applied sciences

Review

A Review of Artificial Intelligence in Enhancing Architectural Design Efficiency

Yangluxi Li [1], Huishu Chen [2], Peijun Yu [3,*] and Li Yang [4,*]

[1] Welsh School of Architecture, Cardiff University, Cardiff CF10 3XQ, UK; liy209@cardiff.ac.uk
[2] School of Architecture & Urban Planning, Shenzhen University, Shenzhen 518060, China; 2161140206@email.szu.edu.cn
[3] School of Materials Science and Engineering, Hainan University, Haikou 570228, China
[4] College of Architecture & Urban Planning, Tongji University, Shanghai 200092, China
* Correspondence: pyu@hainanu.edu.cn (P.Y.); yangli.arch@tongji.edu.cn (L.Y.)

Featured Application: The application of Artificial Intelligence (AI) in architectural design can significantly enhance design efficiency, foster innovation, and improve the sustainability of building projects. AI-driven tools, such as parametric design and AI-assisted design methods, are already helping architects optimize layouts, reduce material waste, and create energy-efficient structures. As AI continues to evolve, its potential to streamline construction processes, provide predictive analytics for building performance, and enable smarter facility management could reshape the entire building lifecycle, making the construction industry more adaptive and resilient to future challenges.

Abstract: At present, Artificial Intelligence (AI) technology is developing rapidly, and the construction industry is facing three major trends: industrialization, greening, and digital intelligence. This paper explores the application of AI technology in the field of architectural design and its impact on design efficiency, with 1810 articles screened from the Science Direct, Web of Science, Scopus, and China National Knowledge Network (CNKI) search engines, 92 of which were selected for meta-analysis and review. The results show that AI has great potential in the architectural design process, including creative development, data analysis, and problem-solving. In addition, AI has other applications throughout the building lifecycle, such as predictive analytics, construction supervision, and facility maintenance. In addition, through the discussion of traditional architectural design methods and AI-driven architectural design methods, this paper summarizes the advantages and challenges of AI technology in architectural design. Finally, through case analysis, this paper believes that the future of AI in the field of construction is full of infinite possibilities; through the correct guidance and regulation of its development, it will certainly bring more innovation and progress for the construction industry.

Keywords: artificial intelligence (AI); architectural design; parametric design; AI-assisted design; human–machine collaboration

check for updates

Academic Editor: João M. F. Rodrigues

Received: 9 January 2025
Revised: 28 January 2025
Accepted: 30 January 2025
Published: 31 January 2025

Citation: Li, Y.; Chen, H.; Yu, P.; Yang, L. A Review of Artificial Intelligence in Enhancing Architectural Design Efficiency. *Appl. Sci.* **2025**, *15*, 1476. https://doi.org/10.3390/app15031476

1. Introduction

Architectural design is a complex creative activity that requires balancing aesthetics and functionality while considering multiple factors, including technology, economics, environment, and socio-cultural aspects [1]. For large-scale, high-complexity projects and increasingly stringent environmental requirements, design teams face growing pressure in information processing, consuming more time and resources.

Therefore, Artificial Intelligence (AI) technology not only optimizes processes but also improves efficiency for traditional building design. Through machine learning, natural language processing, and algorithm optimization, AI assists designers in making faster and more accurate decisions in areas such as creative exploration, data analysis, and problem-solving. Additionally, parameterized design enhances the innovation and quality of design solutions.

At the same time, the application scope of AI is not limited to the early design process, but it can also support the entire lifecycle of the building [2], covering project prediction analysis, construction supervision, and continuous facility maintenance [3]. This comprehensive integration of AI technology can promote the development of the built environment toward greater intelligence and sustainability.

Finally, in the face of the meta-universe [4], how to let AI give full play to its potential in architectural design to revitalize the construction industry remains an open question. This paper reviews the traditional architectural design methods, summarizes cutting-edge AI technologies in construction, analyzes AI's impact on design efficiency, identifies potential challenges, and explores future prospects.

AI technology is now at a critical juncture of rapid development, with the rise of Generative Artificial Intelligence (GAI) signaling transformative changes in visual, artistic, and language-related fields across various industries [5]. These technologies have moved beyond the experimental phase into commercial applications, demonstrating immense potential. In the future, GAI is expected to expand into areas like building information modeling and intelligent design, critical to the complex construction industry, fostering creativity and innovation [6].

Amidst market shifts and emerging influences, the construction industry faces three major trends: industrialization, green development [7], and digital–intelligent transformation [8]. Industrialization emphasizes modular, automated construction methods [9], while green development focuses on lifecycle energy conservation and the use of sustainable materials [10]. Digital–intelligent transformation integrates digitization and intelligent systems, leveraging technologies like GAI to optimize processes and enhance value creation.

AI's evolution from rule-based systems to large-scale models is accelerating the digital–intelligent transformation of the construction sector. This shift improves collaboration, supply chain management, and data-driven decision-making, boosting the competitiveness of organizations and individuals. Conversely, those unable to adapt to this trend risk higher costs and diminished market standing. Continuous innovation in AI is paving the way for a smarter, more efficient, and sustainable future in the construction industry [11].

In response to these technological advancements, the National Council of Architectural Registration Boards (NCARB) has established clear guidelines emphasizing that while AI can serve as a labor-saving tool, architects must maintain responsibility and accountability for all work. NCARB states that AI is not a replacement for professional judgment, and architects must remain in responsible control of all technical submissions under their seal [12,13]. Significant legal uncertainty exists globally and locally regarding intellectual property rights for AI-generated architectural designs. For instance, in the U.S., the Copyright Office has revoked copyrights for AI-generated works, highlighting challenges architects face when using AI. Similarly, the European Union's AI Act outlines strict requirements for high-risk AI systems, including mandatory documentation, testing, and accountability measures [14]. In China, recent guidelines focus on ensuring transparency and ethical use of AI in creative fields. These examples underline the need for robust AI governance frameworks and transparent operational practices across jurisdictions [15]. Architects and related stakeholders must navigate technical documentation, regular testing, and evolving regulations to responsibly integrate AI into practice.

As proven in Ji's study, AI has the potential to revolutionize architectural design by optimizing outcomes, enhancing efficiency, and fostering sustainability, surpassing the limits of traditional methods. In the face of the rapid rise of AI and the development trend and dilemma of the construction industry, this paper aims to systematically review the application of AI in architectural design and its impact on the efficiency of architectural design, aiming to provide new momentum for industry development and uncover novel opportunities.

As is shown in Figure 1, this paper first outlines the rise of AI and the three major trends in the development of the construction industry, as well as the efficiency dilemma currently faced by the construction industry. Then, it introduces AI technology and principles in detail, as well as its applications in architectural design, including early design management and later-stage operation. Then, the traditional architectural design method and GAI design method are analyzed theoretically, highlighting efficiency advantages and addressing emerging challenges. Finally, some case studies are made to look forward to the future.

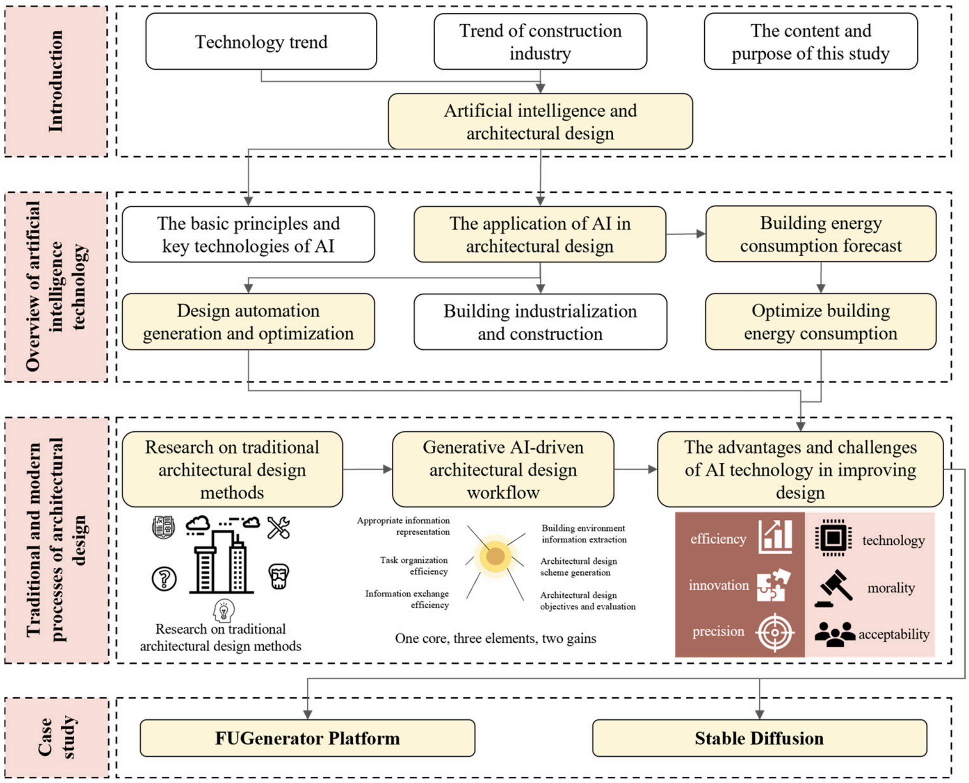

Figure 1. Overall research process.

2. Materials and Methods

This paper uses Science Direct, Google Scholar, and other search engines to review the application research of AI in architectural design, including the research of AI and architectural design methods. Due to the continuous progress of China in the field of AI and architectural design, Chinese scholars have published many articles in Chinese in this field, so an analysis of the English literature alone cannot accurately and comprehensively summarize the research on AI and architectural design. China National Knowledge Network (CNKI) is the largest continuously updated Chinese academic literature database in China. It effectively complements the English database and presents a comprehensive picture of the current state of research in the world. In this paper, we aim to achieve the following:

1. Understand the definition of AI and the AI technology that can be used in architectural design.

2. Discuss and summarize traditional and modern architectural design methods and workflow research.

2.1. Retrieval Process

In the first phase of this review, diverse sources of research (conference papers, books, research papers, journal articles, and other literature reviews) are considered. The search terms are defined and expanded according to the article's topic: "AI", "Artificial Intelligence-generated Content (AIGC)", "Parameterization", "Human-machine collaboration", "Building energy consumption", and "Architectural design". The research field covers computer, engineering, environment, energy, and building disciplines. The search syntax is different for different databases. In the databases of Science Direct, Web of science, and Scopus, a fuzzy search was performed using titles and keywords that the literature might use. In the CNKI database, keywords and indexes are used to search.

The study protocol follows the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) Program Guidelines [16], consisting several stages: (a) identifying the publication, (b) screening the publication, (c) assessing the eligibility of the publication against predefined criteria, and (d) conducting a synthesis and meta-analysis. We use inclusion and exclusion criteria in order to select papers to analyze:

1. Research papers on the application of AIGC, machine learning, AI in the fields of parameterization, energy consumption simulation, human–machine collaboration, etc.
2. Exclude papers that study the application of AI in computer, programming, clinical medicine, agriculture, and other fields.
3. This study takes the influence of AI on architectural design efficiency as the main research topic.
4. The study focuses on the feasibility and future potential of the technology to draw conclusions.

2.2. Analysis of Search Results

Shown in Figure 2 is the PRISMA flow chart tracking and summarizing the article selection process. In the first stage, duplicate papers were deleted, leaving 657 papers. In the second phase, articles on programming, medicine, and agronomy were excluded. At the same time, the literature was filtered according to the influence of the source of the article, reducing the count to 366. In the third stage, the development history of AI and architectural design was systematically expounded, and the application of specific AI technology in architectural design was studied in detail, excluding 283 papers, leaving 83 for detailed analysis and review.

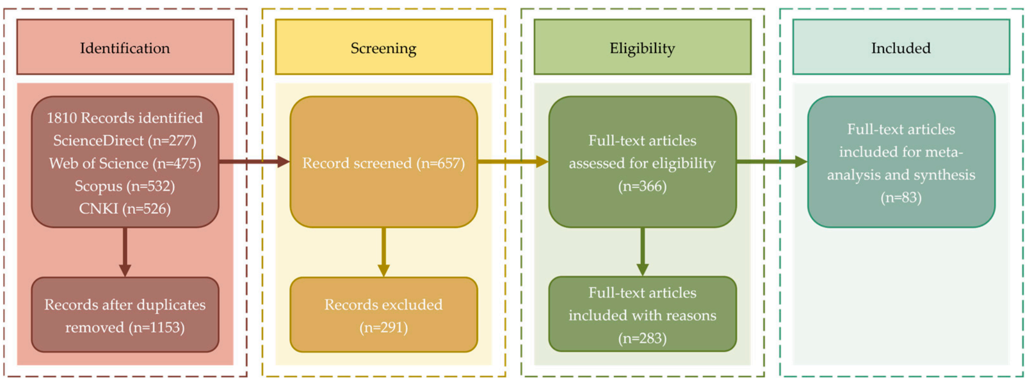

Figure 2. Meta-analysis process.

The 83 articles, classified by year, as shown in Figure 3, reveal that traditional architectural design methods include five parts—"model and theory", "problem", "thinking", "philosophy and ontology", and "tool"—and AI can transform this information into vectorized representations in computer-processable formats, thus greatly improving the processing and generation efficiency. Across all stages—program design, construction, and operation—AI can provide substantial technical support, such as AIGC, artificial neural networks (ANNs), deep neural networks (DNNs), Random Forest (RF), etc.

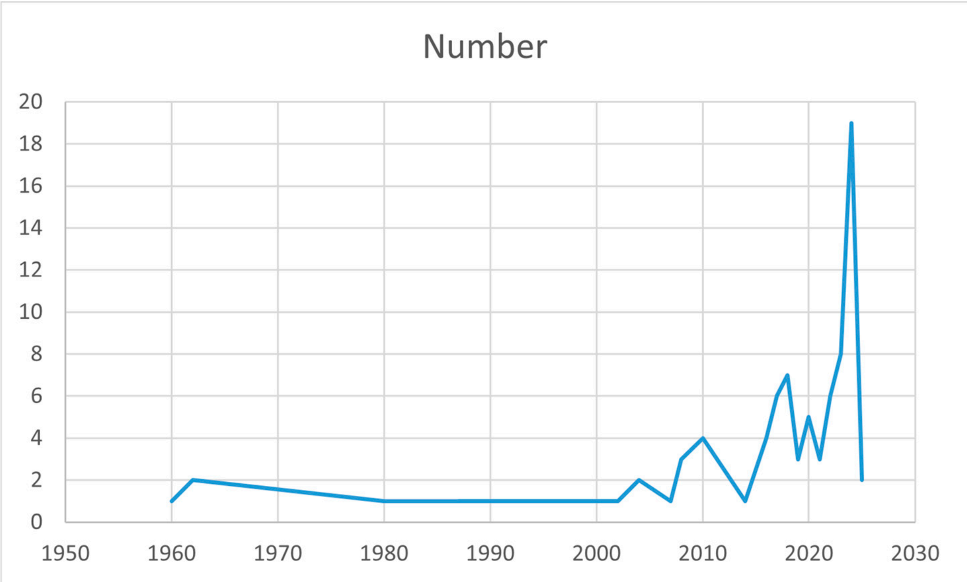

Figure 3. Classification of the literature by year.

3. Overview of AI Technology

3.1. Basic Principles and Key Technologies of AI

AI is a cutting-edge science and technology discipline that extends the application range of technology by simulating human learning and innovation. At the second session of the 14th National People's Congress of China, the concept of "AI+" was recognized as a new quality of productivity, alongside new industrialization, the digital economy, and professional innovation, marking its strategic importance. Driven by this macro policy, integrating AI technology has become an inevitable trend aligned with contemporary needs and innovative development.

AIGC technology utilizes machine learning and natural language processing capabilities [14] to enable computers to simulate human creativity and judgment and automatically produce content that meets requirements [17]. In the field of images, AIGC technology has advanced from passive analysis to automatic generation, and then to composite AI.

3.2. Application of AI in Architectural Design

3.2.1. Design Automation Generation and Optimization

GAI is reshaping architectural design by streamlining processes across various stages. In the conception stage, AI uses genetic algorithms and other technologies to automate site layouts and building plans, which greatly improves the design efficiency. In terms of rendering, advancements in AI improve image and video quality, fostering creative inspiration. In terms of model generation, AI can generate three-dimensional structures by means of parameterization [18]. For instance, platforms like "Construction Drawing Tong" and Professional Knowledge-based Preprocessing & Modelling System (PKPM)-AI Checker automate detailed construction drawings and structural compliance reviews. In addition, AI also facilitates human–computer interaction, parametric design, building performance simulation, and other links [19].

In urban planning, generative design can integrate a variety of key elements, and AI can produce numerous solutions quickly, meeting planning objectives and constraints, greatly improving efficiency and innovation potential. In addition, the simulation capabilities of AI [20–22] also help design teams to explore and evaluate different solutions from multiple perspectives.

In architectural scheme design, the integration of generative design and large language models provides architects with new design tools. Transformer-based language models capture key information in the design description text, enabling natural language input. AI products such as Midjourney and Stable Diffusion can generate high-quality visual images based on text [23], accelerating the realization of creative concepts [24].

In the construction drawing design phase, the application of AI algorithms is revolutionizing design output, inspection, and optimization work.

In the process of building models and drawing construction drawings, intelligent algorithms can extract design information, construction methods, and material usage data from building models and summarize them into a multidimensional database [25]. This not only ensures the floorability of the design, but also improves design quality, ensures feasibility, accurately conveys design intent, and reduces construction change risks.

In the following phase, AI also streamlines construction drawing reviews by identifying and following building codes and guidelines. The intelligent system can quickly identify design problems and track design results in real time, such as material specification deviations, labeling errors, and insufficient red line distance. The introduction of natural language processing (NLP) technology enables precise interpretation of complex guidelines, shortening review cycles, reducing manual effort, and improving design safety and compliance [26–28].

In addition, AI algorithms have further improved parametric design by allowing users to adjust parameters for greater flexibility and diversity while ensuring design consistency and accuracy.

In the creative process of architecture, AI plays a crucial role in improving human–computer interaction (HCI) [29]. With advanced natural language understanding and image recognition, AI algorithms enable design tools to interpret designers' intentions and offer quick recommendations. For example, designers can use voice commands to interact with software to articulate design ideas, while AI can quickly generate a first draft of a design. At the same time, these interactive systems can learn the user's behavior and preferences, and the user interface presents personalized characteristics, ensuring that the user is more direct and efficient.

In the field of parametric design, AI technologies like genetic algorithms (GAs) and ANNs efficiently handle complex rules and parameters, creating both novel and practical design results. AI-assisted parametric design allows designers to explore multiple design possibilities and evaluate the performance of different solutions through simulation, supporting better initial stage decisions.

With the popularity of building information modeling (BIM) technology, AI enhances building performance simulations by analyzing building performance such as energy consumption, sunshine, and lighting and assists designers in continuous optimization of the scheme. In addition, AI also shows great potential in structural performance optimization [30], such as optimizing the structural form of long-span buildings through GAs or predicting stress outcomes with machine learning models.

3.2.2. Building Industrialization and Intelligent Construction

In the application of AI in the field of building industrialization and intelligent construction, data serve as a central driver. In prefabricated buildings, a key aspect of this new construction model lies in effective data application. By combining the strengths of industrialization and modularization, prefabricated buildings not only improve the traditional building process subversively but also enable data-driven decision-making and optimization, advancing intelligence across the entire building lifecycle [31].

At the manufacturing stage, AI algorithms process data into precise instructions. Through big data analysis and machine learning, they enable intelligent production of prefabricated components, optimize cutting routes, refine processes, and enhance quality. In the construction phase, real-time data collection and analysis are pivotal. The intelligent sensor [32] network captures multiple data, transforming it into actionable insights through platform analysis. Intelligent monitoring ensures safety, and predictive analysis adjusts construction plans and resource allocation based on real-time data, demonstrating the efficiency and flexibility of data-driven construction management [33].

3.2.3. Building Energy Consumption Forecast

In building design, predicting energy consumption is a key step in achieving energy efficiency goals and AI has emerged as a research hotspot [34–36]. AI technology excels in analyzing historical data, adapting to environmental changes, and capturing complex nonlinear relationships to estimate energy performance accurately [36,37]. Table 1 illustrates how various AI technologies are applied in predicting building energy consumption.

Table 1. Application of different AI technologies in building energy consumption prediction.

Author	Position	AI Technology Used	Conclusions
Amasyali, K. and El-Gohary, N.M. [34]		Support Vector Machine (SVM) ANN Decision Tree algorithm	Review data-driven building energy consumption prediction, focusing on model scope, data attributes, algorithms, and performance. Emphasize diversity, trade-offs, and growing interest in the field. Future research should target long-term, residential, and lighting energy prediction, improve data availability, and address model limitations to drive progress in the discipline.
Debrah, C., Chan, A.P.C. and Darko, A. [35]		SVM ANN Decision Tree algorithm GA Fuzzy logic and fuzzy sets Convolutional Neural Networks (CNNs)	Provide a comprehensive review of AI applications in green buildings, highlighting research trends and knowledge gaps. Trace the transition from expert systems and fuzzy logic to data mining and intelligent optimization. Future research should focus on integrating AI with emerging technologies, addressing legal and ethical issues, and driving innovation in green buildings.
Li, A. et al. [36]	Hong Kong, China	Recurrent Neural Network (RNN)	Focus on leveraging attention mechanisms to enhance RNN performance for energy consumption prediction, revealing periodic trends and guiding energy management.

Table 1. *Cont.*

Author	Position	AI Technology Used	Conclusions
Seyedzadeh, S. et al. [37]	America Switzerland Germany	RF algorithm Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm	Propose a multi-objective optimization (MOO) method to enhance machine learning models for building energy load prediction, outperforming traditional methods by reducing time complexity and improving accuracy. Highlight the importance of feature selection and model optimization, contributing to energy management research and supporting industry development.
Wong, S.L., Wan, K.K.W. and Lam, T.N.T. [38]	Hong Kong, China	Feedforward Multilayer Perception (MLP) neural networks	Develop an ANN model for energy analysis of office buildings with daylighting systems in subtropical climates. With 9 input variables and 4 power consumption outputs, the model achieves high prediction accuracy, particularly for lighting power. It effectively captures nonlinear relationships, supporting energy-efficient building design.
Milion, R.N., Paliari, J.C. and Liboni, L.H.B. [39]	Brazil	ANN	Propose an ANN-based method for estimating electrical material consumption, outperforming traditional methods in handling multidimensional nonlinear problems and proving suitable for early project stages. Address data limitations by integrating BIM for improved quality, with future potential for applying other algorithms to broader material estimation tasks.
Macas, M. et al. [40]	Italy	ANN	Focus on improving neural network performance in predicting building heating variables. Training sample size and input dimensions significantly affect performance, with overfitting addressed through early stopping. The study suggests refining input selection strategies and enhancing comfort prediction for future improvements.
Ascione, F. et al. [41]	Italy	Feedforward MLP neural networks	Review Transformer-based Generative Adversarial Networks (GANs) in computer vision and introduce a novel approach using ANNs to predict building energy performance and transformation scenarios. The ANN application to office buildings in southern Italy demonstrates high reliability, low error, and a regression coefficient close to 1, supporting energy transformation planning while reducing computational burden. This approach is expected to enhance the widespread adoption of related methods.
Mat Daut, M.A. et al. [42]		SVM ANN ANN/SVM combined with swarm intelligence (SI)	Review building power consumption forecasting methods, highlighting AI's strength in handling nonlinear problems. SVM excels with small samples, while hybrid methods show great potential. The paper emphasizes the importance of input factors in improving prediction accuracy.

Table 1. *Cont.*

Author	Position	AI Technology Used	Conclusions
Olu-Ajayi, R. et al. [43]	Britain	Gradient Boosting (GB) algorithm RF algorithm SVM Decision Tree (DT) algorithm K-nearest Neighbor Algorithm (KNN) Feedforward MLP neural networks	By comparing various machine learning algorithms, the study reveals GB as the most accurate for building energy performance prediction. Feature selection and hyperparameter tuning impact model performance, and while GB excels in accuracy, each algorithm has unique strengths depending on the scenario, offering valuable insights for energy evaluation in building design.
Geyer, P. and Singaravel, S. [44]	Belgium	ANN	Propose a component-based machine learning method to predict building energy performance, validated through testing. It simplifies modeling, provides inter-component information, and expands the design space, but is limited by the range of training data. Future work will explore the link between model effectiveness and training data to handle complex designs.
Pan, Y. et al. [45]	Shanghai, China	DNN	Propose a Deep Reinforcement Learning (DRL)-based multi-objective optimization method for green building design, demonstrating the Deep Deterministic Policy Gradient (DDPG) model's superiority over traditional algorithms in optimization rate, strategy stability, and generalization. Future work will improve the evaluation system to enhance its practicability and address ethical considerations.
Ahmad, M.W., Mourshed, M. and Rezgui, Y. [46]	Spain	ANN RF algorithm	Focus on comparing ANN and RF for predicting hotel HVAC (Heating, Ventilation, and Air Conditioning) energy consumption, finding that ANN is more accurate, while RF has shorter training time and better handling of missing values. Future studies should explore additional algorithms and factors to improve prediction accuracy and energy management.
Deng, H., Fannon, D. and Eckelman, M.J. [47]	America	SVM RF algorithm ANN GB algorithm	Focus on predicting energy consumption in U.S. commercial buildings using multiple algorithms. SVM and RF excel in Total Energy Use Intensity (EUI) prediction, with linear regression showing advantages in some cases. Future work should address performance variations across energy subsystems.
Wang, Z. et al. [48]	America	RF algorithm Regression Tree (RT) algorithm SVR	Focus on using RF to predict hourly building energy consumption, showing superior accuracy and variable sensitivity compared to RT and SVR. It reveals energy factor changes across semesters, offering a new approach for building energy management.

ANN is a common AI technology for predicting building energy consumption [39–41]. A study showed that ANNs demonstrate strong performance in predicting daily electricity use in office buildings and net energy consumption in Turkey. However, ANNs have limitations in adapting to changes in different building components or systems.

In addition to ANNs, SVMs are also considered a powerful data mining technique [42,43]. The application of SVMs in predicting building energy consumption shows good prediction results, though optimizing their parameters remains a challenge.

With advances in computer configuration, the application of deep learning in predicting building energy consumption is also increasing [44]. DNNs significantly improve the accuracy of energy consumption prediction by learning building characteristics [45]. In addition, traditional linear regression (LR) models, RF [46–48], and gradient-boosting models such as XGBoost have all been shown to be effective in predicting the heating and cooling loads of buildings.

More recently, machine learning models based on gene expression have also been developed to predict building shear strength, offering improved accuracy by capturing complex variable relationships, albeit with greater implementation complexity.

3.2.4. Optimize Building Energy Consumption

Energy optimization is a crucial part of building projects, covering strategies ranging from efficient design, intelligent system selection, and operational practices to user behavior modification and renewable energy integration. Central to this process are modern energy-efficient design principles, considering factors such as building orientation, window to wall ratio, insulation of the envelope, efficient HVAC systems, and intelligent control systems connected to the Internet of Things (IoT). According to the International Energy Agency's (IEA) Efficient World Scenario (EWS) and predictions in Energy Efficiency 2019, the building industry is expected to be 40% more energy-efficient by 2040 than in 2017, driven by advancements in technology and policy measures. Specifically, building space heating, water heating, cooking, and lighting will see improved efficiency, while space cooling and appliances will shift from negative growth in 2017 to positive growth by 2040 [9].

To identify optimal solutions, researchers often use software such as DesignBuilder and EnergyPlus for energy simulations, generating and filtering multiple design combinations. For example, Ferrara et al. [49] applied dynamic energy simulation software to optimize residential building energy performance. However, these methods often require long computations and highly detailed information models.

With AI advancements, researchers began to use evolutionary optimization algorithms, such as GA and the Particle Swarm Optimization (PSO) algorithm, to optimize building envelope parameters. Tuhus-Dubrow et al. [50] combined GA and EnergyPlus for residential building optimization. Saryazdi, S. Mohammad et al. [51] combined an ANN model with GA to optimize classical residential design.

Multi-objective evolutionary optimization techniques have been applied to optimize building enclosures. Azari et al. [52] explored energy use and lifecycle environmental impact, and Hosamo et al. [53] utilized NSGAII optimization algorithms to optimize various building elements, such as walls, roofs, floors, and HVAC systems. These studies highlight the potential of evolutionary and intelligent algorithms to address multiple goals and constraints, achieving energy-efficient and cost-effective solutions.

However, such studies often depend on tools, such as Transient System Simulation Tool (TRNSYS) and EnergyPlus, to run repeated energy simulations. These simulations are time-consuming and require detailed parameter settings, which can be impractical during early-stage design adjustments. The integration of multiple repeated simulations into the optimization process adds complexity, especially when managing variable parameters and optimization goals.

Recently, Elbeltagi et al. [54] proposed an integrated optimization approach that combines energy simulation, ANN, and GA to optimize sustainable building design. The results of the study provide valuable information for reducing energy consumption in residential buildings; it focused solely on energy goals, omitted cost considerations, and relied on a single optimization algorithm, without exploring other advanced machine learning algorithms that might improve prediction accuracy.

4. Traditional and Modern Processes of Architectural Design

4.1. Research on Traditional Architectural Design Methods

As early as the 19th century, Violet Le Duc stressed the importance of methodological research in architectural design [55]. In "On Method", he argues that this helps architects apply knowledge, skills, and experience more effectively to practice. About 150 years later, contemporary theorists such as Cross [56] and Negan [57] categorized the evolution of design research into three stages: the origins of design methodology, its progression, and the maturity of design cognition. In China, there are also scholars who have carried out research on this generation [58].

The study of architectural design methods is not a total denial of the previous stage but a supplement and deepening, and the design theory is reconstructed from different perspectives and depths. Based on the research of Shen Kening [59] and Brodpenter [60], design methodology research can be divided into five categories, encompassing both specific design issues and critical reflections on design theory. Through the in-depth analysis of this methodology, the complexity of the design process can be more comprehensively understood and offers more abundant theoretical and practical support for architects.

In architectural design, methodology serves as a key tool for understanding the design process. Christopher [61] first introduced the analytical comprehensive design model, which was further developed by researchers such as Ascher [62] and Asimov [63]. As basic design methods, trial-and-error and generation-test models are often combined with other methods to guide the design process. Case-Based Reasoning (CBR) was proposed by Roger to preserve advanced knowledge by abstracting cases, such as Peirce's concept [64] of icon and Brodpenter's [65] concept of type. Wei et al. [66] combined CBR with machine learning to explore a new path of architectural grammar.

Newell's research [67] provides a theoretical basis and practical guidance for computer-aided architectural design, highlighting the role of information processing in creative work. The problem-space programming model solves complex design problems through Decision Tree optimization. Simon's [68] heuristic method simplifies the problem-solving process to achieve a satisfactory rather than optimal solution, which Perkins [69] describes as effective yet limited. Luo [70] further points out that heuristics include a variety of techniques ranging from explicit decision rules to analogy, similarity, and model building.

In the field of design, problems are presented and solved in various ways. Ascher used clear mathematical or procedural methods to solve the "well defined problem". Christopher points out that the initial stage of design problems is unclear in purpose and means, that is, the "ill-defined problem", common in architecture and urban planning. Simon regards the design problem as an "evil problem" as it characterized by interconnectedness and unclear objectives, and puts forward the hierarchical decomposition method to solve it. Some studies have shown the problem of knowledge and rule consensus in architectural design, involving conflicting goals due to architecture's public nature. This type of problem, termed a "divergence problem", is more complex than an "evil problem". Subsequently, the problems that can be optimally solved by the procedural method of the first-generation design methodology are defined as simple problems, while those that are difficult to decompose are classified as complex problems, which helps us to understand the diversity of design challenges and the complexity of solution strategies.

In the early stage of design method research, the main way to solve problems is to rely on logical reasoning. After the application of information processing methods, scholars at that time used computer algorithms to simulate human brain thinking. During this time, Simon's exploration of rational and intuitive models became significant in understanding complex problem-solving. Since 1980, the study of designer cognitive mechanism has become mainstream, and Chen [71] and Cross [56] delve into its intricacies. The growing use of computers has reshaped traditional cognitive models, as highlighted by discussions in the Symposium on Design Computers and Cognition, enriching the understanding of design thinking and providing new perspectives and methods for design education and practice.

The research of design philosophy and ontology shows that the core of creative activity is problem-solving. Simon views it as a process, and Darke and Hillier stressed its role in forming preliminary plans. With the deepening of the understanding of the problem, problem structuring continues to appear in the design, which helps to clarify the design goals and sub-goals. Design activity is an active process of narrowing the scope of a proposal by setting goals and applying constraints; Lawson distinguishes between external and internal constraints, the former determined by objective conditions and the latter by the experience of the architect. Cross emphasized the unique nature of design and the need to integrate science and art in training designers. Simon proposes that design is an independent body of knowledge alongside technology.

In the study of design tools, Christopher's analysis–synthesis model introduced diagrams to rationalize problem structures. As a tool, the Decision Tree is often used to visualize problem space and knowledge form, while computer technology, especially Computer-Aided Design (CAD), profoundly impacted architectural design. Libich outlined the evolution of CAD, identifying BIM as its advanced stage, first proposed by Isch in 1975 and expanded by Letherin in 2002. The concept of parametric design is derived from Eastman's architectural description system. Brodpenter suggested that assessing computers' strengths and limitations can enhance designers' creative freedom.

4.2. GAI-Driven Architectural Design Workflow

As shown in Figure 4, in the architectural design workflow driven by GAI, the designers first build a computational model or AI keywords according to the design objectives and constraints. GAI generates the design through the model or keywords, iterating to generate numerous variations for evaluation. If the evaluation is passed, the designer combines the AI design to refine the solution and finally integrates it into a complete design, while failed evaluations or improved ideas prompt adjustments to the model or keywords for recalculation.

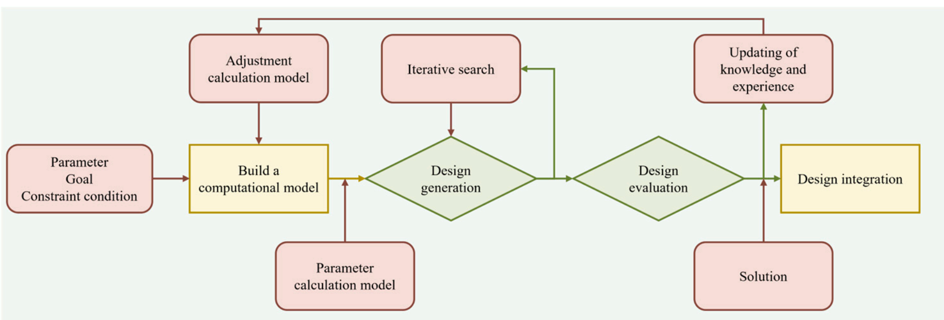

Figure 4. GAI-driven architectural design workflow.

In the pre-analysis phase, shapefile data of the urban space are used to extract building outlines and heights, providing precise geographic and architectural information. These data are then imported into platforms such as Noah or the Rhino and Grasshopper-based solution scheduling mini-program, for initial block arrangement and optimization, ensuring compliance with planning conditions such as floor area ratio and height limits.

Further performance simulations and data analysis ensured that the scheme's daylight, lighting, and wind environment complied with building codes and standards. Through these analyses, the optimal block model can be selected, or adjustments to optimize the design based on the results can be made.

During the conceptual optimization phase, GAI tools such as Midjourney, Stable Diffusion, and Runway generate diverse realistic renderings, offering designers a wide range of visual references and options.

The finalized conceptual scheme uses algorithms and simulations to enhance the structure, components, and building performance to maximize building quality and economic benefits.

As a result, GAI workflows can be applied at different stages of the entire design process, fully reflecting the integration of technology and innovation, which not only enhances efficiency, but also ensures compliance and revolutionizes the architectural design industry.

4.2.1. Quantitative and Qualitative Analysis of AI's Impact on Architectural Design Efficiency and Accuracy

Although limited studies have compared the performance of AI platforms with similar functions, key quantitative metrics like Inception Score (IS) and Fréchet Inception Distance (FID) have emerged as reliable indicators due to their high discriminability and strong correlation with perceptual outcomes. However, while classification-based metrics demonstrate robust discriminability, they often fail to capture the full spectrum of design diversity. Traditional measures such as average log-likelihood have limited utility due to their weak correlation with visual quality and human perception [72,73].

On the qualitative side, human evaluation remains a critical component, despite being subjective and time-consuming. Supplementary methods like nearest neighbor analysis can help identify potential overfitting, but their quantitative comparison capabilities are somewhat constrained [74].

In Nervana's study on AI's role in the design process, platforms such as DALL-E, Midjourney, and Stable Diffusion were compared across various design phases. The study found that DALL-E and Stable Diffusion were more efficient in generating ideations, sketches, and diverse building and style variants than Midjourney, leading to faster concept development. When it comes to accurate representation of construction plans and interior/exterior designs, Stable Diffusion excels in accuracy, closely followed by DALL-E. DALL-E is also effective in handling a wide range of ideation needs, offering strong editing support. Midjourney, while lacking in features like in/out-painting and image combination, is still useful for basic sketches. Stable Diffusion strikes a balance, excelling in both generative design and detailed construction planning.

Despite these valuable insights, the literature remains sparse in comprehensive, real-world comparisons of AI platforms in architectural design. Most available studies provide brief estimations or generalized assessments, leaving a gap in practical guidance for practitioners seeking to implement AI efficiently in their design processes.

4.2.2. Supplement to the Traditional Framework from the Theoretical Point of View of Information

In 1960, Lichridder [75] proposed the concept of "human-machine symbiosis", emphasizing the complementary roles of humans and machines in complex tasks. Norman et al. [76] emphasized the distinction between humans and machines, suggesting that computers could support human innovation. Liu et al. [77] integrated designers and AI in stages in the Double Diamond design process model, emphasizing the importance of information exchange in human–machine collaboration.

Hu Wei et al. [55] proposed a new architectural design framework with information representation as the core, linking environmental data collection, scheme generation, design evaluation, and outcomes. Unlike traditional frameworks, this model integrates AI-extracted information and human architect outputs through algorithms, leveraging AI's computational power and human perceptual strengths.

4.2.3. The Key of Architectural Design Information Processing

Effective information representation is vital for processing architectural design data, involving the organization and description of information. Architectural design information is represented in various forms, including sketches, drawings, models, parameter definitions, code generation, assignment books, and research reports. These representations can be structured, such as vectorized data suitable for computation, or unstructured, such as videos or sketches, which are challenging for computers to interpret.

The core of human–machine collaborative design lies in converting unstructured human representations into vectorized representations. AI facilitates this by structuring unstructured data for computer processing and converting structured data back into human-readable formats.

AI has been widely used in the representation of architectural design information. For example, traditional algorithms such as Principal Component Analysis (PCA) and SVM [78] are capable of data simplification and filtering. Modern algorithms, such as Auto-Encoders (AEs), can be trained to reduce information loss [79] by characterizing raw data into desired dimensions. Vector embedding [80] is another method used to convert high-dimensional discrete data into vector representations, commonly applied in text processing to transform text data into vector groups. Sun and Hu's research [81] combined deep neural networks and vector embedding techniques to process descriptive texts of architectural styles, enhancing human–computer collaboration.

4.2.4. Three Key Elements of Architectural Design

The three key elements of architectural design include environmental information collection, plan generation, and design evaluation.

Building environment information extraction is a foundation in the design process, which involves collecting and screening the information that is essential to building design from the environment. Buildings act as interfaces between internal and external environments, requiring environmental data to shape the design's initial state. The combination of modern sensor technology [82] and AI algorithms makes data collection and analysis more efficient. For example, AI can work with sensors to collect information about human activity patterns, brain wave signals, and social media sentiment, understanding public concerns and preferences.

Plan generation is the creative phase of the design process that generates alternatives based on environmental information and evaluation feedback. AI is increasingly used in this process, including planning algorithms, reinforcement learning, swarm intelligence, and combinatorial variation-based algorithms, helping architects optimize designs. For example, genetic algorithms can optimize the layout of photovoltaic panels on building surfaces to enhance solar energy utilization.

The goal and evaluation of architectural design is the key to ensure that the design meets human needs and expectations. AI aids by optimizing designs for diverse user groups, extracting preferences implicitly, and accelerating evaluations. For example, the use of feedforward neural networks to assess environmental changes and the qualitative assessment of wind environments in architectural buildings through deep neural networks are effective applications of AI in architectural design evaluation.

4.2.5. The Impact of AI on Workflow

In the field of architectural design, AI not only enhances architectural workflows by streamlining information exchange but also significantly improves the efficiency of task organization through advanced computational capabilities.

In terms of information exchange, AI algorithms such as Pix2Pix, developed by a conditional GAN and interactive sketch program based on CNNs, can generate sketches into architectural drawings or models. In combination with VR, architects can fully experience and modify designs in a virtual environment. At the same time, augmented reality and mixed reality technologies build bridges between the real and virtual worlds, further optimizing the way information is exchanged.

In terms of task organization, the decomposition and organization of architectural design tasks are crucial to achieve efficient design processes. AI analyzes information flow by Design Structural Matrix (DSM) and optimizes the complex matrix using heuristic algorithms such as clustering and genetic algorithms, helping to create cohesive task modules, reducing information loss, and improving design efficiency.

4.3. Advantages and Challenges of AI Technology in Architectural Design

AI is widely used in the architectural design industry. It transforms architectural design by automating repetitive tasks like generating documents and construction drawings, which reduces errors, shortens design cycles, and allows designers to focus on creativity. AI-supported project management tools can efficiently allocate resources and schedules to ensure timely completion of projects [83].

AI is outstanding in enhancing design innovation by analyzing vast datasets and cases to inspire designers [84]. It diversifies algorithm-driven and parametric methods, while its simulation capabilities aid in material selection, structural optimization [85], and evaluating energy-saving performance, unlocking new design possibilities.

AI also improves design accuracy, offering precise control over details to optimize building performance and functionality. For example, when designing energy efficiency, it can accurately calculate heat load and light mode, providing customized solutions to improve accuracy and calculation efficiency.

However, AI faces many difficulties in the field of construction. In terms of technology, the quality and quantity of data are the key issues. AI requires high-quality data, but architectural factors are complex, making it difficult to obtain accurate, comprehensive datasets. Algorithm stability and complexity are also concerns, as developing robust algorithms that account for multiple variables is difficult, and unstable outputs may arise. In addition, integration with other technologies is also a problem; architectural design requires a variety of software and tools, and achieving seamless integration of AI with existing technologies to optimize the design process is a challenge.

The use of AI in construction raises ethical concerns, including shifts in designer roles and over-reliance on AI, which may lead to loss of control in the design process. AI generation schemes may raise copyright and intellectual property issues, especially if they resemble existing works. The AI decision-making process is opaque, making it difficult for designers and customers to understand and evaluate its rationality and to determine responsibility when things go wrong. The widespread use of similar AI tools risks homogenizing designs, reducing diversity and innovation.

User acceptance [86] is an important challenge for AI in the construction sector. While some teams embrace AI-driven solutions, some designers worry that the AI-generated solution is not user-friendly and personalized and have doubts about its reliability and stability.

5. Case Studies

5.1. Training of Stable Diffusion and LoRA Models

Stable Diffusion, launched by StabilityAI and academia in 2022, is an advanced AI tool for generating images from text descriptions or reference drawings [24,87]. It is unique in the use of the Low-Rank Adaptation (LoRA) model for natural language processing.

The LoRA model, as a low-rank adjustment method for large language models, allows for behavior modification by adding and training new network layers without changing the parameters of the original model. As a Stable Diffusion plug-in, LoRA can generate images with a specific style using minimal data on the basis of maintaining the model's original feature extraction capabilities, significantly reducing training time and improving accuracy.

As shown in Figure 5, the training process of the LoRA model first needs to prepare the training set and target style images, followed by generating text prompts using WD1.4 tagging. The BooruDatasetTagManager software was used to manually correct the prompt words to clarify the features of removal and retention. The training script then processes the images and prompts, and model performance is optimized using X/Y/ZPlot tools. In the model testing phase, X/Y/ZPlot tools were used to compare and analyze the training parameters to optimize the model performance. The application of the ControNet model and Ultimate plug-in further enable detailed control by incorporating conditions like depth maps and line drawings for more precise image generation. On an ASUS laptop with an RTX 3060 6 GB GPU and an additional 6 GB RAM upgrade, sourced from K-Tronics (Suzhou), Jiangsu Province, China, first-time generation with LoRA can take up to 18 min due to initial model loading, while standard LoRA inference takes approximately 1 min per image after initial loading.

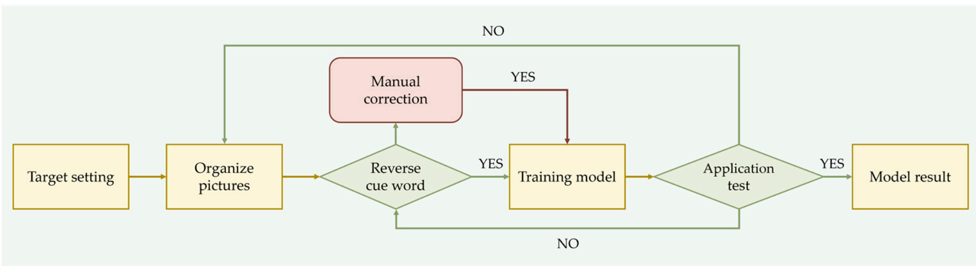

Figure 5. Training process of LoRA model.

5.2. FUGenerator Platform and Interactive Architectural Design Inference

The FUGenerator platform [88] integrates the Diffusion Model, GAN, CLIP (Collaborative Layout Integration Platform), and other algorithm models to support multiple application scenarios from semantic description to sketch generation and control generation. According to the architectural design workflow, the FUGenerator platform fosters collaboration between AI and architects by using a specialized architectural vocabulary library and an interactive interface to enable iterative design optimization.

The FUGenerator platform leverages a Diffusion Model architecture, especially the Stable Diffusion algorithm for semantic to image conversion, Latent Diffusion Models for potential space modeling, and Transformer for encoding semantic information. By representing potential spatial vectors, semantic information is integrated into image generation, enabling the creation of images that align with specific semantics. In addition, the platform can realize image-to-image conversion through image feature combination.

As shown in Figure 6, in terms of interaction mode, FUGenerator adopts the circular strategy of "model reasoning—generation—result optimization—model reasoning". Unlike Midjourney, Stable Diffusion, Dall-E, and other platforms, FUGenerator is designed for architects, facilitating iterative design processes. The platform focuses on workflow efficiency rather than raw generation speed, prioritizing the quality and accuracy of architectural renderings over speed. Users can adjust and optimize generated results semantically, reintroducing AI to refine models and align with architectural workflows. Based on self-evaluation, generation time depends on the complexity of the design and selected parameters, ranging from a few seconds for simple tasks to up to 10 h for medium-scale projects (250 MB to 10 GB) when using high-performance equipment.

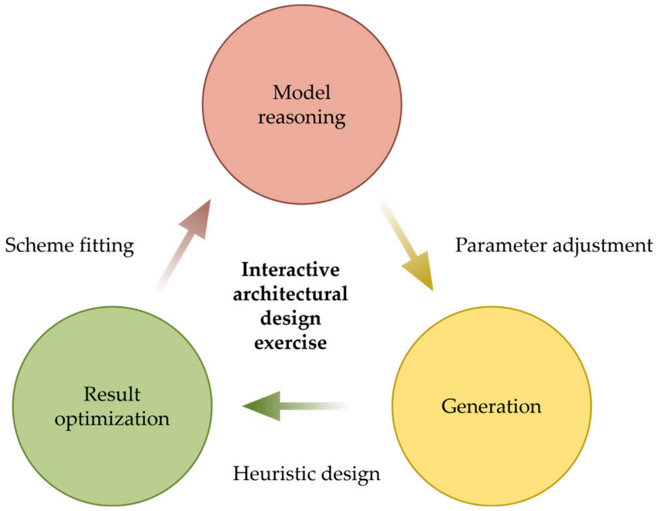

Figure 6. FUGenerator's interactive architectural design inference loop.

6. Future Prospects

With advancements in computing and machine learning, AI is gradually becoming a strong support for the construction field [89]. Future AI will show a higher level of intelligence and greater adaptability. It can predict design outcomes with incredible precision, providing designers with customized solutions. For example, when combined with augmented reality (AR), Virtual Reality (VR) [90], and mixed reality (MR) technologies, AI enables vivid design visualizations, allowing designers and clients to evaluate proposals early, enhancing design quality and client satisfaction [91,92].

Furthermore, the application of AI will extend beyond architectural design into other areas of the construction industry. In construction management, AI-assisted robotic technologies will enhance safety and efficiency by handling high-risk or delicate tasks. During facility operations, AI will monitor building performance, predict maintenance needs, and help extend the life of the building while reducing overall costs. In the realm of market analysis, AI can leverage big data to forecast demand and costs for building materials, optimizing supply chain management processes [93].

7. Conclusions

In conclusion, the integration of AI into the construction industry presents significant opportunities to enhance efficiency, foster innovation, and transform workflows. By automating repetitive tasks, supporting parametric design, and enabling faster, data-driven decision-making, AI has been proven to optimize building performance and streamline design processes. Its application also inspires creative solutions through advanced data analysis and algorithm-driven methods, while contributing to material selection, structural optimization, and energy efficiency. Furthermore, AI extends beyond the design phase, playing a vital role in project forecasting, construction monitoring, and lifecycle management.

However, challenges remain in achieving the widespread adoption of AI technologies. High costs and the limited availability of AI-compatible hardware and software hinder accessibility for many professionals. Future technological advancements should focus on improving software performance and reducing costs to encourage broader usage. Efforts should also aim at improving data quality, building comprehensive databases, and developing robust algorithms that address the complexity of architectural design.

A notable gap in the current research landscape is the lack of comprehensive studies and detailed case analyses that document the progress and practical applications of AI in architecture. Many existing resources provide only brief estimations, leaving practitioners with little guidance on efficiently applying AI technologies. This lack of in-depth research often results in additional time spent experimenting with various AI tools, which is not ideal for optimizing efficiency. To address this, there is a need for clearer task division across different sectors of architectural design, ensuring that AI tools are appropriately matched to specific tasks and user needs.

Over-reliance on AI is another concern, as it could lead to the homogenization of designs driven solely by efficiency. It is crucial to define the collaborative roles of architects and AI to preserve creativity and diversity in architectural outcomes. Policymakers and industry leaders must establish clear legal frameworks and policies, particularly concerning intellectual property, to safeguard originality and innovation.

With the right guidance and regulation, AI is poised to drive continuous progress in architectural design and construction. Its ability to enhance creativity and improve processes ensures a dynamic and innovative future for the built environment.

Author Contributions: Conceptualization, P.Y. and L.Y.; methodology, Y.L. and H.C.; software, Y.L. and H.C.; formal analysis, Y.L. and H.C.; investigation, Y.L. and H.C.; resources, P.Y. and L.Y.; data curation, P.Y. and L.Y.; writing—original draft preparation, Y.L. and H.C.; writing—review and editing, P.Y. and L.Y.; visualization, Y.L. and H.C.; supervision, P.Y. and L.Y.; project administration, P.Y. and L.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

AI	Artificial Intelligence
GAI	Generative Artificial Intelligence
CNKI	China National Knowledge Network
AIGC	Artificial Intelligence-generated Content
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
ANN	artificial neural network
DNN	deep neural networks
RF	Random Forest
PKPM	Professional Knowledge-based Preprocessing & Modelling System
NLP	natural language processing
HCI	human–computer interaction
GA	genetic algorithm
BIM	building information modeling
SVM	Support Vector Machine

CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
MOO	multi-objective optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm II
MLP	Feedforward Multilayer Perception
GANs	Generative Adversarial Networks
CAD	Computer-Aided Design
SI	swarm intelligence
GB	Gradient Boosting
DT	Decision Tree
KNN	K-nearest Neighbor Algorithm
DRL	Deep Reinforcement Learning
DDPG	Deep Deterministic Policy Gradient
HVAC	Heating, Ventilation, and Air Conditioning
EUI	Energy Use Intensity
RT	Regression Tree
LR	linear regression
LoT	Internet of Things
IEA	International Energy Agency
EWS	Efficient World Scenario
PSO	Particle Swarm Optimization
TRNSYS	Transient System Simulation Tool
CBR	Case-Based Reasoning
PCA	Principal Component Analysis
AE	Auto-Encoders
DSM	Design Structural Matrix
LoRA	Low-Rank Adaptation
CLIP	Collaborative Layout Integration Platform
AR	augmented reality
VR	Virtual Reality
MR	mixed reality

References

1. Papandrea, M.; Peternier, A.; Frei, D.; La Porta, N.; Gelsomini, M.; Allegri, D.; Leidi, T. V-Cockpit: A Platform for the Design, Testing, and Validation of Car Infotainment Systems through Virtual Reality. *Appl. Sci.* **2024**, *14*, 8160. [CrossRef]
2. Xu, K.; Chen, Z.; Xiao, F.; Zhang, J.; Zhang, H.B.; Ma, T.Y. Semantic model-based large-scale deployment of AI-Driven Building Management Applications. *Autom. Constr.* **2024**, *165*, 105579. [CrossRef]
3. Chen, Z.L.; O'Neill, Z.; Wen, J.; Pradhan, O.; Yang, T.; Lu, X.; Lin, G.J.; Miyata, S.H.; Lee, S.J.; Shen, C.; et al. A review of data-driven fault detection and diagnostics for building HVAC systems. *Appl. Energy* **2023**, *339*, 121030. [CrossRef]
4. Qian, F. The potential of a retractable roof of the natatorium on the indoor environmental improvement: Taking Jiading natatorium of Tongji University as an example. *Indoor Built Environ.* **2023**, *32*, 1505–1515. [CrossRef]
5. Abumalloh, R.A.; Nilashi, M.; Ooi, K.B.; Tan, G.W.H.; Chan, H.K. Impact of generative artificial intelligence models on the performance of citizen data scientists in retail firms. *Comput. Ind.* **2024**, *161*, 104128. [CrossRef]
6. Gradišar, L.; Dolenc, M.; Klinc, R. Towards machine learned generative design. *Autom. Constr.* **2024**, *159*, 105284. [CrossRef]
7. Ding, Z.K.; Fan, Z.; Tam, V.W.Y.; Bian, Y.; Li, S.H.; Illankoon, I.M.C.S.; Moon, S.K. Green Building Evaluation System Implementation. *Build. Environ.* **2018**, *133*, 32–40. [CrossRef]
8. Li, Y.; Chen, L. A study on database of modular façade retrofitting building envelope. *Energy Build.* **2020**, *214*, 109826. [CrossRef]
9. Asif, M.; Naeem, G.; Khalid, M. Digitalization for sustainable buildings: Technologies, applications, potential, and challenges. *J. Clean. Prod.* **2024**, *450*, 141814. [CrossRef]
10. Sun, D.C.; Xu, J.H.; Zhao, J.J.; Zhang, D.F.; Chen, K.M. Study on a new model for urban residential quarter of 21st century. *J. Shanghai Sci. Technol.* **2000**, *22*, 347–351. [CrossRef]
11. Wang, X.; Pan, Y.; Chen, J. Digital twin with data-mechanism-fused model for smart excavation management. *Autom. Constr.* **2024**, *168*, 105749. [CrossRef]

12. NCARB's Position on the Use of Artificial Intelligence in the Architectural Profession. Available online: https://www.ncarb.org/press/ncarb-position-on-ai (accessed on 26 January 2025).
13. Novelli, C.; Casolari, F.; Hacker, P.; Spedicato, G.; Floridi, L. Generative AI in EU law: Liability, privacy, intellectual property, and cybersecurity. *Comput. Law Secur. Rev.* **2024**, *55*, 106066. [CrossRef]
14. McIntosh, T.R.; Susnjak, T.; Liu, T.; Watters, R.; Xu, D.; Liu, D.W.; Nowrozy, R.; Halgamuge, M.N. From COBIT to ISO 42001: Evaluating cybersecurity frameworks for opportunities, risks, and regulatory compliance in commercializing large language models. *Comput. Secur.* **2024**, *144*, 103964. [CrossRef]
15. Lu, W.S.; Wu, L.P.F. A blockchain-based deployment framework for protecting building design intellectual property rights in collaborative digital environments. *Comput. Ind.* **2024**, *159–160*, 104098. [CrossRef]
16. Liberati, A.; Altman, D.G.; Tetzlaff, J.; Mulrow, C.; Gøtzsche, P.C.; Ioannidis, J.P.A.; Clarke, M.; Devereaux, P.J.; Kleijnen, J.; Moher, D. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *J. Clin. Epidemiol.* **2009**, *62*, 1–34. [CrossRef]
17. Seyedzadeh, S.; Rahimian, F.P.; Rastogi, P.; Glesk, I. Tuning machine learning models for prediction of building energy loads. *Sustain. Cities Soc.* **2019**, *47*, 101484. [CrossRef]
18. Wang, C.; Liu, Y.Y.; Guo, T.Z.; Li, D.P.; He, T.; Li, Z.; Yang, Q.W.; Wang, H.H.; Wen, Y.Y. Systems engineering issues for industry applications of large language model. *Appl. Soft Comput.* **2024**, *151*, 111165. [CrossRef]
19. Oxman, R. Thinking difference: Theories and models of parametric design thinking. *Des. Stud.* **2017**, *52*, 4–39. [CrossRef]
20. Hou, D. Conditional generative adversarial networks for image-based sunlight analysis of residential blocks. *Energy Build.* **2024**, *316*, 114295. [CrossRef]
21. Milla-Val, J.; Montañés, C.; Fueyo, N. Adversarial image-to-image model to obtain highly detailed wind fields from mesoscale simulations in urban environments. *Build. Environ.* **2024**, *266*, 112123. [CrossRef]
22. Lam, B.; Ong, Z.T.; Ooi, K.; Ong, W.H.; Wang, T.; Watcharasupat, K.N.; Boey, V.; Lee, I.; Hong, J.Y.; Kang, J.; et al. Automating urban soundscape enhancements with AI: In-situ assessment of quality and restorativeness in traffic-exposed residential areas. *Build. Environ.* **2024**, *266*, 112106. [CrossRef]
23. Belhadi, A.; Djenouri, Y.; Belbachir, A.N.; Mihalak, T.; Srivastava, G. Shapley Visual Transformers for Image-to-text generation. *Appl. Soft Comput.* **2024**, *166*, 112205. [CrossRef]
24. Hanafy, N.O. Artificial Intelligence's effects on design process creativity: "A study on used A.I. Text-to-image in architecture". *J. Build. Eng.* **2023**, *80*, 107999. [CrossRef]
25. Nik-Bakht, M.; El-Diraby, T. Project collective mind: Unlocking project discussion networks. *Autom. Constr.* **2017**, *84*, 50–69. [CrossRef]
26. Kazemi, M.H.; Alvanchi, A. Application of NLP-based models in automated detection of risky contract statements written in complex script system. *Expert Syst. Appl.* **2025**, *259*, 125296. [CrossRef]
27. Jung, N.; Lee, G. Automated Classification of Building Information Modeling (BIM) case studies by BIM use based on Natural Language Processing (NLP) and unsupervised learning. *Adv. Eng. Inform.* **2019**, *41*, 100917. [CrossRef]
28. Ding, Y.; Ma, J.; Luo, X. Applications of natural language processing in construction. *Autom. Constr.* **2022**, *136*, 104169. [CrossRef]
29. Qu, J.; Bu, L.G.; Zhao, L.; Wang, Y.H. A training and assessment system for human-computer interaction combining fNIRS and eye-tracking data. *Adv. Eng. Inform.* **2024**, *62*, 102765. [CrossRef]
30. He, Z.; Wang, Y.-H.; Zhang, J. Generative AIBIM: An automatic and intelligent structural design pipeline integrating BIM and Generative AI. *Inf. Fusion* **2025**, *114*, 102654. [CrossRef]
31. Zhu, M.Y.; Wang, Y.; Liu, R.; Fan, L.R. Stackelberg game-based method towards carbon-economy equilibrium for the prefabricated construction supply planning: A case study from China. *Sustain. Cities Soc.* **2024**, *106*, 105356. [CrossRef]
32. Yi, W.; Chan, A.P.C.; Wang, X.Y.; Wang, J. Development of an early-warning system for site work in hot and Humid Environments: A case study. *Autom. Constr.* **2016**, *62*, 101–113. [CrossRef]
33. Liu, Z.B.; Li, L.; Fang, X.L.; Qi, W.B.; Shen, J.M.; Zhou, H.Y.; Zhang, Y.L. Hard-rock tunnel lithology prediction with TBM construction big data using a global-attention-mechanism-based LSTM network. *Autom. Constr.* **2021**, *125*, 103647. [CrossRef]
34. Amasyali, K.; El-Gohary, N.M. A review of data-driven building energy consumption prediction studies. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1192–1205. [CrossRef]
35. Debrah, C.; Chan, A.P.C.; Darko, A. Artificial Intelligence in green building. *Autom. Constr.* **2022**, *137*, 104192. [CrossRef]
36. Li, A.; Fu, X.; Chong, Z.; Cheng, F. Attention-based interpretable neural network for building cooling load prediction. *Appl. Energy* **2021**, *299*, 117238. [CrossRef]
37. Seyedzadeh, S.; Rahimian, F.P.; Oliver, S.; Glesk, I.; Kumar, B. Data driven model improved by multi-objective optimisation for prediction of Building Energy Loads. *Autom. Constr.* **2020**, *116*, 103188. [CrossRef]
38. Wong, S.L.; Wan, K.K.W.; Lam, T.N.T. Artificial Neural Networks for energy analysis of office buildings with daylighting. *Appl. Energy* **2010**, *87*, 551–557. [CrossRef]

39. Milion, R.N.; Paliari, J.C.; Liboni, L.H.B. Improving consumption estimation of electrical materials in residential building construction. *Autom. Constr.* **2016**, *72*, 93–101. [CrossRef]
40. Macas, M.; Moretti, F.; Fonti, A.; Giantomassi, A.; Comodi, G.; Annunziato, M.; Pizzuti, S.; Capra, A. The role of data sample size and dimensionality in neural network based forecasting of building heating related variables. *Energy Build.* **2016**, *111*, 299–310. [CrossRef]
41. Ascione, F.; Bianco, N.; Stasio, C.D.; Mauro, G.M.; Vanoli, G.P. Artificial neural networks to predict energy performance and retrofit scenarios for any member of a building category: A novel approach. *Energy* **2017**, *118*, 999–1017. [CrossRef]
42. Mat Daut, M.A.; Hassan, M.Y.; Abdullah, H.; Rahman, H.A.; Abdullah, M.P.; Hussin, F. Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A Review. *Renew. Sustain. Energy Rev.* **2017**, *70*, 1108–1118. [CrossRef]
43. Olu-Ajayi, R.; Alaka, H.; Sulaiman, I.; Sunmola, F.; Ajayi, S. Machine Learning for Energy Performance Prediction at the design stage of buildings. *Energy Sustain. Dev.* **2022**, *66*, 12–25. [CrossRef]
44. Geyer, P.; Singaravel, S. Component-based machine learning for performance prediction in Building Design. *Appl. Energy* **2018**, *228*, 1439–1453. [CrossRef]
45. Pan, Y.; Shen, Y.X.; Qin, J.J.; Zhang, L.M. Deep reinforcement learning for multi-objective optimization in BIM-based green building design. *Autom. Constr.* **2024**, *166*, 105598. [CrossRef]
46. Ahmad, M.W.; Mourshed, M.; Rezgui, Y. Trees vs neurons: Comparison between random forest and ann for high-resolution prediction of Building Energy Consumption. *Energy Build.* **2017**, *147*, 77–89. [CrossRef]
47. Deng, H.; Fannon, D.; Eckelman, M.J. Predictive modeling for US commercial building energy use: A comparison of existing statistical and machine learning algorithms using CBECS microdata. *Energy Build.* **2018**, *163*, 34–43. [CrossRef]
48. Wang, Z.; Wang, T.; Zeng, R.; Srinivasan, R.S.; Ahrentzen, S. Random Forest based hourly building energy prediction. *Energy Build.* **2018**, *171*, 11–25. [CrossRef]
49. Ferrara, M.; Rolfo, A.; Prunotto, F.; Fabrizio, E. EDESSOPT—Energy demand and supply simultaneous optimization for cost-optimized design: Application to a multi-family building. *Appl. Energy* **2019**, *236*, 1231–1248. [CrossRef]
50. Tuhus-Dubrow, D.; Krarti, M. Genetic-algorithm based approach to optimize building envelope design for residential buildings. *Build. Environ.* **2010**, *45*, 1574–1581. [CrossRef]
51. Saryazdi, S.; Etemad, A.; Shafaat, A.; Bahman, A.M. Data-driven performance analysis of a residential building applying Artificial Neural Network (ANN) and multi-objective Genetic Algorithm (GA). *Build. Environ.* **2022**, *225*, 109633. [CrossRef]
52. Azari, R.; Garshasbi, S.; Amini, P.; Rashed-Ali, H.; Mohammadi, Y. Multi-objective optimization of Building Envelope Design for life cycle environmental performance. *Energy Build.* **2016**, *126*, 524–534. [CrossRef]
53. Hosamo, H.H.; Tingstveit, M.S.; Nielsen, H.K.; Svennevig, P.R.; Svidt, K. Multiobjective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II. *Energy Build.* **2022**, *277*, 112479. [CrossRef]
54. Elbeltagi, E.; Wefki, H.; Abdrabou, S.; Dawood, M.; Ramzy, A. Visualized strategy for predicting buildings energy consumption during early design stage using parametric analysis. *J. Build. Eng.* **2017**, *13*, 127–136. [CrossRef]
55. Hu, W.; Sun, C.Y.; Zhang, D.D. Architectural Design Framework with the Participation of Artificial Intelligence. *New Archit.* **2023**, *3*, 50–56. [CrossRef]
56. Cross, N. Forty Years of Design Research. *Des. Stud.* **2007**, *28*, 1–4. [CrossRef]
57. Bayazit, N. Investigating design: A review of Forty Years of Design research. *Des. Issues* **2004**, *20*, 16–29. [CrossRef]
58. Zhao, J. Design and Design Approach Research within 40 Years. *Art Des.* **2008**, *09*, 44–47. [CrossRef]
59. Shen, K. Introduction to Research on Design Methodology. *Archit. J.* **1987**, *03*, 64–66.
60. Broadbest, G. *Architectural Design and Humanities*; China Architecture & Building Press: Beijing, China, 1990; pp. 27–75.
61. Alexander, C. *Notes on the Synthesis of Form*; Huazhong University of Science & Technology Press: Wuhan, China, 2010; pp. 28–53.
62. Wang, T. Methodology of Modern Architectural Design. *World Archit.* **1980**, *02*, 3–5. [CrossRef]
63. Asimow, M. *Introduction to Design*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1962; pp. 32–60.
64. Peirce, C.S.; Liszka, J.J. *C.S. Peirce: On Signs*; Sichuan University Press: Chengdu, China, 2014; pp. 76–90.
65. Broadbent, G. *Sign, Symbols, and Architecture*; China Architecture & Building Press: Beijing, China, 1991; pp. 89–135.
66. Wei, L. Architectural Digital History: Artificial Intelligent Oriented Archeology of Architectural Big Data. *Archit. J.* **2020**, *2*, 79–85. [CrossRef]
67. Newell, A. *The Processes of Creative Thinking*; Atherton Press: New York, NY, USA, 1962; pp. 64–94.
68. Simon, H. *The Science of Artificial*; Shanghai Science and Technology Education Press: Shanghai, China, 2004; pp. 97–125.
69. Perkins, D.N. *The Mind's Best Work*; Harvard University Press: Cambridge, MA, USA, 2010; pp. 24–43.
70. Lorre, P.G. *Design Thinking*; Tianjin University Press: Tianjin, China, 2008; pp. 58–90.
71. Chen, C. *Design Cognition*; China Architecture & Building Press: Beijing, China, 2008; pp. 86–130.
72. Borji, A. Pros and cons of GAN evaluation measures. *Comput. Vis. Image Underst.* **2019**, *179*, 41–65. [CrossRef]

73. Borji, A. Pros and cons of GAN evaluation measures: New developments. *Comput. Vis. Image Underst.* **2022**, *215*, 103329. [CrossRef]
74. Nguyen, T.T.; Nguyen, Q.V.H.; Nguyen, D.T.; Nguyen, D.T.; Huynh-The, T.; Nahavandi, S.; Nguyen, T.T.; Pham, Q.; Nguyen, C.M. Deep learning for deepfakes creation and detection: A survey. *Comput. Vis. Image Underst.* **2022**, *223*, 103525. [CrossRef]
75. Licklider, J.C. Man-Computer Symbiosis. *IRE Trans. Hum. Factors Electron.* **1960**, *HFE-1*, 4–11. [CrossRef]
76. Norman, D.A. *Things That Make Us Smart: Defending Human Attributes in the Age of the Machine*; Perseus Books; Addison Wesley Longman Publishing Co.: Boston, MA, USA, 1993; pp. 26–73.
77. Liu, J.; Nah, K. Design collaboration mode of man–computer symbiosis in the age of Intelligence. *Adv. Intell. Syst. Comput.* **2020**, *1131*, 640–645. [CrossRef]
78. Steele, J. *Architecture and Computers: Action and Reaction in the Digital Design Revolution*; Watson-Guptill Publications: New York, NY, USA, 2002; pp. 38–97.
79. Yuan, D.C.; Shi, Y.X.; Gao, J.N. Performance Improvement of Hourly Heating-Energy Consumption Prediction Model Based on Feature Extraction with Sparse Auto-Encoder. *Build. Sci.* **2020**, *36*, 1–6. [CrossRef]
80. Hegde, T.; Sanjay, K.S.; Thomas, S.M.; Kambhammettu, R.; Kumar, M.A.; Ramanna, S. Impact of vector embeddings on the performance of tolerance near sets-based sentiment classifier for text classification. *Procedia Comput. Sci.* **2023**, *225*, 645–654. [CrossRef]
81. Sun, C.; Hu, W. Preliminary Study on the Research Methods of Architectural Style Form Features from the Perspective of Machine Learning. *Urban. Archit.* **2021**, *18*, 104–111. [CrossRef]
82. Kučera, A.; Pitner, T. Semantic BMS: Allowing usage of building automation data in facility benchmarking. *Adv. Eng. Inform.* **2018**, *35*, 69–84. [CrossRef]
83. Li, L.X.; Liu, Y.Q.; Jin, Y.; Cheng, T.C.E.; Zhang, Q.J. Generative AI-Enabled Supply Chain Management: The critical role of coordination and dynamism. *Int. J. Prod. Econ.* **2024**, *277*, 109388. [CrossRef]
84. Singaravel, S.; Suykens, J.; Geyer, P. Deep-learning neural-network architectures and methods: Using component-based models in building-design energy prediction. *Adv. Eng. Inform.* **2018**, *38*, 81–90. [CrossRef]
85. Barhemat, R.; Mahjoubi, S.; Meng, W.N.; Bao, Y. Automated design of architectured polymer-concrete composites with high specific flexural strength and toughness using sequential learning. *Constr. Build. Mater.* **2024**, *449*, 138311. [CrossRef]
86. Wei, L. Application of Deep Learning based Artificial Intelligence in Architectural Scheme Creation. *Ceramics* **2024**, *7*, 170–172. [CrossRef]
87. Li, J.Y.; Zhao, H.Y.; Wu, J.Y.; Dai, S.Y.; Xu, H.H. Discussion and Exploration of Rural Small Building Design Based on AI-assisted Architectural Design Technology Taking Stable Diffusion as an Example. In Proceedings of the 2023 National Symposium on Teaching and Research of Building Digital Technology in Architecture Department, Changsha, China, 14 October 2023. [CrossRef]
88. Gu, S.J.; Wang, R.X.; Wu, Y.F.; Xu, X.H.; Yan, C.; Gao, T.Y.; Yuan, F. Exploration of AI- inspired Architectural Design Generation Process Based on FUGenerator Platform. In Proceedings of the 2023 National Symposium on Teaching and Research of Building Digital Technology in Architecture Department, Changsha, China, 14 October 2023. [CrossRef]
89. Li, Y. "Will artificial intelligence platforms replace designers in the future?" analyzing the impact of artificial intelligence platforms on the engineering design industry through color perception. *Eng. Appl. Artif. Intell.* **2024**, *138*, 109369. [CrossRef]
90. Zhang, Y.X.; Liu, H.X.; Kang, S.C.; Al-Hussein, M. Virtual reality applications for the built environment: Research trends and opportunities. *Autom. Constr.* **2020**, *118*, 103311. [CrossRef]
91. Chen, X.X.; Gao, W.Z.; Chu, Y.N.; Song, Y.H. Enhancing interaction in virtual-real architectural environments: A comparative analysis of generative AI-driven reality approaches. *Build. Environ.* **2024**, *266*, 112113. [CrossRef]
92. Lyu, K.; Brambilla, A.; Globa, A.; Dear, R.D. An immersive multisensory virtual reality approach to the study of human-built environment interactions. *Autom. Constr.* **2023**, *150*, 104836. [CrossRef]
93. Tuzov, V.; Lin, F. Two paths of balancing technology and ethics: A comparative study on AI governance in China and Germany. *Telecommun. Policy* **2024**, *in press*. [CrossRef]