Intelligent Generative Design in Central Business Districts: A Survey

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Abstract

This survey explores the transformative potential of intelligent generative design within Central Business Districts (CBDs), focusing on the integration of advanced computational techniques such as graph neural networks and spatial optimization with urban planning principles. By leveraging these methodologies, urban planners can optimize urban morphology to enhance social interaction, functionality, and energy efficiency. The survey highlights the role of deep learning in urban morphology analysis and the use of machine learning models to refine urban planning methodologies. The incorporation of facade photovoltaic technologies exemplifies the potential for intelligent design to contribute to sustainability and energy efficiency. The deployment of advanced graph neural network architectures demonstrates improvements in urban data analysis, while satellite-based methods offer new opportunities for urban climate studies. The survey concludes that urban morphology significantly impacts energy efficiency, with potential to reduce cooling loads and increase ventilation, underscoring the importance of morphological considerations in urban planning. The integration of intelligent generative design techniques promises significant advancements in logistics optimization and urban infrastructure planning, contributing to the development of adaptive, resilient, and sustainable CBDs.

1 Introduction

1.1 Significance of Intelligent Generative Design in CBDs

Intelligent generative design significantly enhances the functionality and aesthetics of central business districts (CBDs) by employing advanced computational techniques for urban optimization. The integration of urban functions and their complex relationships with human activities is essential for promoting smart and sustainable urban development [1]. This methodology not only facilitates efficient social interaction across urban landscapes but also fosters greater social engagement within CBDs [2].

The intricate nature of urban environments necessitates innovative resource management and optimization strategies. Traditional optimization methods often struggle to address the dynamic, interconnected aspects of urban systems, particularly with the growing incorporation of renewable energy and sustainable practices [3]. Intelligent generative design addresses these challenges through a morphological framework that considers historical development, hierarchical relationships, and interactions among urban form elements, thereby enhancing planning practices [4].

Beyond functional improvements, intelligent generative design contributes to aesthetic enhancements in CBDs. Utilizing machine learning and spatial data, urban planners can craft visually appealing and legible urban landscapes [5]. This comprehensive approach ensures that CBDs are not only efficient and sustainable but also vibrant and engaging for urban inhabitants.

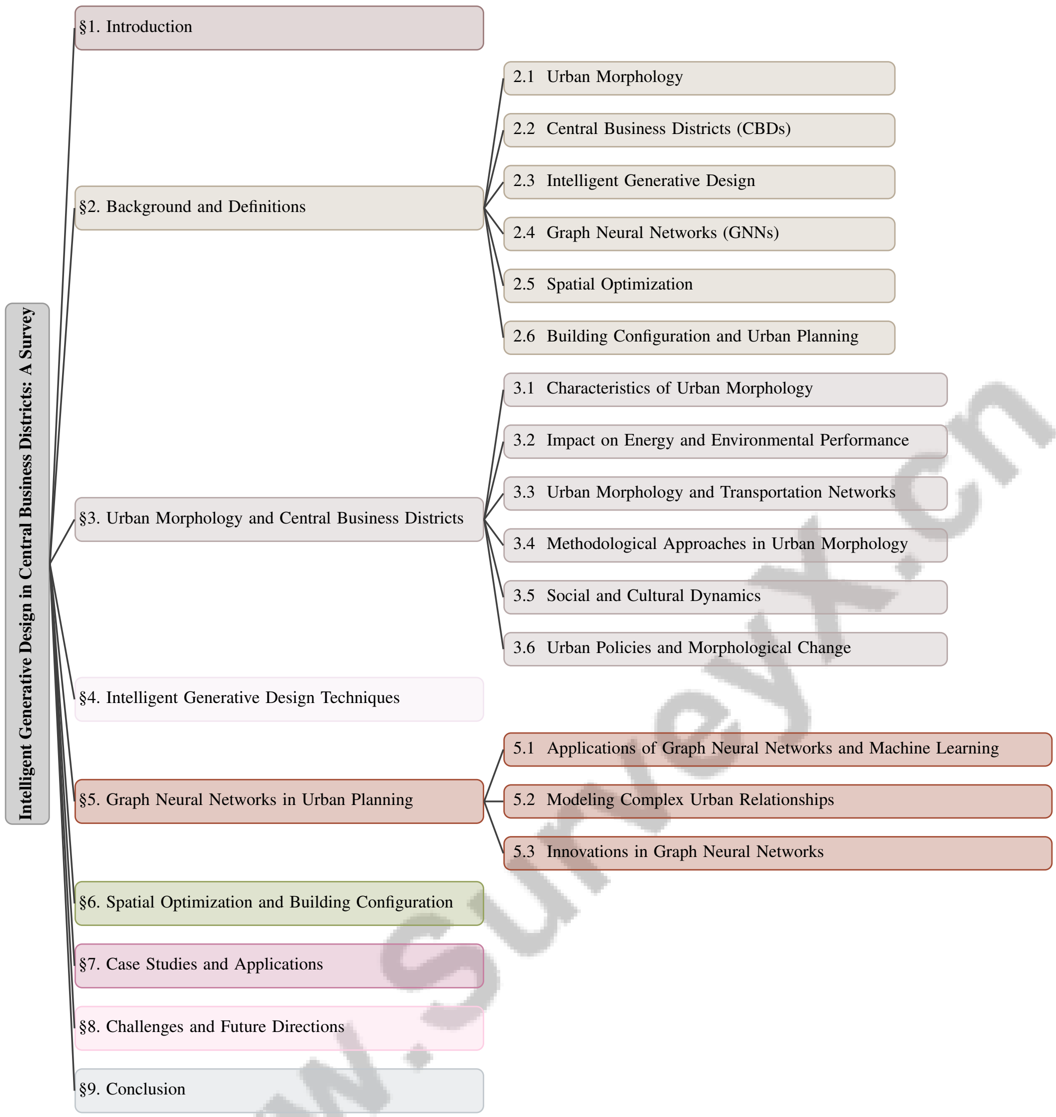

Figure 1: chapter structure

1.2 Interdisciplinary Approach

The interdisciplinary approach to intelligent generative design in CBDs merges urban planning with advanced computational techniques, yielding innovative solutions for complex urban challenges. For instance, the combination of mobile phone positioning data and social media check-in data reveals urban functions and their diurnal patterns, enhancing urban planning through data-driven insights [1]. Such diverse data sources empower urban planners with a holistic understanding of urban dynamics and activity patterns, facilitating informed decision-making.

Moreover, the integration of machine learning algorithms into urban planning exemplifies the potential of interdisciplinary collaboration in fostering intelligent urban environments. This mirrors the integration of data science in healthcare, where machine learning enhances clinical decision-making, underscoring the transformative impact of computational methods across various domains [5]. In the context of CBDs, machine learning analyzes spatial information to enhance the legibility and functionality of urban spaces, ensuring they are efficient, intuitive, and user-friendly.

The synergy of urban planning with advanced computational techniques in intelligent generative design fosters the development of adaptive, resilient, and sustainable CBDs. This approach effectively addresses the diverse and complex needs of urban populations in a rapidly evolving world, utilizing performance-driven computational urban design methodologies. By establishing bi-directional mappings between morphology metrics and urban forms, while leveraging deep learning and Generative Adversarial Networks (GANs), urban planners can optimize urban form generation and performance evaluation, ultimately enhancing urban sustainability and functionality [6, 7, 8].

1.3 Structure of the Survey

This survey provides a comprehensive exploration of intelligent generative design within CBDs, integrating advanced computational techniques with urban planning principles. It begins with an introduction that emphasizes the significance and interdisciplinary nature of intelligent generative design in CBDs, setting the stage for detailed analysis. The second section delves into the background and definitions of key concepts, including urban morphology, CBDs, intelligent generative design, graph neural networks, spatial optimization, building configuration, and urban planning, establishing a foundational understanding for readers.

Subsequent sections examine the interplay between urban morphology and CBDs, focusing on their characteristics, dynamics, and methodological approaches, as well as their implications for CBD design. The role of intelligent generative design techniques in urban planning is explored, emphasizing methodological innovations and the integration of multimodal data. The application of graph neural networks in urban planning is discussed, highlighting their capacity to model complex urban relationships.

Further, the survey analyzes spatial optimization and building configuration, exploring various optimization techniques and their applications in urban infrastructure planning. Case studies and practical applications showcase successful implementations of intelligent generative design in CBDs. Finally, challenges and future directions are identified, addressing issues related to data quality, computational complexity, and the integration of classical and modern techniques. The conclusion synthesizes key insights from the survey, reflecting on the potential impact of intelligent generative design on the future of urban planning in CBDs.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Urban Morphology

Urban morphology examines the physical form and structure of urban environments, playing a crucial role in the planning and dynamics of central business districts (CBDs) [9]. Analyzing spatial patterns enables urban planners to classify and evaluate urban forms, essential for sustainable development strategies [10]. Morphological factors significantly influence energy performance and ventilation in buildings, optimizing urban energy efficiency [11].

Traditional models often fail to capture the complexity of urban forms due to the absence of characteristic lengths, necessitating advanced methods like fractal modeling [12]. Key geometric properties such as street length and intersection angles provide a framework for understanding urban spatial organization [13]. Entropy analysis offers insights into multiscale interactions within urban spaces, reflecting urban complexity [14].

Various data modalities, including OpenStreetMap (OSM) data, enhance urban pattern representation, facilitating detailed urban morphology analysis [15, 16]. However, planning practices often overlook urban spaces' intrinsic qualities, disregarding historical and cultural contexts [4]. Recent research advocates for robust visualization methods in analyzing urban street networks, emphasizing the examination of road network characteristics [17]. Current measurement methods, mainly relying on numerical indices, often fail to capture human visual perspectives [18].

Urban morphology significantly informs CBD design by enhancing functionality and aesthetics. Systematic analysis of urban forms, combined with contemporary tools like big data and spatial technology platforms, provides insights into urban fabric patterns, promoting social interaction and functionality for vibrant and sustainable urban spaces [5, 16, 10].

2.2 Central Business Districts (CBDs)

Central Business Districts (CBDs) are vital urban zones serving as hubs for economic, social, and cultural activities. Defining CBD boundaries is challenging due to the lack of a universal definition, often relying on arbitrary administrative boundaries that do not capture urban growth dynamics [19]. This ambiguity necessitates a nuanced understanding of CBD roles and functions within urban environments.

CBDs are characterized by high-density development, a concentration of commercial and financial institutions, and a mix of retail, entertainment, and cultural amenities. Street network properties reveal significant centrality distribution differences shaped by geographic and planning constraints [13]. These networks are crucial for accessibility and connectivity, essential for CBD economic vitality.

Insights from historical and structural analyses provide a comprehensive understanding of CBD development [10]. Classifying urban places based on visitor attraction patterns influences infrastructure and service development within CBDs [20]. Understanding these patterns allows planners to optimize land use and transportation systems, enhancing CBD functionality and livability.

CBDs stimulate economic development through business concentration and facilitate cultural exchange by attracting diverse populations and visitors, as evidenced by urban attractors [9, 20]. Their complex nature necessitates careful consideration of historical, typological, and network characteristics to ensure sustainable development within the urban fabric.

2.3 Intelligent Generative Design

Intelligent generative design employs advanced computational techniques, including machine learning and optimization algorithms, to create efficient and aesthetically engaging urban environments. This approach categorizes urban patterns, establishing a scalable framework for optimizing urban morphology [21]. Deep learning enhances urban road network classification, providing a nuanced perspective on urban morphology [18]. Local Betweenness Centrality Analysis (LBCA) refines design methodology by improving urban street network understanding [17].

Combining machine learning with traditional optimization methods is crucial for optimizing urban infrastructure and resource allocation, enhancing functionality and sustainability [22]. Efficient 3D urban morphology extraction using satellite methods highlights intelligent generative design's potential in urban planning [23]. Graph neural networks (GNNs) optimize memory efficiency through feature decomposition, enhancing inference speed and reducing peak memory usage [24].

Intelligent generative design recognizes that land cover and impervious surfaces exhibit monofractal characteristics, while population density demonstrates strong multifractality, necessitating models capturing these complex patterns [15]. The proposed entropy measure considers place characteristics and interdependence, essential for comprehending urban complexity [14]. GANmapper utilizes generative adversarial networks (GANs) to synthesize building footprints from coarse geospatial data, exemplifying intelligent generative design's transformative potential [25].

Integrating Building-Integrated Photovoltaics (BIPV) potential assessments into intelligent generative design enhances urban energy efficiency. Utilizing 3D building footprint models and meteorological data improves urban energy planning [26]. The necessity for hyperbolic geometry in representing tree-like structures and power-law distributions underscores the importance of advanced geometric representations [27].

Intelligent generative design signifies a paradigm shift in urban planning, merging computational intelligence with urban morphological insights to create adaptive, resilient, and sustainable environments. The effective use of GNNs for predicting material properties and enhancing new material design through graph-structured representations further illustrates its transformative potential [28]. This survey categorizes prediction methods into statistics-based, traditional machine learning-based, deep learning-based, reinforcement learning-based, and transfer learning-based, highlighting diverse methodologies in intelligent generative design [29].

2.4 Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) offer innovative methods to model complex urban relationships and enhance smart city design. They excel at processing graph-structured data, capturing intricate spatial and temporal dependencies inherent in urban environments. GNNs address traditional graph-based approaches' limitations by leveraging node and edge features to better understand urban dynamics [30].

GNNs are versatile in urban planning scenarios, modeling road networks for accurate ETA predictions by incorporating spatial and temporal data [31]. The Geo-contextual Multitask Embedding Learner (GMEL) model uses GNNs to predict commuting flows, demonstrating their capability in transportation scenario planning [30]. Despite their effectiveness, standard GNNs face expressive power challenges, limited by the 1-dimensional Weisfeiler-Leman (1-WL) algorithm [32].

Recent advancements include Hyperbolic Graph Neural Networks (HGNNs), exploring adaptive curvature to improve performance on diverse hierarchical structures [33]. This adaptability is crucial for accurately modeling hierarchical urban environments. GNNs are also utilized in a unified pre-training and adaptation framework, leveraging the maximum satisfiability (Max-SAT) problem to enhance transferability across various combinatorial optimization problems [34].

In urban planning, GNNs facilitate the analysis of structural feature correlations in geometrical graphs, providing insights into urban spatial organization and connectivity [35]. Integrating semantic scene graphs with geometric information using GNNs enhances urban environment understanding, enabling informed design decisions [36]. However, challenges such as prediction errors and limited performance due to restricted access to large, real-world datasets persist [37].

GNNs play a pivotal role in advancing intelligent generative design within urban planning, offering solutions for analyzing and optimizing urban systems. Their capacity to model intricate urban relationships and discern significant patterns from graph-structured data establishes them as fundamental components in creating adaptive, resilient, and sustainable urban environments. By leveraging urban graph structures and incorporating local and global features, GNNs address challenges such as oversmoothing and information loss, enhancing representation capabilities. This positions GNNs as crucial tools for extracting insights from complex urban data, supporting initiatives aligned with the UN Sustainable Development Goals and advancing intelligent urban systems [38, 39].

2.5 Spatial Optimization

Spatial optimization is essential in urban planning, focusing on the efficient allocation and arrangement of land use and infrastructure to achieve objectives like minimizing energy consumption and enhancing urban micro-climates. Traditional urban design methods often rely on simplified geometries that overlook real-world complexities, leading to suboptimal outcomes [40]. Advanced computational techniques in spatial optimization address these limitations, offering nuanced approaches considering intricate interactions among urban elements.

Integrating spatial optimization with predictive models, such as the Geo-contextual Multitask Embedding Learner (GMEL), underscores its significance in understanding land use changes' impacts on commuting flows and transportation networks [30]. By analyzing spatial data and simulating various urban scenarios, planners can anticipate infrastructure modifications' effects, ensuring urban environments accommodate future growth and evolving human activity patterns.

Spatial optimization fosters resilient and adaptive urban systems, enabling planners to explore diverse design alternatives and evaluate implications for energy consumption, environmental quality, and social dynamics. This capability is vital in CBDs, where high-density development and varied land uses create intricate spatial interactions. Effective management of these dynamics is crucial for enhancing urban functionality and sustainability, allowing for optimized services and strategically placed Points of Interest (POIs) that attract visitors, influencing trip distribution and planning outcomes [16, 9, 20].

2.6 Building Configuration and Urban Planning

The interplay between building configuration and urban planning is fundamental in designing effective and sustainable urban environments, particularly within CBDs. Urban morphology provides critical insights that enhance planning practices [9]. Analyzing building spatial patterns and configurations allows planners to develop strategies optimizing land use, improving accessibility, and enhancing urban spaces' functionality.

Building configuration impacts micro-climates, energy efficiency, and aesthetic appeal. The arrangement and orientation of buildings influence wind flow patterns, sunlight exposure, and thermal comfort—key factors in sustainable urban development. Research indicates that urban morphology parameters, such as building height, density, and layout, affect energy consumption for heating and cooling, as well as natural ventilation and solar energy utilization. Higher building densities can reduce heating energy demands by optimizing solar radiation capture, while thoughtful urban design can lower cooling loads and improve ventilation potential by over 10

Integrating building configuration into urban planning enhances public spaces' aesthetic appeal and functionality, fostering vibrant environments by considering historical context, hierarchical relationships among urban elements, and their interactions. This approach leads to responsive and effective planning practices [20, 4]. By considering spatial relationships between buildings, planners can design urban environments promoting social interaction and community engagement, aligning with intelligent generative design principles to create efficient, visually appealing, and human-centric urban spaces.

3 Urban Morphology and Central Business Districts

The intricate relationship between urban morphology and Central Business Districts (CBDs) necessitates an examination of the fundamental characteristics defining urban forms. This analysis not only elucidates the structural elements of urban environments but also underscores the implications for urban planning and design. As illustrated in Figure 2, the hierarchical structure of urban morphology's influence on CBDs is depicted, highlighting key characteristics and their impacts on energy and transportation. This figure captures the multifaceted relationships between urban forms and CBD functionality, emphasizing the role of analytical tools, cultural contexts, and sustainable policies in shaping urban environments. The following subsection explores the characteristics of urban morphology, providing a framework to understand their influence on the functionality and aesthetics of CBDs.

3.1 Characteristics of Urban Morphology

Urban morphology, which investigates the form, structure, and spatial organization of urban environments, is vital for enhancing the design and operational effectiveness of CBDs. Advanced analytical tools and big data enable urban planners to visualize urban complexities, leading to informed decisions on layout and functionality [5, 16]. Hierarchical classification of urban forms aids in organizing and retrieving diverse urban forms, crucial for CBD design.

Deep learning techniques reveal patterns in urban morphology often overlooked by traditional methods, providing nuanced insights for CBD design [7]. These methods capture complex interrelations with transportation networks, influencing accessibility and connectivity, pivotal for CBD economic vitality [41]. Information theory, particularly Shannon entropy and Transfer Entropy, provides a framework for analyzing urban migration and growth [42]. The logistic growth model highlights urban growth patterns, indicating universal principles in urban expansion [19].

Urban morphology significantly impacts solar capacity and energy efficiency, affecting solar radiation distribution based on building heights and layouts [43]. Traditional numerical indices inadequately represent urban morphology, necessitating sophisticated methods to capture urban complexities [18]. Analysis at different scales reveals urban form's influence on social interaction patterns, underscoring its role in fostering vibrant spaces [2]. Quantitative analyses through spatial point pattern analysis provide insights for urban planning [44], while the correlated percolation model introduces correlations among development units, affecting urban morphology characteristics [45].

Urban morphology's relevance to CBD design is profound, shaping both functionality and aesthetics. Understanding spatial patterns and interactions allows planners to optimize urban forms to enhance social interaction and functionality, fostering vibrant and sustainable CBDs. A theoretical perspective emphasizes the dynamic interrelationship between urban forms and socio-cultural contexts, advocating for a planning approach acknowledging historical continuity and complex urban interactions

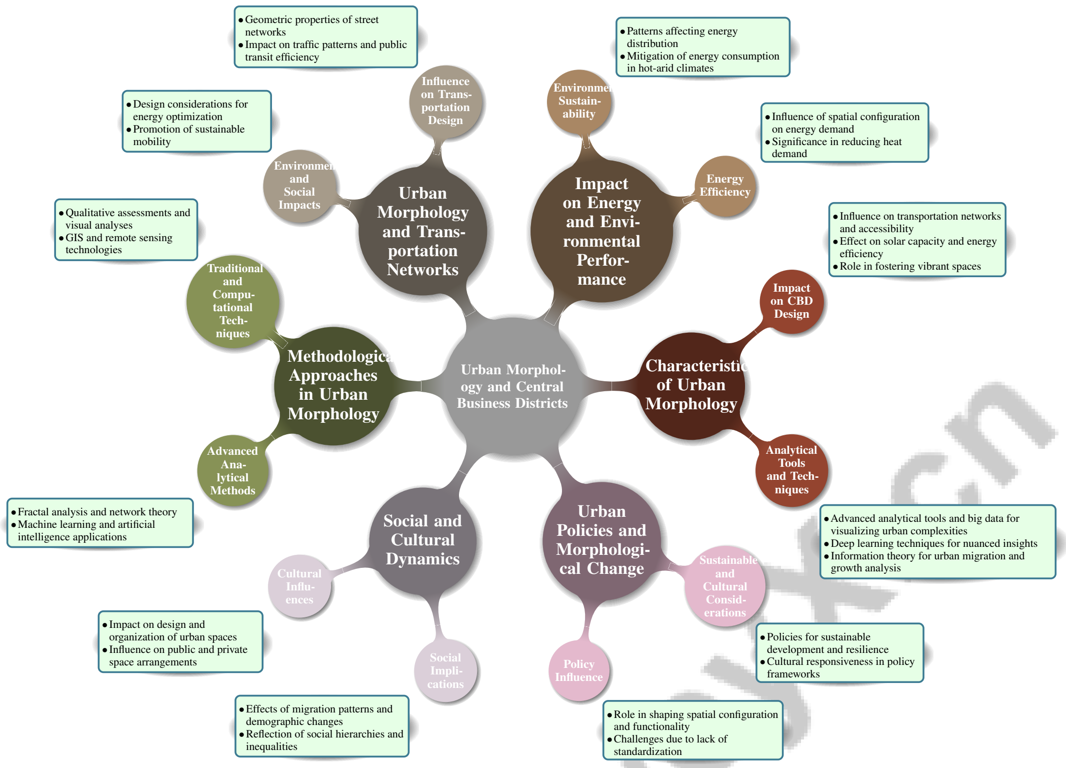

Figure 2: This figure illustrates the hierarchical structure of urban morphology's influence on Central Business Districts (CBDs), highlighting key characteristics, impacts on energy and transportation, methodological approaches, social dynamics, and policy implications. The diagram captures the multifaceted relationships between urban forms and CBD functionality, emphasizing the role of analytical tools, cultural contexts, and sustainable policies in shaping urban environments.

[4]. Research strengths include visualizing complex urban forms and revealing connectivity and organization patterns within cities [16].

3.2 Impact on Energy and Environmental Performance

Urban morphology critically influences energy efficiency and environmental sustainability within CBDs. The spatial configuration of urban areas, including building density, height, and layout, directly impacts energy demand for heating and cooling. Strategic planning of urban morphology can significantly reduce heat demand, highlighting the necessity of considering morphological characteristics in urban planning to enhance energy efficiency [40].

In this context, Figure 3 illustrates the impact of urban morphology, cooling strategies, and building polygon extraction on energy and environmental performance. The figure emphasizes key elements such as building density, spatial configuration, and innovative cooling methods tailored for hot-arid climates, thereby providing a visual representation that complements the discussion on energy efficiency.

In residential areas, urban morphology significantly affects heating energy demand, emphasizing the need for energy-efficient planning practices that consider spatial arrangements and building densities [46]. Clustering of urban forms in major cities reveals patterns crucial for defining city boundaries and understanding energy distribution [19]. These patterns, often modeled using power-law distributions, demonstrate urban morphology's influence on energy efficiency and sustainability [45].

In hot-arid climates, rapid urbanization and inefficient building designs exacerbate energy consumption for cooling, necessitating urban morphology that mitigates such demands [11]. Accurate extraction of building polygons from satellite images is vital for geographic applications, enabling planners to assess and optimize urban spatial configurations [47]. Leveraging these insights allows

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urban planners to design CBDs that meet functional and aesthetic requirements while promoting energy efficiency and environmental sustainability.

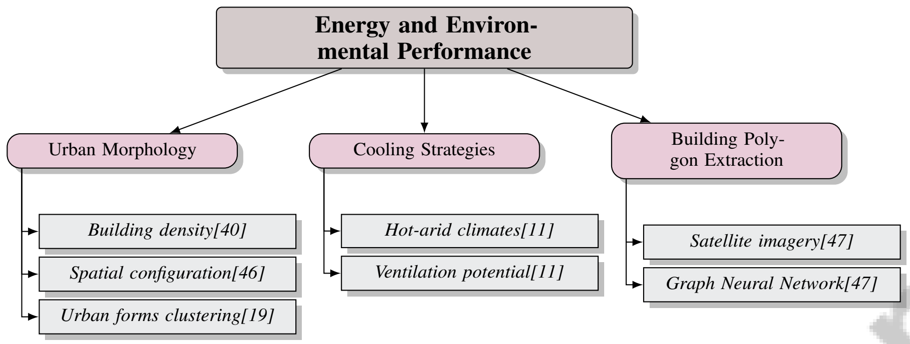


Figure 3: This figure illustrates the impact of urban morphology, cooling strategies, and building polygon extraction on energy and environmental performance, highlighting key elements such as building density, spatial configuration, and innovative cooling methods for hot-arid climates.

3.3 Urban Morphology and Transportation Networks

The relationship between urban morphology and transportation networks in CBDs is fundamental for understanding urban dynamics and optimizing planning. Urban morphology, encompassing the physical layout and structure of urban spaces, directly influences transportation network design and efficiency. Geometric properties of street networks, such as length, intersection angles, and connectivity, shape urban morphology and affect transportation efficiency and accessibility [13]. These properties determine movement ease within CBDs and impact economic and social interactions.

Integrating transportation networks with urban morphology is essential for creating functional and sustainable CBDs. The spatial configuration characterized by street density, layout, and geometric properties significantly influences traffic patterns, public transit efficiency, and pedestrian accessibility. Advanced data analytics and visual communication tools enable planners to understand these configurations and their implications for urban mobility. Big data and computational methods allow for analyzing street network patterns and urban morphology, revealing unique structural characteristics that affect functionality and attractiveness [44, 20, 13, 16, 5]. A well-connected street network enhances public transit accessibility, reducing reliance on private vehicles and promoting sustainable transportation options, particularly critical in CBDs with high-density development and diverse land uses.

Moreover, the interplay between urban morphology and transportation networks significantly impacts CBDs' environmental performance. Transportation infrastructure design must consider spatial arrangements of buildings and open spaces to optimize energy use and minimize environmental impact. Incorporating green transportation corridors and pedestrian-friendly pathways enhances urban livability by promoting sustainable mobility and reducing carbon emissions, contributing to the sustainability of CBDs and fostering healthier urban environments. This approach aligns with contemporary urban planning practices emphasizing interconnected urban forms and green space integration, ultimately supporting the development of resilient and vibrant cities [4, 9, 17].

3.4 Methodological Approaches in Urban Morphology

Urban morphology employs diverse methodologies to analyze and understand complex urban patterns and structures, particularly in CBDs. Traditional approaches often rely on qualitative assessments and visual analyses, providing insights into historical and cultural contexts of urban forms [9]. However, the increasing complexity of urban systems necessitates adopting more sophisticated, quantitative methodologies.

Recent advancements in computational techniques have expanded the methodological toolkit for studying urban morphology. The integration of Geographic Information Systems (GIS) and remote sensing technologies enables detailed mapping and analysis of urban forms, allowing planners to visualize and quantify spatial patterns with greater precision [47]. These technologies facilitate building polygon extraction and urban density assessment, providing valuable data for urban planning.

Additionally, fractal analysis and network theory offer new perspectives on urban morphology, capturing the self-similar and hierarchical nature of urban structures. Fractal analysis enables examination of urban growth patterns and scaling properties, essential for understanding spatial organization [19].

Machine learning and artificial intelligence applications in urban morphology are gaining traction, with deep learning techniques employed to classify and predict urban patterns from large datasets [18]. These methods uncover hidden relationships and trends within urban environments, facilitating informed decision-making in urban planning.

Furthermore, incorporating information theory and entropy measures provides a theoretical framework for analyzing complexity and diversity in urban forms. These approaches quantitatively assess order and randomness levels in urban systems by analyzing visitor attraction patterns, spatial arrangements, and urban morphology. This comprehensive analysis yields insights into urban change dynamics, highlighting the interplay between spatial organization and social functions. Utilizing frameworks that leverage big data and statistical methodologies enables a better understanding of factors influencing urban attraction and the implications for effective urban planning and policy-making [5, 44, 20].

The methodological approaches in urban morphology are continually evolving, driven by technological advancements and increasing data availability. By employing a range of methodologies, including statistical analyses of visitor patterns and urban morphology studies, planners and researchers achieve nuanced understandings of complex urban dynamics. This comprehensive approach aids in identifying urban attractors—such as global, downtown, and residential areas—and informs the strategic placement of services and amenities. Ultimately, these insights contribute to creating more sustainable and resilient CBDs, enhancing urban development and community well-being [9, 20].

3.5 Social and Cultural Dynamics

The social and cultural dynamics inherent in urban morphology significantly influence the development and functionality of CBDs. Urban morphology reflects physical and spatial configurations and embodies the social and cultural fabric of urban environments. The spatial organization of cities is intertwined with cultural practices and social interactions, shaping and being shaped by the built environment [16]. Understanding these dynamics is crucial for urban planners aiming to create vibrant and inclusive CBDs that cater to diverse populations.

Cultural contexts shape urban morphology by influencing the design, organization, and evolution of urban spaces. Comparative studies of different urban morphology schools emphasize historical processes and intrinsic qualities in urban form development [16, 5, 9, 10, 4]. Different cultural values and practices affect public and private space arrangements, street and building designs, and overall urban aesthetics. For instance, a cultural emphasis on community may lead to pedestrian-friendly environments and communal spaces within CBDs, while cultures prioritizing privacy might result in urban forms that emphasize separation.

Social dynamics, including migration patterns, demographic changes, and socioeconomic factors, contribute to urban morphology's evolution. The movement of people significantly influences urban form, prompting adaptations in the built environment to meet community needs. This dynamic process reflects urban morphology principles, examining historical development, structure, and functions of urban spaces. As diverse populations settle in urban areas, they reshape the physical landscape, leading to shifts in spatial patterns and relationships among urban elements, ultimately fostering a more responsive and integrated urban planning approach [10, 5, 7, 4]. These dynamics are particularly pronounced in CBDs, where economic activity concentration attracts diverse populations, resulting in a complex interplay of social and cultural influences.

Urban morphology can also reflect and reinforce social hierarchies and inequalities. The spatial distribution of resources and amenities within CBDs often mirrors broader social and economic disparities, influencing access to opportunities and quality of life. Planners must consider the social implications of urban design, adopting a morphological perspective that emphasizes historical development and interrelationships among urban form elements. This approach is essential for creating equitable and accessible CBDs responsive to complex urban dynamics, ensuring diverse communities' needs and interactions are effectively addressed [5, 16, 9, 4].

3.6 Urban Policies and Morphological Change

Urban policies play a pivotal role in shaping the morphological evolution of CBDs, influencing spatial configuration, functionality, and sustainability. The effectiveness of urban policies often hinges on their ability to classify and respond to diverse urban forms and dynamics within CBDs. This classification reveals significant relationships between urban forms and various dynamics, informing policy decisions and driving morphological change [48].

The development and implementation of urban policies face challenges due to the lack of standardization in datasets and benchmarks, complicating comparisons across different models and applications [49]. This lack of standardization hinders measuring and evaluating urban policies' impact on morphological change, underscoring the need for consistent and robust methodologies in urban research.

Policies prioritizing sustainable development and resilience are crucial for guiding morphological change in CBDs. These policies must address the interplay between urban form, environmental performance, and social dynamics to foster adaptive and resilient environments. By incorporating energy efficiency, transportation networks, and social equity into policy frameworks, cities can facilitate significant morphological transformations that enhance CBD livability and sustainability. This approach recognizes the complex interplay between urban form elements and aims to create environments responsive to historical context and contemporary needs, fostering a more integrated and equitable urban landscape [46, 16, 5, 9, 4].

Moreover, urban policies must respond to the socio-cultural contexts of urban environments, as these contexts significantly influence morphological outcomes. Policies sensitive to cultural values and social practices can create urban spaces resonating with local communities and supporting diverse living styles. Cultural responsiveness is critical for ensuring that morphological changes are effectively tailored to historical contexts, social dynamics, and urban populations' aspirations, facilitating harmonious integration of urban form elements within their complex interactions [16, 5, 9, 10, 4].

4 Intelligent Generative Design Techniques

4.1 Methodological Innovations in Intelligent Generative Design

Method Name	Technological Integration	Urban Planning Applications	Data Utilization
DL-RNC[18]	Deep Learning	Urban Morphology	Openstreetmap Data
GRCP[21]	Graph Neural Networks	-	-
LFMC-A[50]	Graph Neural Networks	-	Real PV Data
3D-SCM[43]	3D Point Clouds	Urban Heat Island	Historical Weather Data

Table 1: This table presents an overview of recent methodological innovations in intelligent generative design, highlighting the integration of advanced technologies such as deep learning and graph neural networks. It details the specific urban planning applications and data sources utilized by each method, underscoring their contributions to enhancing urban morphology analysis and energy efficiency in Central Business Districts.

Recent advancements in intelligent generative design have significantly refined urban planning methodologies, particularly in Central Business Districts (CBDs). The Colored Road Hierarchy Diagram (CRHD) utilizes deep learning to enhance visual representation and classification accuracy, facilitating a more nuanced understanding of urban road networks crucial for effective planning [18]. The Generic Representation of Combinatorial Problems (GRCP) introduces a graph neural network architecture that learns from generic representations, addressing previous methodological limitations and enabling comprehensive urban environment modeling [21].

Innovative methodologies such as a combinatorial auction framework for multi-minded bidding promote dynamic urban planning strategies, optimizing resource allocation and land use [50]. The 3D Solar City Model integrates multiple reflections and shadow effects, essential for accurately assessing solar energy potential and improving energy efficiency in high-density CBDs [43]. The Computation

Graph Transformer (CGT) introduces a novel graph generative model with privacy modules, scalable to large datasets, facilitating innovative urban planning methodologies [37].

These innovations demonstrate the transformative impact of intelligent generative design by integrating user-generated content and big data analytics, offering deeper insights into urban morphology. Tools like OSMnx and data from OpenStreetMap enable planners to analyze street network patterns, revealing critical information for optimizing service placement and enhancing urban experiences. As urban data becomes increasingly prevalent, these methodologies promise to revolutionize city analysis, management, and development [5, 16, 20].

Figure 4 illustrates the key methodological innovations in intelligent generative design, categorizing advancements in urban planning methodologies, energy efficiency models, and data analytics tools. Each category highlights significant contributions to the field, demonstrating the integration of deep learning, graph neural networks, and user-generated data in enhancing urban planning and energy efficiency. Additionally, Table 1 provides a comprehensive summary of the latest advancements in intelligent generative design methodologies, emphasizing their technological integration and applications in urban planning.

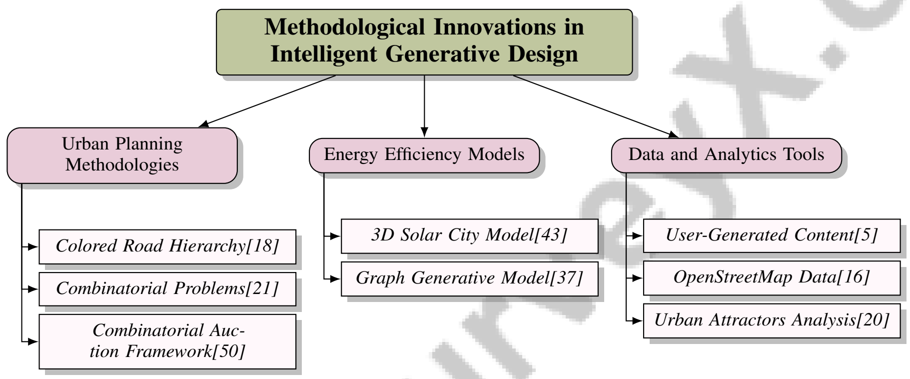


Figure 4: This figure illustrates the key methodological innovations in intelligent generative design, categorizing advancements in urban planning methodologies, energy efficiency models, and data analytics tools. Each category highlights significant contributions to the field, demonstrating the integration of deep learning, graph neural networks, and user-generated data in enhancing urban planning and energy efficiency.

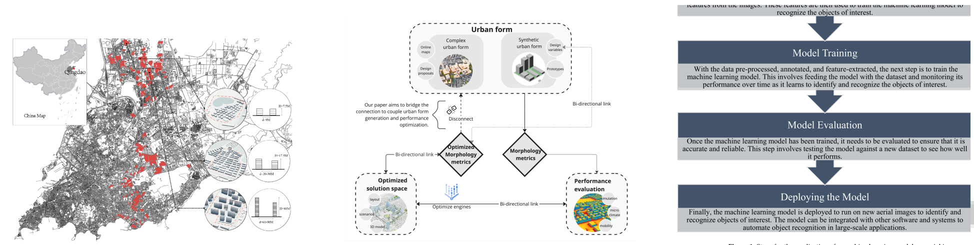
4.2 Techniques for Enhancing Building Configurations

Enhancing building configurations through intelligent design integrates advanced computational methodologies with urban morphology insights to optimize urban environments. The HybridBlock-Metric characterizes block-scale 3D urban forms by combining various urban morphology indicators, facilitating the generation and optimization of urban features [8]. This approach underscores the importance of morphological considerations in achieving functional and aesthetic objectives.

The GANmapper methodology translates street network data into synthetic building footprint data, utilizing generative adversarial networks to enhance building configurations by providing nuanced urban morphology insights [25]. This synthetic data generation allows for diverse urban scenario exploration, contributing to adaptable urban planning strategies. Local betweenness centrality measures offer an innovative approach to improving building configurations by analyzing urban road network connectivity and accessibility, crucial for designing urban layouts that optimize movement and interaction, especially in high-density areas like CBDs [17].

Moreover, integrating spatial relationships and temporal dynamics through weighted stacked GCN-LSTM models enhances understanding of regional traffic patterns and their impact on building configurations [51]. Logistic regression techniques classify aerial images for detecting photovoltaic (PV) installations, showcasing intelligent design's role in promoting sustainable urban development [52]. The generation of 1600 urban case studies using BMC illustrates intelligent design's potential to analyze building configurations' impacts on cooling load and ventilation [11].

These techniques collectively demonstrate intelligent design's transformative potential in enhancing building configurations. By integrating advanced computational techniques with urban morphology insights, planners can develop configurations that are efficient, sustainable, and responsive to the dynamic needs of urban populations, emphasizing a morphological framework that considers the interconnectedness of urban structures [5, 8, 4].



(a) Qingdao City Urban Planning Map[46]

(b) Urban Form Optimization: A Bi-directional Link Between Urban Form Generation and Performance Evaluation[8]

(c) Steps for the application of a machine learning model for object recognition[52]

Figure 5: Examples of Techniques for Enhancing Building Configurations

As shown in Figure 5, enhancing building configurations within intelligent generative design techniques is pivotal for optimizing urban planning and architectural design. The Qingdao City Urban Planning Map provides a detailed, color-coded representation of urban zones, establishing a foundational understanding of spatial distribution and infrastructure planning. Urban Form Optimization illustrates a bi-directional process linking urban form generation with performance evaluation, allowing for dynamic adjustments in design. Lastly, the application of machine learning models for object recognition offers a methodology for enhancing design precision through data preprocessing, feature extraction, and model evaluation. Together, these examples highlight the transformative impact of intelligent generative design techniques in creating efficient and sustainable building configurations [46, 8, 52].

4.3 Integration of Multimodal Data and Advanced Simulations

Integrating multimodal data and advanced simulations into generative design processes represents a significant advancement in urban planning, particularly in CBDs. Multimodal data, encompassing spatial, temporal, and semantic information, provides a comprehensive understanding of urban environments, facilitating informed and adaptive design strategies. Graph neural networks (GNNs) are particularly effective in capturing complex dependencies within multimodal datasets, enhancing forecasting accuracy and design outcomes [53].

Innovative methods leveraging spatial dependencies through graph structures contrast with traditional neural networks that treat data points independently, leading to improved urban morphology generation [7]. By integrating spatial and temporal data, these methodologies enable simulations of urban growth patterns and optimization of urban morphology.

Advanced simulations are crucial in generative design, allowing planners to explore various scenarios and evaluate their implications for urban development. Integrating simulations with multimodal data enhances the exploration of complex urban interactions influenced by local density and network centralities [40], improving the accuracy of urban growth models and supporting resilient urban systems.

The incorporation of algorithms like BalMCTS exemplifies the potential of integrating multimodal data and simulations. By combining Monte Carlo Tree Search (MCTS) with a balancing neural network, BalMCTS effectively guides the search process, minimizing search nodes while maintaining solution quality [54]. Additionally, simpler machine learning models requiring less computational power highlight the feasibility of efficient generative design processes in resource-constrained environments [55].

In solar energy potential assessment, 3D modeling approaches facilitate comprehensive evaluations by modeling urban surfaces as three-dimensional point clouds [43]. The integration of multimodal data and advanced simulations into generative design processes signifies a transformative approach to urban planning. By leveraging GNNs and innovative algorithms, urban planners can develop informed and adaptive strategies enhancing CBDs' functionality, sustainability, and resilience. Future research should continue exploring classical ideas like noise injection during inference and feature engineering to enhance robustness and data efficiency in learned solvers [56].

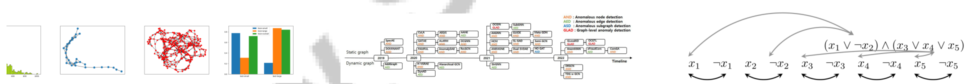
5 Graph Neural Networks in Urban Planning

The intersection of Graph Neural Networks (GNNs) and urban planning has become increasingly prominent, reflecting the complexities of urban environments. This section explores the diverse applications of GNNs and machine learning in urban planning, underscoring their transformative potential in addressing urban challenges. By examining specific methodologies, we illustrate how these technologies enhance urban planning practices.

5.1 Applications of Graph Neural Networks and Machine Learning

GNNs and machine learning are pivotal in urban planning, offering methodologies for modeling, analyzing, and optimizing complex urban systems by capturing intricate spatial and temporal dependencies [57]. These applications span traffic prediction, transportation planning, and infrastructure optimization. For instance, DiglacianGCN achieves state-of-the-art results on heterophilous graphs, vital for optimizing transportation networks [58]. The Edge Enhanced Graph Neural Network (EGNN) integrates multidimensional edge features to enhance urban modeling [59]. Simplifying the GNN learning process, as with LP-GNN, increases accessibility for urban planners [60]. GNNs' ability to model spatiotemporal data has advanced fields like climate modeling and disaster management, demonstrating their versatility [39]. Fea2Fea explores structural feature correlations, refining urban models [61]. In transportation, STZINB-GNN models travel demand, aiding transportation management [62]. The AllSet framework enhances GNNs' ability to model urban relationships [63].

By leveraging urban graph structures and multimodal data, GNNs facilitate improved representation learning and predictive modeling [38, 18, 30, 39]. These technologies support resource allocation and decision-making, contributing to sustainable urban growth.



(a) Comparison of Graph Structures and Performance Metrics for Two Different Data Sets[64]

(b) Timeline of Graph Anomaly Detection Techniques[65]

(c) Logical Connectives and Their Interactions[66]

Figure 6: Examples of Applications of Graph Neural Networks and Machine Learning

Figure 6 illustrates GNNs' transformative role in urban planning through diverse applications. The first image compares graph structures and performance metrics, highlighting GNNs' efficacy in complex data analysis [64]. The second image traces graph anomaly detection techniques, underscoring advancements in identifying anomalies [65]. The third image demonstrates GNNs' ability to model logical relationships, showcasing their impact on urban planning [66].

5.2 Modeling Complex Urban Relationships

GNNs are essential for modeling the intricate relationships in urban environments, offering a framework to understand and optimize urban dependencies. The Edge Enhanced Graph Neural Network (EGNN) exemplifies this by capturing high-order relational information through multidimensional edge features [59, 67]. GNNs effectively integrate spatial and temporal dependencies, crucial in urban settings [39]. MGNN optimizes energy functions for congruent embeddings, handling diverse urban relationships [68]. EMR-GNN incorporates multiple relations, enhancing urban dynamic modeling [32]. In transportation, GNNs predict travel times by integrating spatial and temporal data [31]. AliGraph improves GNN efficiency through distributed storage and optimized sampling [69].

5.3 Innovations in Graph Neural Networks

Recent advancements in GNNs address urban planning challenges, enhancing their effectiveness in modeling complex systems. Deep Modularity Networks (DMoN) optimize cluster assignments, providing nuanced urban dynamics insights [70]. The GPN framework improves graph structure learning, enhancing GNN application in urban contexts [71]. GraphPAS accelerates GNN architecture search, crucial for timely urban modeling [72]. EGNAS explores feature dependencies, improving urban interaction modeling [67]. XGNN offers model-level explanations, enhancing GNN interpretability in urban planning [73]. AliGraph demonstrates efficiency improvements, crucial for handling large-scale urban data [69]. Investigations into OOD generalization highlight GNN adaptability in diverse urban contexts [74].

These innovations enhance GNN capabilities in urban planning, integrating techniques like Coarsened Graph Attention Pooling (CGAP) for improved representation, analyzing urban forms globally, and classifying urban morphology [7, 38, 18, 6, 39]. Evolving GNN technologies promise to develop adaptive, resilient, and sustainable urban systems.

6 Spatial Optimization and Building Configuration

6.1 Optimization Techniques and Heuristic Approaches

Optimization techniques and heuristic approaches are pivotal in urban planning, particularly for enhancing spatial configurations and building arrangements within Central Business Districts (CBDs). These methodologies enable the identification of urban attractors and visitor patterns, crucial for informed urban development and policy-making. By utilizing frameworks that classify districts based on attractiveness and analyze trip distributions via Origin-Destination matrices, planners can gain insights into urban dynamics. A morphological perspective, considering the historical evolution and interrelationships of urban form elements, is essential for developing responsive strategies, optimizing land use, and improving urban functionality [44, 20, 4].

Recent advancements include Deep Modularity Networks (DMoN), which optimize soft cluster assignments in graph neural networks (GNNs) through a differentiable unsupervised clustering objective, thereby enhancing the modeling of complex urban relationships [70]. Similarly, physics-inspired graph neural networks (PI-GNN) offer competitive performance in large-scale combinatorial optimization problems, providing scalable and high-quality solutions critical for urban planning [75].

Heuristic approaches, especially in combinatorial optimization frameworks, allow systematic assessments of various urban scenarios. These frameworks classify urban areas based on visitor attractiveness, analyzing trip flows and identifying characteristics of urban attractors, revealing relationships between different Points of Interest (POIs) and their attraction patterns. By integrating insights from urban morphology and street network structural analysis, planners can leverage these methods to optimize urban design and enhance overall urban functionality [10, 13, 20]. Advanced algorithms guide search processes, ensuring efficient and adaptable urban planning solutions.

The integration of optimization techniques and heuristic approaches equips urban planners with tools to navigate urban complexities. Innovations such as Coarsened Graph Attention Pooling (CGAP) and the ControlCity multimodal diffusion model enhance spatial configurations and building designs by integrating diverse data sources, including POIs and human mobility patterns. These methodologies enable accurate simulations of urban building patterns and assessments of spatial data completeness, fostering informed decision-making and the development of sustainable and resilient CBDs [38, 76].

6.2 Spatial Optimization in Infrastructure and Urban Planning

Spatial optimization is fundamental in urban infrastructure planning, employing advanced methodologies to refine the arrangement of urban components. This process is essential for enhancing energy efficiency, accessibility, and overall functionality within urban environments. By leveraging big data and computational tools within the Smart Cities framework, urban planners can analyze complex spatial patterns, assess the impact of urban morphology on energy demand, and develop strategies that promote sustainable urban development. This data-driven approach provides a nuanced understanding of how urban design influences energy consumption, microclimate conditions, and livability [5, 13, 16, 46]. The application of spatial optimization is particularly critical in CBDs, where high development density necessitates careful planning to balance multiple objectives.

A key aspect of spatial optimization is a quantitative framework assessing the relationship between urban morphology and energy efficiency, aiding planners in making informed decisions about spatial configurations that impact energy consumption [46]. Understanding these relationships enables the design of urban environments that optimize energy use, contributing to sustainability.

The integration of advanced computational techniques, such as GNNs and reinforcement learning, offers innovative solutions for optimizing logistics planning within urban infrastructure. These methods highlight critical nodes in transportation network representations, enhancing urban logistics efficiency and robustness [77].

Moreover, the application of GANmapper in urban planning underscores the importance of spatial optimization in configuring buildings and infrastructures, particularly in data-scarce regions. By utilizing generative adversarial networks to generate synthetic data, GANmapper allows planners to explore diverse urban scenarios and optimize spatial configurations even with limited empirical data [25].

Spatial optimization in infrastructure and urban planning is vital for creating efficient, sustainable, and resilient urban environments. By employing cutting-edge methodologies and computational techniques, urban planners can strategically enhance the spatial organization of urban elements. This optimization not only improves the functionality and sustainability of CBDs and other urban areas but also leverages big data and advanced spatial technologies to analyze and visualize urban patterns. Such tools facilitate a deeper understanding of urban dynamics, enabling planners to identify and classify urban attractors based on visitor flow and POIs. Consequently, integrating data-driven insights into urban design can lead to more effective planning and policy-making that aligns with the evolving needs of urban environments [5, 16, 20, 8].

7 Case Studies and Applications

7.1 Case Studies and Practical Implementations

Intelligent generative design in Central Business Districts (CBDs) is effectively demonstrated through various case studies, showcasing its role in optimizing urban environments. The I-DIDA model, for instance, demonstrates significant advancements over traditional methods by efficiently managing spatio-temporal distribution shifts, thus adapting to dynamic urban contexts [78]. This underscores the model's potential to tackle the complexities of urban dynamics.

Another noteworthy case involves graph representation learning applied to street networks from a dataset of 39,364 cities and towns from OpenStreetMap. This study confirmed the model's scalability and adaptability across diverse urban settings, highlighting the robustness of these methodologies [79]. The Learn Locally, Correct Globally (LLCG) framework also illustrates the practical benefits of intelligent generative design, enhancing training efficiency and accuracy of Graph Neural Networks (GNNs), thereby aiding urban planners in optimizing building configurations and spatial layouts in CBDs [80].

Furthermore, the ACE-HGNN model's application to various real-world graph datasets demonstrates its effectiveness in urban planning. By utilizing adaptive curvature, ACE-HGNN provides a sophisticated tool for modeling urban relationships, enabling planners to create more resilient urban environments [33]. These case studies collectively highlight the transformative potential of intelligent generative design in urban planning, facilitating the creation of adaptive, efficient, and sustainable CBDs. By leveraging advanced computational techniques and models, urban planners can integrate performance-driven metrics to enhance urban design. Additionally, analyzing human activity patterns via mobile and social media data offers deeper insights into urban dynamics, aiding informed decision-making that improves urban quality of life [20, 1, 5, 8, 4].

7.2 Gretel and Path Directionality

The Gretel framework marks a substantial advancement in urban planning by optimizing path directionality within Central Business Districts (CBDs). Utilizing advanced machine learning techniques, Gretel analyzes and enhances the directional flow of urban pathways, improving urban efficiency and functionality. By employing graph-based models, it captures complex interdependencies within urban networks, providing comprehensive insights into path directionality and its implications for urban planning [79].

A key feature of Gretel is its integration of multimodal data sources, including spatial, temporal, and semantic information, which informs decisions on path directionality. This enables nuanced analyses of urban dynamics, allowing planners to design pathways that optimize movement and accessibility within CBDs. The incorporation of graph neural networks (GNNs) enhances Gretel's capability to model intricate urban relationships, offering insights into optimal urban pathway configurations [78].

Gretel's impact is particularly evident in optimizing transportation networks and pedestrian pathways. By analyzing traffic and pedestrian flow directionality, it provides actionable insights for improving connectivity and reducing congestion within CBDs, enhancing urban livability and functionality [80]. The framework's adaptability across various urban contexts underscores its potential as a versatile tool in urban planning, demonstrating robustness in optimizing path directionality and enhancing urban mobility [33].

7.3 AliGraph's Deployment at Alibaba

AliGraph, a sophisticated graph computing framework, is deployed at Alibaba, supporting a diverse range of business scenarios with a dataset comprising 492.90 million vertices and 6.82 billion edges, demonstrating its capacity to manage large-scale graph data efficiently [69]. This framework's robustness and scalability are crucial for processing complex urban datasets in urban planning contexts.

In urban planning, AliGraph exemplifies the efficacy of graph-based methodologies in managing extensive urban datasets. By leveraging advanced graph neural network (GNN) techniques, it facilitates the efficient processing of complex urban data, enhancing urban analysis and decision-making capabilities. This enables planners to gain deeper insights into spatial patterns, evaluate urban morphology, and incorporate community perspectives, fostering informed and responsive urban development strategies [69, 13, 16, 5, 17]. AliGraph's capabilities allow planners to model intricate urban relationships and optimize urban systems, enhancing decision-making processes in urban environments. Its ability to efficiently process large graphs ensures planners can explore various urban scenarios, facilitating the development of adaptive and resilient urban infrastructures.

Moreover, AliGraph's integration within Alibaba's operations highlights the versatility of graph neural networks in addressing diverse challenges, from optimizing supply chains to enhancing recommendation systems. In urban planning, the integration of advanced spatial technologies and big data improves modeling of spatial and temporal dynamics, allowing planners to analyze urban forms and patterns more effectively. This capability enables the design of urban environments that are sustainable, efficient, and responsive to historical context and intricate urban element relationships. By leveraging user-generated content and computational data science, planners can better understand and manage urban morphology complexities, leading to informed decision-making and improved public engagement in the planning process [44, 13, 16, 5, 4]. The deployment of AliGraph thus exemplifies the transformative potential of graph computing technologies in advancing urban planning methodologies.

8 Challenges and Future Directions

Exploring the intricacies of urban planning, particularly in Central Business Districts (CBDs), necessitates addressing the multifaceted challenges of data management and integration. This section delves into the critical issues of data quality and integration, which are vital for informed urban planning decisions. By examining these challenges, we can elucidate the implications of data quality on urban modeling and decision-making processes, paving the way for a deeper exploration of the obstacles in this field.

8.1 Data Quality and Integration Challenges

Data quality and integration are crucial challenges in urban planning within CBDs, where the precision and comprehensiveness of data significantly influence decision-making. Poor data collection and preprocessing can detrimentally affect model performance, exacerbated by variability and lack of standardization across urban areas, complicating comparative analysis and hindering integration efforts [37]. Models like GANmapper underscore the necessity for robust data collection methodologies, as incomplete or low-quality data can lead to suboptimal results, particularly in graph-based approaches reliant on original graph structures. Graph Neural Networks (GNNs) often fail to capture critical global structural information, impairing performance as node embeddings become indistinguishable. Techniques like GraphCrop, which enhance training data by simulating real-world noise, show that preserving structural contexts can significantly boost model generalization and performance [81, 82]. The integration of qualitative insights with quantitative data to develop a holistic understanding of urban morphology necessitates interdisciplinary collaboration.

The availability and quality of urban data also influence models simulating transportation scenarios and optimizing urban planning strategies. Integrating mobile data to understand urban attractors faces challenges in areas with limited data availability or fluctuating mobility patterns. Moreover, privacy concerns often limit access to comprehensive urban datasets, complicating data integration efforts [37]. A comprehensive strategy to address data scarcity should include advancements in data collection methodologies, standardization of data formats, and integration of diverse data sources such as mobile phone positioning and aerial imagery analysis. Leveraging these approaches can improve data quality and comprehensiveness, leading to more accurate insights and enhanced decision-making in urban planning [83, 1, 16, 84, 52].

8.2 Computational Complexity and Scalability

Integrating advanced computational techniques in generative design for CBDs introduces challenges related to computational complexity and scalability. The structural complexity of graphs incurs high computational costs, exacerbated by limitations of the Weisfeiler-Lehman (WL) graph isomorphism test [35]. Path enumeration further affects scalability in large graphs [32]. Training methods for generic representation in combinatorial problems can be time-prohibitive, potentially hindering scalability [21]. Models for ETA prediction may not generalize well to regions with differing traffic patterns, emphasizing the need for adaptable models [31].

Advancements offer potential solutions. Combinatorial auctions demonstrate significant computational efficiency, reducing time complexity, crucial for addressing computational complexity and scalability [50]. Benchmarks for graph generative models provide scalable solutions for generating privacy-preserving synthetic graphs, enhancing GNN applicability [37]. However, limitations such as MGNN's reliance on energy function optimization in non-globally rigid graphs persist [68]. Addressing these issues requires optimizing computational resources, enhancing data quality, and integrating classical and modern methodologies.

8.3 Model Generalization and Adaptability

Model generalization and adaptability are critical in deploying GNNs for urban planning, given the diverse and dynamic nature of urban environments. Models like ACE-HGNN show potential in managing complex hierarchical structures [33], but reproducibility across varied datasets remains a challenge [85]. Methodologies often rely on assumptions like equal cluster sizes, limiting effectiveness in unbalanced contexts [86]. Future research should focus on enhancing model robustness to noise and developing adaptive mechanisms for selecting relevant historical patterns [87].

The Unified Pre-training and Adaptation Framework presents a promising avenue for extracting transferable features across different urban contexts [34]. Advanced multiset function learners could further improve frameworks like AllSet, providing robust solutions for complex urban planning tasks [63]. Enhancing training efficiency to address challenges in model generalization and adaptability is critical [50]. Optimizing energy functions and investigating model scalability remain important research directions [68].

8.4 Integration of Classical and Modern Techniques

Integrating classical urban planning methods with modern computational techniques is crucial for addressing contemporary urban challenges, particularly within CBDs. This synthesis enables leveraging the strengths of both traditional and advanced methodologies, optimizing urban design and functionality. Methods that learn structural information from graph topology facilitate optimal solution prediction without additional search efforts [88].

Future research should focus on enhancing models like EGNN, exploring their applicability to other tasks while addressing privacy and fairness concerns [89]. Integrating insights from GNNs into existing deep neural networks, as demonstrated by LinkSAGE, optimizes job matching and other urban planning tasks [90]. Graph generative models exemplify this integration, enhancing GNN training while ensuring privacy [37]. Future work could explore JBGNN applications to tasks like graph classification and methods to accommodate varying cluster sizes [86].

Emerging trends suggest a focus on hybrid models combining deep learning with reinforcement learning for optimization tasks and exploring transfer learning techniques to address data scarcity [29]. Integrating classical urban planning methods with advanced techniques can refine models for solar energy estimation, optimizing urban energy planning and policy-making [43].

9 Conclusion

The investigation into intelligent generative design within Central Business Districts (CBDs) underscores its significant role in revolutionizing urban planning through the integration of cutting-edge computational methods, including graph neural networks and spatial optimization. These advanced techniques facilitate a comprehensive analysis of urban morphology, enabling the optimization of urban forms to boost social interaction and energy efficiency. By merging visual data with machine learning models, urban planning practices are refined, offering enhanced classification accuracy and deeper insights. Additionally, the application of deep learning in urban morphology analysis highlights the transformative potential of these technologies in reshaping urban planning paradigms within CBDs.

Incorporating facade photovoltaic technologies exemplifies the contribution of intelligent generative design to achieving carbon neutrality and optimizing solar energy utilization. The development of sophisticated graph neural network architectures, such as AGS-GNN, illustrates their efficacy in enhancing node classification tasks, thereby improving urban data analysis. Moreover, satellite-based retrieval of urban morphological parameters introduces novel possibilities for urban climate research and planning.

The strategic consideration of urban morphology is crucial for reducing cooling loads and enhancing ventilation potential, illustrating the importance of morphological factors in urban planning. The correlated percolation model provides valuable insights into urban growth dynamics, informing future urban planning strategies in CBDs. Furthermore, the proposed framework effectively quantifies urban spatial patterns, revealing the intricate complexity and vulnerability of urban morphology across diverse urban landscapes.

AI-generated, for reference only.

References

[1] Wei Tu, Jinzhou Cao, Yang Yue, Shih-Lung Shaw, Meng Zhou, Zhensheng Wang, Xiaomeng Chang, Yang Xu, and Qingquan Li. Coupling mobile phone and social media data: A new approach to understanding urban functions and diurnal patterns. *International Journal of Geographical Information Science*, 31(12):2331–2358, 2017.

[2] Romulo Krafta. On scaling functionality in urban form, 2013.

[3] Mohamed Hassouna, Clara Holzhüter, Pawel Lytaev, Josephine Thomas, Bernhard Sick, and Christoph Scholz. Graph reinforcement learning for power grids: A comprehensive survey, 2024.

[4] Tolga Ünlü. Managing the urban change: A morphological perspective for planning. *ICONARP International Journal of Architecture and Planning*, 7:55–72, 2019.

[5] Geoff Boeing. Spatial information and the legibility of urban form: Big data in urban morphology, 2019.

[6] Weiyu Zhang, Yiyang Ma, Di Zhu, Lei Dong, and Yu Liu. Metrogan: Simulating urban morphology with generative adversarial network, 2022.

[7] Vahid Moosavi. Urban morphology meets deep learning: Exploring urban forms in one million cities, town and villages across the planet, 2017.

[8] Chenyi Cai, Biao Li, Qiyan Zhang, Xiao Wang, Filip Biljecki, and Pieter Herthogs. Bi-directional mapping of morphology metrics and 3d city blocks for enhanced characterization and generation of urban form, 2024.

[9] Vítor Oliveira. *Urban morphology*. Springer, 2020.

[10] Gelareh Sadeghi and Baofeng Li. Urban morphology: Comparative study of different schools of thought. *Current Urban Studies*, 7(4):562–572, 2019.

[11] Kavan Javanroodi, Mohammadjavad Mahdavinejad, and Vahid M Nik. Impacts of urban morphology on reducing cooling load and increasing ventilation potential in hot-arid climate. *Applied energy*, 231:714–746, 2018.

[12] Yanguang Chen. Fractal modeling and fractal dimension description of urban morphology, 2020.

[13] Emanuele Strano, Matheus Viana, Alessio Cardillo, Luciano Da Fontoura Costa, Sergio Porta, and Vito Latora. Urban street networks: a comparative analysis of ten european cities, 2012.

[14] Martin Barner, Clémentine Cottineau, Carlos Molinero, Hadrien Salat, Kiril Stanilov, and Elsa Arcaute. Multiscale entropy in the spatial context of cities, 2017.

[15] Mahmoud Saeedimoghaddam, T. F. Stepinski, and Anna Dmowska. Renyi's spectra of urban form for different modalities of input data, 2020.

[16] Geoff Boeing. Spatial information and the legibility of urban form: Big data in urban morphology. *International Journal of Information Management*, 56:102013, 2021.

[17] Kaoru Yamaoka, Yusuke Kumakoshi, and Yuji Yoshimura. Local betweenness centrality analysis of 30 european cities, 2021.

[18] Wangyang Chen, Abraham Noah Wu, and Filip Biljecki. Classification of urban morphology with deep learning: Application on urban vitality. *Computers, Environment and Urban Systems*, 90:101706, 2021.

[19] A. Paolo Masucci, Elsa Arcaute, Erez Hatna, Kiril Stanilov, and Michael Batty. On the problem of boundaries and scaling for urban street networks, 2015.

[20] May Alhazzani, Fahad Alhasoun, Zeyad Alawwad, and Marta C. González. Urban attractors: Discovering patterns in regions of attraction in cities, 2016.

[21] Léo Boisvert, Hélène Verhaeghe, and Quentin Cappart. Towards a generic representation of combinatorial problems for learning-based approaches, 2024.

[22] Jiawei Lu, Tinghan Ye, Wenbo Chen, and Pascal Van Hentenryck. Boosting column generation with graph neural networks for joint rider trip planning and crew shift scheduling, 2025.

[23] Yong Xu, Chao Ren, Peifeng Ma, Justin Ho, Weiwen Wang, Kevin Ka-Lun Lau, Hui Lin, and Edward Ng. Urban morphology detection and computation for urban climate research. *Landscape and urban planning*, 167:212–224, 2017.

[24] Taoran Fang, Yunchao Zhang, Yang Yang, Chunping Wang, and Lei Chen. Universal prompt tuning for graph neural networks, 2024.

[25] Abraham Noah Wu and Filip Biljecki. Ganmapper: geographical data translation, 2022.

[26] Qing Yu, Kechuan Dong, Zhiling Guo, Jiaxing Li, Hongjun Tan, Yanxiu Jin, Jian Yuan, Haoran Zhang, Junwei Liu, Qi Chen, and Jinyue Yan. Global estimation of building-integrated facade and rooftop photovoltaic potential by integrating 3d building footprint and spatio-temporal datasets, 2024.

[27] Min Zhou, Menglin Yang, Lujia Pan, and Irwin King. Hyperbolic graph representation learning: A tutorial, 2022.

[28] Patrick Reiser, Marlen Neubert, André Eberhard, Luca Torresi, Chen Zhou, Chen Shao, Houssam Metni, Clint van Hoesel, Henrik Schopmans, Timo Sommer, et al. Graph neural networks for materials science and chemistry. *Communications Materials*, 3(1):93, 2022.

[29] Peng Xie, Tianrui Li, Jia Liu, Shengdong Du, Xin Yang, and Junbo Zhang. Urban flow prediction from spatiotemporal data using machine learning: A survey. *Information Fusion*, 59:1–12, 2020.

[30] Ana Alice Peregrino, Soham Pradhan, Zhicheng Liu, Nivan Ferreira, and Fabio Miranda. Transportation scenario planning with graph neural networks, 2021.

[31] Austin Derrow-Pinion, Jennifer She, David Wong, Oliver Lange, Todd Hester, Luis Perez, Marc Nunkesser, Seongjae Lee, Xueying Guo, Brett Wiltshire, Peter W. Battaglia, Vishal Gupta, Ang Li, Zhongwen Xu, Alvaro Sanchez-Gonzalez, Yujia Li, and Petar Veličković. Eta prediction with graph neural networks in google maps, 2021.

[32] Gaspard Michel, Giannis Nikolentzos, Johannes Lutzeyer, and Michalis Vazirgiannis. Path neural networks: Expressive and accurate graph neural networks, 2023.

[33] Xingcheng Fu, Jianxin Li, Jia Wu, Qingyun Sun, Cheng Ji, Senzhang Wang, Jiajun Tan, Hao Peng, and Philip S. Yu. Ace-hgnn: Adaptive curvature exploration hyperbolic graph neural network, 2021.

[34] Ruibin Zeng, Minglong Lei, Lingfeng Niu, and Lan Cheng. A unified pre-training and adaptation framework for combinatorial optimization on graphs, 2023.

[35] Yu Zhou, Haixia Zheng, Xin Huang, Shufeng Hao, Dengao Li, and Jumin Zhao. Graph neural networks: Taxonomy, advances and trends, 2022.

[36] Jose Andres Millan-Romera, Hriday Bavle, Muhammad Shaheer, Holger Voos, and Jose Luis Sanchez-Lopez. Metric-semantic factor graph generation based on graph neural networks, 2024.

[37] Minji Yoon, Yue Wu, John Palowitch, Bryan Perozzi, and Ruslan Salakhutdinov. Graph generative model for benchmarking graph neural networks, 2023.

[38] Zhuo Xu and Xiao Zhou. Cgap: Urban region representation learning with coarsened graph attention pooling, 2024.

[39] Yun Li, Dazhou Yu, Zhenke Liu, Minxing Zhang, Xiaoyun Gong, and Liang Zhao. Graph neural network for spatiotemporal data: methods and applications, 2023.

[40] Etienne Burdet, Morgane Colombert, Denis Morand, and Youssef Diab. Integrated canopy, building energy and radiosity model for 3d urban design, 2014.

[41] Juste Raimbault. An urban morphogenesis model capturing interactions between networks and territories, 2018.

[42] Roberto Murcio, Robin Morphet, Carlos Gershenson, and Michael Batty. Urban transfer entropy across scales, 2015.

[43] Rui Zhu, Man Sing Wong, Linlin You, Paolo Santi, Janet Nichol, Hung Chak Ho, Lin Lu, and Carlo Ratti. The effect of urban morphology on the solar capacity of three-dimensional cities. *Renewable Energy*, 153:1111–1126, 2020.

[44] Hoai Nguyen Huynh. Spatial point pattern and urban morphology: Perspectives from entropy, complexity and networks, 2019.

[45] Hernan A. Makse, Shlomo Havlin, and H. Eugene Stanley. Modeling morphology of cities and towns, 1995.

[46] Yanxue Li, Dawei Wang, Shanshan Li, and Weijun Gao. Impact analysis of urban morphology on residential district heat energy demand and microclimate based on field measurement data. *Sustainability*, 13(4):2070, 2021.

[47] Stefano Zorzi, Shabab Bazrafkan, Stefan Habenschuss, and Friedrich Fraundorfer. Polyworld: Polygonal building extraction with graph neural networks in satellite images, 2022.

[48] Martin Fleischmann, Alessandra Feliciotti, Ombretta Romice, and Sergio Porta. Methodological foundation of a numerical taxonomy of urban form, 2021.

[49] Flavio Corradini, Marco Gori, Carlo Lucheroni, Marco Piangerelli, and Martina Zannotti. A systematic literature review of spatio-temporal graph neural network models for time series forecasting and classification, 2024.

[50] Awadelrahman M. A. Ahmed, Frank Eliassen, and Yan Zhang. Combinatorial auctions and graph neural networks for local energy flexibility markets, 2023.

[51] Theodoros Theodoropoulos, Angelos-Christos Maroudis, Antonios Makris, and Konstantinos Tserpes. West gcn-lstm: Weighted stacked spatio-temporal graph neural networks for regional traffic forecasting, 2024.

[52] Fabio Giussani, Eric Wilczynski, Claudio Zandonella Callegher, Giovanni Dalle Nogare, Cristian Pozza, Antonio Novelli, and Simon Pezzutto. Use of machine learning techniques on aerial imagery for the extraction of photovoltaic data within the urban morphology. *Sustainability*, 16(5):2020, 2024.

[53] Stephen Powers and Carlo Pinciroli. Extracting symbolic models of collective behaviors with graph neural networks and macro-micro evolution, 2022.

[54] Yingkai Xiao, Jingjin Liu, and Hankz Hankui Zhuo. Balmcts: Balancing objective function and search nodes in mcts for constraint optimization problems, 2023.

[55] Huan Zhao, Lanning Wei, and Quanming Yao. Simplifying architecture search for graph neural network, 2020.

[56] Ruth Johnson, Michelle M. Li, Ayush Noori, Owen Queen, and Marinka Zitnik. Graph ai in medicine, 2023.

[57] Ljubisa Stankovic, Danilo Mandic, Milos Dakovic, Milos Brajovic, Bruno Scalzo, Shengxi Li, and Anthony G. Constantinides. Graph signal processing – part iii: Machine learning on graphs, from graph topology to applications, 2020.

[58] Wei Zhuo and Guang Tan. Graph neural networks with feature and structure aware random walk, 2024.

[59] Liyu Gong and Qiang Cheng. Exploiting edge features for graph neural networks. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 9211–9219, 2019.

[60] Matteo Tiezzi, Giuseppe Marra, Stefano Melacci, Marco Maggini, and Marco Gori. A lagrangian approach to information propagation in graph neural networks, 2020.

[61] Jiaqing Xie and Rex Ying. Fea2fea: Exploring structural feature correlations via graph neural networks, 2021.

[62] Dingyi Zhuang, Shenhao Wang, Haris N. Koutsopoulos, and Jinhua Zhao. Uncertainty quantification of sparse travel demand prediction with spatial-temporal graph neural networks, 2022.

[63] Eli Chien, Chao Pan, Jianhao Peng, and Olgica Milenkovic. You are allset: A multiset function framework for hypergraph neural networks, 2022.

[64] Yiqi Wang, Yao Ma, Wei Jin, Chaozhuo Li, Charu Aggarwal, and Jiliang Tang. Customized graph neural networks, 2021.

[65] Hwan Kim, Byung Suk Lee, Won-Yong Shin, and Sungsu Lim. Graph anomaly detection with graph neural networks: Current status and challenges, 2022.

[66] Luis C. Lamb, Artur Garcez, Marco Gori, Marcelo Prates, Pedro Avelar, and Moshe Vardi. Graph neural networks meet neural-symbolic computing: A survey and perspective, 2021.

[67] Shaofei Cai, Liang Li, Xinzhe Han, Zheng jun Zha, and Qingming Huang. Edge-featured graph neural architecture search, 2021.

[68] Guanyu Cui and Zhewei Wei. Mgnn: Graph neural networks inspired by distance geometry problem, 2023.

[69] Rong Zhu, Kun Zhao, Hongxia Yang, Wei Lin, Chang Zhou, Baole Ai, Yong Li, and Jingren Zhou. Aligraph: A comprehensive graph neural network platform. *arXiv preprint arXiv:1902.08730*, 2019.

[70] Anton Tsitsulin, John Palowitch, Bryan Perozzi, and Emmanuel Müller. Graph clustering with graph neural networks. *Journal of Machine Learning Research*, 24(127):1–21, 2023.

[71] Qianggang Ding, Deheng Ye, Tingyang Xu, and Peilin Zhao. Gpn: A joint structural learning framework for graph neural networks, 2022.

[72] Jiamin Chen, Jianliang Gao, Yibo Chen, Oloulade Babatounde Moctard, Tengfei Lyu, and Zhao Li. Graphpas: Parallel architecture search for graph neural networks, 2021.

[73] Hao Yuan, Jiliang Tang, Xia Hu, and Shuiwang Ji. Xgnn: Towards model-level explanations of graph neural networks, 2020.

[74] Kai Guo, Hongzhi Wen, Wei Jin, Yaming Guo, Jiliang Tang, and Yi Chang. Investigating out-of-distribution generalization of gnns: An architecture perspective, 2024.

[75] Martin J. A. Schuetz, J. Kyle Brubaker, and Helmut G. Katzgraber. Combinatorial optimization with physics-inspired graph neural networks, 2022.

[76] Fangshuo Zhou, Huaxia Li, Rui Hu, Sensen Wu, Hailin Feng, Zhenhong Du, and Liuchang Xu. Controlcity: A multimodal diffusion model based approach for accurate geospatial data generation and urban morphology analysis, 2024.

[77] Zangir Iklassov and Dmitrii Medvedev. Robust reinforcement learning on graphs for logistics optimization, 2022.

[78] Zeyang Zhang, Xin Wang, Ziwei Zhang, Haoyang Li, and Wenwu Zhu. Out-of-distribution generalized dynamic graph neural network with disentangled intervention and invariance promotion, 2024.

[79] Mateo Neira and Roberto Murcio. Graph representation learning for street networks, 2022.

[80] Morteza Ramezani, Weilin Cong, Mehrdad Mahdavi, Mahmut T. Kandemir, and Anand Sivasubramaniam. Learn locally, correct globally: A distributed algorithm for training graph neural networks, 2022.

[81] Davide Buffelli and Fabio Vandin. The impact of global structural information in graph neural networks applications, 2021.

[82] Yiwei Wang, Wei Wang, Yuxuan Liang, Yujun Cai, and Bryan Hooi. Graphcrop: Subgraph cropping for graph classification, 2020.

[83] Jingzhao Gu and Haoyang Huang. Research and implementation of data enhancement techniques for graph neural networks, 2024.

[84] Zara Lisbon. Review of digital asset development with graph neural network unlearning, 2024.

[85] Alaa Bessadok, Mohamed Ali Mahjoub, and Islem Rekik. Graph neural networks in network neuroscience. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(5):5833–5848, 2022.

[86] Filippo Maria Bianchi. Simplifying clustering with graph neural networks, 2022.

[87] Amit Roy, Kashob Kumar Roy, Amin Ahsan Ali, M Ashraful Amin, and A K M Mahbubur Rahman. Unified spatio-temporal modeling for traffic forecasting using graph neural network, 2021.

[88] Shiqing Liu, Xueming Yan, and Yaochu Jin. End-to-end pareto set prediction with graph neural networks for multi-objective facility location, 2022.

[89] Zirui Liu, Zhimeng Jiang, Shaochen Zhong, Kaixiong Zhou, Li Li, Rui Chen, Soo-Hyun Choi, and Xia Hu. Editable graph neural network for node classifications, 2023.

[90] Ping Liu, Haichao Wei, Xiaochen Hou, Jianqiang Shen, Shihai He, Kay Qianqi Shen, Zhujun Chen, Fedor Borisyuk, Daniel Hewlett, Liang Wu, Srikant Veeraraghavan, Alex Tsun, Chengming Jiang, and Wenjing Zhang. Linksage: Optimizing job matching using graph neural networks, 2024.

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