Urban Dynamic Cognition Methods and Micro-Scenario Applications Based on Knowledge Graphs

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Abstract: As complex systems jointly constituted by physical space and human activity, cities are characterized by continuously evolving, feedback-driven operational processes. The rapid development of the Internet and the Internet of Things in recent years has made it possible to capture real-time urban activities; however, extracting interpretable knowledge structures from fragmented perceptions remains a central challenge for achieving dynamic urban cognition. This study employs knowledge graphs as a representational framework, integrates multi-source spatiotemporal data, and constructs a cognition methodology for urban human activities centered on the semantic structure of "human–object–place–time–event–effect," enabling multidimensional networked cognition and structured expression of urban space and human activity. Taking a university campus as a representative micro-scenario, a knowledge graph comprising approximately 54,000 entity nodes and 118,000 relational edges was constructed to perform relation extraction and causal tracing analysis. Results demonstrate that this approach effectively supports activity attribution and spatial governance response in complex environments through activity backtracking and semantic linkage. It also exhibits strong cross-scale scalability and transferability, providing a feasible pathway and methodological foundation for behavior-driven planning and governance in the era of emerging urban technologies.

Keywords: urban dynamic cognition; human activity; knowledge graph; spatial governance; university campus

Cities are complex systems characterized by multi-element coupling and multi-scale evolution. Their operation is not merely the equilibrium outcome of static structures, but rather a process of continuous, dynamic reconstitution. The interaction between physical space and human activity places the city in a state of perpetual reorganization[1] — a dynamism that is not a byproduct of urbanization, but the very mode of urban existence. Consequently, urban cognition should not be confined to structural spatial form; rather, it must focus on capturing and interpreting the ongoing processes of activity–environment interaction and the underlying mechanisms and logics they reveal[2–3].

With advances in information technology, urban dynamism can now be recorded and quantified with unprecedented fidelity. Multi-source spatiotemporal big data — including sensor networks, mobile signaling, and social media[5] — enable the real-time perception of the spatiotemporal distribution and evolutionary characteristics of human activity, propelling urban research from static description toward dynamic analysis[6]. Yet the accumulation of massive datasets has not naturally translated into deeper understanding of urban operations: existing studies remain predominantly descriptive and statistical[7], lacking mechanisms for transforming multi-dimensional perceptual outputs into interpretable knowledge frameworks. Moving from data aggregation to cognitive deepening has thus become a central challenge confronting urban science today.

While current sensing technologies and analytical methods can capture activity characteristics, they struggle to systematically represent the semantic relationships and causal chains among multiple actors and elements. To address this, knowledge graphs (KGs) — as tools for structured semantic representation and knowledge reasoning — have been introduced into urban research. Unlike methods relying on static information, knowledge graphs employ "entity–relation–entity" triples as their fundamental unit, constructing dynamic semantic networks that interconnect multi-dimensional information and enabling structured representation of urban activity processes[8]. The application potential of knowledge graphs in causal reasoning and logical expression of urban activities has been validated across specific governance scenarios such as urban function cognition, traffic management, and energy consumption control.

Building on this foundation, this study proposes a knowledge graph–based method for urban dynamic cognition. The method employs a closed-loop structure of "perception–understanding–intervention" to integrate multi-source data acquisition, semantic modeling, and mechanism reasoning. Through constructing a full-element knowledge mapping of "human–object–place–time–event–effect," it achieves a coherent pipeline from data integration to mechanism cognition. Using a representative campus environment as an experimental setting, the study validates the model's feasibility and scalability in activity identification, outcome tracing, and dynamic intervention. This exploration aims to provide a novel cognitive framework for understanding the coupling mechanisms between urban human activity and the physical spatial environment, as well as methodological innovation and theoretical support for behavior-driven urban governance.

1 From Spatial Perception to Integrated Analysis

1.1The Evolution of Urban Cognition Theory

Urban cognition generally refers to the process of representing and understanding spatial structures, functional relationships, and social meanings during human interaction with the urban environment. It concerns not only "how the city is perceived" but, more critically, "how the city is understood and interpreted," serving as a vital intermediary linking physical space, behavioral mechanisms, and planning decisions.

Early urban cognition research was deeply influenced by structuralism and spatial morphology, focusing primarily on the organizational principles and visual order of urban physical form. In the mid-twentieth century, Kevin Lynch proposed the five-element theory of urban image through empirical investigation — paths, edges, districts, nodes, and landmarks[9–10] — systematically revealing the cognitive logic by which individuals perceive urban space. This theory established the foundational paradigm of urban cognition research. Jane Jacobs[11], from the perspective of social interaction, emphasized the complexity and diversity of street life, broadening the scope of attention to urban activities. Positivist geography further strengthened the quantitative characterization of spatial processes through deductive and inductive reasoning. This phase focused on urban visibility and sense of order, revealing through descriptive methods the influence of spatial form on individual perception, and laying the theoretical groundwork for planning's attention to spatial legibility and place value.

However, excessive simplification of spatial problems led research to temporarily neglect the role of "people" in cities, triggering a wave of scholarly reflection[12]. Behavioral geography, which emerged in the 1960s, emphasized the importance of individuals and micro-processes[13–14], offering new perspectives for understanding the complex spatiotemporal relationships between human activity and the geographic environment.

Norberg-Schulz[15] and Yi-Fu Tuan[16] further deepened the intellectual foundations of urban cognition from phenomenological and humanistic perspectives, emphasizing the generation of perceptual experience, emotion, and meaning in space. Torsten Hägerstrand's time-geography revealed the dynamic relationships among activity, constraint, and opportunity through "time–space paths"[17], expanding the perspective of urban cognition from static spatial perception to systematic understanding of spatiotemporal behavioral processes. Research on behavioral constraints and decision-making mechanisms further demonstrated that individual activities are not randomly distributed, but exhibit analyzable patterns under multiple constraints of time, resources, and social networks — advancing urban cognition from visual representation toward process analysis and providing new theoretical foundations for understanding the causal chain between spatial configuration and behavioral choice.

Building on these foundations, scholars gradually recognized that urban complexity cannot be explained from a single dimension of either space or behavior alone. A new round of theoretical integration, represented by social space theory and space–behavior interaction theory, propelled urban cognition into a research phase centered on "physical space–human activity coupling"[18]. With the advent of the information age, the rise of urban informatics and the introduction of multi-source spatiotemporal data, artificial intelligence, and knowledge graph technologies have enabled urban cognition to advance from theoretical concept to systematic modeling; the city is no longer merely an object of perception and representation, but a complex system amenable to real-time understanding, prediction, and intervention[19].

Overall, urban cognition theory has undergone an evolutionary trajectory from spatial characterization to behavioral analysis and then to data-driven systematic cognition. This trajectory has not only provided an intellectual foundation for methodological innovation but has also established "space–activity interaction" as the central issue for understanding complex urban operational mechanisms.

1.2Advances in Urban Sensing Technologies

As theoretical frameworks progressively shifted from space–behavior coupling toward systematic cognition, related research began to focus on achieving dynamic perception of urban operational mechanisms through technological means — acquiring, identifying, collecting, and classifying information on the physical environment and human activity in cities to provide a computable basis for urban cognition. The development of urban sensing technology has evolved from empirical inference and manual survey to intelligent sensing. Its core trajectory lies in the expansion of sensing targets from physical space to human activity, the transition of sensing methods from single-source to multi-source fusion, and the transformation of sensing content from static characterization to dynamic spatiotemporal processes.

Early urban sensing relied primarily on manual observation and empirical investigation, obtaining urban spatial characteristics through researchers' field surveys, questionnaires, and statistical data, with inherent limitations in data completeness and coverage. With the widespread application of remote sensing imagery and geographic information systems (GIS), urban sensing entered a digital mapping phase centered on "space–image–indicators"[20]. Sensing targets at this stage were predominantly physical spatial elements such as land features, buildings, and roads; data structures were primarily in raster or vector format, achieving refined quantitative representation of static spatial information.

With the development of mobile Internet and IoT technologies, integrated space–air–ground intelligent infrastructure has been progressively established, ushering urban sensing into an intelligent and multi-source stage[21]. Based on multi-temporal, multi-spectral remote sensing imagery, streetscape images, and environmental monitoring data collected by professional sensors, combined with human-carried social sensing (e.g., mobile phone signaling, social media, trajectory data) and crowdsourced sensing (e.g., user-uploaded photographs, text, and location information), urban dynamic characteristics can now be captured in real time, with the sensing focus extending from "objects" to "people"[22]. Research in this phase attends not only to the physical form of urban space but also to the identification and analysis of processual information such as individual and group behavior, travel patterns, and energy consumption changes[23]. Representative studies include identifying population activity intensity and dynamic functional boundaries through mobile phone signaling data[24–25], recognizing urban emotions and spatial preferences using social media data[26–27], and achieving real-time urban travel perception through traffic sensors and video surveillance[28–29]. The fusion of such multi-source heterogeneous data has transformed the city from an object observed as "static image" to one observed as "dynamic process," laying the foundation for fine-grained analysis of urban operations[30].

Currently, urban sensing is deepening in the direction of integration, intelligence, and cognitivization. However, relying solely on sensing methods to acquire and integrate data remains insufficient to reveal the intrinsic logical relationships among urban elements. How to systematically analyze spatial structure and human activity to support urban cognition and decision-making has become the core agenda for the next phase of research.

1.3Deepening of Urban Analytical Methods

Urban analysis — building upon perception — is the process of identifying, interpreting, and predicting the interactive relationships between physical space and human activity, aiming to reveal the internal mechanisms of urban operations and support decision-making. Urban analytical methods have evolved from spatial statistics to network modeling and then to semantic reasoning; their core objective has progressively shifted from static pattern analysis to dynamic mechanism cognition.

Early urban analysis relied primarily on spatial statistics and regional models to reveal macro-level patterns of urban form and functional configuration. Methods represented by spatiotemporal distribution analysis revealed spatial autocorrelation and evolutionary characteristics of geographic elements[31]; quantitative research typified by traditional statistical models (e.g., gravity models, regression models) emphasized the statistical correlation of spatial relationships[32–33]; research centered on spatial models and network analysis quantitatively characterized the organizational logic of spatial structures through methods such as space syntax and accessibility analysis[34–35]. With the development of artificial intelligence, machine learning and deep learning models were introduced into urban research, greatly enhancing analytical capacity for complex problems[36]. Urban analysis at this stage transitioned from structural description to mechanism reasoning, yet remained predominantly at macro-scales with aggregated data, struggling to capture the self-organizing characteristics and spatiotemporal interaction processes of multiple elements within the urban complex system.

Consequently, complex network theory was introduced, abstracting the city as a relational network of people, places, facilities, and events, and analyzing network degree distribution, small-world properties, and clustering coefficients to reveal potential patterns in urban operations[37]. Multi-layer neural network models developed on this basis described the cross-hierarchical cascading relationships among land, industry, population, and transportation[38]; multi-agent interaction models further incorporated behavioral logic and decision-making mechanisms into the analytical framework, revealing the dynamic response between crowd behavior and spatial states. Together, these three approaches constructed the foundation for urban complex system analysis, propelling the transformation of urban analysis from "parallel perception" to "interactive reasoning" and achieving significant progress in understanding the space–activity–effect coupling.

However, these models still exhibit limitations in semantic expression and logical reasoning, particularly in integrating cross-domain information and explaining causal mechanisms when confronted with multi-source heterogeneous data. The introduction of knowledge graphs provides a breakthrough for addressing this challenge — inheriting the advantages of network structure analysis while strengthening cross-domain data integration and causal relationship modeling. POI, social media, and visual perception data–driven urban function cognition has become a research hotspot; urban function knowledge graphs based on multi-source data have been applied to support urban function cognition and spatiotemporal evolution analysis[39]. Chen et al.[40] constructed dynamic graphs from mobility data during the pandemic to assist in real-time crowd guidance and lockdown strategy adjustment. Zhu et al.[41] utilized traffic flow and weather data graphs to improve short-term traffic prediction accuracy. Hu et al.[42] integrated knowledge graphs with graph neural networks to model the causal relationship between pedestrian flow and building energy consumption in urban centers, enabling intelligent building system control. These studies demonstrate that knowledge graphs can serve not only for semantic integration of urban elements but also as intermediaries for behavioral modeling and governance reasoning, organizing urban elements into a computable and interpretable knowledge system.

Against this backdrop, this study attempts to construct an urban cognition methodology centered on knowledge graphs, establishing a knowledge representation paradigm for the full-process interaction between urban physical space and human activity through structured, semanticized, and dynamic analytical frameworks. It explores a dynamic cognition system integrating "perception–understanding–response" to support multi-scenario, multi-scale, behavior-driven urban governance applications.

2 Full-Spectrum Mapping of Urban Human Activities Based on Knowledge Graphs: Logic and Methods

To perceive and analyze the complex processes of urban operations, this study constructs an urban dynamic cognition system targeting multi-dimensional information on urban physical space and human activity, using knowledge graphs as its representational framework. The system supports structured expression and dynamic management of elements including "human–object–place–time–event–effect"[43], formally defined as:

$$K_G = \{E, R, S, A\} \tag{1}$$

where: K_G (knowledge graph) denotes the knowledge graph; E (entity) represents entities, encompassing the specific objects and phenomena of human activity as nodes in the knowledge graph; R (relationship) represents the relationships among these entities, constituting the edges in the knowledge graph, where $R = \{(e_1, r, e_2) | r \in R, e_1, e_2 \in E\}$; S (set) denotes the entity–relation–entity triples formed by connecting nodes through edges, constituting the fundamental semantic units of the knowledge graph; A (attribution) represents entity attributes, satisfying $\forall e \in E$, with corresponding attribute $a_e \in A$, used to describe the identity, temporal, spatial, and numerical characteristics of entities.

2.1 Key to Translating Urban Dynamic Processes into Knowledge Graph Representation: Entity Definition and Attribute Annotation

The primary task in constructing a knowledge graph for urban human activity is identifying and defining multi-dimensional entities. Human activity in cities involves a vast array of heterogeneous elements, which can be parsed into a series of information categories: human, object, place, time, event, and effect (Figure 1). These semantic entities collectively constitute the fundamental information nodes of urban operations and the structural basis for knowledge graph construction. Among these, human and object serve as the subjects of activity, encompassing the various individuals and carriers that execute activities in urban space; place refers to the spatial venues where activities occur, including buildings, roads, plazas, and the districts and networks formed by their combinations; time captures the temporal context of activities, supporting modeling of behavioral rhythms and periodic patterns; event corresponds to the specific operations performed by activity subjects within particular temporal and spatial contexts, encompassing both static resource use (e.g., energy consumption of electricity, water, and gas) and dynamic behavioral processes (e.g., commuting paths, spatial flows, social gatherings); effect reflects the impacts generated by urban human activities across different times and spaces, including but not limited to information from diverse sensing devices on building energy consumption, traffic load, and spatial intensity — serving as the critical endpoint of the dynamic cognition chain oriented toward governance intervention.

Each entity type in the graph requires complete attribute information. Attribute types are not fixed in dimensionality but should be flexibly defined according to the real-world contextual characteristics of the entities themselves, typically including identity markers (e.g., name, ID), spatiotemporal attributes (e.g., latitude/longitude, timestamps), behavioral attributes (e.g., role, state), numerical information (e.g., energy consumption, flow volume), and other information capable of characterizing entity features, to achieve multi-perspective depiction of entity states. Entities and their attributes constitute the first structural dimension of the knowledge graph, serving as the foundation for subsequent logical construction and causal expression.

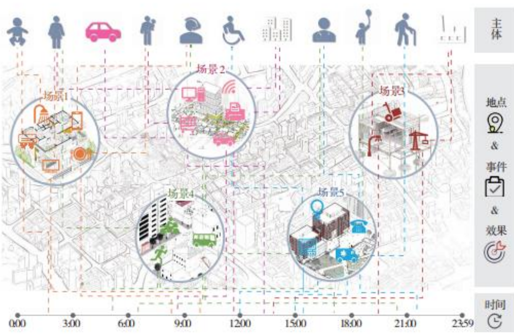

Figure 1. Multidimensional entities in the urban activity knowledge graph

2.2Core of Translating Multi-Dimensional Urban Elements into Semantic Network Construction: Structured Processing and Relationship Mapping

Within the framework of entity and attribute definition, the vast volume of human activity sensing data must be transformed into uniformly operable structured information. This study employs deep learning methods to process multi-dimensional information from video images, social media text, location trajectories, and other sources. Specifically, video images are processed through object detection models to identify crowd and traffic subjects; social media text is processed via language models to extract behavioral events, spatial locations, and temporal labels; trajectory data is analyzed in combination with temporal sequence modeling methods to identify path patterns and activity characteristics. All data undergo format conversion and spatial coordinate parsing in the Python environment and are uniformly stored in the Neo4j graph database, achieving the transformation from multi-source heterogeneous raw data to structured semantic units.

On the basis of structured data, semantic relationships among entities must be further identified to construct a structurally network capable of logical expression. Semantic relationships in urban systems include but are not limited to spatial adjacency and membership, temporal sequence and duration, behavioral execution, and event response. These relationships reflect the genuine interactions among urban elements at the semantic level, providing semantic support for constructing logical chains of "who–where–why–how–what result."

Accordingly, a rule system coupling spatial, temporal, and behavioral constraints is constructed to enable semi-automatic inference of semantic relationships among structured data. Specifically: basic relationships (e.g., "occurs at," "belongs to") are automatically generated through field matching using pandas functions in Python; spatial relationships are computed based on latitude/longitude using the geopandas and shapely libraries to calculate spatial distances, and when the distance falls below a set threshold, the system automatically generates relationships such as "located at," "adjacent to," and "passes through." Temporal relationships (e.g., "synchronized," "sequential") are identified through timestamp differentials; behavioral relationships (e.g., "participates in," "co-occurs with") are automatically inferred based on the overlap of subject identifiers and event records within time windows, with logic implemented by pandas time series functions. For complex semantic relationships (e.g., "influences," "responds to," "causes"), expert knowledge is integrated to establish logical rules, forming a hybrid generation mechanism of "manual annotation + rule inference" to balance semantic accuracy and computational scalability.

Ultimately, structured segments are mapped into triples centered on "human–event–place–time–object–effect" and embedded into the knowledge graph using platforms such as Neo4j, enabling the organization, querying, and dynamic updating of nodes and relationships, thereby providing an actionable knowledge 载体 for understanding and governing urban operational mechanisms. See Figure 2.

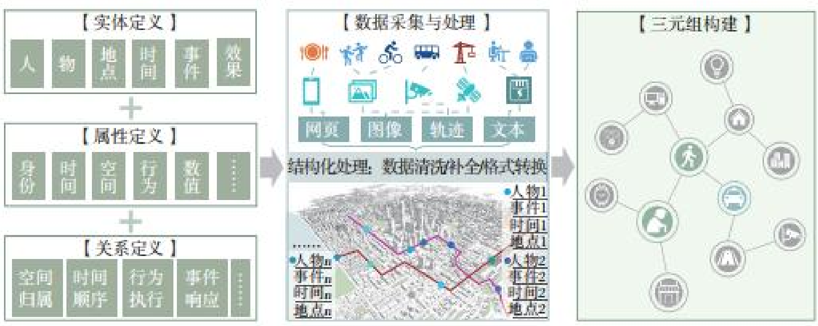

Fig.2 Mapping pathway of urban physical space and human activities based on the KG

2.3Bridge from Data Integration to Knowledge Cognition: Path Querying and Reasoning Analysis

Following knowledge graph construction, this study further introduces graph reasoning and analytical methods based on relational path matching and semantic similarity computation to achieve knowledge cognition from explicit relationships to potential causal chains within the multi-dimensional semantic network.

Relational path matching reveals potential behavioral chains or spatial dependencies through multi-hop relational path reasoning. For example, when "Subject A — participates in — Event B — occurs at — Building C" and "Building C — adjacent to — Building D" coexist, path reasoning can identify the implicit relationship that "Subject A may be active near Building D." This method leverages the path pattern matching capabilities of the Cypher query language in the Neo4j graph database, combined with Python's NetworkX graph analysis library, to achieve automatic retrieval and path inference of multi-hop relationships.

Semantic similarity computation identifies objects with similar attributes, proximate functions, or consistent behavioral patterns across multi-source entities. By employing Python's gensim and scikit-learn libraries to vectorize the attribute information of entity nodes, combined with Neo4j's node similarity algorithm, a comprehensive evaluation of semantic similarity among spatial places and behavioral events is conducted, thereby revealing pattern recurrence and functional coupling phenomena within urban systems.

The graph reasoning system is implemented in the Neo4j graph database environment; data preprocessing, path retrieval, and semantic similarity computation are all completed on the Python platform; reasoning results are written back to the Neo4j database via Cypher statements, forming a dynamically updated knowledge network. This process not only achieves full-spectrum representation of urban physical space and human activity but also facilitates the revelation of behavioral chains, spatial dependencies, and their causal mechanisms.

3 Multi-Dimensional Cognition of Urban Micro-Scenarios Based on Knowledge Graphs: A University Campus Case

3.1Research Object and Scenario Selection

To validate the feasibility and application potential of the proposed method, the new campus of University A in the suburbs of Tianjin was selected as the micro-scale experimental platform, based on its representativeness and data accessibility. The new campus of University A covers a total area exceeding 2.4 million m^2, with a building area of 1.55 million m^2. Its spatial layout adopts a planning model of disciplinary belt + functional belt, with clear functional zone boundaries and diverse activity types. Additionally, the campus is equipped with comprehensive video surveillance systems and intelligent metering devices, providing data support for knowledge graph construction.

3.2Multi-Source Data Acquisition and Structured Processing

Combining field investigation with Internet big data, activity information for the fall semester of 2023 (September 1, 2023 — January 1, 2024) was obtained, constructing a composite data system encompassing architectural engineering drawings, geographic information, social media information, traffic monitoring, and energy metering text. Data primarily originated from statistical materials provided by the university's logistics management department and open-source data from public network platforms. Given that mobile phone signaling data is difficult to obtain due to privacy protection and data authorization constraints, motor vehicle travel was used as a proxy variable for human travel to characterize campus commuting behavior.

During the data processing phase, intelligent methods including the YOLOv8 model and SDV (Synthetic Data Vault) algorithm were introduced to perform format standardization, timestamp alignment, and unified entity encoding on multi-modal data, integrating them into a unified campus multi-dimensional information map (Figure 3), providing high-quality, standardized data interfaces for knowledge graph construction.

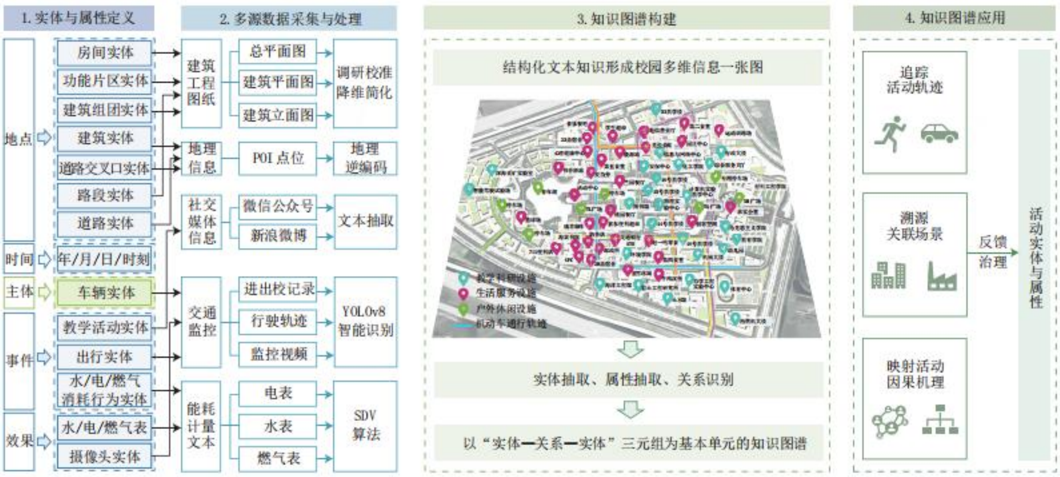

Fig.3 Technical roadmap for constructing KG of campus A, Tianjin

3.3Modeling Results and Characteristics of the Campus Activity Knowledge Graph

Based on the structured data, the campus activity knowledge graph was constructed using the Neo4j graph database (Figure 4), comprising approximately 54,000 nodes and 118,000 relational edges, covering various activity subjects, behavioral events, spatial entities, and energy consumption records within the campus. In the graph, the multi-level relationships among entities and their temporal, spatial, and causal attributes collectively form a knowledge network capable of rapid response analysis of key governance issues — such as anomalous activity trajectories, high-energy-consumption locations, and densely aggregated events — through semantic querying and causal tracing.

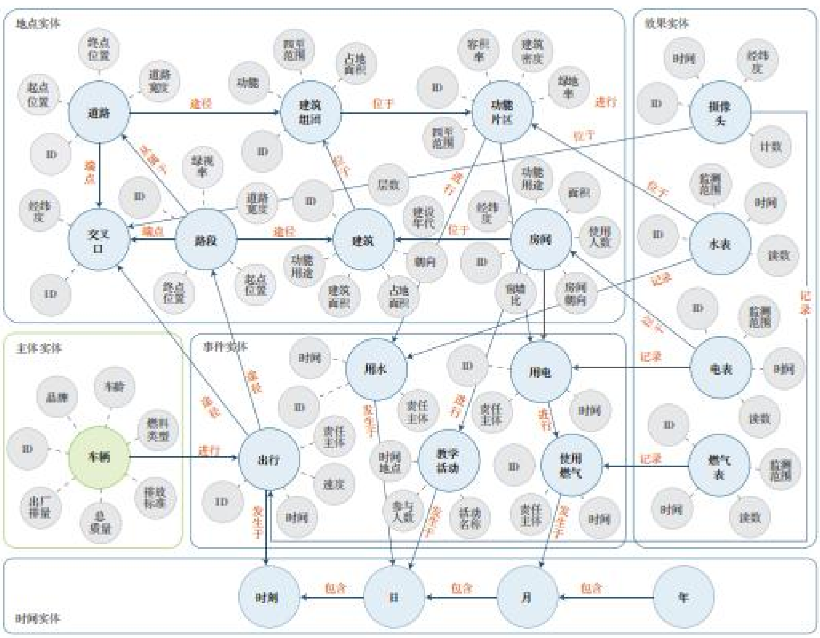

Fig.4 Entity and attribute definitions in the activity KG of campus A, Tianjin

4 Applications and Insights of Knowledge Graphs in Urban Cognition

4.1Governance Applications in the Campus Scenario

The knowledge graph–driven urban dynamic cognition method proposed in this study enables structured representation of activity patterns across the entire domain and supports multi-dimensional information aggregation and causal analysis from any node. The "effect" dimension characterizes the consequential response of human activity in time and space, constituting the core component of graph cognition and the practical endpoint of urban governance. Accordingly, leveraging the activity knowledge graph of University A, the morning peak period (7:30–8:30) of December 18, 2023 — a typical teaching day — was selected as the observation window. A randomly selected vehicle entering the campus served as the starting point for semantic querying, with focus on the attribute characteristics and semantic connotations of its effect dimension, to explore the application potential of knowledge graphs in semantic integration and causal logic identification.

4.1.1Commuting Path Identification: Individual Activity and Spatial Trajectory

Leveraging the structured organization and semantic querying capabilities of the knowledge graph, the system initiated querying from vehicle plate Jing H1Z*, captured by the north gate surveillance camera, identifying the travel activity node T041 generated after the vehicle entered the campus at 8:17 on December 18, 2023, and backtracked this commuting behavior [Figure 5(a)]. The graph automatically retrieved the path attributes and adjacent node relationships of this commuting event, completing the semantic reconstruction of the individual vehicle trajectory within the campus spatial network.

Path tracking results showed that after entering the campus from the north gate, the vehicle sequentially passed through five intersections — P01, P37, P56, P57, and P58 — ultimately stopping near Teaching Building 55, forming the commuting route "XY North Road — XY Middle Road — MD North Road." Based on the traffic flow attributes of camera nodes in the graph, this commuting route was identified as the main corridor with the most concentrated traffic pressure during the morning peak period, with average traffic density significantly higher than other concurrent routes, carrying a substantial volume of cross-district movement within the campus.

The reconstruction of the vehicle trajectory demonstrates the knowledge graph's capacity to construct complete behavioral chains from individual nodes, providing a structural basis for subsequent identification of high-frequency travel patterns and exploration of spatial use logic.

4.1.2Semantic Information Linkage: Spatial Element Networks and Aggregation Characteristics

On the basis of the identified commuting path, the system further analyzed the multi-dimensional spatial structures and functional nodes connected through the entity attributes and semantic association mechanisms of the knowledge graph, revealing the underlying spatial-behavioral logic.

Results indicate that the commuting destination, Teaching Building 55, belongs to the Computer Science School cluster, which is one of the units with the highest number of faculty and students and the densest teaching and research activities on campus — a typical destination for high-frequency commuting [Figure 5(b)]. Along this commuting route, multiple student dormitories, the library, activity centers, and Teaching Building 45 and other important public venues are passed, linking the daily behavioral chain of student groups: "living–studying–socializing." Simultaneously, this path also covers service facility nodes within the living cluster, including supermarkets, restaurants, and postal outlets. The superposition of spatial agglomeration effects from commercial and educational facilities significantly enhances the pedestrian attraction capacity of this area, forming a spatial–behavioral hotspot coupling relationship jointly driven by teaching functions and living services.

The linked querying of spatial information validates the knowledge graph system's capacity to automatically associate from individual behavioral chains to domain-wide multi-dimensional information, providing a cognitive pathway for understanding the interactive relationships between complex spatial structures and behavioral mechanisms on campus.

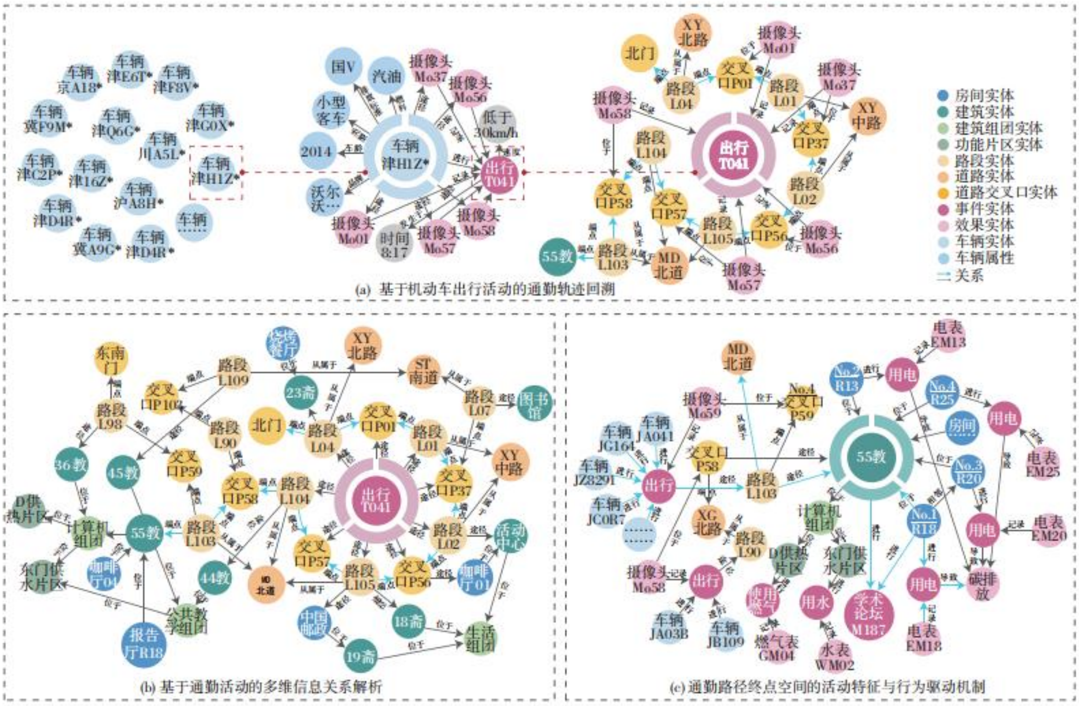

Figure 5. Governance applications of the knowledge graph in the campus scenario

Source: Redrawn from the activity knowledge graph of University A

4.1.3Causal Logic Analysis: Event-Driven and Energy Consumption Response

Based on the endpoint location of the aforementioned commuting behavior, the system further invoked the semantic association module of the knowledge graph to conduct in-depth querying and structural tracing of the spatial entities and activity content associated with Teaching Building 55.

First, querying results based on building node attributes showed that the Computer Science teaching cluster where Building 55 is located falls within Heating District D and the East Gate water supply district, with its water and energy use activities recorded in district metering tables. The building contains 174 rooms, encompassing diverse functional uses including classrooms, laboratories, conference rooms, auditoriums, cafés, and restrooms. Electricity data is collected daily by individual room meters and recorded in real time in the energy consumption node attributes of the graph. Further retrieval of daily aggregated room node energy consumption attributes revealed that among the 29 rooms ranking in the top 3‰ for daily electricity consumption, 11 were located within Teaching Building 55, accounting for 37.9%. Notably, Auditorium R18 recorded daily electricity consumption of 87.3 kWh, equivalent to 69.4 kg of carbon emissions — the highest among nearly 10,000 rooms across the campus that day, with energy load significantly exceeding other conventional teaching spaces.

Second, the system invoked the semantic tracing functionality of the knowledge graph to link multi-dimensional information including the upper-level spatial structure of Teaching Building 55 (teaching cluster, energy sub-district), that day's behavioral events, and surrounding traffic nodes [Figure 5(c)]. Results showed that on December 18, the Computer Science School hosted a large-scale academic forum in this building, with multiple rooms used for different types of seminars, result exhibitions, and teaching activities. Among these, Auditorium R18 served as the main forum venue, with the largest number of participants and the longest activity duration, thereby forming the most concentrated energy demand of the day. Meanwhile, the two main commuting road sections L90 and L103 adjacent to Teaching Building 55 exhibited highly consistent temporal fluctuations with the electricity consumption changes of multiple rooms in the building on that day's traffic intensity curves, revealing the typical mechanism of "behavioral trigger–spatial agglomeration–energy consumption" driven by large-scale teaching activities, and reflecting the dynamic process of multi-element interaction in urban micro-scale units.

Through tracing the semantic association paths among graph nodes, the system effectively integrated originally dispersed multi-dimensional information, reconstructing the causal logic underlying campus activities and providing structural support for governance intervention.

4.2Multi-Scenario Promotion and Methodological Insights

The knowledge graph–based empirical study in the campus scenario not only validates the method's capacity for information integration and semantic modeling in high-density spaces but also provides a generalizable analytical approach for understanding behavioral processes at larger urban scales. Through identifying individual activity chains, spatial use frequency, and behavioral co-occurrence relationships, it is possible to reveal behavioral logic and spatial response patterns widely present in urban spatial organization, providing micro-level reference for dynamic cognition of complex urban problems.

As a core vehicle integrating the full process of "identification–attribution–simulation–feedback," the semantic framework of the knowledge graph possesses high reconstructability: entity and relationship types can be flexibly defined or adjusted according to application scenarios, and attributes can be dynamically updated, thereby adapting to diverse data sources and cognitive requirements without altering the overall semantic logic. This characteristic enables the cognitive model constructed in this study to maintain semantic consistency and logical interpretability across different spatial hierarchies and thematic domains. Accordingly, the method can be further extended to residential communities, industrial parks, commercial districts, and other urban spatial types,乃至 the entire urban domain, enabling multi-dimensional cognition and response modeling in diverse fields such as energy management, environmental regulation, heritage conservation, and urban regeneration.

From a disciplinary perspective, knowledge graphs advance urban planning research from static spatial description to dynamic cognitive analysis, constructing a logical chain of "information–knowledge–cognition." The significance lies not only in achieving structured integration and full-spectrum representation of multi-dimensional urban elements but, more importantly, in revealing urban operational mechanisms in a computable and interpretable manner, providing new implementation pathways for digital twin city construction and intelligent governance, promoting the transformation of planning decisions from experience-oriented to data-driven and knowledge-driven, and realizing the bidirectional integration and innovation of disciplinary theory and governance practice.

5 Conclusions and Outlook

Addressing the current challenges of insufficient granularity in coupling analysis between urban physical space and human activity and the disconnection of response mechanisms, this study proposes a knowledge graph–based urban dynamic cognition method. Centered on the semantic structure of "human–object–place–time–event–effect," the method achieves a full-process closed loop from multi-source data acquisition and behavioral modeling to response support.

In the empirical study at a university campus, the constructed human activity knowledge graph demonstrated strong information aggregation and semantic association capabilities, effectively supporting multi-dimensional analytical tasks from individual trajectory tracking and spatial relationship identification to causal mechanism analysis. The study validates the method's applicability and scalability in micro-scale spatial governance, demonstrating the potential of knowledge graphs in enhancing semantic integration, structured expression, and reasoning and deduction capabilities of dynamic cognition methods. From the perspective of urban planning governance, the method provides a technical pathway for constructing a dynamic cognition system centered on the "human–scenario–behavior" logic, with generalizable analytical approaches and portable, extensible methodological models that can be embedded in diverse planning practice scenarios — including central district traffic organization optimization, industrial park environmental monitoring and regulation, and historical-cultural heritage conservation and regeneration — supporting the governance paradigm transformation from static allocation orientation to dynamic behavior-driven approaches.

Looking ahead, urban dynamic cognition systems require continued deepening in three key directions: first, promoting automation of input-side data integration to enhance real-time processing capabilities for heterogeneous data; second, strengthening the depth of information mining within the graph to enhance the identification and construction of complex behavioral patterns and semantic relationships; and third, expanding the coupling mechanisms between the graph and decision-making endpoints to improve strategy feedback, scenario simulation, and cross-departmental coordination capabilities. These pathways will collectively advance the transformation of urban knowledge graphs from data organization tools to urban governance platforms, providing support for the construction of new urban governance systems.

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