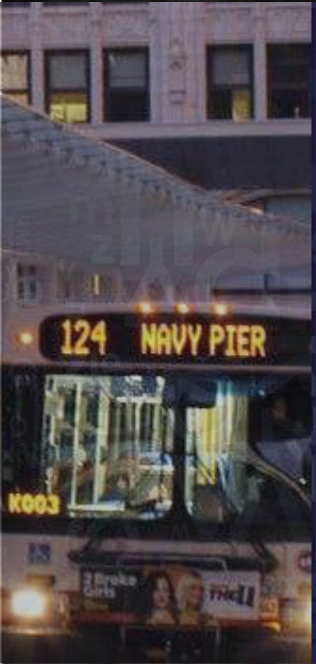
Control

Assist

AI for Bus Dispatching to Improve Reliability

Joseph Rodriguez, Haris Koutsopoulos & Jinhua Zhao

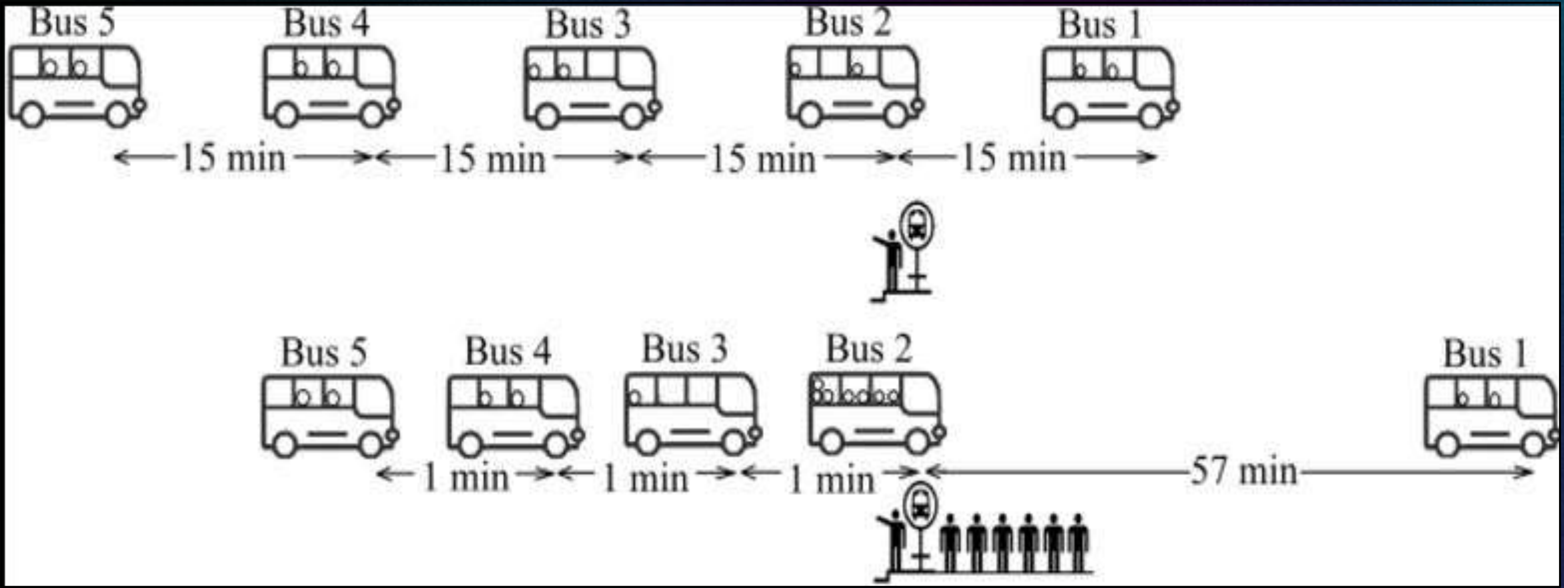


JTL URBAN MOBILITY LAB AT MIT

Transit Lab


1 HARVARD

Bus bunching



Control strategy

At the bus terminal,

1. **Hold the bus by 1 min, 2 mins, 3mins, …**
2. **Move departure time forward by 1 min, 2 mins, 3 mins,…**

Transit agencies experience major service reliability issues caused by driver shortage and driver absenteeism


TransitCenter

Bus Operators in Crisis

The Steady Deterioration of One of Transit's Most Essential Jobs, and How Agencies Can Turn Things Around

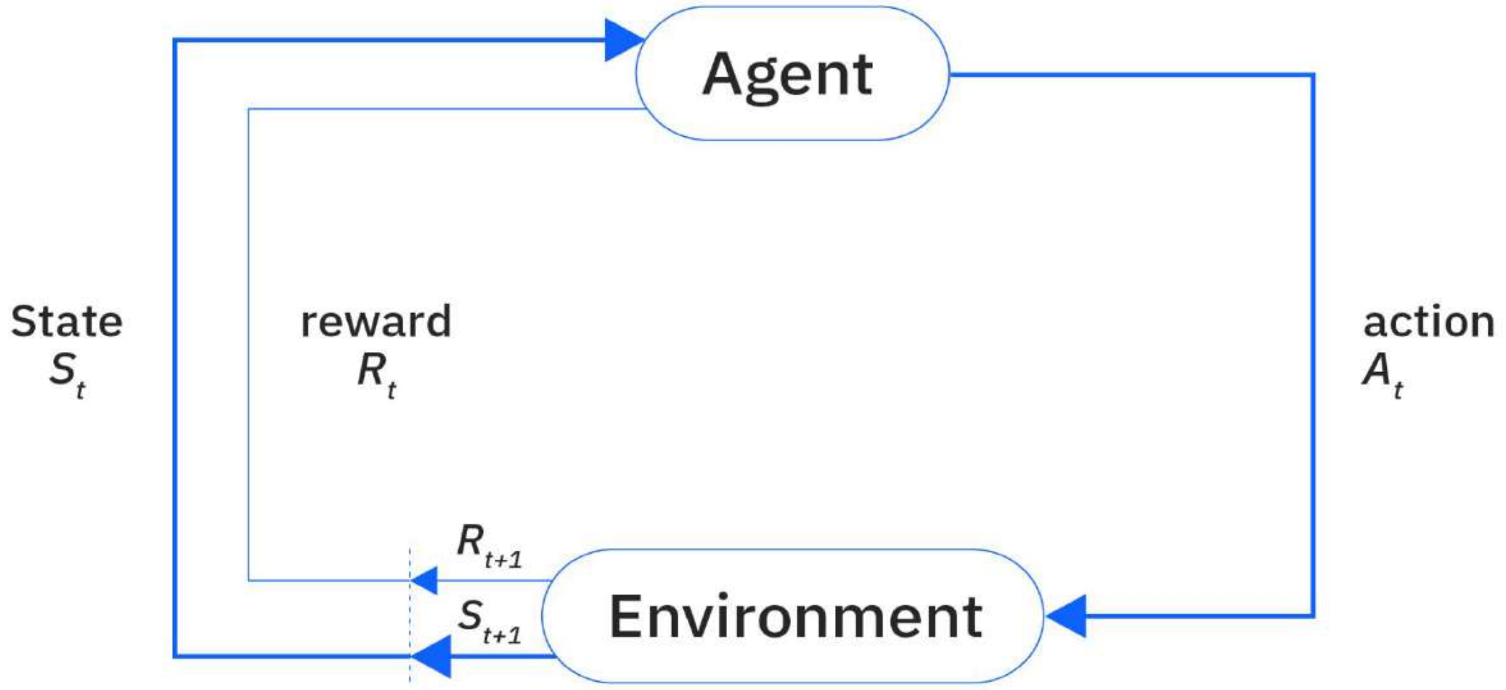
CTA Service delivered: 84%

Improve service reliability through bus control using reinforcement learning

Robustness to uncertainties:

- Demand uncertainty: # of passengers
- Supply uncertainty: driver absenteeism

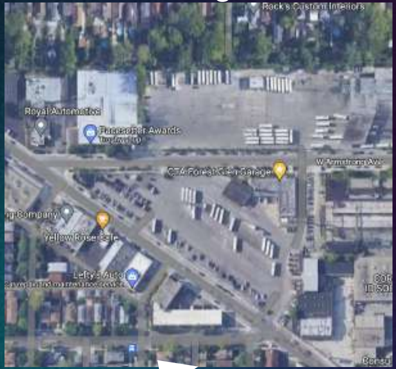
- Environment uncertainty: traffic conditions
- Operation uncertainty: non-compliance
- Information uncertainty: Incomplete or inaccurate


Agent
State
S_t
reward
R_t
action
A_t
R_{t+1}
S_{t+1}
Environment

Human in the loop #1: Bus route 81 (actual) vs. 20 (initial)

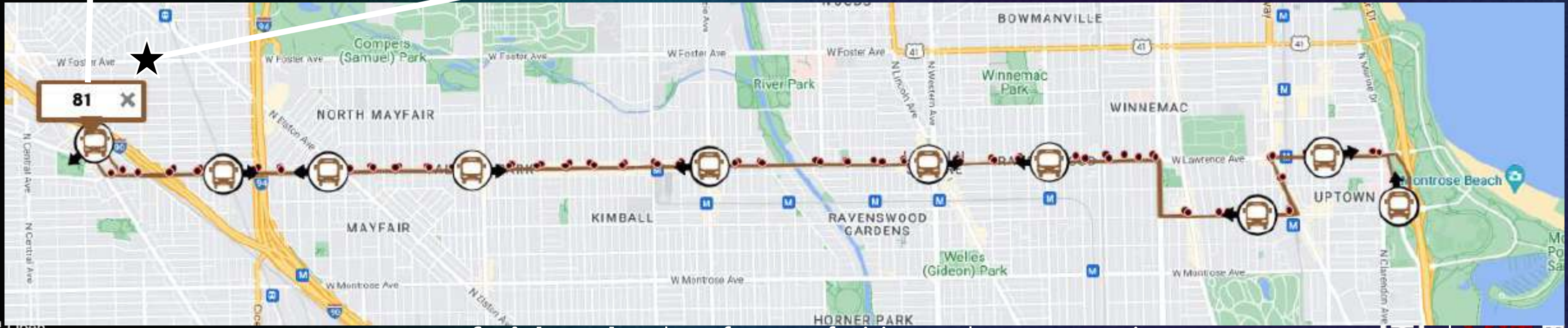
Terminal: Jefferson Park, serves 10 routes

Garage: Forest Glen, North Chicago routes

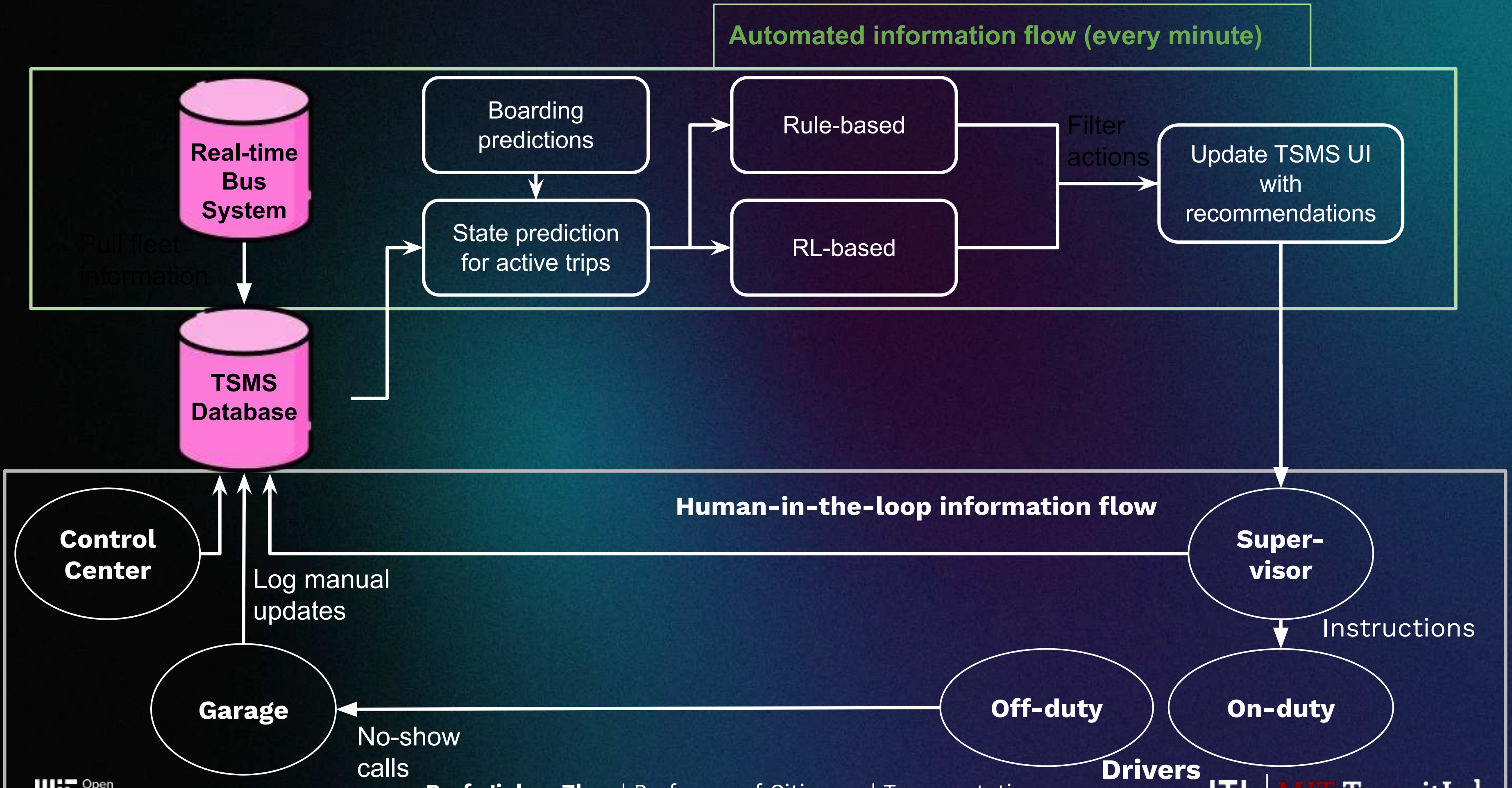


Route:

- ➔ 4 transfers to subway
- ➔ 50 stops each direction
- ➔ AM peak: 6-9 mins
- ➔ 15-25% missing trips
- ➔ 7,500 riders per weekday



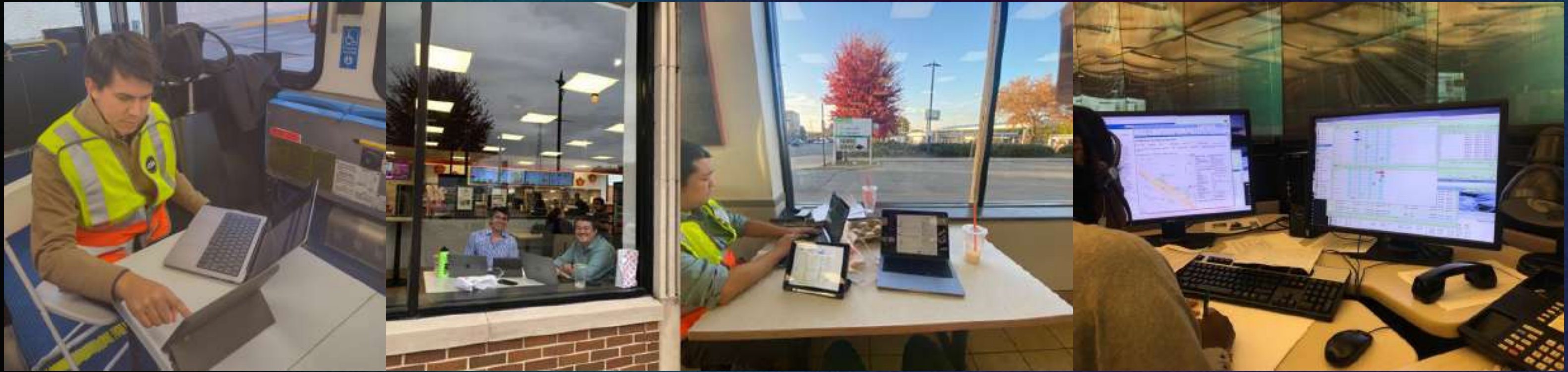
Human in the loop #2: AI recommendation → Human control execution



Human in the loop #3: Field experiment in Chicago

Substantive support from the Chicago Transit Authority (CTA)

- President and CAA
- VP operation
- Garage supervisors
- Drivers



MIT developed the real-time control TSMS database, algorithm, and user interface

Impacts

Excess Waiting Time: reduced >30%

Impacts of Our Control Strategy: Performance Evaluation

<u>Access wait time by # of bus trips in AM period (6-9am)</u>

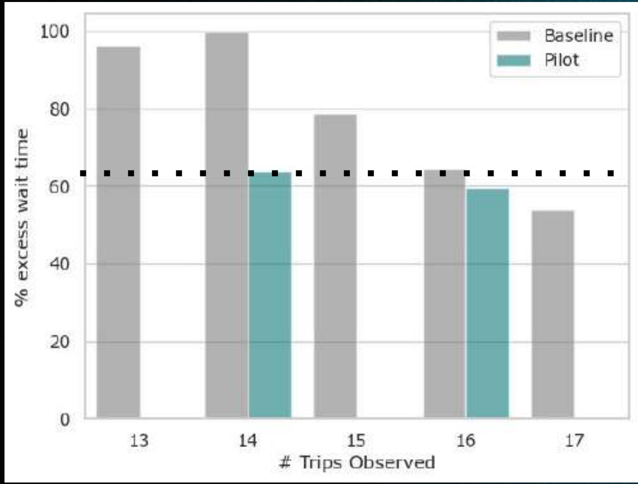
37% reduction,
equivalent to adding 2 trips

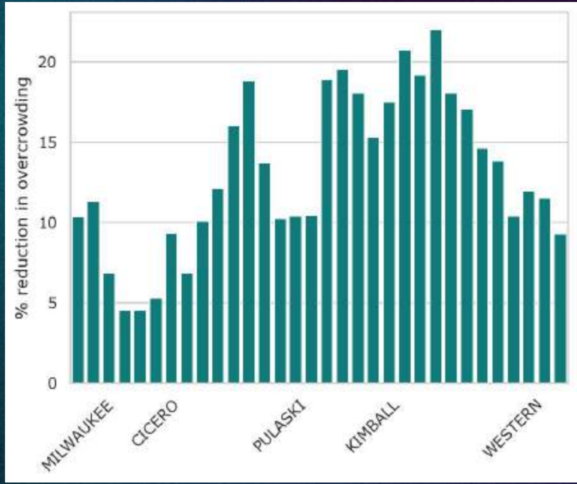
<u>Overcrowding</u>

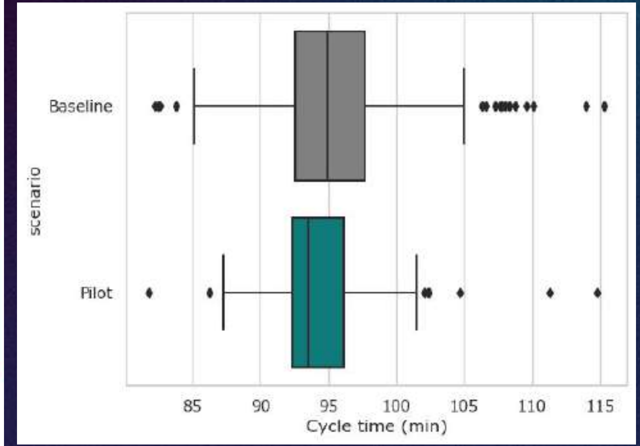
5-20% reduction

<u>90th Cycle Times</u>

2.5 minutes reduction
(2.4%) reduction



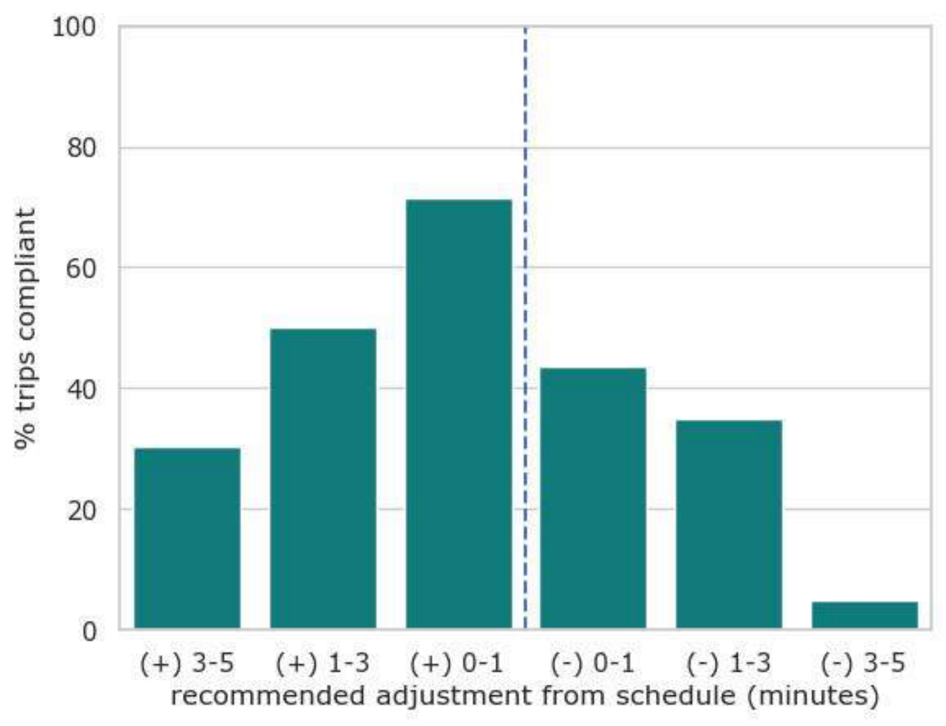




Observation #3

Do drivers follow the AI guidance?

Human in the loop #4: Do drivers follow A.I.?



Driver compliance decreases with the aggressiveness of the recommended control actions.

Robustness to operational uncertainties

	Average excess wait time reduction (mins)		
Baseline (minutes)	Trips with information issues	Trips with non-compliant drivers	Trips with compliant drivers
3.6	Reduce 0.7 mins (19%)	Reduce 0.7 mins (19%)	Reduce 2.1 mins (58%)
	90th percentile headways reduction (mins)		
27.6	Reduce 7.2 mins (26%)	Redue 5.8 mins (21%)	Reduce 11.2 mins (40%)

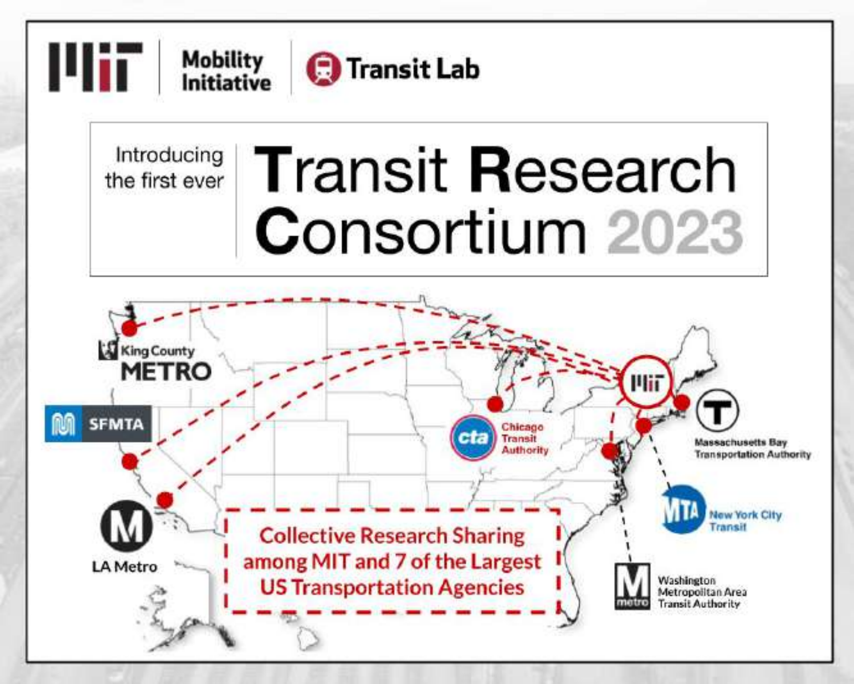
Robustness to uncertainties: Driver compliance

	90th percentile headways	
Baseline (minutes)	Trips with non-compliant drivers	Trips with compliant drivers
27.6	21.8 (-21%)	16.4 (-40%)

Knowledge Transfer: MIT → Chicago

Category	Pilot (BP2)	Full-scale (BP3)
Time period	1 week	1 month
Routes	81	All routes at the Jefferson Park terminal
Control actions	Terminal dispatch	Mid-route holding, dynamic interlining, short-turning
Implementation	RAs overseeing operations	CTA staff takes over the software

Scaling Up: the US transit industry at large



Observation #4

Human in the loop

- Control level
- Garage level
- Organizational level

Create

Work

AI for Generative Urban Design

Qingyi Wang, Shenhao Wang, Mingyi He, Yuebing Liang & Jinhua Zhao

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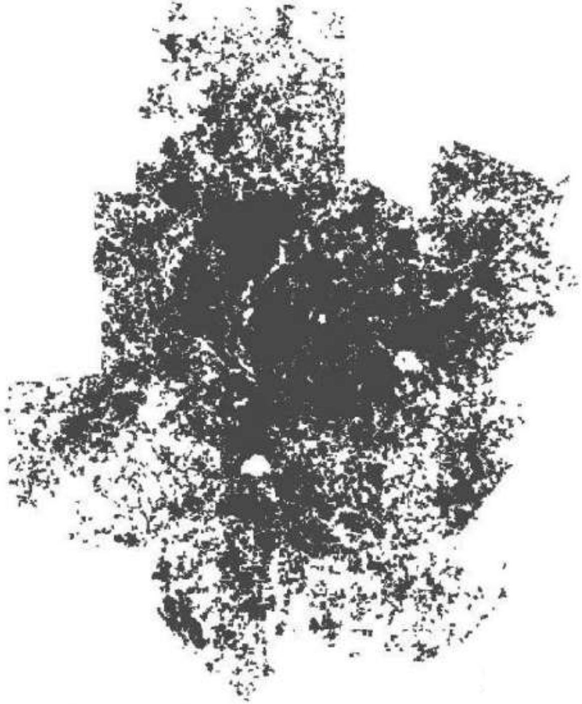
Mobil

The New York High Line

Decarbonize Mobility: Urban structure is the starting point

Atlanta, USA
Population: 2.5 million (1990)
Built-up Area: 4,280 sq. km.



Barcelona, Spain
Population: 2.8 million (1990)
Built-up Area: 162 sq. km.

(15 minute city)

Source: Alain Bertaud and Harry Richardson, Transit and Density: Atlanta, the United States and Western Europe.
https://www.researchgate.net/publication/248151171_Transit_and_Density_Atlanta_the_United_States_and_Western_Europe/download

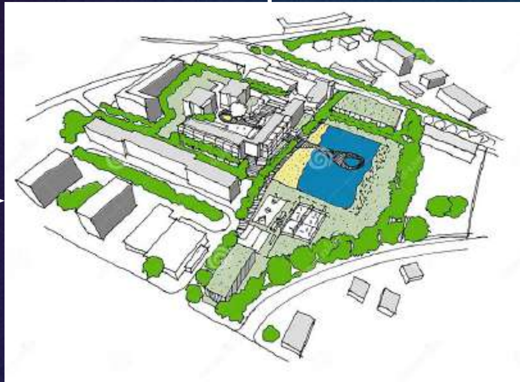
Typical planning process

Zoning, Policy, Traffic, Social interactions, Natural Environment, Infrastructure, Public Engagement, ……

Feedback and Iterate (weeks and months)

Urban Planner

Generate plans, layouts and visualizations



https://www.123rf.com/photo_16135751_sketch-of-a-new-development-urban-idea.html

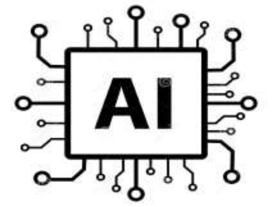
The human-machine planning collaboration

Zoning, Policy, Traffic, Social interactions…

Urban Planner

Human Guidance

Give me a design in Chicago with 70% apartments, 10% park, 10% retail, and a lot of green space!



Generative AI

Generate Designs

Feedback and Iterate (minutes)

What do planners want?

An Example

A piece of land 35 mile north of downtown Chicago

A target land use

- 35% residential
- 15% commercial
- 10% open parking

What do planners want?

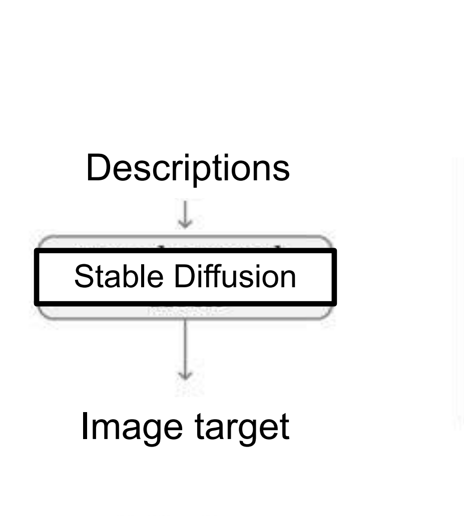
Expectations of Generative Planning Tools

1. Having **control** over AI-generated land-use patterns
2. **Respecting** existing infrastructure and natural environment
3. Learn and apply **different urban textures**

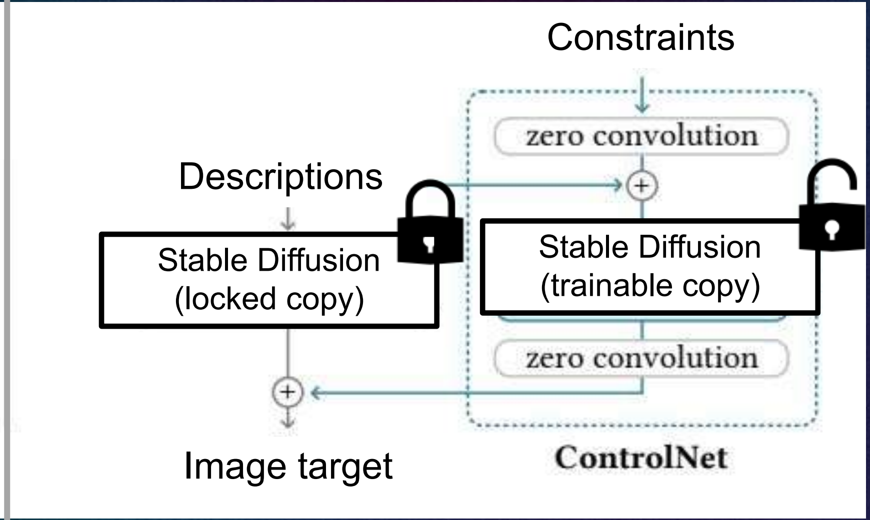
Can A.I. do it?

Fine-tuning stable diffusion using ControlNet

Stable Diffusion



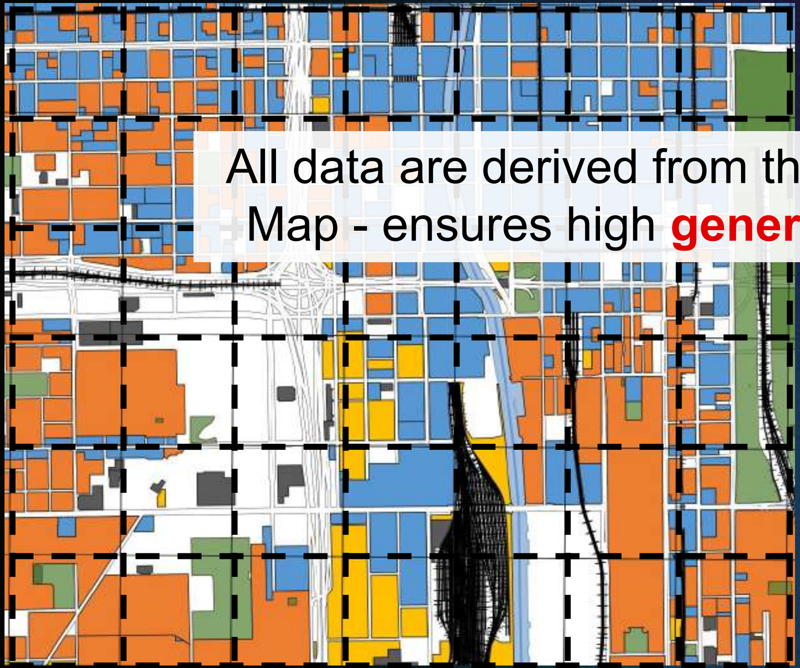
Stable Diffusion with ControlNet



Data: Open Street Map

OpenStreetMap

Land use patterns



Existing infrastructure and natural environment

All data are derived from the publicly available Open Street Map - ensures high **generalizability** and **reproducibility**

Residential | Commercial | Park | Industrial | Open parking | Farmland

A piece of land 35 mile north of downtown Chicago

A target land use

- 35% residential
- 15% commercial
- 10% open parking

A piece of land 35 mile north of downtown Chicago

A target land use
- 65% industrial,
- 20% commercial,
- 5% open parking

A piece of land 35 mile north of downtown Chicago

A target land use

- 100% residential

1. Having **control** over AI-generated land-use patterns

35% residential,
15% commercial,
10% open parking

65% industrial,
20% commercial,
5% open parking

100% residential

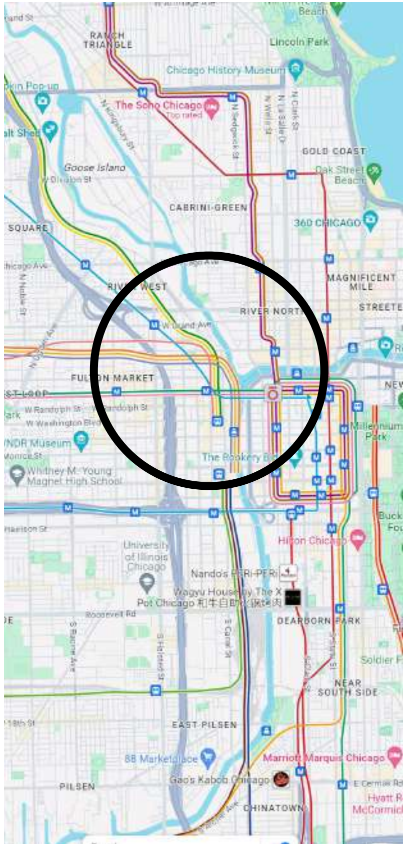
2. Respecting **existing** infrastructure and natural environment

Descriptions

City in Chicago.
35% residential
20% commercial,
5% open parking.
Mix of houses and apartments.
Dense building coverage.

Constraints

Generated Aerial Imagery



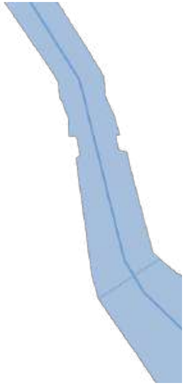
2. Respecting existing infrastructure and natural environment

Add waterways

Descriptions

City in Chicago.
35% residential
20% commercial,
5% open parking.
Mix of houses and apartments.
Dense building coverage.

Constraints



Generated Aerial Imagery

2023-12-05

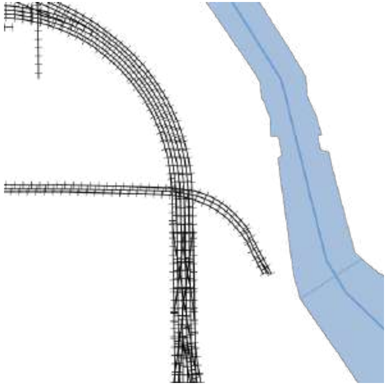
2. **Respecting existing** infrastructure and natural environment

Add railways

Descriptions

City in Chicago.
35% residential
20% commercial,
5% open parking.
Mix of houses and apartments.
Dense building coverage.

Constraints



Generated Aerial Imagery

2. **Respecting existing** infrastructure and natural environment

Descriptions

City in Chicago.
35% residential
20% commercial,
5% open parking.
Mix of houses and apartments.
Dense building coverage.

Constraints

Add roads

Generated Aerial Imagery

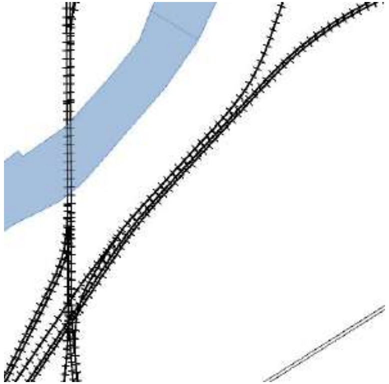
True Satellite Image

3. Learn and apply **different urban textures**

Descriptions

City in {city name}.
40% residential
15% industrial,
15% commercial,
10% park,
5% open parking.
All houses.
Medium building coverage.

Constraints



Chicago

Dallas

Los Angeles

What do planners want?

Expectations of Generative Planning Tools

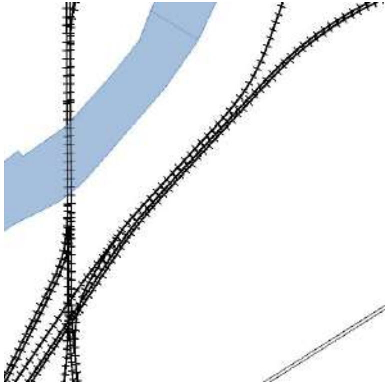
1. Having **control** over AI-generated land-use patterns
2. **Respecting** existing infrastructure and natural environment
3. Learn and apply **different urban textures**

Bonus: Producing **alternate** designs for the same inputs

Descriptions

City in Chicago.
40% residential
15% industrial,
15% commercial,
10% park,
5% open parking.
All houses.
Medium building coverage.

Constraints



Design 1

Design 2

Design 3

How do planners and AI work together?

Generative Urban Design

A Stepwise Approach Integrating Human Expertise with Diffusion Models

Mingyi He
(mingyihe@mit.edu)

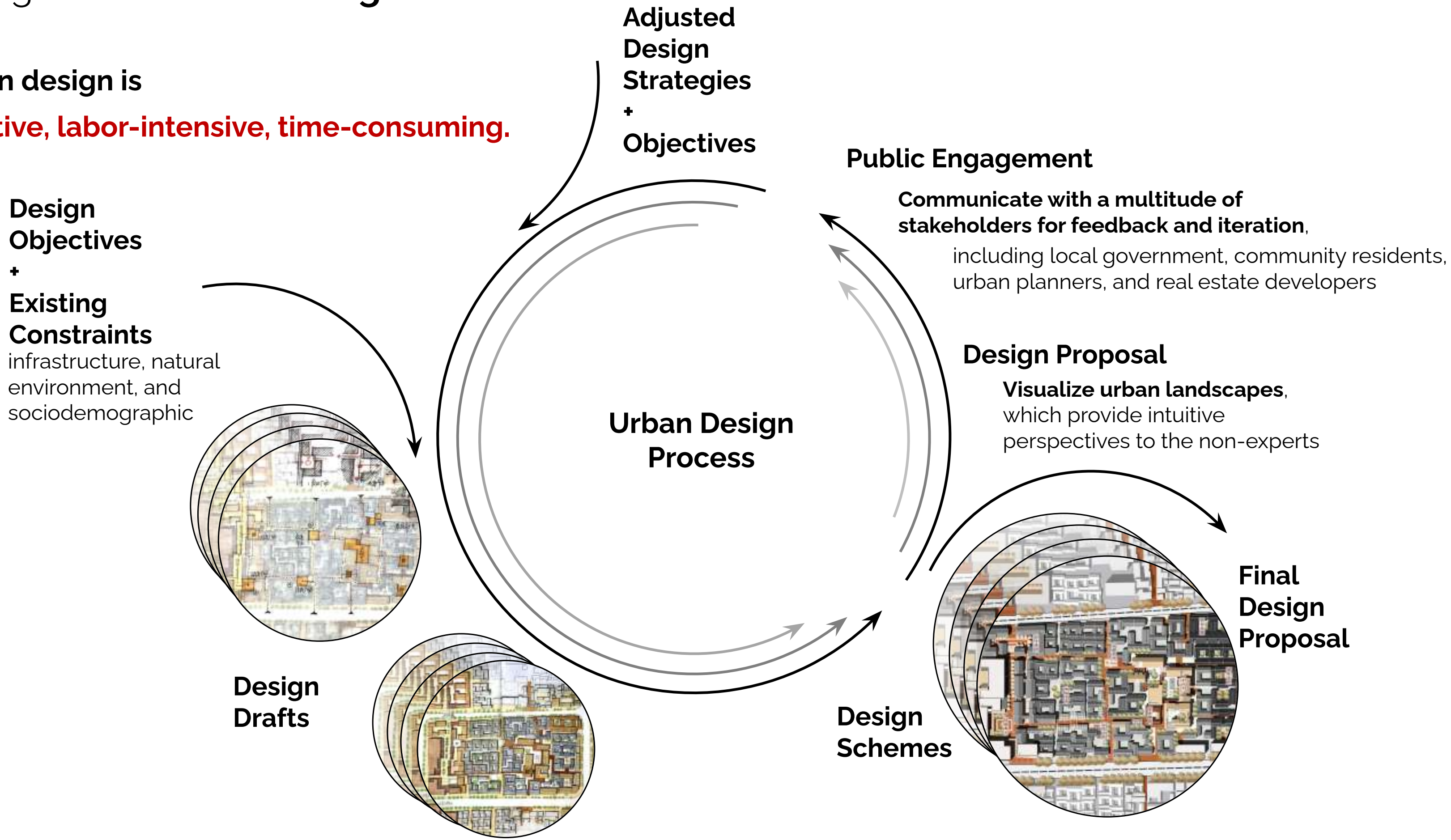
Massachusetts Institute of Technology

He, M., Liang, Y., Wang, S., Zheng, Y., Wang, Q., Zhuang, D., Tian, L., & Zhao, J. (2025). *Human-guided urban form generation using multimodal diffusion models.* **Building and Environment**, Article 113892. https://doi.org/10.1016/j.buildenv.2025.113892

Background / **Urban Design**

Urban design is

iterative, labor-intensive, time-consuming.



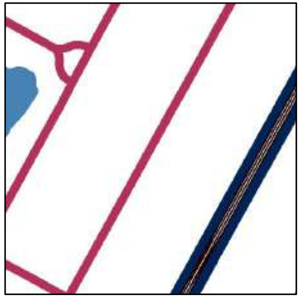
Research Gap / **Generative Urban Design**

GenAI has potential to enhance design efficiency, support participatory design…
Existing approaches fall short of addressing real-world design complexities…

Incorporating site constraints and expert input ?

Iterative refinement for public participation ?

Evaluation on AI adherence to human designers ?



Input:
Site constraints

Human Expertise x **Diffusion Models**

Output:
Final urban layout

Research Framework / **Human-Centered AI for Urban Design**

A Stepwise Approach Integrating Human Expertise with Diffusion Models

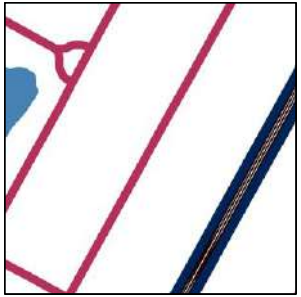
Human-in-the-loop Design Process:

Integrates human expertise with AI capabilities.
Human designers maintain control over the design process, enabling iterative adjustments and refinements at each stage.

Stage 1 - Road Network and Land Use Planning

Stage 2 - Building Layout Planning

Stage 3 - Detailed Planning and Rendering



Input 1
Site constraints (skeleton roads + railway + water)

Output 1 / Input 2
Cohesive road network and land use plan

Output 2 / Input 3
Spatial arrangement of buildings

Output 3
Final urban layout (e.g., satellite image)

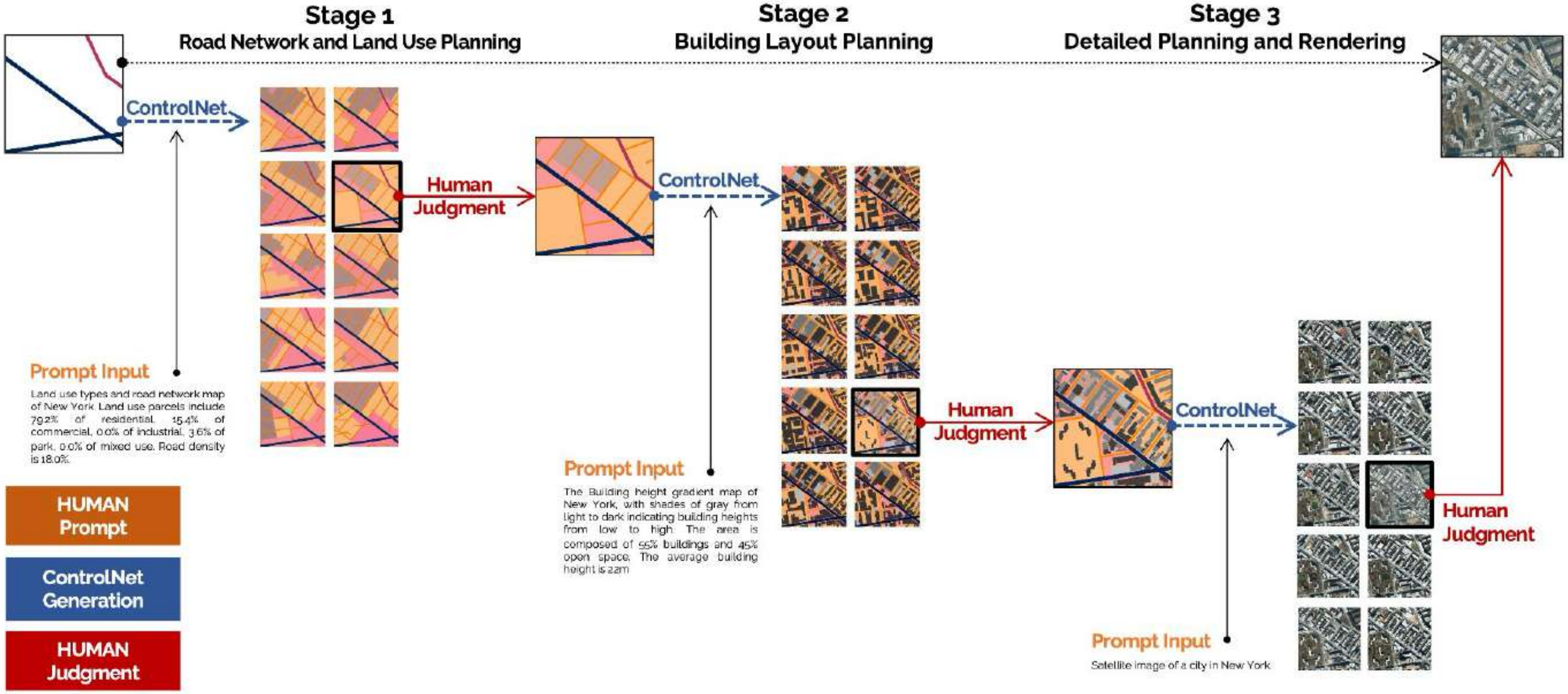
Human Instructions

Human Instructions

Human Instructions

Research Framework / **Human-Centered AI for Urban Design**

A Stepwise Approach Integrating Human Expertise with Diffusion Models



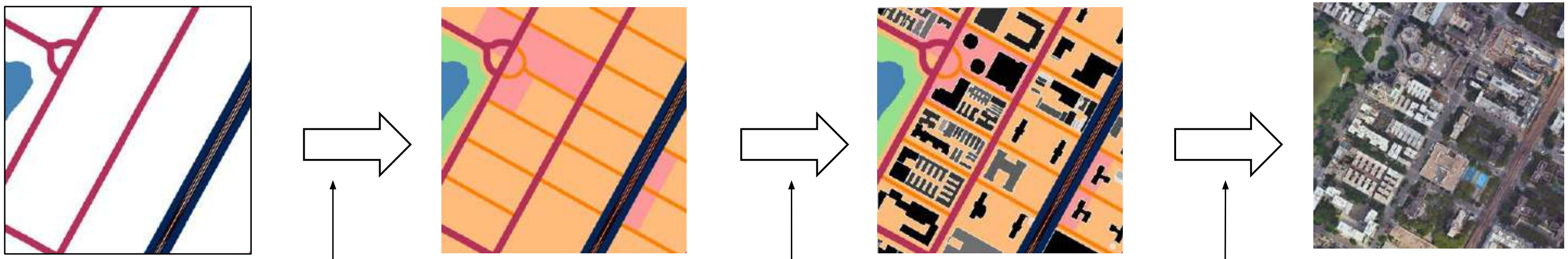
Research Framework / **Human-Centered AI for Urban Design**

A Stepwise Approach Integrating Human Expertise with Diffusion Models

Stage 1 - Road Network and Land Use Planning

Stage 2 - Building Layout Planning

Stage 3 - Detailed Planning and Rendering



Input 1 | Output 1 / Input 2 | Output 2 / Input 3 | Output 3

Human Instructions (land use ratio, road density)

Land use and road network map of New York. Land use parcels include 79.2% of residential, 15.4% of commercial, 3.6% of park. Road density is 18.0%.

Human Instructions (built coverage, height)

Building height gradient map of New York. The area is composed of 15% low-story buildings, 25% medium-story buildings, 15% high-story buildings, and 45% open space.

Human Instructions (city name)

Satellite image of New York.

Method / **Data Processing**

Study Area:

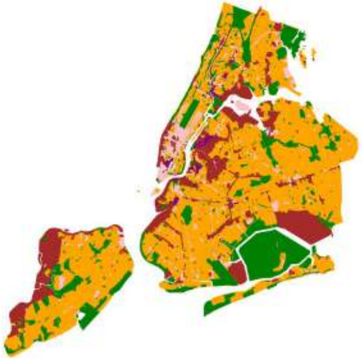
- New York City
- Chicago

Data Source:

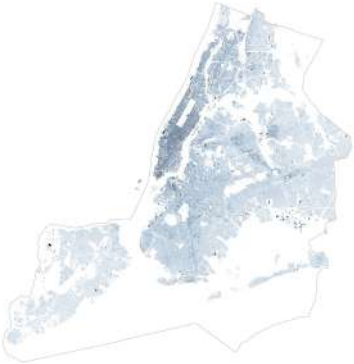
- OpenStreetMap (OSM)
- City official data hub
- Mapbox

Basic data

Road network data

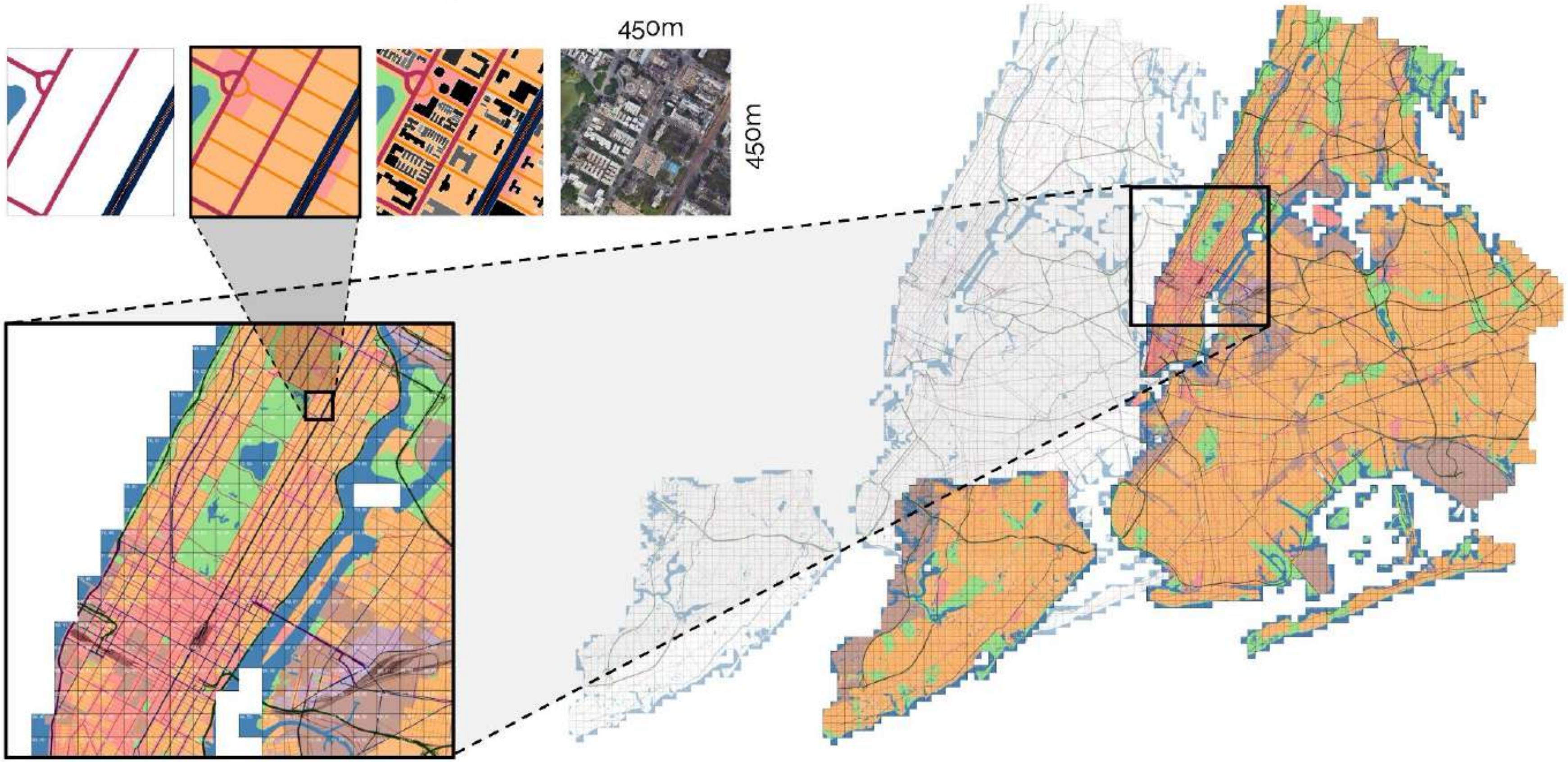


Land use data



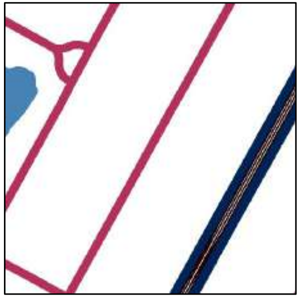
Building height data

Method / **Data Processing**



Method / **Feature Extraction**

Feature Extraction



+

Residential: 79.2%
Commercial: 15.4%
Manufacturing: 0.0%
Park: 3.6%
Mixed use: 0.0%

Road density: 18.0%

Building Coverage area: 28.1%
Average building height: 79.25
Building volume density: 2224.73%

Urban layout | **Design Constraints** | **Design Descriptions (Features)**

Prompt - Stage 1 - Road Network and Land Use Planning

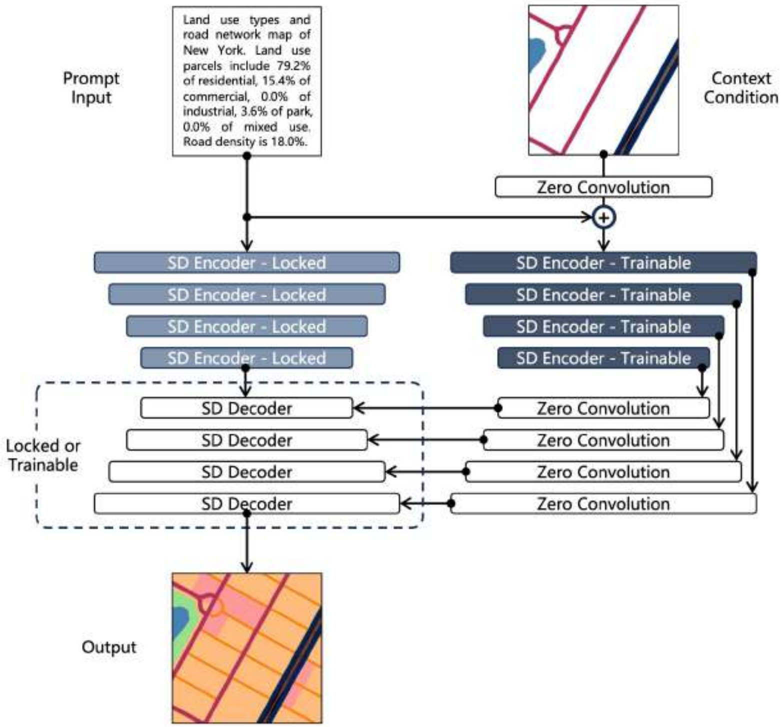
Land use types and road network map of New York.
Land use parcels include **79.2%** of residential, **15.4%** of commercial, **0.0%** of industrial, **3.6%** of park, **0.0%** of mixed use.
Road density is **18.0%.**

Prompt - Stage 2 - Building Layout Planning

Building height gradient map of New York.
Buildings include **15%** of low-story, **25%** of medium-story, **15%** of high-story, and **45%** open space.

Method / Model Training: **ControlNet**

A neural network structure designed to enhance control over diffusion models



Diffusion models exhibit **better scalability, parallelization**, **more stable training, and higher fidelity images, comparing to GAN.**

ControlNet framework shows promising generalization capability **on in-context learning and controllable image editing**.

Method / **Model Evaluation**

Baseline model

1. **Pix2Pix** (image-only inputs)
2. **Metric-enhanced Pix2Pix** (image + metrics inputs)
3. **LoRA-SD** (Stable Diffusion fine-tuned with Low-Rank Adaptation, text-only inputs, see Appendix)
4. **ChatGPT-5** (see Appendix)

Evaluation

1. Visual Fidelity

Measures the quality by comparing their distribution similarity to real images.

FID (Fréchet Inception Distance) between real and generated urban images.

2. Instruction Compliance

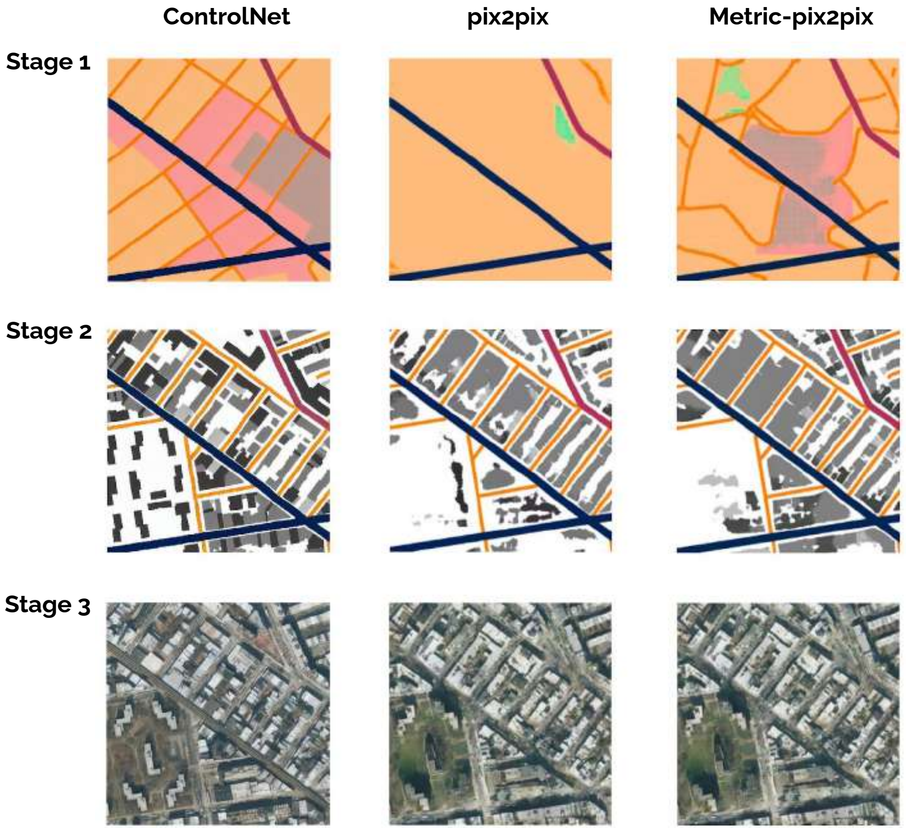
Whether the model accurately follows instructions regarding land use ratios, road density, building density, building height.

Performance Metrics (RMSE, MAE, MAPE, R^2) of Proportions of land use types, building categories, and road density.

3. Output Diversity

Whether the model generates diverse design diagrams conditioned on the same site constraints and human instructions.

Experiments / 1. **Visual Fidelity**



Lower FID means **higher fidelity.**

ControlNet clearly **outperforms Pix2pix in terms of image fidelity.**

ControlNet generates images with **greater clarity** and **more precise edge definition**.

Table 1: Fidelity performance (FID score) comparison of generated images

Stage	City	ControlNet	Pix2Pix	Metric-Pix2Pix
Stage 1	NYC	**30.68**	127.78	178.33
	Chicago	**34.28**	131.35	77.78
Stage 2	NYC	**12.84**	29.87	20.34
	Chicago	**17.88**	23.76	23.95
Stage 3	NYC	**53.50**	56.51	56.51
	Chicago	**35.40**	44.33	44.33

Experiments / 2. **Instruction Compliance**

Stage 1 Road network and land use planning

Pix2pix struggles to generate roads and land use layouts following human instructions.

ControlNet generates land use and road layouts, reflecting human intent.

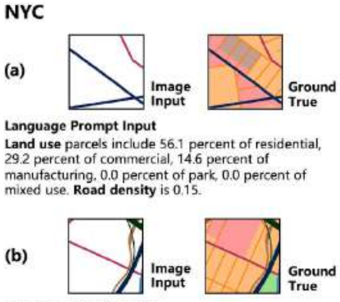
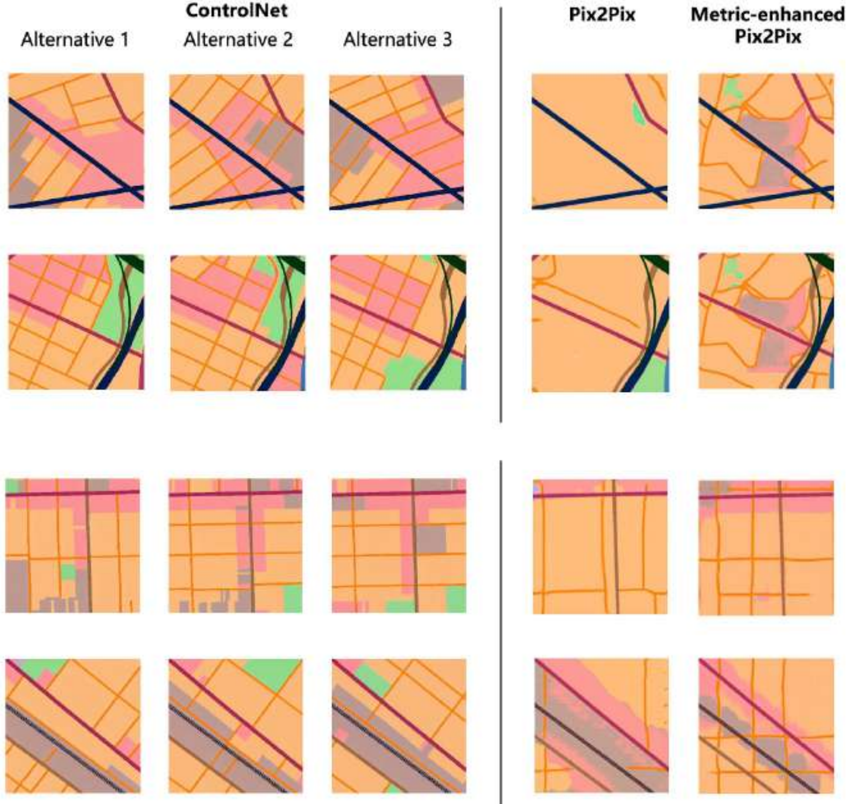


Table 2
Quantitative evaluation of instruction compliance for stage 1 (mean ± std).

Model	Metric	Road density		Land use	
		NYC	Chicago	NYC	Chicago
ControlNet	RMSE	**0.02 ± 0.00**	**0.02 ± 0.00**	**0.06 ± 0.05**	**0.06 ± 0.05**
	MAE	**0.01 ± 0.01**	**0.01 ± 0.01**	**0.04 ± 0.04**	**0.04 ± 0.04**
	R^2	**0.92 ± 0.01**	**0.91 ± 0.01**	**0.84 ± 0.27**	**0.78 ± 0.49**
Pix2Pix	RMSE	0.06 ± 0.00	0.03 ± 0.00	0.20 ± 0.13	0.16 ± 0.10
	MAE	0.05 ± 0.04	0.03 ± 0.02	0.14 ± 0.09	0.12 ± 0.08
	R^2	0.07 ± 0.12	0.58 ± 0.06	−0.71 ± 2.19	−0.12 ± 1.51
Metric-Pix2Pix	RMSE	0.03 ± 0.00	**0.02 ± 0.00**	0.10 ± 0.06	0.08 ± 0.05
	MAE	0.02 ± 0.02	0.02 ± 0.01	0.07 ± 0.04	0.06 ± 0.04
	R^2	0.80 ± 0.03	0.83 ± 0.03	0.33 ± 1.89	0.68 ± 0.47
LoRA-SD	RMSE	0.15 ± 0.00	0.19 ± 0.01	0.22 ± 0.09	0.25 ± 0.08
	MAE	0.13 ± 0.08	0.16 ± 0.10	0.16 ± 0.07	0.18 ± 0.06
	R^2	−4.25 ± 0.62	−11.23 ± 1.56	−0.22 ± 0.96	−0.64 ± 2.51



Experiments / 2. **Instruction Compliance**

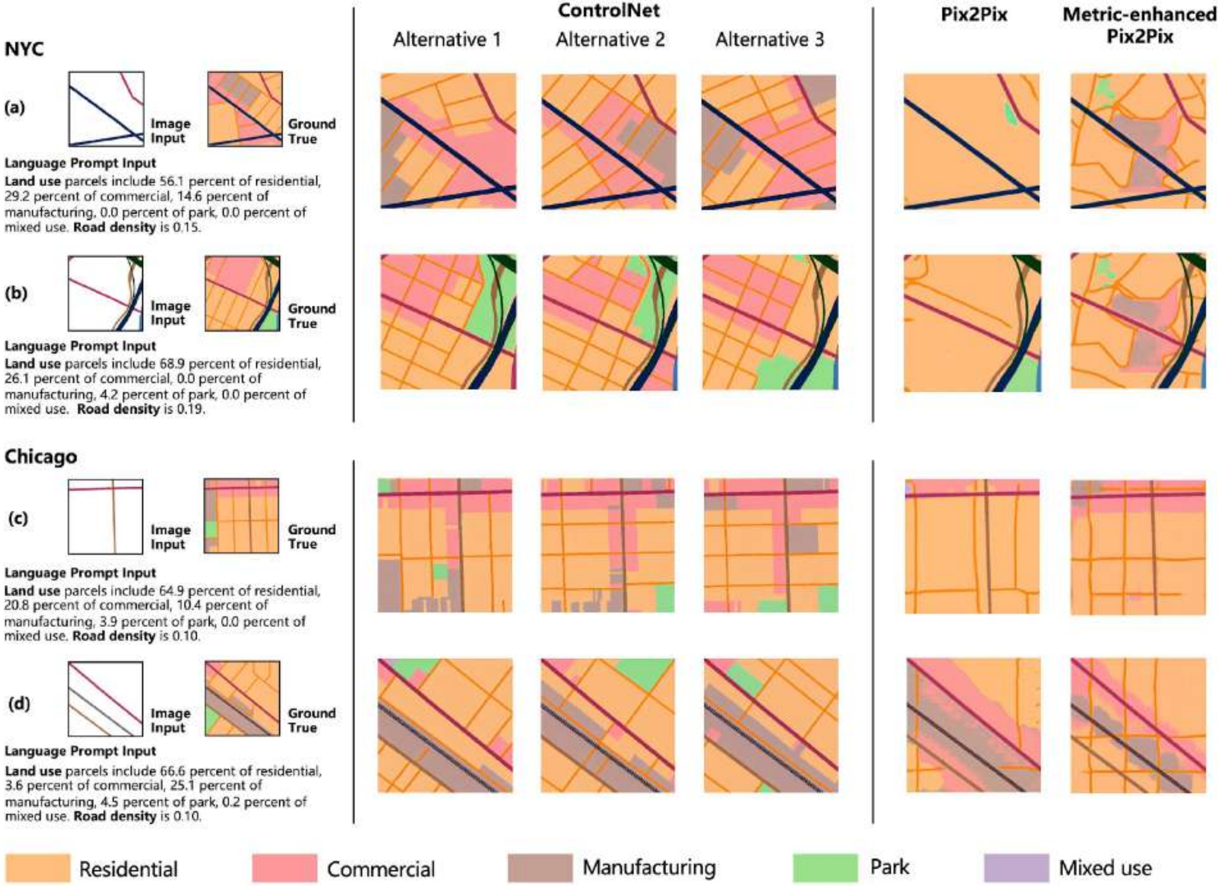
Stage 1 Road network and land use planning

Pix2pix struggles to generate roads and land use layouts following human instructions.

ControlNet generates land use and road layouts, reflecting human intent.

ControlNet shows spatial awareness:

- **Captures interactions between land use types and transportation infrastructure.**
- **Commercial** areas align with high-order roads.
- **Residential** zones cluster along lower-order streets.



Experiments / 2. **Instruction Compliance**

Stage 2 Building layout planning

Pix2pix struggles to generate building layouts following human instructions.

ControlNet generates building layouts and height, reflecting human intent.

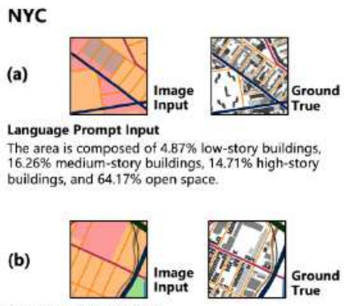
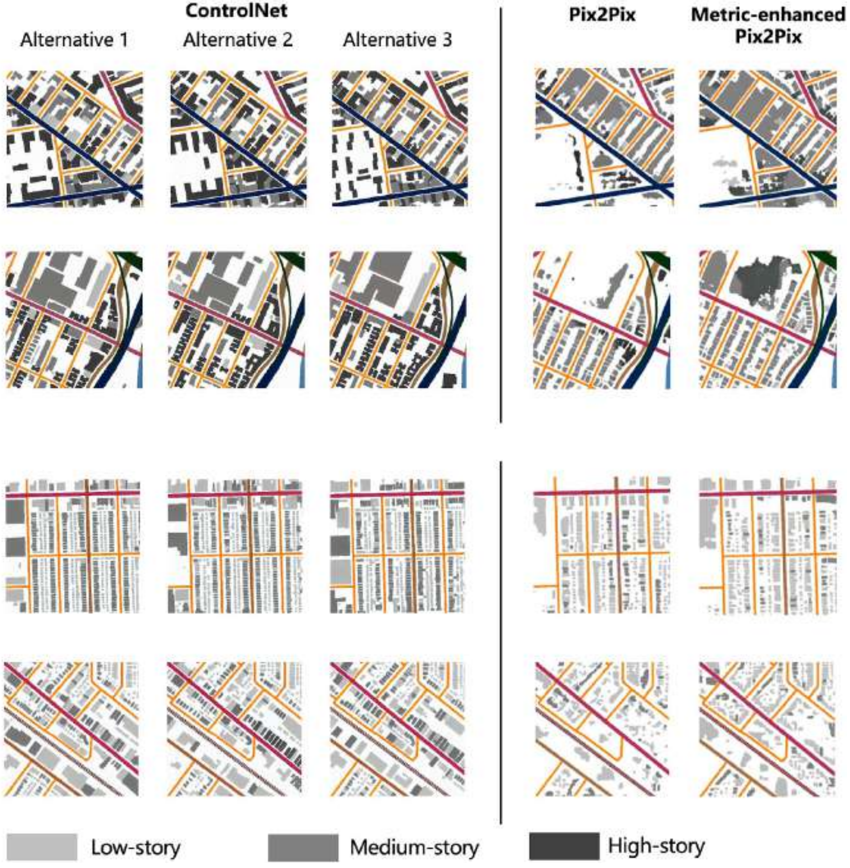


Table 3
Quantitative evaluation of instruction compliance for stage 2 (mean ± std).

Model	Metric	Building height NYC	Building height Chicago	Open space NYC	Open space Chicago
ControlNet	RMSE	**0.03 ± 0.00**	**0.04 ± 0.00**	**0.05 ± 0.00**	**0.05 ± 0.00**
	MAE	**0.02 ± 0.00**	**0.02 ± 0.00**	**0.03 ± 0.04**	0.04 ± 0.03
	R^2	**0.87 ± 0.01**	0.81 ± 0.04	0.91 ± 0.01	**0.90 ± 0.02**
Pix2Pix	RMSE	0.06 ± 0.00	0.06 ± 0.00	0.07 ± 0.00	0.08 ± 0.00
	MAE	0.03 ± 0.00	0.04 ± 0.00	0.05 ± 0.05	0.05 ± 0.05
	R^2	0.62 ± 0.03	0.49 ± 0.04	0.81 ± 0.03	0.77 ± 0.04
Metric-Pix2Pix	RMSE	0.04 ± 0.00	**0.04 ± 0.00**	**0.05 ± 0.00**	0.06 ± 0.02
	MAE	0.03 ± 0.00	**0.02 ± 0.00**	**0.03 ± 0.03**	**0.03 ± 0.06**
	R^2	0.79 ± 0.02	**0.84 ± 0.02**	**0.92 ± 0.01**	0.84 ± 0.10
LoRA-SD	RMSE	0.16 ± 0.00	0.07 ± 0.00	0.37 ± 0.01	0.26 ± 0.01
	MAE	0.11 ± 0.00	0.05 ± 0.00	0.34 ± 0.16	0.22 ± 0.14
	R^2	−1.83 ± 0.27	0.33 ± 0.04	−4.00 ± 0.36	−1.65 ± 0.28



Experiments / 2. **Instruction Compliance**

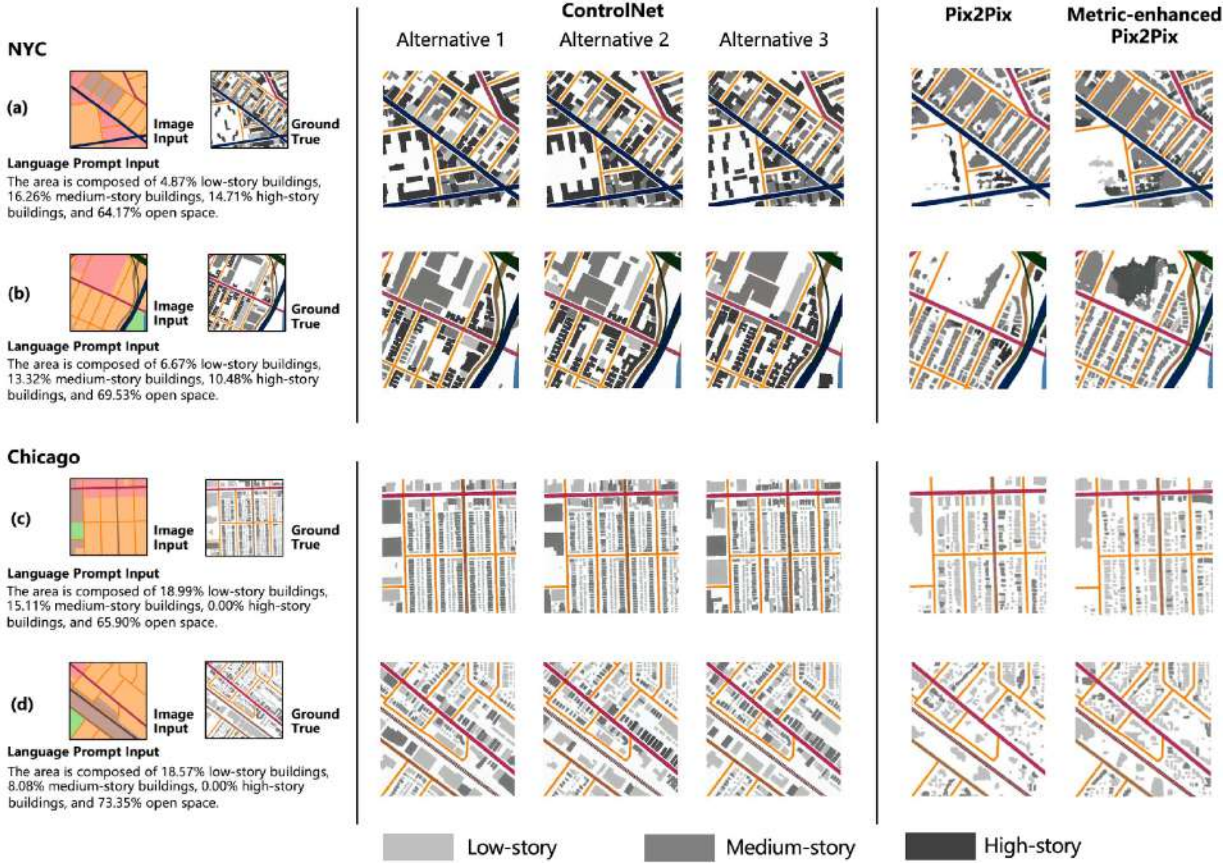
Stage 2 Building layout planning

Pix2pix struggles to generate building layouts following human instructions.

ControlNet generates building layouts and height, reflecting human intent.

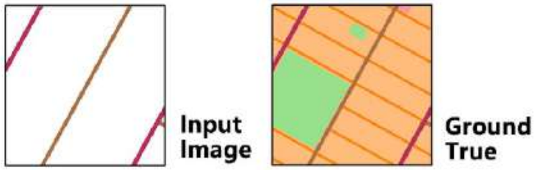
ControlNet shows spatial coherence:

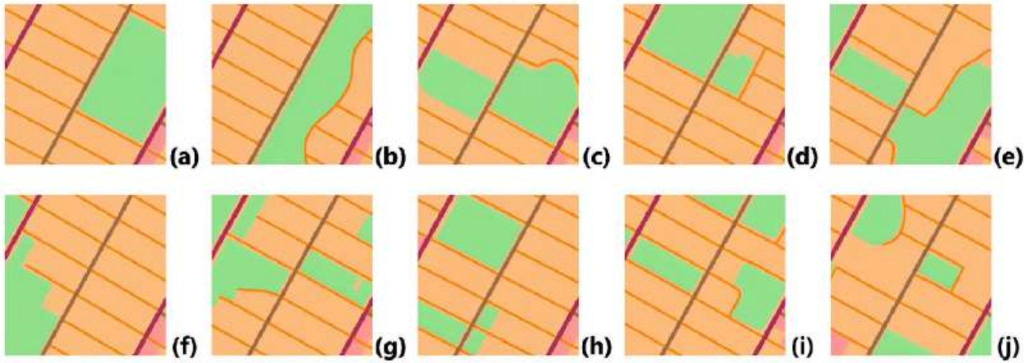
- **Aligns buildings along streets, forming continuous street edges.**
- Baseline models produce fragmented or misaligned layouts.
- **Captures realistic land use patterns:**
    - Larger buildings in **commercial and industrial areas**.
    - Smaller ones in **residential zones.**



Experiments / 3. **Output Diversity**

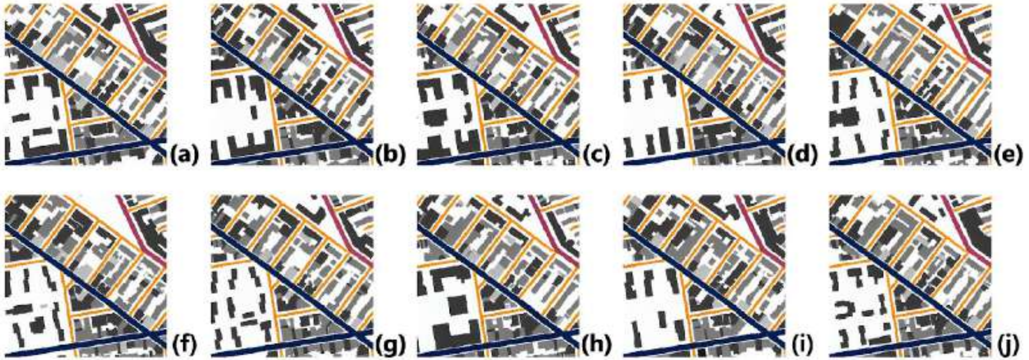
Stage 1 Road Network and Land Use Planning





Same land use composition, **diverse spatial layouts**—from centralized parks to dispersed green spaces enhancing accessibility.

Stage 2 Building Layout Planning



Same building height proportion, **diverse residential layouts**—from linear rows to courtyard and clustered forms.

Experiments / 3. **Output Diversity**

Stage 3 Detailed Planning and Rendering

Satellite image of a city in New York.

ControlNet **strictly follows the constraint** of the input image while **generating diverse detailed planning**, such as landscape design, rooftop design, etc.

Experiments / 4. **User Study**

Experiment Design

- Experts rated real or generated images (1–10 scale), seeing only one per case.
- Evaluations covered **site alignment** and **stage-specific design quality** across three stages.

Results

Table 5: User study results across three stages (mean $\pm$ std scores).

	Stage 1			Stage 2		Stage 3	
	Site constr.	Land use	Road network	Site constr.	Building layout	Site constr.	Realism
Real	8.25 ± 2.19	7.37 ± 2.21	7.08 ± 2.35	7.72 ± 2.28	6.45 ± 2.33	8.45 ± 1.79	8.24 ± 1.82
Generated	7.78 ± 2.26	6.99 ± 2.38	7.21 ± 2.33	8.05 ± 1.92	6.52 ± 2.41	8.12 ± 1.88	7.77 ± 1.91
Difference	-0.47	-0.38	+0.13	+0.33	+0.07	-0.33	-0.47
t-stat	1.41	1.12	-0.36	-1.05	-0.19	1.18	1.64
p-value	0.16	0.26	0.72	0.30	0.85	0.24	0.10

- **Generated images scored closely to real ones in all stages.**
- **Slight advantages in road network rationality and site constraint alignment.**
- **No statistically significant differences → perceptually close to real images.**

Experiments / 5. **Stepwise v.s. End-to-End**

Stepwise: Site Constraints -> Land Use Layout ->Building Layout

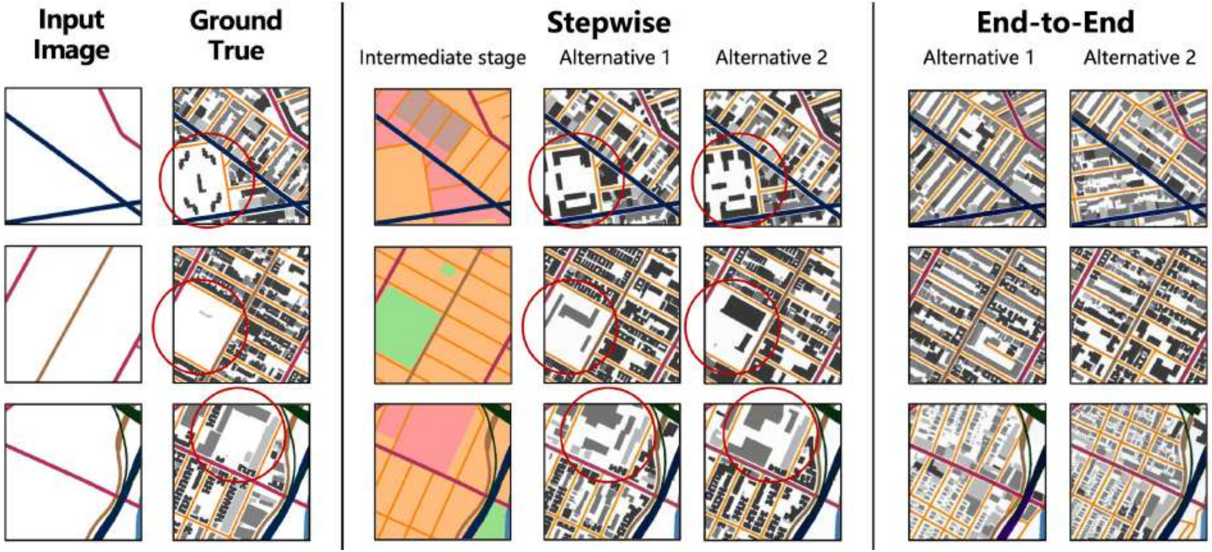
- produces **clearer and more functionally coherent layouts.**

End-to-End: Site Constraints -> Building Layout

- generates **repetitive, uniform patterns** that **lack diversity.**

Table 6: Comparison of stepwise and end-to-end framework

	Stepwise			End-to-end		
FID	12.84			32.38		
	RMSE	MAE	R^2	RMSE	MAE	R^2
Road density	0.02	0.01	0.92	0.05	0.04	0.44
Building Height	0.03	0.02	0.87	0.04	0.02	0.78
Open Space	0.05	0.03	0.91	0.12	0.09	0.48



The stepwise approach proves superior to end-to-end:

- **Alignment with instructions:** better follows human guidance through intermediate decision points.
- **Output quality:** generates more realistic and functionally coherent urban forms.
- **Better human control:** enables meaningful review and refinement at each stage.

Experiments / 6. **Human-in-the-loop Generation Case**

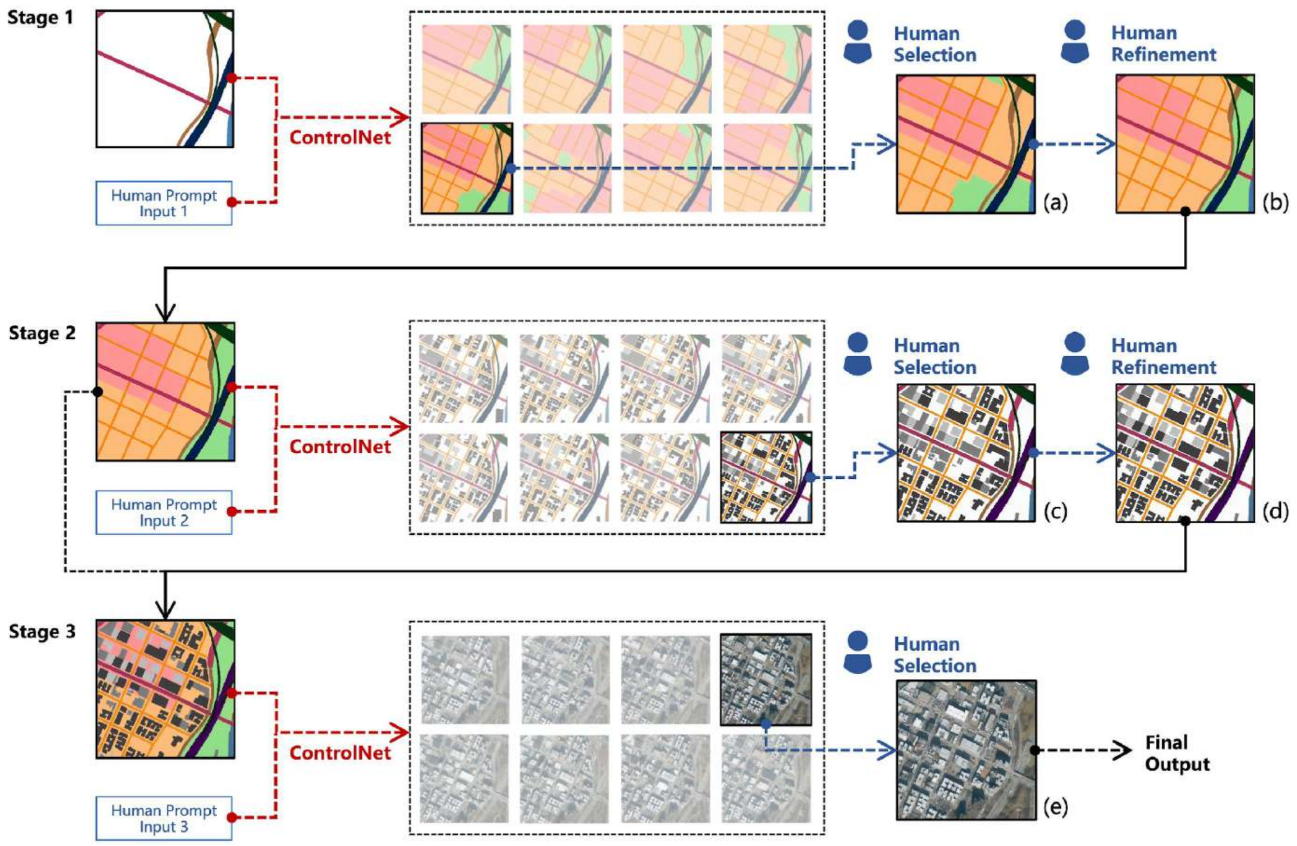
Demonstrates iterative collaboration between diffusion models and human expertise.

Three-stage process for urban form generation and refinement.

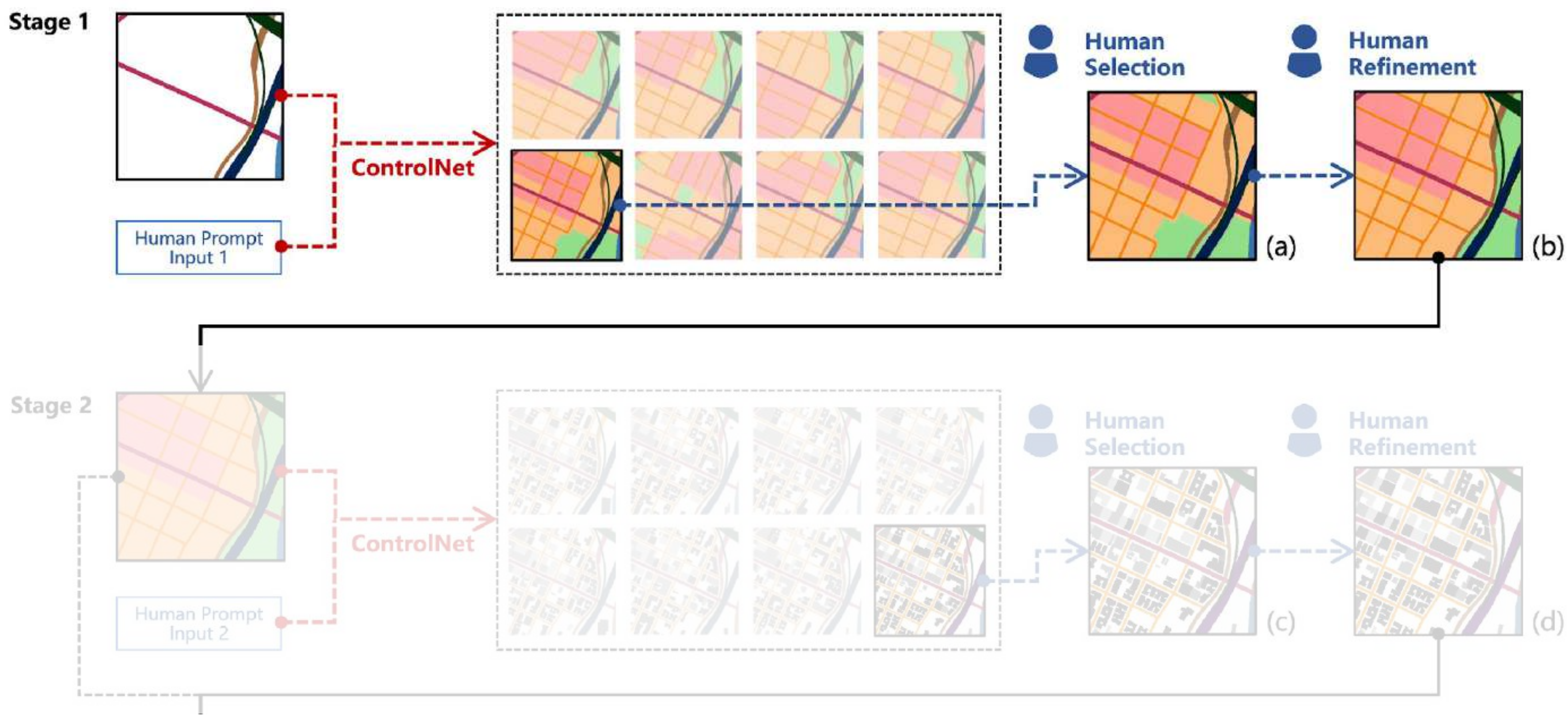
- Human Prompt

- Human Selection

- Human Refinement



Experiments / 6. **Human-in-the-loop Generation Case**



Experiments / 6. **Human-in-the-loop Generation Case**

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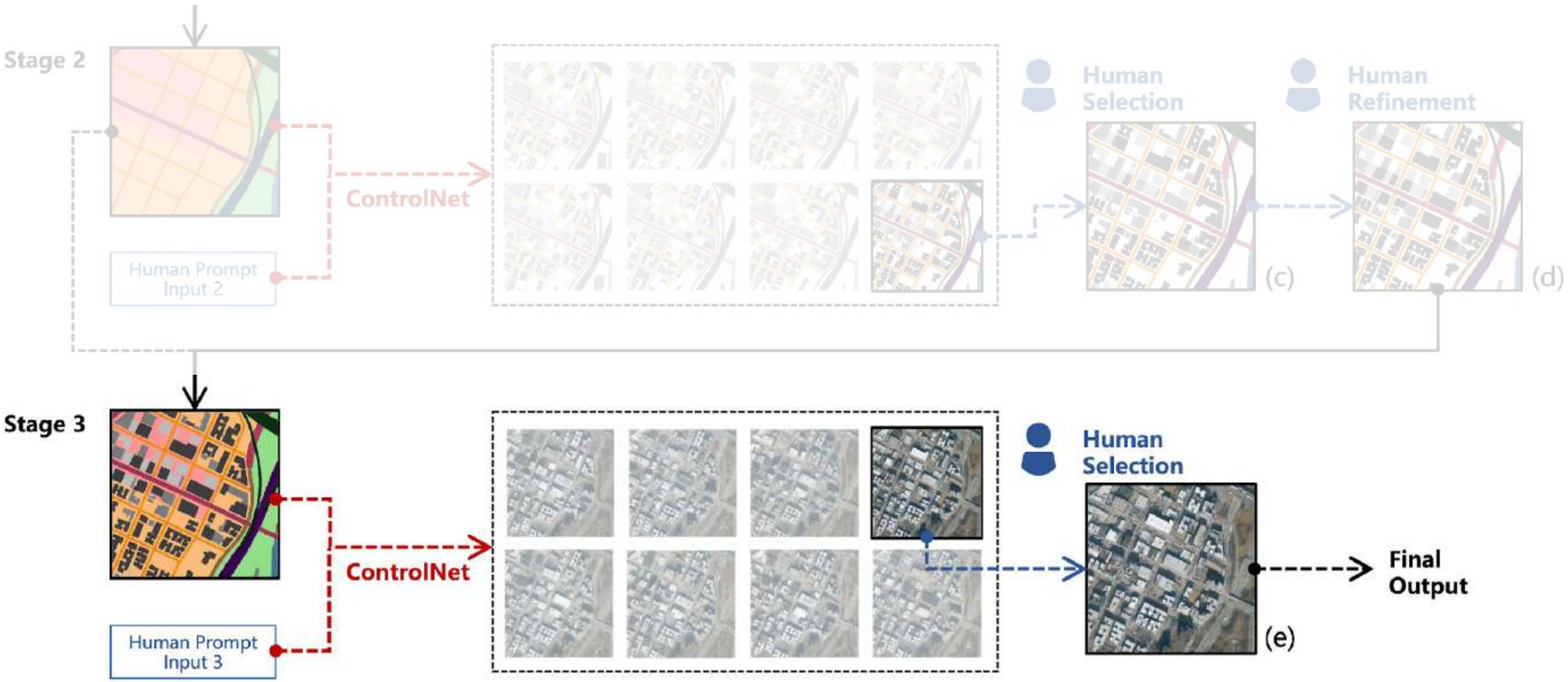
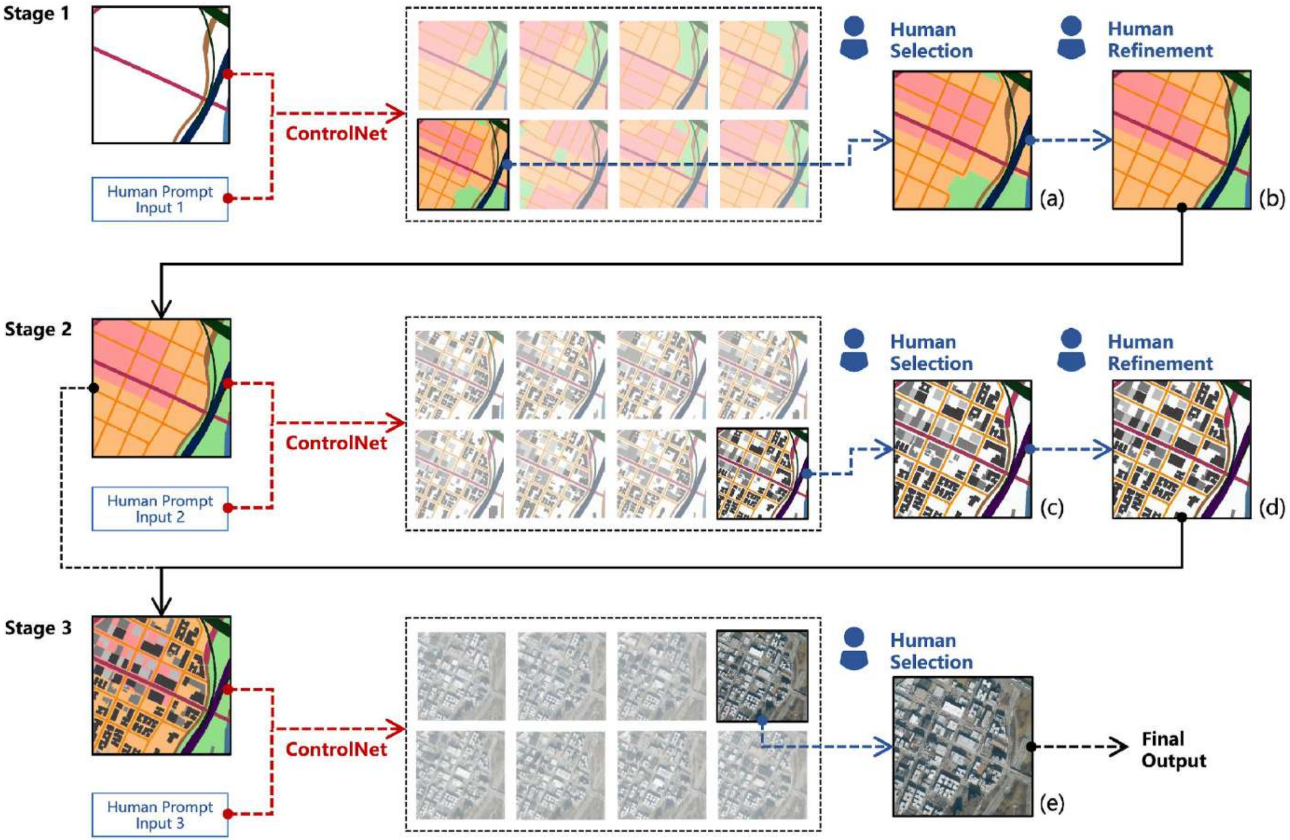


Experiments / 6. **Human-in-the-loop Generation Case**

Demonstrates iterative collaboration between diffusion models and human expertise.

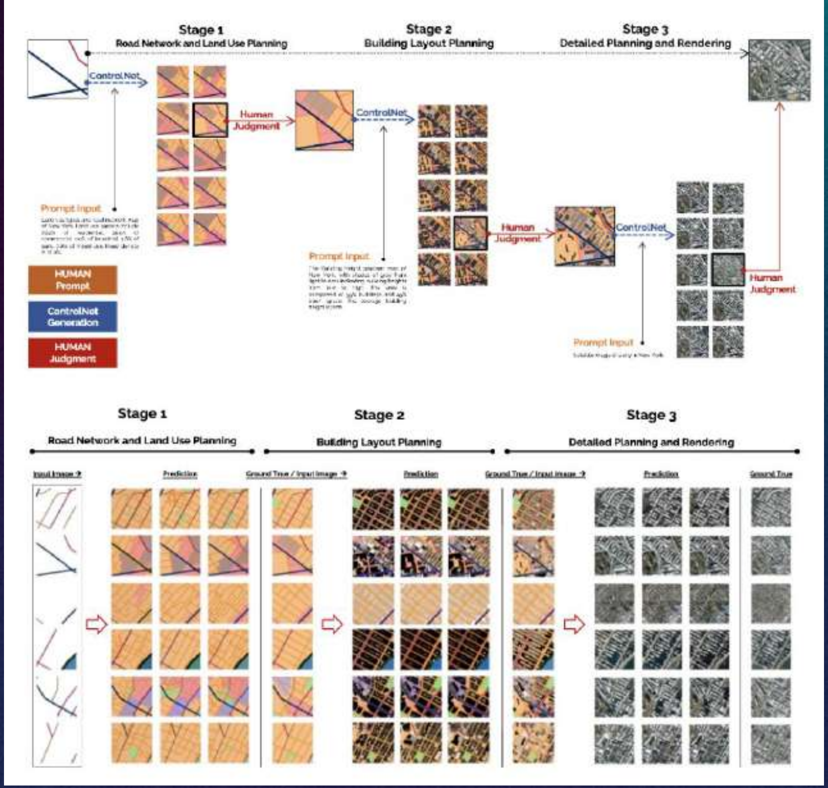
Three-stage process for urban form generation and refinement.

- **Human Prompt**
- **Human Selection**
- **Human Refinement**



Main Findings

1. **Model Effectiveness**
   - ControlNet understands designer prompts and generates effective urban layouts, **outperforming the baseline model in both image fidelity and prompt alignment**.
2. **Stepwise Control Advantage**
   - Stepwise generation is superior to end-to-end in terms of **human control, output quality, and alignment with instructions**.
   - An Example of Neuro-symbolic AI.
3. **Collaborative Design**
   - **Human-Centered AI** for Urban Design enhances diversity and human control, promoting efficiency in urban design and facilitating public communication and iterative refinement.
4. **Design Pattern Discovery**
   - Through cross-city comparisons and the application of city model transfer, the model uncovers **hidden urban design patterns.**



What will future planners do?

1. Immediacy changes the dialog

Planners have to be more responsive

2. A.I. enables the public

Planning is a tool to allocate power

3. Essense of planners’ job

Design creator → Design critique
Design creator → Design communicator
Design creator → Design negotiator

AI for Future of Mobility

What is success and what defines the future

AI for City Planning

Human In the Loop, Power Balance and Future Role of City Planners

AI for Autonomous Vehicles

human agency and AV deployment

What’s essential differences between AV and human driven cars?

Human Agency

Spectrum of human vs machine decision making

Levels of decision making

High level:
single vs. pooling;
destination choice;
ownership choice

Mid level:
route choice;
departure time choice

Low level:
Acceleration, deceleration, change lanes

"The Agency Frontier

— where human preference and

machine intelligence meet."

Fully human

A variety of middle points

Fully machine

Spectrum of human vs machine decision making

Operation scenarios

Emergency (large scale)

Emergency (small scale)

Accidents

Events

Normal

“The Command Matrix

— the right actor in charge for

each scenario.”

consumers | operators | car makers | authorities

Decision-making parties

AI and Human Agency

Incentive design framework

- motivate each decision party to acquire or release the control
- private purposes (pay for it) vs. public purposes (to be paid for it)

Public policy

- Different layers of property rights
- A richer set of policy tools

Three ways to change behavior

- Price
- Rules
- Norms

Direct control

Conclusion

Two Roles of Models

Communicative planning

Behavior + Computation

Behavioral Thinking

~

Transportation Technology

- Emotional
- Social
- Perceptional

- Electrification
- Automation
- Connectivity
- Sharing

Computational Foundation

- Representation
- Explanation

- Prediction
- Control
- Creation

Representation

Prediction

Explanation

Control

Creation

Communication

What is success?