



Seeing Cities

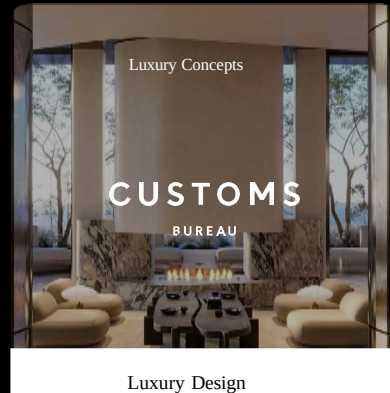
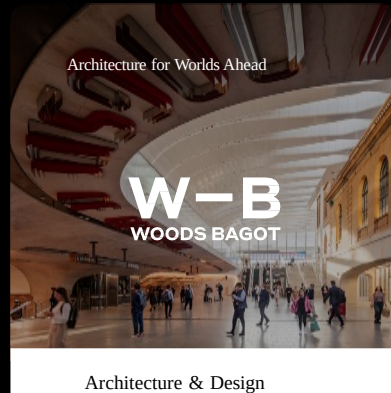
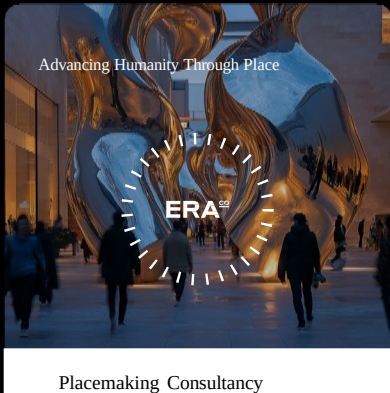
Differentiating Perceptual Qualities of Urban Space for Evidence-Based Design

● WHO ARE WE?



Total Place Design Network

Our network of leading place brands



PART OF THE ●7C.NETWORK

Our Collective Ambition

To be the most trusted and influential voice for the future of our built world

WOODS BAGOT AND ERA-CO ARE PART OF THE 7C NETWORK.

We are on a mission to improve our built world across seven continents.

A wholly owned network of leading place brands operating from 18 global cities.

We understand the complexity and challenges of our time. To generate the best possible outcomes for people and place, our brands provide visionary thinking and a holistic approach to design.

We connect specialist knowledge across our network to deliver strategic outcomes and long-term impact.

Through Total Place Design, we stay ahead of the greatest challenges, the limitless opportunities, and the rising ambition of the built world.

Genesis of ERA-co

PLACE
AMBITION

relevance & insight
of a proposed experience



DESIGN
RESPONSE

rationale & inspiration of a
proposed form



FROM
CITY



TO
COMMUNITY



TO
CURB

● OUR PROJECTS

MARAFY MASTERPLAN, JEDDAH, KSA



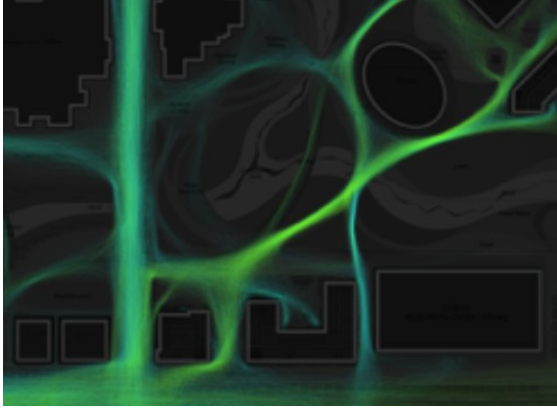
RUZINOV MASTERPLAN, BRATISLAVA, SLOVAKIA



85 GRACECHURCH, LONDON, UK

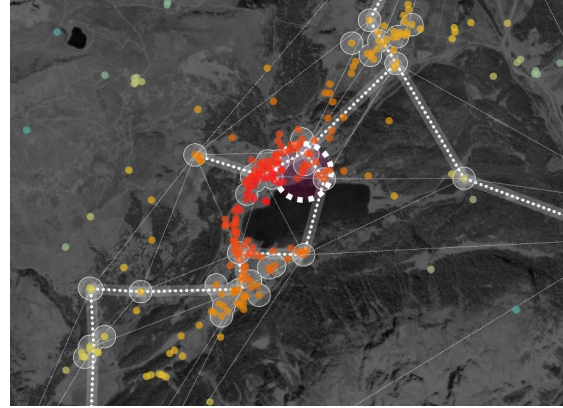


● QUANTIFYING PLACE : FORECASTING EXPERIENCE



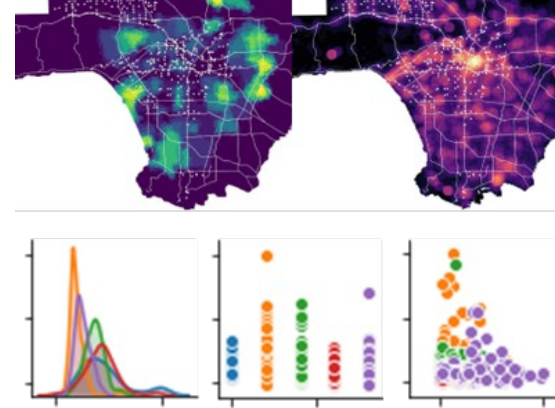
/ Persona Movement

Flow Analysis models how people move through cities, testing layouts and land uses to shape public experiences.



/ Clustering Models

Clustering and connectivity analysis reveal drivers of place types and guide refinement of emerging designs.



/ Geospatial Analysis

Data and statistical analysis reveal hidden urban patterns, unlocking overlooked opportunities and insights across scales.



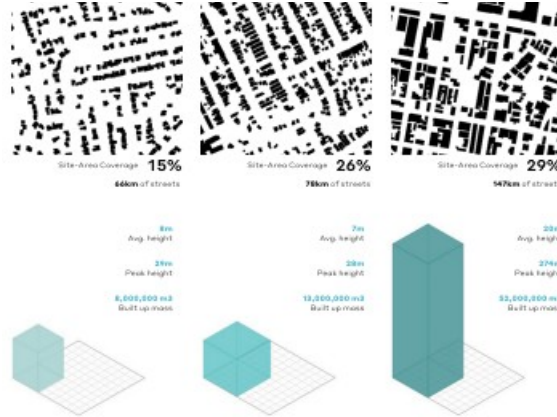
/ Land Use Studies

Our tools objectively guide land-use allocation by linking movement and hierarchy while adapting to project ambitions and context.



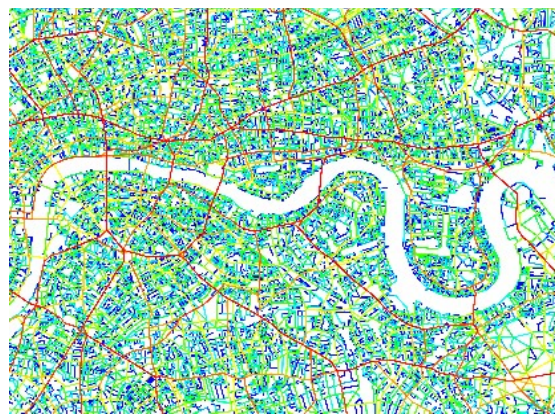
/ AI Place Definition

We use AI models to quantify image and video data, giving an objective lens on urban environments which we use for benchmarking.



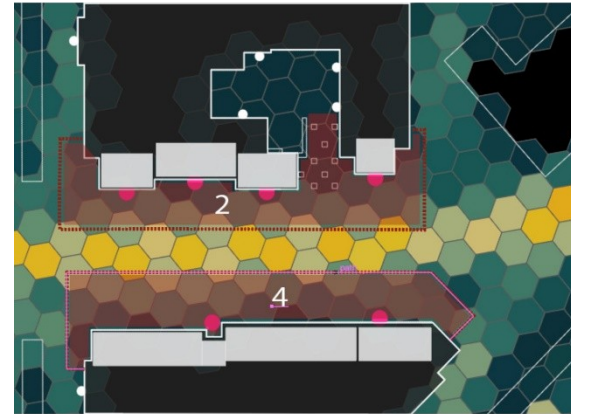
/ Benchmarking Places

Our benchmarking identifies key local features, compares them globally, and uses data analytics to reveal measurable insights.



/ Spatial Opportunities

Our spatial network models assess how streets and paths attract movement, helping us test and optimize proposals for urban integration.



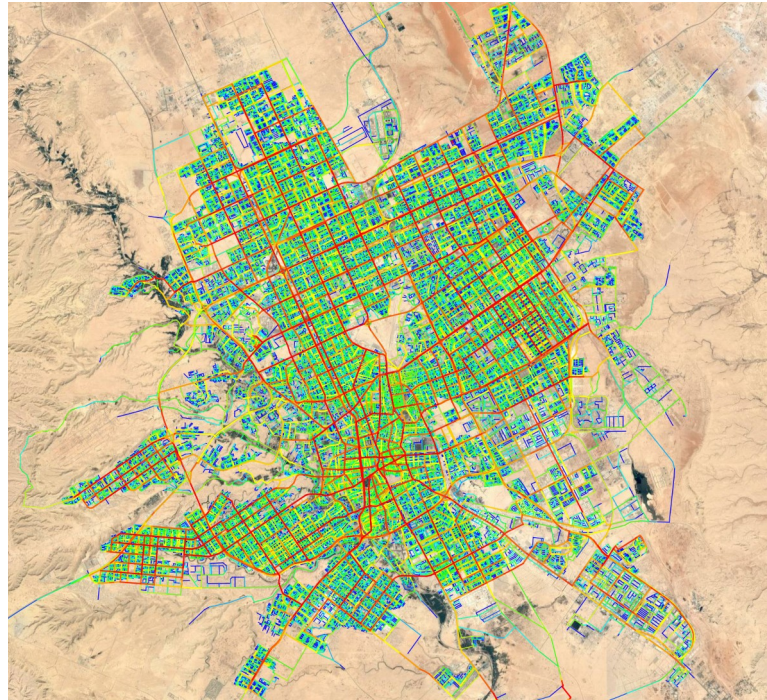
/ Movement & Activation

We simulate people-movements and journeys, combined with land use and layout, to assess asset placement, footfall potential, and public-realm effectiveness.

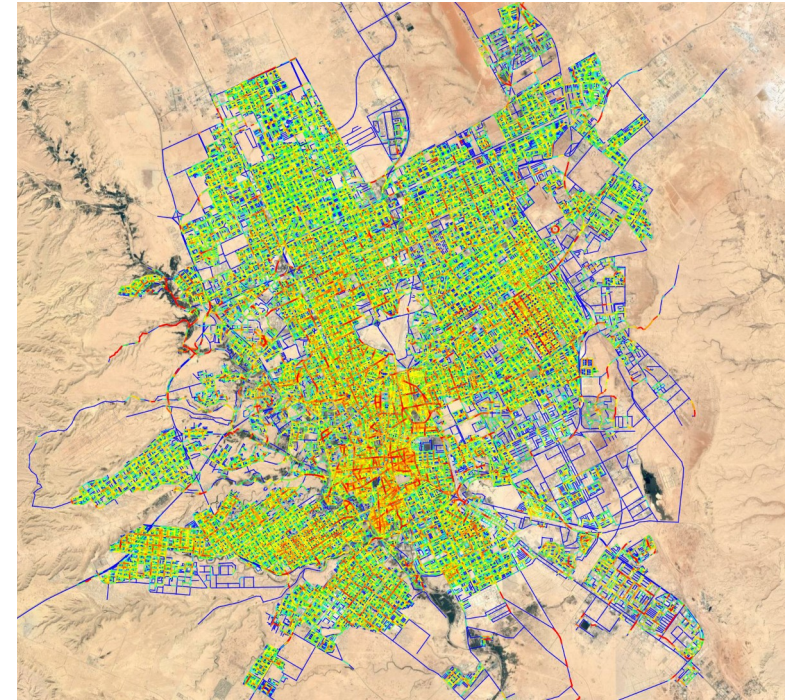
● EVIDENCE-BASED ANALYTICS



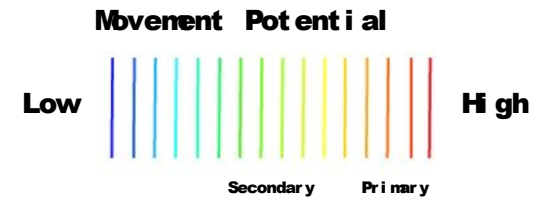
**Exploring Connections
and Configurations of
Cities**



**Strategic connections
(10kns +)**



**Strategic connections
~800m ~1,200m**



Our clients are wanting to gauge future experience

“Impressions are born in the first 40 feet of experience—where the building meets the ground. **The challenge facing owners and managers is how to develop that first impression.**”

Architectural solutions alone—which provide form, function and visual interest above ground level—don’t always impact **how a person feels when moving in front of, around and through a building.**”

~ *Conceptual Construction Group, Hines*

The fundamentals haven't changed



Striving for human-centricity in an increasingly digital world.

● **QUANTIFYING PLACE : FORECASTING EXPERIENCE**

Scenario 2: Weekend Evening Peak

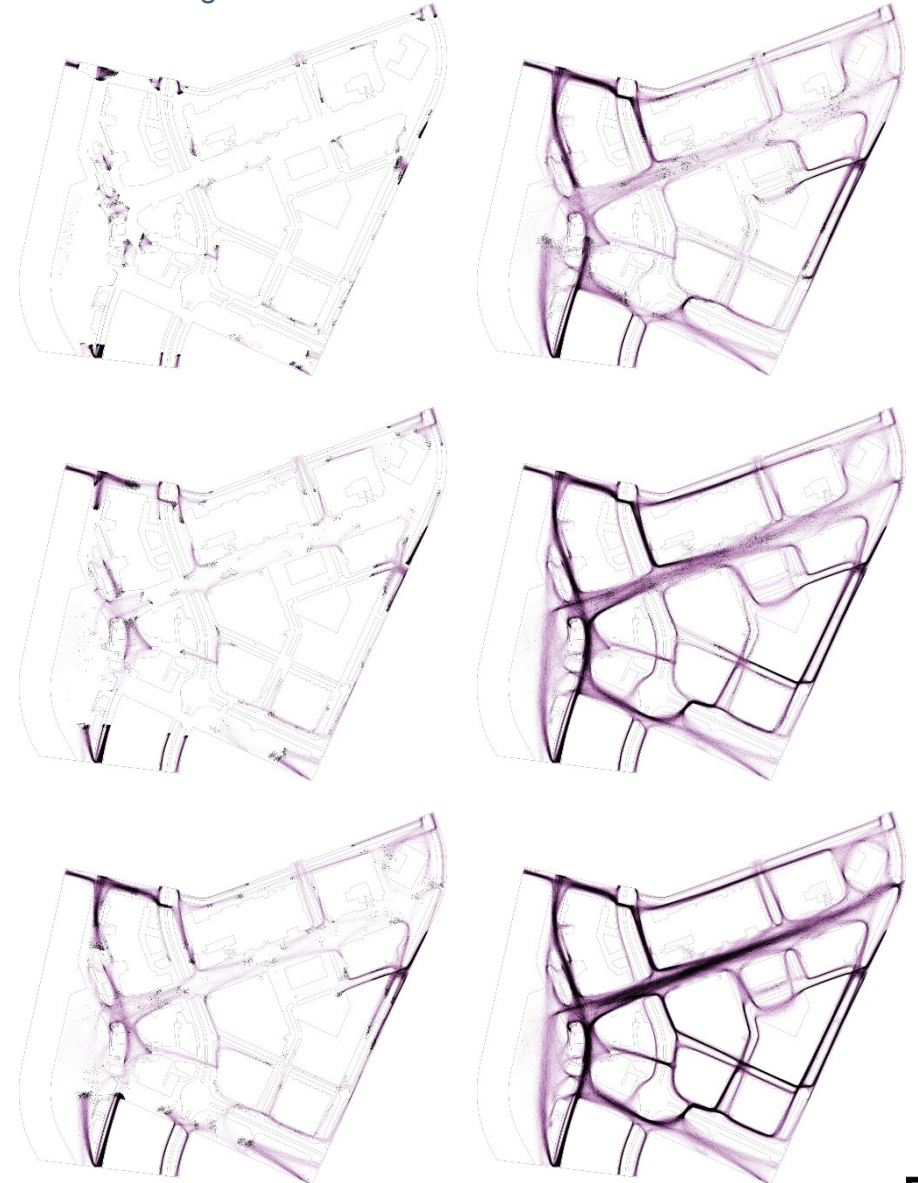
Simulation of pedestrian flows across a walkable area based on predefined origins, destinations, and population assumptions.

BRIDGE

MALL

BRIDGE

Flow Progression

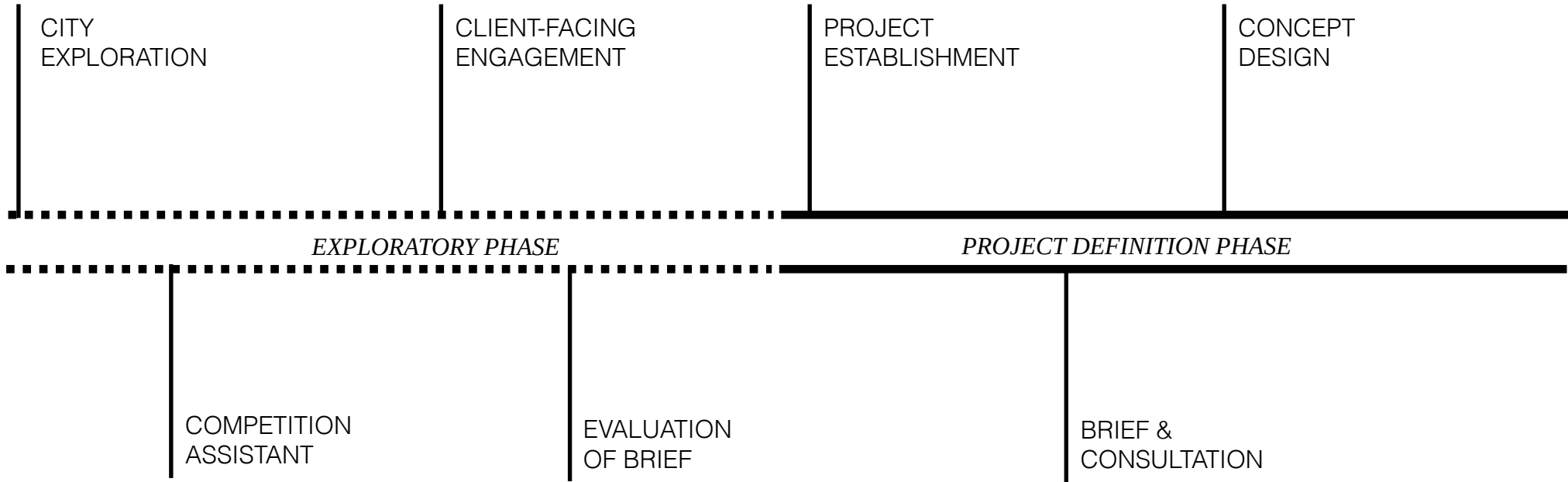


A city street scene with AI-powered perceptual mapping overlaid. The scene includes buildings, trees, a bus, and pedestrians. The mapping uses semi-transparent colored overlays: red for pedestrians, green for trees, and blue for the road. A central text overlay reads "AI-POWERED PERCEPTUAL MAPPING".

AI-POWERED PERCEPTUAL MAPPING

● **WEAVING AI METHODS INTO PROJECT LIFE CYCLES**

Deeper understanding of your context, share insights with clients, enhance how we respond to briefs, and question our assumptions



AI-POWERED PERCEPTUAL MAPPING

● RESEARCH AND SCOPE

1

Explore visual perception of streets as a key element of urban form.

■

2

Develop scalable methods for street-level perceptual assessment.

■

3

Apply open-source computer vision to street-view imagery (SVI).

■



Street scene from field survey in Southampton Row, London

How can semantic segmentation models be applied to street-view imagery to develop scalable, data-driven methods for evaluating the **perceptual qualities** of urban form?

Work of **Dr Nicolas Palominos**

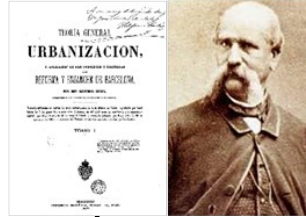
● PERCEPTUAL QUALITIES

Theoretical foundations in Urban Design Addressing **Perceptual Qualities**

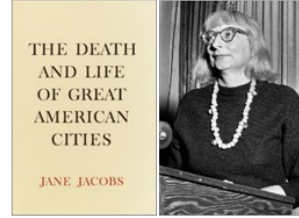
Life and Labour of the People in London (1886). Charles Booth



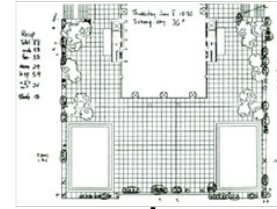
General Theory of Urbanization (1867). Ildefons Cerdà



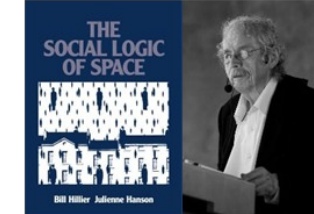
The Death and Life of Great American Cities (1961). Jane Jacobs



The Social Life of Small Urban Spaces (1970-75). William H Whyte

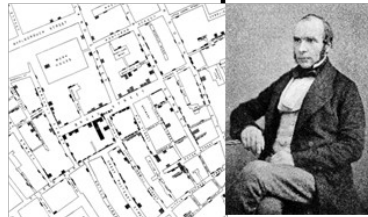


The Social Logic of Space (1984). Bill Hillier & Julienne Hanson

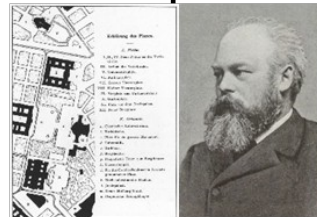


ECONOMIC, SOCIAL, HEALTH AND ENVIRONMENT

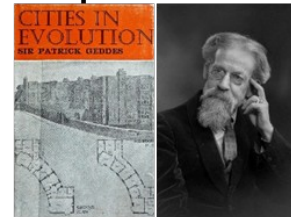
OBSERVATION & THE SCIENTIFIC METHODS



Soho Cholera Maps (1851). John Snow



City Planning According to Artistic Principles (1889). Camillo Sitte



Cities in Evolution (1915). Patrick Geddes



Geographic Information System (1963). Roger Tomlinson



Life Between Buildings (1971). Jan Gehl



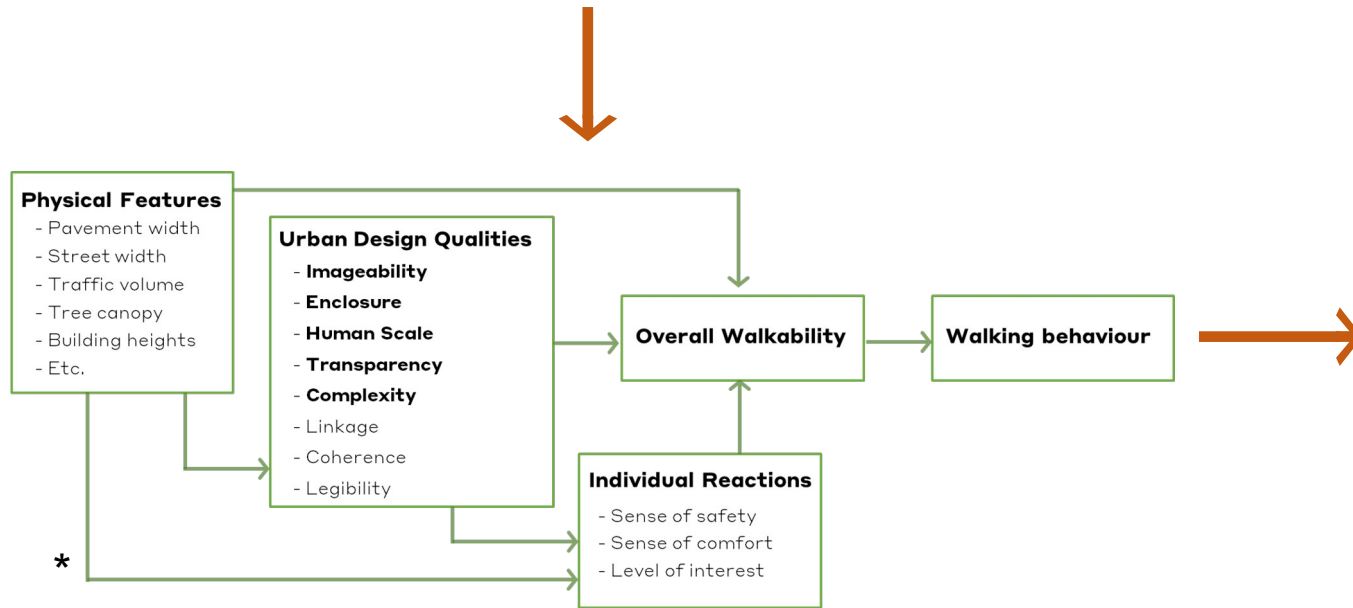
Inventing Future Cities (2018). Mike Batty

- 1889: *City Planning According to Artistic Principles*, Camillo Sitte
- 1909: *Town Planning in Practice*, Raymond Unwin
- 1960: *The Image of the City*, Kevin Lynch
- 1961: *The Concise Townscape*, Gordon Cullen
- 1961: *The Death and Life of Great American Cities*, Jane Jacobs
- 1977: *A Pattern Language: Towns, Buildings, Construction*, Christopher Alexander, Sara Ishikawa, and Murray Silverstein

● PERCEPTUAL QUALITIES

Leveraging on Theoretical Foundations

Lynch, Alexander, Jacobs, and others: Defined key perceptual qualities like enclosure, human scale, and imageability as core to urban form and experience.



Perceptual Quality	Definition	Key Segmentation Classes	Formula Concept	Formula
Imageability	Memorability and distinctiveness of a place through physical features and human activity.	person, rider, vegetation, building	Weighted sum of memorable features	$0.4 * (\text{person} + \text{rider}) + 0.3 * \text{vegetation} + 0.3 * \text{building}$
Enclosure	Degree to which a street feels spatially enclosed by vertical elements.	building, vegetation, wall, fence, sky	Ratio of vertical elements to sky	$\frac{(\text{building} + \text{vegetation} + \text{wall} + \text{fence})}{(\text{building} + \text{vegetation} + \text{wall} + \text{fence} + \text{sky} + 1e-6)}$
Human Scale	Presence of human-level details and proportions matching pedestrian perspective.	person, rider, pole, traffic sign, traffic light	Sum of small-scale elements normalized	$\frac{(\text{person} + \text{rider} + \text{pole} + \text{traffic_sign} + \text{traffic_light})}{(1 - \text{sky} + 1e-6)}$
Transparency	Ability to visually perceive human activity and openness beyond the street edge.	person, rider, wall, fence, vegetation	Visible activity divided by visual barriers	$\frac{(\text{person} + \text{rider})}{(\text{wall} + \text{fence} + \text{vegetation} + 1e-6)}$
Complexity	Visual richness from variety of elements, forms, and activity in the scene.	person, rider, bicycle, motorcycle, traffic sign, pole, car, vegetation	Entropy (distribution of elements)	Shannon entropy([class proportions])

Work of **Dr Nicolas Paloni**

* From 2013: Ewing, R; Clemente, O. *Measuring Urban Design: Metrics for Livable Places*

● AI-POWERED PERCEPTUAL MAPPING

Assessing Urban Form through Street-View Imagery.

From site photo survey



To advanced place analysis

Step 1:
Semantic Segmentation

Step 2:
K-means Clustering



AOI in Barnet, Brent and Camden, London



(1) Hamstead G S, residential, Barnet



(2) Staples Corner, industrial, Brent



(3) Bloomsbury, mixed-use, Camden

● image
— Route

SEMANTIC SEGMENTATION

Sorting pixels into meaningful categories for perceptual analysis.

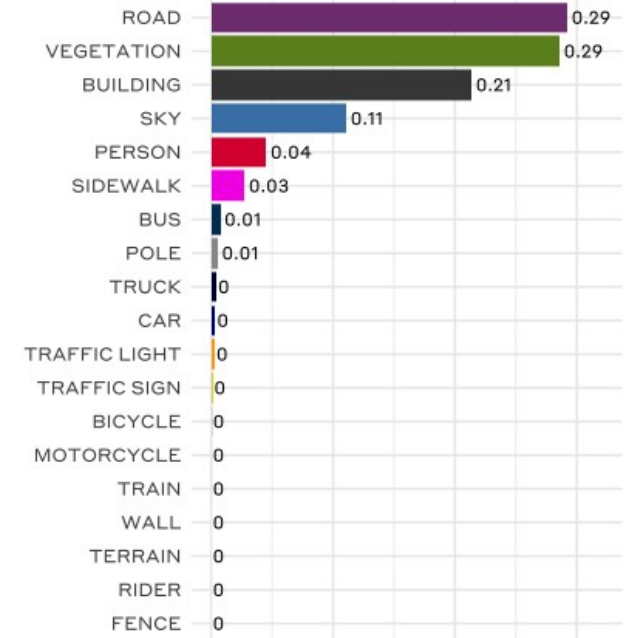
METHODOLOGY	Computer Vision
TRAINING MODEL	TensorFlow (DeepLabv3+, TFLite, trained on Cityscapes)
INPUT	Images
GOAL	Turn raw pixels into labeled elements



Street scene from Bloomsbury



Segmented image with color coded labels



Labels distribution

image	road	sidewalk	building	wall	fence	pole	traffic light	traffic sign	vegetation	terrain	sky	person	rider	car	truck	bus	train	motorcycle	bicycle
IMG_3483.JPG	0.29199	0.02719	0.21380	0.00000	0.00000	0.00541	0.00297	0.00113	0.28564	0.00000	0.11136	0.04497	0.00000	0.00355	0.00431	0.00744	0.00004	0.00004	0.00016

Segmentation metrics by image

● SEMANTIC SEGMENTATION

From pixels to Ingredients: Semantic Segmentation Results.



RStudio: Notebook Output

A tibble: 156 x 20

image <chr>	road <dbl>	sidewalk <dbl>	building <dbl>	wall <dbl>	fence <dbl>	pole <dbl>	traffic light <dbl>	traffic sign <dbl>	vegetation <dbl>	terrain <dbl>	sky <dbl>	person <dbl>
IMG_3509.JPG	0.167928521	0.070657028002	0.27660247	0.000000000000	0.010477009814	0.00089093797	0.000000000000	0.0013445265259	0.39938619762	0.000000000000	0.0000300793060	0.00777522380
IMG_3521.JPG	0.255950536	0.134643277884	0.47512109	0.000000000000	0.006826710719	0.00387672430	0.0000324782691	0.0002214427438	0.03647254258	0.000000000000	0.0784309600576	0.00513857887
IMG_3535.JPG	0.293558526	0.001117732249	0.20584376	0.0000108876016	0.000000000000	0.00163904538	0.0000592359340	0.0006838890070	0.24038550967	0.000000000000	0.0813612011645	0.02425222476
IMG_3496.JPG	0.284334328	0.053438193854	0.21781957	0.0000164236702	0.009131376075	0.00215537604	0.0000011072137	0.0002694220049	0.25390237475	0.000000000000	0.0727491083239	0.04008464280
IMG_3483.JPG	0.291991080	0.027185233903	0.21380426	0.000000000000	0.000000000000	0.00541039984	0.0029689935870	0.0011280662439	0.28564139414	0.000000000000	0.1113591269841	0.04497243776
IMG_3497.JPG	0.358234570	0.073313787320	0.16949209	0.0003245981552	0.018215880102	0.00208506797	0.0000769513535	0.0000142092427	0.25057150681	0.000046318441	0.0680286871693	0.00597784687
IMG_3534.JPG	0.260156841	0.123582212833	0.29673512	0.0027645281203	0.000002029892	0.00432200875	0.0000184535620	0.0010095943759	0.23024804540	0.000029894770	0.0218276112528	0.01636757133
IMG_3520.JPG	0.263337496	0.071161917458	0.41265892	0.0002299313823	0.064590419501	0.00313562925	0.0000446576200	0.0001699573058	0.01440300513	0.000000000000	0.0942120771920	0.01628526845
IMG_3508.JPG	0.002854397	0.234412645266	0.56160094	0.000000000000	0.000000000000	0.00110979722	0.000000000000	0.0019322724750	0.11305316397	0.000000000000	0.0502833728978	0.03243047436
IMG_3522.JPG	0.242403591	0.016570006909	0.56892535	0.0004844060020	0.003859931559	0.00028400032	0.000000000000	0.0001127512637	0.11056433207	0.000000000000	0.0540386727608	0.00048938846
IMG_3495.JPG	0.294236141	0.025777227123	0.29859026	0.0184923144605	0.001295809122	0.00272872821	0.000000000000	0.0007440476190	0.25058977584	0.000000000000	0.0670165092947	0.00540634005
IMG_3494.JPG	0.246912904	0.082110046710	0.16964341	0.0001323120394	0.022368669690	0.04266998683	0.000000000000	0.0389770600080	0.28801120057	0.000560065606	0.0235063317862	0.03286284132
IMG_3523.JPG	0.274944602	0.004347105596	0.56396005	0.0082112814744	0.000000000000	0.00001384017	0.0000250968443	0.0000001845356	0.05177368256	0.000000000000	0.0468061682138	0.01095680243
IMG_3533.JPG	0.262449511	0.071555162864	0.21238463	0.0002673921131	0.015229355631	0.00049898432	0.000000000000	0.0005071038832	0.38239489589	0.003724851486	0.0119676885511	0.03406435274

1-14 of 156 rows | 1-13 of 20 columns

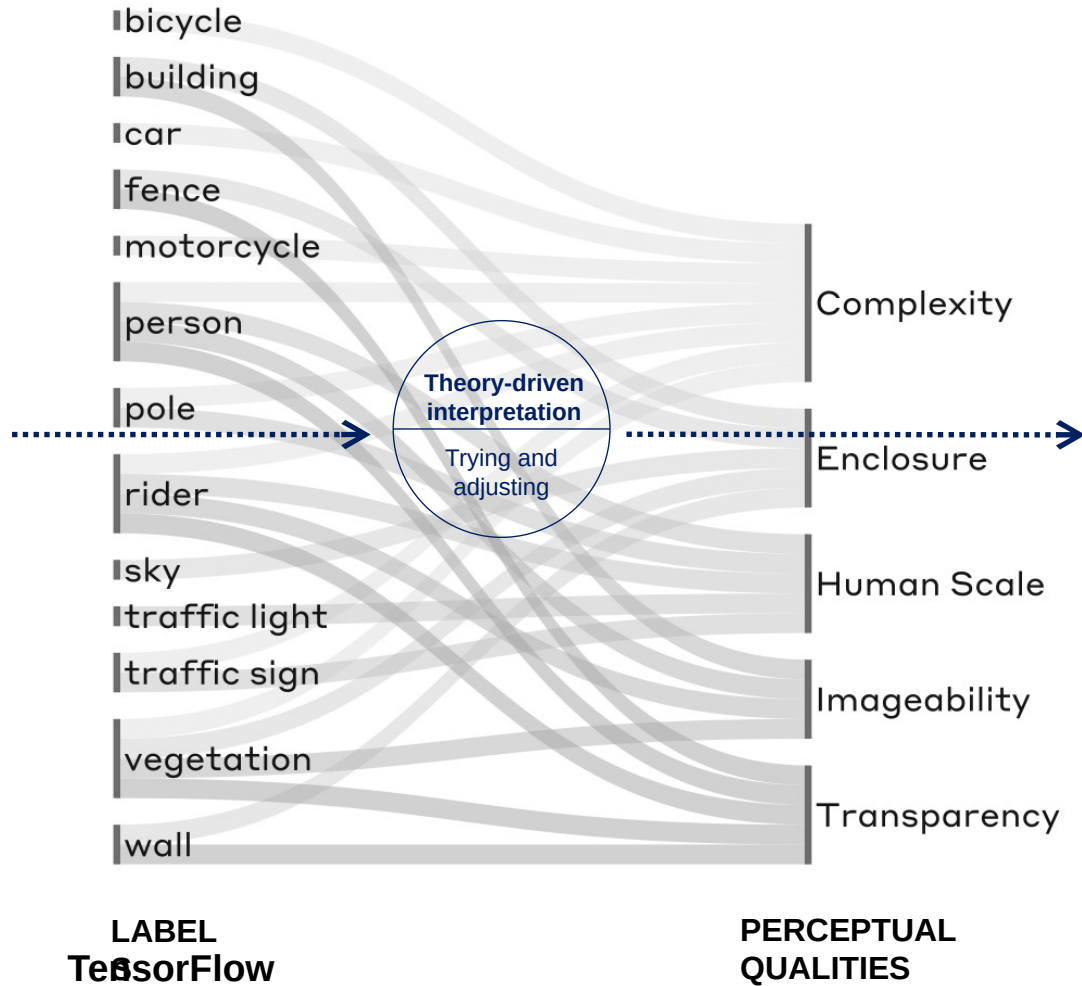
Previous 1 2 3 4 5 6 ... 12 Next

● FROM LABELS TO PERCEPTUAL QUALITIES: THEORY MEETS DATA

Translating segmentation labels into metrics that reflect how streets feel and function.



Recipe 1:
Sorting Ingredients



● FROM LABELS TO PERCEPTUAL QUALITIES: THEORY MEETS DATA

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Complexity	Visual richness from variety of elements, forms, and activity in the scene.	person, rider, bicycle, motorcycle, traffic sign, pole, car, vegetation	Entropy (distribution of elements)	Shannon entropy([class proportions])

PERCEPTUAL
QUALITIES

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PERCEPTUAL QUALITIES

Imageability	Enclosure	Human_scale	Transparency	Complexity
0.47722	0.73904	0.31766	0.01106	0.74643



Low Complexity



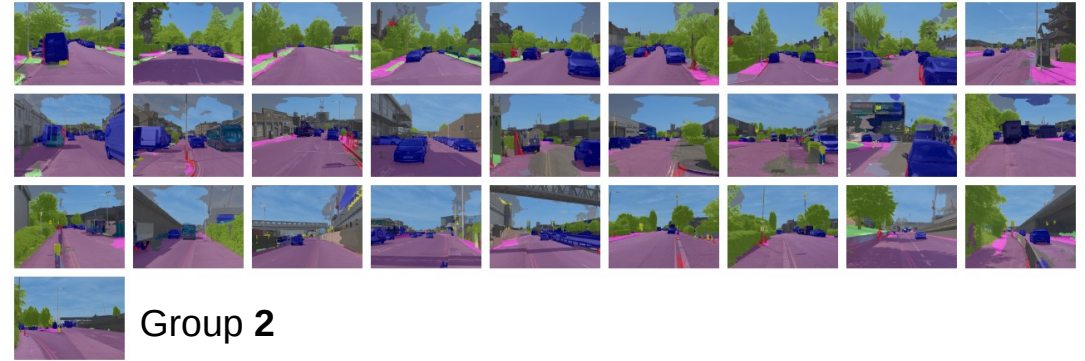
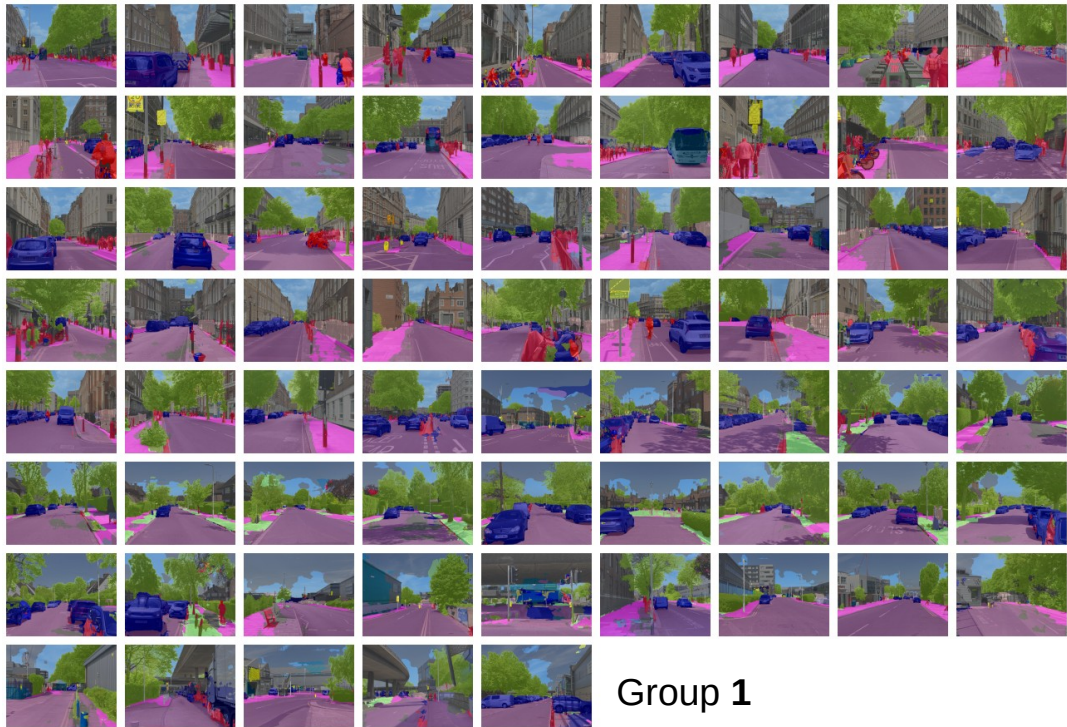
High Complexity

Each image has a different mix

● **STATISTICAL CLUSTERING**

Grouping similar flavour mixes. Finding patterns in prepared ingredients to reveal urban typologies.

Approach	Machine Learning
Stat Method	*K-means algorithm
Input	Perceptual quality metrics derived from segmentation
Outcome	Cluster street-views into perceptual types



*K-means algorithm: an unsupervised machine learning algorithm designed to partition unlabeled data into K distinct, non-overlapping clusters based on similarity

● **STATISTICAL CLUSTERING**

From labels to Urban Types: Clustering Results

Cluster	Imageability					Enclosure					Human scale					Transparency					Complexity				
	mean	median	min	max	sd	mean	median	min	max	sd	mean	median	min	max	sd	mean	median	min	max	sd	mean	median	min	max	sd
1	0.48	0.47	0.25	0.91	0.09	0.87	0.88	0.71	1.00	0.08	0.20	0.15	0.01	1.00	0.20	0.02	0.01	0	0.17	0.04	0.73	0.72	0.58	1.00	0.09
2	0.24	0.25	0.00	0.39	0.10	0.46	0.54	0.00	0.67	0.19	0.11	0.10	0.01	0.22	0.06	0.01	0.00	0	0.16	0.04	0.72	0.72	0.59	0.99	0.08
3	0.66	0.63	0.48	1.00	0.13	0.97	1.00	0.57	1.00	0.06	0.07	0.04	0.00	0.30	0.07	0.02	0.00	0	1.00	0.13	0.48	0.51	0.00	0.69	0.14

Statistical summary of Groups by Perceptual Quality

Values (0-1 norm.)
Low High

Hamstead G S, residential, Barnet

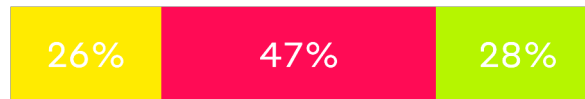
Largely highly imageable and enclosed with low human scale and simpler scenes, complemented by some enclosed and complex areas and a few open, varied segments.



Group 3

Staples Corner, industrial, Brent

Primarily open and varied with low imageability but still complex, mixed with enclosed and complex areas and some highly imageable, enclosed simpler spots



Group 2

Bloomsbury, mixed-use, Camden

Mostly enclosed and complex with strong human scale, with some highly imageable and enclosed simpler pockets.



Group 1

● **SERVING EVIDENCE-BASED DESIGN**

Blending AI's precision with human creativity for better urban environments.

-
- Urban Design & Planning**
- Which streets score highest on enclosure or human scale?
 - Where should greening be prioritized?

-
- Real Estate & Development**
- How does street character affect value?
 - Which areas show the most visual diversity?

-
- Mobility & Accessibility**
- Which streets feel most walkable?
 - How do visual qualities correlate with pedestrian comfort and safety?

-
- Policy & Place-Making**
- How can perceptual analysis guide planning?
 - Which typologies align with placemaking goals?
-

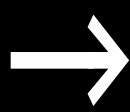
From site photo survey → To advanced place analysis



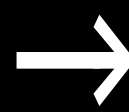
Data → AI prep → Theory seasoning → Insights served

● WORKING IN THE AGE OF AI

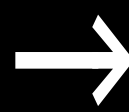
THE HUMAN EXPERIENCE



ARTIFICIAL INTELLIGENCE



ANALYTICAL EXPERIENCE



DESIGN INTELLIGENCE

- making choices shaped by experience, memory, inspirations and relationships







Thank you



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