

Re-imagining Urban Places: Can Generative AI Re-imagine "Good" Urban Places?

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Abstract. This paper investigates whether generative AI can meaningfully re-imagine "good" urban places by translating qualitative constructs, such as imageability and context, into operationalised metrics. Drawing on existing research for quantifying urban quality, the study benchmarks nine spatial metrics associated with public perceptions of Ambience, Beauty, Comfort and Safety. These metrics are applied to a selection of streetscapes, in Abu Dhabi, UAE, through an image segmentation exercise and processed through a weighted deviation analysis. The results show that visual metrics reliably identify structural strengths and weaknesses across contrasting climatic and cultural contexts, revealing key compositional urban patterns. A second experiment tests whether generative AI can improve urban scenes using the established metrics. The AI-modified images demonstrated consistent but non-uniform gains, confirming the capacity for metric-driven prompting to street spatial quality while highlighting the multidimensional and interdependent nature of urban form. Although limited by its reliance on single-frame visual data, the study establishes a practical pathway for operationalising qualitative urban values and positions generative AI as a potential co-design tool for context-aware urban place-making.

Keywords. Quantifying urban quality, Operationalise, Imageability, Context sensitivity, Segmentation analysis

1. Introduction

Over the last two decades, urban researchers have established a common perspective that views cities as complex adaptive systems in a constant state of flux, growing much like organisms through a biological evolutionary model (Batty, 2007; Marshall, 2012; Weinstock, 2010). Batty (2007) explains that within such systems, even small-scale

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urban design interventions can catalyse disproportionate socio-ecological impacts.

Cities are rigorously measured, and their relative success claimed through quantitative indicators, yet one of the greatest challenges of the modern urbanist remains largely unresolved: how to quantify the qualitative dimensions such as character, belonging and imageability, going beyond the physical boundaries of life (Wesz et al., 2023). These considerations of urban environments begin to pull apart their complexities shaping their unique plural dimension (Quan, 2022) which engages systemic urban morphologies, socio-political networks, and temporal dynamics of change (Madanipour, 2006).

Qualitative city metrics powerfully shape how people live and feel, but this form of quantification is inherently complex spanning diverse definitions, relying on multiple, often non-aligned measurement methods (Makki et al., 2025a). Parallel strands in urban design research operationalise concepts like imageability, the legibility and collective memory of a place (Lynch, 1964), and human scale, a scale that is directly visible, touchable, and appreciable (Long & Ye, 2016), into metrics such as frontage continuity, doors per metre, height-to-width ratios and tree canopy cover (Carmona, 2019; Ewing & Handy, 2009). Recent research advances this move by statistically relating public evaluations of streets and plazas to specific spatial attributes, yielding compact indicator sets for perceived comfort, safety, beauty and character (Makki et al., 2025b). Yet these tools repeatedly collide with the complexity of the urban fabric compromising scale or erasing crucial contextual nuance (Abeynayake et al., 2022; Hernández Aja, 2009). The gap reflects the need for a rigorous, operational treatment of imageability and context, where legible spatial structure and systematic, context-specific variation in metric weights replace rhetorical appeals to place (Abeynayake et al., 2022).

Into this unsettled terrain enters Generative AI, which has already profoundly altered design processes across numerous disciplines including urban design (Shao et al., 2022). It has promised support for advanced analysis and preliminary concept development, as well as the production of high-quality realistic visuals, all with an extremely efficient turn around (Beyan & Rossy, 2023; Meng et al., 2024). Most Generative AI tools do not consider legibility, publicness or the environmental challenges needed to capture the essence of urban environments generally produce semantically incoherent spatial outcomes.

Nevertheless AI-based tools have the capacity to do more than image generation, and complete previously impossible tasks, analyses and simulations, enhancing urban thinking (Kamrowska-Zaluska, 2021). They can be conditioned, programmed and calibrated, to combine simple but precise urban data, encoding qualitative constructs such as imageability and contextual awareness.

In this context, the presented research examines two empirical studies. The first is an interrogation of a context-sensitive approach to urban quality, attempting to quantify “good” by statistically linking measurable spatial characteristics to expert and public evaluations across contrasting climatic and cultural settings. The second examines whether AI can structurally express an operational definition of “good” by producing imageable urban scenes and adhere to desirable metric constraints. Collectively, these experiments establish whether generative AI can be reconfigured from a purely representational medium into a co-design instrument capable of understanding,

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evaluating and quantifying the living quality of cities.

2. Contextual Overview

2.1. QUANTIFYING URBAN QUALITY

Quantifying the living quality of cities must extend beyond functional performance to interrogate how accessibility, safety, resilience and sustainability translate into lived experiences. Its fundamental goals are to foster social interactions, inclusivity and economic vitality through forms that are both legible and contextually responsive. Improvements in legibility and context-sensitive design have seen a strong correlation with increased quality of life (Wesz et al., 2023), underscoring the need for identifying key qualitative measures for successful cities (Abeynayake et al., 2023). Simultaneously, considering context as a parameter sets the boundary condition that shapes adaptive urban processes, where factors such as climate, culture, morphology, and governance precondition the perceived visual and spatial qualities of the built environment (Lynch, 1960). From this approach, imageability becomes the perceptual expression for contextual adaptation, both symbiotically operationalising how a city can communicate its internal logic to its occupants.

Subjective indicators of urban quality have sought to capture how people feel about their environments by measuring perceptions, satisfaction and well-being (Wesz, 2023). Berhe et al. (2014) combined a qualitative assessment of social well-being with quantitative ratings to characterise satisfaction. Sousa Gomes et al. (2010) and Makki et al. (2025a), both conducted a bottom-up approach that privileges a local-level user perception to capture an understanding of impacts and realities directly tying into a macro urban scale.

Although these studies demonstrate the value of a bottom-up approach, they also reveal persistent limitations as subjective measures are difficult to standardise and the correlations with objective indicators often remain inconclusive (Wesz et al., 2023), consequently limiting their integration into policy frameworks which still privilege universal metrics. As a result, there is a persistent gap between subjective public perception and operationalised expert theory in the form of policy. This persistent gap highlights the need for more robust and consistent (ideally context-specific) methods of evaluating the quality of cities and their subsystems, and to replace purely rhetorical notions of place (Abeynayake et al., 2022).

2.2. GENERATIVE URBAN QUALITY

Contemporary applications of AI in urbanism have been explored through the lens of computational design, with literature focussing largely on the "smart city paradigm" (Yan et al., 2023). For instance, Big Data Technologies capture data and curate AI-driven systems and frameworks applied throughout cities on an international scale (Yigitcanlar et al., 2020) and are now applied as benchmarking system to understand urban performance at a regional scale (Kamrowska-Zaluska, 2021; Quan, 2022). AI and machine learning have been operationalised across specific urban domains to optimise transportation systems, enhance safety through data-driven surveillance technologies and support urban diagnostics, simulations and resource allocation through performance oriented urban frameworks (Raihan et al., 2024; Yan et al., 2023).

Despite these achievements, these systems remain primarily focused on objective indicators while neglecting subjective indicators of urban life. Consequently, despite AI advancing the narrowly defined functional intelligence of cities (Yan et al., 2023), its potential in capturing and generating qualitative urban value remains largely unrealised. Image-based generative AI platforms predominantly prioritize material realism, atmospheric ambience, and discrete form generation (Beyan & Rossy, 2023; Meng et al., 2024). Nevertheless, amidst the proliferation of sketch-to-image architectural tools, the essence of urban environments is lost.

To overcome "image-likeness" in generative AI, spatial conditioning measures can be adopted to refine the logical urban structure. The emergence of ControlNet and segmentation through image recognition, allow for controlled sketch-to-image workflows that maintain geometric fidelity and contextual awareness, as well as prompting strategies to identify key structural and compositional elements (Gokhale et al., 2022). Thus, the emerging challenge, and opportunity, is to move beyond plausible "image-likeness" toward a framework where generative-AI can encode imageability, context and qualitative urban values as measurable design intelligence, forming the foundation for this research's focus.

The research tests the adaptability and transferability of qualitative metrics established within the field (Makki et al., 2025a) across contrasting climatic-cultural settings, evaluating their construct validity, context sensitivity, and their capacity to bridge subjective perception with expert theory. AI is utilised to generate an improved urban space through analysing the gaps identified between the established qualitative metrics, and the existing urban condition.

3. Method

3.1. OPERATIONALISE CONSTRUCTS

This study takes imageability (Abeynayake et al., 2023; Lynch, 1960) and context (Marshall, 2011; Makki, 2019) as the perceptual constructs to be operationalised. Imageability will be defined as referring to spatial attributes linked to and affecting the perception of human scale and legibility, whereas context will be defined as linked to key characteristics such as building façade variation, canopy coverage and shading.

3.2. ESTABLISHING THE BASE LINE

Prior to analysing the images, the study extracts the key nine spatial metrics identified in Quantifying Quality (Makki et al., 2025a) as key indicators of ambience, beauty, comfort and safety. These nine metrics include: shading, sky, tree, traditional façade, modern façade, façade activation, plant, paving, seating. Makki et al. (2025a) purposefully selected perceptual key works that were clear, non-technical and cross-cultural to ensure transferability. As a result, the research provides an internationally applicable framework for evaluating urban quality based on responses from an international audience.

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Figure 1. Survey results of Best (green) and worst (red) locations (left) and the correlating quantification of ambience, beauty, comfort and safety (right). Extract from *Quantifying Quality* (Makki et al., 2025a)

3.3. IMAGE SELECTION

The case study features a set of 5 streetscape images based in Abu Dhabi, UAE. Images are compiled across varied urban typologies such as boulevard edges, neighbourhood edges, and city scape edges. The diversification will aid in capturing climatic, cultural and morphological variations of Abu Dhabi (refer to figure 3. for image selection).

4. Results

4.1. IMAGE SEGMENTATION ANALYSIS

Each image is manually measured and analysed to capture the proportion of visual area occupied by the nine metrics specified above, subsequently compared to the benchmarked target value for Ambience, Beauty, Comfort, and Safety.

The segmentation results convey clear spatial patterns across the tested images. Low façade activation (0-8%) and limited planting (0-14%) appear across most scenes, aligning with lower comfort and safety scores in the benchmark data. Opposingly, images with more building façade presence (cumulatively 4-24%) align more closely with the benchmark patterns for beauty and safety. This correlates the methods ability to detect legible differences in street structure.

Sky coverage is consistently high (15-46%) and shading low (0-7%), reflecting the vast, wide-scale nature of Abu Dhabi's environment and its climatic emphasis on hard-built form. These patterns demonstrate a contextual responsiveness of urban elements, typical of Gulf-region streetscapes.

SEGMENTATION ANALYSIS						
		IMAGE 1	IMAGE 2	IMAGE 3	IMAGE 4	IMAGE 5
METRIC	Shading	2.65%	1.69%	4.81%	0.00%	1.42%
	Sky	25.38%	14.96%	25.60%	45.56%	41.05%
	tree	21.87%	12.03%	21.31%	2.42%	12.06%
	Traditional facade	8.03%	0.00%	3.72%	4.44%	5.57%
	Modern facade	0.00%	17.27%	4.85%	5.74%	0.00%
	Facade activation	0.00%	0.00%	0.00%	0.00%	0.00%
	Plant	2.69%	5.26%	5.83%	0.30%	14.19%
	Paving	22.35%	18.78%	6.32%	15.50%	10.42%
	Seating	0.00%	0.00%	0.00%	0.00%	0.00%

Figure 2. Proportions of the urban and spatial characteristics extrapolated from the Abu Dhabi images

However, the analysis remains compositional. Human scale can only be indirectly approximated through inverse correlates of sky and shade values. Imageability is partially reflected through façade variation and pavement proportions but fails to account for spatial connections. Contextual responsiveness is apparent but other significant environmental and behavioural factors remain outside of the 2D visual data. Overall, segmentation provides reliable perceptual insights into a scene, although it remains limited to surface-level measures by its two-dimensional nature.

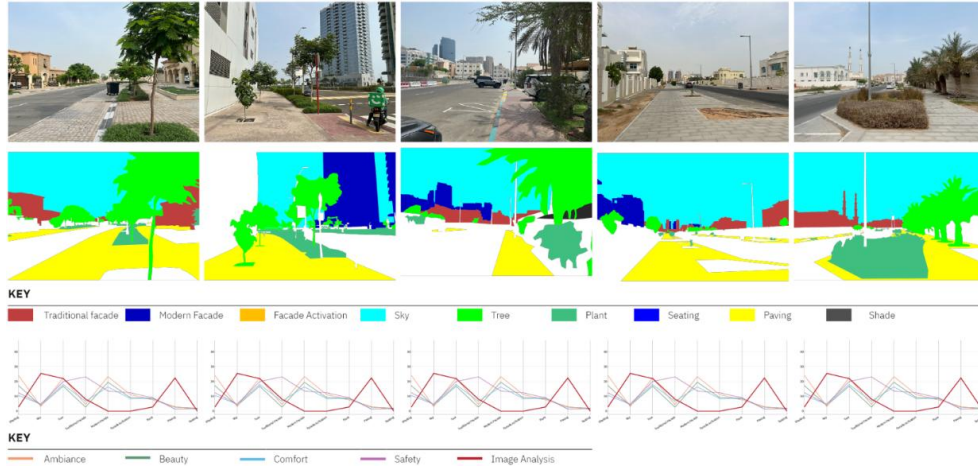


Figure 3. Image segmentation process and parallel coordinate plot showing how the images score relative to the benchmarked target values.

4.2. UNDERSTANDING DEVIATION

Two Images from the dataset are selected and moved forward. They are compared against the benchmark metrics for ambience, beauty, comfort and safety, using a weighted difference method.

Each metric's deviation is weighted by its empirically deduced importance in the benchmark dataset. The following expression calculates the weighted difference, where: x_i = the percentage value of metric 'i' in the image; b_i = the percentage value of metric 'i' in the benchmark; w_i = the benchmark-derived weight for metric 'i'.

$$\text{WeightedDiff} = \sum_i w_i |x_i - b_i|$$

$$\text{and } w_i = \frac{b_i}{\sum b_i}$$

The maximum possible weighted difference is then calculated, which represents the worst-case mismatch of an image relative to a benchmark. For each metric, the farthest possible value from the benchmark is 100% (since metrics range from 0–100). Thus:

$$\text{MaxWeightedDiff} = \sum_i w_i |100 - b_i|$$

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Normalising against the maximum possible weighted difference (i.e. WeightedDiff /MaxWeightedDiff) enabled results to be expressed on a 0–1 scale, allowing direct comparison across contexts and quality dimensions. This provides an evaluative assessment of how closely each Abu Dhabi scene aligns with the documented perceptual qualities of "good" urban space.

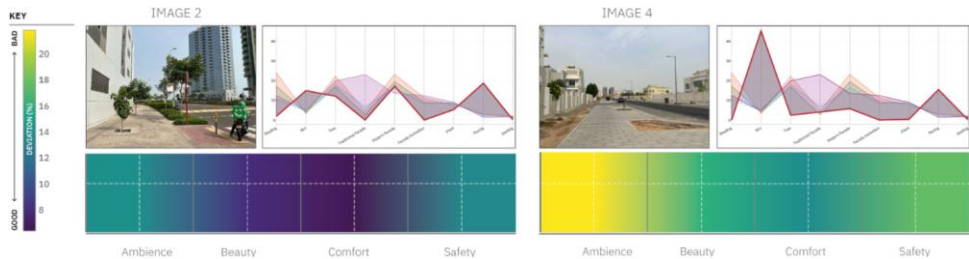


Figure 4. Deviation heatmap visualises the degree of variation between the benchmarked target values and the two images.

The divergence results reveal a clear contrast between image2 and image 4 in relation to the benchmarked profiles. Where image 2 shows minor deviations across all four qualities, image 4 displays the highest deviation values of any tested image driven by sky exposure (45.56%), absence of shading and planting, as well as limited tree cover (2.42%). Drawing on previous pattern findings, image 4 corroborates a weak sense of human scale, poor imageability and no microclimatic responses.

Based on these divergences, Google Gemini's latest Generative AI model "Nano Banana" is used to re-imagine an improved version of image 2 and 4, ultimately testing whether operationalised metrics can meaningfully guide AI toward producing more imageable, context-aligned urban scenes. The method is repeated to interrogate divergence improvement, and the results are captured in the table below.

		DEVIATION ANALYSIS					
		IMAGE 2	IMAGE 2 AI-MOD	CHANGE	IMAGE 4	IMAGE 4 AI-MOD	CHANGE
METRIC	Ambience	14.16%	13.53%	0.63%	21.82%	14.62%	7.21%
	Beauty	8.44%	7.67%	0.78%	16.37%	11.86%	4.52%
	Comfort	6.54%	6.67%	-0.13%	13.92%	8.56%	5.36%
	Safety	13.67%	6.43%	7.24%	17.88%	12.53%	5.35%

Figure 5. Deviation analysis of "good" urban quality; extrapolated from the Abu Dhabi images and the paired AI-modified images.

4.3. GENERATIVE URBAN QUALITY

The deviation analysis confirms that the AI-modified scenes consistently improve overall, but non-uniformly across all qualities.

Image 2 AI-MOD exhibits small but meaningful improvements in Ambience (+0.63%) and Beauty (+0.78%) and a substantial gain in Safety (+7.24%), while Comfort decreased almost insignificantly (-0.13%). This indicates that the model enhances shading and façade variation without resolving microclimatic deficits. Image 4 AI-MOD shows far more significant improvements across all categories. This confirms generative AI's capacity to correct major structural challenges but is unable to satisfy a "perfect" profile. The aspirations to improve and optimise for one quality,

may shift the balance away from another. This reinforces one of the central findings of the study: urban quality is multi-dimensional and interdependent.

Figure 6. Deviation analysis comparison between the Abu Dhabi images and the AI-modified images.



5. Discussion and Conclusions

This research study demonstrates that qualitative constructs such as imageability and context can be translated into measurable spatial attributes using a structured, metric-based framework. By combining segmentation analysis with the qualitative benchmark targets from Quantifying Quality (Makki et al., 2025a), the study confirms that "good" urban form can be operationalised through quantifiable patterns that reliably reflect public perception through contrasting cultural and climate settings. Understanding the deviation analysis provides a clear representation of urban space's strengths and weaknesses, offering actionable insights and an empirically validated perception of Ambience, Beauty, Comfort and Safety.

Simultaneously, the study findings confirm a measurable but incomplete representation of deeper perceptual and spatial urban qualities. As the methodology operates on a single-frame visual data set, it fails to capture the lived experience of a place through soundscapes, sequence, temporal rhythms or human behaviour (Gehl, 2013; Lynch, 1964; Mahmoudzadeh et al., 2024). As such, the method is effective for, and limited to, detecting broad tendencies and urban patterns, establishing a practical bridge between theory and application, and laying the groundwork for guiding generative AI. This prompts future research to adopt a strong spatial parameter, focusing results on a three-dimensional environment.

While this research adopts a thorough experimental framework, several limitations must be acknowledged. First, the AI model utilised is inherently shaped by the biases present in its training data, which may influence the representational and conceptual outcomes. Second, the universal application of case study findings may be constrained by the specificity of urban contexts and typologies selected. Third, while the proposed evaluation framework incorporates public review and comparative analysis, the subjective interpretation of urban quality and place identity remains partially resistant to purely quantitative assessment. Fourth, the image sample size ($n=5$) constrains generalisability. Lastly, the accelerated pace of AI technology development presents potential challenges for maintaining methodological relevance over the research

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timeline. These limitations should be systematically addressed through reflexive iterative adjustments and critical transparency in future work. As such, future iterations will expand the image sample size from single digits to several hundred views, across multiple climatic zones and cultural contexts, to improve generalisability and provide a stronger statistical foundation limiting contextual bias.

Future work by authors will extend and validate the proposed framework by undertaking a deeper exploration of the Quantifying Quality database, including finer-grain segmentation classes, demographic filtering, and sub-construct correlations that may reveal more nuanced or context-specific perceptual patterns suitable for conditioning generative models. This expanded analysis will test the cross-cultural and cross-climatic capacity of the framework, by incorporating context-specific weighting where local policy or cultural priorities require adjustments. In parallel, integrating volumetric, sequential, or microclimatic data may mitigate the inherent limitations of two-dimensional image analysis and offer a richer account of human-scale experience, legibility, and comfort. Together, these extensions will further strengthen the framework's ability to support AI-augmented urban design and contribute to a more rigorous, context-aware and publicly grounded approach to shaping "good" urban places.

Attribution

ChatGPT (OpenAI, 2025) was used to (1) refine the writing of the research paper, (2) to improve the overall flow of the piece.

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