

Article

# How Architectural Design and Utility Infrastructure Impacts AI Supporting Campus and Drive Future Innovation, Operational Efficiency and Sustainable Advancement in Utility-Critical Environment

Qiyuan Liang <sup>1,\*</sup><sup>1</sup> HGA Architects and Engineer, San Jose, United States

\* Correspondence: Qiyuan Liang, HGA Architects and Engineer, San Jose, United States

**Abstract:** The construction of artificial intelligence-supported parks is rapidly driving the fundamental transformation of public building service facilities and utility infrastructure from a traditional, single-purpose configuration toward a highly comprehensive and coordinated development paradigm. Based on the strategic spatial planning layout of the campus, the optimized deployment of energy and water support facilities, the seamless connection of transportation and communication networks, and the advanced application of key technological facilities, the complex spatial coupling relationship between architectural design construction and public building service infrastructure tools is rigorously analyzed and studied. Furthermore, the profound value reconfiguration brought by artificial intelligence for the aforementioned collaborative model is systematically clarified. The critical dimensions of spatial elasticity, facility elasticity, dynamic system linkage, intelligent resource allocation, robust disaster recovery, and green low-carbon sustainability proposed in this comprehensive study are precisely the paramount factors influencing the future innovation capacity, operational efficiency, and overall development level of the modern utility-critical environment. The specific technical paths proposed herein, such as constructing a centralized big data center, utilizing sophisticated AI models to promote seamless facility collaboration, conducting adaptive elastic control strategies for critically important facilities, and ensuring high-resilience operation in critical contexts, provide essential strategic directions for the architectural design concept and infrastructure integration development of future artificial intelligence-supported parks.

**Keywords:** artificial intelligence; architectural design; utility infrastructure; coordinated development; operational efficiency; sustainable advancement

Received: 14 March 2026

Revised: 02 May 2026

Accepted: 15 May 2026

Published: 19 May 2026



**Copyright:** © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

Industrial parks serve as critical spatial frameworks for fostering industrial concentration, driving technological innovation, and supporting manufacturing services alongside public infrastructure [1, 2]. These parks necessitate meticulous planning and harmonized arrangements for public facilities to ensure optimal functionality. Historically, the design of such parks has often been fragmented, with individual components like buildings, road networks, and power systems being planned in isolation. This disjointed approach can result in poor coordination across spatial layouts, facility capacities, operational controls, and maintenance strategies. However, advancements in artificial intelligence technology offer transformative potential to address these challenges. AI can significantly enhance the optimization of building structures, accurately estimate facility capacities, streamline energy distribution, detect hazards, and improve environmental management practices within these parks. Given the intrinsic link between architectural design and public infrastructure, it is imperative to evaluate their combined

impact on fostering future technological advancements, improving operational efficiency, and promoting sustainable development. Such analyses hold substantial practical value for guiding real-world projects in critical industrial environments.

## **2. The Collaborative Relationship between Architectural Design and Public Facilities Infrastructure in Artificial Intelligence-Powered Industrial Parks**

### *2.1. Spatial Coupling between Architectural Design and Public Facilities Infrastructure*

In an artificial intelligence-supported industrial park, public infrastructure operates as an interconnected system, forming an organic spatial relationship through elements such as land use layout, zoning design, road traffic, pipeline installation, and power supply. The dimensions of building volumes, spacing between structures, basement depths, pedestrian pathways, and vehicular traffic patterns significantly influence the arrangement of water supply, drainage systems, telecommunications networks, HVAC systems, fire protection measures, and comprehensive pipe trenches. If the spatial configuration of buildings fails to account for the capacity and requirements of these facilities during the planning phase, it can result in operational conflicts, reduced efficiency in facility utilization, restricted access for maintenance, or increased energy consumption. By leveraging advanced technologies such as Building Information Modeling (BIM), Geographic Information Systems (GIS), and the Internet of Things (IoT), planners can identify and address constraints between the physical design of buildings, the configuration of facilities, and the operational and maintenance needs. This integration enables a more precise and accurate design process for the entire park space, ensuring optimal functionality and sustainability [1, 3]. Furthermore, such technological synergy facilitates predictive analysis, allowing for proactive adjustments to spatial layouts and infrastructure planning to meet future demands effectively.

### *2.2. The Reconfiguration of the Building-Facility Synergy Model by Artificial Intelligence*

Under the architecture-facility collaboration model, the primary value of artificial intelligence (AI) lies in facilitating the transition from traditional experience-based approaches to advanced data-driven analysis, and from static, pre-defined designs to dynamic, adaptive optimization. By employing machine learning algorithms, generative design techniques, and multi-objective optimization methods, comprehensive modeling can be achieved for critical aspects such as the functional layout of the park, equipment capacity, load distribution, human traffic patterns, and operational and maintenance costs. These models enable a more precise and efficient approach to planning and managing facilities. Leveraging foundational public infrastructure, technologies such as sensors, edge computing, and digital twins can be integrated to monitor facility operations in real time. This allows for the rapid detection of faults, predictive maintenance, and optimized scheduling, ensuring that facilities operate in their most efficient state. The continuous interaction and feedback loop between design parameters and operational data enable dynamic adjustments to layouts, equipment configurations, and maintenance strategies [4]. This iterative process enhances technological innovation, operational efficiency, energy conservation, and environmental sustainability within the park, ultimately fostering a more synergistic and sustainable development model.

## **3. The Comprehensive Impact of Architectural Design and Public Facilities Infrastructure on the Development of the Park**

### *3.1. The Impact of Spatial Elasticity and Facility Adaptation on Future Innovation*

The adaptability of facilities and the level of spatial elasticity play a crucial role in shaping the future industrial development patterns, technological advancements, and functional evolution of the park. These parks are often characterized by dynamic and multifaceted functionalities, including research and development offices, intelligent manufacturing facilities, experimental testing zones, data analysis centers, and interactive display and experience areas. When the structural design of buildings incorporates features such as adjustable spatial layouts, expandable floor heights, elastic load capacities,

modular electrical connection points, and mixed shared areas, it significantly reduces the costs associated with later-stage functional transformations [4, 5]. This adaptability also accelerates the integration and promotion of innovative activities within the park. Furthermore, the infrastructure supporting public facilities has a direct impact on the timely implementation of innovation projects. For instance, high power loads, stable temperature control systems, large-scale communication networks, flexible water and drainage interfaces, and comprehensive manhole configurations are essential to meet the operational demands of high-energy-consuming equipment, intelligent manufacturing lines, data centers, and information platforms. When building spaces and facility systems are designed to work in close synergy, the park is better positioned to foster the emergence of new business models, innovative economic development patterns, and interconnected industrial development chains. This integrated approach ensures that the park remains adaptable and competitive in a rapidly evolving technological landscape.

### *3.2. The Impact of System Interconnection and Capacity Matching on Operational Efficiency*

From the perspectives of system coordination and system load capacity ratio, the operational efficiency of the park is influenced by factors such as resource allocation capability, load response capability, and the level of regulation refinement during its operation. Once the park becomes operational, the energy consumption demands, peak water usage, start-stop frequencies, and behavioral patterns of various buildings will experience significant shifts. If facilities continue to operate based on fixed thresholds, certain locations may experience excessively high loads, while other machines may operate inefficiently for prolonged periods, thereby diminishing the overall economic efficiency of the facilities. To address these challenges, AI prediction models can be utilized to analyze parameters such as energy consumption paths, machine health, weather conditions, and usage frequency. This enables the division of time and space for dynamic adjustments across subsystems, including cooling and heating sources, power supply and distribution, water supply and drainage, HVAC, and communication systems [3, 6]. By transitioning capacity matching from static settings established during the design phase to dynamic corrections and configurations during the operational phase, energy waste can be minimized, equipment response speed can be enhanced, and a more refined management model can be implemented. Furthermore, this dynamic approach allows for real-time optimization, ensuring that the system adapts to fluctuating demands and environmental conditions. Such advancements not only improve operational efficiency but also contribute to sustainable energy practices, reducing the environmental impact of the park's operations while maintaining high performance standards.

### *3.3. The Impact of Resilience Assurance and Low-Carbon Configuration on Sustainable Development*

The resilience guarantee and low-carbon configuration play a pivotal role in ensuring the continuous operational capability of parks, particularly in scenarios involving critical public facilities, as well as in enhancing the quality of their long-term development. In the face of sudden events such as heavy rainfall, high-temperature heat island effects, power outages, equipment malfunctions, or communication disruptions, the adaptability of spatial forms and infrastructure becomes a decisive factor in controlling the extent of disaster impact and the speed of recovery. Measures such as designing evacuation routes for personnel, strategically positioning computer rooms, reserving emergency exits, establishing fire compartments, and implementing basement waterproofing can significantly mitigate the adverse effects of major incidents on essential business operations. Additionally, the incorporation of dual power supply systems, battery energy storage devices, backup water sources, redundant communication systems, and robust pipeline layouts with line-breaking handling capabilities can substantially enhance the operational resilience of critical buildings. From an energy efficiency perspective, the integration of advanced insulation materials, natural ventilation systems, expanded light areas, photovoltaic power generation systems, and efficient heating and cooling equipment, alongside rainwater reuse systems and the development of energy

management platforms, collectively determines the overall energy consumption and carbon emissions during the park's operational lifecycle. These strategies not only contribute to energy conservation but also align with broader goals of sustainable development and environmental stewardship.

#### 4. Technical Path for the Synergistic Development of Building and Public Facility Infrastructure in Artificial Intelligence-Powered Industrial Parks

##### 4.1. Build a Data Foundation That Integrates the Architectural Space and Facility Systems

For the integration of building space and facility systems, the geometric model of BIM serves as the fundamental element object, with GIS coordinates acting as the spatial benchmark of the park and real-time IoT data functioning as the calibration factor for operational accuracy. This approach enables a unified data representation that encompasses various facilities, including buildings, energy systems, water supply, transportation networks, communication infrastructure, and pipelines. At the technical level, critical parameters such as room area, functional type, occupancy levels, equipment power, pipe diameter, and load capacity can be standardized and encoded. This allows for the construction of a "space unit - equipment node - working state" relationship network model. By employing this model, the facility load can be preliminarily calculated using a comprehensive demand model, ensuring a more precise and data-driven approach to infrastructure planning and management [7].

$$L_i = \sum_{j=1}^n (A_j \cdot q_j \cdot \alpha_j) + P_i \quad (1)$$

Among the variables,  $L_i$  represents the predicted load of the  $i$ -th type of facility, while  $A_j$  denotes the building functional area of the  $j$ -th type. Additionally,  $q_j$  signifies the unit area demand intensity,  $\alpha_j$  accounts for the usage correction coefficient, and  $P_i$  represents the additional load of specialized equipment. This model facilitates the transformation of changes in building space into corresponding variations in demand for power, cooling, water, and communication bandwidth. By adopting this method, reliance on experience-based design is minimized, and a more systematic and accurate approach to infrastructure planning is achieved.

In a practical application within a science and technology park project, the electricity consumption characteristics of various functional buildings, such as research facilities, experimental areas, computer centers, and administrative service halls, exhibited significant variability. During the design phase of this project, a comprehensive BIM and GIS data base model was developed. This model incorporated detailed elements such as building functional zoning, underground pipeline layouts, transformer rooms, energy stations, water and heating outlets, and access points [8, 9]. Furthermore, data from each metering device was integrated into the model. The subsequent calculations revealed that the cooling load in certain areas of the test building was nearly 18% higher than initially estimated. Similarly, the communication network bandwidth demand for the data center was found to be concentrated in the core area. Based on these findings, the design team redefined the energy supply zones and optimized the original placement of the integrated pipeline room and the communication main corridor path. This process enabled the mutual verification of spatial layouts and equipment room capacities during the architectural design stage, ensuring a more efficient and effective infrastructure design.

##### 4.2. Establish an AI-driven Model for the Coordination of Building Layout and Facility Capacity

In the development of a comprehensive simulation model for building layout and infrastructure carrying capacity driven by artificial intelligence, various parameters must be meticulously analyzed and converted into constraints for public facilities. These parameters include the total floor plan of the building, the density of functional zones, population distribution, mechanical entrance and exit flow, working hours, and traffic density. By integrating these factors, the model enables synchronous verification of architectural design and public facility configuration. Utilizing machine learning-based load prediction methods combined with multi-objective optimization strategies, the building space can be divided into distinct grids or functional blocks. Each block is

independently assessed for its demand capacity in terms of power, heating and cooling systems, water supply, communication networks, fire prevention measures, and road infrastructure. This approach ensures that the capacity matching relationship is accurately expressed and optimized for practical implementation [9, 10].

$$C_i \geq \beta_i \cdot \max(\sum_{k=1}^m A_k q_{ik} \gamma_k + S_i) \quad (2)$$

In this formula,  $C_i$  represents the capacity of the  $i$ -th type of facility configuration, while  $A_k$  denotes the floor area of the  $k$ -th type of building function. The unit demand intensity corresponding to the facility is expressed as  $q_{ik}$ , and  $\gamma_k$  accounts for the function usage correction coefficient. Additionally,  $S_i$  represents the extra demand for specialized equipment or processes, and  $\beta_i$  serves as the safety redundancy coefficient [11–13]. This mathematical framework is instrumental in determining whether the adjusted facility capacity aligns with peak operational requirements. Furthermore, it establishes constraint boundaries for the AI optimization algorithm, ensuring that the system operates within safe and efficient limits.

For instance, consider the case of a biomedical research base project, which includes a research center building, a pilot production workshop, an office building, and supporting facilities. Initially, the highly clean research area was positioned on the east side of the base, leading to increased electricity consumption, fresh air volume, and purified water usage in that region. By incorporating the AI collaborative model during the design phase, the system adjusted critical infrastructure elements such as the locations of power supply and distribution stations, the supply radius, the pipe diameter of water supply pipelines, and the dimensions of flood discharge facilities. These adjustments were based on the functional load curves of each building. The model revealed that the maximum electricity demand in the east area exceeded the estimated value by approximately 15%, while the instantaneous drainage flow in the pilot production area approached full capacity. Through repeated simulations and updates, experimental units were redistributed to the central area, resulting in an increased number of power distribution nodes and the independent installation of exhaust shafts. This strategic reconfiguration not only ensured the uniformity of facility requirements but also enhanced functionality, safety reliability, and scalability for future expansions [1, 14].

#### *4.3. Establish a Coordinated Scheduling Mechanism for Energy, Water Supply, Transportation and Communication Facilities*

After the park becomes fully operational, the management of its water, energy, transportation, and communication systems should transition from isolated control to an integrated and collaborative scheduling approach. The advanced predictive and analytical capabilities of artificial intelligence (AI) are pivotal in achieving this transformation. For instance, the energy system can dynamically regulate the operation of cooling and heating sources, manage the charging and discharging cycles of energy storage systems, optimize photovoltaic energy collection, and adjust the operational strategies of air handling units (AHU). These adjustments are based on real-time factors such as building load demands, weather forecasts, fluctuations in electricity prices, and the performance metrics of equipment. Similarly, the water system can optimize the operation of pump houses, valves, reservoirs, and reclaimed water utilization by analyzing variables such as peak water demand, rainfall storage capacity, pressure variations, and sewage treatment capabilities [15, 16]. The transportation system, on the other hand, can enhance route planning, manage entry and exit controls, provide parking guidance, optimize cargo handling schedules, and streamline pedestrian pathways. These improvements are informed by data such as vehicle flow rates, the availability of parking spaces, freight vehicle booking times, and employee commuting schedules. The communication system ensures efficient allocation of network resources by considering the specific requirements of office areas, production workshops, security facilities, and internet terminal access points. For example, in an intelligent manufacturing park, peak commuting hours typically see a significant increase in the number of people and vehicles, alongside heightened activity on production lines, leading to elevated power

consumption. Previously, isolated systems struggled to respond effectively to such scenarios. However, with the implementation of an AI-driven scheduling platform, all critical systems—including access control, parking, power equipment, air conditioning, water and electricity management, and network monitoring—can be integrated into a centralized command center. This integration enables predictive adjustments, such as preemptively activating cooling and heating equipment or reallocating stored energy. Additionally, it is essential to reserve adequate emergency capacity and enforce regular access control measures for external vehicles to ensure smooth operations and safety.

#### *4.4. Improve the Resilience Operation and Low-Carbon Management System for Critical Environments*

In critical environments of public facilities, the technical approach for park operations must achieve a balance between safety resilience and low-carbon functionality. Resilience is primarily dependent on identifying and mitigating risks such as extreme weather conditions, equipment failures, power outages, water pipe ruptures, communication disruptions, and fire hazards. Advanced AI technologies play a pivotal role in reducing the impact of disaster events by enabling predictive analysis and real-time monitoring. At the architectural design level, enhancements such as elevated equipment rooms, optimized drainage systems, improved fire escape routes, strategically located emergency exits, and reinforced underground protection measures are essential. At the facility system level, the integration of dual power supplies, battery banks, water storage tanks, fire water reservoirs, backup communication systems, key valves, and regional control units ensures operational stability during emergencies. Low-carbon management strategies should incorporate external insulation materials, efficient ventilation systems, optimized lighting designs, photovoltaic components, advanced battery banks, energy-efficient cooling and heating systems, sewage treatment facilities, and comprehensive energy consumption monitoring systems [17]. For instance, in a coastal data research park exposed to typhoons, heavy rainfall, and high humidity, core facilities such as data centers, energy hubs, communication rooms, and underground passages require robust planning. During the early design phase, digital modeling was employed to simulate scenarios like flooding, power outages, and cooling tower failures. Consequently, the main computer room was elevated, rainwater storage ponds were installed, and emergency diesel generator backup units were incorporated alongside energy storage battery banks for peak shaving. An AI-driven platform continuously monitors metrics such as PUE values, photovoltaic output, air conditioning efficiency, and equipment alarm events. It also predicts anomalies in energy consumption and equipment aging trends, ensuring uninterrupted operations under extreme conditions while significantly reducing overall energy consumption and carbon emissions within the park.

## **5. Conclusion**

The construction of an artificial intelligence-supported park represents a significant advancement in transforming the traditional one-way collaborative relationship between building layouts and public facilities into a deeply integrated and dynamic collaboration. This transformation emphasizes the importance of architectural space layout design, the precise scale configuration of energy-using equipment, innovative operation and management strategies, and effective carbon emission reduction measures. These elements collectively serve as critical technical foundations for fostering the high-quality development of such parks. By leveraging a comprehensive database of building spaces and facility systems, the integration of layout-capacity collaborative simulation design powered by artificial intelligence becomes feasible. This approach enables holistic planning across energy, water, land, transportation, communication, and other essential domains. Furthermore, the implementation of disaster resistance strategies and carbon emission control measures under varying environmental conditions enhances the park's resilience and adaptability to technological advancements and evolving scenarios. This adaptability not only strengthens operational efficiency but also elevates the park's

sustainable development potential. Looking ahead, future work should prioritize the integration of multi-disciplinary data standards, the real-world validation of artificial intelligence models, and the continuous real-time correction of digital twins. Additionally, feedback mechanisms throughout the life cycle of the park's infrastructure will be essential. These efforts will collectively drive the intelligence, precision, and low-carbon evolution of the park's building complexes and their associated public facilities, ensuring their alignment with the goals of intelligent, coordinated, and sustainable development.

## References

1. A. U. Umana, B. M. P. Garba, A. Ologun, J. S. Olu, and M. O. Umar, "Architectural design for climate resilience: Adapting buildings to Nigeria's diverse climatic zones," *World Journal of Advanced Research and Reviews*, vol. 23, no. 03, pp. 397-408, 2024.
2. R. A. Elshapasy and S. F. Mohamed, "A framework transformation of a traditional campus into a bio-tech smart-digital campus," *International Journal of Environmental Impacts*, vol. 7, pp. 269-275, 2024.
3. A. Verma, P. Bagyalakshmi, R. Pavaiyarkarasi, R. R. Al-Fatlawy, G. Rajalakshmi, and B. Arunkumar, "A Structured Architecture Development for 6G Technology for the Accurate Communication," in \*2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)\*, pp. 109-114, May 2024.
4. G. Gallo, G. F. Tuzzolino, and F. Wirz, "The role of Artificial intelligence in architectural design: conversation with designer and researchers," in \*Conference proceedings of the 7th International Conference on Architecture and Build Environment S. ARCH\*, pp. 1-8, 2020.
5. J. E. Mustoe, "Artificial intelligence and its application in architectural design," 1990.
6. Y. Li, H. Chen, P. Yu, and L. Yang, "A review of artificial intelligence applications in architectural design: energy-saving renovations and adaptive building envelopes," *Energies*, vol. 18, no. 4, p. 918, 2025.
7. H. Li, Q. Wu, B. Xing, and W. Wang, "Exploration of the intelligent-auxiliary design of architectural space using artificial intelligence model," *PLOS ONE*, vol. 18, no. 3, p. e0282158, 2023.
8. J. Cudzik and K. Radziszewski, "Artificial intelligence aided architectural design," 2018.
9. A. Harapan, D. Indriani, N. F. Rizkiya, and R. M. Azbi, "Artificial intelligence in architectural design," *International Journal of Design (INJUDES)*, vol. 1, pp. 1-6, 2021.
10. N. M. Matter and N. G. Gado, "Artificial intelligence in architecture: integration into architectural design process," *Engineering Research Journal*, vol. 181, pp. 1-16, 2024.
11. I. As, S. Pal, and P. Basu, "Artificial intelligence in architecture: Generating conceptual design via deep learning," *International Journal of Architectural Computing*, vol. 16, no. 4, pp. 306-327, 2018.
12. Y. Li, H. Chen, P. Yu, and L. Yang, "A review of artificial intelligence in enhancing architectural design efficiency," *Applied Sciences*, vol. 15, no. 3, p. 1476, 2025.
13. Y. Yoshimura, B. Cai, Z. Wang, and C. Ratti, "Deep learning architect: classification for architectural design through the eye of artificial intelligence," in *International Conference on Computers in Urban Planning and Urban Management*, Cham: Springer International Publishing, pp. 249-265, May 2019.
14. M. Bhatt, J. Suchan, C. Schultz, V. Kondyli, and S. Goyal, "Artificial intelligence for predictive and evidence based architecture design," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 30, no. 1, Mar. 2016.
15. I. N. Albukhari, "The role of artificial intelligence (AI) in architectural design: a systematic review of emerging technologies and applications," *Journal of Umm Al-Qura University for Engineering and Architecture*, pp. 1-20, 2025.
16. A. Cocho-Bermejo, "Artificial intelligence and architectural design before generative AI: Artificial intelligence algorithmics approaches 2000-2022 in review," *Engineering Reports*, vol. 7, no. 4, p. e70114, 2025.
17. Z. Zhang, J. M. Fort, and L. G. Mateu, "Exploring the potential of artificial intelligence as a tool for architectural design: A perception study using Gaudí's works," *Buildings*, vol. 13, no. 7, p. 1863, 2023.

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of Publisher and/or the editor(s). Publisher and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.