From Static Coupling to Dynamic Interaction: An Intelligent Approach to Mesoscale Urban Design

HUANG Yuyue, YANG Junyan, SUN Haocheng, YANG Qingxin, CUI Ao

Abstract. As the critical link between the macro urban scale and the micro block scale, mesoscale urban design has the dual responsibility of coordinating two-dimensional functional order and three-dimensional morphological order. In the face of dynamically changing urban demands, conventional mesoscale design methods are constrained by static and singular function-morphology coupling and by relatively low adjustment efficiency. Drawing on reinforcement learning, this study develops an intelligent mesoscale urban design workflow comprising a network-control module, a scheme-iteration module, and a comparison-and-optimization module. Based on the spatial configuration of function-morphology coupling elements, the study identifies several interaction modes, including high coupling, core clustering, axis-driven development, function-led development, and morphology-led development, and applies them in an empirical design experiment. The results show that the proposed method substantially improves scheme diversity and design efficiency, strengthens adaptability, and offers an effective pathway toward dynamic interaction in future urban design.

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The Measures for the Administration of Urban Design state that urban design is an effective means of implementing urban planning, guiding architectural design, and shaping distinctive urban character [1]. In response to increasingly complex economic, social, and ecological demands, urban design creates "three-dimensional spatial form in the urban environment" through multiple approaches [2], with the aim of optimizing the overall urban environment [3]. In the middle and later stages of China's new urbanization, urban design is especially important for improving spatial quality and advancing sustainable development.

Because the city is a complex mega-system with multiscale spatial characteristics, urban design assumes different contents and priorities at different scales. Mesoscale urban design focuses mainly on urban districts that are relatively independent in function and relatively integrated in environmental terms [4], and spans several levels, including the urban area, community, street, and building [5]. Positioned between macro-level overall urban design and micro-level block design, it bears two responsibilities [6]. At the level of two-dimensional functional layout, it translates the overall structural control of the macro scale into a rational arrangement of functional spaces. At the level of three-dimensional spatial morphology, it coordinates development intensity, building height, and other variables across the district, thereby guiding design at the block scale. Through the integrated control of function and form, mesoscale urban design becomes a key link in implementing urban design intentions.

As social demands continue to change, urban design must support more flexible interaction between urban functions and spatial form. Existing mesoscale design methods, however, remain limited in both diversity and efficiency. On the one hand, conventional approaches often rely on subjective professional judgment and address only a static, singular mode of function-morphology coupling [7], making it difficult to accommodate diverse interaction requirements. Intelligent design methods based solely on stylistic transfer from precedent cases likewise lack adaptability and flexibility when applied to specific, complex environments [8]. On the other hand, conventional workflows may require a new underlying design logic for each site [9]. They are time-consuming, labor-intensive, and lack effective real-time feedback mechanisms [10], making timely adjustment and optimization difficult and constraining large-scale application in practice.

To address these limitations, this study builds on the coupling characteristics of function and morphology at the mesoscale and uses self-learning artificial intelligence to enable dynamic interaction between them. It therefore moves beyond methods that depend primarily on subjective experience or transfer learning from massive precedent databases. It also differentiates scheme iteration and optimization according to multiple interaction modes among functional and morphological elements, thereby improving the adaptability and effectiveness of design outcomes. The empirical case shows that the proposed intelligent urban design method can simulate the dynamic process through which function and morphology influence one another and engage in coordinated negotiation. It can also generate multiple design alternatives within a short period, providing useful support for future-oriented urban design.

1 Reflections on Mesoscale Urban Design

1.1 Key task: coordinating two-dimensional functional layout and three-dimensional spatial form

As the visible expression of the deep structure and developmental logic of urban space [11], function and morphology have always been central to urban design. Two-dimensional functional layout directly affects the future direction of urban development, the efficiency of spatial use, and residents' quality of life. At the mesoscale, it not only implements the district-level development positioning established at the macro scale, but also provides the principal basis for organizing building functions at the micro scale. It must therefore refine broad land-use categories into a more detailed spatial arrangement. A rational-functionalist approach can integrate functional elements within the district on the basis of use efficiency, enabling more precise land-use planning and more intensive development.

Three-dimensional spatial morphology, by contrast, is the outward expression of urban design and directly reflects local cultural identity and aesthetic value. Building on macro-scale control of the overall urban form, mesoscale morphological design further organizes the spatial form of individual blocks and translates it into three-dimensional control indicators for block units. Particular attention is paid to building height, building density, floor area ratio, and other morphological attributes. This approach can compensate for insufficiently detailed morphological control at the macro scale and for the fragmentation of form-making at the micro scale.

In summary, the key task of mesoscale urban design is to coordinate two-dimensional functional layout and three-dimensional spatial morphology in accordance with higher-level planning objectives, guide the next level of block design, and achieve a two-way balance between functional layout and spatial form.

1.2 Problem: spatial disorder caused by the mismatch between function and morphology

Function and morphology are the two core components of the mesoscale urban spatial system. They influence one another spatially and are interactively embedded. It is generally accepted that effective dynamic coupling between function and morphology can maximize the potential of each system under limited land-resource constraints, create mutually reinforcing development, improve urban operational efficiency, and support sustainable urban development [12].

With rapid urban development, however, mesoscale urban design projects increasingly confront complex existing conditions and a growing diversity of stakeholders. The mismatch between diversified, rapidly changing functional activities and relatively fixed spatial forms has become increasingly evident, particularly in the gap between low-density functional vitality and high-intensity building form. For residents, the irrational allocation of production and living spaces aggravates traffic congestion and contributes to urban heat-island effects and air pollution, thereby reducing quality of life. For urban operation and governance, the mismatch between function and form produces a misallocation between spatial supply and demand. It suppresses spatial vitality, wastes resources, and ultimately generates a series of crises involving spatial disorder and an imbalance between people and land.

1.3 Dilemma: enabling dynamic interaction between function and morphology at the mesoscale

For designers, achieving dynamic interaction between function and morphology at the mesoscale presents two major challenges. First, the interaction mechanism is difficult to disentangle. A city is a dynamically changing system in which social structure and human needs evolve over time. The relationship between function and space therefore fluctuates continuously under the combined influence of external drivers—such as planning policy and transportation networks—and internal drivers, including natural conditions, the economy, and population (Figure 1). During design, adjustment of one functional area may trigger changes in the overall spatial form, while changes in spatial morphology feed back into functional layout. This “indivisibility” and “incomplete predictability” [13] make it difficult for designers to analyze and anticipate spatial change with precision.

Second, dynamic feedback is delayed. The decision-making and implementation of urban design schemes are affected by multiple stakeholder interests and by complex built environments. Designers must repeatedly adjust and verify schemes in response to feedback from different stages. Without efficient methods and tools, however, this feedback cycle is slow and undermines the effectiveness of the design.

Addressing the challenge of dynamic function-morphology interaction therefore requires a departure from conventional methods. On the basis of a clear understanding of dynamic interaction mechanisms, an intelligent urban design method is needed that is fast in workflow, broadly applicable, and accessible to users [14], so that function and morphology can develop through dynamic coupling.

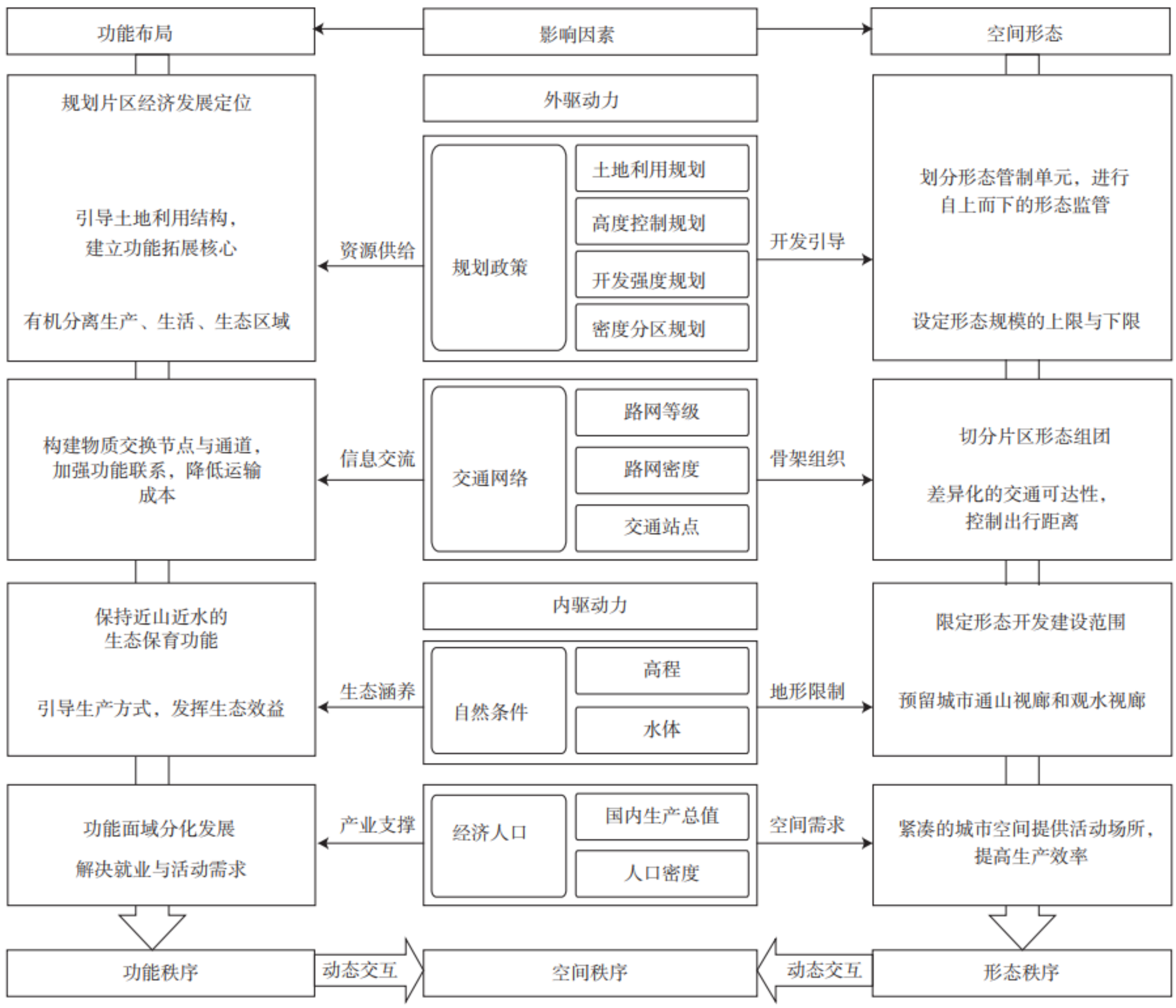


Figure 1. Mechanisms through which multiple factors influence dynamic function-morphology interaction

2 Constructing an Intelligent Mesoscale Urban Design Pathway

2.1 Methodological foundations

2.1.1 Coupling elements of function and morphology

Coupling coordination within a spatial system does not imply either complete overlap or complete independence between systems; rather, it refers to a harmonious structural relationship among their elements. Drawing on the spatial-structure tradition of classical location theory, which treats nodes, networks, and areas as the three basic components of spatial development [15], the coupling elements of function and morphology can likewise be abstracted as point, line, and area elements [16].

For the functional system, point elements represent centers of public functions and constitute the principal spaces of production and everyday life. Line elements are the connecting corridors among major functional centers; in practice, they often take the form of public-function belts along arterial roads, urban waterways, or green spaces and serve as economic corridors within the district. Area elements are the spatial extents of functional zones, such as business, residential, and administrative clusters. Together, functional cores, economic corridors, and functional base areas form the functional structure that guides mesoscale development.

For the morphological system, point elements generally take the form of large public-building complexes or clusters of high-rise business buildings, which serve as prominent landmarks and spatial reference points [17]. Line elements create visual corridors through continuous high-rise building belts or low-density development strips. Area elements form the morphological base of urban space and are created by the aggregation of buildings within each block. Landmark clusters, visual corridors, and building base areas together shape a recognizable structural framework at the mesoscale.

Functional and morphological elements jointly construct the overall spatial pattern through a mutually reinforcing cycle of coupling and symbiosis. On the one hand, functional elements drive the formation of morphological elements. In the conventional urban design process, functional cores and economic corridors are generally identified first on the basis of development objectives and resource conditions, after which spatial form is designed. The configuration of spatial morphology therefore depends to a considerable extent on the rationality of the functional layout [18], which provides its internal supporting framework. On the other hand, morphological elements feed back into the functional system. The physical urban environment provides the material setting in which functions can emerge and develop, while compact and diverse spatial forms attract people and activities and thereby strengthen functional vitality.

Function and morphology are thus connected through human activity and are continuously optimized according to patterns of spatial use under the combined regulation of the market, government, and other actors [19]. Their dynamic interaction gradually produces a relatively stable urban spatial structure.

2.1.2 Technical framework based on reinforcement learning

Reinforcement learning is a machine self-learning paradigm driven by environmental performance. Unlike supervised learning and related methods, it does not require large sample datasets for pre-training. Instead, it determines subsequent actions autonomously on the basis of reward signals and accumulated experience. When confronted with multiple possible environmental states, the algorithm can adapt its decisions to changing conditions and is therefore well suited to the design of dynamic urban space [20].

Taking dynamic interaction between mesoscale functional and morphological elements as the theoretical basis, the proposed method uses reinforcement learning to treat each block unit as a spatial agent. The generation of an urban design scheme is consequently understood as a process of cooperation, interaction, and strategic negotiation among multiple agents. Executable functional and morphological actions are used to define the policy network; the degree of coupling coordination between functional and morphological elements is used as the reward function of the evaluation network; and the Markov decision process is used to iterate schemes. Human-computer interaction is then introduced to compare and optimize the alternatives. The resulting workflow consists of three components: a network-control module, a scheme-iteration module, and a comparison-and-optimization module (Figure 2).

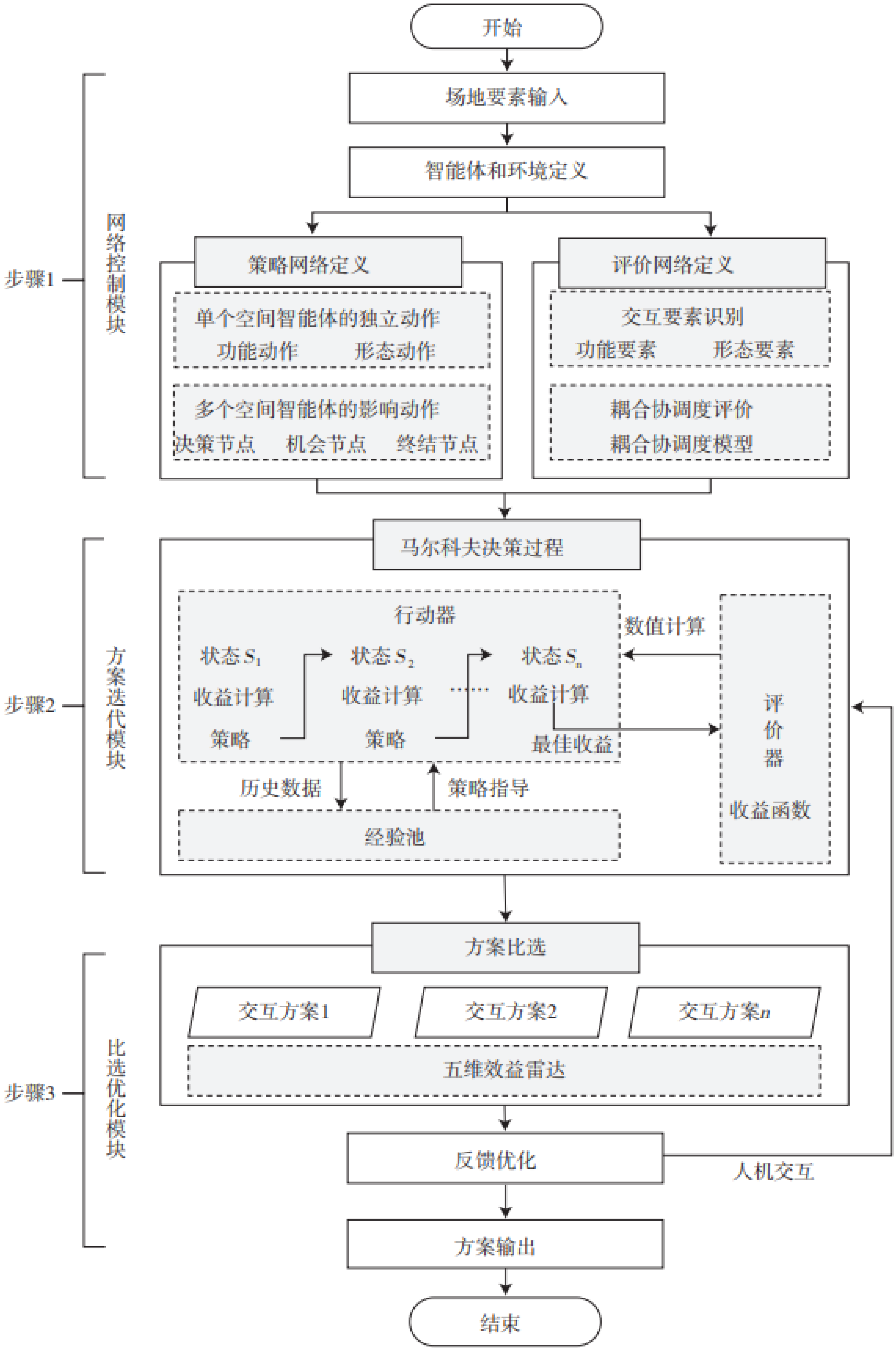


Figure 2. Technical pathway for intelligent mesoscale function-morphology interaction design

2.2 Network-control module for intelligent urban design

2.2.1 Constructing the policy network from functional and morphological actions

The policy network defines both the functional and morphological actions available to an individual block agent and the interactions among multiple block agents.

(1) Policy network for an individual spatial agent. For the independent actions of a single block unit, the action spaces are defined as A = [a1, a2, ..., an]^T and B = [b1, b2, ..., bn]^T. Under feedback from the evaluation network, the agent takes a functional action at and a morphological action bt. For functional actions, the principal land-use categories added in mesoscale urban design generally include Class B, A, G, and R uses. Because B1 and B2 differ substantially in spatial form, they are treated as separate functional actions, corresponding respectively to consumer services, producer services, public-interest services, parks and green space, and residential functions. For morphological actions, nine indicators are established under three dimensions—scale, landmark quality, and diversity (Table 1). The generation range for each morphological indicator is determined by higher-level planning requirements.

Table 1. Morphological indicators for mesoscale urban design

空间形态属性	指标名称	计算方式	指标释义
规模性	总体积/m³	$V_{sum} = \sum_{i=1}^{n} V_i$	V_i为街坊内第i个建筑单体体积
	总基底面积/㎡	$S_{sum} = \sum_{i=1}^{n} S_i$	S_i为街坊内第i个建筑单体的基底面积
	建筑密度	$B = \frac{\sum_{i=1}^{n} S_i}{S}$	S为街坊面积
	容积率	$P = \frac{V_{sum}}{S}$	/
	平均高度/m	$H_{avg} = \frac{V_{sum}}{S_{sum}}$	/
标志性	最高高度/m	H_{max}	/
	最大基底面积/m²	S_{max}	/
多样性	高度错落度	$D_h = \frac{\sqrt{\sum_{i=1}^{n}\left(H_i - H_{avg}\right)^2 / n}}{n}$	H_i为街坊内第i个建筑单体高度
	基底面积错落度	$D_s = \frac{\sqrt{\sum_{i=1}^{n}\left(S_i - S_{avg}\right)^2 / n}}{n}$	S_{avg}为街坊内的平均基底面积

(2) Policy network for multiple spatial agents. Urban blocks are not fully independent units separated by the road network; rather, they form a complex spatial network shaped by the attraction of agglomeration effects and the constraints of balancing effects [21]. Within a given sphere of influence, a change in the functional or morphological attributes of one block may alter the original attributes of other blocks. The action space and state space must therefore be clearly defined. The action space is the spatial range within which a change in one block triggers changes in other blocks. This study applies the k-nearest neighbors algorithm and treats the nine blocks closest to the target block as the influence range. The state space is the entire mesoscale study area, because any change in the action of an individual block affects the overall state of the district.

Because a peripheral block affected by the target block may itself become the next spatial agent and influence neighboring blocks, unrestricted recursive iteration could generate an infinite number of environmental states. To balance computational constraints and the need for scheme differentiation, the method borrows three node types from decision theory to limit iteration. A decision node is the first agent to change its action; a chance node is the first agent whose state changes under the influence of the decision node; and a terminal node is an agent whose state changes for a second time because of the decision node. Blocks beyond the terminal node retain their current state.

Functional and morphological influence rules are then defined within the action space. A classification and regression tree (CART) repeatedly divides continuous or discrete data into binary subsets and automatically selects the combination with the minimum Gini impurity. The calculation is:

$$\mathrm{Gini}(A) = 1 - \Sigma^{c}_{i=1} p_i^2$$

where A denotes a node, p_i is the probability of belonging to class i, and C is the number of classes.

2.2.2 Constructing the evaluation network from function-morphology coupling

The objective is to generate mesoscale urban design schemes in which function and morphology are well coordinated; their coupling coordination is therefore the core evaluation criterion. Conventional coupling-coordination models based on coupling degree and coordination indices are widely used to assess the relationship between two systems [22-23], especially when both systems can be expressed numerically. Functional and morphological systems, however, have pronounced spatial properties. A single numerical indicator cannot adequately express spatial differences in coupling, while manual scoring is both subjective and labor-intensive, particularly when large volumes of state data must be assessed. Such methods are therefore difficult to apply effectively in mesoscale design.

Building on the conventional coupling-coordination model and the coupling characteristics of functional and morphological elements, the proposed evaluation network establishes an intelligent process comprising scheme grayscale conversion, coupling-element identification, block-unit scoring, and coupling-coordination calculation.

(1) Scheme grayscale conversion. Functional and morphological schemes are converted to grayscale. The functional system is graded according to the structural importance of different use types (B2 > A > B1 > G > R), while morphological indicator values are divided into five levels by the natural-breaks method.

(2) Identification of coupling elements. Based on rules for point, line, and area elements, grayscale results are automatically converted into coupling-element maps. For point elements, the blocks closest to each road intersection are identified and their average grayscale value is calculated as the potential of the intersection. After all potentials are compared, the top N intersections are selected as functional or morphological point elements. For line elements, blocks adjacent to primary and secondary roads and ranking in the top 50% of functional or morphological grayscale are selected; the N corridors with the largest number of qualifying blocks are designated as functional or morphological line elements. For area elements, blocks ranking in the top 75% of functional or morphological grayscale within the study area are selected.

(3) Block-unit scoring. To translate spatially differentiated coupling-element attributes into quantitative fields, each block is scored according to its role in the composition of functional or morphological coupling elements. Point elements, serving as functional cores or landmark clusters, play a decisive role in promoting economic growth, shaping district identity, and strengthening spatial vitality; they therefore have the strongest radiation effect and the highest degree of identification. Line elements, acting as economic and visual corridors, receive the next-highest score. Area elements form the basic surface of functional and morphological structure and receive the lowest score. If a block participates in more than one coupling element, its scores are accumulated.

(4) Coupling-coordination calculation. The coupling-coordination model is used to calculate the score of every block under a given state, and the overall coupling coordination of the study area is the sum of all block-level scores.

2.3 Scheme-iteration module for intelligent urban design

A coupling mode represents an interaction state [24] and indicates the developmental direction that emerges after dynamic interaction between systems. In intelligent urban design, different coupling modes therefore correspond to differentiated paths of interaction and iteration.

By comparing the spatial relationships between functional and morphological elements—and focusing primarily on point and line elements because area elements have weaker identifying effects—the study identifies several coupling situations. First, when both functional and morphological elements are complete, the systems may exhibit extensive overlap, substantial overlap of point elements, substantial overlap of line elements, partial point-line overlap, or almost no overlap. Second, when only one system has a complete set of elements, the result is either function-led or morphology-led development. Third, when neither system is complete, the pattern is spatially dispersed.

Following existing classifications based on coupling degree, a coupling-coordination score of 80-100% is treated as good coordination, while a score below 20% represents uncoordinated development [25-26]. Using 80% and 20% as thresholds, the study derives eight function-morphology coupling modes: high coupling, core clustering, axis-driven development, moderate coupling, uncoordinated development, function-led development, morphology-led development, and dispersed distribution (Table 2).

Table 2. Eight function-morphology coupling modes

Coupling mode	Functional elements	Morphological elements	Point-element coupling	Line-element coupling	Principal spatial characteristic
High coupling	Complete	Complete	≥80%	≥80%	Functional cores and landmark clusters coincide; economic and visual corridors are also aligned.
Core clustering	Complete	Complete	≥80%	<80%	Strong concentration around shared core nodes, with weaker alignment of linear elements.
Axis-driven development	Complete	Complete	<80%	≥80%	Strong alignment along shared economic and visual axes, with weaker point correspondence.
Moderate coupling	Complete	Complete	20-80%	20-80%	Partial coordination of both point and line elements.
Uncoordinated development	Complete	Complete	≤20% or <80%	<80% or ≤20%	Pronounced mismatch in at least one major element system.

Coupling mode	Functional elements	Morphological elements	Point-element coupling	Line-element coupling	Principal spatial characteristic
Function-led development	Complete	Incomplete	/	/	Morphological elements are generated to fit an established functional structure.
Morphology-led development	Incomplete	Complete	/	/	Functional uses are matched to an established morphological structure.
Dispersed distribution	Incomplete	Incomplete	/	/	Both systems lack a clear structural framework and are spatially fragmented.

Among the eight modes, uncoordinated development, dispersed distribution, and moderate coupling have relatively low coordination and are therefore excluded from subsequent scheme generation. The remaining five modes—high coupling, core clustering, axis-driven development, function-led development, and morphology-led development—represent comparatively rational forms of dynamic coupling and embody different spatial-development orientations. They provide designers with diverse alternatives for scheme iteration (Figure 3).

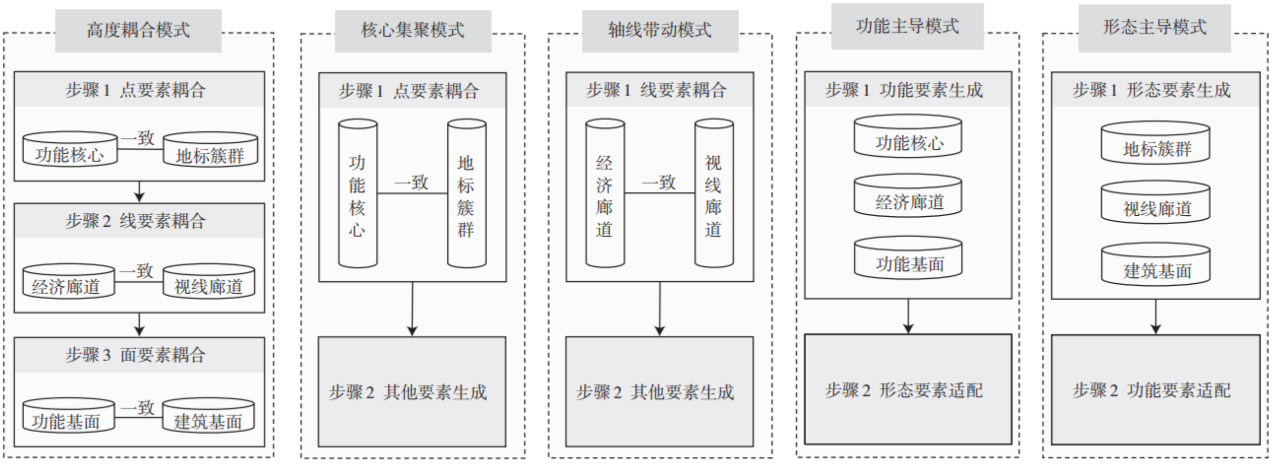


Figure 3. Schematic generation processes guided by different coupling modes

2.4 Comparison-and-optimization module for intelligent urban design

Some design requirements cannot be translated directly into control parameters. The method therefore introduces a human-computer comparison-and-optimization module after intelligent scheme generation so that the resulting alternatives can be transformed into practicable design proposals.

First, a five-dimensional radar framework is constructed to compare comprehensive value across economic, ecological, social, landscape, and accessibility benefits. Economic benefit is represented by the area of B1 and B2 land uses and by building volume. Ecological benefit is measured by the proportion of Class G and Class E land. Social benefit is evaluated by the share of construction associated with Class A public-service land. Landscape benefit is assessed through 360-degree visual simulation of the visibility of green spaces and water bodies from each block. Accessibility benefit is compared through the average shortest distance from residential units to nearby public-service land.

Using these criteria, the computer automatically calculates and labels multidimensional benefit indicators for a large number of initial schemes. Designers then use the radar results to identify alternatives for further development and optimize them through human-computer interaction in response to the demands of multiple stakeholders. Finally, vectorized mesoscale urban design models and drawings are produced.

3 Empirical Application: Intelligent Urban Design for a Sample District

3.1 A representative “relative blank slate”

A district in Chuzhou was selected as the empirical sample. It represents a large number of urban-edge areas with relatively low levels of development that, under current policy conditions, have become priority zones for decentralizing functions from the old city and expanding the new urban area. Such districts contain relatively few existing elements that must be retained and are less constrained by complex property-rights structures, historical conservation requirements, and other limitations. They therefore offer favorable conditions for realizing a spatial design blueprint and for conducting intelligent urban design experiments.

The exploration of this “relative blank slate” first establishes the basic process of intelligent dynamic interaction between function and morphology. Subsequent experiments can then incorporate increasing numbers of existing-condition constraints, ultimately producing a mature mesoscale intelligent urban design method suitable for engineering practice.

The existing land in the sample district is dominated by agricultural, forestry, and village uses. In accordance with higher-level governmental planning, the area is converted into urban construction land for the purposes of the design experiment. Before intelligent design begins, a digital base is established to assess the existing resource endowment. Water systems and green spaces with high ecological value, together with residential and cultural facilities of good building quality, are retained. The geometric center of each block is then used as its coordinate, producing 155 spatial agents. Agents whose functional or morphological attributes must be preserved are assigned one-hot codes [27], ensuring that no actions are applied to them during scheme iteration (Figure 4).

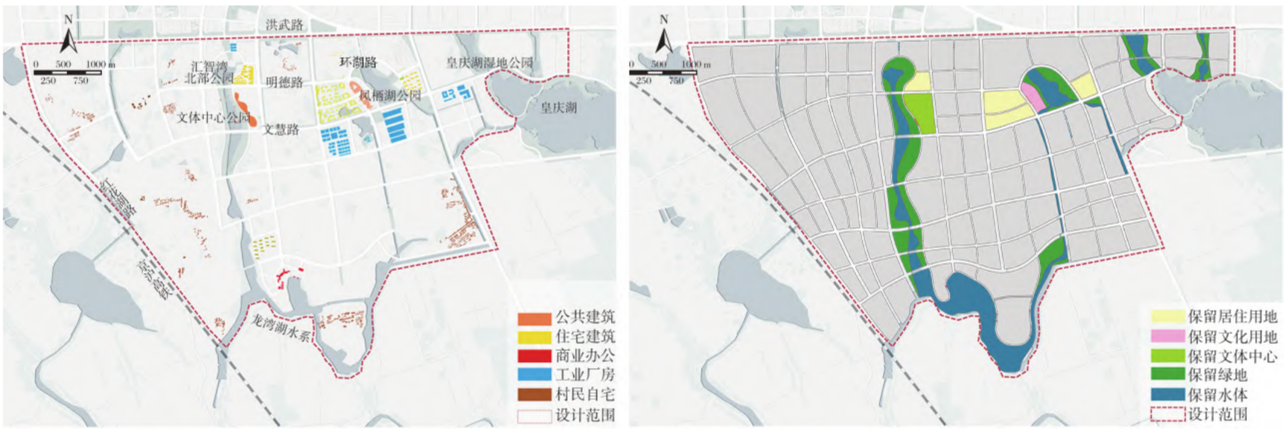


Figure 4. Existing conditions and digital base of the sample district

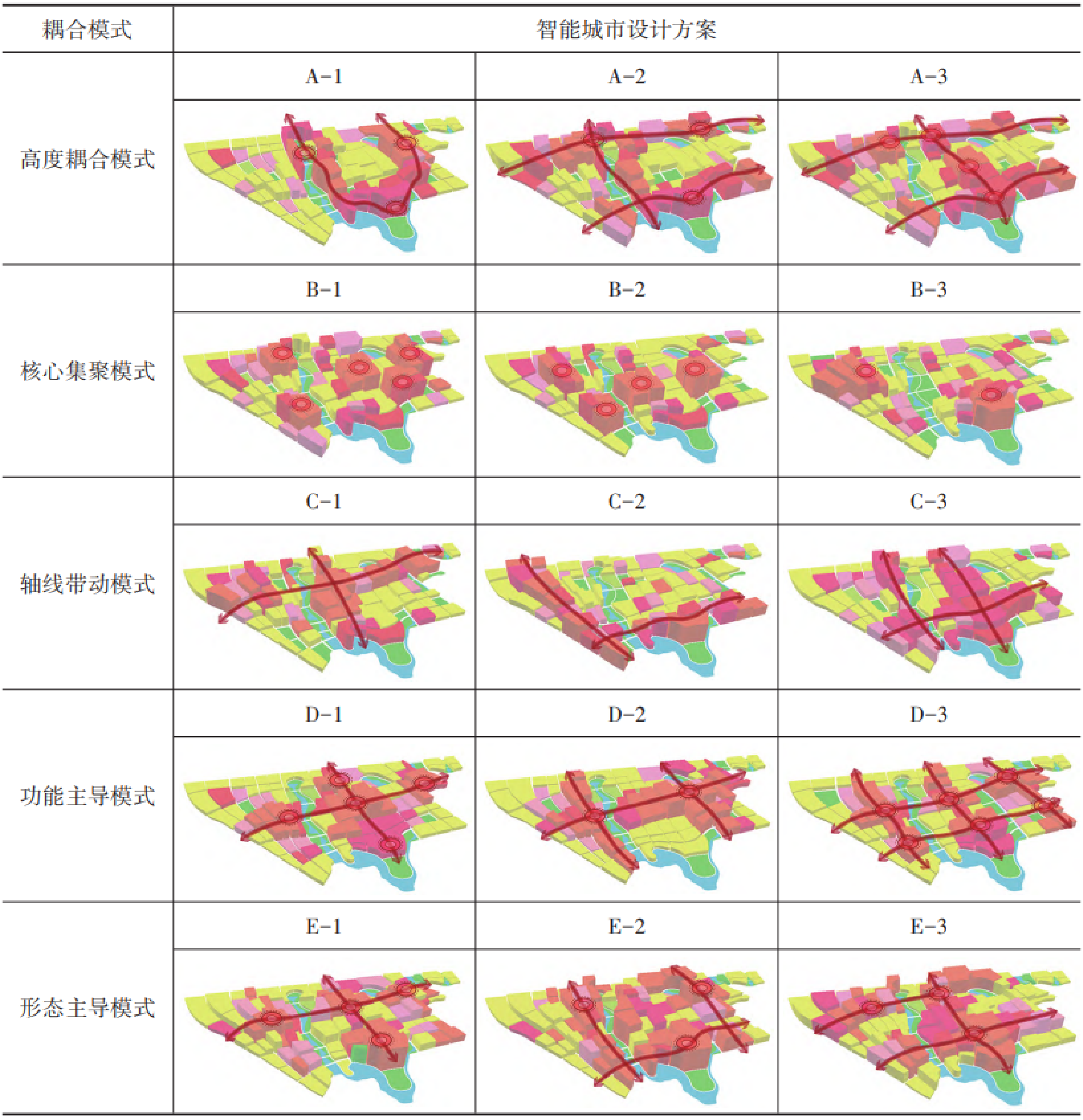
3.2 Intelligent urban design results from dynamic function-morphology interaction

Using the mesoscale intelligent urban design pathway developed above, the system automatically generated fifteen design alternatives under five function-morphology coupling modes (Table 3).

Table 3. Intelligent urban design alternatives for the sample district

Coupling mode	Generated intelligent urban design schemes
High coupling	A-1; A-2; A-3

Coupling mode	Generated intelligent urban design schemes
Core clustering	B-1; B-2; B-3
Axis-driven development	C-1; C-2; C-3
Function-led development	D-1; D-2; D-3
Morphology-led development	E-1; E-2; E-3



3.2.1 Scheme generation under the high-coupling mode

Iteration under the high-coupling mode includes separate processes for point and line elements. The five road intersections with the highest mean grayscale values among neighboring agents are selected as coupled point elements, while the three highest-ranking primary and secondary roads are selected as coupled line elements.

Spatial overlap increases continuously with the number of iterations. Point elements reach their optimal reward after approximately 1,200 iterations, while line elements reach their optimal reward after slightly more than 500 iterations. Random pairwise combination produces multiple spatial alternatives. To obtain more systematic outcomes, the three combinations with the shortest total perpendicular distance from point elements to neighboring line elements are selected as the intelligent urban design schemes for the high-coupling mode (Schemes A-1, A-2, and A-3 in Table 3).

3.2.2 Scheme generation under the core-clustering mode

The core-clustering mode forms key nodes through a high spatial concentration of production factors. Early-developing cores then guide the development of other blocks through spillovers of capital, labor, and related resources. Under this mode, functional cores and landmark clusters exhibit a high degree of spatial coincidence, maximizing agglomeration effects.

The iteration of point elements in the sample district is similar to that under the high-coupling mode and stabilizes after more than 1,200 iterations. Three schemes with relatively high coupling rewards and different numbers of coupling nodes are selected (Schemes B-1, B-2, and B-3). The results indicate that different node counts generate markedly different spatial schemes and that the overall integrity of the spatial structure weakens as the number of nodes increases.

3.2.3 Scheme generation under the axis-driven mode

The axis-driven mode uses the transportation network to organize block units with more public functions and more visually distinctive morphology, producing a belt-like pattern in which development axes drive the district as a whole.

After slightly more than 500 iterations, the line elements of the sample district gradually form highly coupled spatial schemes. The three schemes with the highest reward values are selected (Schemes C-1, C-2, and C-3). Schemes with higher coupling rewards generally take the form of a cross-axis structure or a variation thereof. Axes located in the central portion of the district also produce stronger radiating and catalytic effects.

3.2.4 Scheme generation under the function-led mode

Under the function-led mode, spatial morphology is generated as an adaptive response to functional layout, and a rational functional structure plays the decisive role. To exploit the uncertainty of machine generation as a source of design inspiration, no rigid functional zoning is imposed at the initial stage. Instead, the reinforcement-learning algorithm autonomously explores possible combinations of functional elements.

During early iterations, land uses are relatively dispersed and do not form a clearly identifiable functional-element system. After approximately 1,000 iterations, the functional structure becomes more legible, producing business cores, public-service cores, economic corridors, and other elements. A spatial decision engine then matches the morphological indicators and outputs the three schemes with the highest reward values (Schemes D-1, D-2, and D-3). In general, once the number of functional line elements exceeds three, the resulting morphology tends to become homogeneous. Although function and form remain well coupled, the spatial form is less distinctive.

3.2.5 Scheme generation under the morphology-led mode

Under the morphology-led mode, the policy network first generates a morphological scheme and then intelligently assigns functional types on the basis of learned correlations. Unlike the generally even form with localized height peaks produced by the function-led mode, morphology-led schemes contain more landmark high-rise blocks. Their height range expands to 0-250 m, creating a richer vertical composition.

After approximately 900 iterations, the fluctuation pattern of spatial form becomes increasingly clear, enabling the system to identify high-rise landmark clusters and continuous high-rise development belts. Functional layouts are then matched automatically, and the three schemes with the highest morphological reward values are selected (Schemes E-1, E-2, and E-3). The resulting schemes exhibit highly mixed functional layouts and do not display the pronounced functional zoning found in function-led schemes.

The fifteen schemes and the five coupling modes are compared using the five-dimensional benefit radar (Figure 5). Scheme E-3, a morphology-led alternative with the highest overall benefit, is selected as the initial scheme and entered into the feedback-and-optimization process. Through successive rounds of human-computer interaction, it develops into a spatial proposal organized around a U-shaped water system, with public-service functions and landmark buildings arranged along the main framework and multiple development branches extending outward.

The case demonstrates the feasibility and transferability of intelligent design at the mesoscale. In particular, when applied to diverse and complex urban environments, the method can provide richer and more evidence-based spatial-organization alternatives within a short time. It should also be emphasized that schemes under different coupling modes are not isolated static states. By adjusting relevant parameters, they can be dynamically transformed into one another, improving adaptability and flexibility and enabling a more effective response to changing urban needs.

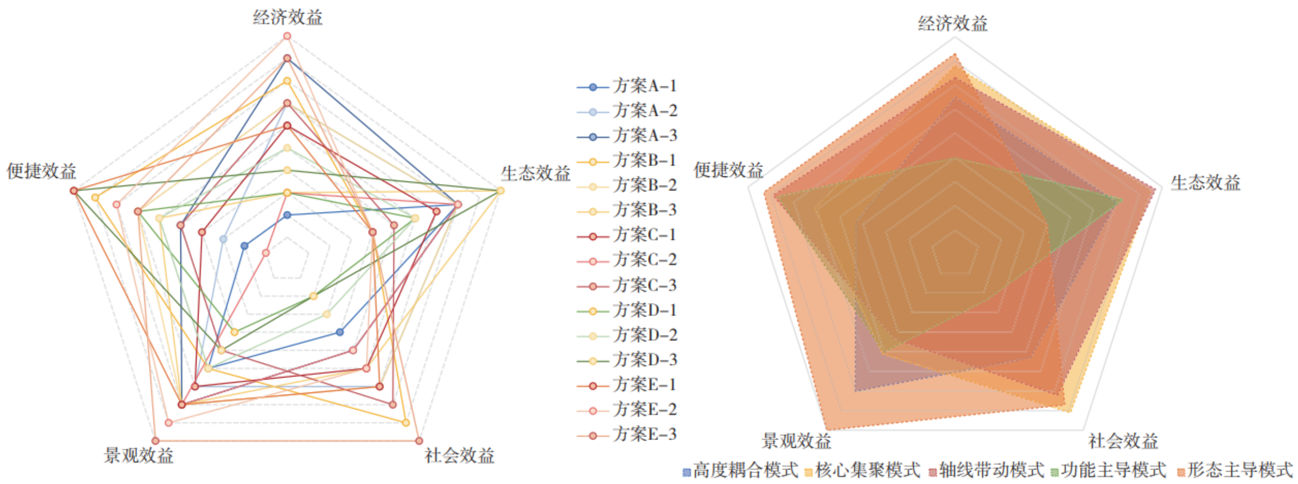


Figure 5. Radar-chart evaluation of different schemes and coupling modes

4 Conclusion

As the urban spatial mega-system continues to evolve, the interaction between function and morphology at the mesoscale becomes increasingly complex. From the perspective of dynamic function-morphology interaction, this study uses artificial-intelligence algorithms to construct a broadly applicable intelligent method for mesoscale urban design. Through interaction between designers and intelligent algorithms, urban space moves from disorder toward order and from dynamic fluctuation toward a relatively stable state. The method simulates the dynamic evolution of coordinated negotiation between functional and morphological systems and expresses the inherently generative nature of urban space.

Amid the continuing transformation of emerging technologies, digital urban design supported by intelligent technologies is developing rapidly. As changes in production and everyday life reshape future urban space, the crucial role of intelligent technology in urban design deserves greater recognition. How to combine human intelligence with machine computing power to design high-quality urban spaces across multiple scales, dimensions, and scenarios will remain an important scientific question for a considerable period. The path toward future intelligent urban design has only just begun.

Note

① Reinforcement learning (RL) is a machine-learning method in which an agent obtains rewards through continual trial and error while interacting with an environment. Its core components include a policy network, a critic network, and a Markov decision process (MDP). Different agent actions produce different reward feedback; reward signals then guide subsequent actions toward higher returns. Multi-agent reinforcement learning extends single-agent RL by enabling multiple agents to cooperate, making it possible to optimize design tasks in high-dimensional, complex, and dynamic spaces.

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