and energy transfer between the indoors and outdoors, significantly influencing green performance factors such as natural lighting, thermal comfort, and energy efficiency. To achieve low energy consumption and high comfort, the building skin needs to be able to intelligently respond to changes in the external environment, such as sunlight, temperature, and humidity, and adopt effective shading and ventilation. This design can reduce energy consumption while keeping the indoor environment healthy and comfortable.

However, improving the performance of a building envelope in cold areas is challenging due to the need to balance energy consumption, lighting, and thermal comfort, which often conflict. Therefore, the design of the building skin must carefully balance these properties. Secondly, the interaction between indoor and outdoor environments is complex, involving the coupling of a variety of physical fields, such as the interaction between fluids and solids, further complicating the design. However, it also provides an industrial demand and innovation impetus for the intelligent development of building skins in cold areas. By applying intelligent technology, these relationships can be better coordinated, leading to optimized building performance and advancing the construction industry toward greener, more sustainable solutions.

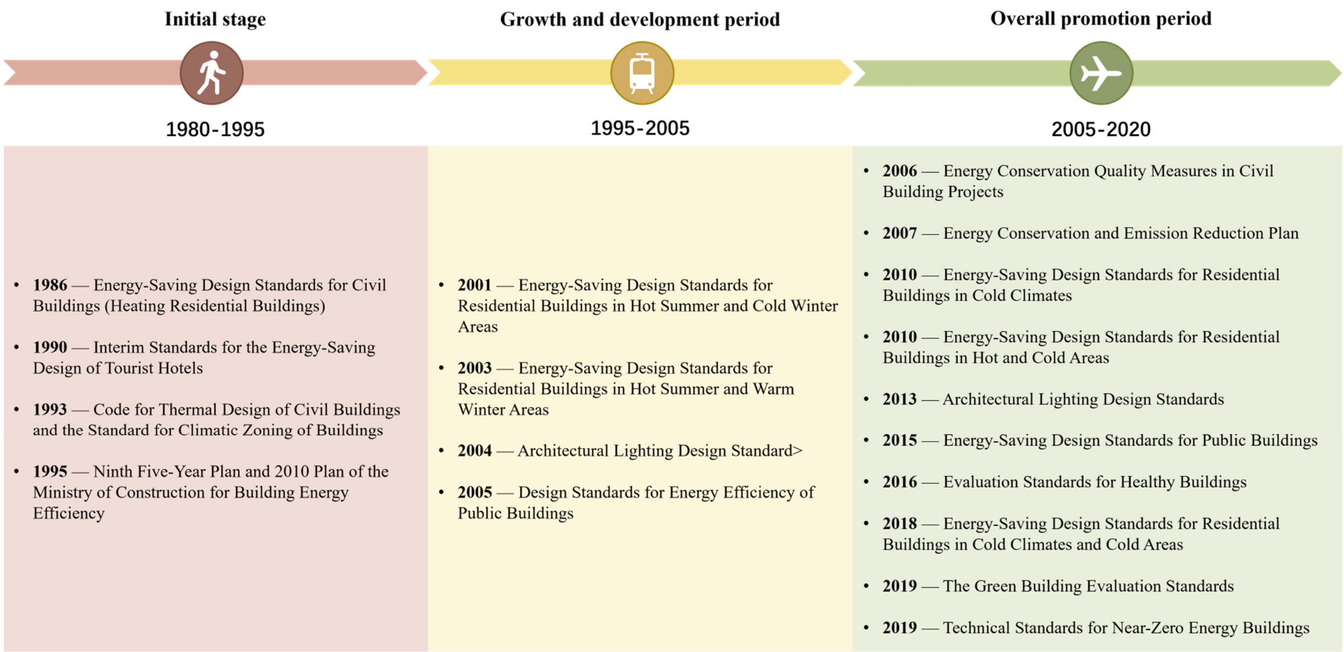


**Figure 6.** History of the development of building energy efficiency standards in China [35]).

In modern architectural design, intelligent skin form design is related to the architectural aesthetic expression, regional characteristics, and environmental interaction performance. The dynamic skin adjusts the indoor and outdoor environments to optimize the green performance of the building. As technology advances, building envelope design has become a four-dimensional space–time problem, requiring the creation of intelligent skins that adapt to environmental changes through "dynamic shape finding".

In cold regions, the dynamic response of a building skin is very important [39], but some current designs have not considered the climate characteristics of cold regions enough. For example, research shows that in cold regions, the preheated air from PV-DSF integrated with air source heat pumps could achieve temperature increases of 4–10 °C and cover over 65% of the building air demands, demonstrating an effective dynamic response to the environmental conditions. To improve responsiveness, scholars have explored intelligent skin designs that account for the elasticity of spatial structures, enabling an adaptation to environmental changes while emphasizing dynamic characteristics and realizing the efficient adjustment of indoor and outdoor environments through innovation.

In architectural design in cold areas, the "efficient transmission" of an intelligent skin is the key problem, which involves dynamically adjusting the building form for environmental adaptability. Transmission systems are categorized into mechanical and material types. Mechanical transmission relies on physical mechanical devices, which may face the problems of a large space occupation and freezing in cold environment. The design should consider weather resistance, reliability, and the challenge of snow freezing. Material transmission allows a dynamic adjustment of the skin through a change in the material's properties, with smart materials such as phase change materials [40] having the potential to optimize indoor light, thermal comfort, and energy efficiency. The advantages are compact equipment and high controllability, but the weather resistance, reliability, and cost effectiveness should be considered.

The exploration of material transmission in some non-cold region building projects provides valuable insights for the intelligent skin design of buildings in cold regions. For example, the intelligent skin of a French art museum was designed based on the principle of material hygroscopic expansion and can automatically open and close according to changes in air humidity [41].

Overall, the efficient transmission design of an intelligent skin in cold buildings requires a balance between mechanical and material transmission, considering the system reliability, adaptability, cost, and ease of maintenance. Future designs can explore new smart materials and innovative drive mechanisms to achieve more efficiency, economy, and environmental sustainability.

In addition, the application of intelligent control technology is crucial to improve building performance and indoor environmental comfort by accurately adjusting the building skin shape and structure to adapt to changes in the external environment, optimizing light and thermal comfort.

In practical applications, researchers have explored intelligent control methods to adjust the indoor light and thermal environment in cold climates. For example, through an analysis of measured data, it was found that a dynamic adjustment of the skin unit's angle can improve indoor lighting and reduce glare, while controlling natural ventilation boosts thermal comfort. For example, the adaptive exterior wall of the near-zero energy office building in Helsinki, Finland, adjusts the indoor thermal environment, and similar intelligent responses to solar radiation improve comfort [42], as seen in the dynamic facade system of the Keling Campus project [43]. They applied AI-driven facade control with 1600 sensor-equipped aluminum panels that adjust the angles (30–60°) based on the light and heat levels. This system achieves energy consumption as low as 38 kWh/m$^2$/year, making it one of the world's first low-energy universities. These methods enhance indoor comfort and boost building energy efficiency.

However, there are complex interaction effects among the multiple performance objectives of buildings in cold regions, and balancing multiple performance objectives in cold-region buildings is a key challenge in intelligent control design. Some studies improve indoor photothermal comfort performance and energy efficiency by dynamically adjusting shutters [44], while others enhance photothermal comfort and ventilation through dynamic shading and louver rotation, demonstrating the diversity and flexibility of building intelligent control technologies [45].

### *3.3. Thermal Imaging Detection of the Building Envelope*

The synergies in high-performance architectural design are conceptually explained, and these effects have crucial impacts on the quality of the final project [46].

With the global push for Sustainable Development Goals, the focus has shifted from new building standards to renovating existing structures to enhance energy efficiency [47,48]. For example, a study of an educational building in Benevento, Italy, showed that utilizing a high-performance building envelope while preserving its historical character achieved a 15-year payback period, proving that sustainable upgrades are feasible. Assessing energy efficiency is challenging due to the lack of detailed evaluations in older buildings and maintenance issues in new ones. Energy management agencies and renovation companies need efficient, fast ways to evaluate buildings and identify inefficient or malfunctioning components.

Passive infrared thermal imaging (PIRT) is a common tool for civil engineering and building inspections [49], effectively detecting energy efficiency anomalies by reconstructing target temperatures. However, PIRT image interpretation requires domain knowledge and an understanding of the complex interactions of multiple factors [50], and despite advances in algorithms, building inspections using PIRT are still labor-intensive and time-consuming [51].

Traditional algorithms are commonly used to process and enhance thermal images, but have limited success in automated interpretation, especially in cases of high variability [52]. Despite rapid advances in AI, the field of thermal imaging inspection in buildings has yet to fully leverage these opportunities [53].

The current state-of-the-art research focuses on supervised learning methods that rely on the meticulous annotation of RGB and thermal images and acquisition of large datasets covering variability. While studies have explored deep learning models for thermal imaging, these models often fail to generalize effectively to real-world commercial building inspections.

To fill the knowledge gap, Polina Kurtser et al. [24] proposed a depth-based method for a normality representation applied to RGB–thermal image pairs. The technology is designed to improve the generalization and applicability of building inspections, supporting manual inspections or integration with mobile platforms for automated large-scale assessments.

Among generative models, GANs have attracted much attention due to their unique training mechanism [54]. GANs consist of generators and discriminators that compete with each other in training to improve performance. The generator learns the statistical distribution of the training dataset and generates new composite data, and the discriminator determines the source of the test sample. Through competition, the generator produces increasingly realistic data while the discriminator refines its detection ability. Currently, GANs are essential for applications requiring high-quality data generation.

In addition to GANs, an image-to-image translation network is an important branch in the field of deep learning, which can realize image style conversion and domain migration. For example, CycleGAN [55] performs image translation across domains without paired training samples, utilizing architectures such as ResNet or U-Net. Some Transformer based GANs utilize a self-attention mechanism to improve the image-to-image translation performance [56].

In the field of deep learning, color-to-thermal imaging networks, a subset of image-to-image conversion networks, specialize in translating color images into heat profiles. Kniaz et al. [57] demonstrated the method to predict the heat distribution of objects through ThermalGAN, and Mizginov [58] tested and compared the performance of different GAN architectures in terms of color and thermal imaging. Both studies focused on buildings as generative categories, highlighting their potential for analyzing building exteriors.

Single-class classification, a paradigm for identifying positive (target) or negative (outlier) samples [59], is particularly useful when negative samples are unavailable. The objective of this paper is to detect heat leakage in RGB–thermal imaging pairs with a single class classification. The model leverages normal RGB–thermal image pairs to identify a standard distribution, relying on loosely supervised training that only requires single-class labeling for color-to-thermal imaging networks and normal thermal images, eliminating the need for abnormal instance labeling.

Summarized in Table 2, the integration of AI in building envelope applications has demonstrated significant potential in improving building performance across multiple dimensions. From energy-saving renovations to intelligent building skins and thermal imaging detection, AI technologies have enabled more precise, efficient, and adaptive building envelope solutions. These advancements not only contribute to energy conservation but also enhance building functionality and occupant comfort, setting new standards for sustainable architecture.

**Table 2.** Applications of different AI technologies in the thermal imaging detection of the building envelope.

| Author | Year | AI Technology | Advantages | Limitations | Conclusions |
| --- | --- | --- | --- | --- | --- |
| Khan, S.S. and Madden, M.G. [59] | 2014 | Support Vector Machine (SVM)<br>ANN<br>Decision tree algorithm<br>Nearest neighbor algorithm | • Simple and easy to use.<br>• Works well with small datasets. | • Limited for complex data.<br>• Needs manual tuning. | Single-class classification (OCC) algorithms are reviewed, with a method proposed based on the data and applications. Despite the challenges, OCC holds potential in various fields. |
| Zhu, J.-Y. et al. [55] | 2017 | GANs<br>Cyclic consistent adversarial network (CycleGAN) | • Handles unpaired image conversion.<br>• Effective for the RGB-to-thermal conversion. | • Struggles with geometric accuracy.<br>• Needs large datasets. | Proposes CycleGAN for unpaired image-to-image conversion. Outperforms the baseline but has limitations in handling geometric transformations. Advances unsupervised image conversion technology. |
| Kniaz, V.V. et al. [57] | 2018 | GANs<br>ThermalGAN framework | • Accurate color-to-thermal conversion.<br>• Produces high-quality images. | • Time-consuming.<br>• Needs labeled data. | Proposes ThermalGAN for cross-modal pedestrian re-recognition, achieving color-to-thermal conversion. ThermalWorld outperforms in this field and provides valuable data for research. |
| Shariq, M.H. and Hughes, B.R. [53] | 2020 | ANN<br>Convolutional neural networks (CNNs) | • Extracts complex features.<br>• Works with 5G for a real-time analysis. | • Risk of overfitting.<br>• Time-consuming. | Building energy detection research has gaps but identifies promising technologies like monocular photogrammetry and UAV with IRT. The 5G technology is highlighted to address challenges and guide future research. |
| Mizginov, V.A., Kniaz, V.V. and Fomin, N.A. [58] | 2021 | GANs | • Creates realistic thermal images.<br>• Helps with data training. | • Hard to evaluate quality.<br>• Needs careful tuning. | Proposes a GAN-based method for generating synthetic thermal images. An FID evaluation shows high similarity to real models, improving training datasets and related technologies. |
| Chai, P. et al. [54] | 2024 | GANs | • Reviews applications and challenges.<br>• Suggests improvements. | • Training instability.<br>• Hard to apply practically. | Reviews GAN applications in construction, covering principles, uses, limitations, and future directions. While applied in design generation, issues like unstable training remain. Future integration with new technologies could improve efficiency and sustainability. |
| Dubey, S.R. and Singh, S.K. [56] | 2024 | GANs<br>Transformer network | • Improves vision tasks.<br>• Useful for architecture. | • Needs a lot of computing power.<br>• Long training times. | Reviews Transformer-based GANs in computer vision, highlighting their impacts on vision methods and applications. Discusses the model architecture and performance, and suggests future improvements in architecture, feature integration, and pre-training. |

**Table 2.** *Cont.*

| Author | Year | AI Technology | Advantages | Limitations | Conclusions |
|---|---|---|---|---|---|
| Kurtser, P. et al. [24] | 2025 | GANs Image-to-image translation network (pix2pix architecture) | • Detects thermal issues well.<br>• Learns from diverse data. | • May create image errors.<br>• Data variety affects the results. | Proposes a label-free AI method for building envelope anomaly detection using color images to predict heat distribution. The pix2pix model detects anomalies like thermal bridges after training on diverse data, advancing automated building thermal detection. |

## 4. The Impact of AI on the Indoor Environment

As buildings become increasingly complex and user expectations evolve, the role of AI in indoor environmental design has become crucial. This section examines how AI technologies are reshaping the understanding and management of indoor environments, from basic environmental parameters to sophisticated design applications. The integration of AI in indoor environments represents a paradigm shift in how designers conceptualize and create comfortable, efficient, and sustainable indoor spaces

### 4.1. Indoor Environment of the Building

The human sensory interpretation of the surrounding environment begins with the human sensory system receiving environmental impulses, which are processed by the brain as environmental attributes. The indoor environment can be divided into five sub-environments, with automatic control fields defined during architectural design and BAS implementation. The problem of the proposed method lies in its complexity and many interactions. Factors beyond traditional technology should be prioritized for control based on user comfort, such as active noise reduction systems [60] or the automatic control of mobile absorbers for indoor reverberation. The dynamic changes in thermal, visual, and olfactory factors present both a risk of user dissatisfaction and a significant potential for energy savings. As illustrated in Figure 7, these factors encompass various elements that influence the thermal, visual, and olfactory aspects of the indoor environment [61]. The control of thermal energy, vision, and indoor air quality will be further discussed.

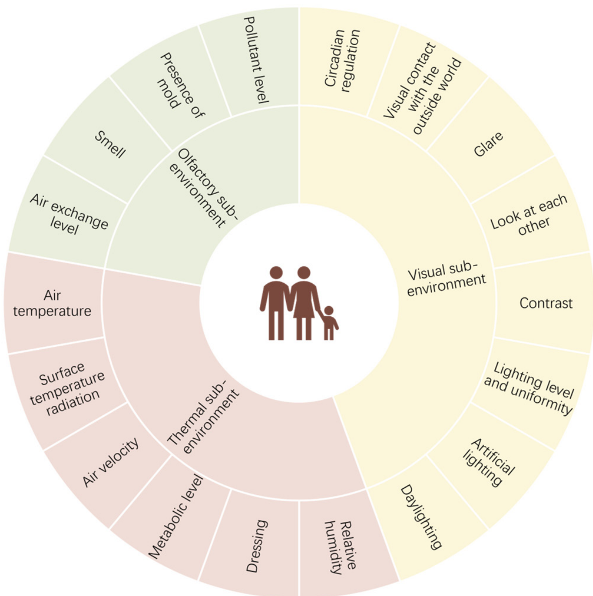


**Figure 7.** Thermal, visual, and olfactory sub-environments and their influencing factors [61].

#### 4.1.1. Thermal Sub-Environment

The indoor thermal environment primarily reflects the external climate characteristics of the building location. In most modern buildings, solar radiation significantly impacts indoor thermal conditions [62], and the thermal environment also depends on the heat exchange with the exterior and building usage. For example, scholars have utilized solar radiation simulations to analyze and optimize building orientation decisions, revealing that different orientations significantly impact energy consumption and indoor comfort. For instance, east-facing zones experienced excessive solar radiation, leading to high cooling demands, while north-facing zones have minimal direct solar exposure. South-facing zones consume a moderate amount of energy, benefiting from steeper solar angles that limited heat gain compared to east and west orientations. It highlights the importance of tailored design strategies to achieve energy efficiency while maintaining indoor comfort. The thermal comfort of the human body in an indoor environment is influenced by various factors, but all of these factors are related to the control mechanism of human blood vessel movement [63]. For designers, the main problem is to correlate influencing factors to affect the satisfaction of the human thermal environment. Among various measurement systems, Fanger's PMV index [64], developed in the 1970s, is the most complex, linking multiple factors to human thermal sensation but with limitations [65] that complicate its use in building automation. Simpler metrics, such as the concept of thermal neutrality [66], which is relevant to a specific region and culture, and a simple measurement of dry bulb temperature can be used for BMS applications if the building radiation environment is uniform and the air flow is limited.

#### 4.1.2. Visual Sub-Environment

In building activities, the full implementation of visual tasks is one of the main needs of occupants, and the reasonable design of indoor visual sub-environment is crucial in architectural design and can be divided into visual and non-visual effects, where daylight is the key factor.

Studies show that classrooms with ample daylight improve student performance by 20% in math and 26% in reading compared to those without daylight [67]. Similar results were found for office environments [68] and retail sales environments. For most visual tasks, the amount and uniformity of the horizontal illuminance of the working plane are important.

On the other hand, glare is a common problem in daylighting. The design and control of transparent parts are crucial for visual comfort, the shading control level is critical, daylight and artificial lighting coordination can save energy, and visual sub-environmental parameters are difficult to adjust with BAS but most promising for long-term dividends [69].

#### 4.1.3. Olfactory Sub-Environment

Despite indications that indoor air quality is linked to occupant health and comfort, indoor air conditions are poorly understood and often overlooked. Environmental factors influencing olfaction include organic substances in air [70] and occupants' metabolic byproducts. Poor air quality can stem from the building location [71], and indoor air quality usually maintained by natural, mechanical, or combined ventilation. Some buildings prioritize energy conservation with minimal ventilation rates [70], compromising occupant comfort. From the perspective of BAS design, the most practical control strategy is side ventilation according to the demand of the CO2 concentration [72]. Studies indicate that users prefer natural ventilation, and BAS can optimize heating, cooling, and ventilation for enhanced building performance.

### *4.2. AI and Indoor Environment Perception*

With accelerating scientific and industrial advancements, intelligent manufacturing has become a global trend and has been actively adopted by Chinese industry [73]. Researchers are committed to developing more intelligent service robots [74], which need to have advanced perception capabilities. Perceptual intelligence is the basis of the interaction between robots and environmental information. Research on environmental perception technology is of great significance to robot indoor operation, involving core technologies such as target detection and ranging.

Environment perception technology is an important bridge connecting robots with the real world, and it is crucial for the application of augmented reality (AR) and virtual reality (VR) technology [75]. With AI advancements and the growing service robot market, environmental perception holds significant potential and practical value [76,77]. Despite significant progress in deep learning-based approaches to environment awareness, there are still many challenges and issues that need to be addressed.

At present, research on indoor environment perception mainly relies on LiDAR and visual image technology [78]. LiDAR excels at mapping, but it has limitations. Visual image technology, by reducing hardware dependence and computational needs, enhances object detection and localization, advancing robotic intelligence and efficiency.

#### 4.2.1. LiDAR Environment Awareness Method

Visual environment perception technology plays a vital role in a robot's interaction with the real world, particularly in augmented reality (AR) and virtual reality (VR) applications. As a key sensor, LiDAR is mainly used for three-dimensional target detection [79] by collecting point cloud data through laser reflection, and is valued for its stability and anti-interference properties. LiDAR is widely used in digital city construction, terrain mapping, cultural relic reconstruction, and other fields [80].

There are three methods to process LiDAR data: direct, indirect, and fusion. The direct processing method utilizes the characteristics of point cloud data to analyze and process them using deep neural networks, such as PointNet, PointNet++, and SpiderCNN algorithms. The indirect processing method uses sampled point cloud data combined with deep neural networks for target detection, such as BirdNet and RT3D algorithms [81]. The fusion processing method combines 3D point cloud data and image data to improve the accuracy of environment perception through multi-sensor data fusion, such as AVOD and KPP3D object detection models based on key point information fusion.

Despite LiDAR's strong performance, its high costs and equipment requirements limit its application in certain scenarios. In cost-sensitive contexts, visual environment awareness technology offers a more economical alternative.

#### 4.2.2. Visual Environment Perception Method

Visual environment perception technology recognizes the surrounding environment through image analysis and recognition technology, while deep learning has revolutionized image processing since 2012 [82]. Target detection technology determines the target location and category in images, but traditional methods cannot meet the requirements [83]. Deep learning, with its robustness, generalization ability [84], and automatic feature extraction, has become the mainstream algorithm, offering broad application prospects in target detection and supporting automation and intelligence.

Object detection technology has been developed since 2001. It initially relied on manual feature extraction and a sliding window method combined with a classifier to process images [85], and a representative algorithm was used for pedestrian, vehicle, and animal detection [86].

The Scale Invariant Feature Transform (SIFT) algorithm, proposed for detecting and describing local features, is robust to illumination changes and noise [87,88], but suffers from a high computational cost and slow matching speed. However, in some cases, integrating different algorithms can improve computational efficiency. For example, combining Histogram of Oriented Gradient (HOG) features with Support Vector Machines (SVMs) can enhance performance.

The Histogram of Oriented Gradients (HOG) can capture local shape information and is invariant to geometric deformation, performing well in pedestrian detection [89]. Despite early successes, traditional methods have been largely replaced by more efficient and accurate deep learning algorithms.

Two-stage target detection algorithms rely on a regional candidate network and neural network classification theory [90]. The regional convolutional neural network (R-CNN) algorithm, proposed by Ross Girshick in 2014 [91], marked a breakthrough in applying deep learning to target detection. Subsequently, LiJi et al. [92] proposed the Fast R-CNN algorithm to improve detection performance, and He Keming et al. [93] proposed the space pyramid pool network. ChenXi et al. [94] studied non-maximum inhibition, and in 2017, He Keming et al. proposed the Mask R-CNN algorithm. In practice, Faster R-CNN has demonstrated competitive accuracy and speed, particularly in pedestrian detection. For example, For example, the method proposed by Zhang Hui et al. [95] showcased its effectiveness, and Zhang Li et al. achieved an improved accuracy on INRIA datasets using Faster R-CNN. These algorithms promote the progress of object detection technology and provide tools for visual recognition tasks.

A one-stage object detection algorithm combines classification and regression problems. The YOLO algorithm, a milestone in the field of deep learning object detection, treats detection tasks as regression problems to achieve end-to-end optimization [96]. The SSD algorithm introduces multi-scale prediction, and YOLOv2 improves the basic model for better speed and accuracy [97]. YOLOv3 introduces multi-scale training and testing, and YOLOv4 and YOLOv5 further enhance the detection performance.

Overall, traditional target detection methods are effective in the early stage. With the development of deep learning, target detection has become more efficient and accurate. The combination of deep learning and practical application scenarios has become the mainstream trend, promoting the widespread use of target detection technology.

### *4.3. Application of AI Technology in Interior Space Design*

Smart home systems have become integral to indoor space design by integrating sensors and intelligent algorithms for comprehensive environmental management. These systems teach user behavior patterns and automatically adjust lighting, temperature, and security, such as smart thermostats and smart lighting systems. They also offer remote control and scheduling to provide a convenient life experience. They improve energy efficiency and reduce environmental impacts through data analysis.

The application of 3D modeling technology in the field of interior design enhances the design accuracy and efficiency by allowing designers to preview and modify schemes in virtual environments. Three-dimensional models visually represent interior spaces and simulate effects such as lighting, aiding both designers and clients in understanding the design intent. With advancement of VR and AR technology, 3D modeling offers immersive virtual tours, enabling users to experience design spaces interactively and realistically before implementation.

The application of big data analytics into interior design allows designers to align spaces with market trends and user expectations. By analyzing extensive data, designers can predict design trends, optimize solutions, improve market competitiveness, identify potential problems early in the project, and conduct risk assessments to minimizes design changes and cost overruns while enabling real-time tracking of design implementation to refine strategies.

Intelligent spatial layout design personalizes and optimizes the spatial layout by analyzing users' behavioral data and preferences. Using advanced AI algorithms, it creates functional, humanized spaces that adapt dynamically to users' needs. Combined with the Internet of Things (IoT) technology, it enables the interconnection of equipment and systems, providing a more intelligent and automated living experience.

The intelligent security system uses AI technology to provide all-round security for the indoor environment. It prevents and addresses security threats through real-time monitoring and automated alarm mechanisms, such as facial recognition and behavioral analysis to identify suspicious individuals, while intelligent fire alarm systems detect smoke and high temperatures, triggering suppression and evacuation protocols. It also works with other smart home systems. With the advancement of technology, the intelligent security systems continue to evolve, bringing peace of mind and a convenient life experience to users.

### *4.4. Interior Environment Design Methods Based on the AI Era*

#### 4.4.1. Development Trends in Interior Design

Virtual reality (VR) technology is increasingly applied in interior design, creating immersive three-dimensional environments through computer graphics and digital processing technology. Designers can use VR technology for initial layout planning to meet the actual needs and optimize solutions in real time according to customer feedback. During construction, VR enables real-time site monitoring, enhancing safety and efficiency, and provides a new display means for customers to experience the design scheme through panoramic imaging and virtual simulations, improving communication and design expression.

As a new method of interior design, digital shadow technology deeply integrates the real environment with computer graphic technology to simulate virtual reality scenes. Its interactivity enhances users' experience, improving design efficiency and quality while reducing noise and pollution through remote control functions and providing a comfortable and environmentally friendly living environment. With the advancement of AI technology, digital shadow technology is expected to play a more important role in future interior design, creating more intelligent and personalized living spaces.

#### 4.4.2. The Impact of AI on Interior Design

Interior design style tends to be intelligent, personalized, and pays more attention to the harmony between man and nature.

In contemporary interior design, intelligence is a significant trend. Smart home systems include smart appliances, energy-efficient devices, and home control solutions. Energy-saving appliances such as smart thermostats and smart lighting promote sustainability, while small appliances such as vacuum cleaners and dishwashers enhance convenience and comfort of life. Micro smart appliances such as smart speakers and electric curtains enhance the smart home experience through voice control and automation.

People's demand for personalized interior design is growing, and it is more obvious in the era of AI. The application of AI technology in the fields of smart homes, transportation, healthcare, and education brings new possibilities for interior design so that the design can more accurately reflect the personality and lifestyle of the occupants.

In interior environment design, the harmonious coexistence of man and nature is the core concept. The interior environment's design should prioritize living comfort and aesthetics, integrating natural elements to create spaces that strengthen the connection to nature and reflect respect for the environment.

The application of AI in indoor environment design has demonstrated transformative potential across multiple domains. From environmental perception to practical design implementation, AI technologies have enabled more sophisticated, user-centered, and efficient approaches to indoor space design. These developments have not only enhanced the ability to create more comfortable and sustainable indoor environments but have also opened new possibilities for personalized and adaptive space solutions. The continued evolution of AI applications in this field suggests an increasingly intelligent and responsive future for indoor environment design.

## 5. Conclusions

With the continuous progress of AI technology, its applications in the fields of architecture and interior design have broad prospects, indicating a more intelligent and personalized future. The integration of AI has enhanced design efficiency and building performance, and supports the creation of comfortable, healthy, and eco-friendly indoor environments. The future interior design will pay more attention to the harmonious symbiosis between man and nature, and meet the residents' pursuit of a better living space through deep customization and personalized design.

This study underscores the role of AI in optimizing building envelope performance, emphasizing its impact on energy-saving and thermal comfort improvements. By narrowing the focus to this specific architectural component, it bridges gaps in the existing literature and fosters a deeper understanding of this emerging area. Practically, the findings highlight the importance of leveraging AI to address challenges in energy efficiency, particularly in extreme climate regions, where the integration of AI into building envelopes could significantly reduce energy consumption.

In terms of environmental protection, AI will further promote the development of green buildings and ecological homes and achieve the efficient use of resources and sustainable development of the environment through intelligent design and management. Additionally, AI technology will improve the safety and controllability of the indoor environment, providing a safe and healthy living space through accurate monitoring and regulation.

However, as technology advances, integrating personalized design with environmental protection remains a challenge. Designers need to continuously improve their professional quality and in-depth understanding of users' needs while applying intelligent technologies to balance innovation and users' requirements. Future interior design will rely more on data-driven decision-making, using big data and AI algorithms to predict trends and optimize designs.

In short, AI technology will profoundly change the future of the architecture and interior design industries and bring a more intelligent, efficient, and environmentally friendly lifestyle to mankind. With the continuous development and improvement of technology, we have reason to believe that AI will become a key force driving progress in these industries and creating better living environments.

## 6. Research Gaps and Future Directions

The review reveals several significant research gaps in AI applications for architectural design and building environments. Current AI systems face technical limitations, particularly in their output mechanisms, which remain primarily one way and lack effective feedback mechanisms when generating architectural designs, which still require significant human intervention for optimal performance.

In cold-region architecture, while progress has been made in modelling building envelope effectiveness, there is a notable lack of generalization in these studies. Thermal effect simulation can be utilized for building optimization, enhancing thermal comfort and energy consumption through thermal imaging analysis, but more research is needed in developing innovative AI applications for enhanced energy efficiency, expanding AI integration in material science for improved building insulation, and creating more robust models that can adapt to extreme climate conditions. The field faces substantial challenges in environmental control and monitoring, as current AI systems struggle to model the complex coupling of multiple physical fields between indoor and outdoor environments, with notable limitations in coordinating various environmental factors simultaneously, including thermal comfort, visual comfort, and air quality.

Despite technological advances, building inspection capabilities show gaps, particularly in thermal imaging inspection, which has not fully capitalized on the available AI technologies, while current deep learning models show limited effectiveness in generalizing to real-world commercial building inspections. Implementation barriers persist, with high-end technologies like LiDAR remaining cost-prohibitive for widespread adoption, and the deployment of AI solutions in building design and management requires extensive computational resources and specialized expertise.

These gaps highlight the pressing need for continued development in AI applications for architecture, with a particular focus on creating more autonomous, integrated, and accessible solutions that can address the complex challenges of modern building design and management.

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