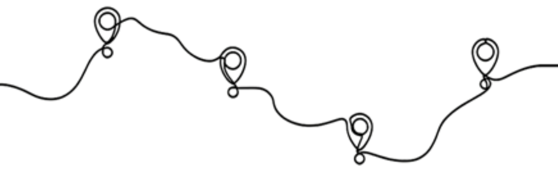


PORTFOLIO

SELECTED WORKS | 2021-2025

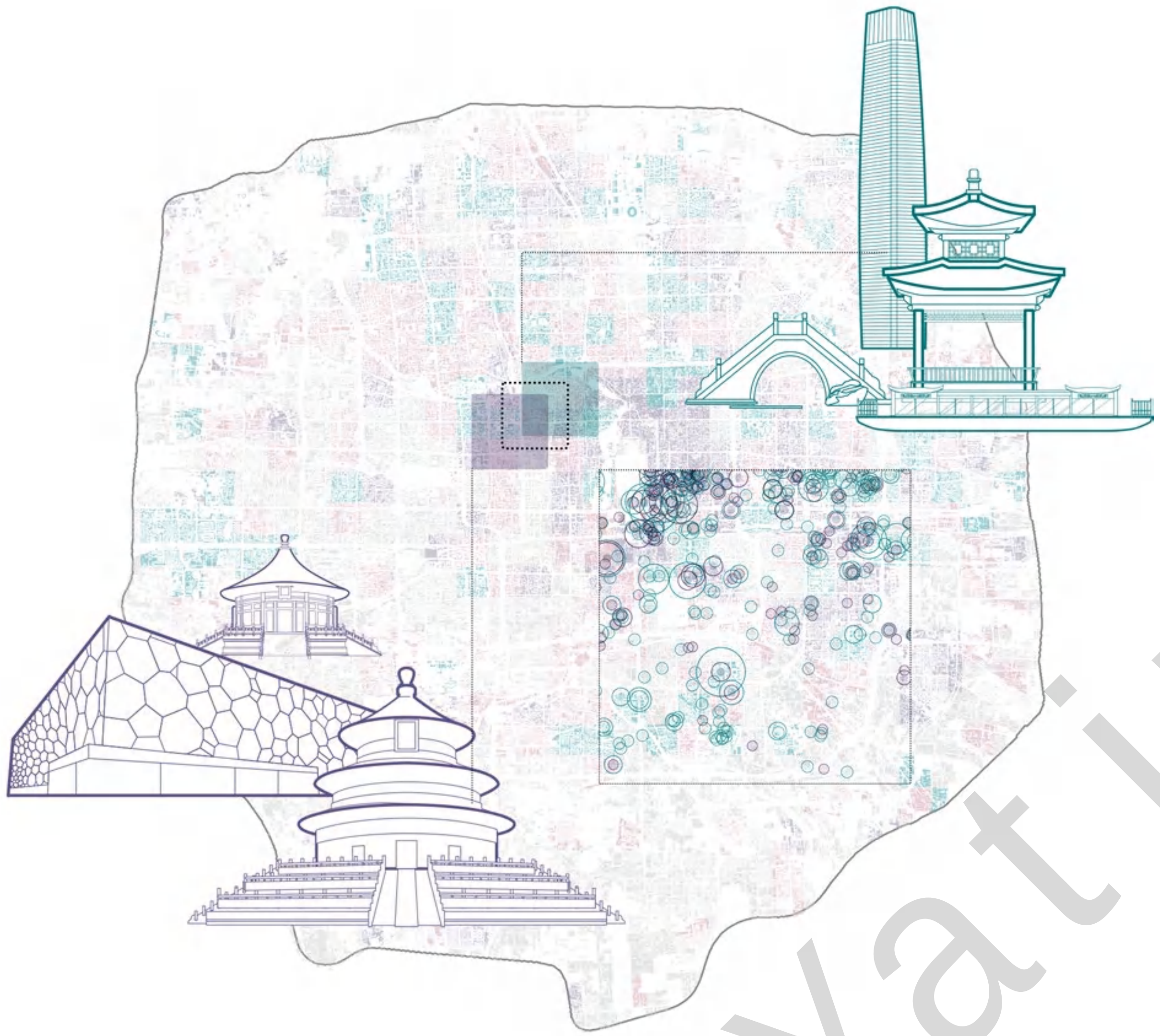
Yating Wang
wangyati20@gmail.com

CONTENTS

01

WHOSE CITY IMAGE | Does Social Media Have a Filter Effect?

Exploring Social Media's Biased City Image between Tourists and Residents

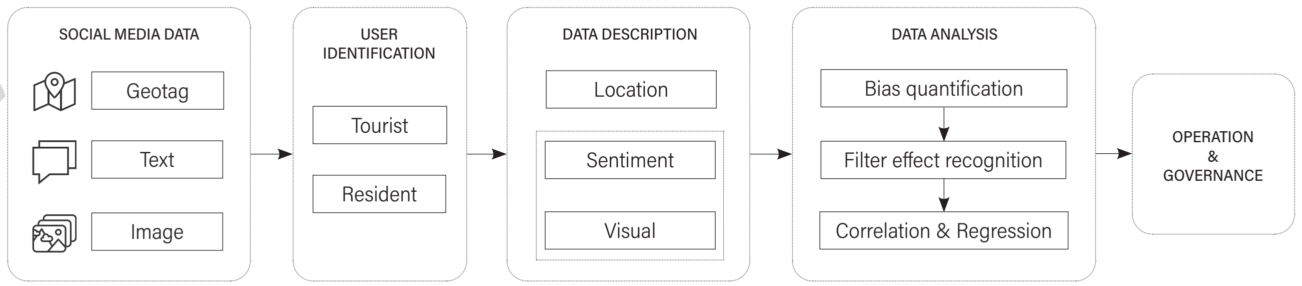


Individual work | Spatial Analysis, Data Visualization, ML Modeling

Site: Beijing, China

Time: 2025.07 - 2025.09

Instructor: Prof. Yuan Lai, yuanlai@tsinghua.edu.cn



Residents and tourists construct distinct spatial narratives on social media.

Residents foreground everyday and functional spaces, while tourists emphasize iconic and symbolic places; the study asks whose images dominate and what spatial dynamics they create.

K-means clustering reveals three narrative-driven spatial types.

Tourist Consumption Zones, Resident Stability Zones, and Mixed Vitality Zones show how digital expressions correspond to different patterns of urban use, emotion, and complexity. The three clusters make visible the underlying structure of narrative divergence across the city.

Findings extend city-image theory and inform governance.

Divergence and convergence across groups provide practical insights for mitigating conflicts in residential neighborhoods and supporting integration in mixed-use spaces. The results highlight where policies should respond to narrative imbalance and experiential tension.

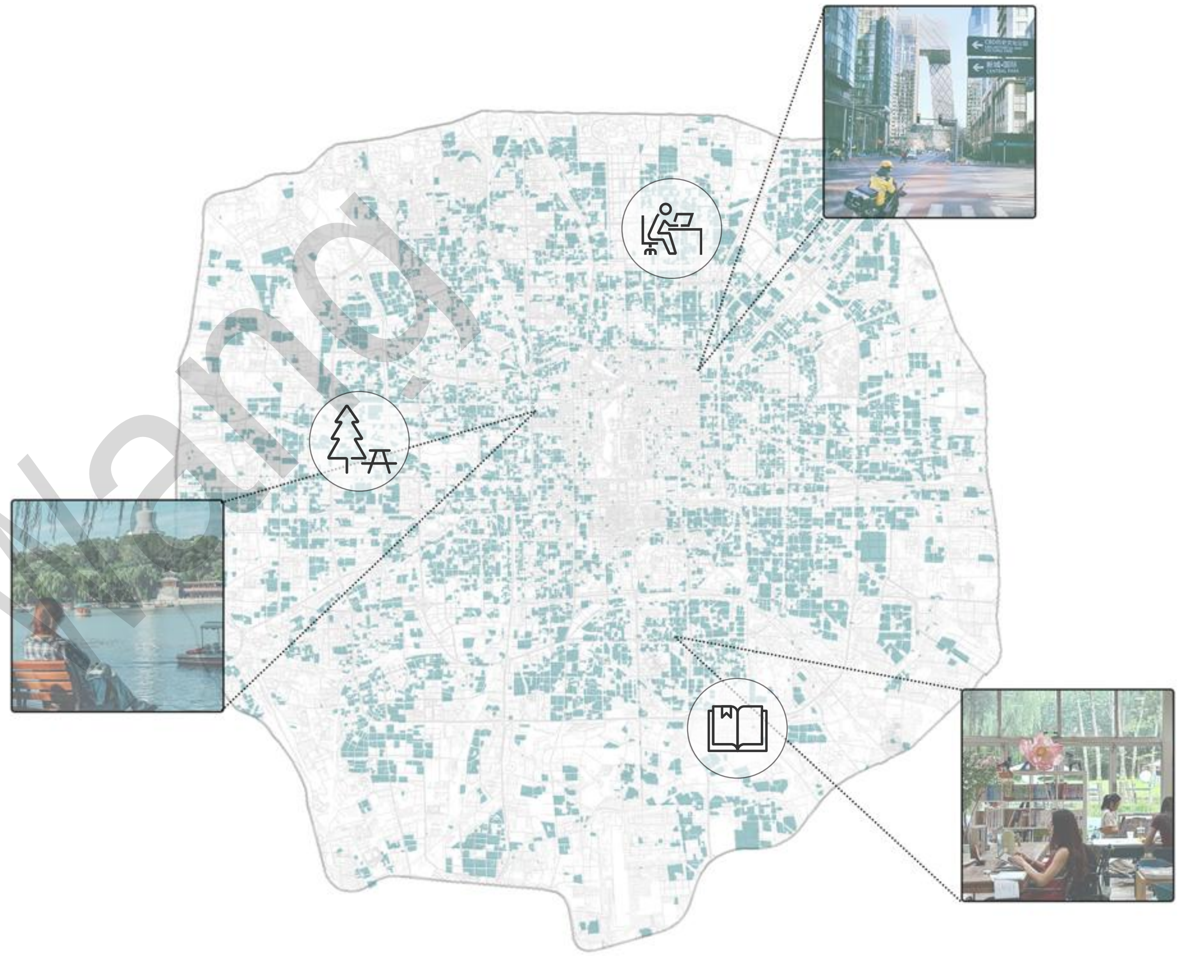
BACKGROUND & CONCEPT

Tourist

Short-stay visitors navigate Beijing through platform guides and "check-in" routes. Their narratives center on landmarks, cafés, views, and photogenic streets, with timing optimized for queues and light. Posts tend to celebrate novelty and aesthetics, but also note costs, congestion, and distance between sights. The result is a city image stitched from highlights—curated, enthusiastic, and sometimes stressed by crowds.

Resident

Residents describe Beijing through routines and access: the reliability of commutes, proximity to groceries and clinics, pocket parks for evening walks, and affordable places to eat. Their posts weigh services, noise, and policy changes that shape daily comfort. Pride in convenience and community coexists with frustration over tourist spillovers, weekend congestion, and rising prices around popular areas.



Coffee in a hutong courtyard, sunset on Liangma River. Every corner feels like a movie set. Clean, safe, super walkable between spots. #Beijing #CityWalk ☺

Beautiful, but the queues at Summer Palace and the crush in Sanlitun drained my energy. Tickets add up, traffic back to the hotel took forever. Next time I'll skip the hotspots. #TooCrowded #TouristDiaries ☹

Sightseeing
Visiting famous landmarks and scenic spots.

Photography
Taking pictures and sharing on social media.

Posting
Sharing "check-in" moments and comments online.

Shopping
Buying souvenirs and exploring local markets.

Smooth Line 10 commute, lunch at the small noodle shop by the office, evening jog in Olympic Forest Park. Busy city, but the rhythm works. Feels like home. #DailyBeijing #Convenience ☺

Weekend crowds flooded our hutong again, delivery bikes blocking the lane, prices creeping up. Love the neighborhood, not the "check-in" chaos. #NeighborhoodLife #Overtourism ☹

Errands
Handling groceries, shopping, and community tasks.

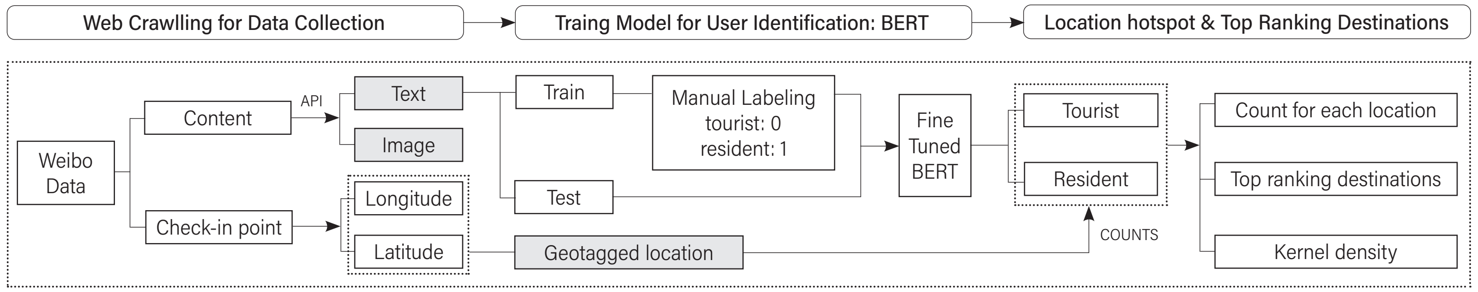
Commuting
Traveling daily between home and workplace/school.

Working
Engaging in jobs, office tasks, or local business.

Leisure
Taking relaxation in parks, cafés, or at home.

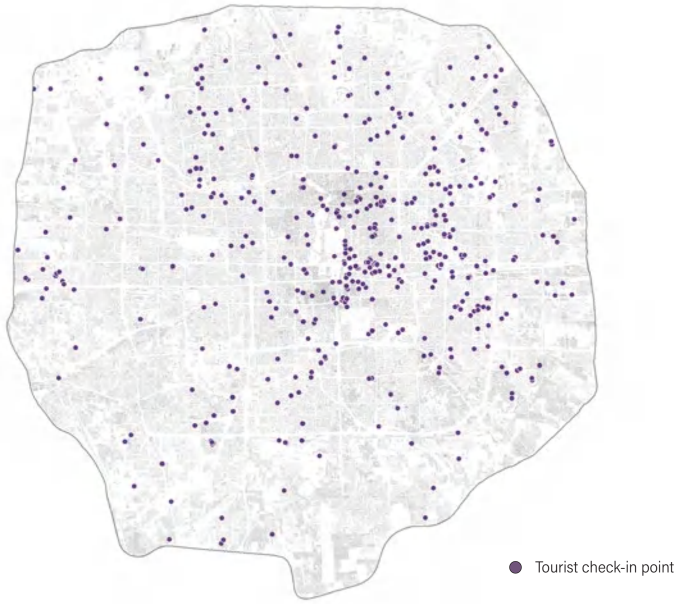
LOCATION | DISTRIBUTION OF CHECK-IN POINTS

Weibo Data Collection

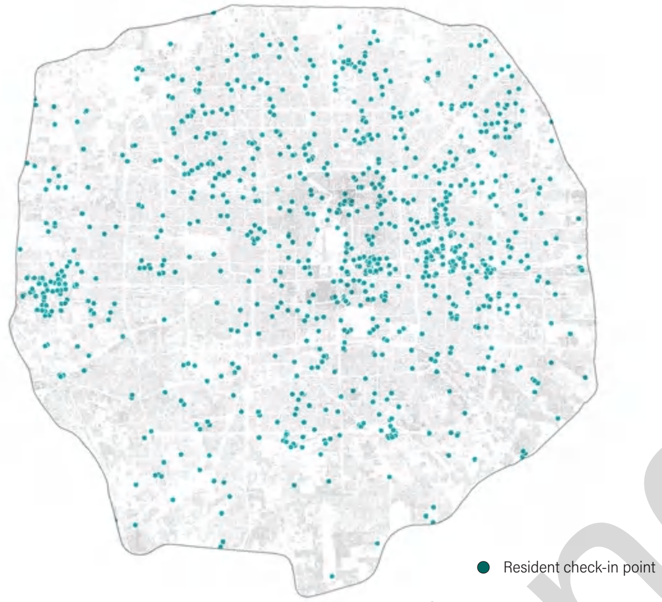


Location Distribution

Tourist: 5961 posts | 365 points

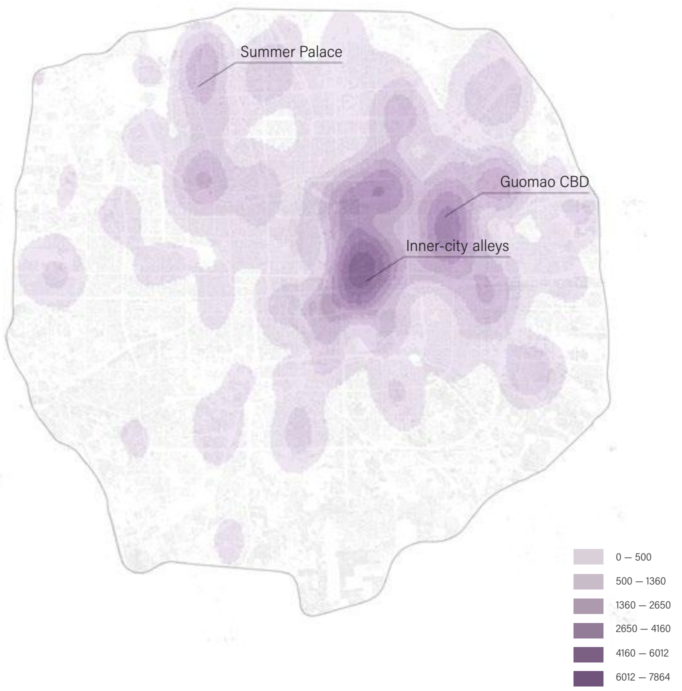


Resident: 6784 posts | 482 points

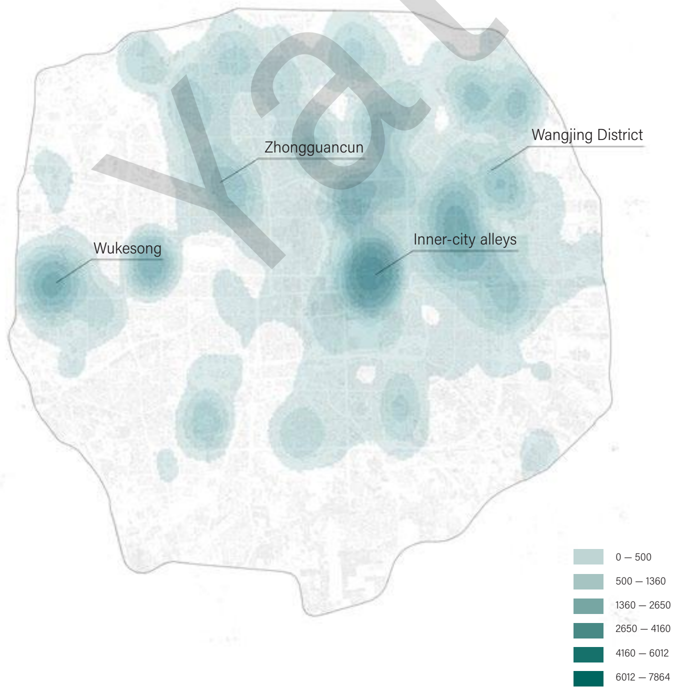


Kernel Density of Check-in Points

Tourist: Clustered around key landmarks

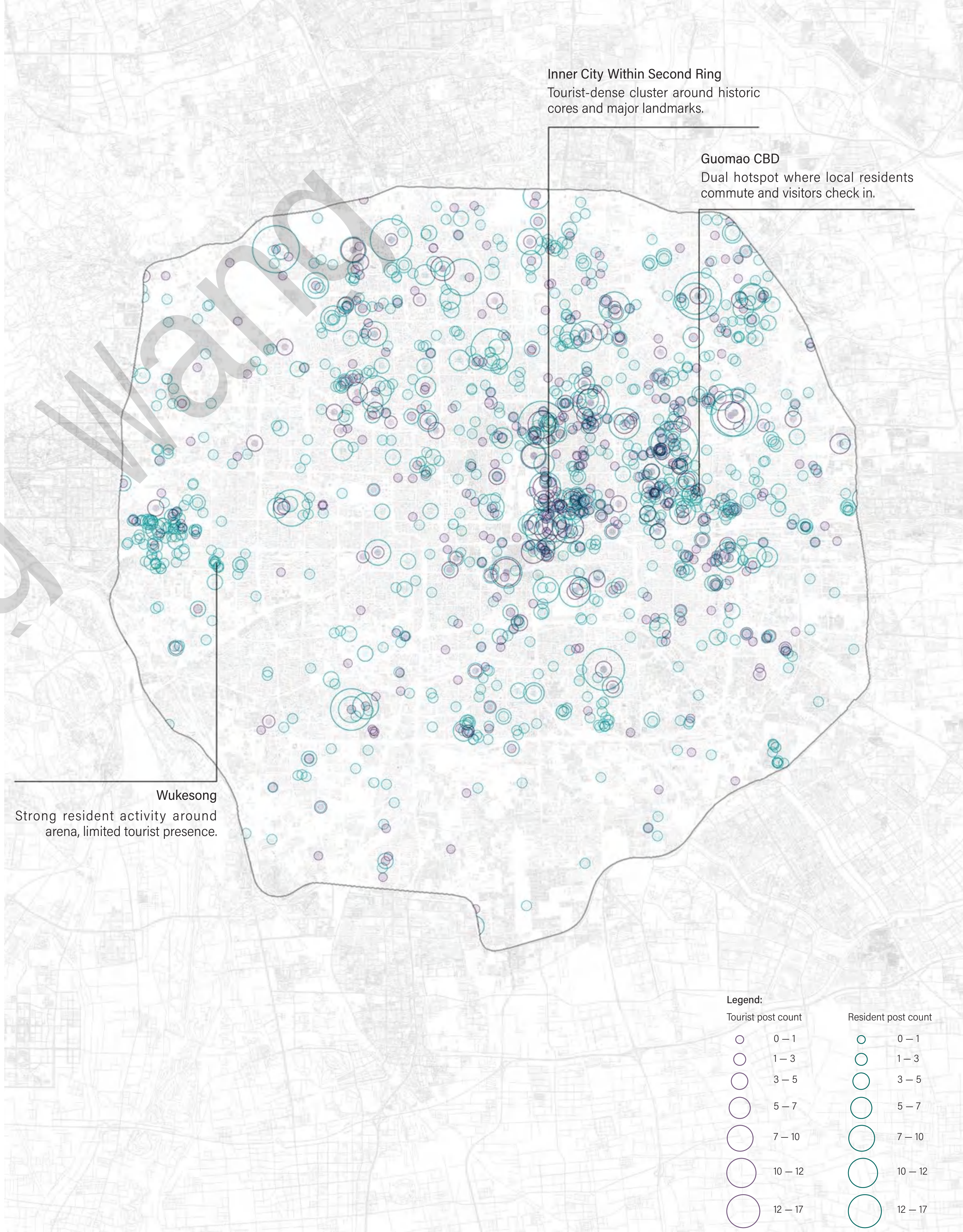


Resident: Spread across multi-centers



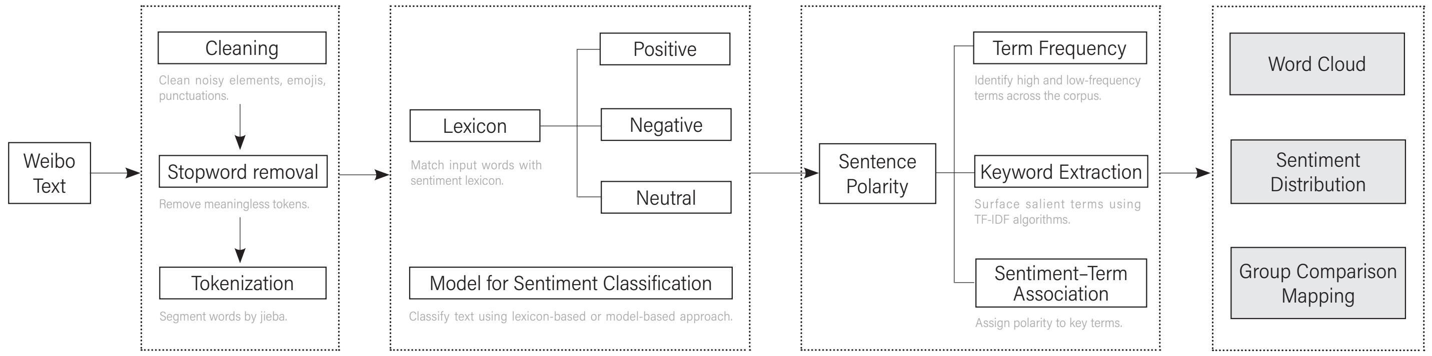
Check-in Location: Tourist vs Resident

Tourist check-ins form dense clusters with high post volumes, especially around well-known attractions. In contrast, residents are distributed across a wider range of neighborhoods, with lower but more consistent engagement. This visualizes two coexisting yet distinct spatial footprints in the same city.

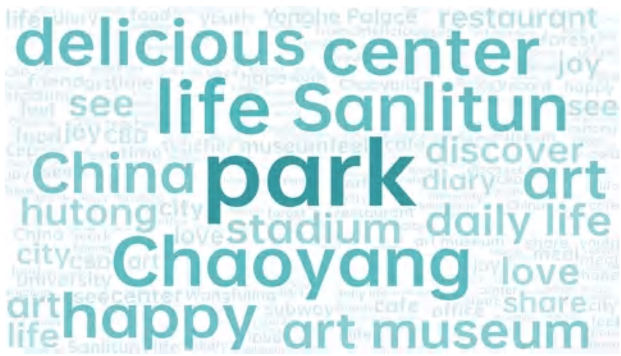


CONTENT | HOW DO PEOPLE EXPRESS DIFFERENTLY?

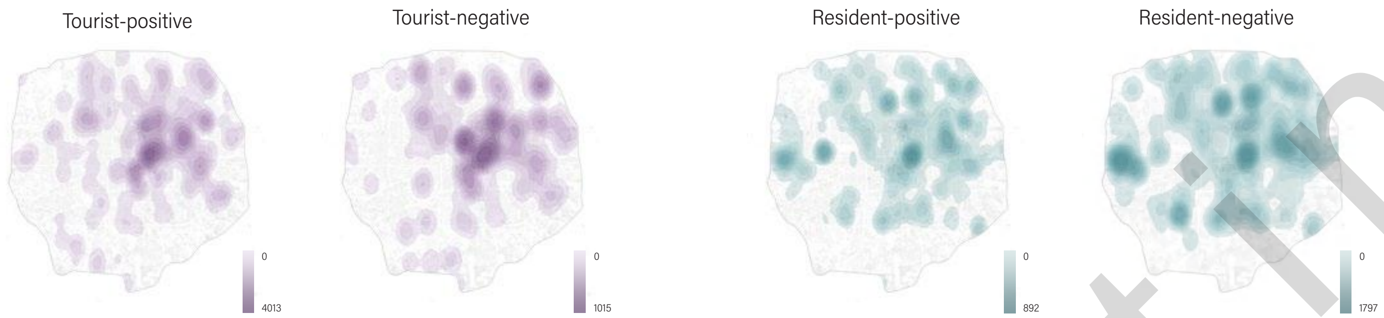
Framework for Sentiment Analysis of Text Data



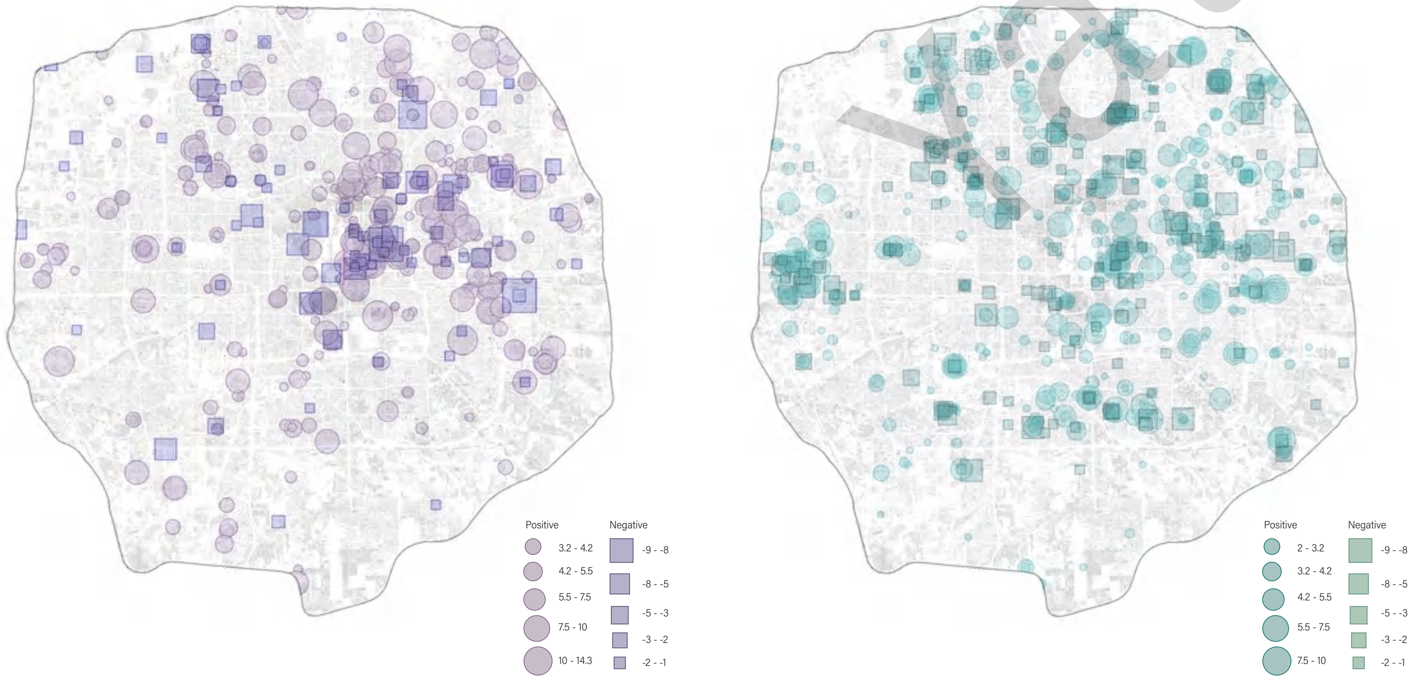
Word Cloud



Kernel Density of Sentiment Score

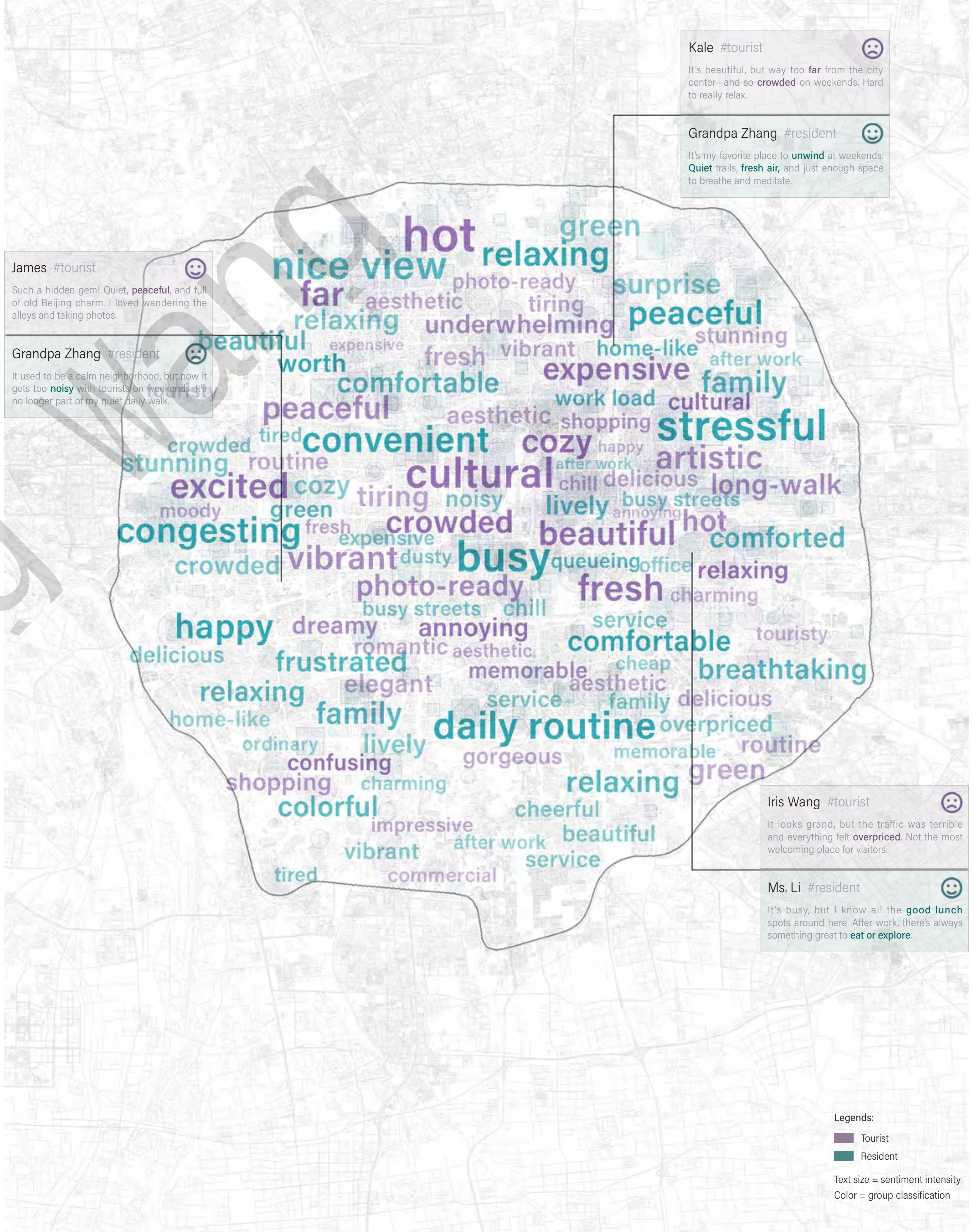


Sentiment Score Mapping



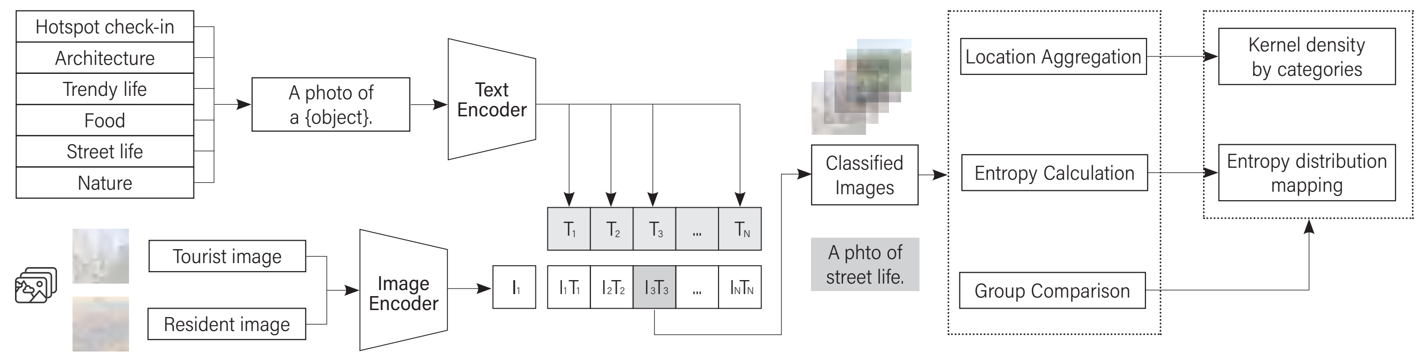
Comparison of Sentiment Words

This visualization compares how tourists and residents express emotions across the city. Tourists show more positive emotions, often shaped by novelty and attraction. Residents display a wider emotional spectrum—reflecting daily routines, occasional frustration, and local attachment. These patterns highlight how different groups emotionally inhabit the same urban spaces.

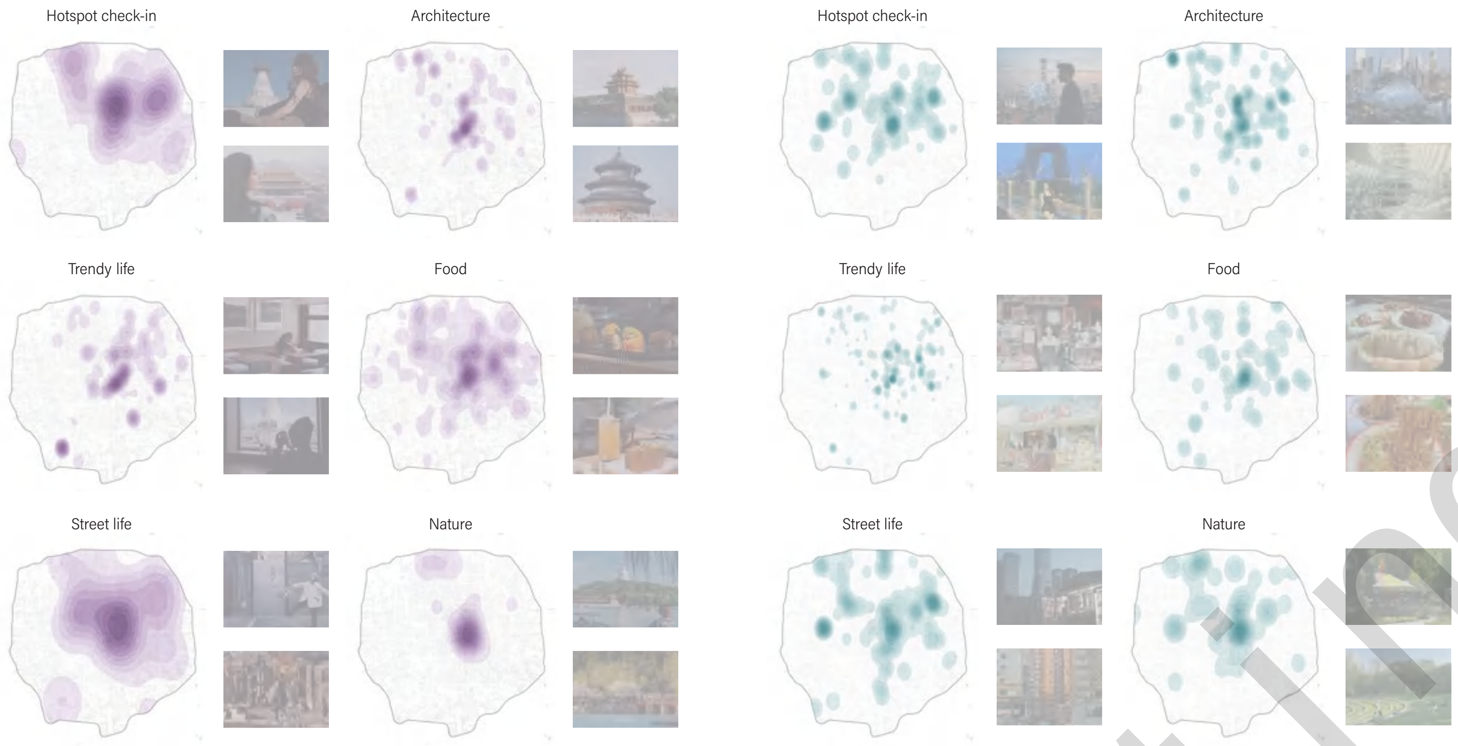


CONTENT | HOW DO PEOPLE SEE DIFFERENTLY?

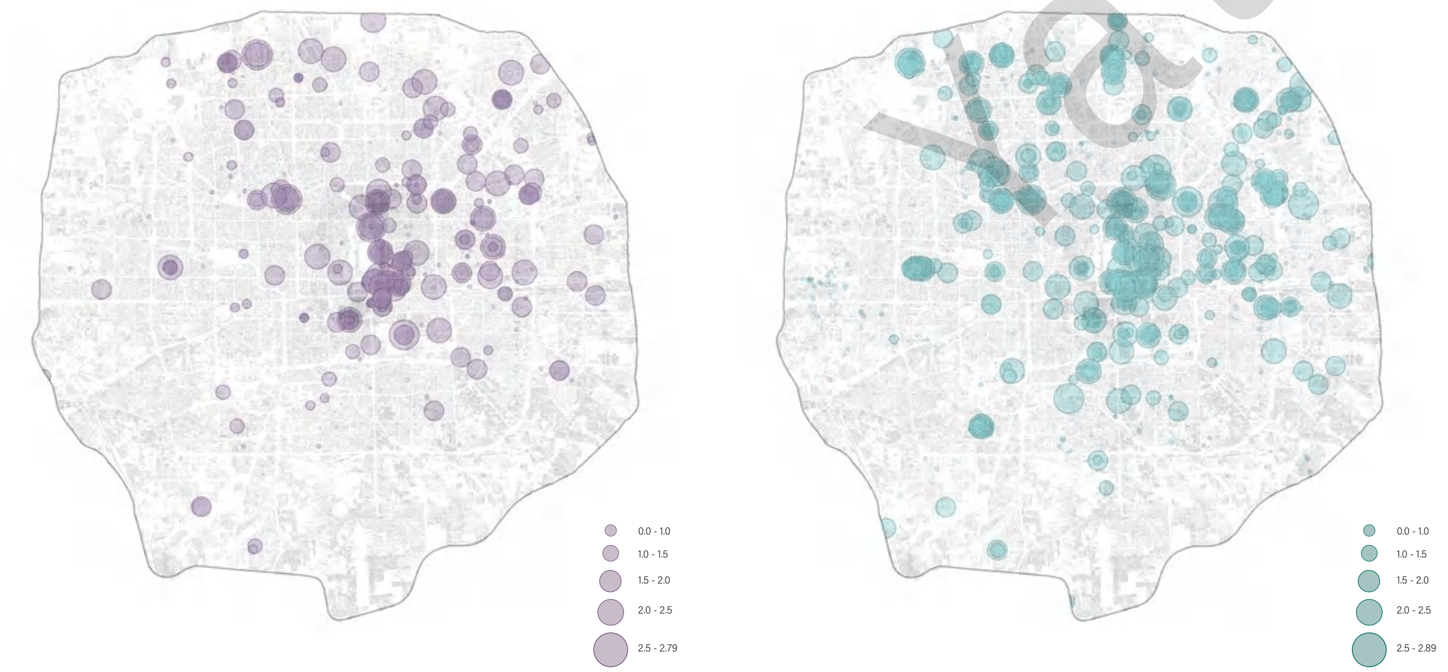
Framework for Image Analysis



Kernel Density by Categories

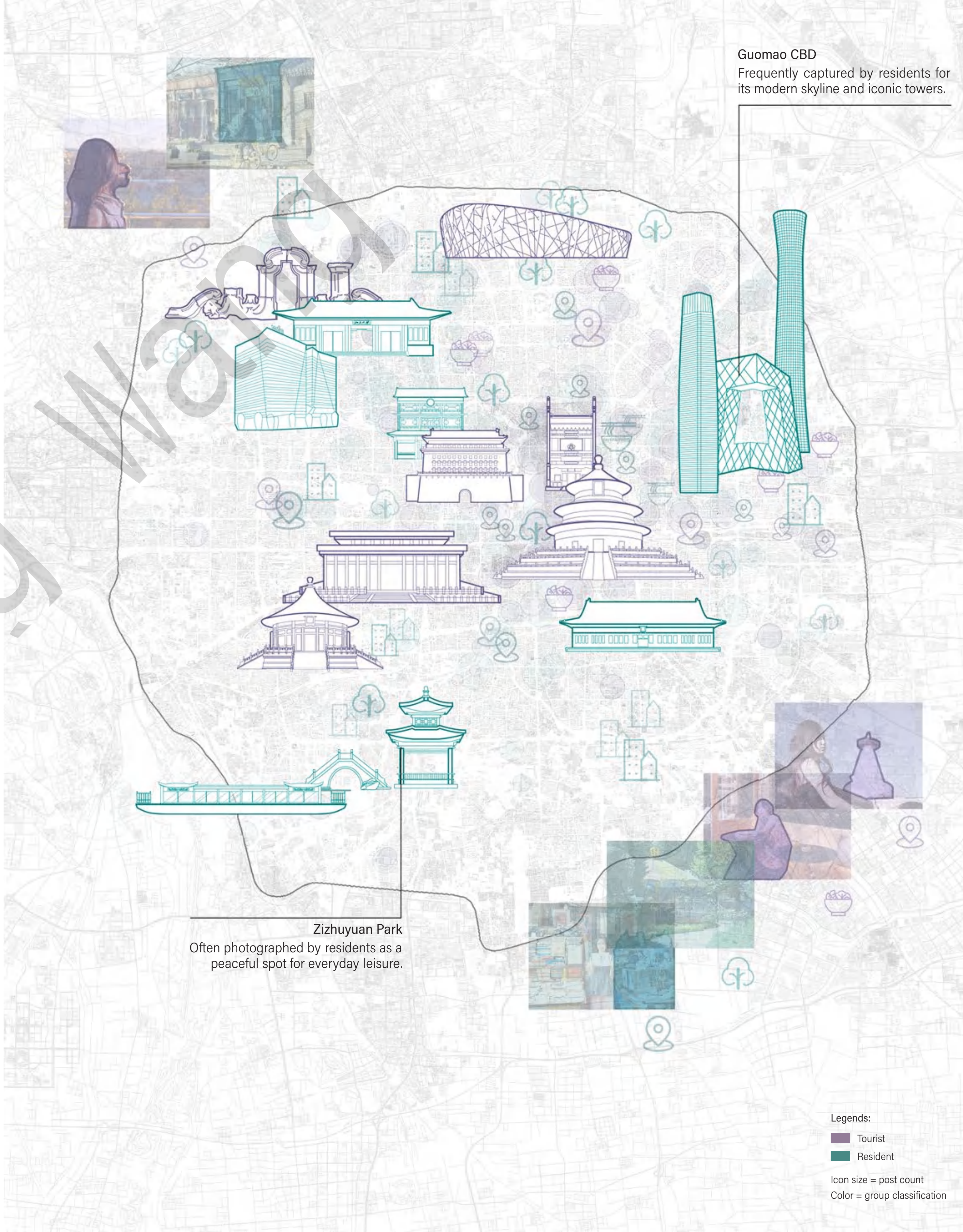


Entropy Distribution Mapping



Comparison of Visual Topic Entropy

Each icon represents a frequently photographed location, with size reflecting the volume of image posts and color indicating the user group. Tourists tend to capture iconic landmarks with consistent visual themes, while residents share more varied scenes across everyday settings. Higher entropy values among residents suggest broader visual perspectives and locally embedded experiences.

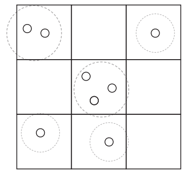


SUMMARY | GRID SYSTEM & BIAS QUANTIFICATION

Spatial Unit Construction

1. Grid System:
Divide study area into 1 km grids.

2. Spatial Join
Assign tourist or resident posts to corresponding grid cells.



Indicator Computation

3. Aggregation
Compute mean values of count, sentiment and entropy per grid.

$$I_g = \frac{1}{N_g}\sum_{i=1}^{N_g} I_i$$

4. Normalization
Apply z-score to standardize indicators across grids.

$$Z_g = \frac{I_g - \mu_I}{\sigma_I}$$

Bias Quantification

5. Difference Calculation
Subtract resident values from tourist values according to results above.

$$D_g = Z_g^{(tourist)} - Z_g^{(resident)}$$

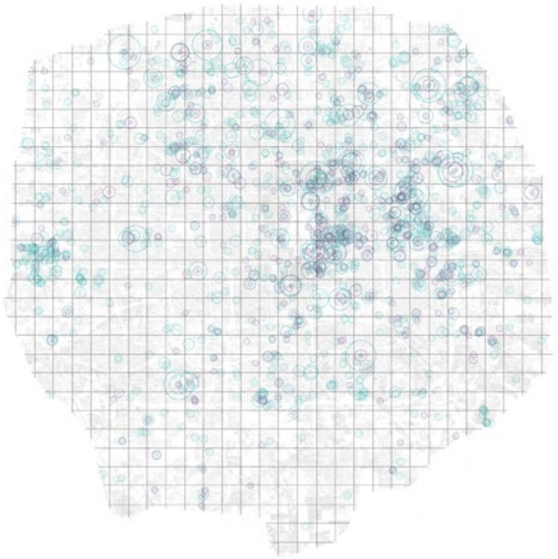
6. Bias Outputs
Three complementary dimensions of spatial expression differences.

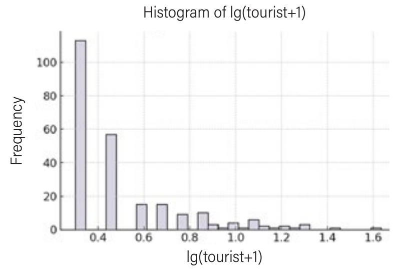
Count bias
Difference in posting intensity between groups

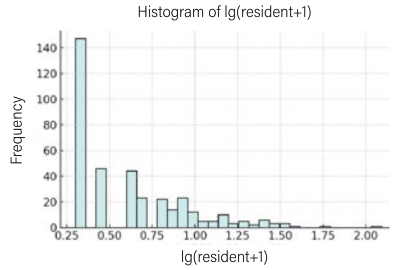
Sentiment bias
Divergence in emotional polarity

Image Entropy bias
Variation in the semantic diversity of images

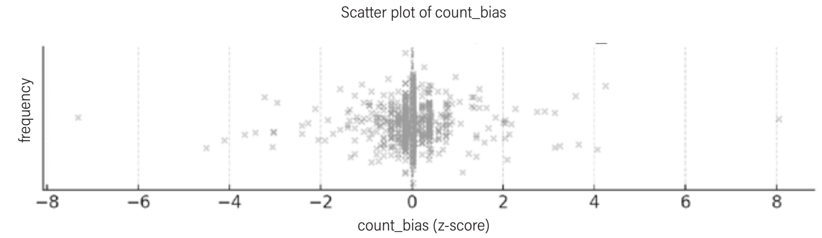
Check-in post count

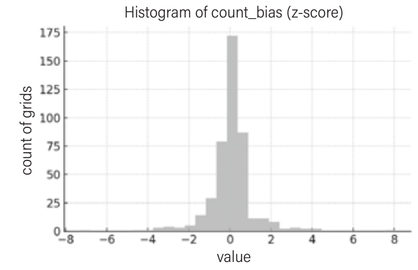






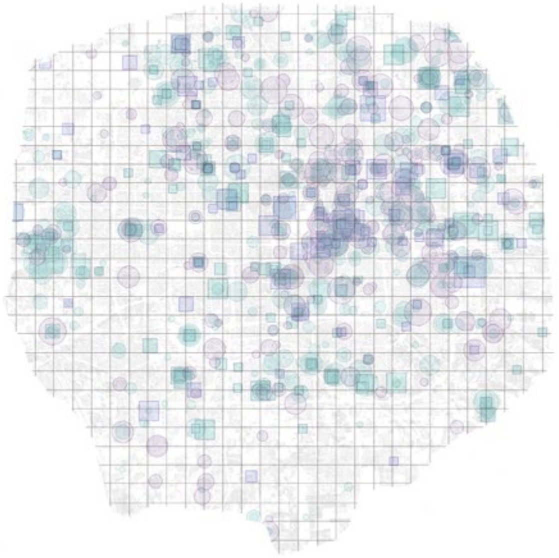
Count bias

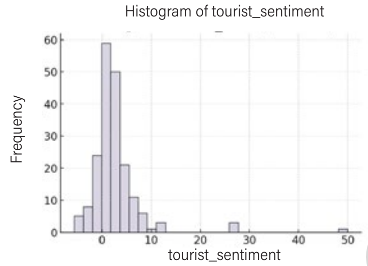


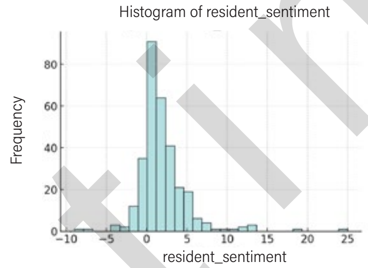


Uneven posting intensity—landmark/commercial hotspots vs. quieter residential belts, mostly near zero with localized positives.

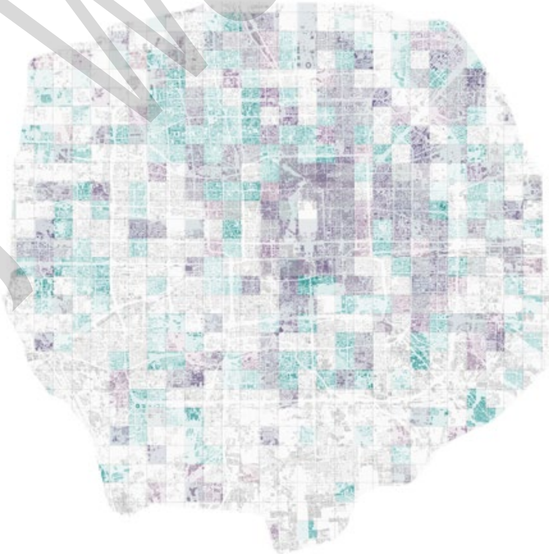
Average sentiment score

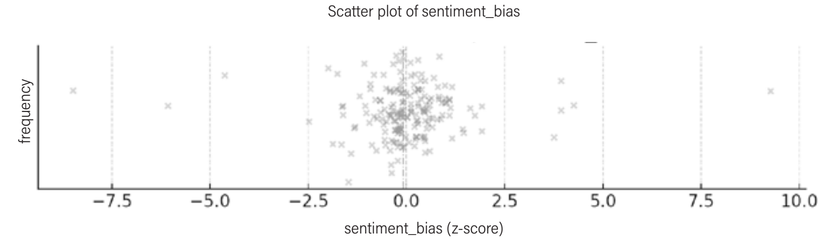


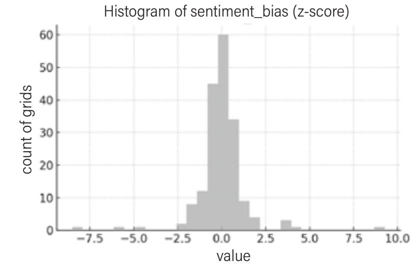




Sentiment bias

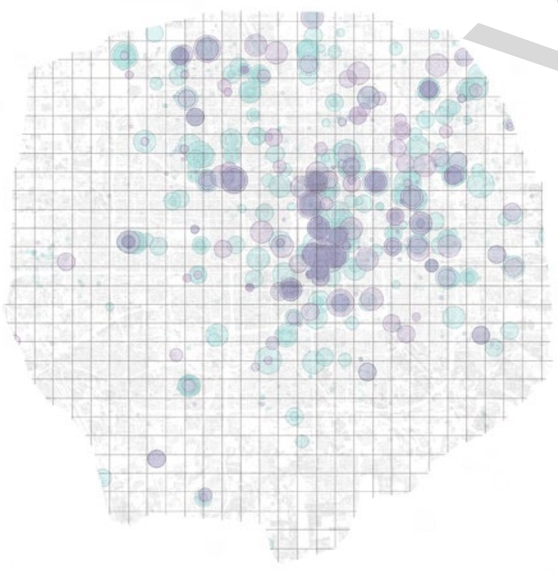


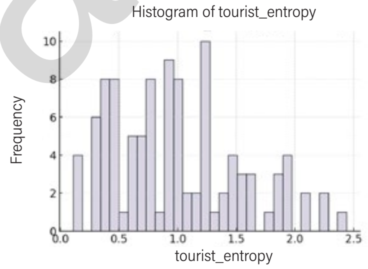


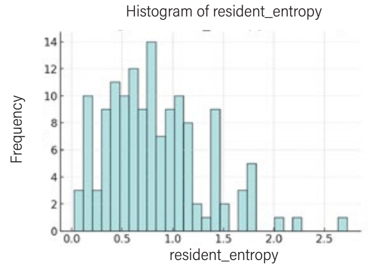


Overall positive, but tourists are slightly more upbeat at scenic cores while residents lean neutral/negative in congested or costly areas.

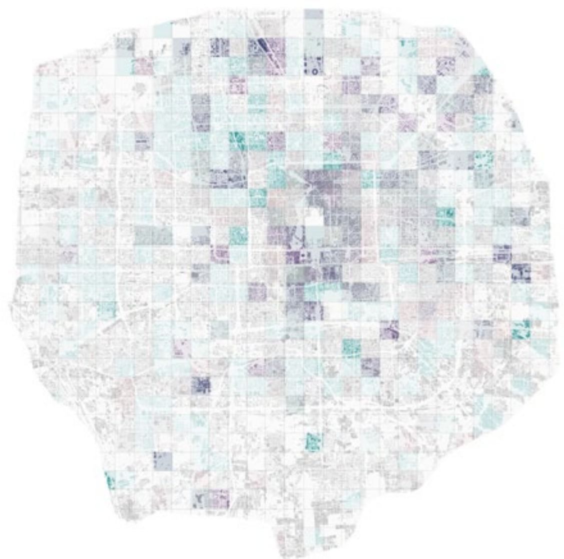
Average image entropy

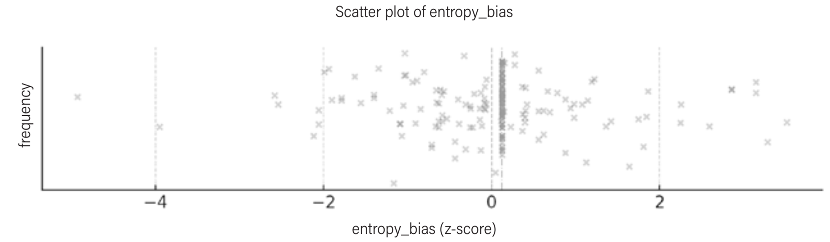


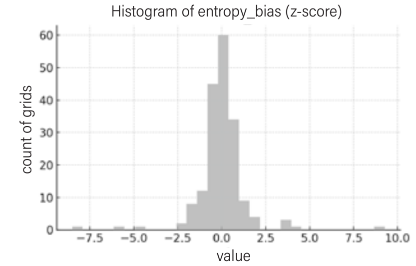




Entropy bias







Residents show higher scene diversity across everyday settings, whereas tourists cluster around iconic, single-theme visuals near attractions.

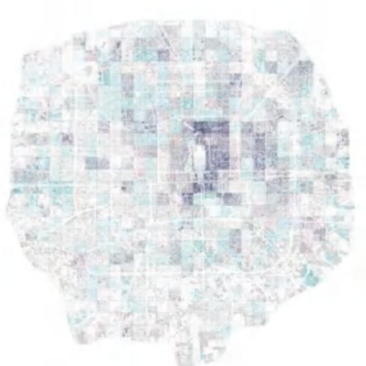
RECOGNITION | CLUSTERING OF THREE DIFFERENT SPACES

Framework for Clustering

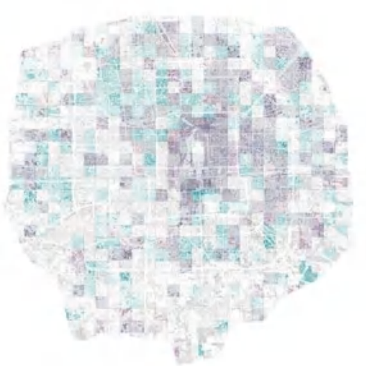
Input Features

Use three standardized biases (count, sentiment, and entropy) as inputs; adjust weights to emphasize tourist, resident, or shared signals.

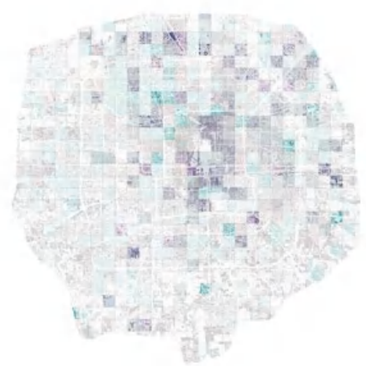
Count bias



Sentiment bias

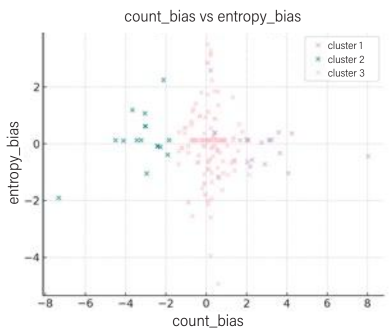


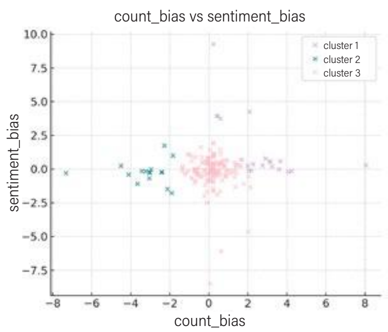
Entropy bias

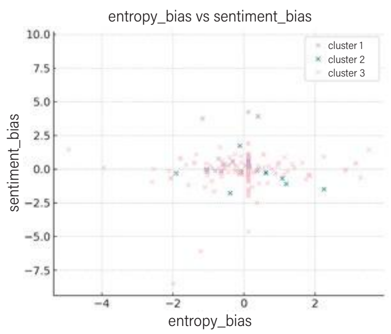


Scattered plot of three features

Pairwise scatters show how the three biases co-vary under the chosen weights and reveal separations that prefigure clusters.

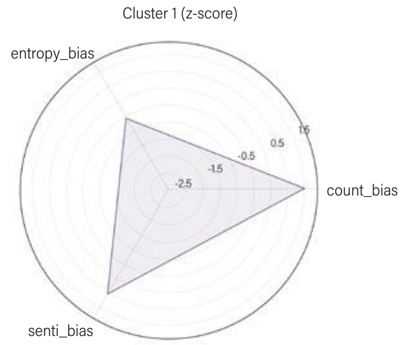


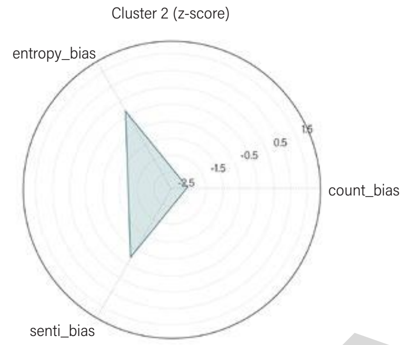


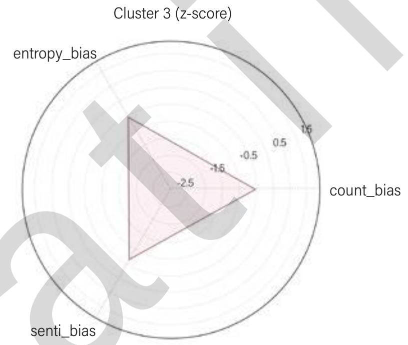


Radar graph of three types after K-means clustering

K-means (k=3) summarizes each cluster in z-scores, showing its characteristic mix of intensity, emotion, and diversity.







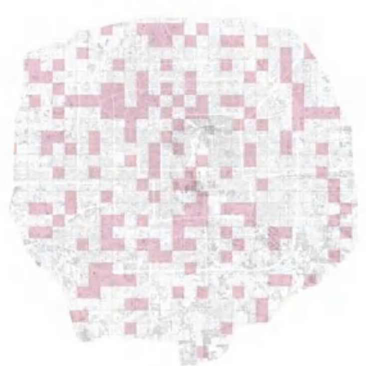
Spatial distribution of three types of areas

Map cluster labels back to grids to reveal citywide patterns: Tourist Consumption, Resident Stability, and Mixed Vitality zones.

Tourist Consumption Zone

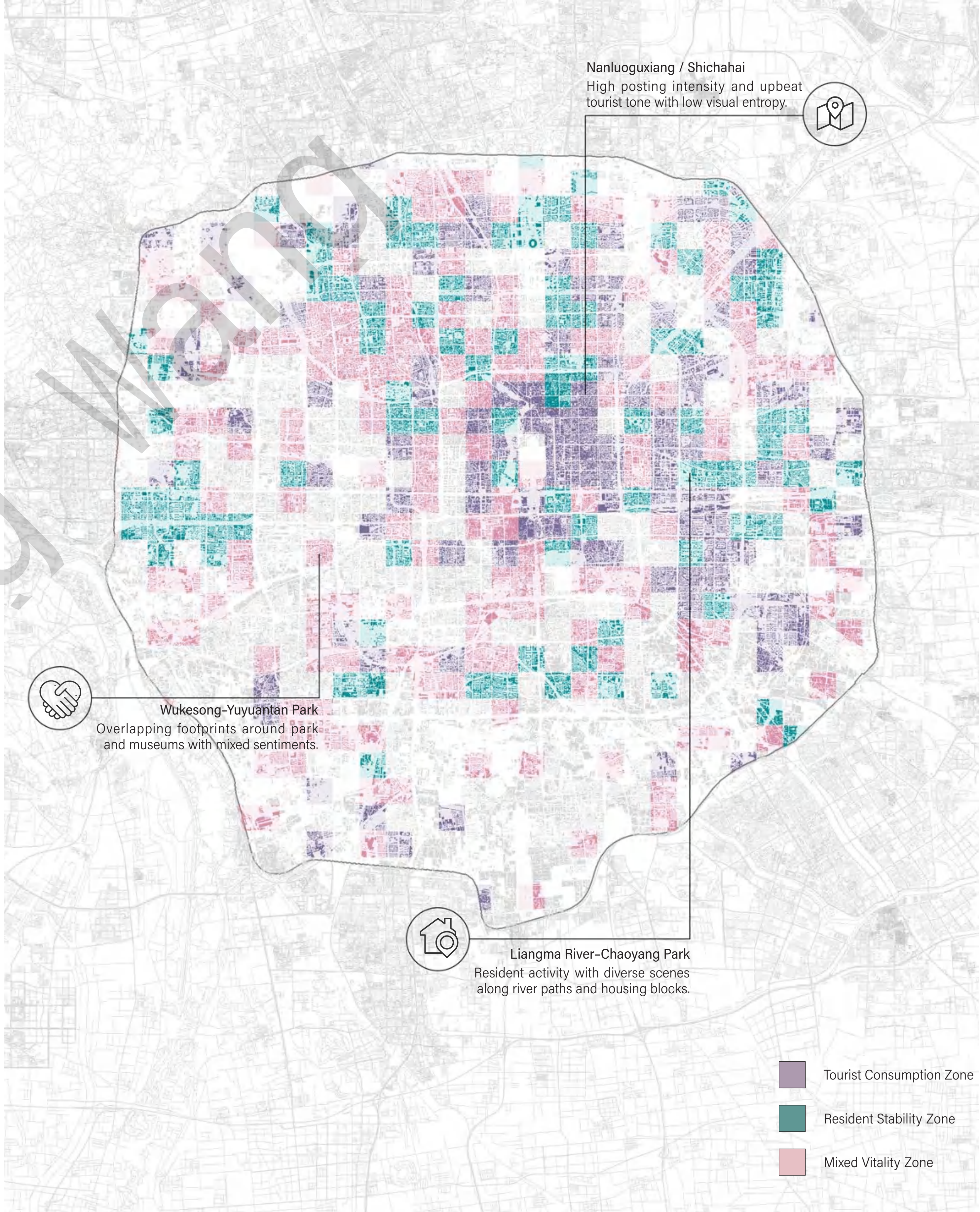
Resident Stability Zone

Mixed Vitality Zone



Three Types of Spaces after K-means Clustering

Using K-means clustering on count, sentiment, and entropy biases, we identify three spatial types across the city: Tourist Consumption Zones with high visitor presence and strong emotional tones, Resident Stability Zones characterized by consistent local narratives, and Mixed Vitality Zones where diverse groups and expressions converge. These clusters reveal how digital narratives reflect differentiated patterns of urban use, emotion, and complexity.



RECOGNITION | CORRELATION & REGRESSION

Correlation

We calculated Pearson correlations between each cluster's deviation score and a set of urban features, including built environment, functional structure, and socio-economic variables. This step identifies which spatial attributes are most associated with variations in narrative dominance across Tourist Consumption, Resident Stability, and Mixed Vitality zones.

Regression

We then conducted linear regressions for each cluster's deviation score, treating it as the dependent variable. Explanatory variables include catering and attraction density, function diversity, junction density, and online popularity, among others. The results quantify how specific spatial factors drive the emergence and strength of each narrative-biased space type.

Correlation Analysis

Dependent variables:

Cluster Membership
categorical outcome from K-means clustering, representing three types of spatial units.

Independent variables:

Built Environment Variables

- Catering: density of restaurants and food services
- Tourist Attraction: presence of scenic spots and landmarks
- University: presence of higher-education institutions
- Shopping Mall: density of commercial complexes
- Community Service: density of public service facilities
- Office: density of office buildings
- Residential: density of resident housing areas

Functional Structure Variables

- Function Density: overall intensity of urban functions within a grid
- Function Mix: degree of land-use diversity
- Junction Density: density of road intersections

Socio-economic Variables

- Online popularity: volume of social media posts
- Population: resident population density
- Age: average age of residents
- Income: average income level of residents

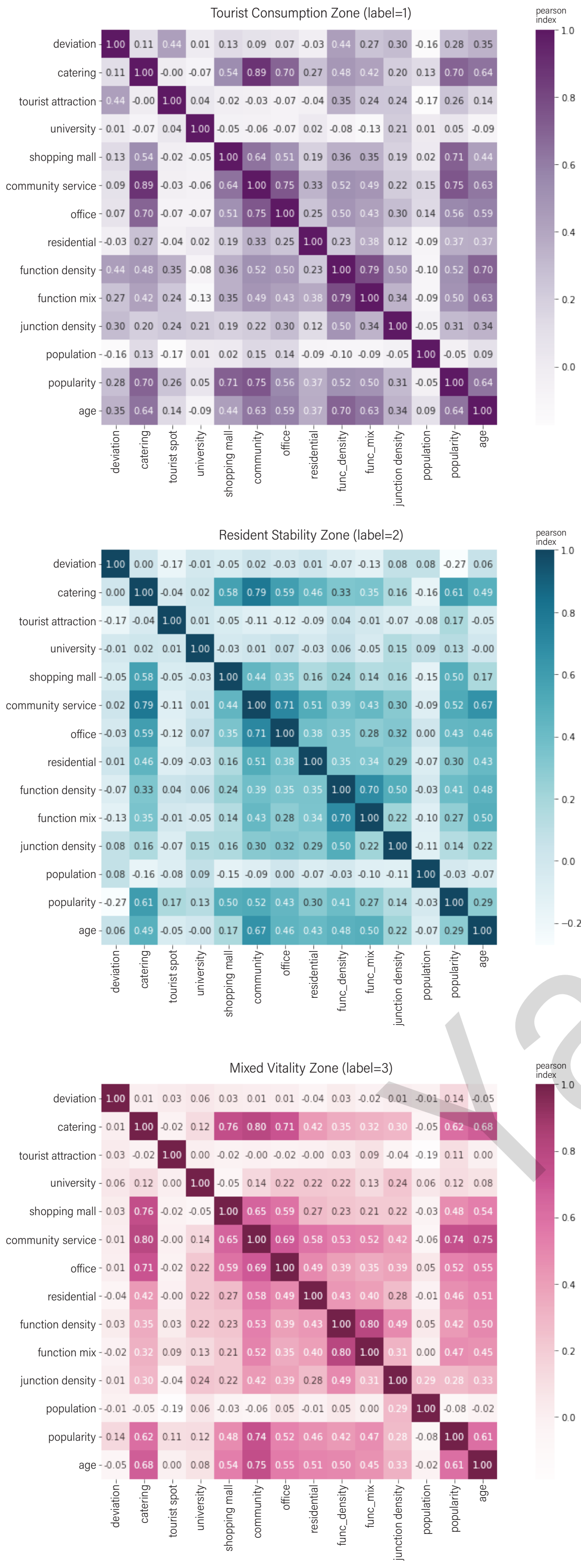
Regression

3. Aggregation
Compute mean values of count, sentiment and entropy per grid.

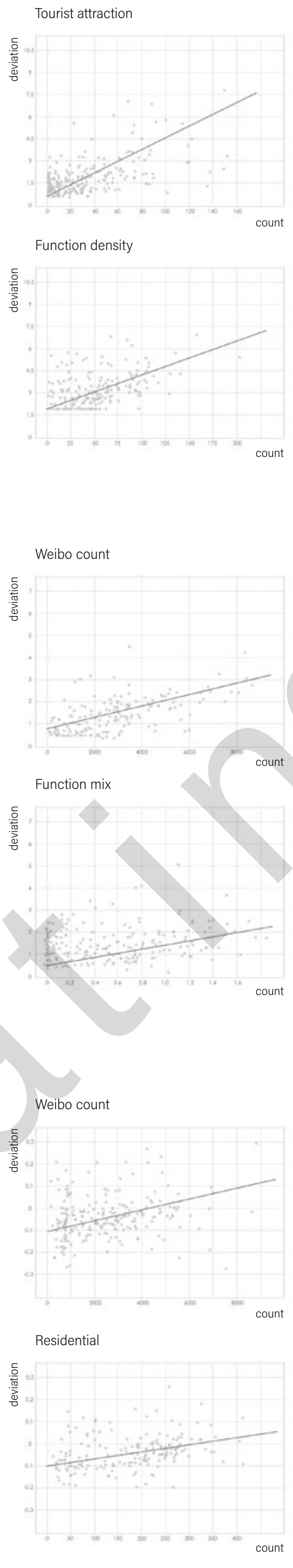
$$I_g = \frac{1}{N_g}\sum_{i=1}^{N_g} I_i$$

N_g: number of data points in grid g
I_i: indicator value of the i-th data point
I_g: mean indicator value of grid g

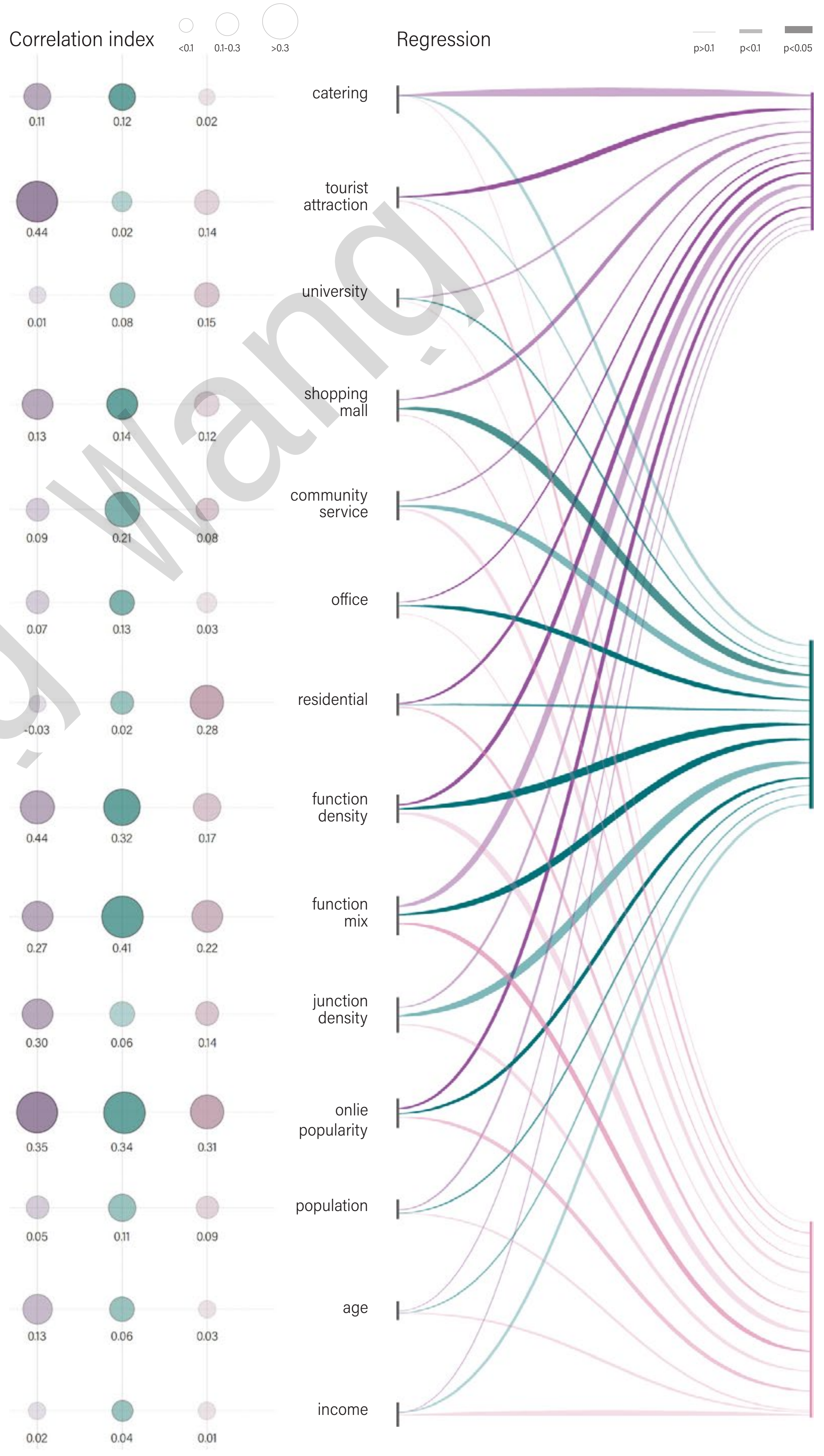
Pearson Heatmap

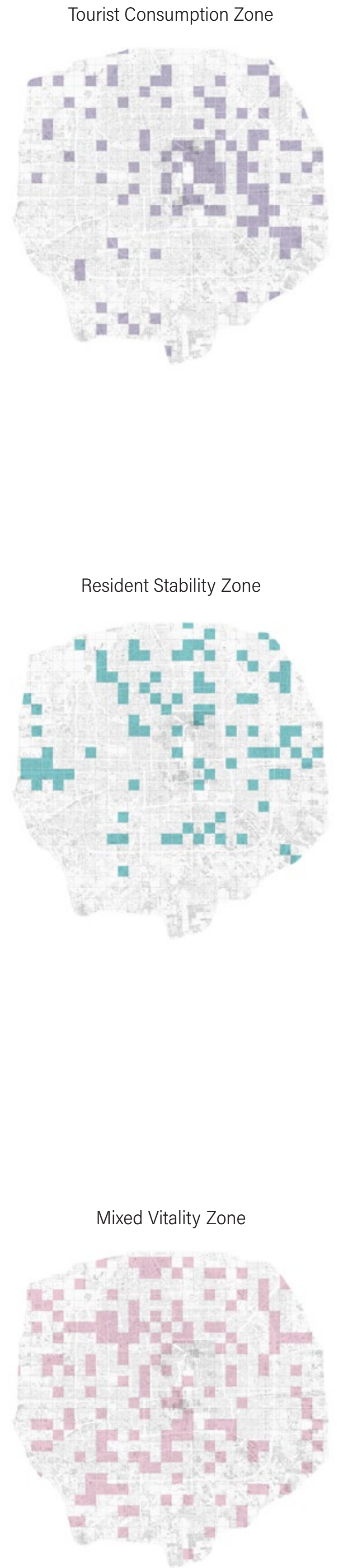


Scattered Plot

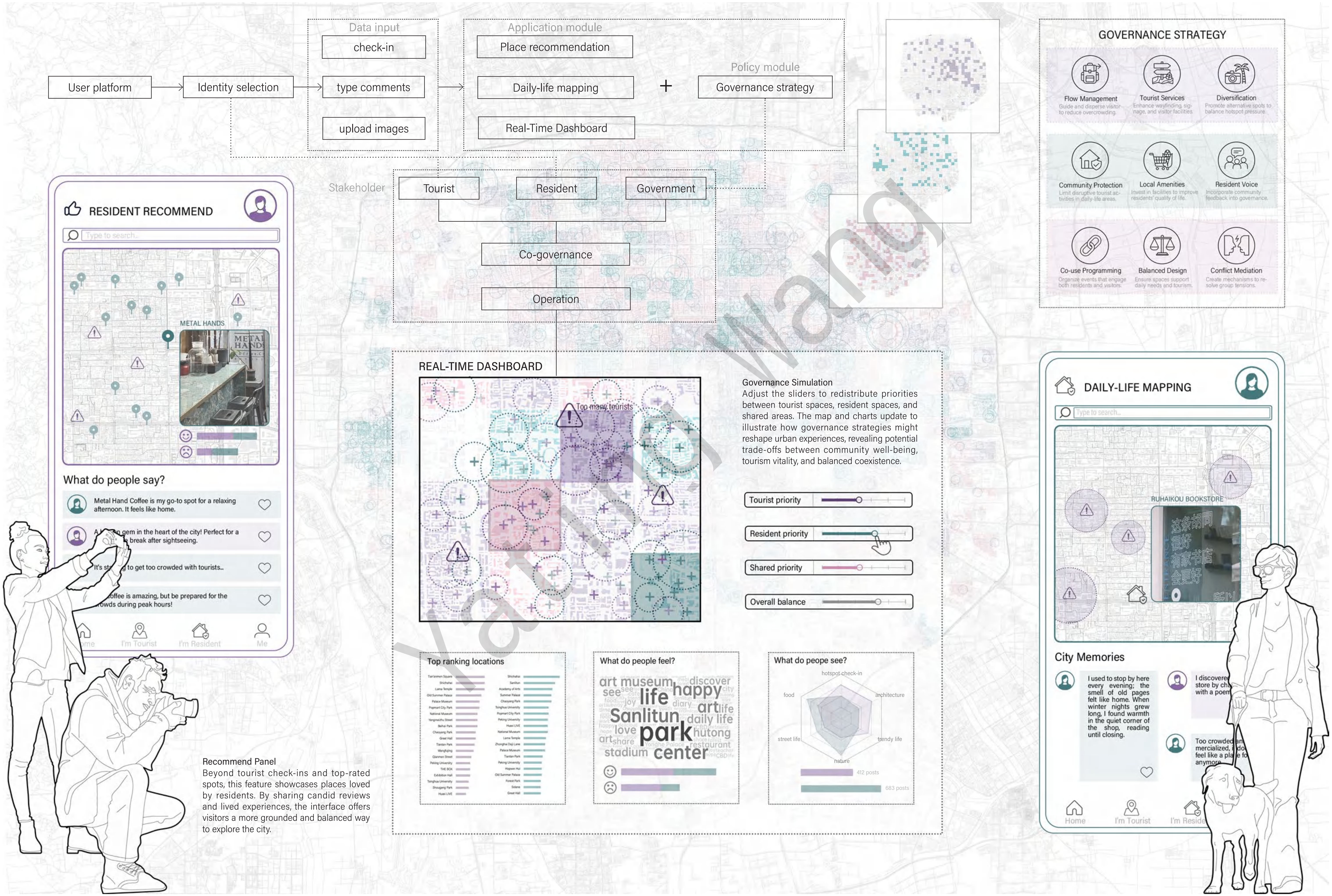


Correlation index





FROM RECOGNITION TO ACTION



02

TOURISM NETWORK | Temporal Dynamic of Beijing Tourist Attractions

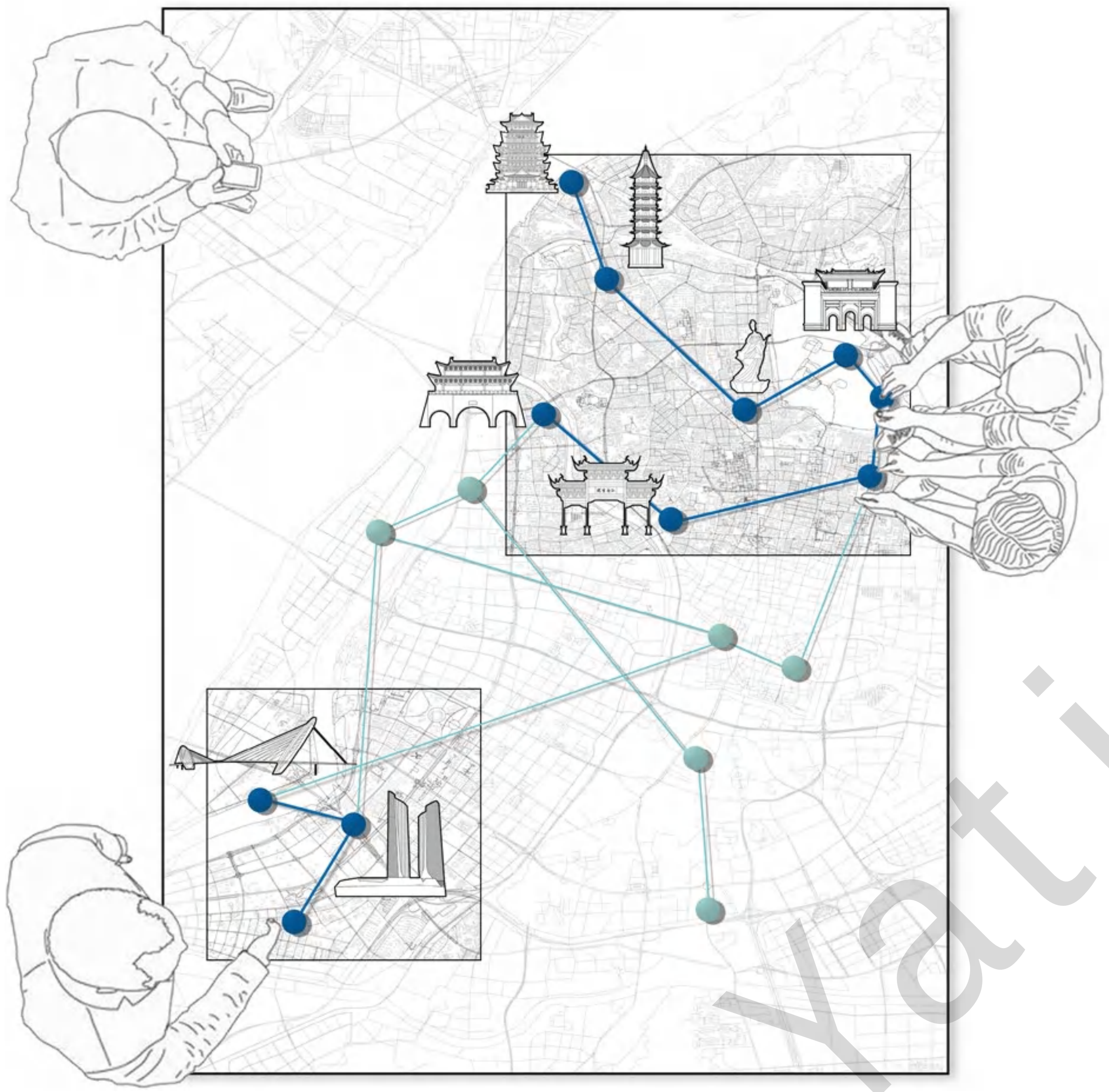
Comparing Visitor Flow Networks between 2018 and 2023 by SNA

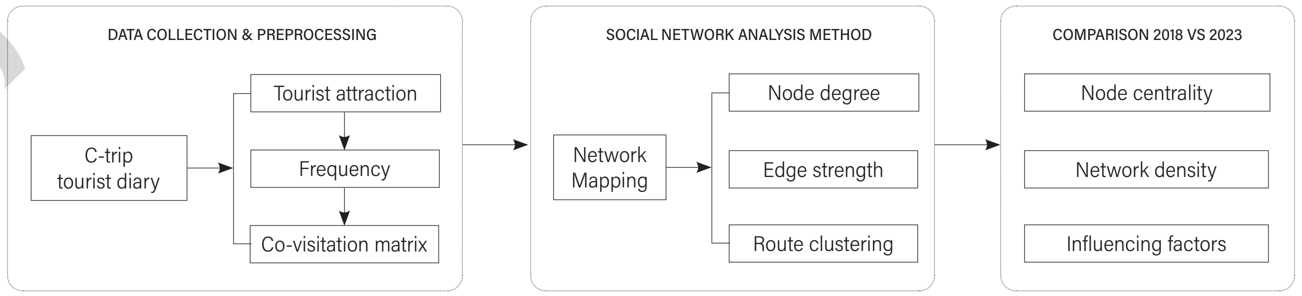
Group work | Social Network Analysis, Tourism Network Evolution

Site: Nanjing, China

Time: 2023.10 - 2023.12

Instructor: Prof. Lu Zheng, l-zheng@tsinghua.edu.cn





Reconstructs two years of tourist co-visitation networks from 5,000+ Ctrip travel notes.

Tour sequences were parsed into weighted co-visitation graphs, revealing evolving patterns of centrality, density, and clustering. These shifts show how platform-mediated paths reconfigure what visitors perceive as the city.

Network metrics uncover structural transitions in the tourism system.

2018's heritage-centered, sparse network gives way to a denser 2023 system shaped by lifestyle and internet-famous destinations. The comparison highlights how digital visibility reshapes tourist flows and elevates previously peripheral nodes.

Findings support new ways of planning and navigating tourist experience.

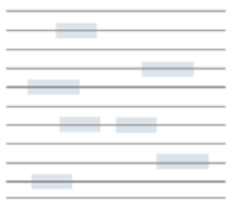
A customizable citywalk tool integrates spatial proximity with digital popularity to generate adaptive routes. This demonstrates how platform logics can be translated into planning insights for destination management.

WORKFLOW

Five Steps

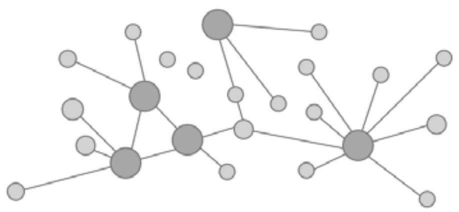
Step1: Data Collection & Processing

Text from Ctrip and co-visitation matrix



$$M(G) = \begin{array}{c|cccc} & v1 & v2 & v3 & v4 \\ \hline v1 & 0 & 1 & 2 & 2 \\ v2 & 1 & 0 & 1 & 0 \\ v3 & 2 & 1 & 0 & 2 \\ v4 & 2 & 0 & 2 & 0 \end{array}$$

Step2: Network Construction



Step3: Mapping & Path Recognition

Step4: Comparison (Node & Network Metrics)

Node-level Indicator:
Degree Centrality
Measures how many direct connections node i has relative to the maximum.

$$C_D(i) = \frac{deg(i)}{N-1}$$

Network-level Indicator:
Density
Proportion of actual edges compared to all possible edges.

$$D = \frac{2E}{N(N-1)}$$

Average Path Length
Mean shortest distance between all pairs of nodes.

$$L = \frac{1}{\binom{N}{2}} \sum_{i<j} d(i,j)$$

Clustering Coefficient
Likelihood that neighbors of a node are connected.

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i, \quad C_i = \frac{2e_i}{k_i(k_i-1)}$$

Centralization
Indicates how strongly the network is organized around its most central node.

$$C_{net} = \frac{\sum_{i=1}^{N}\left[C_D^{max} - C_D(i)\right]}{(N-1)(N-2)}$$

Step5: Correlation

ontaining 50 different topological forms, each with 100 variants, and introducing real-world interference factorsstructural defects and boundary disturbances.each world interference.

METHOD | SOCIAL NETWORK ANALYSIS

Data Preprocessing

Ctrip Text Data

We crawled 5,146 public travel notes from Ctrip, removed ads and duplicates, and split long narratives into day-level trip segments. The text was cleaned (punctuation, emoji, stop-words) and tokenized, then matched to an attraction gazetteer containing official names, aliases, and abbreviations. Mentions were disambiguated with fuzzy rules and local context (nearby POIs, district cues), standardized to unique attraction IDs with coordinates, and labeled by broad functions. We also parsed temporal cues and movement verbs to reconstruct within-day visit sequences for each trip.

An Example of Ctrip Travel Diary:

Visiting Nanjing felt like entering a vivid history book. I began at the Sun Yat-sen Mausoleum, where the long staircase and solemn architecture conveyed the city's modern legacy, and from the top I enjoyed a sweeping view of Purple Mountain. Nearby, the Ming Xiaoling with its Sacred Way and stone animals offered a quieter, more meditative atmosphere. Later I walked along the Nanjing City Wall at Zhonghua Gate, imagining the ancient defenses while reading the small exhibits about its construction. I then spent some time at the Nanjing Museum, which surprised me with its well-curated collections, from ancient ceramics to modern art, making it one of the best museums I have visited in China. For relaxation, I stopped at Xuanwu Lake Park, where families rowed boats and lotus flowers dotted the water, giving the city a softer side. To add some fun, I visited the Hongshan Zoo, watching children laugh at the pandas and tigers while locals enjoyed a leisurely afternoon. As evening arrived, I exp
Temple, tasting local snacks beside the Qinhuai River as lanterns lit up the night. Th
with historic scenery created a unique charm that felt both traditional and moder
sense that every corner of Nanjing carries a story waiting to be discovered.

Category:
Places of Interest
Historical & Cultural

Total Frequency: 102

Category:
Places of Interest
Leisure

Total Frequency: 56

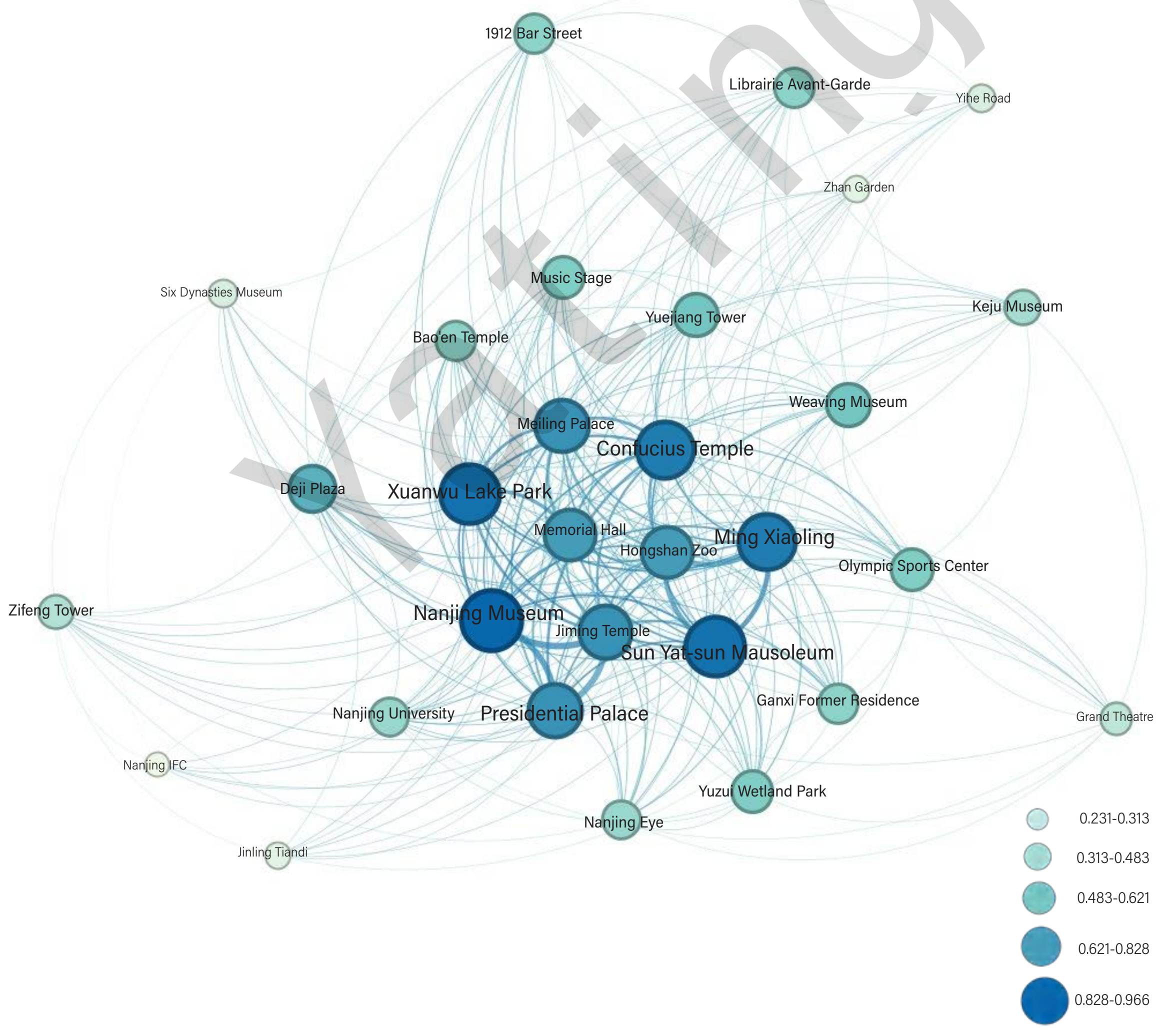
Category:
Places of Interest
Nature

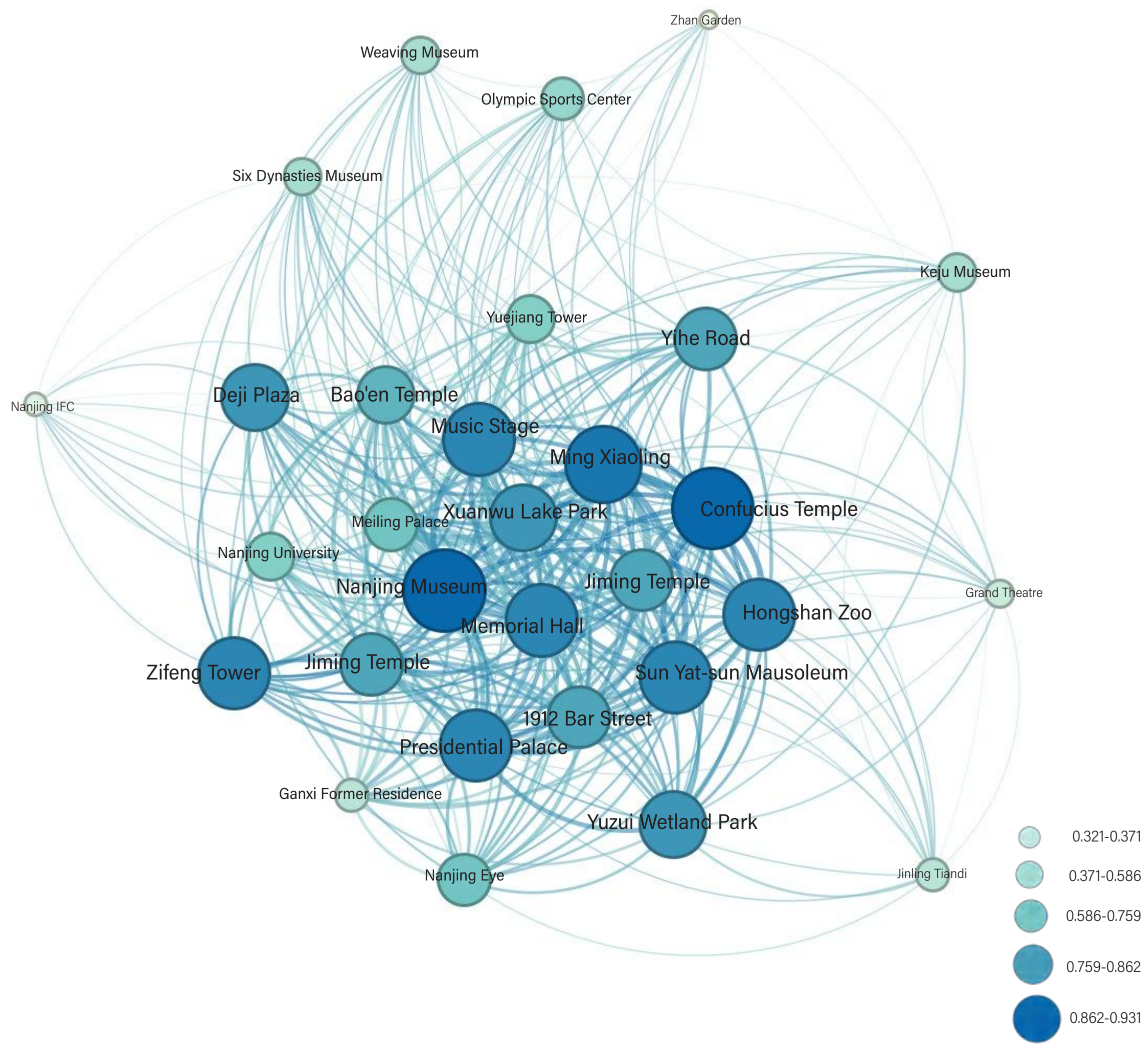
Total Frequency: 23

Co-visitation Matrix

From these day-level sequences, we identified attractions visited within the same itinerary and recorded pairwise co-visits across all trips to obtain co-visitation strength between attractions. To curb popularity bias and noise, we filtered out extremely rare pairs, down-weighted ties created only by ubiquitous hotspots, and retained the strongest links under a consistent percentile threshold; obvious spam itineraries were excluded. The resulting undirected, weighted network uses nodes as attractions and edges as co-visitation ties; edge width encodes tie strength and node size reflects visit frequency.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Confucius Temple	**1**	0	73	71	16	22	19	29	18	16	22	1	1	4	2	12	0	1	3	0	9
Sun Yat-sen Mausoleum	**2**	73	0	66	15	20	17	15	21	11	16	1	1	3	2	4	0	8	6	2	7
Ming Xiaoling Mausoleum	**3**	71	66	0	17	18	12	15	20	19	28	0	1	4	2	3	0	3	2	1	6
Xuanwu Lake Park	**4**	16	15	17	0	53	55	21	14	13	15	2	1	4	2	10	3	3	3	1	6
Nanjing Museum	**5**	22	20	18	53	0	55	19	19	14	16	2	2	6	0	8	1	6	5	0	7
Nanjing Presidential Palace	**6**	19	17	12	55	55	0	8	23	21	24	0	0	5	0	2	1	6	9	2	8
Jiming Temple	**7**	29	15	15	21	19	8	0	37	31	25	2	0	4	1	3	2	5	7	2	3
Nanjing Massacre Memorial Hall	**8**	18	21	20	14	19	23	37	0	33	23	0	1	7	1	7	0	10	4	0	5
Hongshan Forest Zoo	**9**	16	11	19	13	14	21	31	33	0	32	1	0	4	0	4	1	5	6	1	2
Meiling Palace	**10**	22	16	28	15	16	24	25	23	32	0	1	0	11	0	4	3	4	8	2	6
Deji Plaza	**11**	1	1	0	2	2	0	2	0	1	1	0	3	1	0	0	0	1	0	0	0
Yuejiang Tower	**12**	1	1	1	1	2	0	0	1	0	0	3	0	1	0	1	0	1	0	0	0
Jiangning Weaving Museum	**13**	4	3	4	4	6	5	4	7	4	11	1	1	0	0	1	0	0	0	1	1
Nanjing Olympic Sports Center	**14**	2	2	2	2	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Ganxi Former Residence	**15**	12	4	3	10	8	2	3	7	4	4	0	1	1	0	0	0	0	2	0	2
Music Stage	**16**	0	0	0	3	1	1	2	0	1	3	0	0	0	0	0	0	0	0	0	0
Bao'en Temple	**17**	1	8	3	3	6	6	5	10	5	4	1	1	0	0	0	0	0	0	2	0
Yuzui Wetland Park	**18**	3	6	2	3	5	9	7	4	6	8	0	0	0	0	2	0	0	0	0	0
Nanjing Eye Pedestrian Bridge	**19**	0	2	1	1	0	2	2	0	1	2	0	0	1	0	0	0	2	0	0	0
Nanjing University	**20**	9	7	6	6	7	8	3	5	2	6	0	0	1	0	2	0	0	0	0	0

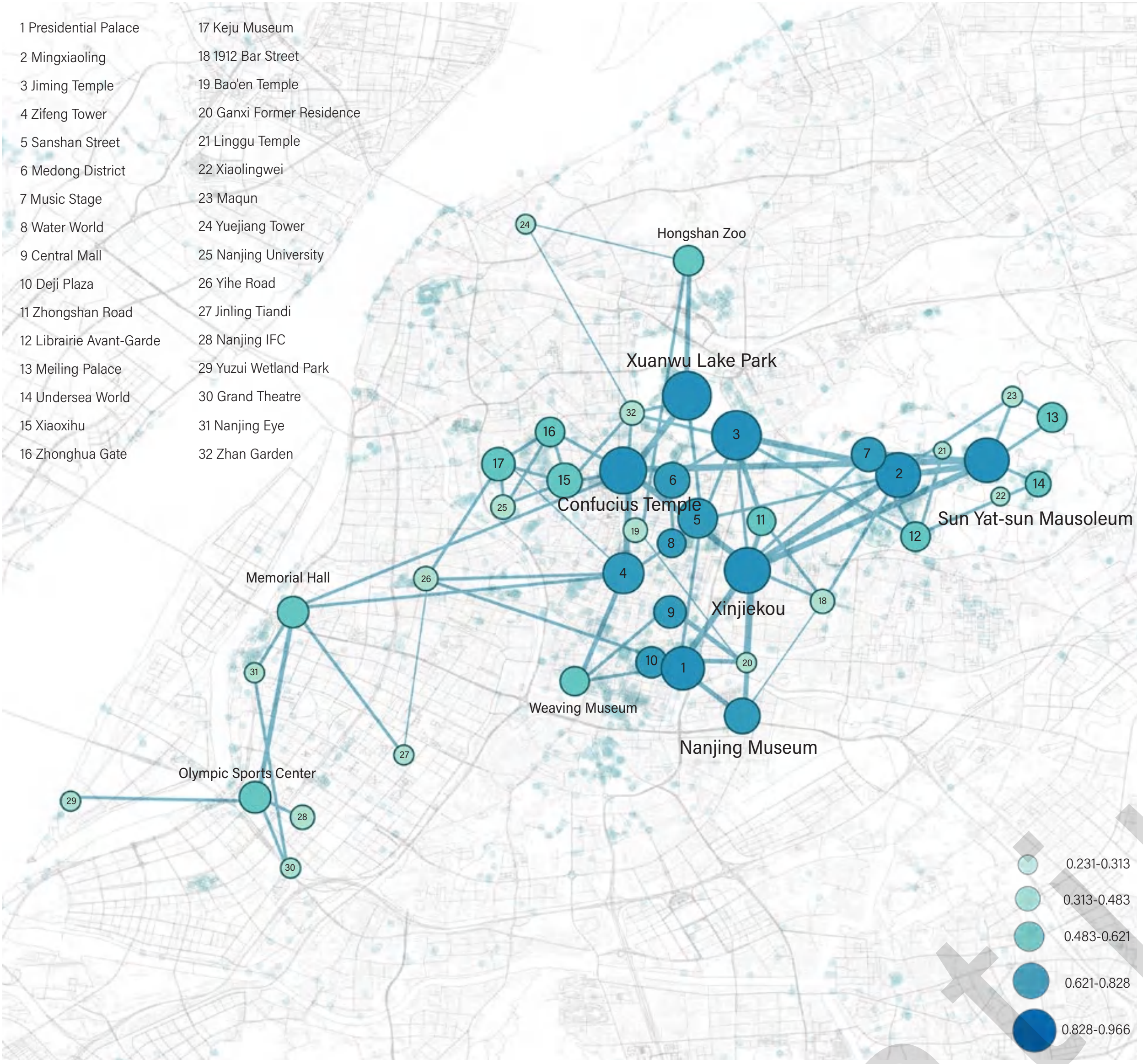




TOURISM NETWORK EVOLUTION | MAPPING

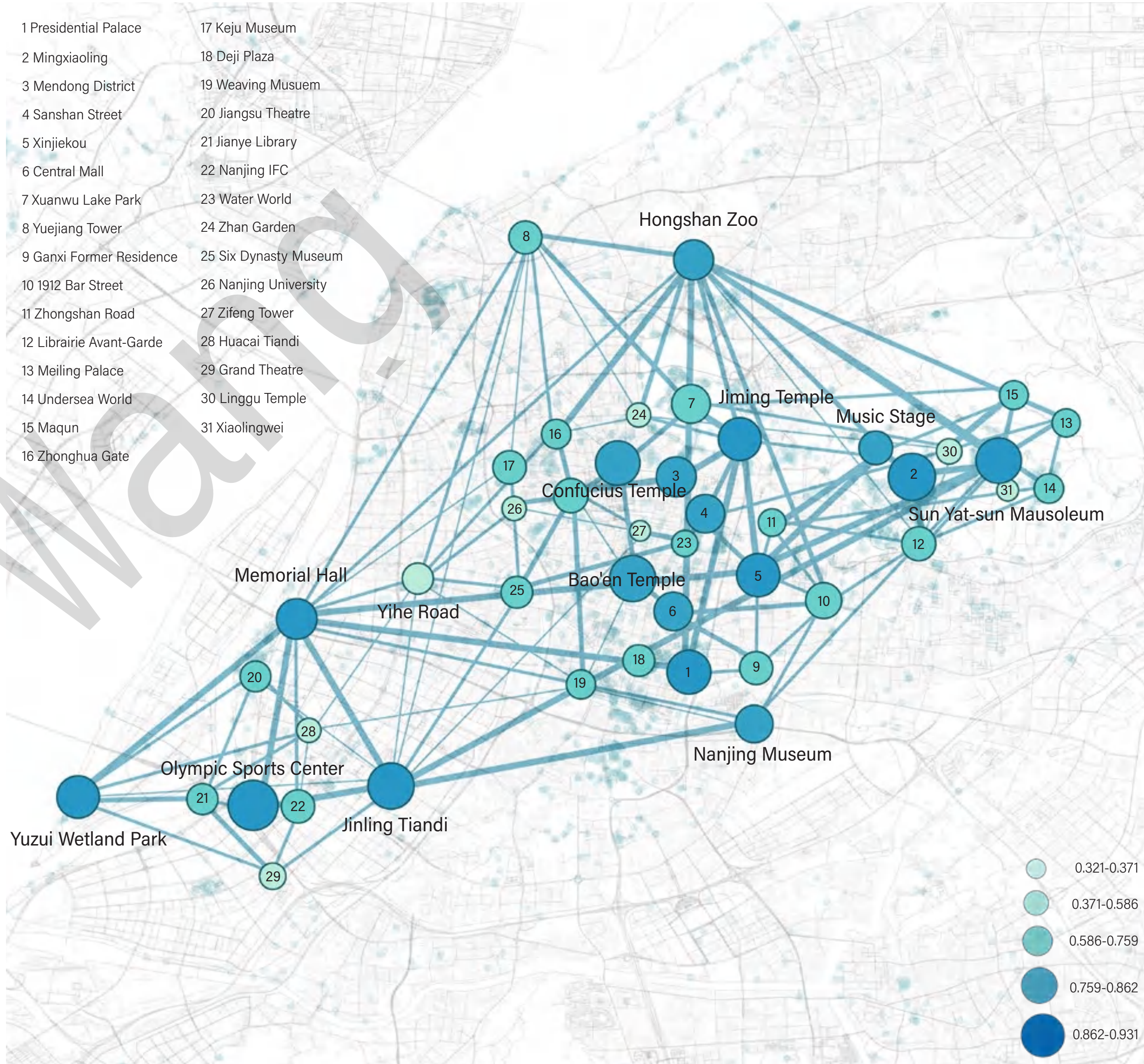
2018

In 2018, the tourism network was primarily structured around classic heritage attractions, with traditional landmarks like Confucious Temple forming the core. The overall network density was low, and peripheral routes remained sparse. Niche or lifestyle-oriented sites had low degree centrality and played a marginal role in shaping tourist flows.



2023

By 2024, the network expanded significantly, incorporating popular lifestyle and internet-famous destinations into the central structure. Degree centrality increased for previously peripheral spots, and the overall network became denser and more interconnected. This reflects a shift from heritage-driven tourism toward diversified, socially-mediated travel behaviors.



Main Landmark Route:
Direct chain linking Nanjing's core heritage attractions.

Traditional Classic Route:
Heritage-focused loop linking mausoleums, temples, and lake.

Iconic & Trendy Route:
Major landmarks combined with trendy niche spots.

Hybrid Convergence Route:
Combines trending lifestyle places with cultural landmarks.

Conservative City Walk:
Emphasis on landmarks, less attention to leisure or lifestyle.

Classic Core Loop:
Concentrated visits around Purple Mountain's historical cluster.

Neighborhood Lifestyle Path:
Local cafés, bookstores, and parks forming micro leisure loops.

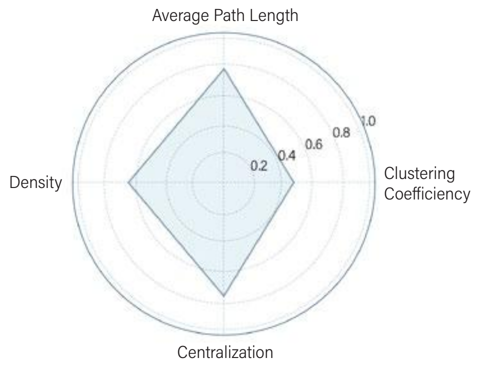
Influencer Hotspot Route:
Viral cafés, malls, and photogenic sites dominate flows.

EXPLANATORY | COMPARISON & QAP REGRESSION

Metrics for Nodes & Whole N etwork

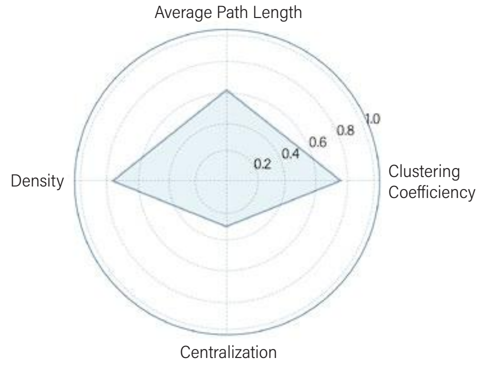
Network scores of 2018

2018 tourism network exhibits relatively low density and clustering coefficient, indicating a sparse connected structure and a decentralized pattern driven by physical proximity.

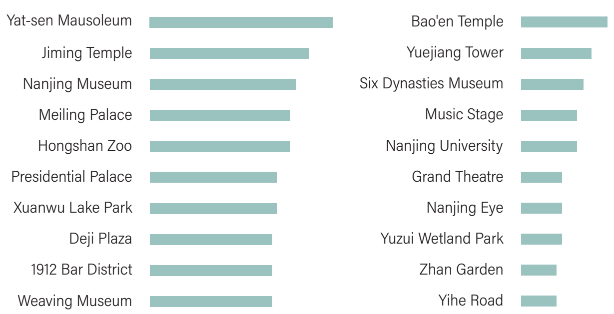


Network scores of 2023

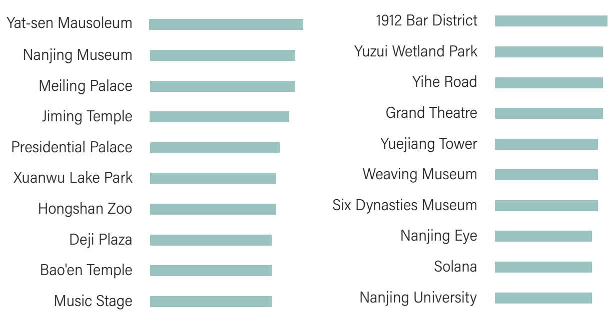
2023 tourism network demonstrates higher density and clustering, revealing stronger internal connectivity and the emergence of more cohesive attraction clusters.



Degree centrality of nodes, 2018



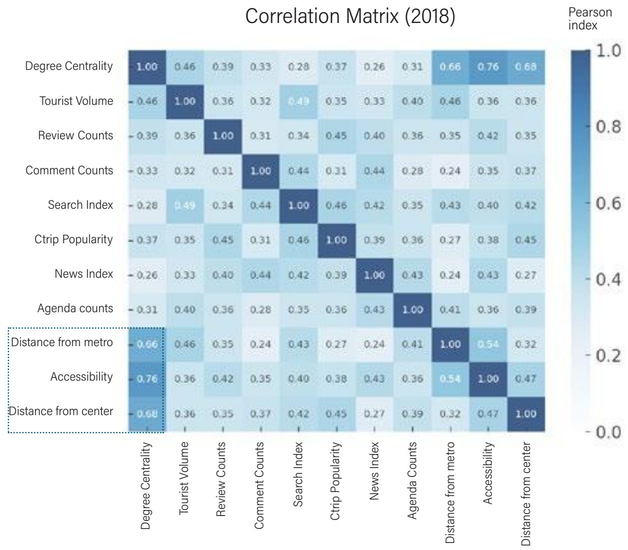
Degree centrality of nodes, 2023



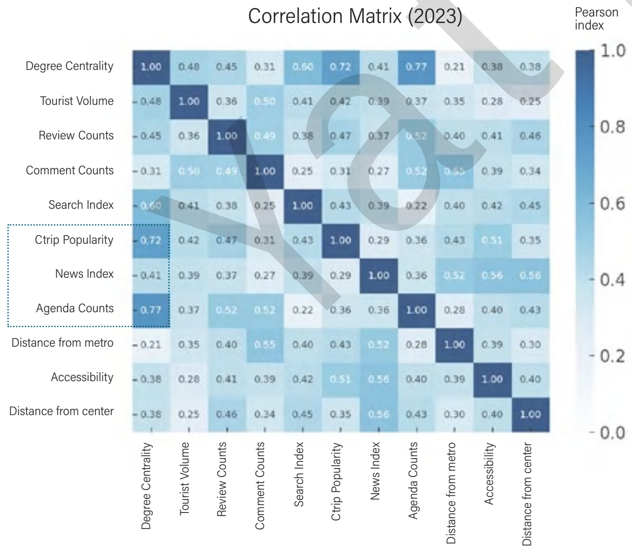
Correlation Matrix for Explanation

We examined the correlation between node centrality and multiple explanatory variables to understand what drives attraction connectivity within the tourism network. Results reveal a significant shift in influencing factors from 2018 to 2023.

Correlation Matrix (2018)



Correlation Matrix (2023)

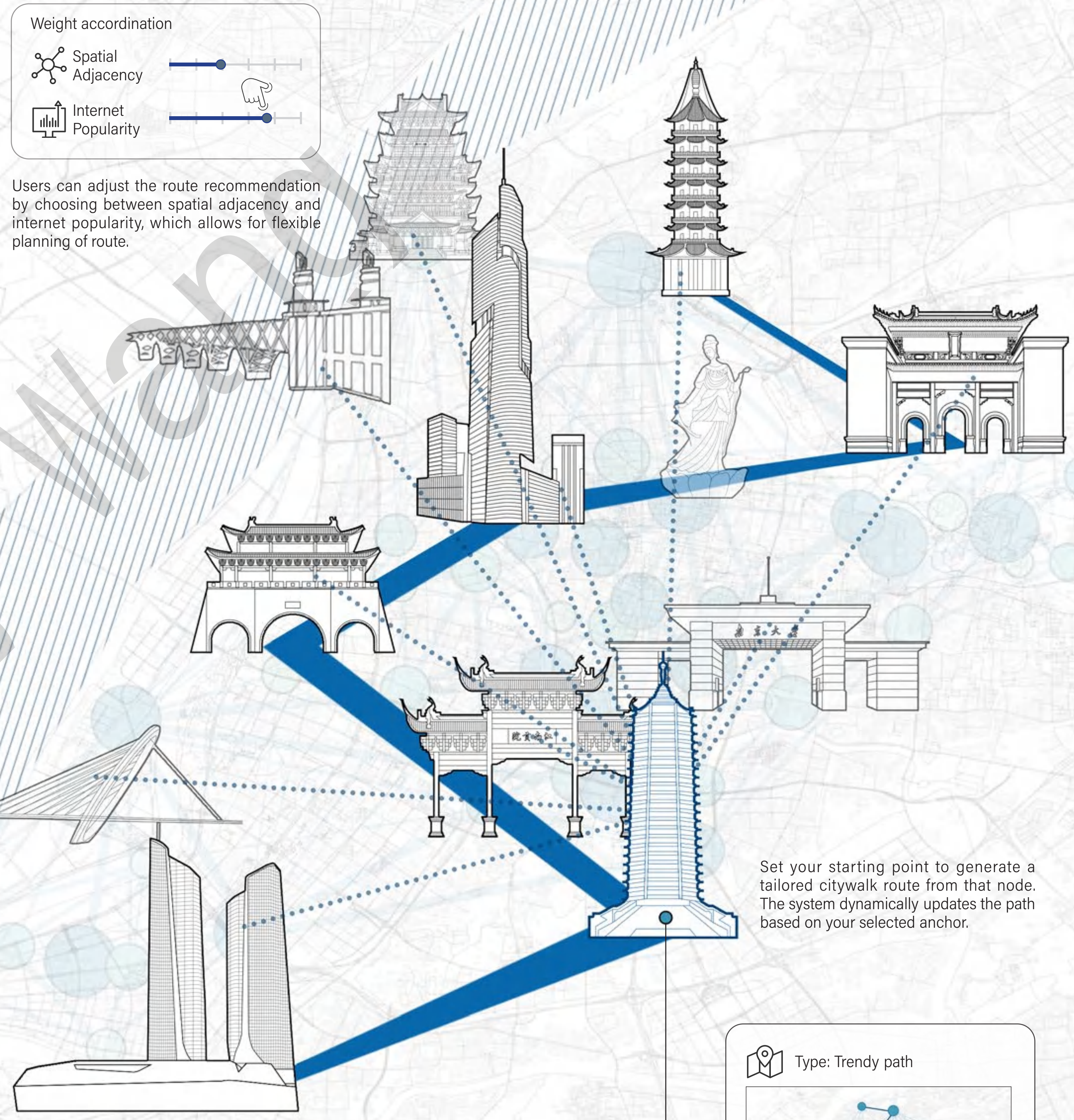


Degree centrality was primarily associated with spatial factors (accessibility, distance to city center), indicating that physical adjacency was the dominant logic shaping movement patterns.

Degree centrality more correlated with internet popularity and digital visibility, highlighting a shift towards digital-driven tourism shaped by online engagement and media exposure.

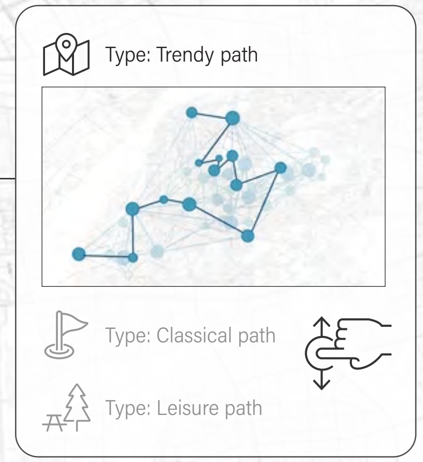
APPLICATION

Based on the network structure and centrality results, we designed a citywalk planning tool that integrates spatial proximity, internet popularity, and real visitation patterns. Users can adjust weight preferences, set custom starting points, and choose from different route types—Trendy, Classical, or Leisure. The system offers personalized, data-informed itineraries that respond to both physical context and digital influence, enhancing urban exploration through flexible path design.

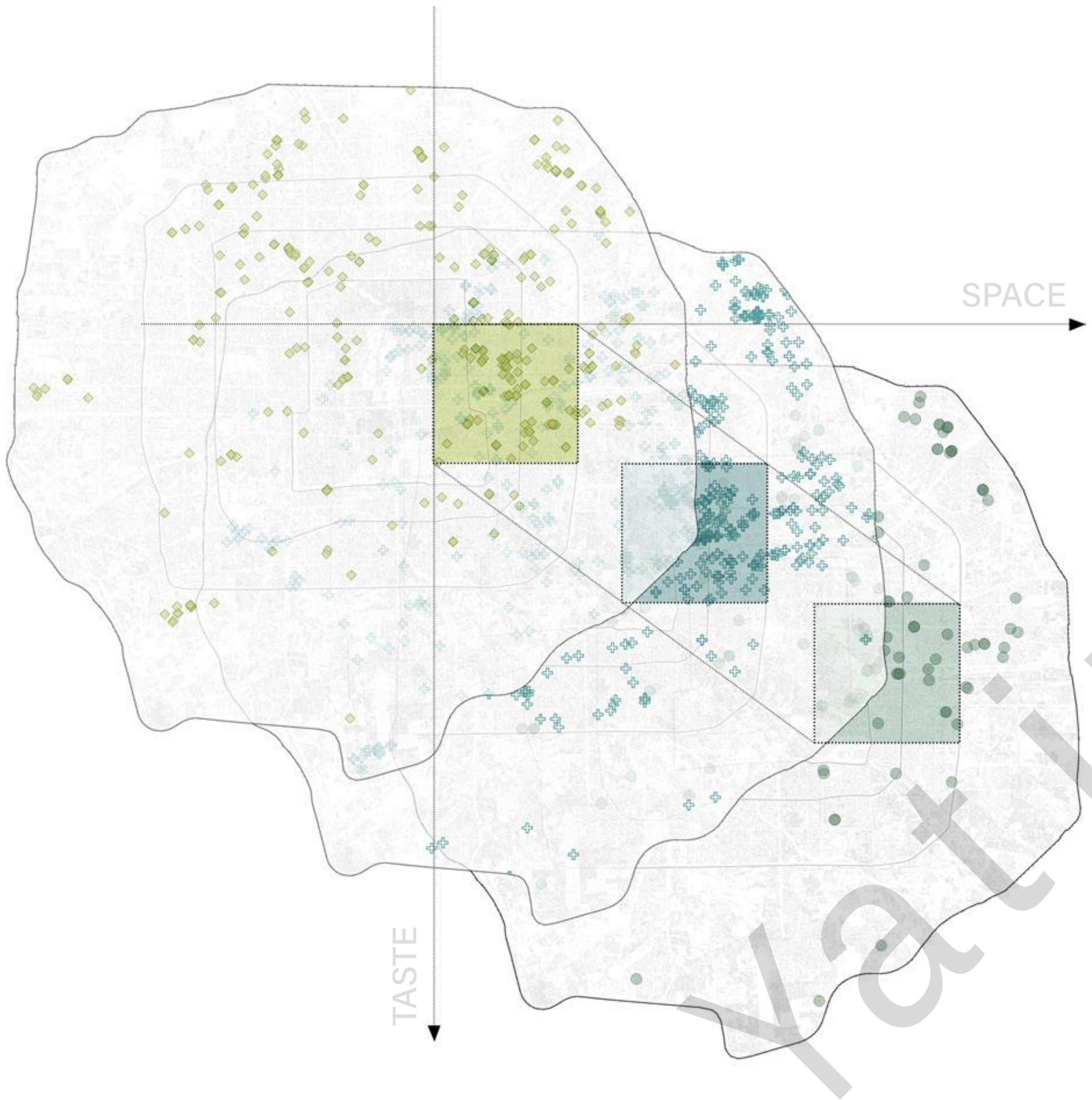


Users can adjust the route recommendation by choosing between spatial adjacency and internet popularity, which allows for flexible planning of route.

Set your starting point to generate a tailored citywalk route from that node. The system dynamically updates the path based on your selected anchor.



Each route is labeled by type reflecting different urban experiences. Users can view and switch between path types based on their interest and travel style.



03

TASTE AND SPACE | Spatial Stratification of Light Meal Outlets

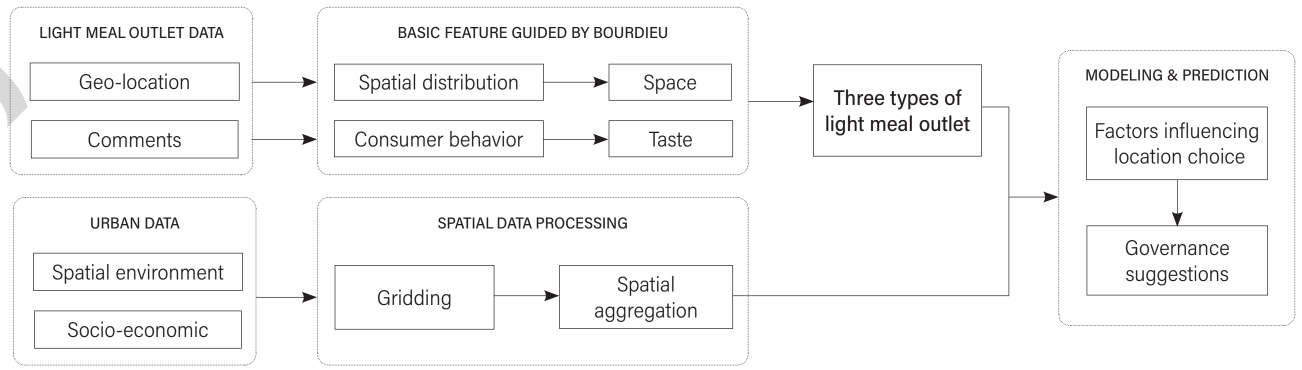
Data-Driven Analysis of Urban Distribution and Consumer Behaviors

Group work | Spatial Stratification, GIS, Location Prediction

Site: Beijing, China

Time: 2024.10 - 2024.12

Instructor: Prof. Ying Long, ylong@tsinghua.edu.cn



Classifies 986 outlets into three types reflecting distinct social and spatial patterns.

Light-meal outlets—fast-casual cafés and salad/sandwich shops offering quick, relatively healthy, affordable meals—serve as an entry point to examine classed consumption in Beijing. Drawing on consumption patterns, operation modes, and target users, the outlets are grouped into three socio-spatial types—check-in, white-collar, and community-based.

Bivariate spatial autocorrelation reveals how the three outlet types align with urban socio-spatial factors.

The analysis examines each outlet type in relation to variables such as income density, job-housing structure, and commercial intensity, uncovering clear high-high and low-low clustering patterns.

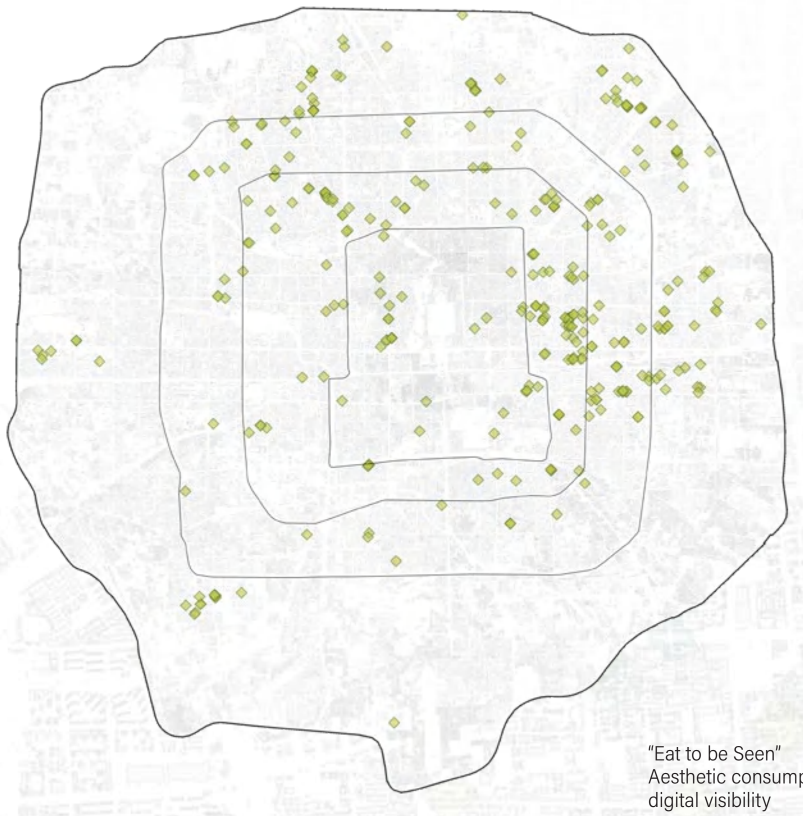
Findings inform planning strategies for food access and neighborhood equity.

Insights support cultural zoning, workplace meal programs, and 15-minute community food solutions. The analysis exposes where representational and physical inequalities intersect in platform-mediated cities.

TYPES OF LIGHT-MEAL OUTLETS & CONSUMER PROFILE

Distribution of Different Types of Light-meal Outlets

Check-in Oriented



"Eat to be Seen"
Aesthetic consumption for digital visibility

Located in the trendy commercial areas, these light-meal outlets emphasize aesthetic presentation and branded ambiance. They attract students and young professionals who value visual appeal, social sharing, and the "check-in" experience.

Location:
Commercial hubs, trendy areas

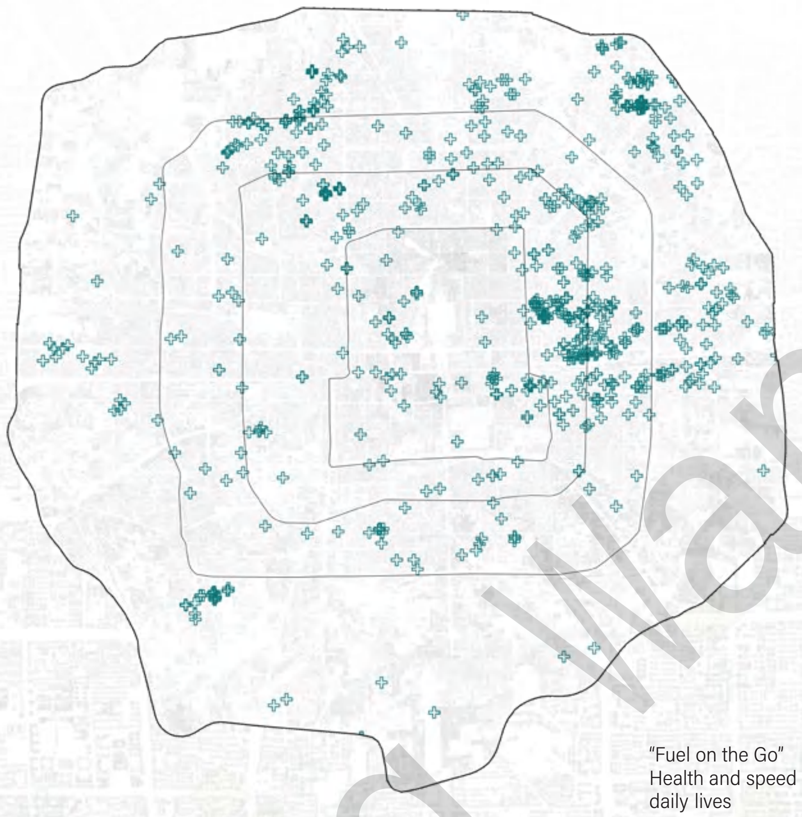
Users:
Students, Young professionals, Social media users

Price: ●●●● 40–80 RMB

Comments on dianping:
☆☆☆☆ 4.6 320

Keywords:
Visibility / Branding / Landmark

Delivery Oriented



"Fuel on the Go"
Health and speed for busy daily lives

Typically found near offices & gyms, delivery oriented outlets cater to fast-paced urban workers and students. Their offerings focus on low-calorie, protein-rich meals with efficient delivery and high meal frequency.

Location:
Office, gym, university areas

Users:
White-collar workers, Fitness crowd, Students

Price: ●●● 20–40 RMB

Comments on dianping:
☆☆☆☆ 4.3 410

Keywords:
Health / Frequency / Efficiency

Neighborhood-Based

"Tastes Like Home"
Embedded in everyday neighborhood life

Situated in residential areas, these outlets serve affordable, home-style meals tailored for local families and elderly residents. They prioritize familiarity and convenience over trendiness.

Location:
Residential, neighborhood areas

Users:
Families, Elderly residents, Neighbors

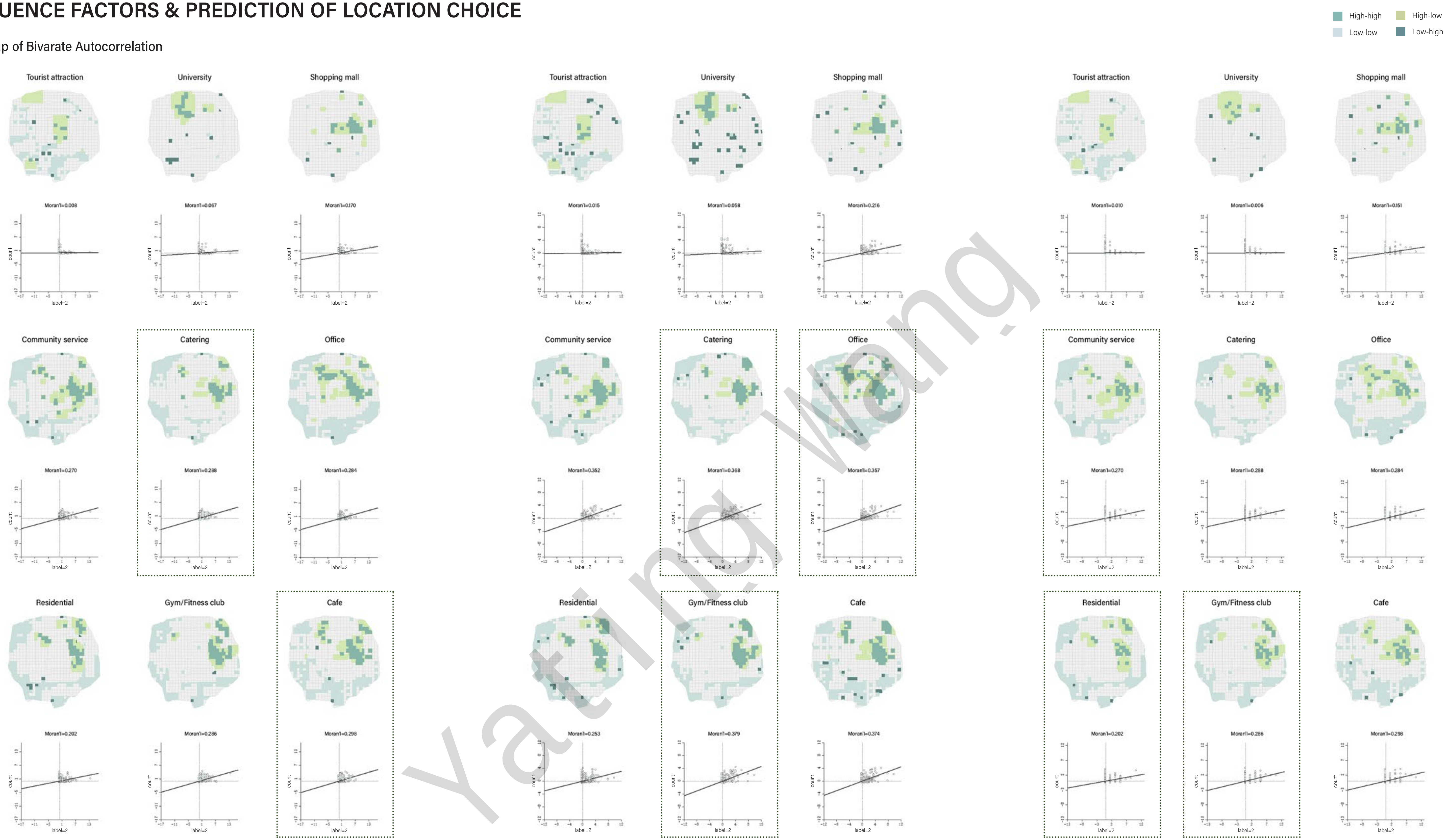
Price: ●● <20 RMB

Comments on dianping:
☆☆☆☆ 4.0 95

Keywords:
Everyday / Affordable / Embedded

INFLUENCE FACTORS & PREDICTION OF LOCATION CHOICE

LISA Map of Bivarate Autocorrelation



City branding & crowd stewardship

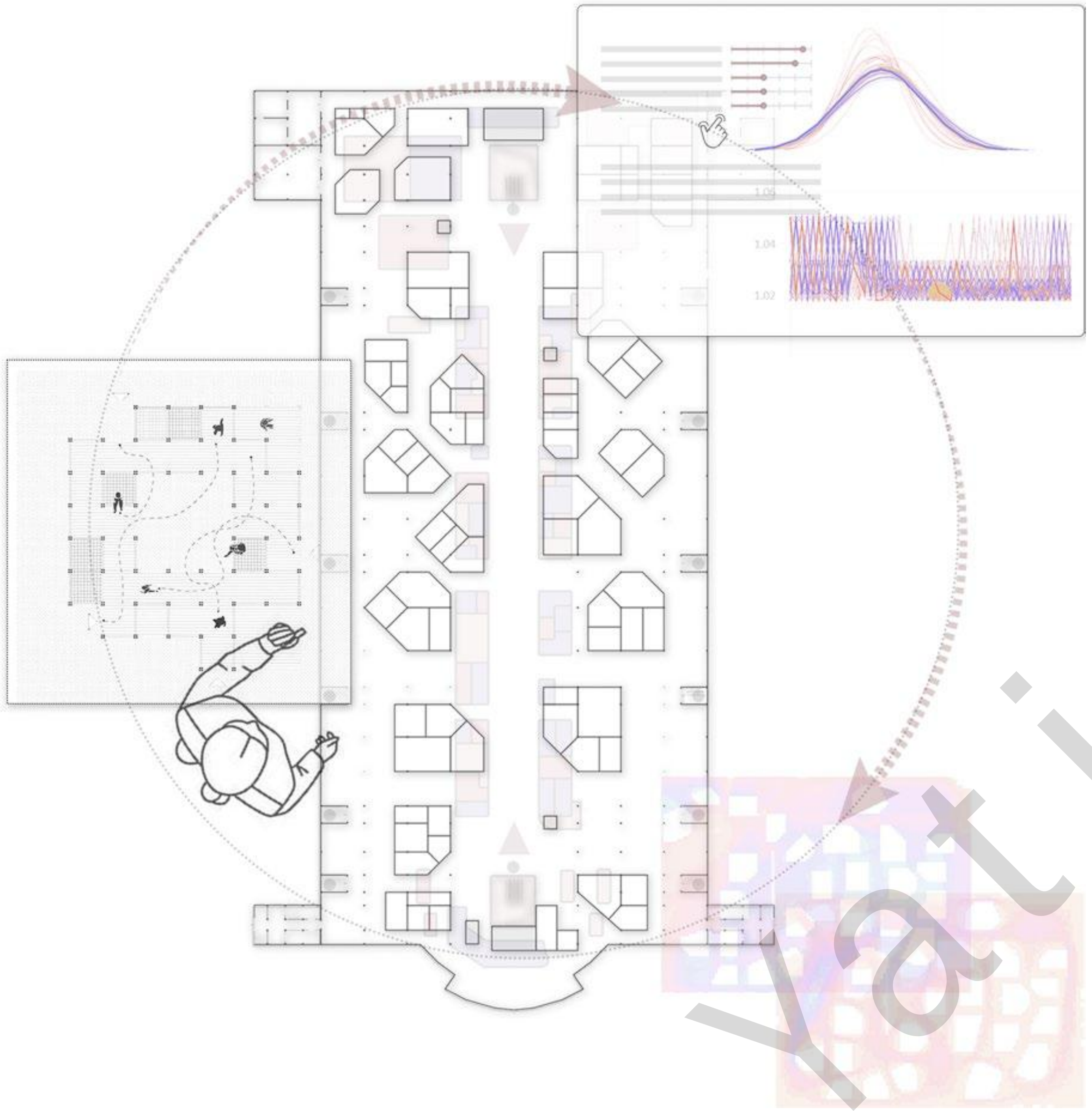
Clustered around tourist spots and commercial hubs, these outlets reflect symbolic visibility and digital exposure. Governance should include cultural zoning, nightlife regulation, and public space management to balance branding appeal with safety and local tolerance.

Health governance & logistics

Located near offices and campuses, these outlets serve fast, health-conscious consumers. Policy tools include nutrition labeling, workplace meal programs, and delivery hub regulation to ensure efficient logistics and promote daily health equity.

Access & affordability

Found in residential zones, these outlets serve families and the elderly with daily meals. Strategies include food subsidies, shared kitchens, and integration into 15-minute neighborhood planning to improve walkable access to affordable food.



04

LONG WALKWAY DESIGN | Human–Machine Generative Approach

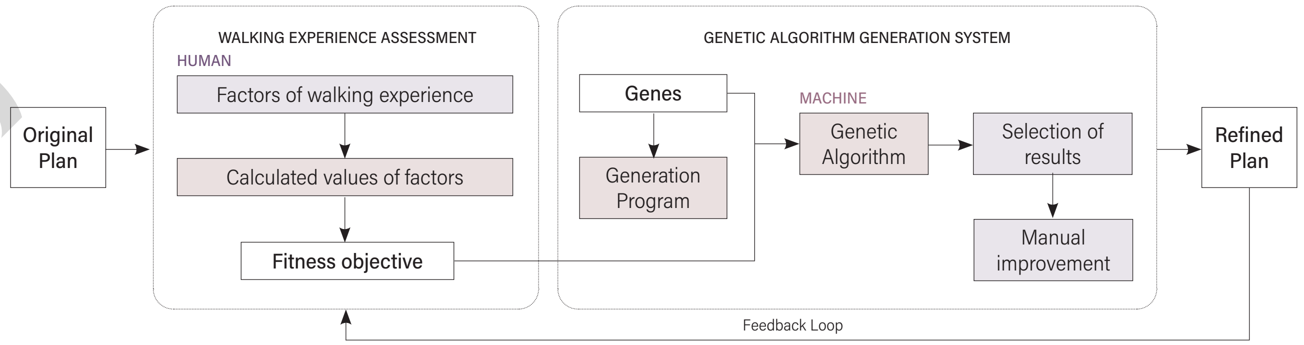
Design–Evaluation Feedback Loop with Walking Experience and Genetic Algorithms

Group work | Plan Generation, Genetic Algorithm, Human-Machine Collaboration

Site: Beijing, China

Time: 2023.11 - 2024.01

Instructor: Prof. Hui Wang, wh-sa@mail.tsinghua.edu.cn



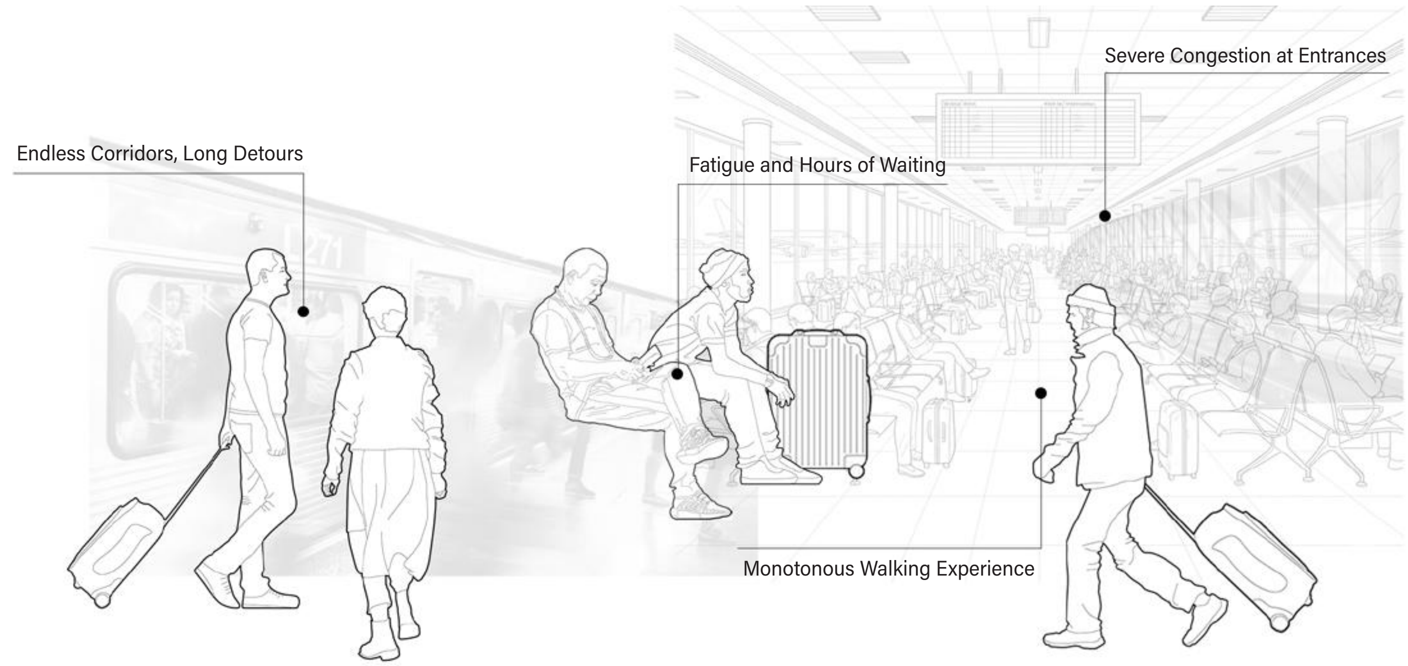
Identifies systemic issues in long walkway environments of major transport hubs.
Depthmap simulations show congestion, fatigue, detours, and poor functional distribution across large stations. These problems demonstrate why manual iteration alone is insufficient for multi-objective spatial optimization.

A genetic algorithm evolves layouts under six walking-experience metrics.
Wallacei generates design variants by optimizing path length, detour rate, functional mix, and circulation complexity. Designer selection and refinement form a feedback loop that balances computational efficiency with spatial judgment.

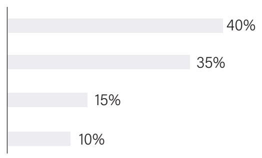
Results demonstrate measurable gains in performance and usability.
Optimized plans reduce bottlenecks, distribute flows, and improve functional accessibility across stations. The method offers a scalable workflow for similar complex spatial typologies across the S-M-L scale.

BACKGROUND | RESEARCH QUESTION

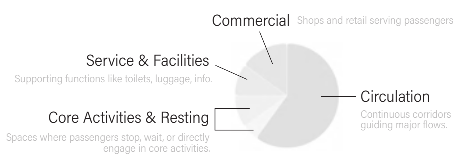
Long Walkway Spaces: Everyday Congestion and Fatigue



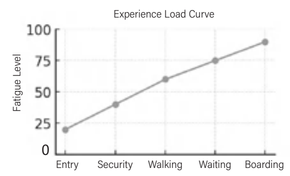
Time allocation of long walkway sapces



Excessive Circulation Area in Large Hubs

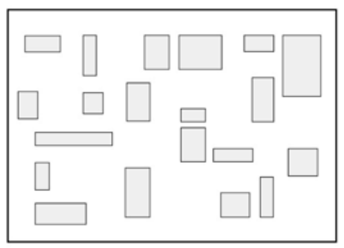


Increasing Fatigue in Process

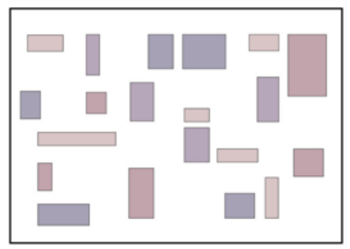


Features of Long Walkway Space

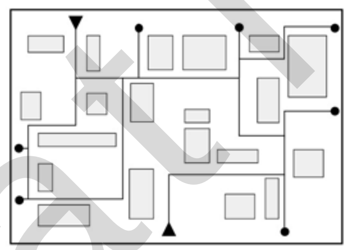
Boundary Line



Function box

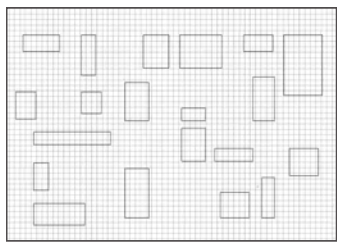


Long flow+Start/end



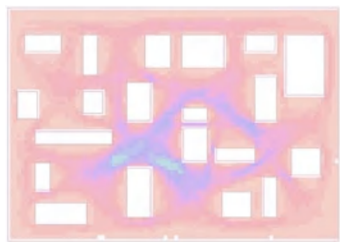
Simulation: Connectivity & Agent Density

Setting Grid for Simulation



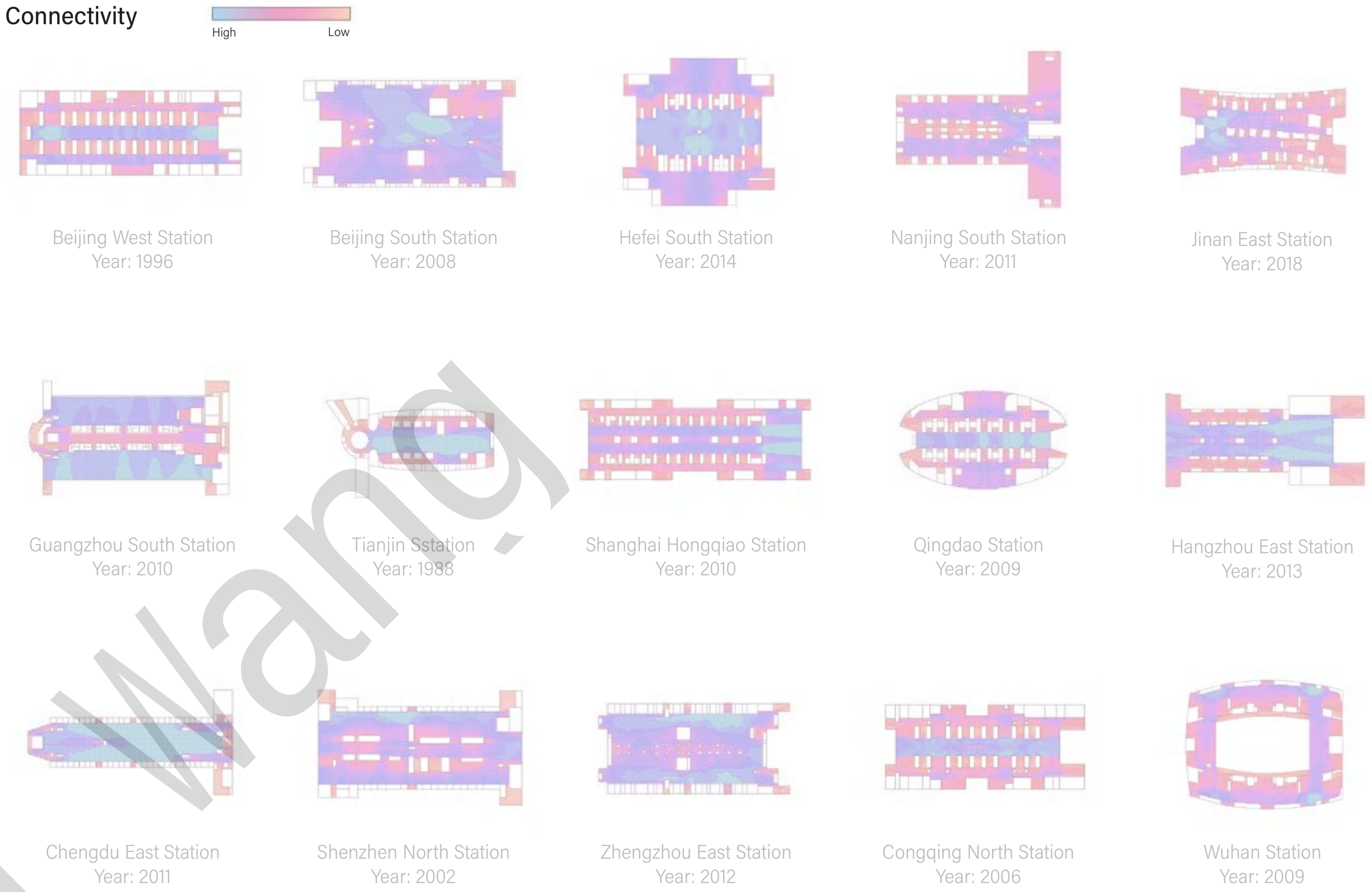
Connectivity of Function Boxes

Agent Density of Flows

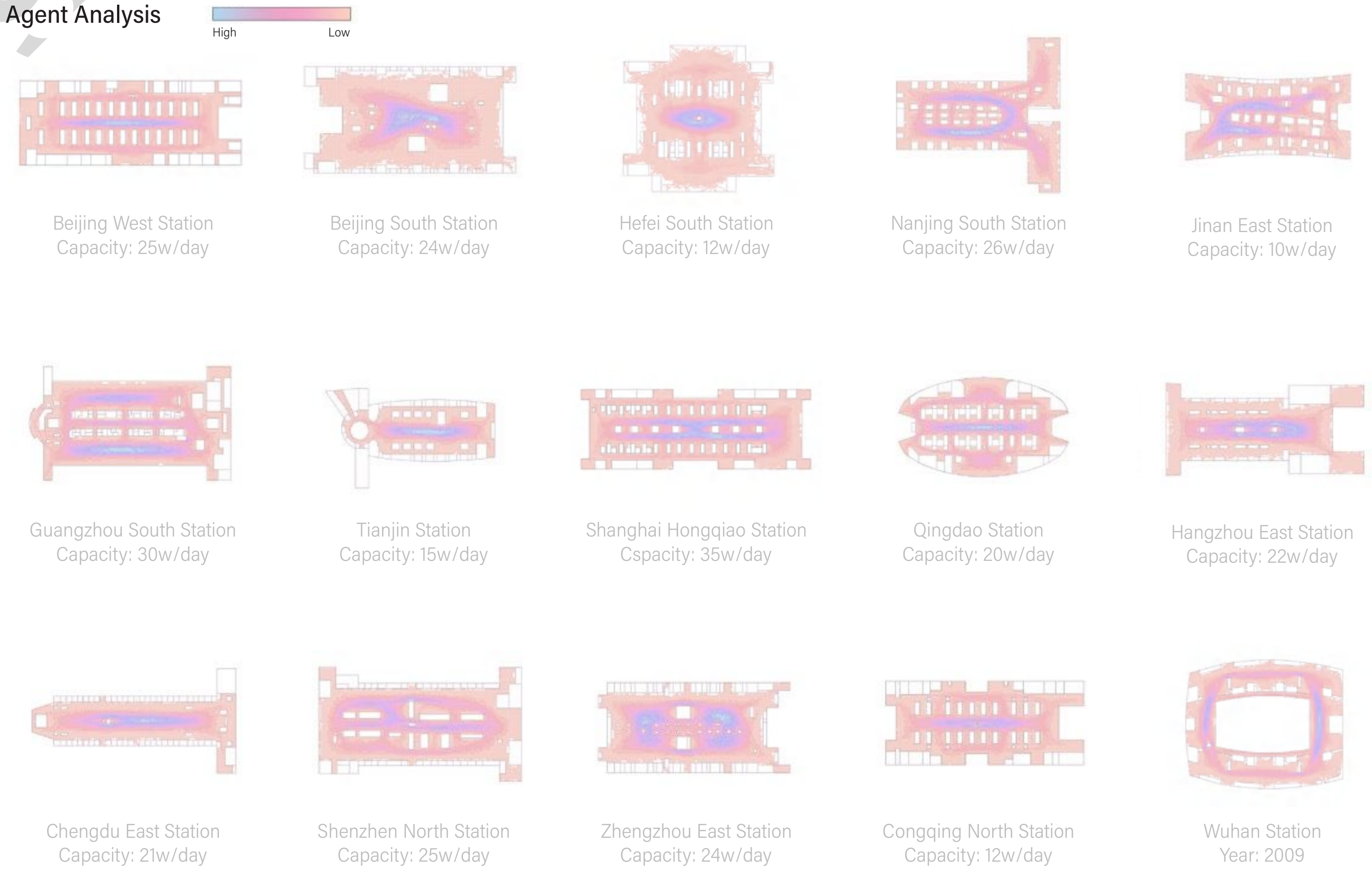


PROBLEM EVIDENCE | SIMULATION BY DEPTHMAP

Connectivity



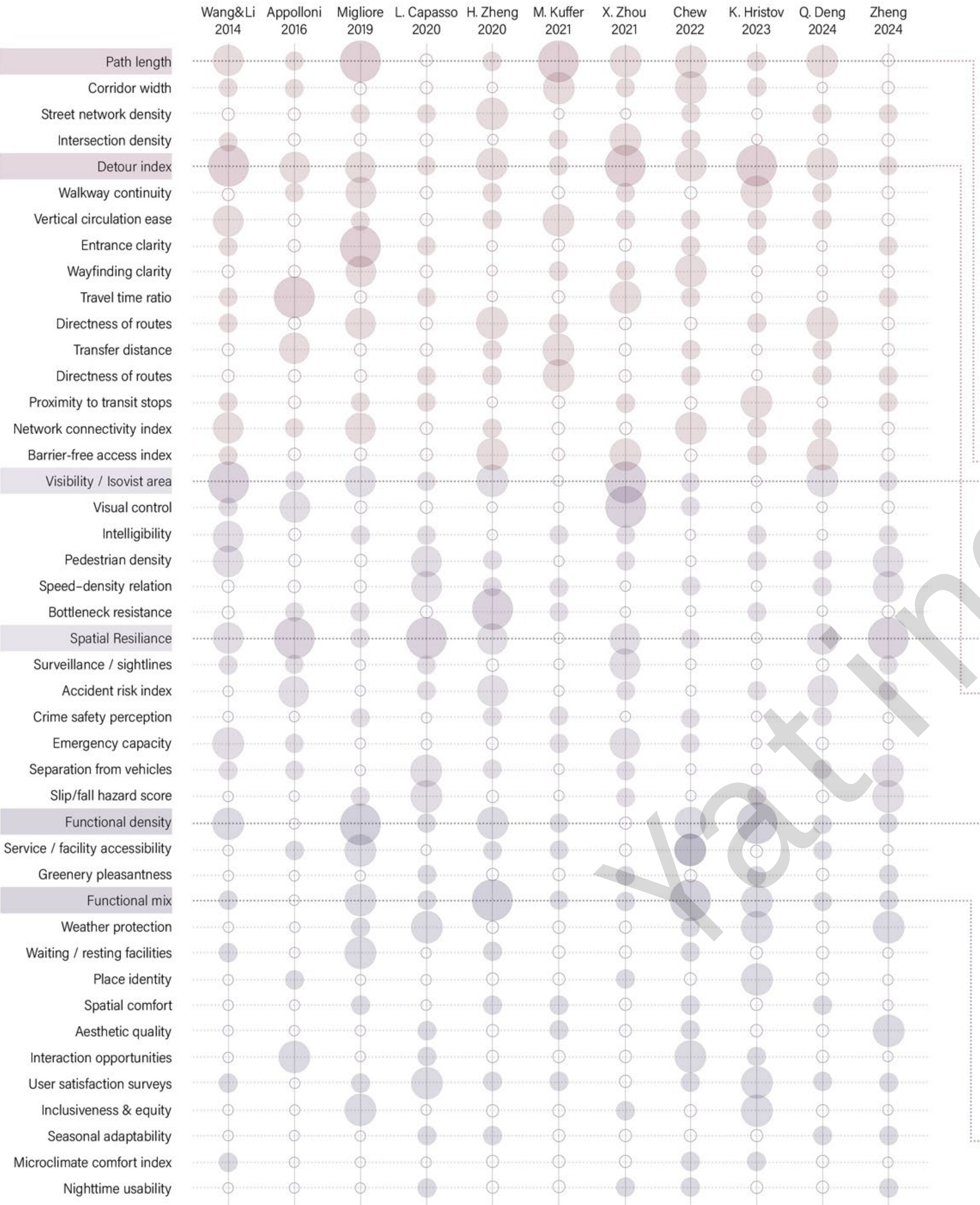
Agent Analysis



WALKING EXPERIENCE ASSESSMENT

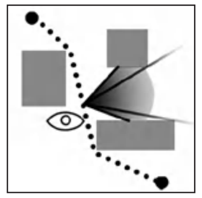
Literature Review of Walking Experience & Walkability

A comprehensive review of walking experience studies identified key spatial performance indicators. Six metrics were selected based on frequency and relevance, spanning the core dimensions of convenience, safety, and experience. These metrics form the quantitative foundation for evaluating and optimizing long walkway spaces through computational methods.



Six Metrics as Fitness Values

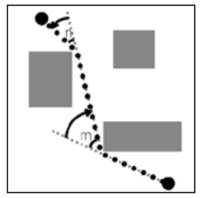
Parallex Rate



$$V = \frac{N \cdot \log_2(3N - N + 1)}{4TD - 4N + 4}$$

N: number of nodes
TD: topological depth

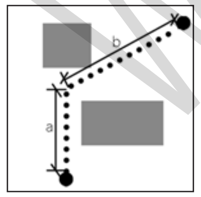
Turn Rate



$$SR = \sum_{i=1}^{M} \theta_i$$

θ_i: turning angle at node i
M: number of nodes along the path

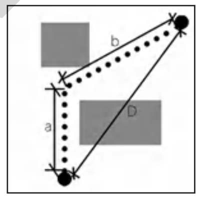
Path Length



$$D = \frac{1}{N} \sum_{i=1}^{N} L_i$$

L_i: path length of route i
N: total number of routes

Detour Degree



$$DR = \frac{L_{\text{actual}}}{L_{\text{straight}}}$$

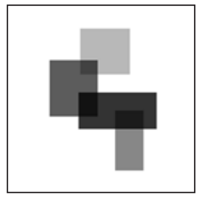
L_{actual}: actual path length
L_{straight}: straight-line distance

Functional Density

$$FD = \frac{\sum_{j=1}^{m} A_j}{A_{\text{total}}}$$

A_j: area of functional block j
A_{total}: total floor area

Functional Mix

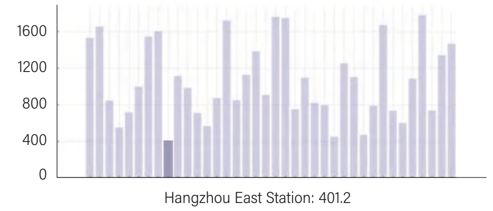


$$FM = -\sum_{k=1}^{m} p_k \ln(p_k)$$

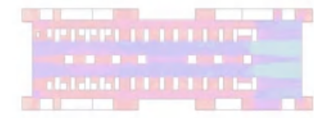
N: number of nodes
TD: topological depth

Results of 30 Typical Stations

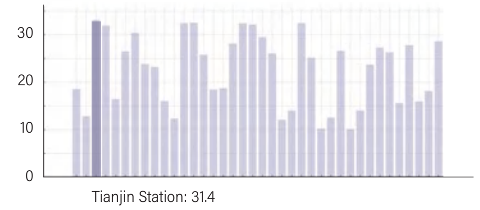
Parallex Rate | Mean: 852.9



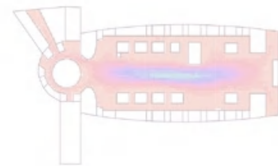
Hangzhou East Station



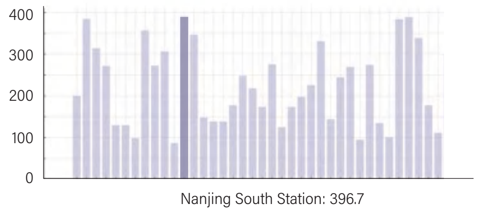
Turan Rate | Mean: 27.3



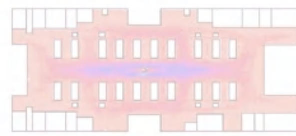
Tiannjin Station



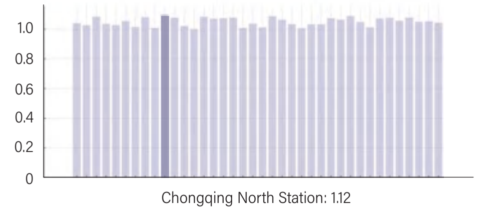
Path Length | Mean: 245.5



Nanjing South Station

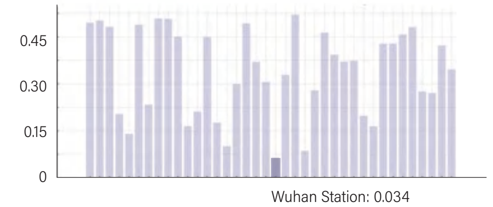


Detour Degree | Mean: 1.03



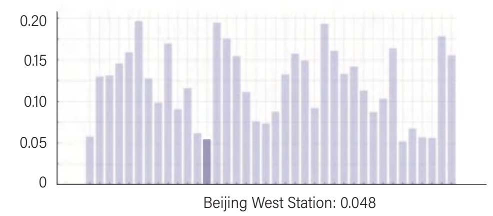
Chongqing North Station

Functional Density | Mean: 0.25



Wuhan Station

Mean: 0.13

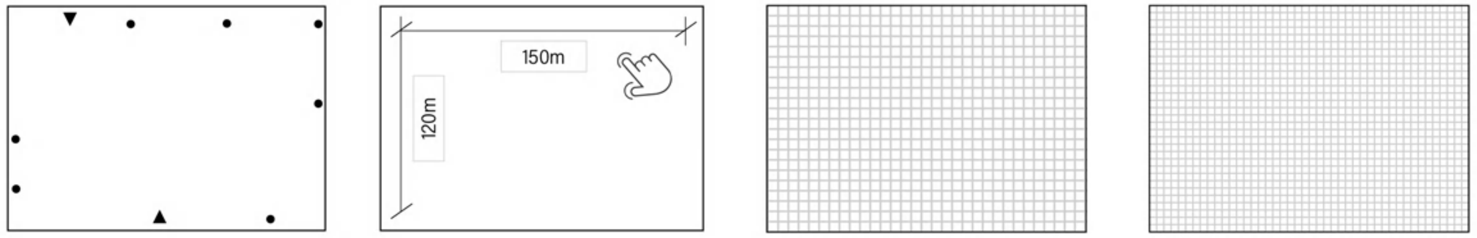


Beijing West Station

GENETIC ALGORITHM GENERATION SYSTEM | WALLACEI

Step1: Gridding

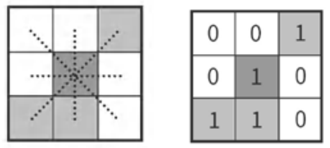
According to the scale size of the selected optimization target, the optimized plane is subdivided into suitable scale grid points.



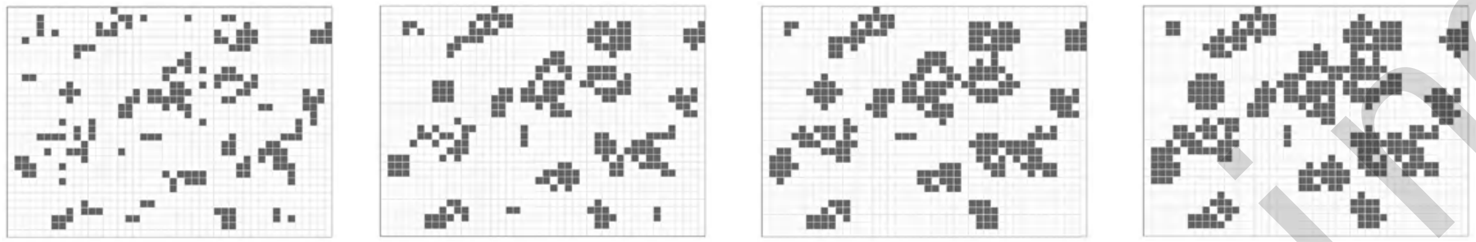
Boundary, entrances & exits | Scaling: length & width | Grid size : 5×5m (too large) | Grid size : 3×3m ☑

Step2: Generation of Point Sets

The random factor (Gene1) in the Genetic Algorithm plug-in is used to assign a value to each grid point, where 0 represents an empty point and 1 represents a real point. Using the principle of similar cellular automata, the program fills in some of the vacancies within the point set, close to the reality of the plane of the layout logic.



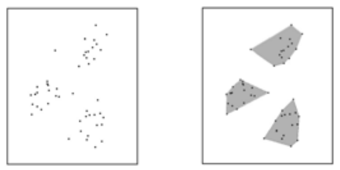
Cellular automata:
Iteration of point sets collection



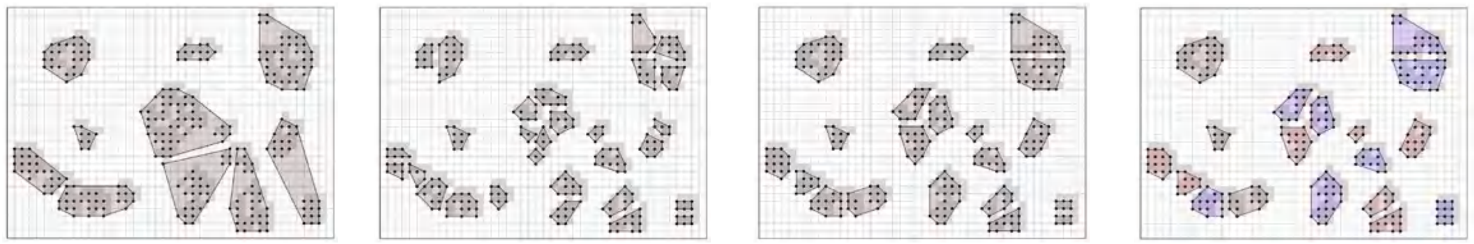
Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 ☑

Step3: Functional Classification

Through the K-means clustering algorithm, we try to analyze and sort out each independent functional block, and seek convex envelope for it to form the basic outline of the plane functional block, and give different functional attributes to different blocks through the random factor of Wallacei plug-in (Gene2).



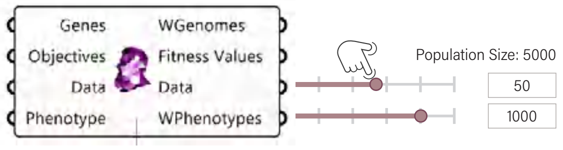
Algorithm of clustering:
Convex envelope seeking



N=10 | N=20 | N=16 ☑ | N=16, with functional label

Control Panel : Initialization

Initial settings for the genetic algorithm using Wallacei.



Algorithm Parameters

Crossover Probability	0.9
Mutation Probability	0.8
Crossover Distribution Index	20
Mutation Distribution Index	20
Random Seed	4

Simulation Parameters

Number of Genes	2
Number of Values	102
Number of Fitness Objectives	6
Size of Search Space	2.6e

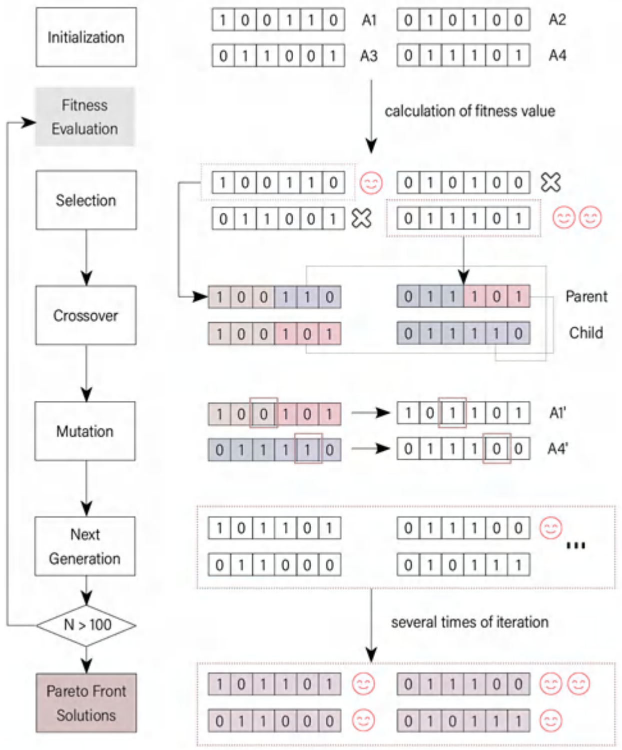
Run Time

0:12:37 / 1:25:49

Current Solution / Generation	49/99
Number of Pareto Front Solutions	50

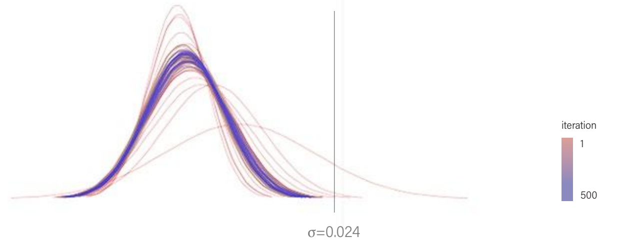
Iteration Process

The algorithm evolves populations over generations. It generates a Pareto Front—a set of non-dominated solutions representing the optimal trade-offs between conflicting objectives.

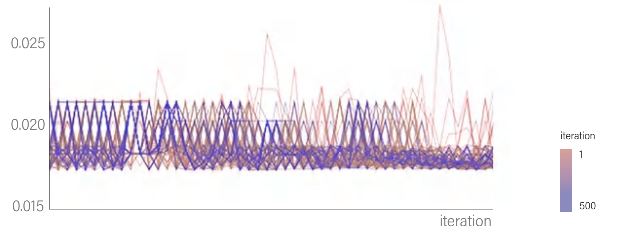


Statistics for Result Selection

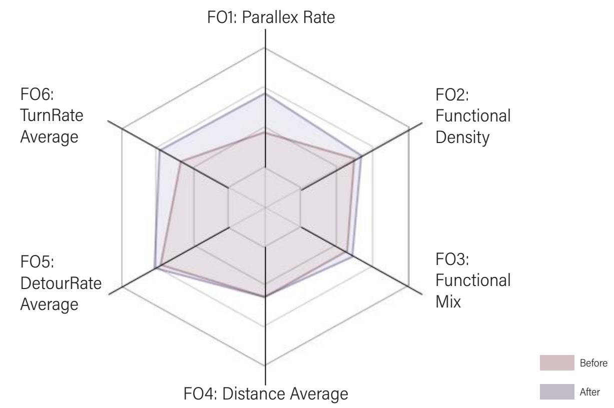
Different statistical graphs for selecting appropriate results.



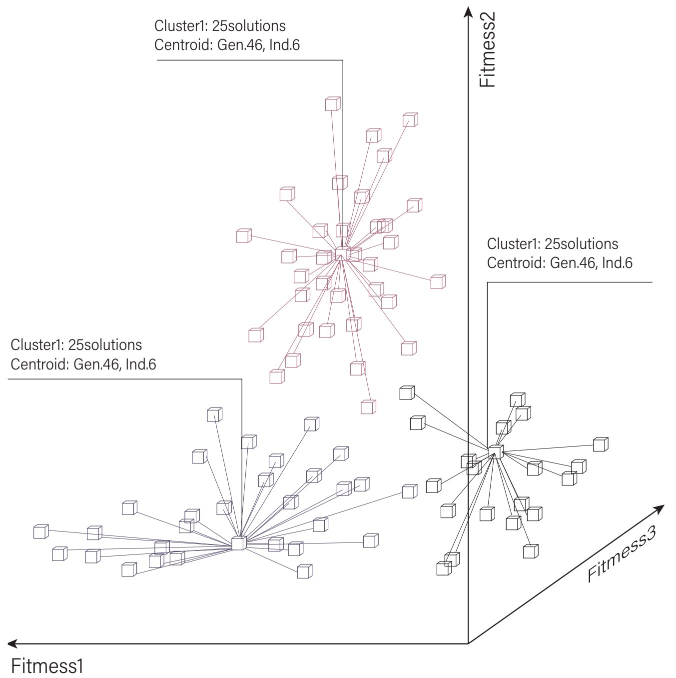
Standard deviation graph



Mean value trend line graph



Radar graph



Clustering scatter plot

CASE STUDY | CURRENT SITUATION & GENERATION

Case1: Beijing West Station

The current layout centralizes functions around a core atrium, creating congestion near ticket gates during peak hours. This large transport hub requires improvements in pedestrian flow distribution and spatial efficiency to alleviate queue interference and enhance commercial space utilization. Agent-based simulation reveals bottlenecks that necessitate better integration of service functions with circulation paths.

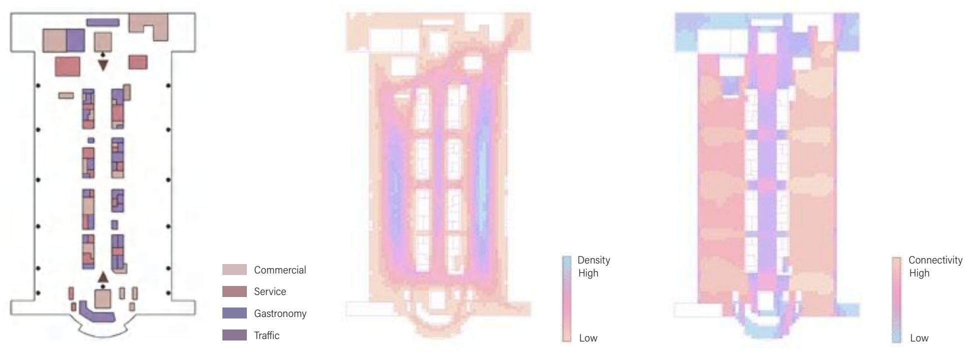
Case2: National Exhibition Hall

The modular exhibition layout provides clear circulation but suffers from poor spatial integration and limited functional diversity. As a national-scale venue, it requires enhanced connectivity between zones and more flexible spatial narratives to support diverse events while maintaining intuitive navigation. Space syntax analysis indicates opportunities for better visual and physical integration.

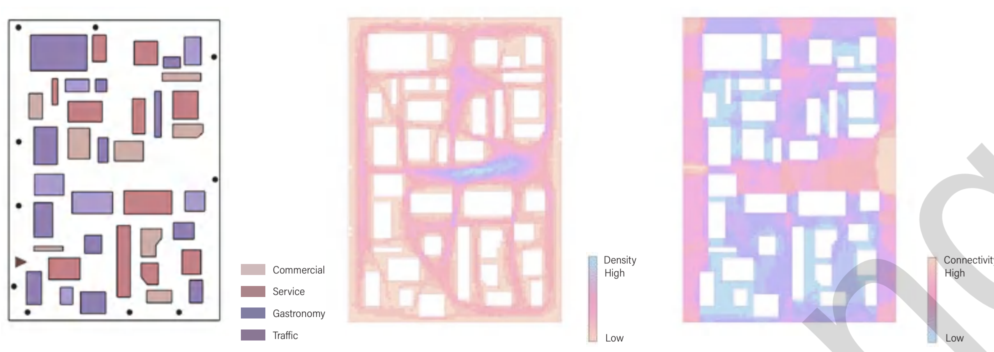
Case3: Yuyuantan Park

This historic urban park prioritizes scenic experience over functional efficiency, requiring improvements in wayfinding systems and spatial hierarchy. The leisure-oriented circulation needs enhanced nodal visibility and multi-functional pockets to better accommodate diverse activities while preserving ecological character. Connectivity assessment reveals opportunities to strengthen key transitional zones.

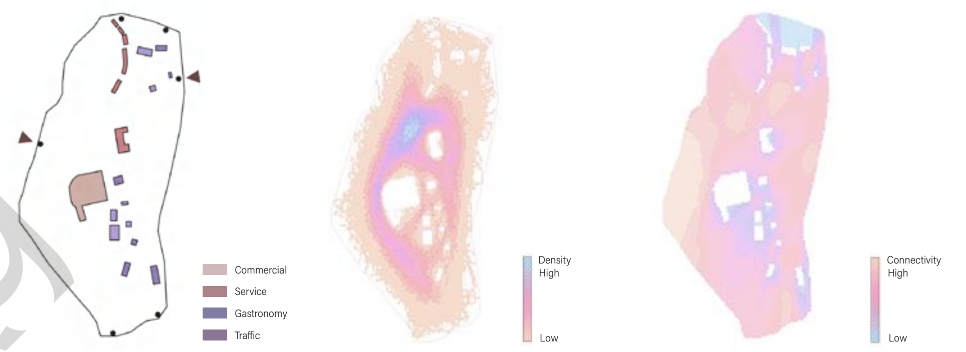
PLAN 1:1000 | Agent Analysis | Connectivity



PLAN 1:1000 | Agent Analysis | Connectivity

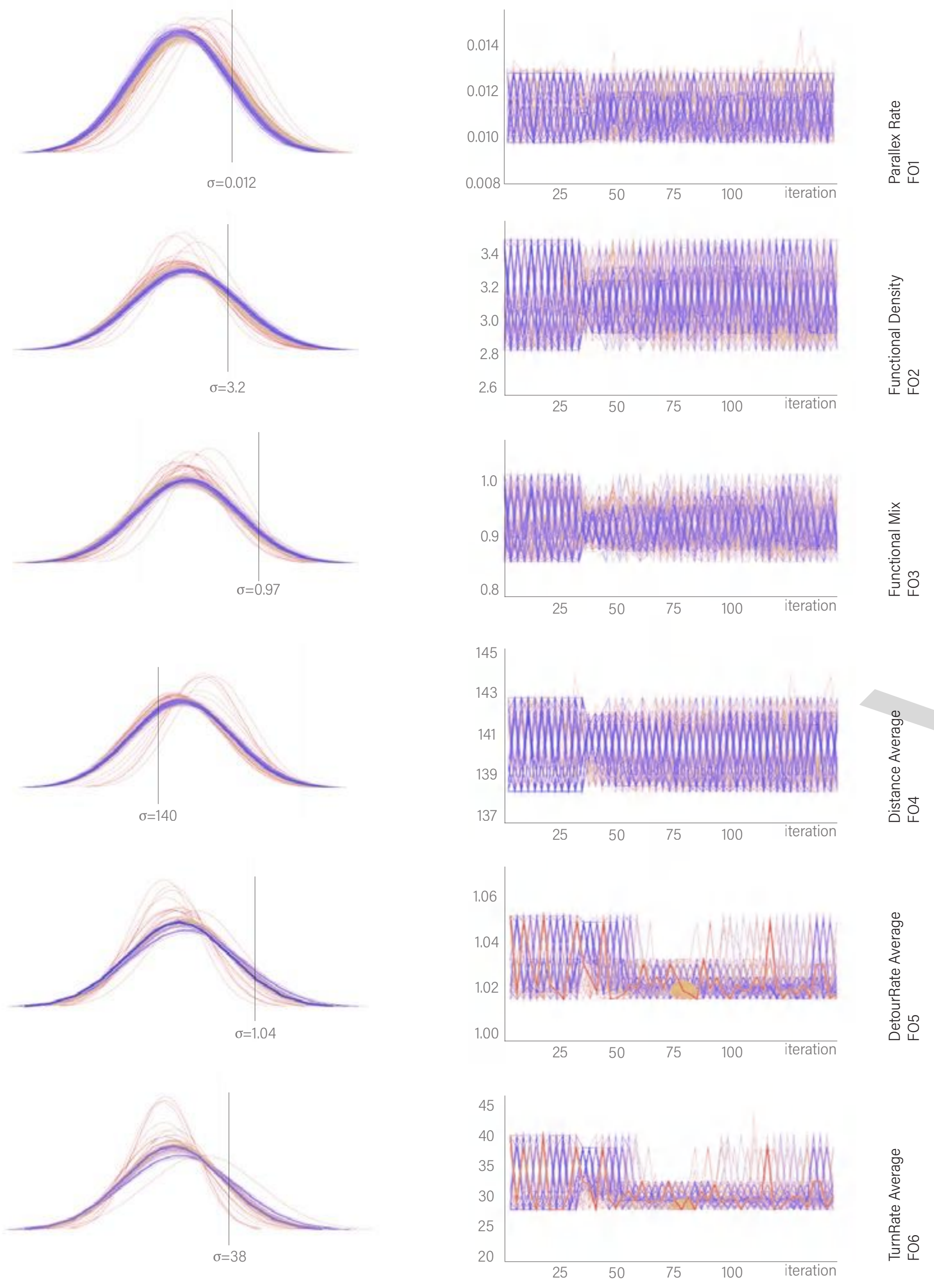


PLAN 1:2000 | Agent Analysis | Connectivity

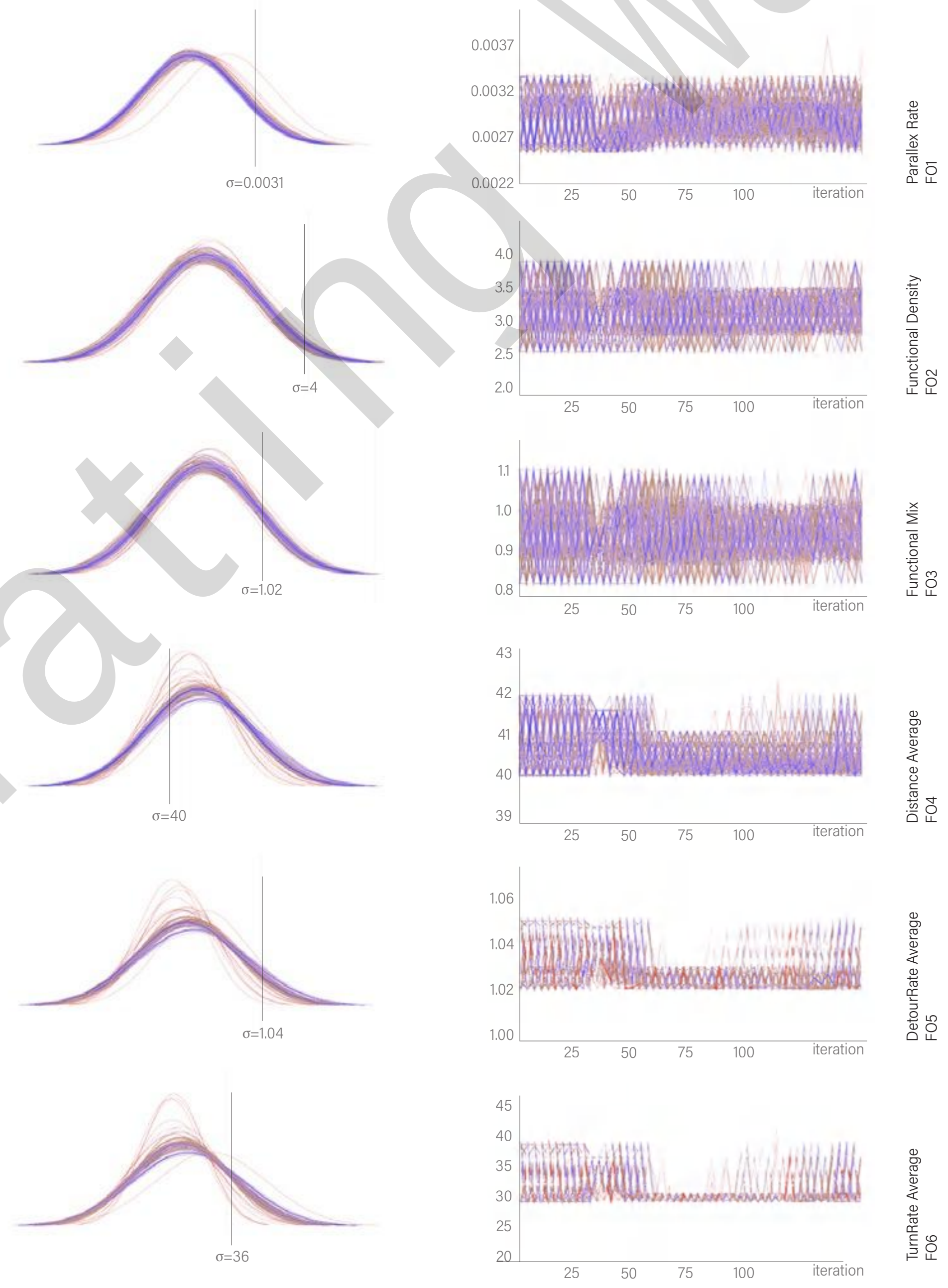


Iteration Process of Genetic Algorithm

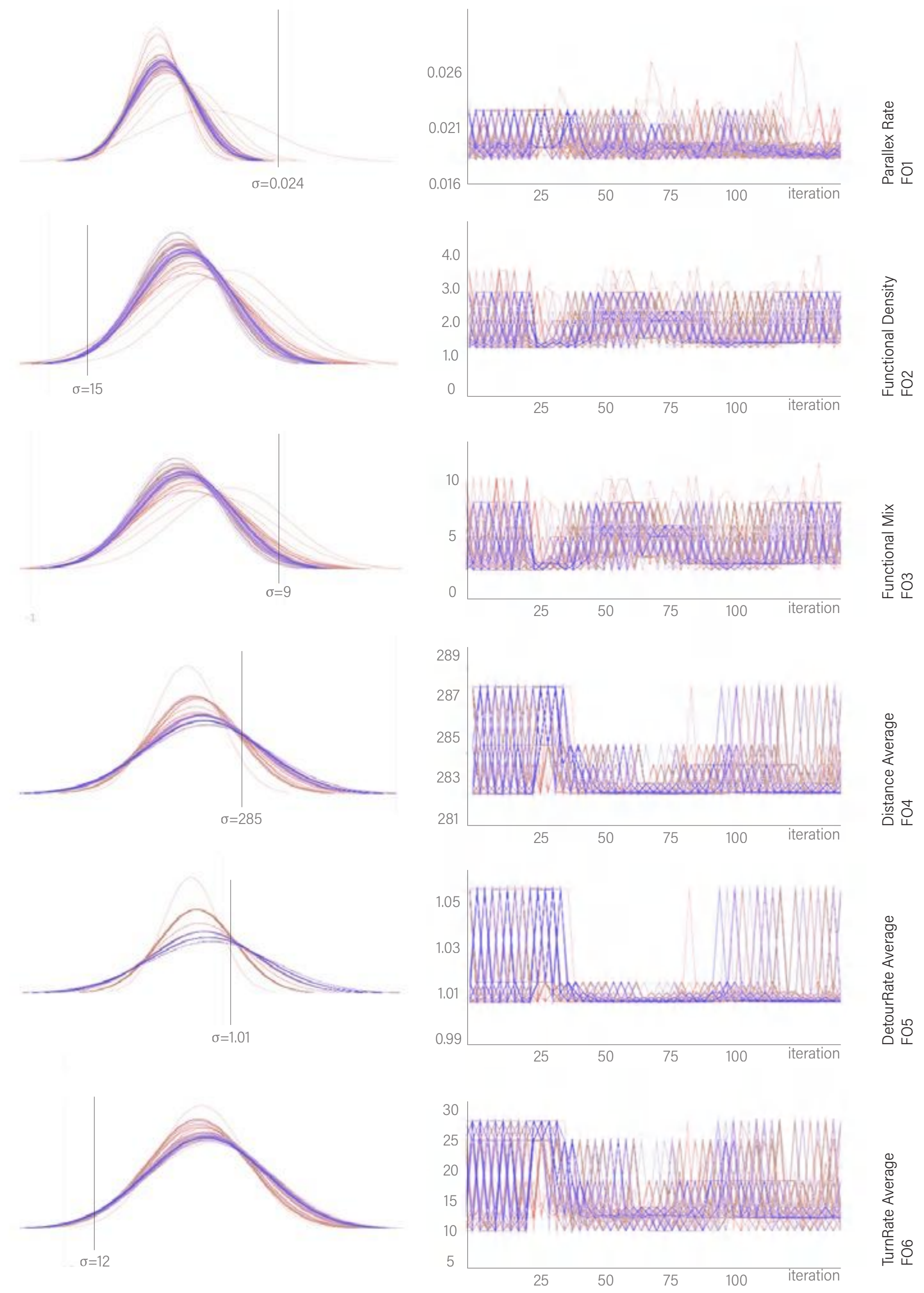
Standard Deviation | Mean Value Trend Line



Standard Deviation | Mean Value Trend Line

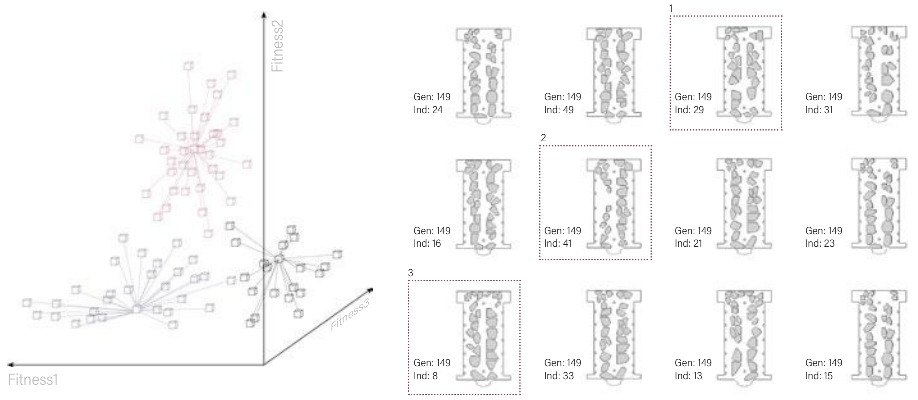


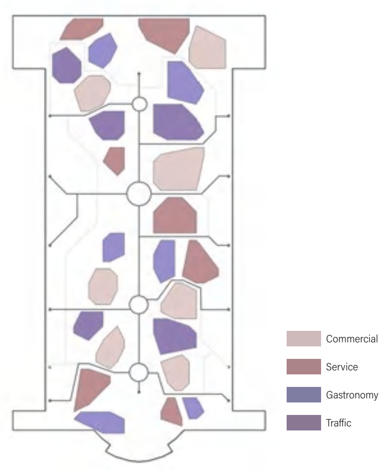
Standard Deviation | Mean Value Trend Line



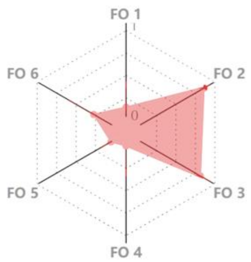
CASE STUDY | SELECTION & CLUSTERING

Case1: Beijing West Station





1 Experiential type



FO1: Parallex Rate
Fitness Value: 0.009661
Fitness Rank: 1101 / 7499

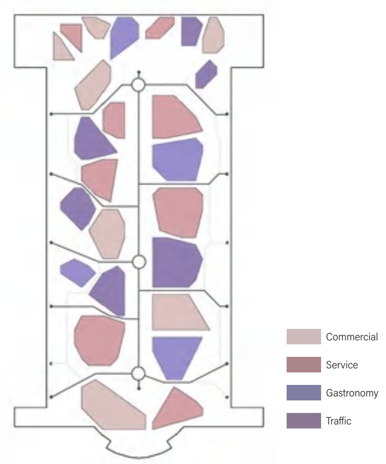
FO2: Functional Density
Fitness Value: 3.497005
Fitness Rank: 6728 / 7499

FO3: Functional Mix
Fitness Value: 1.007519
Fitness Rank: 6758 / 7499

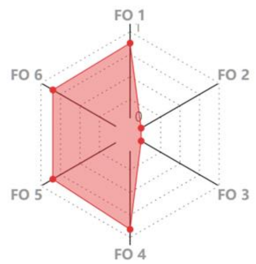
FO4: Distance Average
Fitness Value: 138.1355
Fitness Rank: 0 / 7499

FO5: DetourRate Average
Fitness Value: 1.024849
Fitness Rank: 385 / 7499

FO6: TurnRate Average
Fitness Value: 23.61897
Fitness Rank: 2049 / 7499



2 Convenience type



FO1: Parallex Rate
Fitness Value: 0.012536
Fitness Rank: 6547 / 7499

FO2: Functional Density
Fitness Value: 2.822148
Fitness Rank: 0 / 7499

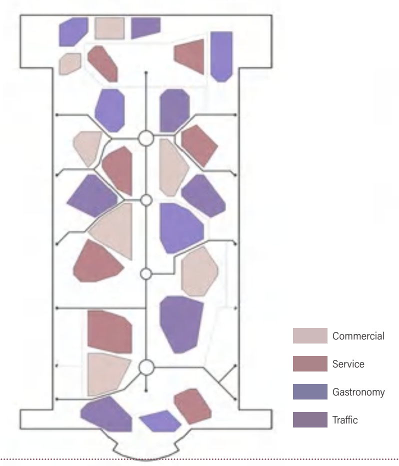
FO3: Functional Mix
Fitness Value: 0.876811
Fitness Rank: 0 / 7499

FO4: Distance Average
Fitness Value: 142.748733
Fitness Rank: 6830 / 7499

FO5: DetourRate Average
Fitness Value: 1.055417
Fitness Rank: 6370 / 7499

FO6: TurnRate Average
Fitness Value: 34.633037
Fitness Rank: 6366 / 7499

☑ selected



3 Balanced type

FO1: Parallex Rate
Fitness Value: 0.010969
Fitness Rank: 4055 / 7499

FO2: Functional Density
Fitness Value: 3.032131
Fitness Rank: 3053 / 7499

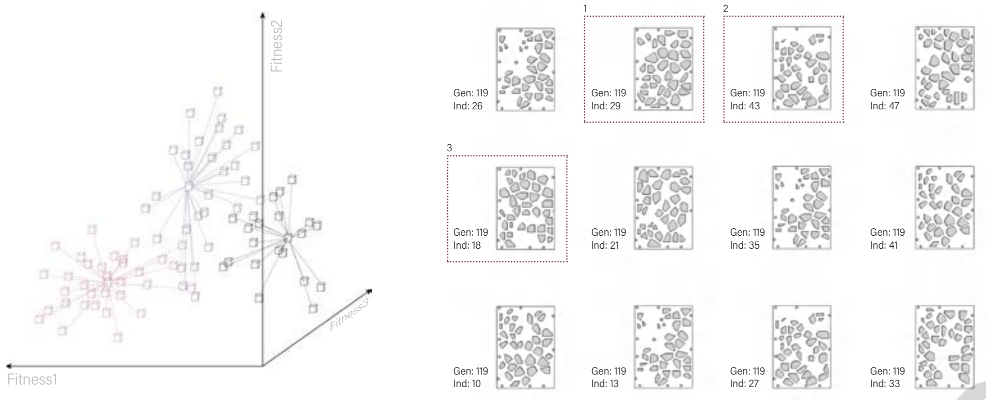
FO3: Functional Mix
Fitness Value: 0.925359
Fitness Rank: 3699 / 7499

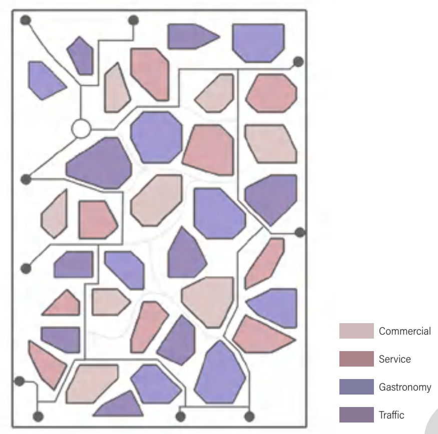
FO4: Distance Average
Fitness Value: 141.394144
Fitness Rank: 4520 / 7499

FO5: DetourRate Average
Fitness Value: 1.051303
Fitness Rank: 5495 / 7499

FO6: TurnRate Average
Fitness Value: 30.797332
Fitness Rank: 4959 / 7499

Case2: National Exhibition Hall





1 Experiential type

FO1: Parallex Rate
Fitness Value: 0.002714
Fitness Rank: 2373 / 5999

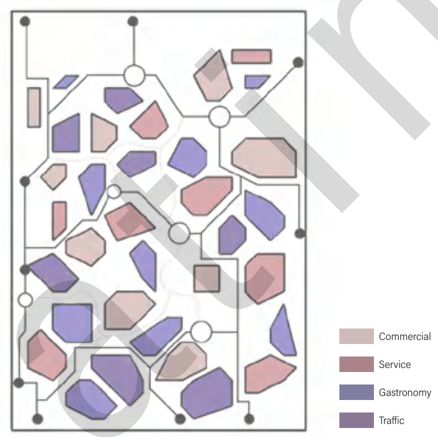
FO2: Functional Density
Fitness Value: 3.69343
Fitness Rank: 5159 / 5999

FO3: Functional Mix
Fitness Value: 1.04532
Fitness Rank: 4877 / 5999

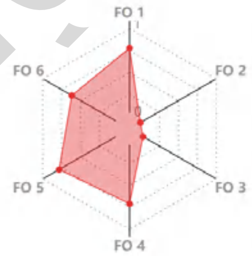
FO4: Distance Average
Fitness Value: 39.873428
Fitness Rank: 1802 / 5999

FO5: DetourRate Average
Fitness Value: 1.019863
Fitness Rank: 851 / 5999

FO6: TurnRate Average
Fitness Value: 25.412132
Fitness Rank: 3325 / 5999



2 Convenience type



FO1: Parallex Rate
Fitness Value: 0.003015
Fitness Rank: 4669 / 5999

FO2: Functional Density
Fitness Value: 2.735133
Fitness Rank: 0 / 5999

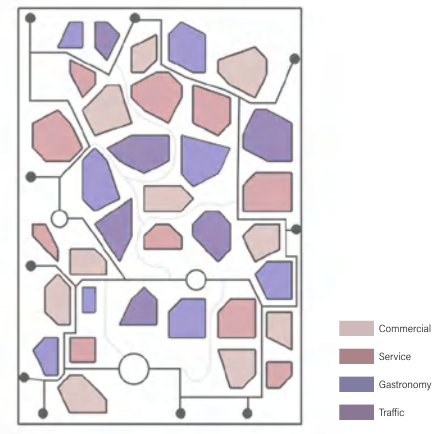
FO3: Functional Mix
Fitness Value: 0.860407
Fitness Rank: 211 / 5999

FO4: Distance Average
Fitness Value: 40.33191
Fitness Rank: 4259 / 5999

FO5: DetourRate Average
Fitness Value: 1.033413
Fitness Rank: 4707 / 5999

FO6: TurnRate Average
Fitness Value: 26.519647
Fitness Rank: 3707 / 5999

☑ selected



3 Balanced type

FO1: Parallex Rate
Fitness Value: 0.002951
Fitness Rank: 4114 / 5999

FO2: Functional Density
Fitness Value: 3.072876
Fitness Rank: 1876 / 5999

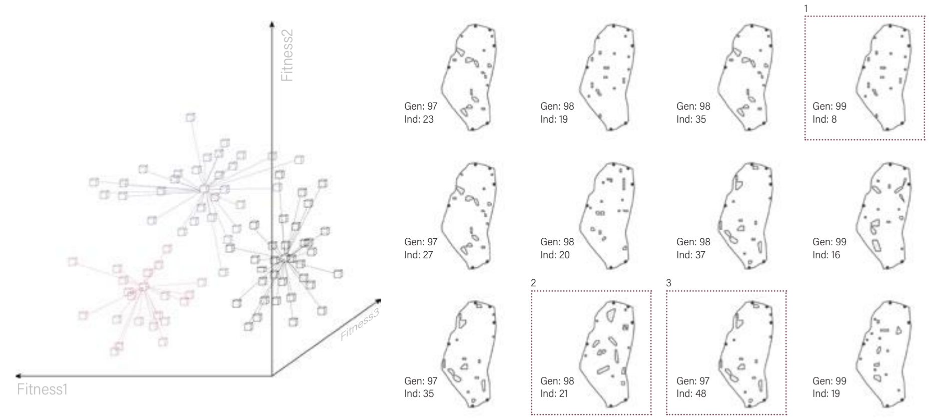
FO3: Functional Mix
Fitness Value: 0.928407
Fitness Rank: 1765 / 5999

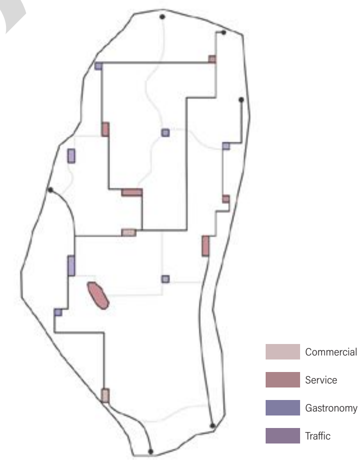
FO4: Distance Average
Fitness Value: 39.970113
Fitness Rank: 2746 / 5999

FO5: DetourRate Average
Fitness Value: 1.023871
Fitness Rank: 3319 / 5999

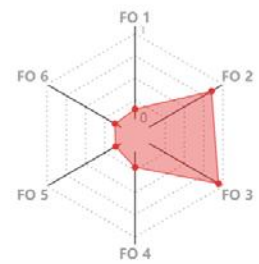
FO6: TurnRate Average
Fitness Value: 26.563871
Fitness Rank: 4261 / 5999

Case3: Yuyuantan Park





1 Experiential type



FO1: Parallex Rate
Fitness Value: 0.018482
Fitness Rank: 762 / 4999

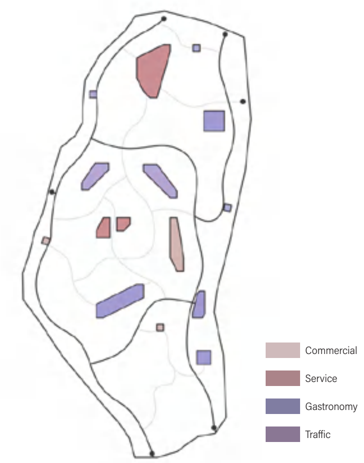
FO2: Functional Density
Fitness Value: 54.268193
Fitness Rank: 4254 / 4999

FO3: Functional Mix
Fitness Value: 8.662809
Fitness Rank: 4707 / 4999

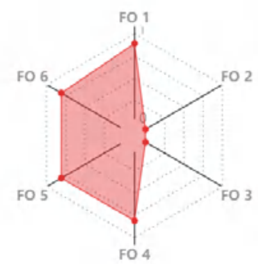
FO4: Distance Average
Fitness Value: 283.018575
Fitness Rank: 1083 / 4999

FO5: DetourRate Average
Fitness Value: 1.000198
Fitness Rank: 550 / 4999

FO6: TurnRate Average
Fitness Value: 4.195852
Fitness Rank: 595 / 4999



2 Convenience type



FO1: Parallex Rate
Fitness Value: 0.022178
Fitness Rank: 4455 / 4999

FO2: Functional Density
Fitness Value: 14.988459
Fitness Rank: 0 / 4999

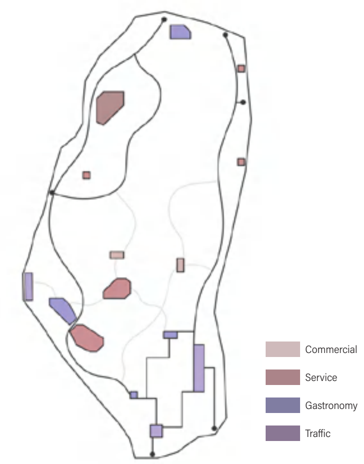
FO3: Functional Mix
Fitness Value: 2.96728
Fitness Rank: 0 / 4999

FO4: Distance Average
Fitness Value: 285.307105
Fitness Rank: 4058 / 4999

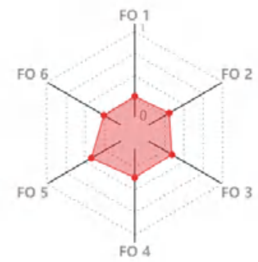
FO5: DetourRate Average
Fitness Value: 1.008343
Fitness Rank: 4058 / 4999

FO6: TurnRate Average
Fitness Value: 22.659348
Fitness Rank: 4057 / 4999

☑ selected



3 Balanced type



FO1: Parallex Rate
Fitness Value: 0.018647
Fitness Rank: 1356 / 4999

FO2: Functional Density
Fitness Value: 18.51509
Fitness Rank: 1536 / 4999

FO3: Functional Mix
Fitness Value: 3.552814
Fitness Rank: 1711 / 4999

FO4: Distance Average
Fitness Value: 283.052508
Fitness Rank: 1789 / 4999

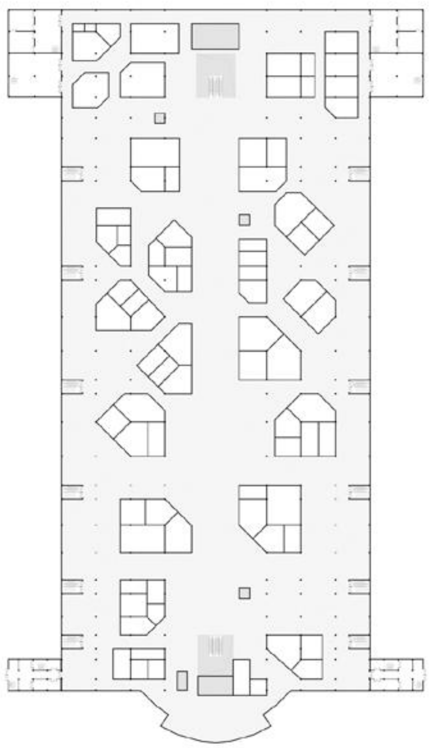
FO5: DetourRate Average
Fitness Value: 1.000589
Fitness Rank: 2115 / 4999

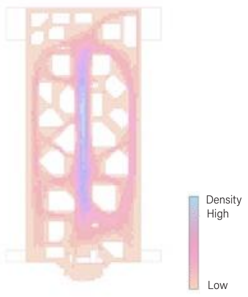
FO6: TurnRate Average
Fitness Value: 4.41882
Fitness Rank: 1295 / 4999

CASE STUDY | MANUAL IMPROVEMENT RESULT

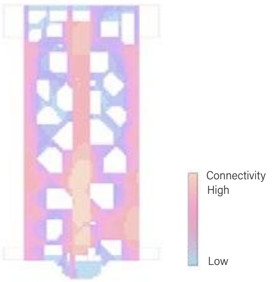
Case1: Beijing West Station (3. balanced type)

The optimized "Balanced Type" layout significantly enhances spatial connectivity and pedestrian distribution efficiency. It successfully alleviates congestion at ticket gates by introducing a more decentralized, fish-bone-like functional arrangement.

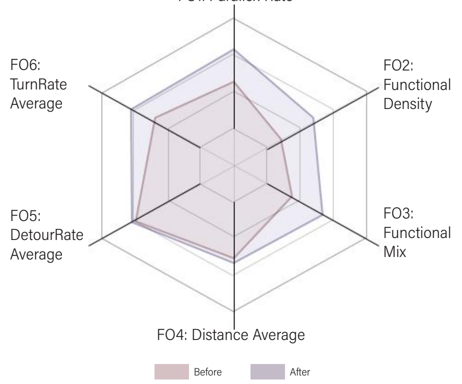




Agent Analysis



Connectivity



FO1: Parallex Rate
Fitness Value: 0.010969
Fitness Rank: 4055 / 7499

FO2: Functional Density
Fitness Value: 3.032131
Fitness Rank: 3053 / 7499

FO3: Functional Mix
Fitness Value: 0.925359
Fitness Rank: 3699 / 7499

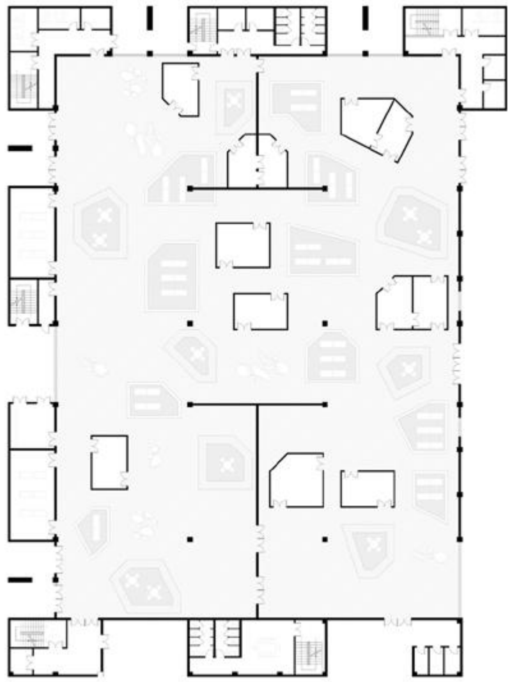
FO4: Distance Average
Fitness Value: 141.394144
Fitness Rank: 4520 / 7499

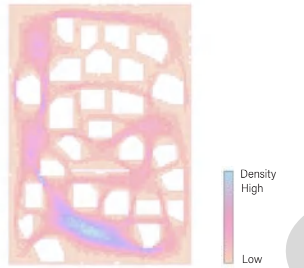
FO5: DetourRate Average
Fitness Value: 1.051303
Fitness Rank: 5495 / 7499

FO6: TurnRate Average
Fitness Value: 30.797332
Fitness Rank: 4959 / 7499

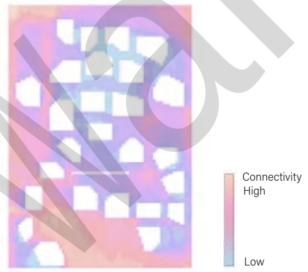
Case2: National Exhibition Hall (3. balanced type)

The improved plan adopts a "Balanced Type" strategy to strengthen the integration between adjacent exhibition zones. This intervention boosts both visual connectivity and physical accessibility, transforming the segmented experience into a more cohesive spatial narrative.

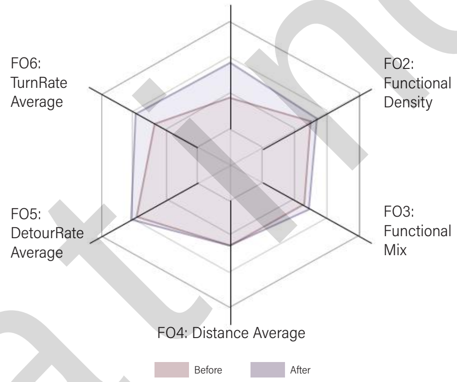




Agent Analysis



Connectivity



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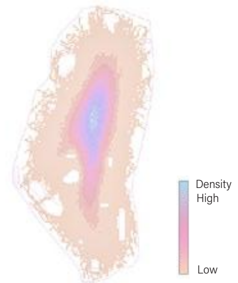
FO5: DetourRate Average
Fitness Value: 1.051303
Fitness Rank: 5495 / 7499

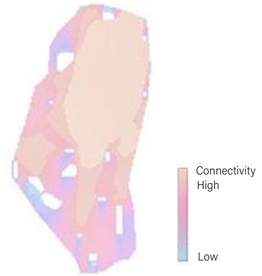
FO6: TurnRate Average
Fitness Value: 30.797332
Fitness Rank: 4959 / 7499

Case3: Yuyuantan Park (3. balanced type)

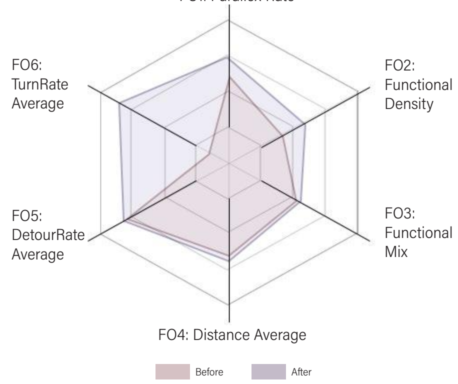
The redesign applies a "Convenience Type" approach at key entrances and an "Experiential Type" logic within the park, tailored to its leisure character. This hybrid strategy improves nodal visibility and wayfinding, better accommodating diverse recreational activities.



Agent Analysis



Connectivity



FO1: Parallex Rate
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FO2: Functional Density
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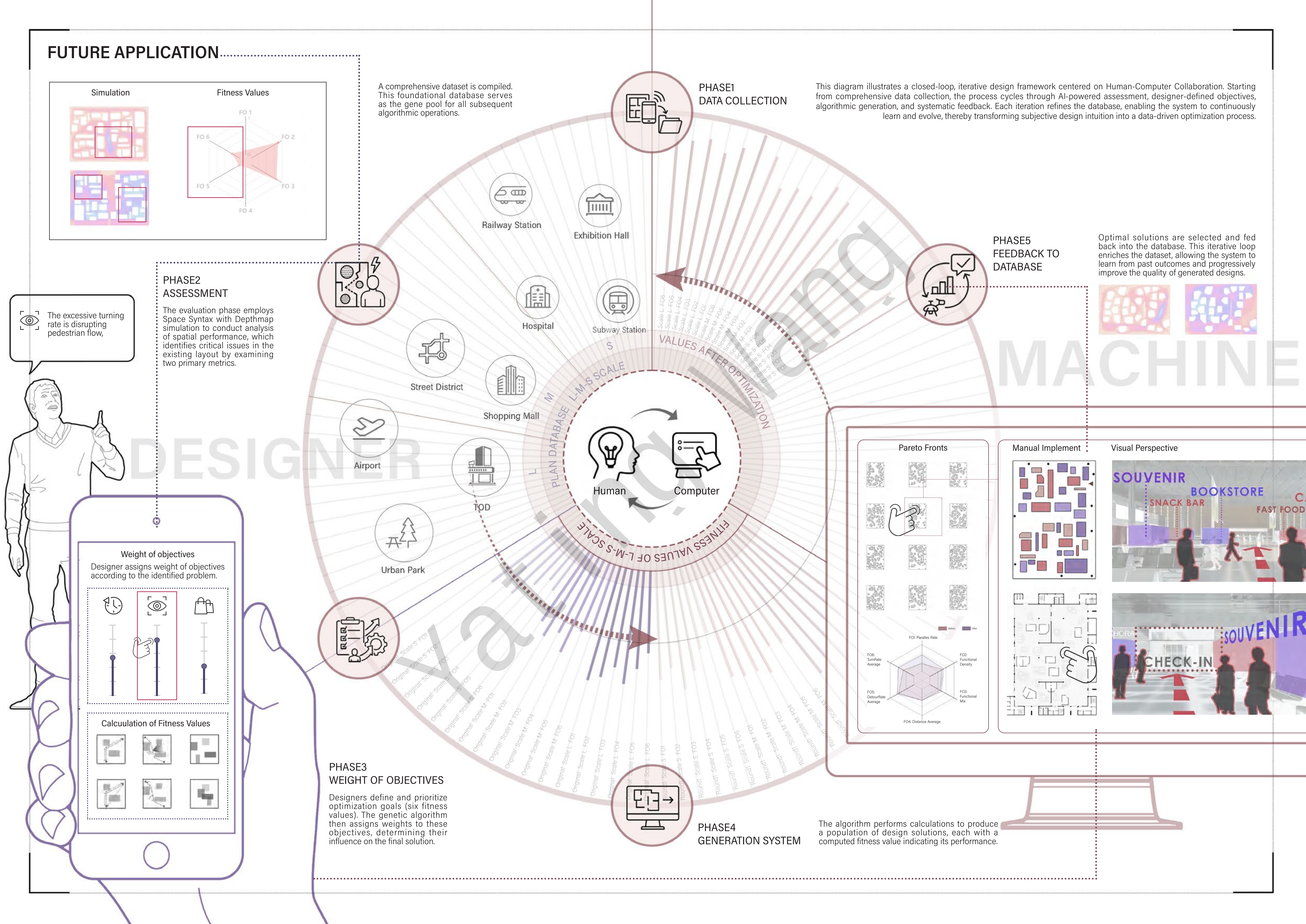

FUTURE APPLICATION
Simulation
Fitness Values
FO 1
FO 2
FO 3
FO 4
FO 5
FO 6
A comprehensive dataset is compiled. This foundational database serves as the gene pool for all subsequent algorithmic operations.
PHASE1
DATA COLLECTION
This diagram illustrates a closed-loop, iterative design framework centered on Human-Computer Collaboration. Starting from comprehensive data collection, the process cycles through AI-powered assessment, designer-defined objectives, algorithmic generation, and systematic feedback. Each iteration refines the database, enabling the system to continuously learn and evolve, thereby transforming subjective design intuition into a data-driven optimization process.
Railway Station
Exhibition Hall
Hospital
Subway Station
Street District
Shopping Mall
Airport
TOD
Urban Park
PHASE5
FEEDBACK TO
DATABASE
Optimal solutions are selected and fed back into the database. This iterative loop enriches the dataset, allowing the system to learn from past outcomes and progressively improve the quality of generated designs.
PHASE2
ASSESSMENT
The evaluation phase employs Space Syntax with Depthmap simulation to conduct analysis of spatial performance, which identifies critical issues in the existing layout by examining two primary metrics.
The excessive turning rate is disrupting pedestrian flow,
MACHINE
DESIGNER
VALUES AFTER OPTIMIZATION
L-M-S SCALE
PLAN DATABASE
S
M
L
Human
Computer
FITNESS VALUES OF L-M-S SCALE
Pareto Fronts
Manual Implement
Visual Perspective
SOUVENIR
BOOKSTORE
SNACK BAR
FAST FOOD
CHECK-IN
FO1: Parallax Rate
FO2: Functional Density
FO3: Functional Mix
FO4: Distance Average
FO5: DetourRate Average
FO6: TurnRate Average
Weight of objectives
Designer assigns weight of objectives according to the identified problem.
Calcuulation of Fitness Values
PHASE3
WEIGHT OF OBJECTIVES
Designers define and prioritize optimization goals (six fitness values). The genetic algorithm then assigns weights to these objectives, determining their influence on the final solution.
PHASE4
GENERATION SYSTEM
The algorithm performs calculations to produce a population of design solutions, each with a computed fitness value indicating its performance.

05

MR GUIDING SYSTEM | Personalized Navigation for Chinese Garden

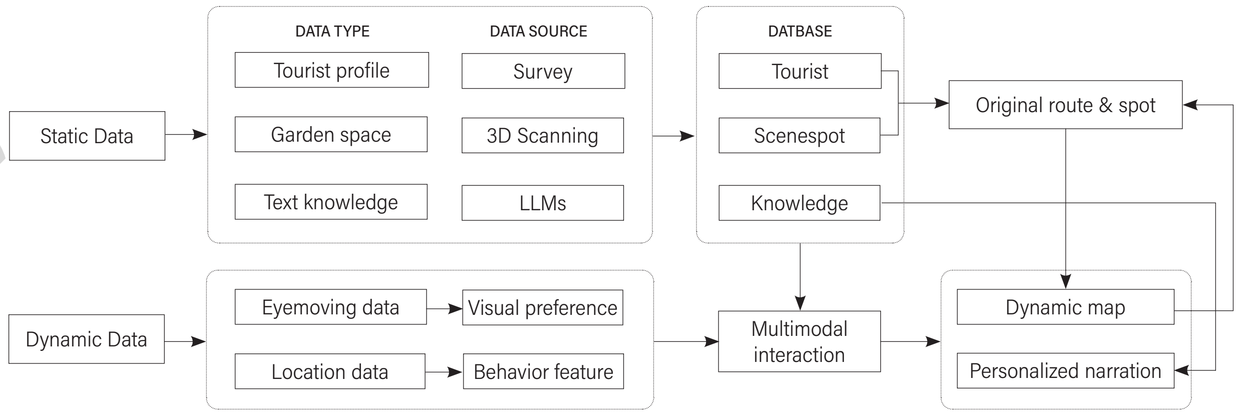
Dynamic Path Planning and Personalized Narration via Visual Interest Prediction

Group work | MR System Design, Route Planning, Interest Prediction

Site: Suzhou, China

Time: 2024.11 - 2025.01

Instructor: Prof. Xin Zhang, zhx@tsinghua.edu.cn



Builds an integrated dataset of tourists and scenespots for MR guiding.
Static survey profiles capture persona, preferences, and expected tour duration, while HMD-based gaze and motion tracking record real-time behavior in the garden. In parallel, panoramic images are segmented into four labeled elements to construct a quantified scenespots database.

Combines adaptive path planning with LLM-generated narration.
The system aligns tourist behavior with scenespots features to recommend next destinations and update routes based on time, density, and visual interest. LLM-generated narration is triggered by fixation and scene matching, tailoring content style and depth to different user types.

Delivers a full application and interface for dynamic MR guiding.
Users interact with dynamic maps, spot cards, and adjustable settings that reflect their current path and preferences. The interface links movement, spatial attributes, and storytelling into a coherent MR experience (tested with 45 participants).

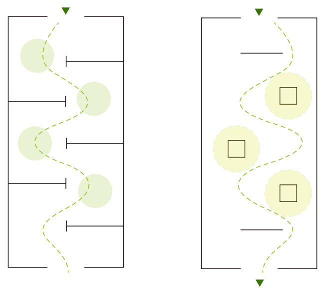
BACKGROUND | COMPARISON OF GUIDING APPROACHES

Guiding Approaches across Different Scales: Museum, Park & City

SCALE S

In museum settings, guidance is centered around exhibited content rather than movement. Visitors focus on objects or displays arranged in a curated order, while navigation plays a secondary role. The experience is shaped by interpretive materials such as exhibit cards or audio guides.

Museum



Node: Exhibited items

- Exhibition Card
  Basic profile introducing real-world interference
- Audio Guide
  Basic profile introducing real-world interference
- AR Interaction
  Basic profile introducing real-world interference

SCALE M

Classical gardens and urban parks balance exploration and content. Visitors often roam freely while engaging with spatially distributed features, such as pavilions, stone arrangements, or framed views. Both the route and the nodes matter, enabling a layered and personal experience.

Urban parks/gardens

Node: Park regions

- Audio Guide
  Basic profile introducing real-world interference
- Map Sign
  Basic profile introducing real-world interference
- More ways...
  An intersection of museum and city guiding system

SCALE L

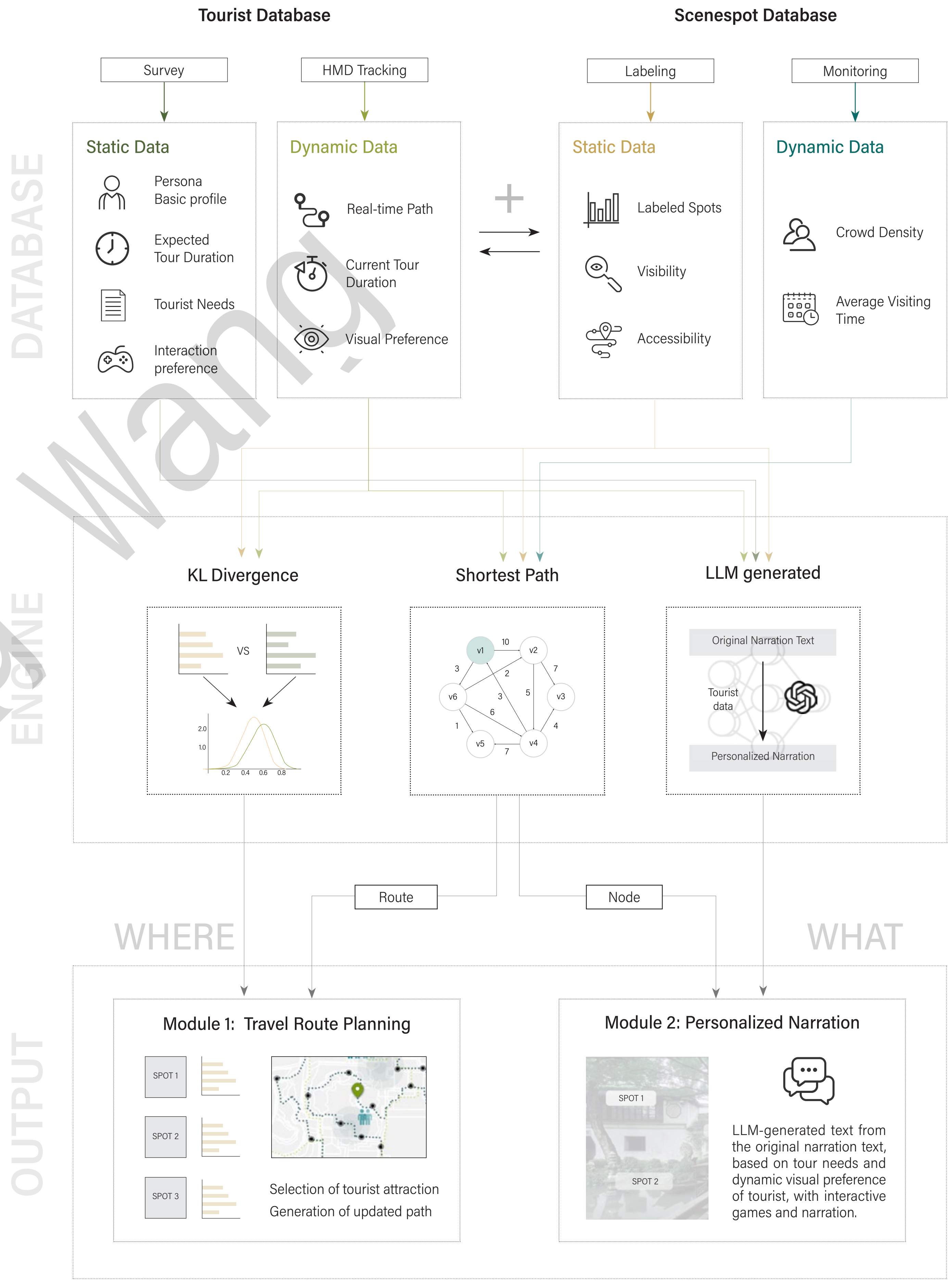
Citywalk experiences emphasize path-making across open urban environments. Visitors navigate through streets, alleys, and landmark buildings, often guided by map signs or digital apps. Here, the route itself becomes the main narrative, punctuated by spatial anchors and visual cues.

Citywalk

Node: Scenic spots

- Map Sign
  Basic profile introducing real-world interference
- Guiding App
  Basic profile introducing real-world interference

FRAMEWORK | MR GUIDING SYSTEM FOR CHINESE GARDEN



DATABASE FOR TOURISTS

Static Profile Data from Survey

This survey collects static profile information, including personal background, expected tour duration, content preferences, and interaction modes. The data helps inform customized MR guidance experiences.

Persona Basic profile

Age:

Gender:

Job:

Purpose of trip:

- ☐ Map and route
- ☐ Audio narration
- ☐ Real-time Q&A

Travel Frequency:

- ☐ 2-3 days
- ☐ 4-7 days
- ☐ 10 days or more

Expected Tour Duration

Expected Duration: How long do you plan to stay at this destination?

- ☐ 1 day
- ☐ 2-3 days
- ☐ 4-7 days
- ☐ More than 7 days

Preferred Duration for Each Activity: How long do you prefer each activity to last?

- ☐ Less than 1 hour
- ☐ 1-2 hours
- ☐ More than 2 hours

Tourist Needs

Preferred Information Delivery: How do you prefer to receive tourist information?

- ☐ Voice navigation
- ☐ Screen-based instructions
- ☐ Real-time AR/VR
- ☐ Human assistance

Special Needs: Do you have any special requirements? (e.g. language support, accessibility, etc.)

- ☐ None
- ☐ Yes, please specify

Interaction preference

Preferred Mode of Interaction: Which type of interaction do you prefer while touring?

- ☐ Gesture control
- ☐ Touchscreen interface
- ☐ Voice control
- ☐ No interaction

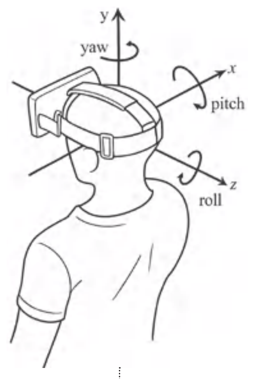
Desired Content: What content would you like to interact with during your tour?

- ☐ Map and route
- ☐ Audio narration
- ☐ Real-time Q&A

+

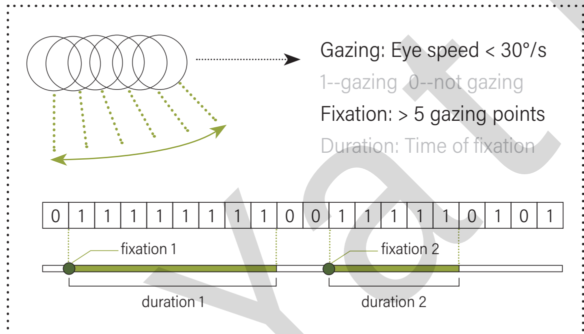
Dynamic Behavior Data from

Through eye-tracking and motion capture, tourists' gaze patterns, fixation points, and movement trajectories are recorded and analyzed to reveal attention and spatial engagement dynamics during MR tours.



Source	Name
Headset Pose	Velocity
	Orientation
Eye-tracking	Eye Speed
	Pupil Diameter
	Eye Openness

Gaze & Fixation Detection



Data processing steps

Step 1: Data Collection
- Raw Data from HMD
- Dynamic Database

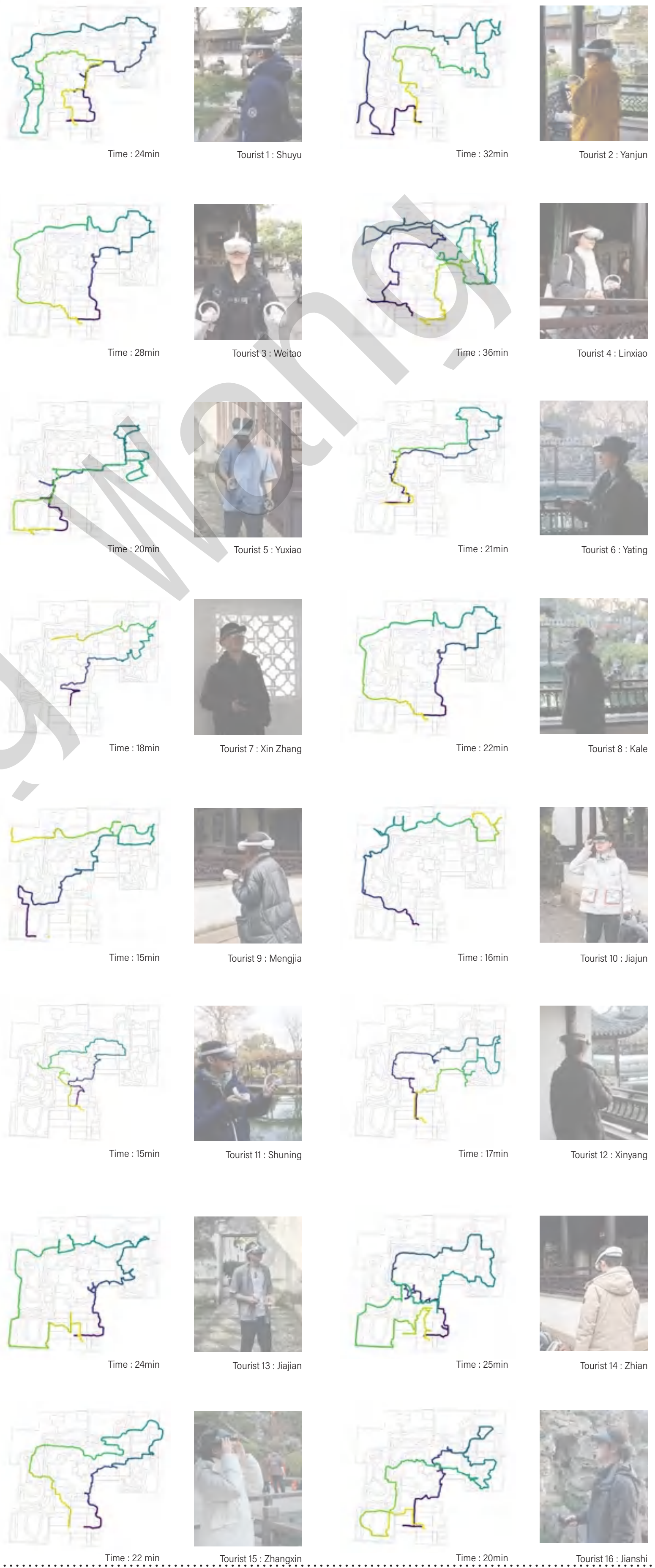
Step 2: Data Cleaning
- Median Filtering
- Time Alignment

Step 3: Path Analysis
- Real-time Path
- Current Tour Duration

Step 4: Visual Analysis
- Fixation Analysis
- Visual Preference

Results of 20 Participants & Clustering

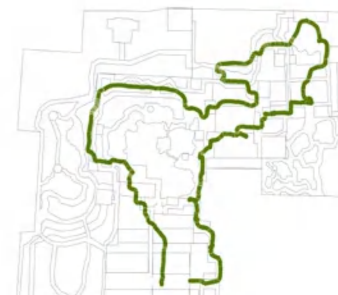
Participants were grouped into four distinct clusters based on their real-time movement trajectories collected through HMD tracking. By analyzing path complexity, duration, spatial coverage, and fixation behavior, we identified representative behavioral patterns across different user types. These clusters reveal how individuals engage with the garden space differently, offering a foundation for personalized MR content delivery and spatial experience design.



Exploratory Wanderers

Tourists with broad and self-directed movement across the entire garden.

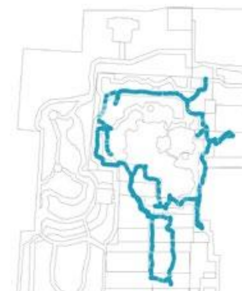
Duration
Spatial Range
Path Complexity
Exploration



Thematic Seekers

Visitors who focus on specific zones with clear thematic interests.

Duration
Spatial Range
Path Complexity
Exploration



Quick Passers

Visitors with short stays and routes through the main path.

Duration
Spatial Range
Path Complexity
Exploration

Leisure Strollers

Visitors who maintain a relaxed gentle rhythm across the space.

Duration
Spatial Range
Path Complexity
Exploration

DATABASE FOR GARDEN SCENESPOT

Dynamic Data: Real-time Detection of Garden

Containing 50 different topological forms, each with 100 variants, and introducing real-world interference factorsstructural.

Path detection & Visiting time

Real-time visitor trajectories were recorded and mapped to calculate average visiting time at different locations.

People detection & Crowd Density

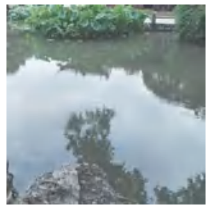
We applied YOLOto detect human presence in video frames, generating dynamic crowd density map.

Static Data: Four Labels of Spots

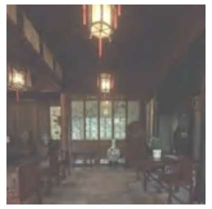
Based on visual and spatial characteristics, we classified garden elements into four major scene types.

Flora
Natural floral clusters and trees/plants

Rockery
Rock formations and arrangements



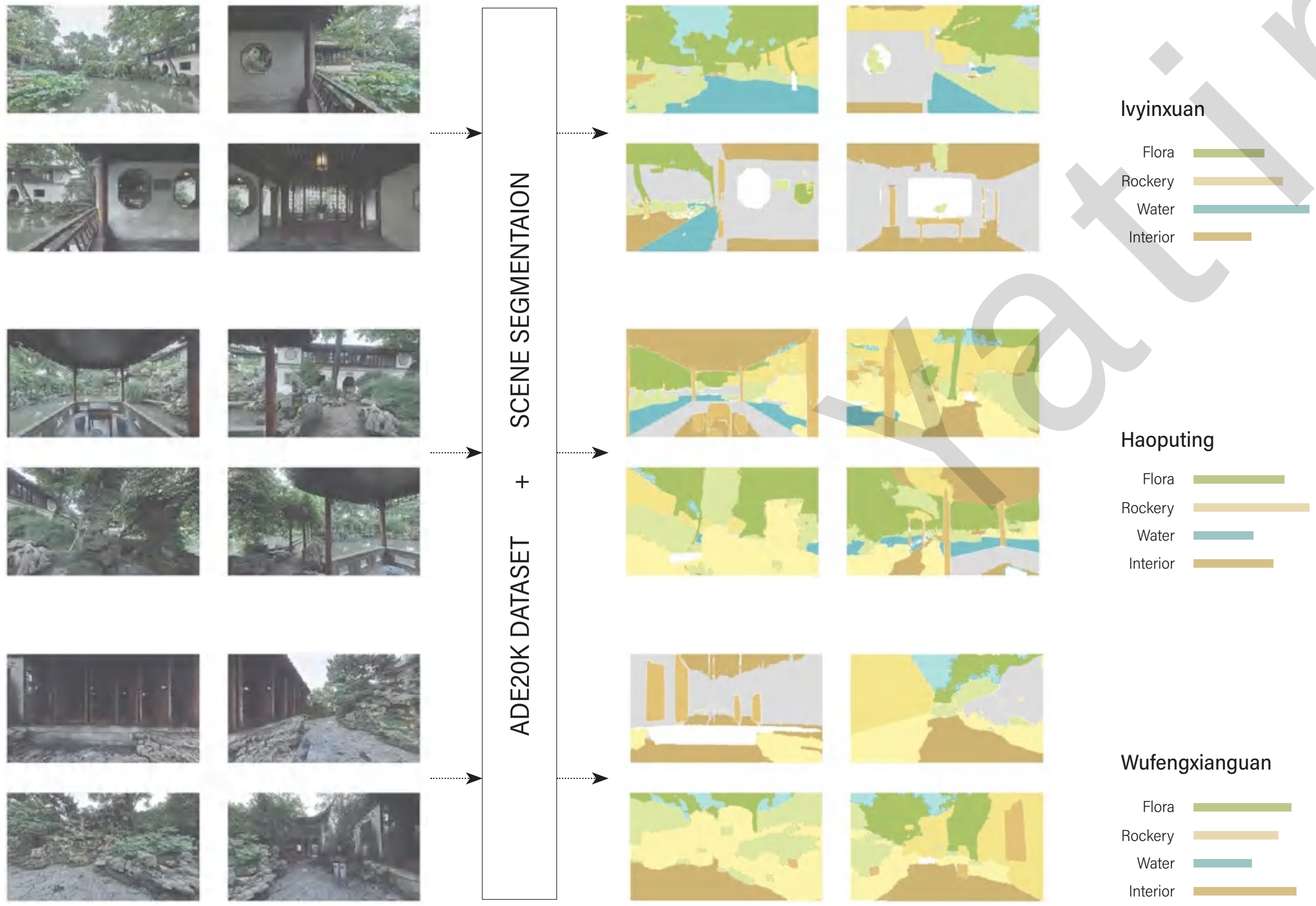
Water
Ponds, streams, and waterfront edges

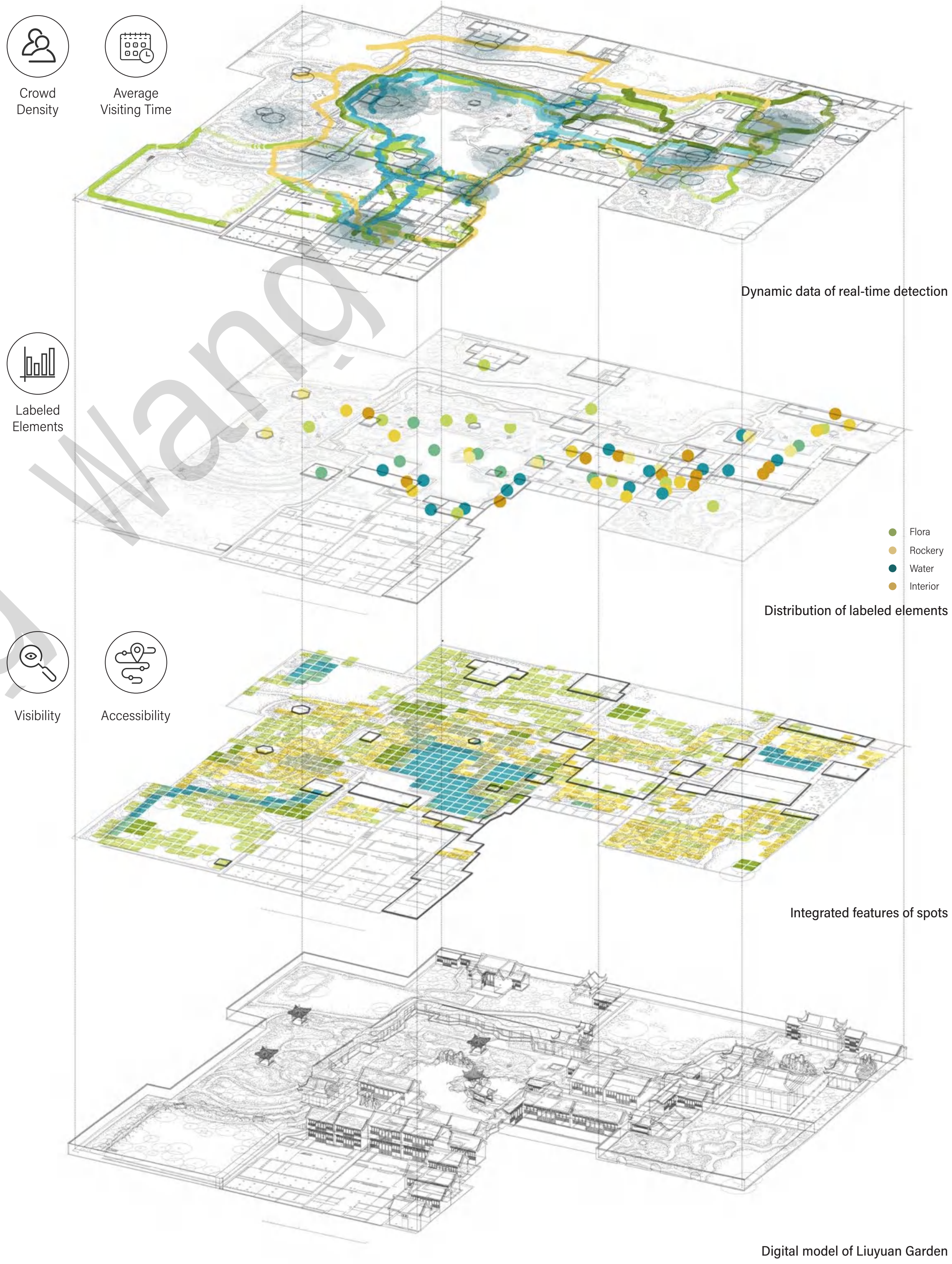


Interior
Framed views and interior-style pavilions

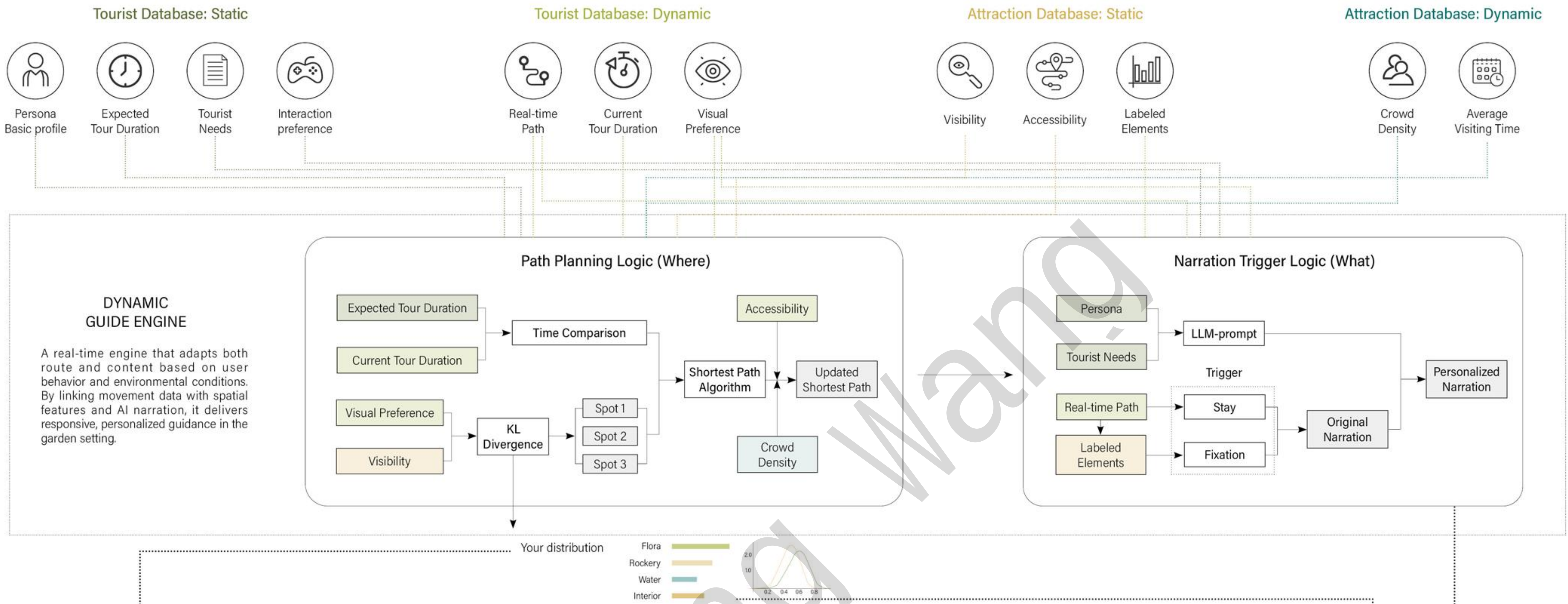
Static Data: Visibility and Accessibility of Spots

Visibility was derived through ControlNet-based segmentation of panoramic images, quantifying the proportion of visual content (four labeld elements).



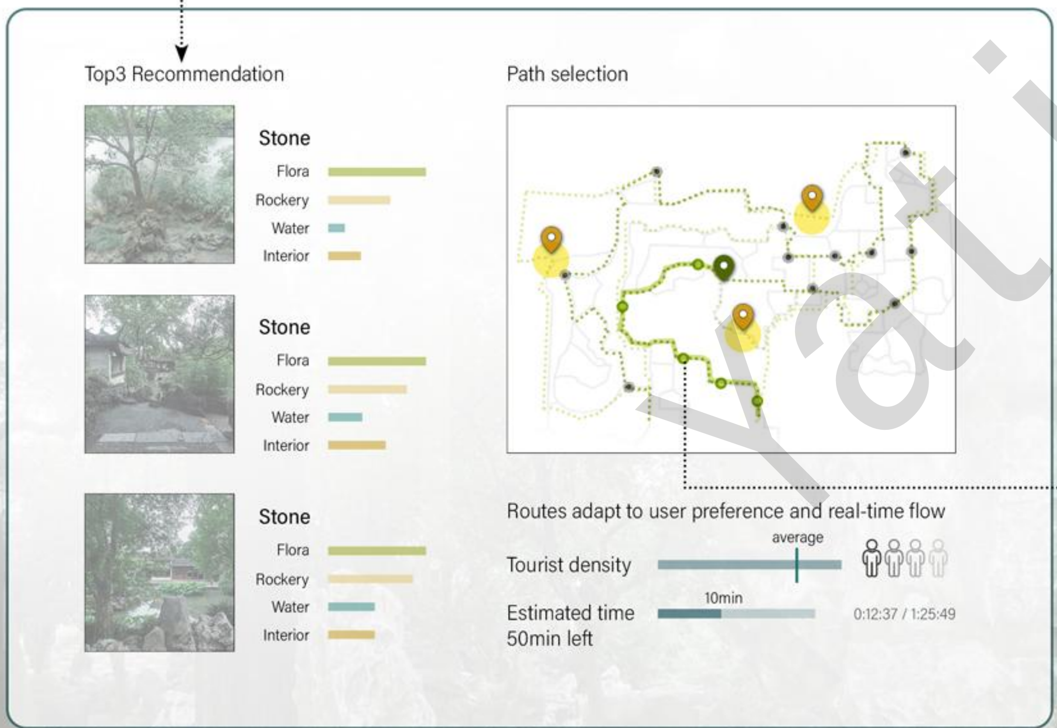


ENGINE SYSTEM DESIGN



DYNAMIC GUIDE ENGINE

A real-time engine that adapts both route and content based on user behavior and environmental conditions. By linking movement data with spatial features and AI narration, it delivers responsive, personalized guidance in the garden setting.

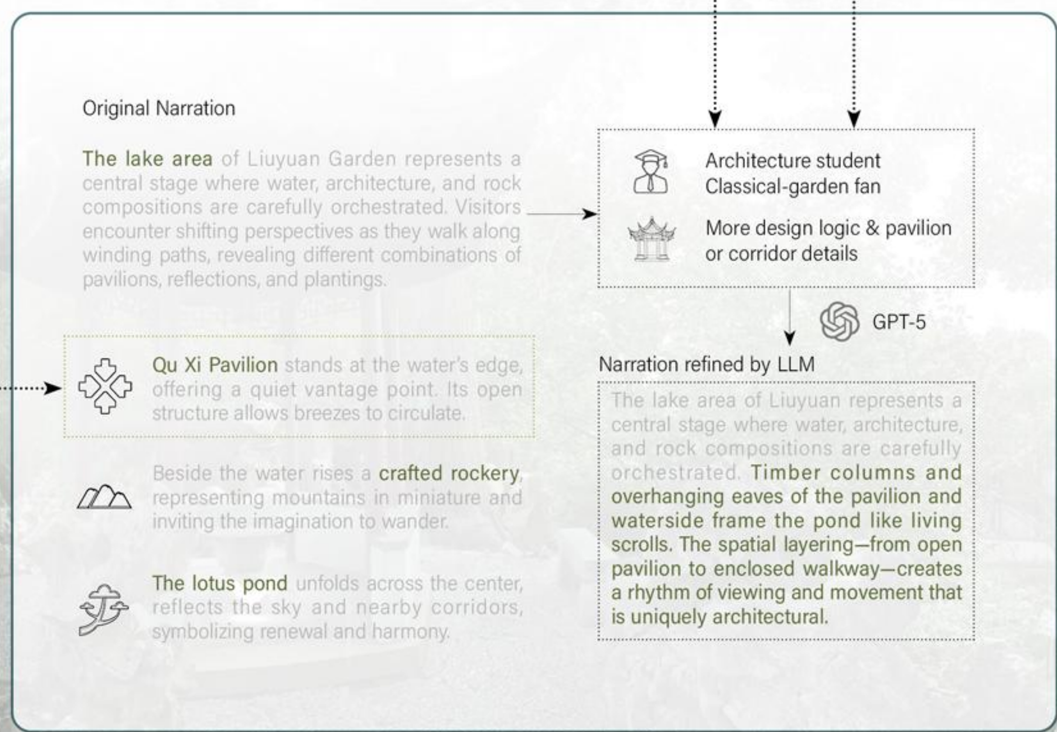


Function Module 1: Travel Route Planning

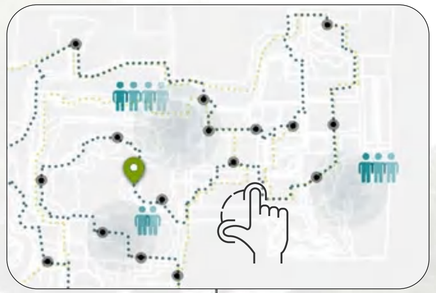
Based on the user's distribution of preferences and available time, the system recommends the top 3 spots and generates an adaptive route. Paths are adjusted in real time according to tourist density and updated user inputs. Estimated tour time and walking distance are visualized for each plan.

Function Module 2: AI Personalized Narration

At key moments, such as arrival at a scene or fixation, the system triggers personalized narration using LLMs. Narration is adapted to the user's profile, enriching the experience with thematic storytelling and contextual information.



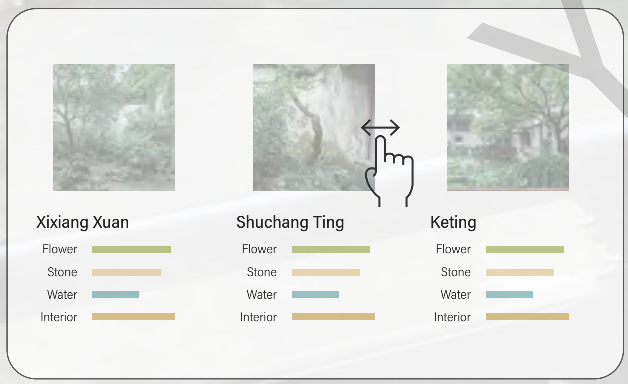
INTERFACE & APPLICATION

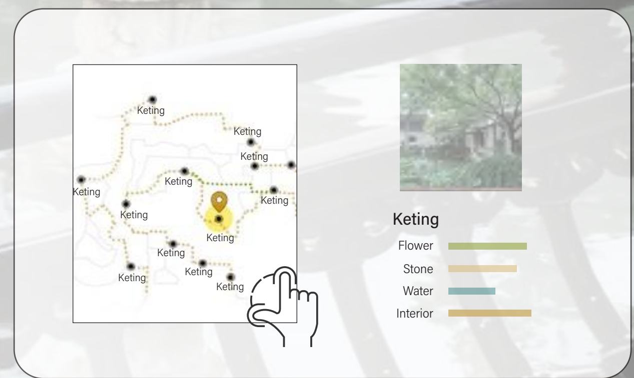


Dynamic Map
Displays current location, visited spots, and suggested routes. The map updates in real time based on tourist movements and system recommendations.

Narration Label

Setting Panel
Allows users to adjust preferences, such as desired tour time, mood, or interaction level. These settings influence the guiding logic.





Tourist Attraction Recommendation
Users receive visual cards suggesting next destinations. Each card presents a breakdown of scene types for easy comparison.

Path Updating
The system dynamically recalculates the best route using shortest path logic, tourist density, and scene matching.

06

URBAN DESIGN | Prototyping a densified Hong Kong

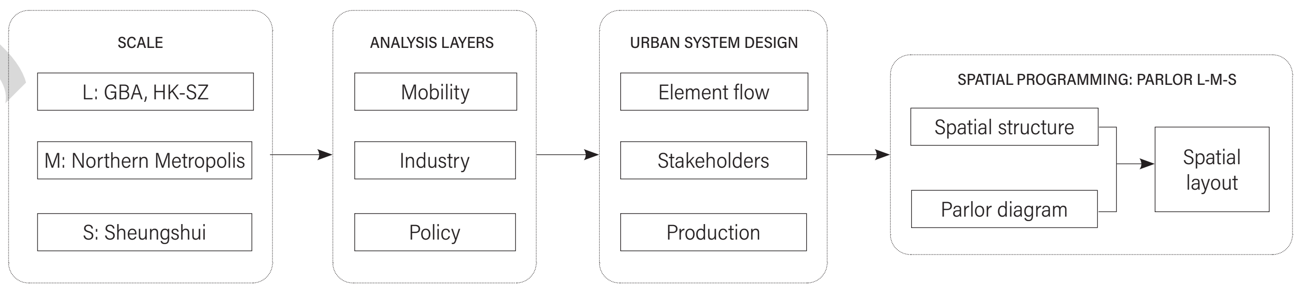
Designing Spatial Prototypes for Cross-Border Innovation and Community Engagement

Group work | Urban Design, Industry Programming

Site: Hong Kong, China

Time: 2025.02 - 2025.06

Instructor: Prof. Ye Zhang, zhang-ye@mail.tsinghua.edu.cn



Analyzes site across L-M-S scale through industrial, mobility, and policy flows.

It traces how components, workers, and regulations move between labs, logistics hubs, and neighborhoods, from the cross-border region down to the street block. This cross-scale reading reveals where current systems disconnect and where new interfaces are needed.

Develops a cross-border biotech urban innovation framework.

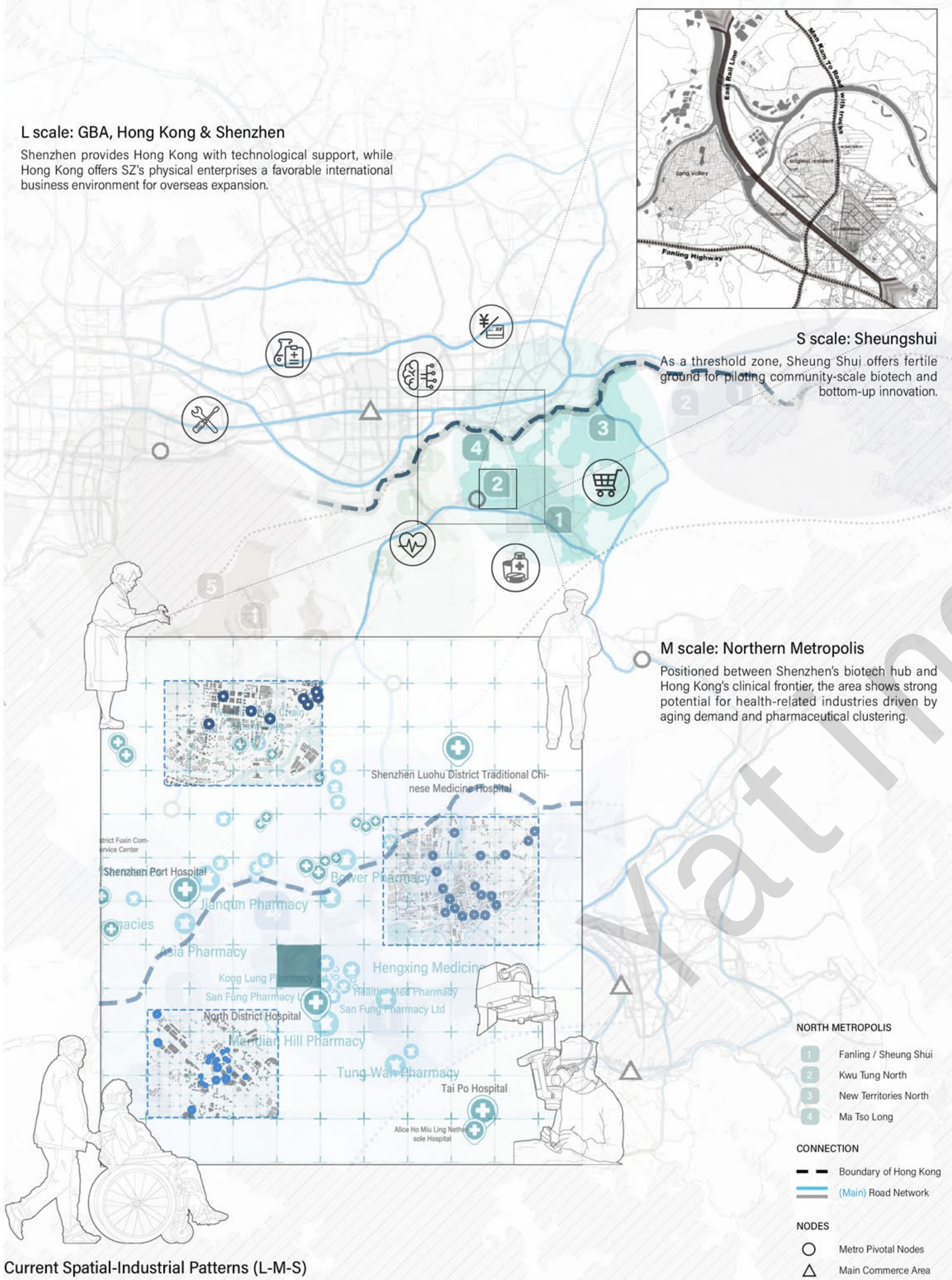
Stages of R&D, prototyping, clinical testing, and community application are aligned with the roles of different stakeholders. This framework clarifies how spatial organization can accommodate evolving production modes and support more continuous, adaptable innovation processes.

Translates the framework into an L–M–S parlor system for co-making.

L-, M-, and S-Parlors are positioned as physical interfaces where experts, workers, and residents jointly engage with biotech practices. Densification is thus framed as creating shared co-making spaces rather than simply increasing built volume.

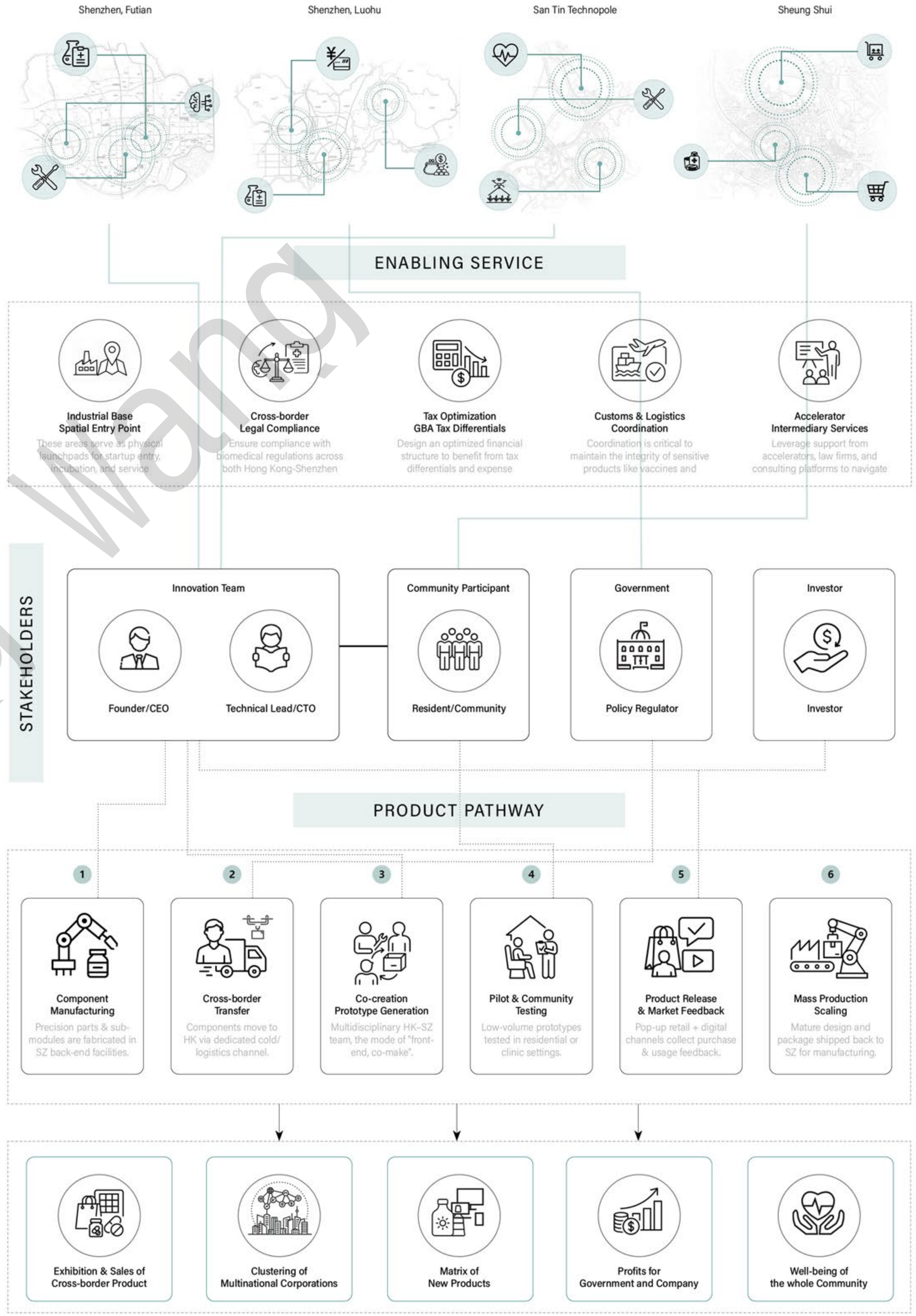
ANALYSIS | MOBILITY, INDUSTRY & POLICY

Current Spatial-Industrial Patterns (L-M-S)



Current Spatial-Industrial Patterns (L-M-S)

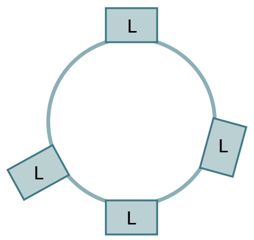
A CROSS-BORDER URBAN INNOVATION SYSTEM



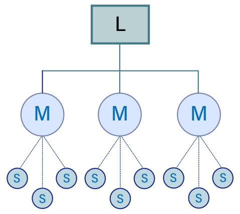
SPATIAL STRATEGY | PARLOR MODE

Parlor Diagram

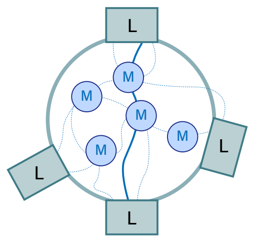
Step 1: Ring + L-Parlor



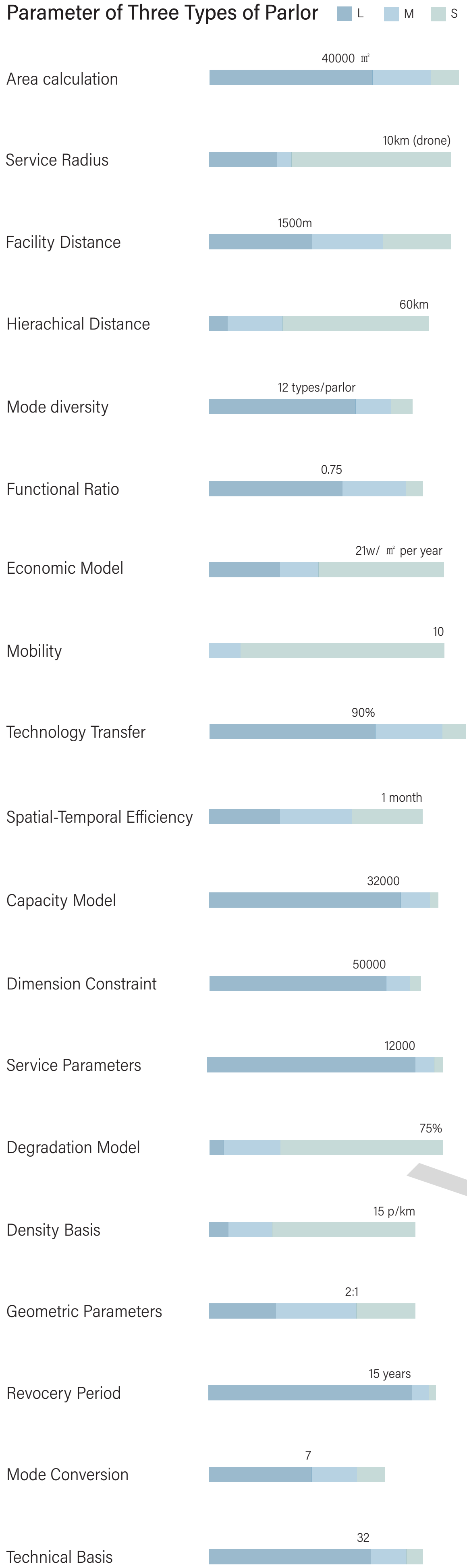
Step 2: Parlor Typology



Step 3: Inner Link of Parlors

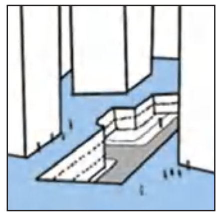


Parameter of Three Types of Parlor

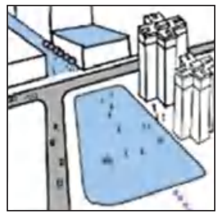


Space Diagram

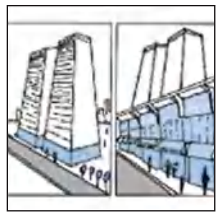
Platform Garden



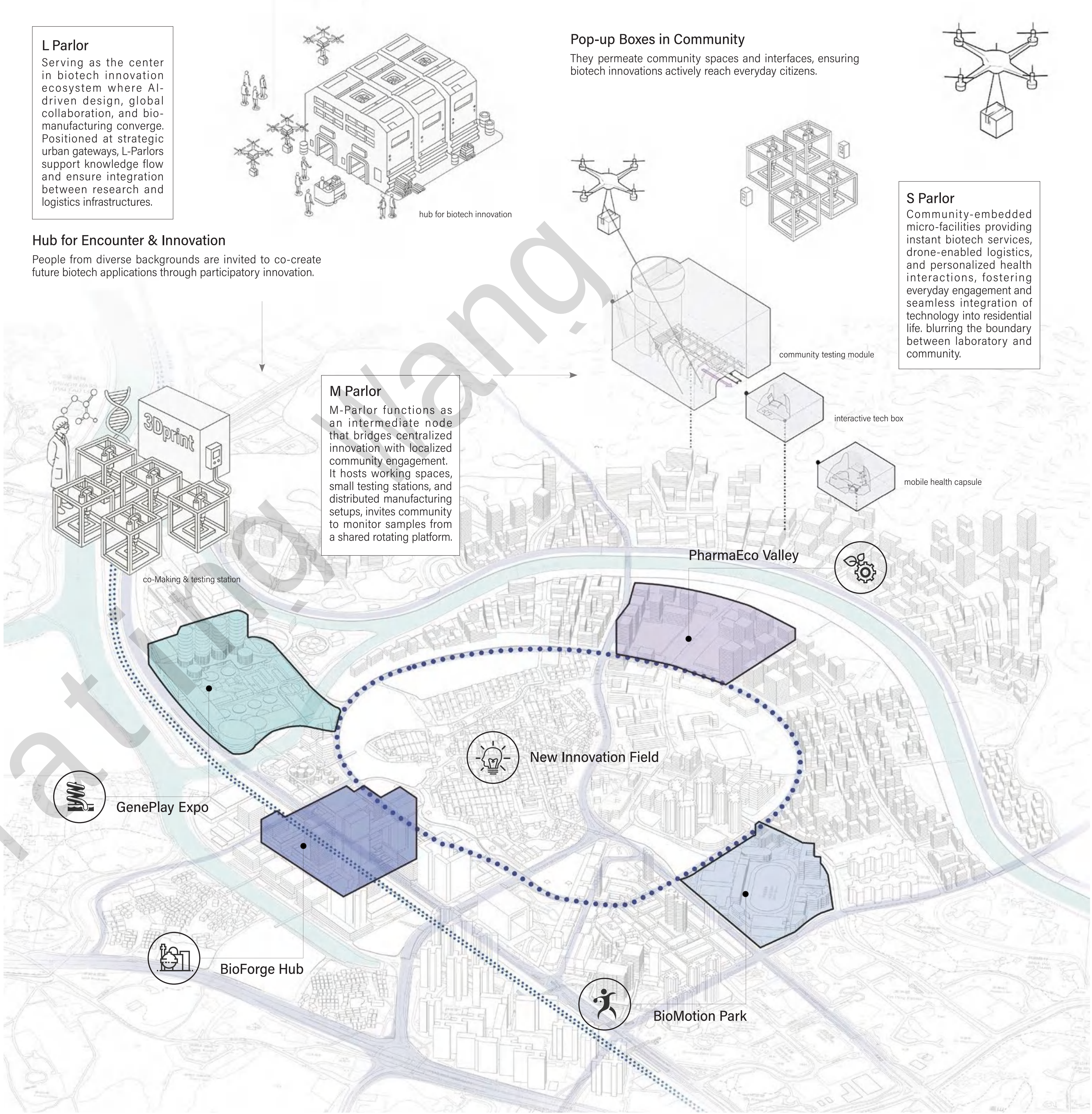
City Public Plaza



Street Interface



URBAN PARLOR | AN EXHIBITIONARY URBANISM



L Parlor

Serving as the center in biotech innovation ecosystem where AI-driven design, global collaboration, and bio-manufacturing converge. Positioned at strategic urban gateways, L-Parlors support knowledge flow and ensure integration between research and logistics infrastructures.

Hub for Encounter & Innovation

People from diverse backgrounds are invited to co-create future biotech applications through participatory innovation.

Pop-up Boxes in Community

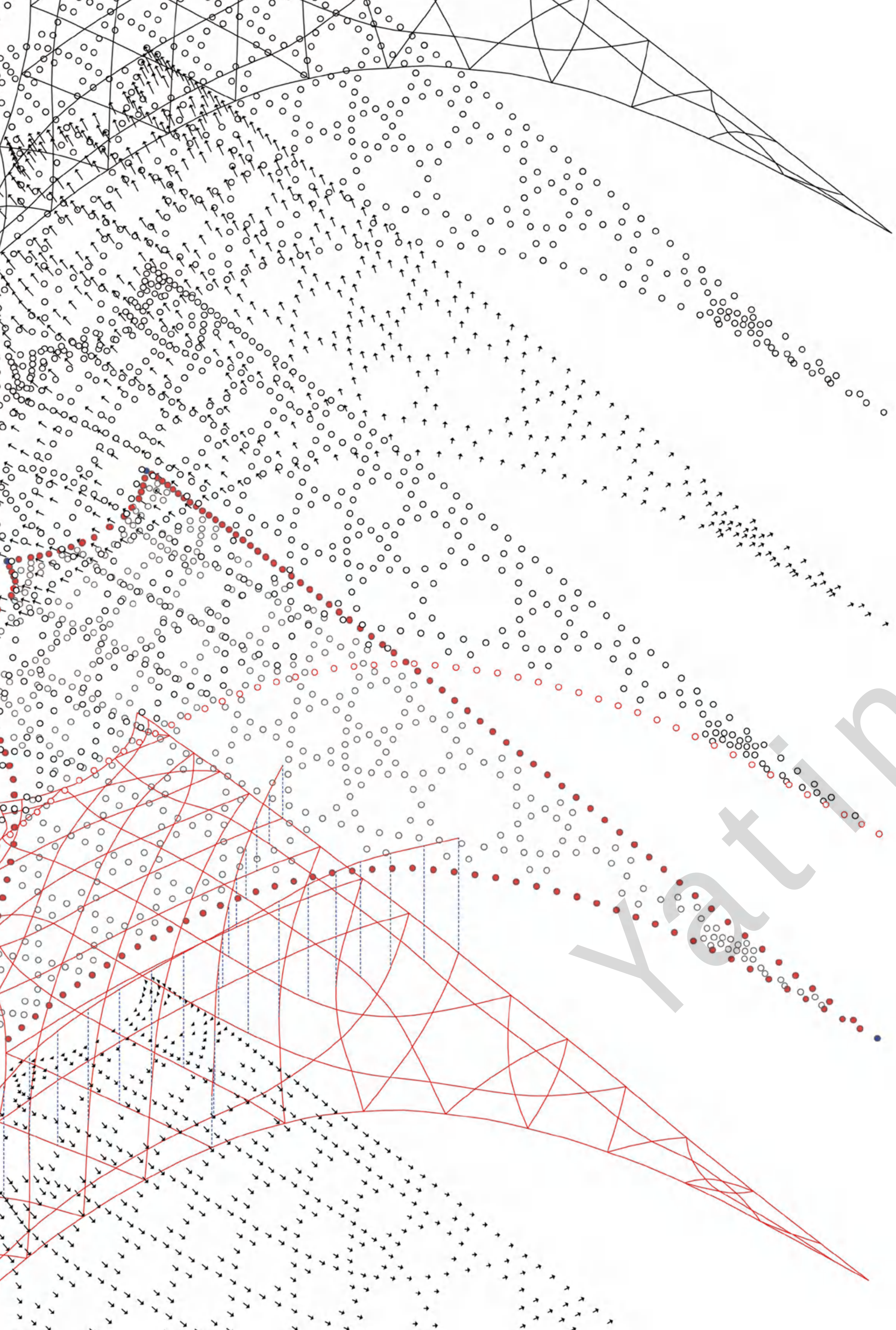
They permeate community spaces and interfaces, ensuring biotech innovations actively reach everyday citizens.

S Parlor

Community-embedded micro-facilities providing instant biotech services, drone-enabled logistics, and personalized health interactions, fostering everyday engagement and seamless integration of technology into residential life. blurring the boundary between laboratory and community.

M Parlor

M-Parlor functions as an intermediate node that bridges centralized innovation with localized community engagement. It hosts working spaces, small testing stations, and distributed manufacturing setups, invites community to monitor samples from a shared rotating platform.

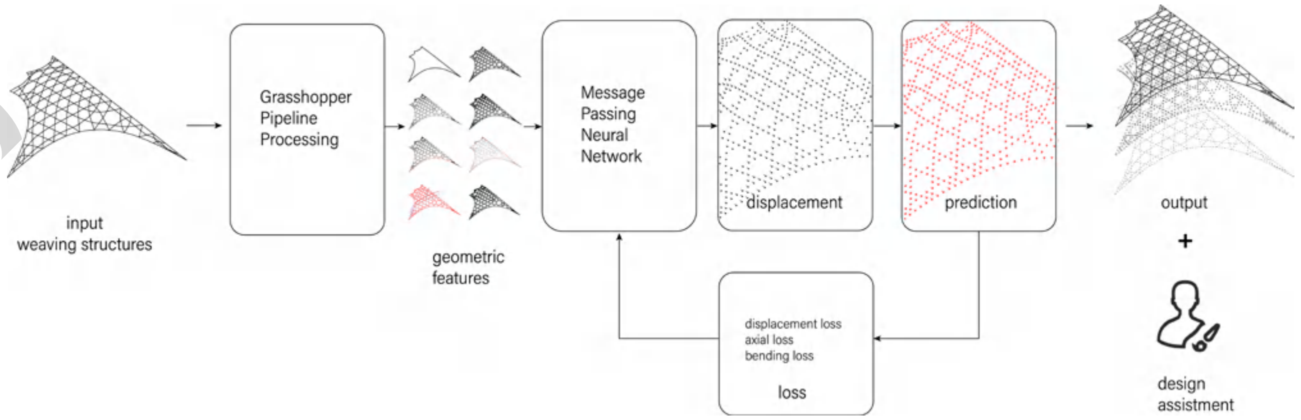


OTHER WORK 01

Displacement Prediction of Weaving Structures based on GNN

Group work | Weaving structure, GNN, CAAD

Instructor: Prof. Weixin Huang, huangwx@tsinghua.edu.cn

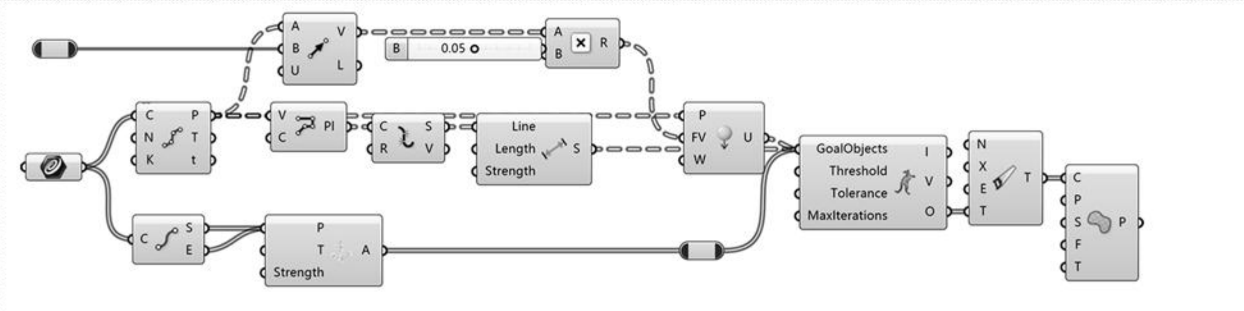


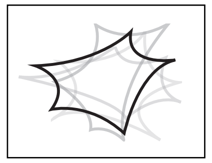
Builds a woven-structure dataset through a Grasshopper-based geometric and simulation pipeline.
Randomly generated base surfaces are rotated, scaled, and woven into diverse lattice typologies, with Karamba producing node-level displacement under external forces. This pipeline captures the geometric variability and nonlinear mechanical behavior inherent to woven systems.

Trains a MeshGraphNet-based GNN with physics-informed constraints tailored to woven mechanics.
The graph representation encodes anchors, flexible connections, and structural topology, while loss terms enforce hinge preservation, axial elasticity, bending energy, and anchor constraints.

Demonstrates a predictive tool that accelerates early-stage structural exploration.
The model achieves higher accuracy, robustness, and efficiency than conventional numerical simulations across complex woven geometries. It showcases the potential and engineering value of GNNs in architectural structural design.

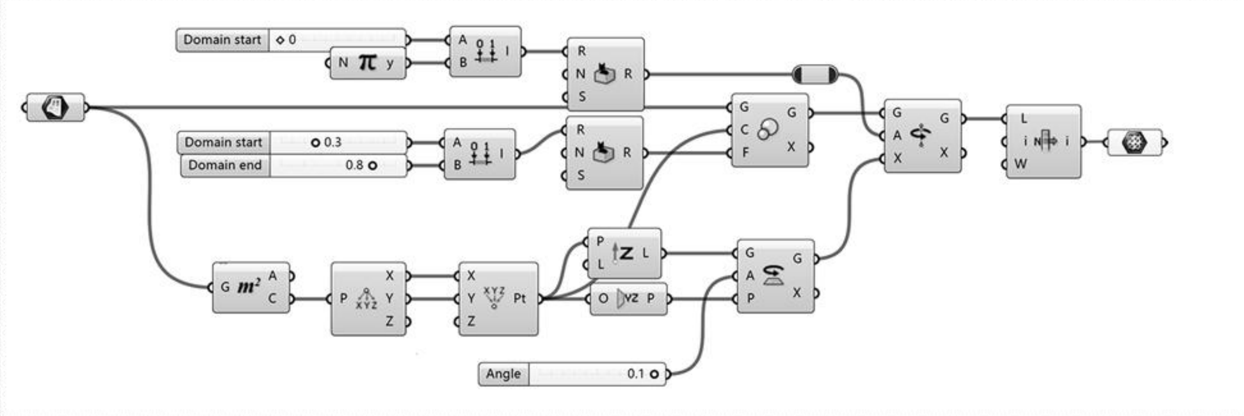
DATASET GENERATION | GRASSHOPPER PIPELINE

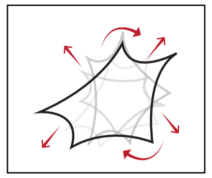




Generation of arch base surface

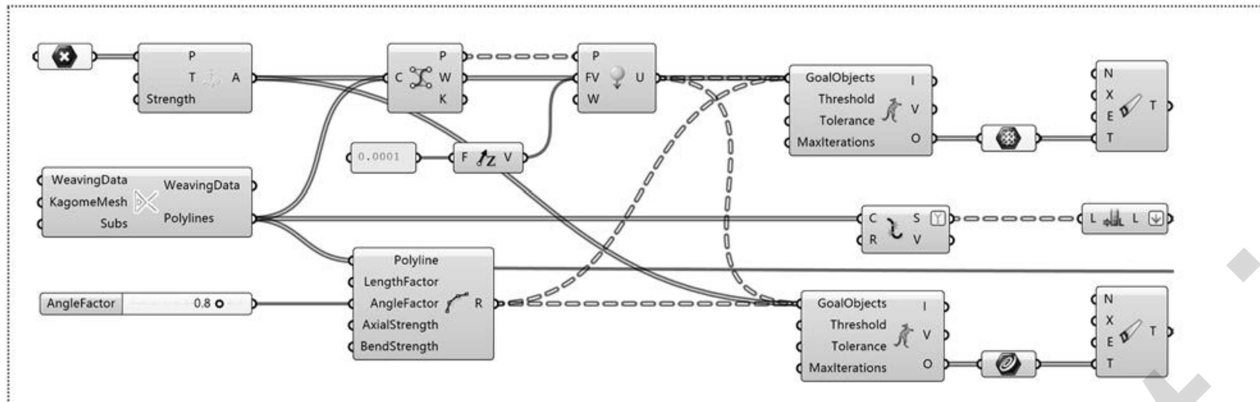
Step1: Random arch surface generation

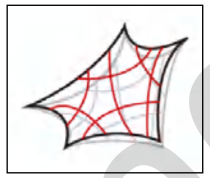




Random rotate and scale

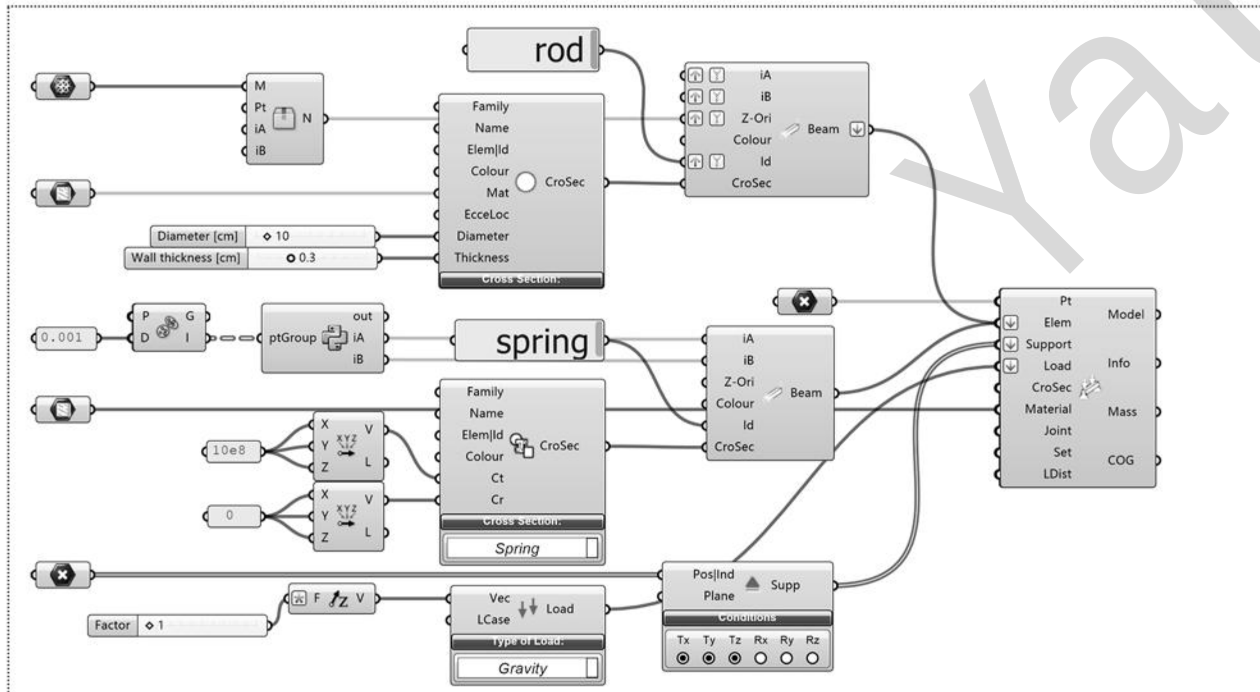
Step2: Random rotation and scaling of surface

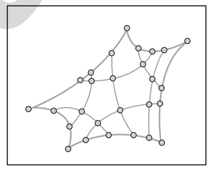




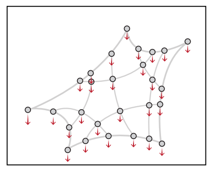
Weave mesh, relax geometry

Step3: Weaving structure generation and relaxation





Sample rod/spring simulate



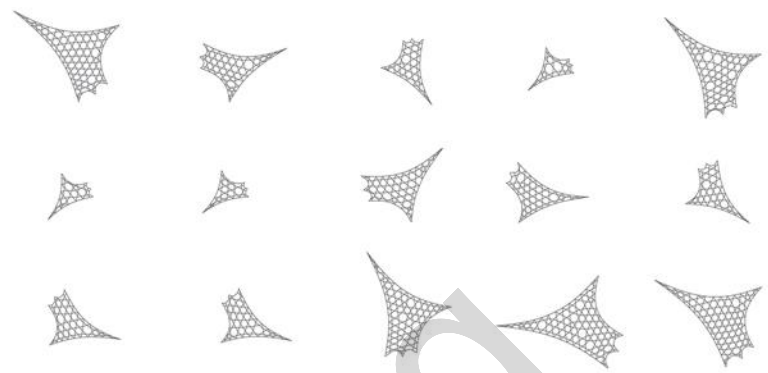
Karamba displacement graph out

Step4: Structural displacement calculation based on Karamba

Typological Forms

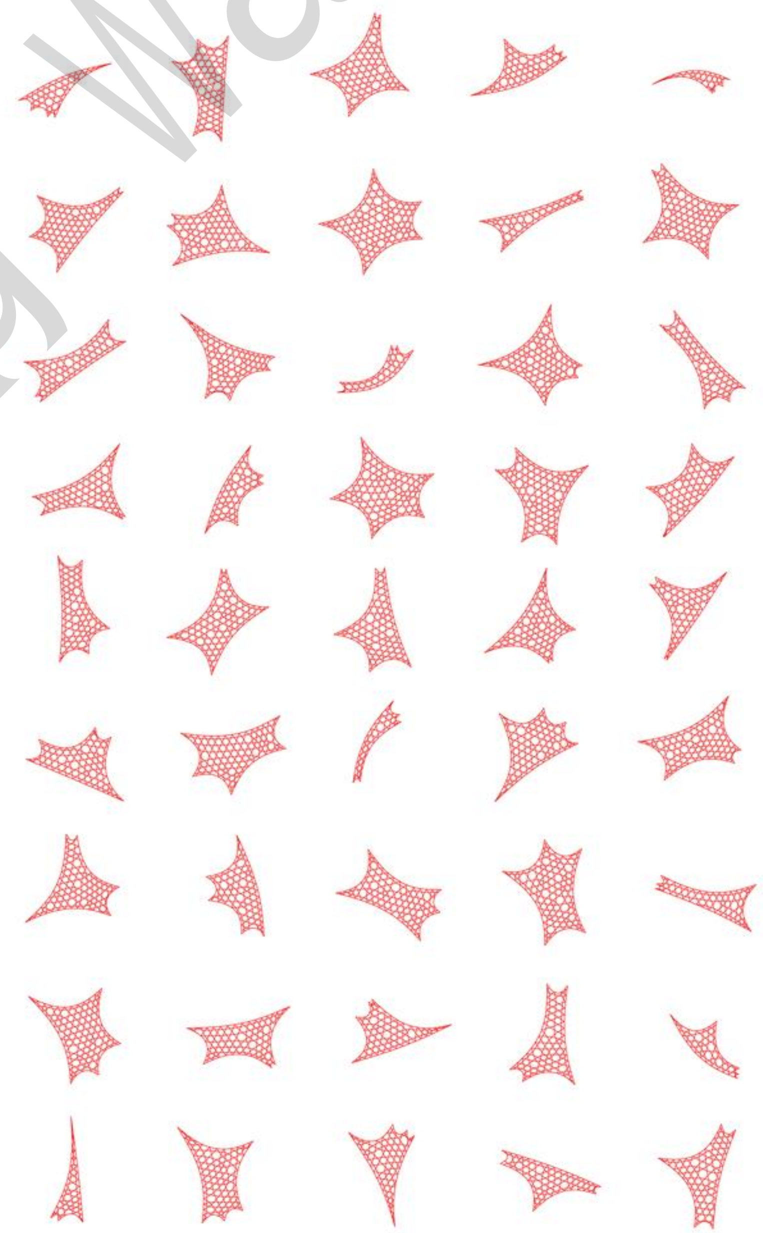
Dataset A for basic model and parameter tuning

Containing single topology structure and performing 500 rotations and scaling.



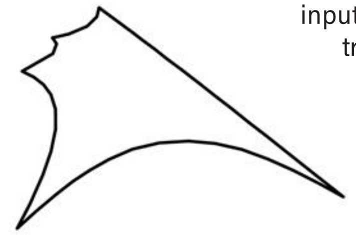
Dataset B for main model and validation of generalization

Containing 50 different topological forms, each with 100 variants, and introducing

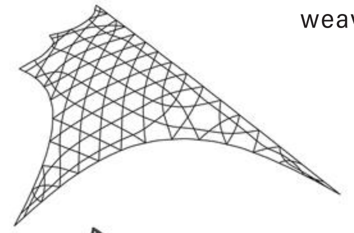


Graph Data for Training

input

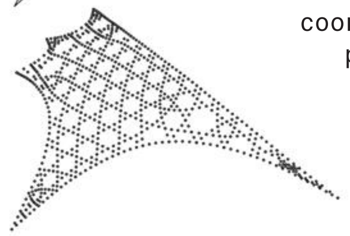


input mesh surface: triangulated base

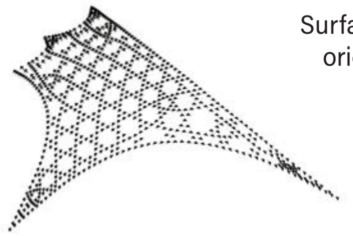


weaving structure: relaxed lattice

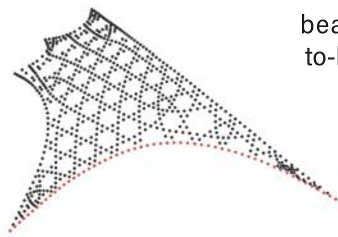
node attribution



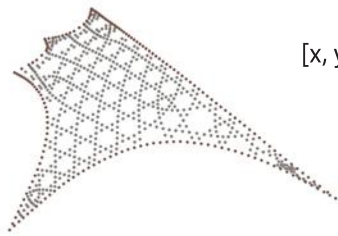
coordinates (x,y,z): position of vertex



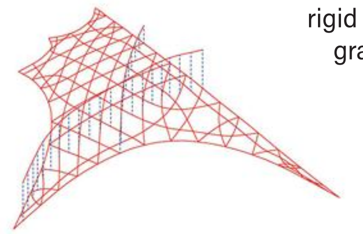
Surface normal: unit orientation vectors.



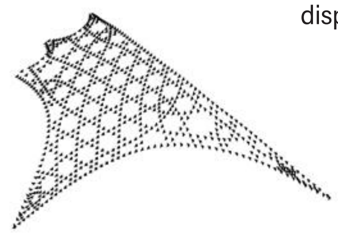
beam index: edge-to-beam mapping ID



features of point: [x, y, z, nx, ny, nz, tag]

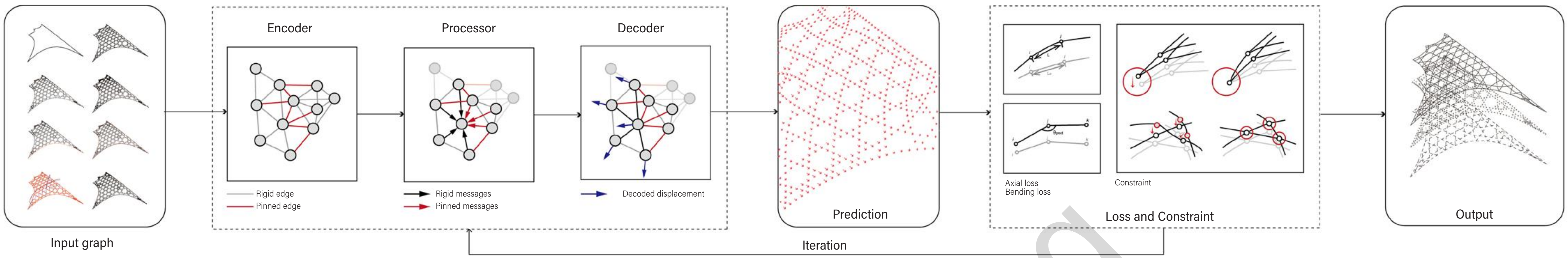


rigid & hinge edges: graph connectivity

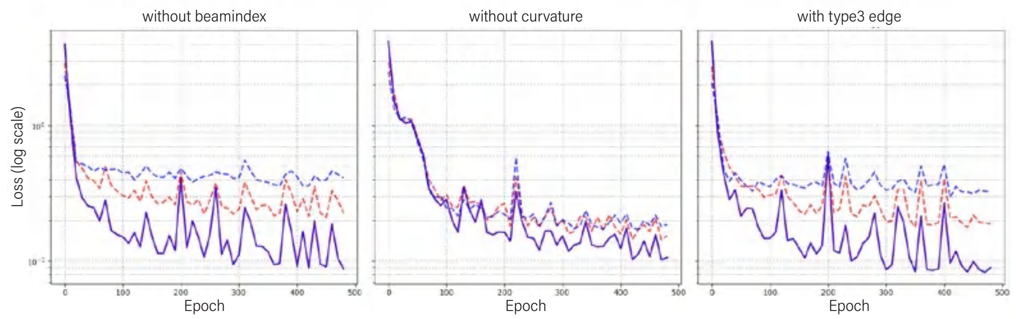


displacement: (x, y, z) from Karamba

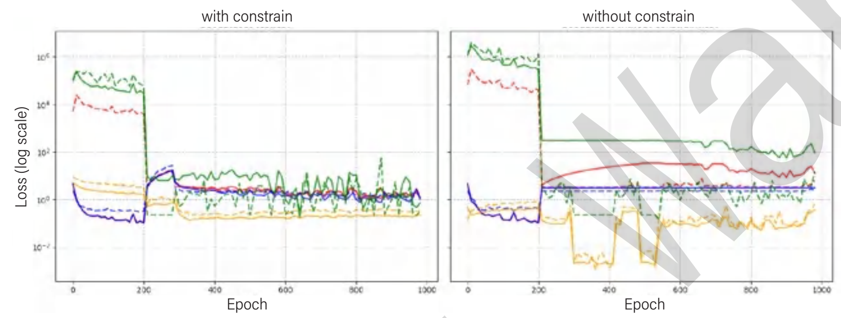
MODEL TRAINING & PREDICTION | GRAPH NEURAL NETWORK



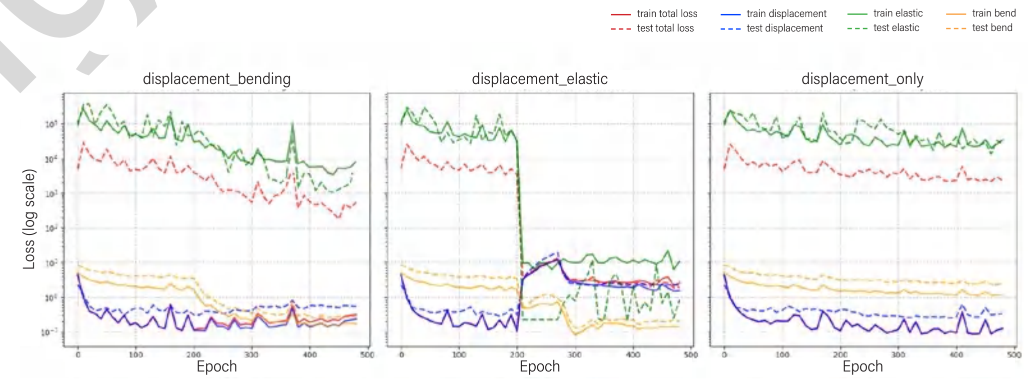
Method Framework for GNN Training



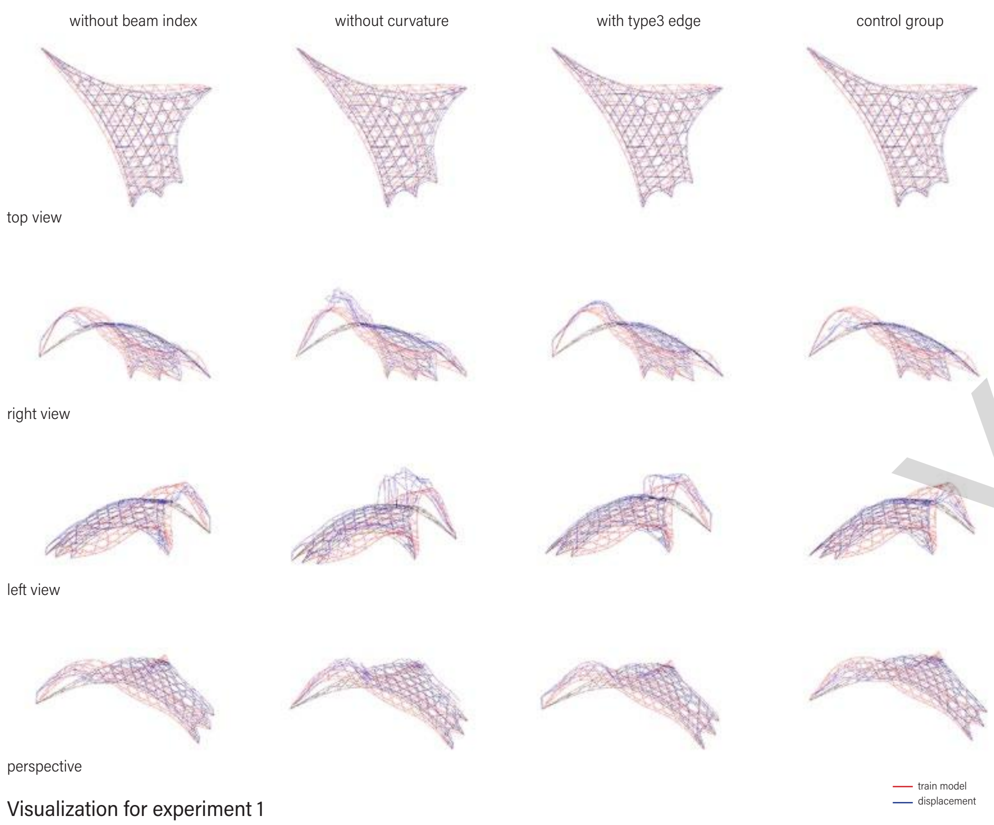
Loss comparison for experiment 1



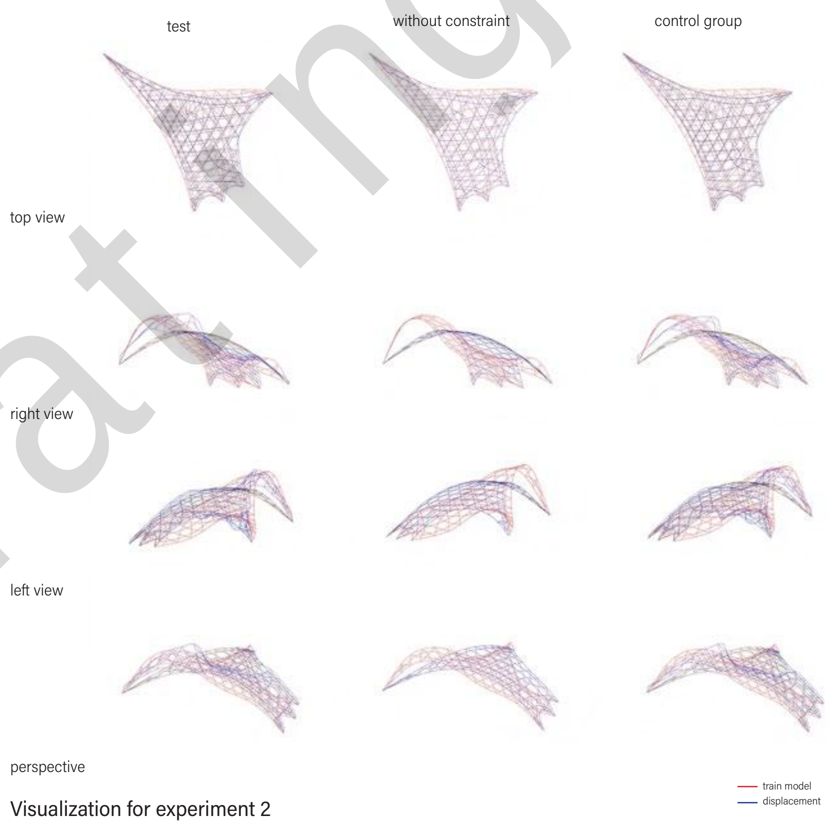
Loss comparison for experiment 2



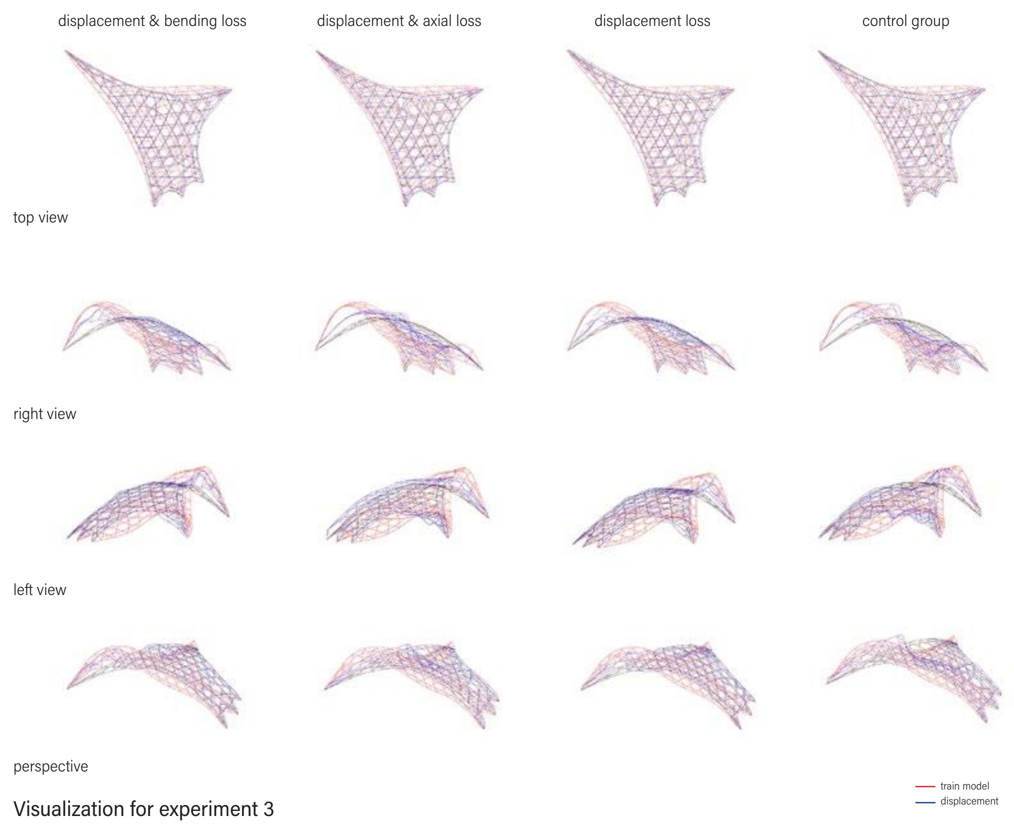
Loss comparison for experiment 3



Visualization for experiment 1



Visualization for experiment 2



Visualization for experiment 3

Performance evaluation of graph data modeling

From the loss curve and prediction visualization results, it can be seen that deleting the beam index or replacing the type-3 edges has no significant impact on training performance; after removing the curvature features, although the training loss decreases faster, the model shows evident physical fluctuations in the outputs on the test set, indicating poor stability; this suggests that curvature information is significantly important in capturing structural geometric constraints, helping the model learn more physically consistent dynamic behavior.

Ablation experiment of anchor points and hinge point constraint

The model showed a stagnation in loss during the early stages of training, with the final predicted displacement almost being zero, and the structural response lacked dynamic changes. Combining the trends of loss and output performance, it can be inferred that the model is unable to effectively learn the structural response patterns in the absence of boundary constraints, leading to the training getting trapped in a local optimum state of 'giving up on prediction'.

Ablation experiment of physical loss term

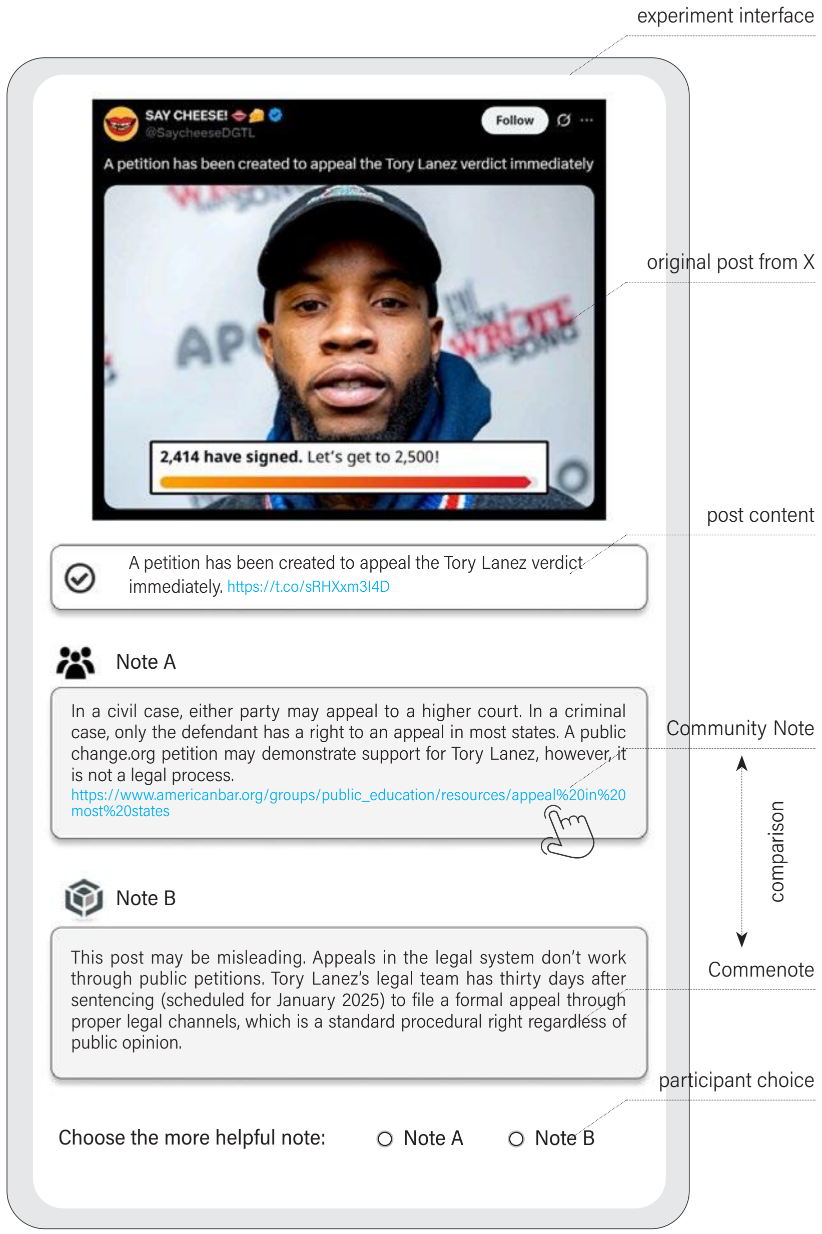
Models that use only displacement loss are prone to getting stuck in local optima. After adding bending loss, the model's deformation curvature shows slight improvement, but the effect is limited; with the introduction of axial loss, although the overall MSE shows a slight increase, the model's overall predictions become smoother and the structural responses are more physically reasonable. When all three loss terms are used together, the prediction results are closest to the true simulation state, enhancing model's structural perception ability and convergence stability.

OTHER WORK 02

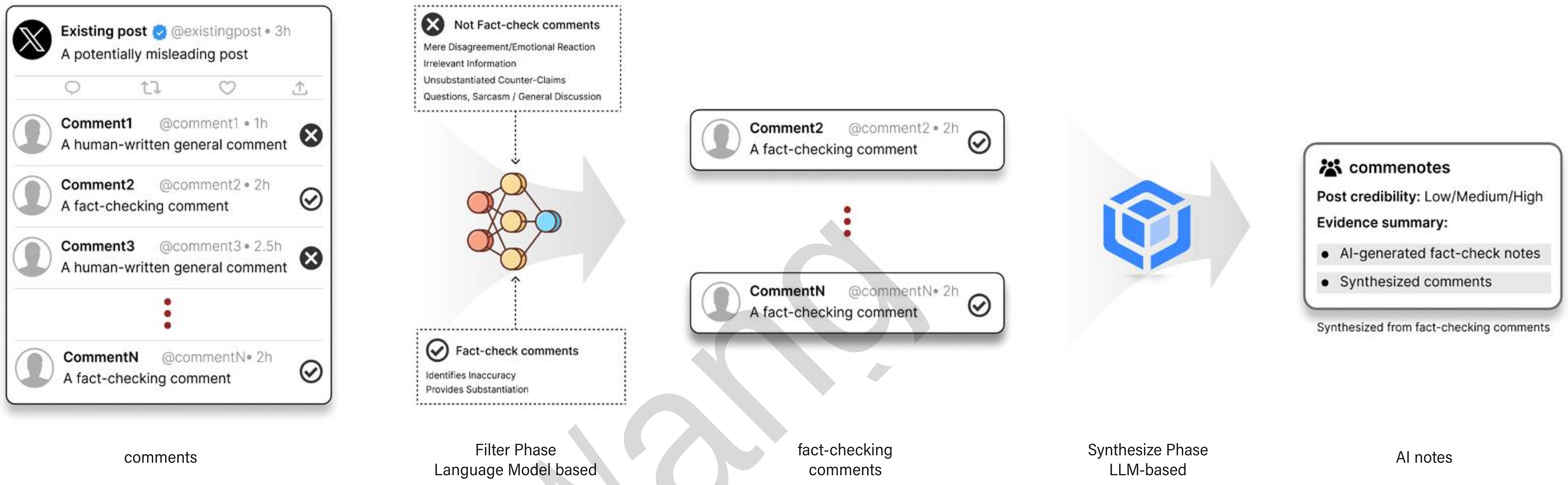
Commenotes:
Synthesizing Organic Comments to Support Community-Based Fact-Checking

Group work | LLM Synthesization, Misinformation Intervention, User Study
Instructor: Prof. Xin Yi, yixin@tsinghua.edu.cn

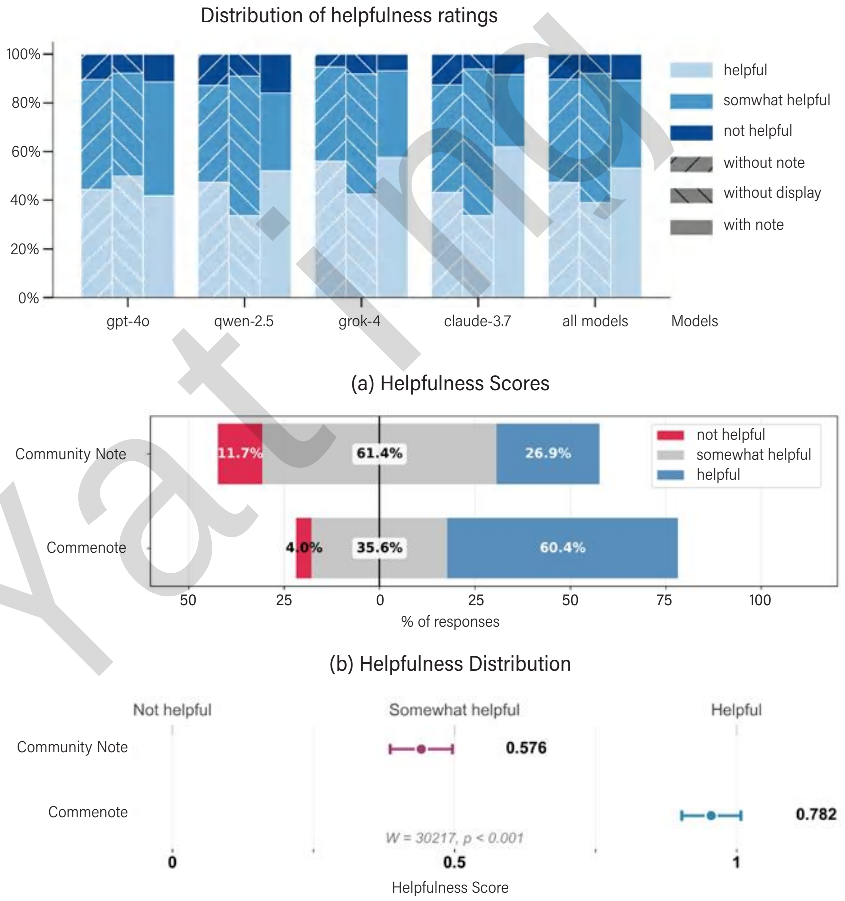
Community-based fact-checking is promising to reduce the spread of misleading posts at scale. However, its effectiveness can be undermined by the delays in fact-check delivery. Notably, user-initiated organic comments can contain debunking information and have the potential to help mitigate this limitation. Here, we investigate the feasibility of using LLM to synthesize comments and generate timely high-quality fact-checks. To this end, we analyze over 2.2 million replies on X and introduce Commenotes, a two-phase framework that filters and synthesizes comments to facilitate fact-check delivery. Our framework reveals that fact-checking comments appear early and sufficiently: 99.3% of misleading posts receive debunking comments within the initial two hours since post publication, with synthesized commenotes successfully earning user trust for 85.8% of those posts. Additionally, a user study (N=144) find that synthesized commenotes are often preferred, with the bestperforming model achieving a 70.1% win rate over human notes and rated as more helpful in all dimensions.



Research Framework

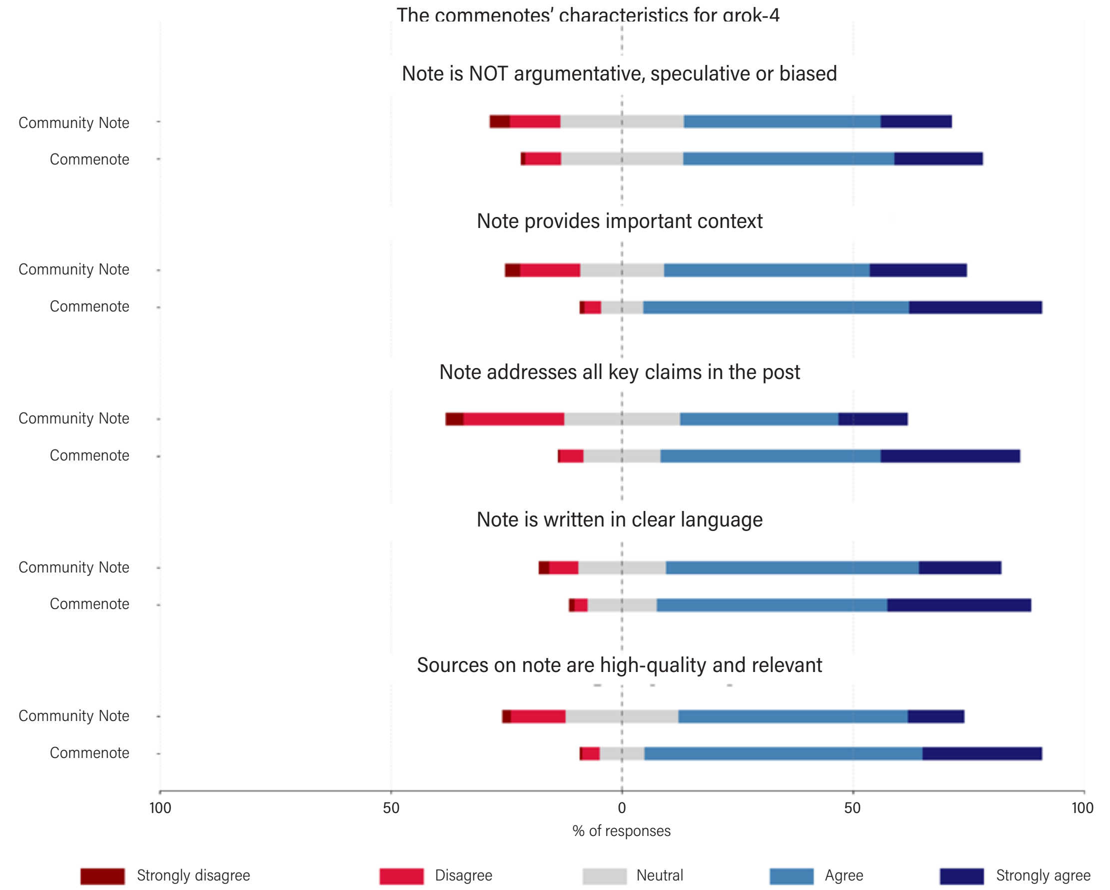


User Preference and Overall Helpfulness



We conducted a user study comparing AI-synthesized commenotes with human-written Community Notes. As shown in the figure, commenotes were consistently rated as more helpful. Figure 6 further shows that a large majority of users preferred commenotes, with the best model achieving a 70.1% win rate. These results highlight that commenotes are not only accurate and clear, but also more trusted and well-received—supporting their value as a scalable fact-checking tool.

User Ratings on Note Characteristics



To assess the quality of synthesized notes beyond overall helpfulness, we evaluated user perceptions across five key dimensions: quality, clarity, coverage, context, and impartiality—aligned with the official Community Notes rating guidelines. As shown in the figure, Commenotes received high ratings across all dimensions, with particularly strong scores in clarity and coverage, suggesting that LLMs are effective in summarizing diverse user inputs into clear, informative notes that comprehensively address misleading claims. Importantly, the ratings on impartiality were comparable to human-written notes. These results highlight the ability of Commenotes to generate timely and trustworthy fact-checking content.

FILM PHOTOGRAPHY

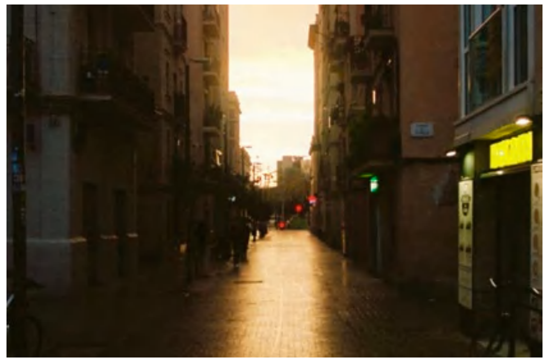
Glimpses of a City, Developed in Light and Time

Street of Istanbul, Turkey
Kodak Tri-X 400 | 2025.01

St. Peter's Square, Vatican City
Kodak Gold 200 | 2023.02

Rijksmuseum, Amsterdam
Fujicolor C200 | 2023.07

The Colosseum Heritage, Rome
Kodak Ultramax 400 | 2024.01



Golden hour of Barcelona, Spain
Kodak Gold 200 | 2024.02

Walk the city with data in mind and people at heart.

Gratitude for all my friends, mentors and family who have helped me in finishing this portfolio