A Multifaceted Exploration of Spatial Openness in Rental Housing: Big Data Analysis Across Tokyo's 23 Wards

賃貸住宅における空間開放性の多面的探究：東京23区のビッグデータ分析

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1 Introduction

Spatial openness is a critical factor in property selection and residential design, encompassing perceived spaciousness, visual connectivity, and flow within living environments. Traditional approaches rely on structured data using standardized metrics such as floor area and room count, failing to capture nuanced spatial qualities and rarely leveraging unstructured data sources like interior imagery and floor plan (madori) data.

This research proposes a novel methodology integrating interior images with semantic segmentation, floor plan images, and optical image-based visibility graph analysis (VGA). Our approach breaks traditional VGA constraints that required manual data inputs and proprietary software like DepthMapX. Beyond the innovation of utilizing multiple data types, we analyze the correlations between them, from 2D floorplan representations to 3D visual images, linking these with tabular data to better understand the impact of user selections and actual property attributes.

Our method utilizes open-source frameworks that accelerate data processing, enabling analysis of larger datasets through fully automated pipelines. This opens new possibilities for comprehensive urban-scale studies of residential spatial quality.

2 Data Source and Preprocessing

2.1 Dataset Collection

Our dataset comprises rental properties from the Lifull dataset, focusing on Tokyo properties constructed from 1960 to present. We sampled approximately 1000-1500 properties per decade for balanced distribution. After filtering for image quality and data completeness required for semantic segmentation and VGA analysis, 6000 properties remained. Figure 1 shows comprehensive coverage across Tokyo's 23 wards spanning multiple construction decades.

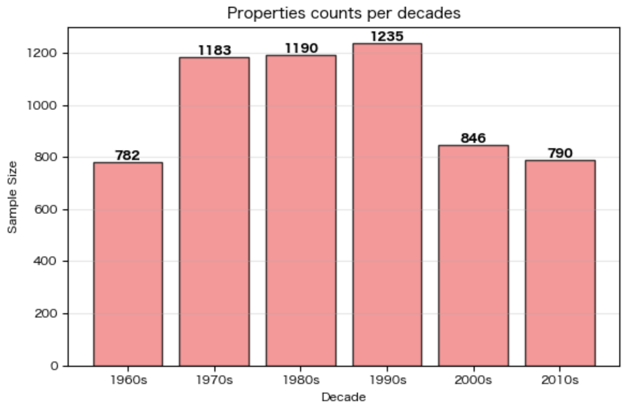


Figure 1: Dataset overview showing property construction date distribution across Tokyo's 23 wards.

2.2 Processing Pipeline

The entire data processing pipeline remains stable and fast in this level, the whole processing time can be finished within a couple of hours, though depends on the actual specs of the machine. The pipeline consists of data cleaning to remove properties with incomplete information or poor-quality images, followed by data reformatting to standardize image dimensions and tabular data structures for consistent processing. We will mention about the details in the thesis when it comes to the actual technical steps.

3 Quantifying the Openness of Residential Spaces

3.1 Feature Extraction from Interior Images

We extract quantifiable statistics related to property openness beyond traditional tabular features. For interior images, we filter main living room photos and apply semantic segmentation using Mask2Former pretrained on ADE20K dataset. Key components including walls, ceilings, and windows are identified, with component ratios extracted as features. Figure 2 shows example results. This process quantifies spatial elements contributing to perceived openness, providing measurable visual features complementing traditional property specifications.

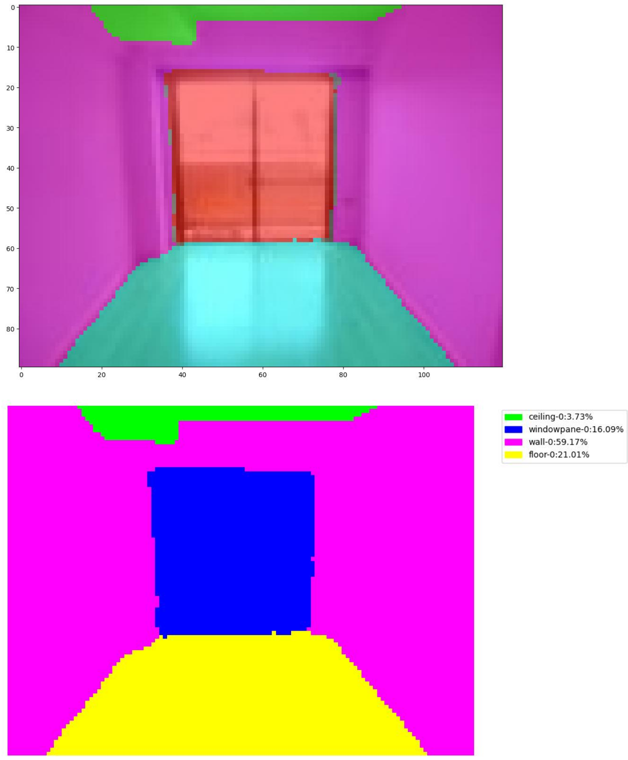


Figure 2: Example of interior semantic segmentation results.

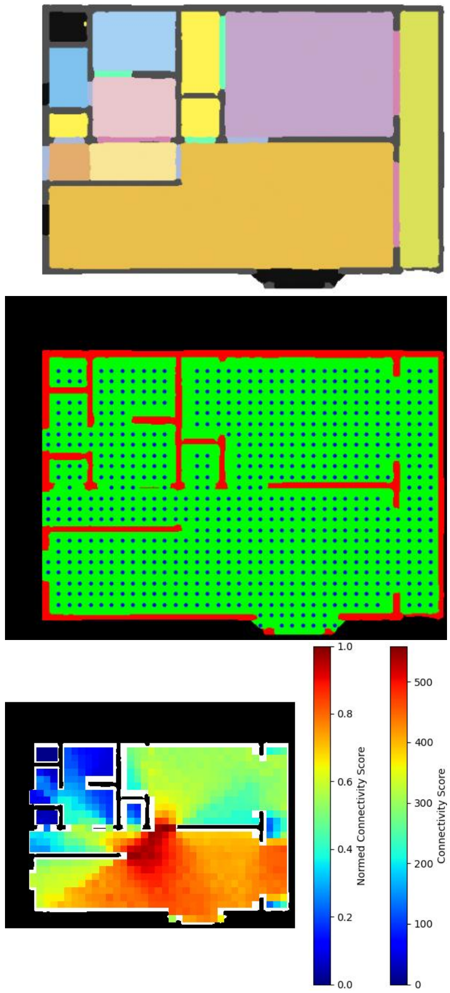
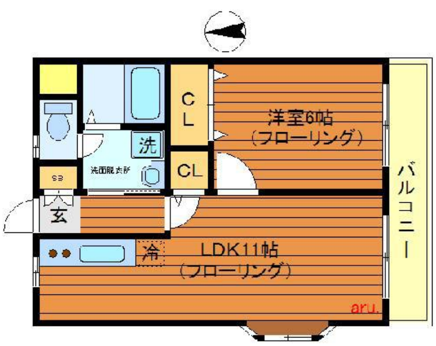


Figure 3: From top to bottom: raw floorplan, the semantic segmentation output, the physical gridding, and the heatmap of VGA.

3.2 Floorplan Semantic Segmentation and Gridding

For madori (floorplan) data, we perform semantic segmentation using a model fine-tuned on labeled floorplan data to classify walls, bedrooms, and living rooms. We extract open areas by filtering out background and wall regions, then create a grid over the open area with cell size normalized to approximately 20 cm.



3.3 VGA Calculation and Feature Aggregation

The VGA value at each grid node is defined as the number of other nodes visible from that node:

$$S(i) = \sum_{j=1}^{N} V_{ij} \tag{1}$$

where $S(i)$ is the visibility score at node i, N is the total number of nodes, and $V_{ij} = 1$ if node j is visible from node i, otherwise $V_{ij} = 0$. We extract summary statistics (mean, standard deviation, minimum, maximum) from the resulting VGA heatmap to represent spatial openness features, as demonstrated in Figure 3.

4 Influence of Building Age and Geographic Factors

4.1 Temporal Analysis of Spatial Openness

From the tabular features of the properties, we have various information, with the most interesting being building age and geographic factors. We examined the distribution of VGA mean values across construction dates in decades, as shown in Figure 4. Similarly, we examined the distribution of q3 impression scores across construction dates in decades, as shown in Figure 5.

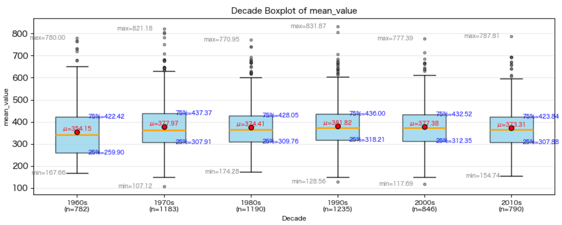


Figure 4: Distribution of VGA mean values across construction dates by decade

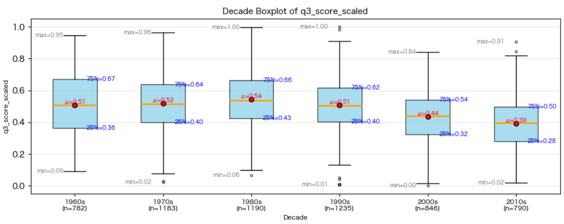


Figure 5: Distribution of q3 impression scores by property construction decade

From the distribution analysis, we observe that VGA mean values, which are heavily influenced by floorplan layout and property size, contain more large outliers while remaining relatively stable across decades. This pattern potentially reflects the impact of large-area properties on the overall distribution. Meanwhile, the q3 impression scores show a more balanced distribution, which is reasonable since impression scores evaluated from single interior photographs are more independent of the entire property layouts.

4.2 Geographic Distribution Analysis

Figure 6 presents VGA analysis results and q3 impression score distributions across Tokyo's 23 special wards. The visualization demonstrates regional variations in spatial openness characteristics, providing insights into urban housing design patterns at the metropolitan scale.

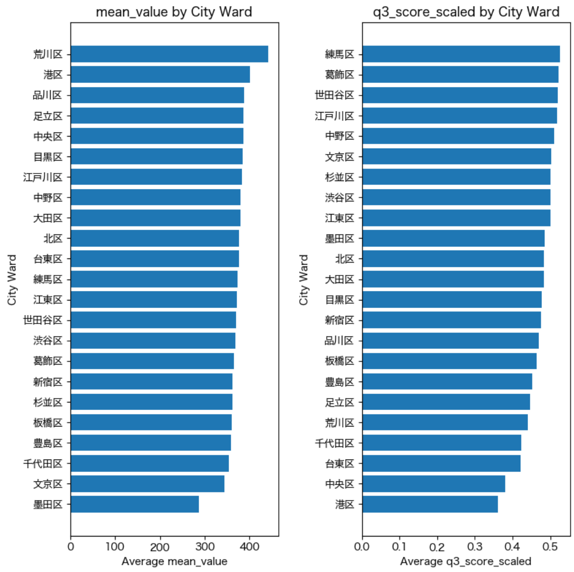


Figure 6: VGA mean values and q3 impression score distributions across Tokyo's 23 special wards

5 Correlation Analysis Between Subjective Impressions and Openness

5.1 Validation Through Subjective Impression Analysis

To validate our approach, we analyzed correlations between computed spatial metrics and subjective impressions using a pre-trained model by Shimomura et al. that outputs impression scores (q3) from interior images. We extracted VGA statistics from floorplans overlaid with living room masks to match the q3 model's training data scope. However, no significant correlation was found between VGA metrics and q3 scores, as shown in Figure 7. This stems from a fundamental mismatch: q3 uses limited-view interior photographs while VGA analyzes complete floorplan layouts.

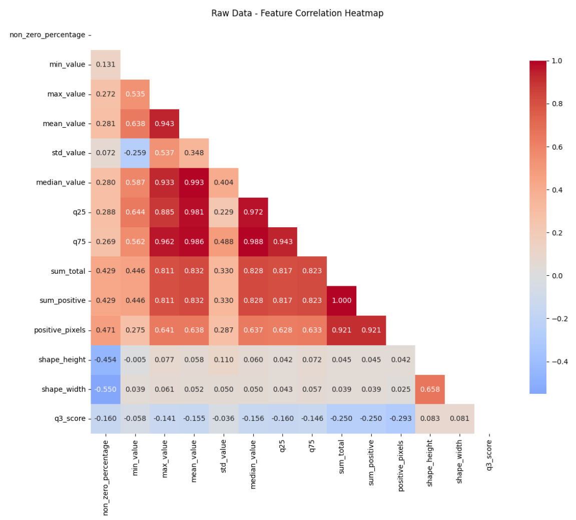


Figure 7: Correlation matrix between q3 impression scores, VGA metrics (mean, std, min, max)

5.2 Interior Semantic Segmentation Analysis

We also examined correlations between interior semantic segmentation component ratios and q3 scores. After filtering outliers using centered clustering with a 75th percentile cutoff, the results are shown in Figures 8 and 9.

Interior segmentation analysis shows window and wall components have very weak correlation with impression scores, while floor and ceiling exhibit mild to moderate negative correlations. This suggests excessive floor or ceiling visibility negatively impacts quality perceptions, emphasizing the importance of balanced camera angles.

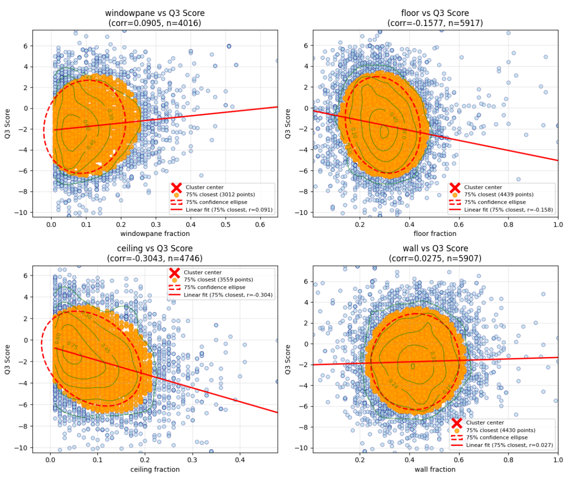


Figure 8: 2D distributions of q3 scores vs. interior semantic segmentation component ratios

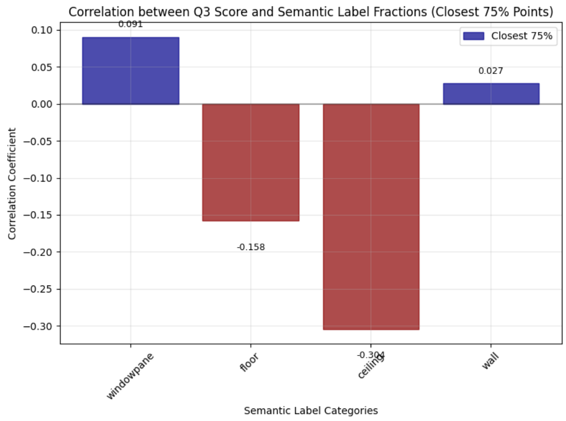


Figure 9: Correlation analysis between q3 scores and semantic segmentation ratios after outlier filtering

5.3 Temporal Pattern Analysis

We also analyzed correlations between VGA statistics, interior segmentation results, and property data. Figure 5 shows q3 impression scores by construction decade, revealing trends in perceived spatial quality over time. This demonstrates how our framework can identify temporal patterns in housing design preferences.

Detailed analysis will be presented in the full thesis.

6 Conclusion and Future Work

This research presents a framework for analyzing spatial openness in rental housing through automated madori interpretation, visibility graph analysis, and interior semantic segmentation. Our methodology quantifies subjective spatial qualities using visual data from rental platforms for scalable urban analysis. Key findings reveal weak correlations between VGA metrics and user impression scores, with interior segmentation showing that excessive floor/ceiling visibility negatively impacts quality perceptions. Limitations include: (1) q3 impression scores with potential alignment bias, (2) VGA accuracy depending on segmentation quality, and (3) interior segmentation capturing visual elements rather than aesthetic qualities. Future work should improve scoring methodologies, segmentation validation, and integrate aesthetic analysis. This open-source framework provides practical tools for data-driven spatial quality assessment in real estate and urban planning.

7 References

[References would be listed here.]