iSpace: Conceptual Exploration and Urban Planning Practices from 246 Global Cases

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Abstract. As smart-city development moves from strategic design to implementation, the intelligence of urban spaces is becoming a critical means of realizing smart-city visions. Drawing on 246 iSpace projects completed or under construction worldwide over the past decade, this study reviews the current state of practice. Integrating this evidence with theoretical research, it defines iSpace as an urban setting in which advanced technologies enable the sensing of user needs and environmental conditions, informed decision-making, adaptive responses, and continual learning and optimization. iSpace has two defining attributes - technological enablement and a spatial carrier - and four planning elements: comprehensive perception, precise judgment, appropriate response, and learning-based optimization. The paper further proposes actionable pathways for the intelligent transformation of urban spaces, offering a theoretical framework and practical guidance for wider implementation.

Keywords: iSpace; smart city; concept; Internet of Things; artificial intelligence.

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Technological change is superimposing the physical and digital dimensions of cities, generating new urban imaginaries and reshaping how people interact and use space. In recent years, smart-city research and practice have focused largely on strategic concepts and platform architectures [1-2], or on the intelligent upgrading of infrastructure such as transportation, logistics, and utility tunnels [3-5].

Yet streets, squares, residential neighborhoods, and other everyday settings are the places where urban life unfolds and where residents directly encounter smart-city services. Extending intelligence from top-level strategies and foundational infrastructure into urban living spaces has therefore become a central priority for the high-quality development of smart cities. Projects such as Sidewalk Toronto in Canada, Woven City in Japan, and The Line in Saudi Arabia contain numerous visualizations of intelligent urban-life scenarios. Although these projects remain largely at the design stage, they offer important references and inspiration for the future development of intelligent urban spaces.

1 Current State of iSpace Practice

This study conducted a broad review of intelligent urban-space projects completed or under construction worldwide during the past decade. Searches used terms including “smart space,” “smart place,” “smart building,” and “smart residential community.” A total of 246 projects were identified and organized into an analytical framework and case database.

The completed projects range in scale from several square meters to several hundred thousand square meters. Clients include private companies, public institutions, and government agencies, while delivery teams range from conventional architecture and planning firms to smart-technology teams and electrical-equipment companies. To address safety, energy consumption, and comfort, these projects employ new materials such as carbon fiber and biosensors, together with technologies such as the Internet of Things

(IoT) and digital twins, to create urban spaces with lower-carbon energy use, novel sensory experiences, and more individualized feedback.

The cases span a wide range of spatial types, including housing, culture, education and research, health care, commerce and offices, industry, logistics and warehousing, roads and transport, infrastructure, green space, and public squares (Figure 1). Residential settings, in particular, have seen the rapid adoption of whole-home intelligence. By linking household sound, lighting, and electrical systems, these applications create personalized and more comfortable living environments while addressing practical needs such as aging in place and childcare. A relatively complete industrial chain has also emerged in standards, industrial policy, design solutions, and business models.

（a）Aqara Home全屋智能 （b）柏林立方智能办公建筑 （c）德国斯图加特自适应折叠凉亭

（d）芬兰中部新星医院新型诊疗空间 （e）MIT Sensable Lab 拉瓦尔市未来公园实验

Figure 1. Typical project cases

In commercial and office buildings, intelligent transformation primarily aims to reduce energy use. Heating, ventilation, air-conditioning, elevators, and other systems are automatically controlled, while building-wide electrical systems are managed through integrated platforms. The recent rise of flexible working, combined with workstation-occupancy sensing, has also generated new approaches to the design and use of office space. In health-care, educational, and cultural settings, intelligent platforms are usually built around specific functions, such as smart operating rooms, smart classrooms, and multimedia exhibition halls.

In urban green spaces, streets, squares, and other public settings, conventional spatial and activity design is supplemented either by technology-enabled street furniture - including seating, canopies, and transit stops - or by naked-eye 3D, holographic projection, augmented reality (AR), and virtual reality (VR), thereby enriching the experience of urban public space.

Across these projects, digital-system development and the design and construction of physical space are typically undertaken by different industries. High disciplinary and industrial barriers therefore lead to weak integration and insufficient coordination, and the two systems may even conflict in operation. Moreover, the use of new technologies and materials remains exploratory, and research, development, and construction costs are relatively high. As a result, some projects primarily serve as experiments or innovation demonstrations. This technology- and display-oriented intelligence still differs from intelligence that begins with genuine user pain points [6].

2 Concept and Characteristics

Current research on intelligent spatial settings comes mainly from fields such as refrigeration and HVAC engineering, computer science, automation, and the IoT [7-8]. It generally pursues specific technical advances or simulation experiments in areas such as energy consumption, automated equipment control, space occupancy, and virtual reality [9-12]. Research has also recently emerged within the built-environment disciplines. Examples include conceptualizing the city as an integration of people, technology, and space [13]; proposing intelligent building terminals that combine architectural carriers with ambient intelligence [14]; and identifying new spatiotemporal modules of social activity at the micro-spatial scale [15]. Nevertheless, the connection between front-end smart-city visions and back-end technical products remains inadequate [16]. In particular, "intelligent scenario" carries different meanings in different contexts and has yet to receive a clear definition or systematic synthesis.

2.1 Conceptual Definition of iSpace

Based on the analysis of global intelligent-space projects and existing academic research, this study defines iSpace as an urban setting in which advanced technologies enable diverse spaces to perceive human behavioral needs and environmental conditions, make judgments and decisions, alter environmental states to improve safety, energy efficiency, and comfort, and continually learn and optimize their operation.

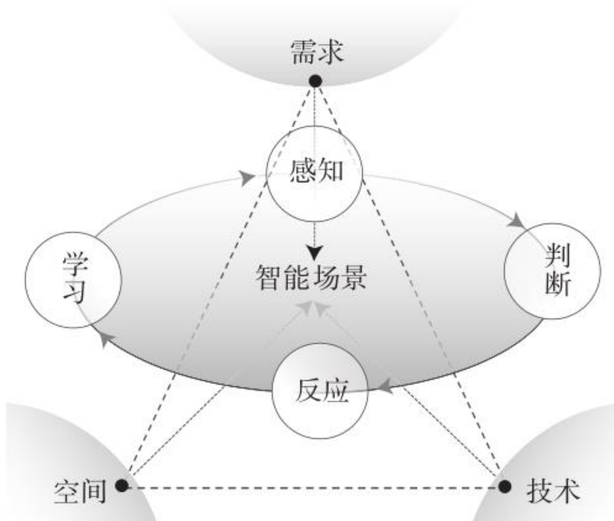

Figure 2. Structure of iSpace

2.2 Key Characteristics of iSpace

iSpace is created by using emerging intelligent technologies (i) to make urban space (space) intelligent. It is a new spatial form for future smart cities, produced through the deep integration of advanced technologies with the built environment of architecture, planning, and landscape design. Intelligent technology and a spatial carrier are its two defining characteristics.

Characteristic 1: Application of "i" technologies. Realizing iSpace requires advances from computer science, mechatronics, psychology, ergonomics, and other fields. Six major groups of technologies - including intelligent sensing, IoT and communications, smart-building and environmental management, data analytics and AI, automated control, and virtual or augmented reality - integrate spaces and equipment, data and networks, and physical and information environments into an interconnected whole (Table 1).

Table 1. Technologies used in iSpace

Technology dimension	Technology	Target	Technology dimension	Technology	Target
Intelligent sensing	AI road-survey sensors	Users	Data analytics and AI	Data analytics platform	Users
	Drone-based intelligent sensing	Environment		Deep-learning algorithms	Users
	Millimeter-wave radar	Users		Federated-learning algorithms	Users
	Thermal imaging	Environment		GPT technologies	Users
	Depth sensors	Users		AI-based data analytics	Users

Technology dimension	Technology	Target	Technology dimension	Technology	Target
IoT and communications	IoT sensors	Environment	Automated control	Automated control system	Environment
	Smart lighting control	Environment		Intelligent monitoring platform	Environment
	NB-IoT	Environment		SLAM algorithm	Environment
	Smart planting system	Environment		AI control algorithm	Environment
Smart building and environmental management	Energy management system	Environment		Adaptive structural technologies	Environment
	Smart building management system	Environment	Virtual and augmented reality	AR, VR, and MR technologies	Users
	Environmental monitoring system	Environment		Holographic projection	Users

Characteristic 2: Space as the carrier. Space is fundamentally a volumetric system enclosed by surfaces. Urban places accommodate diverse activities, constitute the point at which smart-city services are delivered, and are the interfaces through which residents directly experience intelligent applications. They therefore shape residents' sense of benefit, well-being, and security.

Sensors, networks, computing equipment, and other components required for intelligence must be physically deployed in space. Road surfaces [17], building facades [18], streetlights [19], waste bins [20], and other street-furniture surfaces can all serve as spatial carriers. Based on the case database, the spatial carriers used in iSpace can be grouped by their role within the spatial system into two categories and five surface types (Table 2): boundary surfaces and intermediate surfaces, comprising walls, floors, ceilings, street-furniture surfaces, and pipelines.

Table 2. Types of spatial surfaces and representative cases

Category	Carrier	Representative cases
Boundary surfaces	Wall	LUMES interactive wall at Cabrini Hospital[1]; adaptive photovoltaic facade at ETH Zurich[2]
	Floor	SensFloor smart flooring at Fisher Care Home[3]
	Ceiling	Intelligent interactive ceiling at the Ping An Property & Casualty Insurance Building, Shenzhen[4]
Intermediate surfaces	Street-furniture surface	Smart-lamppost demonstration section on Huahua Road, Shenzhen[5]; outdoor smart cat shelter[6]
	Pipeline	AR application for the underground utility network in Tongzhou, Beijing[7]

Figure 3. Representative iSpace cases

3 Planning Elements

A smart city advances sustainable intelligence through a recurring cycle of perception, judgment, response, and learning [21]. The planning and design of urban spatial settings follow the same four-element logic (Figure 4). Six categories of built-environment data are comprehensively sensed; multiple AI algorithms then support precise judgment; appropriate responses are delivered through interaction or control; and recurring patterns are learned to enable the setting to optimize itself.

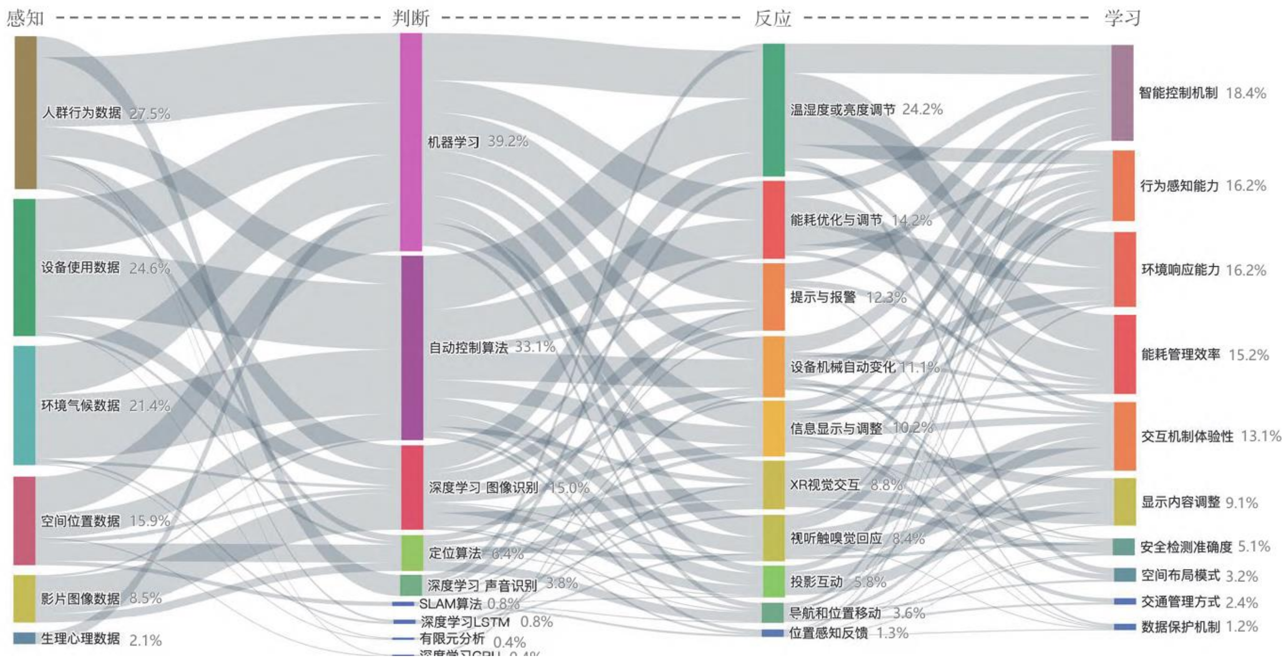

Figure 4. Sankey diagram linking the four elements of iSpace

3.1 Comprehensive Perception

Comprehensive perception is the foundational and indispensable first step in constructing iSpace. The built environment generates diverse forms of data [22], and sensors and monitoring instruments are widely used to collect spatial information for real-time observation and integrated management of the environment and human activity.

According to their nature and purpose, perceptible information in urban space can be grouped into six categories: environmental and climatic data, equipment-use data, spatial-location data, video and image data, crowd-behavior data, and physiological and psychological data. Table 3 summarizes these data types and their sensing devices, providing a basis for accurately analyzing their properties and uses and for supporting subsequent stages of spatial intelligence.

Table 3. Data types and sensing devices

Data category	Data type	Data details	Sensing devices
Environmental and climatic data	Environmental conditions	Wind speed, illumination, temperature, humidity, air quality, atmospheric pressure, and noise	Weather stations; temperature-humidity sensors; anemometers; sound-level meters; air-quality sensors
	Illumination data	Indoor and outdoor light intensity, solar position, and ambient light	Illuminance sensors; solar-position trackers
Equipment-use data	Equipment-status data	Equipment condition, operation, and use	RFID; NFC; equipment-monitoring systems; equipment sensors
	Energy-consumption data	Energy use and load data	Energy monitors; smart meters

Data category	Data type	Data details	Sensing devices
	Equipment-operation data	User-control data, device settings, and operation logs	User-control terminals; operation recorders; logging systems
Spatial-location data	User-location data	User location, personnel coordinates, and visitor location	Millimeter-wave radar; infrared detection; Wi-Fi positioning devices
	Mobility data	Movement trajectories, travel routes, and walking paths	GPS devices; mobile trackers; gait sensors
	Vehicle-location data	Vehicle positions, parking-space data, and traffic flow	On-board GPS; vehicle-tracking systems; parking-monitoring equipment
	Space-use data	Occupancy, room-utilization rates, and patterns of spatial use	Indoor surveillance cameras; occupancy sensors; infrared detectors
Video and image data	Video data	Surveillance video, photographs, and captured images	Surveillance cameras; digital cameras; dashboard cameras
	Thermal-imaging data	Thermal and infrared images	Thermal imagers; infrared cameras
	Facial-recognition data	Facial images, identity recognition, and personal-feature data	Facial-recognition cameras; high-resolution cameras
	Virtual-reality data	Virtual scenes, VR data, and holographic projection	VR headsets; panoramic cameras; motion-capture devices
Crowd-behavior data	User-behavior data	Movement, behavioral trajectories, voice, and touch	Millimeter-wave radar; microphones; pressure-sensitive sensors
	Crowd-flow data	Pedestrian volumes, movement conditions, and pedestrian data	People counters; thermal cameras; pressure-sensitive floors
	Feedback and interaction data	User feedback, evaluations, and social interaction	Social-media data collection; social-analytics software
Physiological and psychological data	User-emotion data	Emotion recognition, psychological state, and emotional fluctuation	Facial-expression analysis cameras; speech-emotion recognition devices
	Health data	Electrocardiograms, electroencephalograms, electromyograms, health status, and vital-sign monitoring	ECG instruments; health-monitoring devices such as wristbands and watches
	Stress data	Stress level and psychological burden	Pressure sensors; heart-rate monitors

3.2 Precise Judgment

Sensing devices in urban spaces capture predominantly real-time, high-frequency, and large-volume data. Machine-learning and deep-learning algorithms [23] are needed to perform descriptive, diagnostic, and predictive analyses and thereby judge environmental and equipment conditions, human behavior, and user needs with precision (Table 4).

Machine-learning algorithms such as support vector machines (SVMs) and random forests are well suited to structured data and can efficiently perform classification and regression. A random-forest model, for example, can predict the state of spatial equipment and identify potential failures in advance, while an SVM can classify behavioral data to recognize the needs and preferences of different users.

Deep-learning algorithms such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) perform particularly well with unstructured data, including images, audio, and video, because they can automatically extract features and identify complex patterns. RNNs can process sequential data to predict human movement and behavioral trends, whereas CNNs can support image recognition by automatically detecting and classifying objects in the spatial environment (Figure 5).

Table 4. Algorithms and data used for spatial judgment

Spatial judgment	**Data**	**Common algorithms**
Environmental monitoring	Air-quality, noise, temperature, and humidity data	K-means clustering; decision trees
Energy management	Energy-consumption, equipment-status, and environmental data	Linear regression; gradient boosting trees (GBT)
Equipment-status monitoring	Equipment-operation data, energy-consumption data, and maintenance logs	Support vector machines (SVM); random forests
Behavior recognition	User-behavior, sensor, and video data	Convolutional neural networks (CNN); hidden Markov models (HMM); OpenPose; YOLO object detection
Speech recognition	Speech data and user-command data	Natural language processing (NLP); BERT; long short-term memory networks (LSTM)
Facial recognition	Video and image data; user-identity data	Generative adversarial networks (GANs); convolutional neural networks (CNN)
Safety detection	Video-surveillance, equipment-status, and intrusion-detection data	Deep residual networks (ResNet); convolutional neural networks (CNN)
Path planning	Spatial-location information, obstacle data, and map data	Simultaneous localization and mapping (SLAM)

Figure 5. Examples of spatial judgment

3.3 Appropriate Response

Whether a setting can generate an appropriate response on the basis of its judgment is a decisive measure of its intelligence. Spatial responses can be divided into two broad categories: interaction and control (Table 5).

Interactive responses primarily engage users by presenting visual information. They not only enhance the user experience but also enable real-time feedback and processing. An LED display, for example, can use real-time data analysis to update traffic conditions or advertisements dynamically; users can gesture to interact with projected content and inspect or manipulate virtual objects; and a gallery guide can automatically play relevant information according to a visitor's location.

Control responses intelligently operate electronic equipment and mechanical components and therefore involve higher technical requirements and greater engineering complexity. Lighting can adjust brightness and color temperature in real time according to ambient light and user activity; gait monitoring can detect a fall and automatically issue an alarm to designated personnel; and elevators and building facilities can change state in response to a user's position to provide barrier-free vertical access.

Table 5. Response modes in iSpace

Type	Response mode	Illustrative response
Interaction	Information display and adjustment	Real-time updating of LED-screen content; rotating walls that display interactive patterns
	Posture-projection interaction	Gesture interaction with 3D imagery; adjustment of projected content according to position
	Location-aware feedback	Tracking user location to provide health and social reminders; personalized exhibition content
	Holographic interaction	Interaction with holographic 3D imagery; rotating displays of floating images
Control	Temperature, humidity, or brightness adjustment	Automatic temperature and humidity adjustment; control of lighting and air-conditioning
	Energy optimization and regulation	Real-time monitoring of power generation; optimization of energy use
	Automated mechanical transformation	Adjustment of folding mechanisms; optimization of panel angles; regulation of curtains and shading
	Multisensory response	Fall detection and alarms; low-frequency vibration; electrical muscle stimulation

3.4 Learning and Optimization

Most current iSpace projects have achieved intelligent improvement only at the three stages of perception, judgment, and response. They have not yet entered a self-optimizing cycle of perception, judgment, response, and learning. This lack of continual iteration limits their capacity to provide effective long-term services in complex and changing urban environments.

Self-optimization in iSpace is founded on the analysis of recurring patterns. Valuable information is modeled and extracted from large volumes of complex, heterogeneous data to identify regularities and predict trends (Figure 7), allowing the setting to optimize itself and generate more effective intelligent feedback (Table 6). As iSpace applications expand, collaborative learning among different spaces will become another important means of increasing intelligence. By integrating sensed data and sharing learning experience, collective spatial intelligence can support more efficient urban management and service optimization.

Table 6. Directions for self-optimization in spatial settings

Optimization direction	Implementation method	Explanation
Behavior-sensing capability	Analysis of user behavior and gait; fall-prediction optimization; health-data analysis	Analyze user gait, activity, and health data to refine anomaly-detection and behavior-analysis algorithms and improve responsiveness.
Environmental responsiveness	Machine-learning model training and dynamic adjustment	Analyze historical environmental data to improve the speed of response to environmental change and dynamically adjust spatial configuration.
Energy-management efficiency	Real-time data analysis and energy-efficiency monitoring	Continuously monitor energy use through sensors and apply data analytics to optimize energy strategies and reduce waste.
Interactive-display experience	Analysis of user-behavior data and optimization of interaction patterns	Analyze user-space interaction data to optimize display content, deepen immersion, and improve interactivity and user experience.
Intelligent control mechanisms	Analysis of user and environmental data; optimization of control algorithms	Use user and environmental data to optimize control-system algorithms, improve equipment intelligence, and enhance system stability.
Spatial-layout patterns	Analysis of user-behavior patterns and dynamic content optimization	Adjust display and interactive content through user-behavior analysis to improve the dynamic adaptability of space.
Data-protection mechanisms	Data-encryption technologies and privacy-protection algorithms	Analyze users' privacy requirements, improve encryption algorithms, and strengthen data protection and privacy security.
Safety-detection accuracy	Optimization of thermal-imaging data and event detection	Use thermal-imaging data to refine camera privacy protection and event-detection algorithms, reduce false alarms, and improve accuracy.

Figure 7. Spatial data analysis and learning-based optimization

4 Conclusion and Outlook

After more than a decade of exploring macro-level strategies and top-level design, smart-city development is accelerating into a deeper and more systematic phase of implementation. As the physical carriers of urban life and the settings residents encounter directly, intelligent urban spaces will inevitably become a central trend and a critical means of realizing the smart-city vision.

The integration of technological innovation with urban regeneration - especially the deep combination of information and communications technology (ICT), artificial intelligence (AI), and the Internet of Things (IoT) with spatial transformation - is turning urban space into an important field for applying new quality productive forces. Looking ahead, iSpace characterized by comprehensive perception, precise judgment, appropriate response, and learning-based optimization will not only stimulate technological innovation and improve urban safety, but also reshape ways of life and urban functional structures, promoting a deeper integration of sustainable development and human-centered care.

Notes

[1] https://www.eness.com/permanent/cabrini

[2] https://systems.arch.ethz.ch/research/adaptive-solar-facade

[3] https://future-shape.com/

[4] https://www.archiposition.com/items/20210118062458

[5] https://mp.weixin.qq.com/s/J871vUp2AzuPxoK1iCby2A

[6] https://www.gooood.cn/outdoor-intelligent-cat-nest-china-by-zaoshi-architecture.htm

[7] https://k.sina.cn/article_1893892941_70e2834d02000vnnn.html

References

[1] ZHANG Weiwen, JIN Han, LENG Jiaxin. How can smart-city construction modernize social governance? Hangzhou's “City Brain” under the test of the COVID-19 pandemic [J]. Journal of Zhejiang University (Humanities and Social Sciences), 2020, 50(4): 117-129.

[2] WU Xibo, YANG Zaigao. The smart-city concept and the development of future cities [J]. Urban Development Studies, 2010, 17(11): 56-60.

[3] WANG Mengshu, WANG Yonghong, TAN Zhongsheng, et al. Exploring the integrated use of underground space in China's smart cities [J]. Journal of Beijing Jiaotong University, 2016, 40(4): 1-8.

[4] ZHANG Xiaochun, SHAO Yuan, SUN Chao. An integrated conception of intelligent transportation for future cities [J]. Urban Transport of China, 2018, 16(5): 1-7.

[5] CHEN Yulan, ZHANG Ling. A comparative study of smart-industry development in the Yangtze River Delta [J]. Journal of Nantong University (Social Sciences Edition), 2017, 33(6): 6-11.

[6] WU Zhiqiang, WANG Jian, LI Deren, et al. “Cold” reflections amid the smart-city boom: An academic forum [J]. Urban Planning Forum, 2022(2): 1-11.

[7] NIZETIC S, SOLIC P, LOPEZ-DE-IPINA D, et al. Internet of Things (IoT): Opportunities, issues and challenges towards a smart and sustainable future [J]. Journal of Cleaner Production, 2020, 274: 122877.

[8] JAVED A R, SHAHZAD F, REHMAN S U, et al. Future smart cities requirements, emerging technologies, applications, challenges, and future aspects [J]. Cities, 2022, 129: 103794.

[9] ZHU C, FONG L H N, GAN M. Rethinking the consequences of postmodern authenticity: The case of a world cultural heritage in augmented reality [J]. Current Issues in Tourism, 2023, 26(4): 617-631.

[10] COPIACO A, HIMEUR Y, AMIRA A, et al. An innovative deep anomaly detection of building energy consumption using energy time-series images [J]. Engineering Applications of Artificial Intelligence, 2023, 119: 105775.

[11] PENG Y, RYSANEK A, NAGY Z, et al. Using machine learning techniques for occupancy-prediction-based cooling control in office buildings [J]. Applied Energy, 2018, 211: 1343-1358.

[12] JEON Y, CHO C, SEO J, et al. IoT-based occupancy detection system in indoor residential environments [J]. Building and Environment, 2018, 132: 181-204.

[13] ZHEN Feng, KONG Yu. A smart-city planning framework integrating people, technology, and space [J]. Urban Planning Forum, 2021(6): 45-52.

[14] ZHOU Ying, XU Yayin, DING Lieyun. Intelligent building terminals based on ambient intelligence [J]. Journal of Huazhong University of Science and Technology (Natural Science Edition), 2022, 50(8): 1-10.

[15] LIU Quan, SHI Yiting, LAI Yani. Conceptual interpretation and characteristic cognition of smart-city scenarios [J]. Urban Planning International, 2023.

[16] LIU Quan, CHEN Yaoyao, HUANG Dingfang, et al. A modular design method for ternary integrated smart-street scenarios: The future-street concept design for Huaqiangbei [J]. Urban Planning Forum, 2023(2): 110-118.

[17] HIJJI M, IQBAL R, PANDEY A K, et al. 6G connected vehicle framework to support intelligent road maintenance using deep learning data fusion [J]. IEEE Transactions on Intelligent Transportation Systems, 2023, 24(7): 7726-7735.

[18] LIU Xiaoqing, HE Rui. Planning new urban information infrastructure: Practice and exploration in Xiong'an [J]. Urban Planning Forum, 2022(5): 112-118.

[19] DE PAZ J F, BAJO J, RODRIGUEZ S, et al. Intelligent system for lighting control in smart cities [J]. Information Sciences, 2016, 372: 241-255.

[20] ABUGA D, RAGHAVA N S. Real-time smart garbage bin mechanism for solid waste management in smart cities [J]. Sustainable Cities and Society, 2021, 75: 103347.

[21] WU Zhiqiang, PAN Yunhe, YE Qiming, et al. Evaluation index system for intelligent cities: Development and application [J]. Engineering, 2016, 2(2): 105-137.

[22] PERERA C, ZASLAVSKY A, CHRISTEN P, et al. Sensing as a service model for smart cities supported by the Internet of Things [J]. Transactions on Emerging Telecommunications Technologies, 2014, 25(1): 81-93.

[23] ZHANG J, TAO D. Empowering things with intelligence: A survey of the progress, challenges, and opportunities in artificial intelligence of things [J]. IEEE Internet of Things Journal, 2021, 8(10): 7789-7817.

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AI-assisted translation