Linguistic Landscape Research on the Relationship of Urban Language and Commerce Based on Large-scale Street View Images

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Abstract. Urban linguistic landscape studies examine visible written languages in urban areas, revealing socio-economic information, such as the place identity of minority groups and the localization processes of exotic language varieties. However, studies mainly utilize qualitative analysis or small-scale image acquisition without integrating socioeconomic quantitative analysis. Our research aims to expand the quantitative indicators of linguistic landscape in city-wide scale to explore the relationship between detailed quantitative text analysis and consumer prices in spatially differentiated and temporally controlled urban street view images. We examine such correlation through street view images scrapping of historical Baidu Street View images, semantic segmentation machine learning tools, and Optical Character Recognition. Our study reveals a negative correlation between linguistic landscape indicators in street signage and consumption levels. This research provides quantitative methods for large-scale and repeatable study of linguistic landscape, introducing a novel perspective on linguistic landscape evidence for further urban economic development and urban segmentation.

Keywords: Cultural landscapes and new technologies, Linguistic landscape, Machine learning, Urban economy, Street view

1 Introduction

The concept of "Linguistic Landscape" is define as "the language of public road signs, advertising billboards, street names, place names, commercial shop signs, and public signs on government buildings" that collectively constitute the linguistic landscape of a given territory or urban agglomeration (Landry & Bourhis, 1997). In sociolinguistics field, urban linguistic landscape studies examine visible written languages in urban areas (Landry & Bourhis, 1997). Urban linguistic landscape research can reveal socio-economic information, such as the place identity of minority groups (Leeman & Modan, 2009; Manan et al., 2015) ,the localization processes of exotic language varieties (Backhaus, 2006; Manan et al., 2017) and the degree of gentrification (Lou, 2010; Papen, 2012; Shcherbakov & Bagirova, 2020). However, most studies mainly utilize qualitative analysis or small-scale image acquisition without integrating urban street views and socioeconomic quantitative analysis (Backhaus, 2007; Ma et al., 2019).

In urban field, quantitative correlation analysis of extracted features from large-scale street view images with socio-economic data has gained academic interests in recent years (Liu & Wang, 2019). Existing research mainly focused on the directly measurable physical features in urban streets (Biljecki & Ito, 2021), such as greenery, sky view factor and landmarks (Long & Tang, 2019; Long & Zhou, 2017; Meng et al., 2020; Yin, 2017). However, there has been relatively little attention directed towards textual information.

This research aims to integrate material spatial environments and economic characteristics of linguistic landscapes using more precise and comprehensive quantitative methods, exploring the correlation between linguistic landscapes and economic features, and providing valuable insights for large-scale and replicable urban linguistic landscape studies.

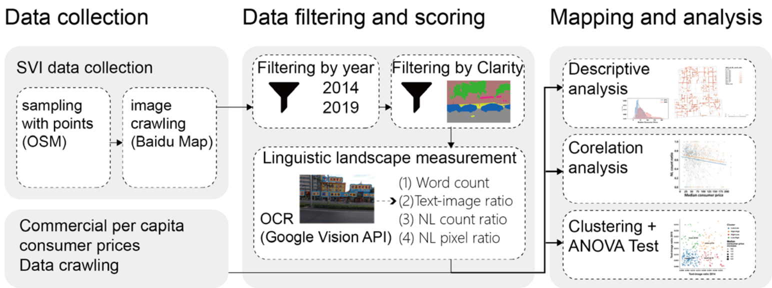

Figure 1. Data processing and analysis framework. Source: Authors.

2 Methodology

2.1 Street View Image Data

Street networks were sourced from OpenStreetMap (OSM), providing morphological data and the "highway" values to determine road function. We scraped 54,119 points of street view images from Baidu Street View API at 20m intervals along the OSM road network. At each sampling point, images encompassing historical street view images around year 2014 and 2019 were captured in the two perpendicular directions to the road, minimizing lens perspective distortion of linguistic features, e.g., signboards and brand names (Fig. 1).

2.2 Semantic Segmentation

We adopted the Google Cloud Vision model for formal text detection tasks. To minimize the misidentification of linguistic elements, we undertook the following actions: (1) Removal of the Baidu watermark from the lower left corner of dataset images. (2) Employing the ade20k-based DPT-Segmentation model, we selected images with a "brand name" label area proportion exceeding 0.0001 to be categorized as "street view images with clear and recognizable signs". This step ensured the prioritization of optical character recognition results for text elements that reflect urban commercial information on streets.

2.3 Language identification

After extracting the text information using Google Cloud Vision from our Baidu Street view dataset, the Google translate_v2 API was used for language identification, retaining results with a confidence score higher than 0.6. The study distinguishes between native language (including "zh-CN" for simplified Chinese and "zh-TW" for traditional Chinese) and foreign language ("en" for Latin English, etc.)

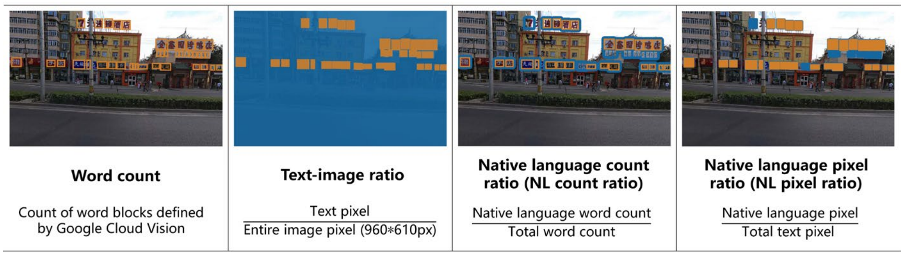

Figure 2. Linguistic landscape characterization indicators. Source: Authors.

2.4 Linguistic Landscape Characterization Indicators

We detected four indicators of word count, text-image ratio, native language count ratio, and native language pixel ratio averaged over all valid sampling points on each street segment (Fig. 2).

Word count. The indicator is defined as the number of word blocks comes from the default segmentation principle of Google Cloud Vision. In non-space-separated languages recognition, the principle groups adjacent words into one word block, such as yang-rou (mutton) and hu-tong (hutong). The word count indicator objectively reflects the total amount of text in each street view image.

Text-image ratio. In each street view image, the text pixel is defined as the area enclosed by the smallest quadrilateral that completely covers the text area. This area is calculated based on the coordinate values returned by the Vision API. The text-image ratio represents the ratio of the text pixel to the entire image pixel (960*610px), reflecting the density of text within the field of view.

Native language (NL) count ratio and pixel ratio. NL count ratio is the proportion of native language (Chinese) words in the total word count, while NL pixel ratio represents the size of native language (Chinese) text on signboards in relation to the total text pixels. Both indicators reflect the proportion of native languages from different data perspectives, which could be used to analyze how the linguistic landscape reflects the population composition and social changes in neighboring areas.

2.5 Consumption Data

"Dazhong Dianping", a Chinese equivalent to "Yelp", provided user-generated data widely used in urban studies. Our study focuses on "per capita price", reflecting average expenditure for dining and leisure in the area. For each research unit, the Median Consumer Price (MCP), which serves as the dependent variable in this study, equals to the median “per capita price” of businesses located within a 50-meter buffer along the street segment. For the MCP indicator and the four linguistic landscape indicators, the Median Absolute Deviation (MAD) method was applied to remove excessively large outliers.

2.6 Data Analysis Method

This study initiates with a thorough descriptive analysis and spatial distribution depiction of linguistic landscape and consumer price indicators. Subsequently, the study validates the importance of conducting grouping analysis for both residential and non-residential samples through ANOVA tests. Additionally, it explores the correlation between linguistic landscape indicators and consumer prices, with a particular focus on residential roads. Finally, to examine changes over a two-year period, the study utilizes K-means clustering and ANOVA tests to provide a more detailed characterization of the correlation among residential roads. The approach uses data from both 2014 and 2019 as factors for K-means clustering on the same linguistic landscape indicator. With a selection of 4 clusters, the aim is to achieve high-high, low-low, high-low, and low-high groupings. After each clustering, Brown-Forsythe ANOVA tests are applied to analyze consumer price variations over the two-year period.

3 Results

3.1 Descriptive Statistical Results

As a whole, the overall distribution of all four linguistic landscape indicators witnessed a decrease between 2014 and 2019, while consumer prices showed an overall upward trend (Fig. 3). Table 1 confirms significant differences between the word count, text-image ratio, NL pixel ratio, and median consumer price indicators for the two years through the Brown-Forsythe ANOVA Test.

Fig. 4 displays the spatial distribution of the linguistic landscape indicators from a geographical perspective. The figure reveals that residential roads within historically preserved areas like hutongs generally exhibit higher NL pixel ratios, while prominent commercial districts such as Xidan tend to have lower values of this metric. We observed through interviews that the commercial activities in these hutong areas primarily cater to the local residents, with minimal influence from external cultures and relatively lower degrees of internationalization. Thus, the cultural environment remains largely intact, and the population tends to be older. These regions demonstrate a preference for utilizing the native language.

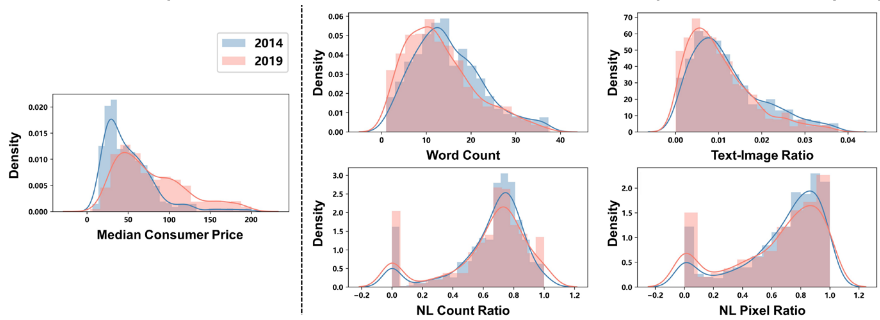

Figure 3. Comparison of distribution of the indicators over two years. Source: Authors.

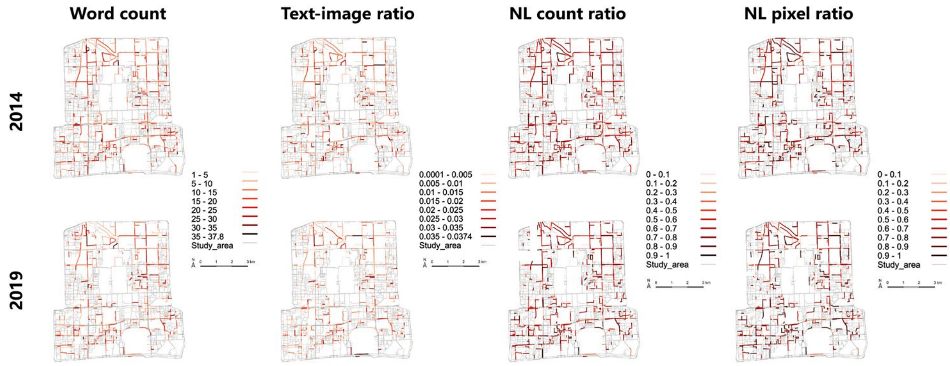

Figure 4. Distribution map of the indicators over two years. Source: Authors.

Table 1. Brown-Forsythe ANOVA Test for grouping by road type and year.

	Indicators	Grouped by Road Type			Grouped by Year		
		statistic	p-value		statistic	p-value	
Linguistic Landscape Indicators	Word count	0.674	0.412		27.478	0.000	***
	Text-image ratio	45.954	0.000	***	25.854	0.000	***
	NL count ratio	0.848	0.357		2.192	0.139	
	NL pixel ratio	13.429	0.000	***	8.454	0.004	***
Consumption Data	Median consumer price	0.528	0.467		232.062	0.000	***

* *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01, Statistic: Asymptotic F-distribution (Source: Authors)

The spatial variations of each indicator based on road types are further explored. Residential roads (n=350, 38.5%) primarily serve residential functions, while other road types (n=559, 61.5%) mainly facilitate traffic flow. The distinct functional roles of these road types may result in differences in the distribution patterns and correlation. The ANOVA Test (Table 1) confirms significant differences in the text-image ratio and NL pixel ratio between the two types of roads, validating the necessity for spatial grouping in our study.

Comparing the non-residential road group, the text-image ratio and NL pixel ratio, show higher distributions in residential roads (Fig. 5). Correspondingly, Table 2 presents the descriptive statistics for both years and provides the statistical percentage changes from 2014 to 2019. The results indicate that the median values of all four linguistic landscape indicators decreased from 2014 to 2019, with a rising trend of the median consumer price. Specifically, the median consumer price experienced a higher increase in residential roads (46.6%) compared to non-residential roads (30.6%). This discrepancy may be attributed to the fact that residential roads are closer to residents' daily lives and are more responsive to the process of urban renewal.

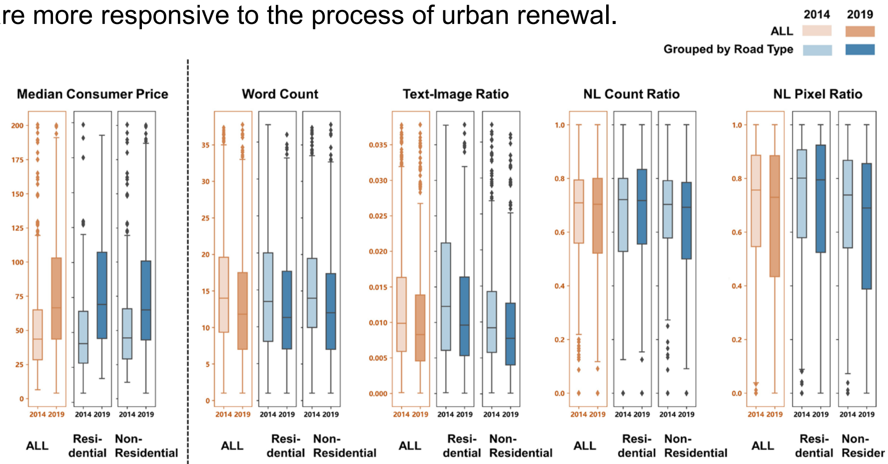

Figure 5. Distribution of indicators for street segments grouped by road type. Source: Authors.

Table 2. Descriptive statistics for street segments grouped by road type.

	Indicators	2014		2019		Growth Rate*	
		Median	**Std.**	**Median**	**Std.**	**Median**	**Std.**
Total (n=909)	**Median consumer price**	43.500	31.551	66.500	42.582	36.2%	0.962
	Word count	14.000	7.722	11.800	7.759	-17.9%	0.828
	Text-image ratio	0.010	0.008	0.008	0.008	-18.5%	1.722
	NL count ratio	0.709	0.244	0.704	0.280	-2.3%	0.580
	NL pixel ratio	0.756	0.287	0.730	0.323	-3.6%	1.460
Residenti al Rd (n=350)	**Median consumer price**	42.000	32.048	70.000	43.865	46.6%	1.071
	Word count	13.414	8.276	11.250	7.949	-18.2%	0.899
	Text-image ratio	0.012	0.009	0.010	0.008	-20.5%	1.843
	NL count ratio	0.721	0.263	0.718	0.277	-0.7%	0.609
	NL pixel ratio	0.802	0.307	0.795	0.316	-1.2%	1.830
Non-Residenti al Rd (n=559)	**Median consumer price**	44.500	31.264	65.000	41.748	30.6%	0.879
	Word count	14.000	7.357	12.000	7.644	-17.9%	0.782
	Text-image ratio	0.009	0.007	0.008	0.007	-18.5%	1.644
	NL count ratio	0.703	0.232	0.692	0.281	-2.8%	0.560
	NL pixel ratio	0.738	0.274	0.690	0.323	-4.7%	1.179

*Samples with infinity growth rates (0 for the previous year) were rounded in the calculations. (Source: Authors)

Table 3. Correlation between consumer price and linguistic landscape indicators

	Linguistic Landscape Indicators	Median Consumer Price					
		2014			2019		
		correlation	p-value		correlation	p-value	
Total	Word count	-0.049	0.144		-0.059	0.077	*
	Text-image ratio	-0.054	0.104		0.002	0.945	
	NL count ratio	-0.093	0.005	***	-0.072	0.029	**
	NL pixel ratio	-0.082	0.014	**	-0.069	0.039	**
Residential	Word count	0.023	0.669		-0.073	0.173	
	Text-image ratio	-0.049	0.360		-0.047	0.377	
	NL count ratio	-0.115	0.032	**	-0.141	0.008	***
	NL pixel ratio	-0.123	0.021	**	-0.161	0.003	***
Non-Residential	Word count	-0.100	0.017	**	-0.048	0.258	
	Text-image ratio	-0.058	0.173		0.030	0.474	
	NL count ratio	-0.078	0.065	*	-0.033	0.439	
	NL pixel ratio	-0.052	0.224		-0.018	0.664	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (Source: Authors)

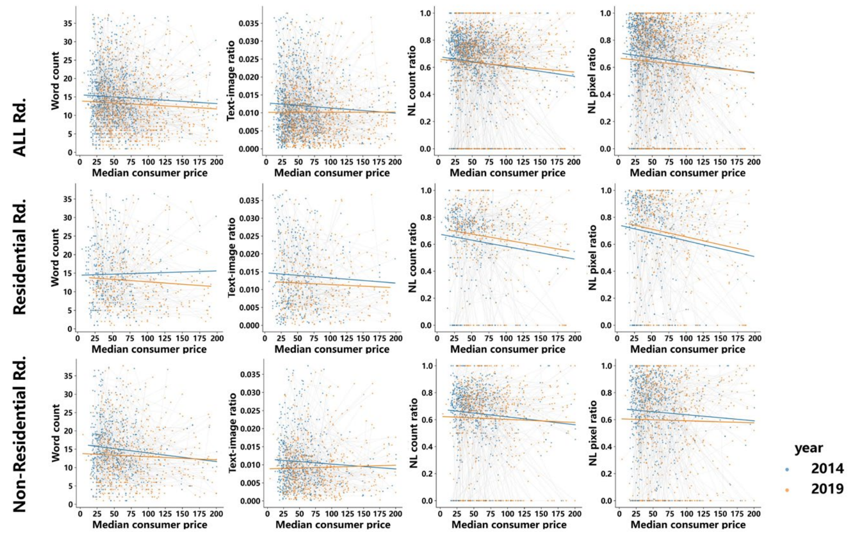

Figure 6. Correlation between consumer price and linguistic landscape indicators. Source: Authors.

3.2 Correlation Analysis Results

Building upon the quantified characteristics and spatial distribution of linguistic landscape and consumer prices, we further explore their correlation (Table 3 and Fig. 6). When considering all streets collectively, we observe a significant negative correlation between the NL count ratio and NL pixel ratio, with the average consumer price over the two years. Within the residential subgroup, this negative correlation is not only significant but also characterized by a stronger coefficient. We can infer that the reduction in the proportion of native language within street storefront signage might lead to an increase in consumer levels, and that this increase is greater in residential roads. Furthermore, the decrease in the proportion of Chinese text may suggest a shift in the target customer demographic of street-front businesses, reflecting the urban renewal and upgrading associated with gentrification processes.

To better comprehend the spatial correlation, the two NL indicators and consumer levels for residential roads are displayed as Fig. 7. From 2014 to 2019, there is a trend of transition from localized clustering to a more uniform distribution of high consumer levels and low NL proportions within the area.

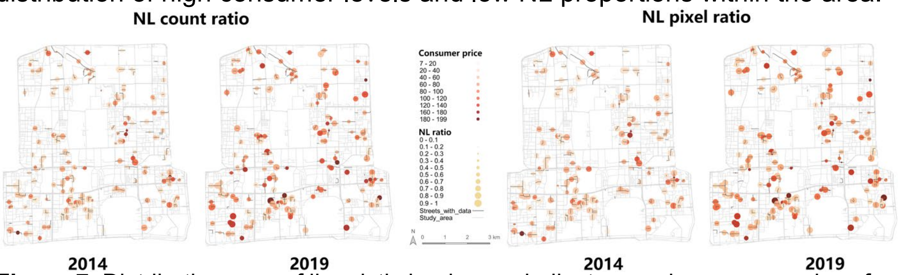

Figure 7. Distribution map of linguistic landscape indicators and consumer prices for residential roads. Source: Authors.

Table 4. Brown-Forsythe ANOVA Test

	Clustering Factors：Linguistic Landscape Indicators for two years	Growth Rate of Median Consumer Price		
		statistic	p-value	
Residential	Word count	3.772	0.011	**
	Text-image ratio	2.846	0.038	**
	NL count ratio	0.673	0.570	
	NL pixel ratio	0.660	0.578	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, Statistic: Asymptotic F-distribution (Source: Authors)

3.3 Chronological Change Correlation Results

The clustering outcomes (Table 4) reveal significant differences in the consumer price increments based on word count and image-text ratio as clustering factors for residential roads (Fig. 8). For example, for the clusters where the indicators remain relatively stable (bottom-left and top-right of Fig. 8), the group with lower word counts in both years (low-low) exhibits the highest average increase in consumer prices (mean=0.95). The groups with indicators transitioning from high to low have higher average consumer price increments than those with opposite transitions. Similar patterns are observed in the clustering results for the text-image ratio. These patterns underscore the association between reductions in the number and size of characters and increased levels of consumption. Together with existing theoretical explanations (Backhaus, 2005; Papen, 2012), they collectively indicate that the reduction in the number and area of signage text represents a facet of the urban gentrification process. These observed trends offer valuable insights into the relationship between linguistic landscape indicators and consumer prices.

4 Discussion

The fact that the signage characters went from concrete and detailed to concise and abstract corresponds to an increase in consumer prices. The detailed and functional listing of signage information may be a move in the face of homogenized competition, while the generalization and conciseness of signage text is one of the manifestations of the gentrification process of urban regeneration, which may indicate that stores are able to increase their competitiveness through branding or abstract semantics with some "sophisticated" imagery (Trinch & Snajdr, 2017).

For example, the consumer price increase for the street segment shown in Fig. 9(c) (high-low cluster of word count), is substantial at 613.6%. Visibly, the storefront signs have undergone aesthetic upgrades. In 2014, the signage provided a detailed display of the main services offered by a renovation company, such as waterproofing and tiling. However, after transitioning into a restaurant, the signage in 2019 no longer enumerates specific business offerings. Similarly, the street segment shown in Fig. 10(c) (high-low cluster of text-image ratio) showcases a reduction in both the area and quantity of characters on storefront signs. The conveyed information is more succinct. In 2014, "knife-cut noodles" specified a particular dish, while in 2019, "home-cooked cuisine" adopted a more abstract and genteel connotation. This transformation corresponds to a consumer price increase of 92.86%. In contrast, the price increases for the street segments presented in Fig. 9(d) (low-high cluster of word count) and Fig. 10(d) (low-high cluster of text-image ratio) are -1.9% and -50%, respectively.

For urban planners and designers, recognizing the differences in linguistic landscapes across various types of areas is crucial. These disparities may be linked to the primary service types of different streets and the characteristics of the clientele they predominantly serve. For instance, hutong businesses favor local languages, while innovative districts prefer foreign languages. Community service establishments use descriptive representations, whereas luxury commercial businesses lean towards abstract expressions.

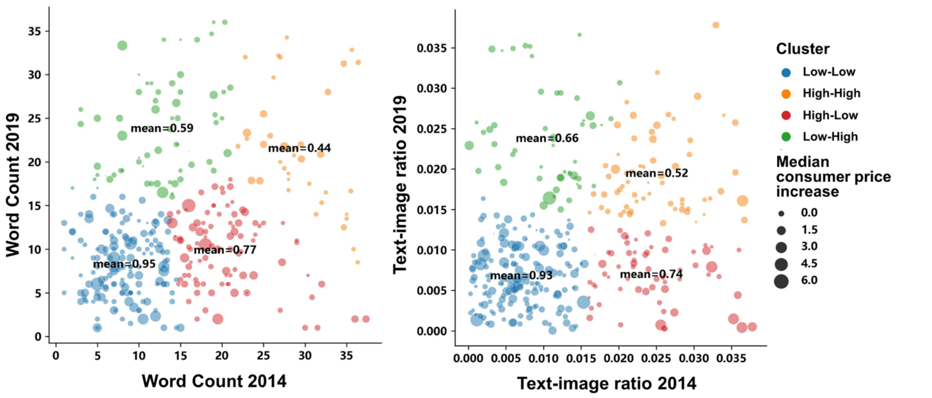

Figure 8. Word count & text-image ratio clusters for residential roads. Source: Authors.

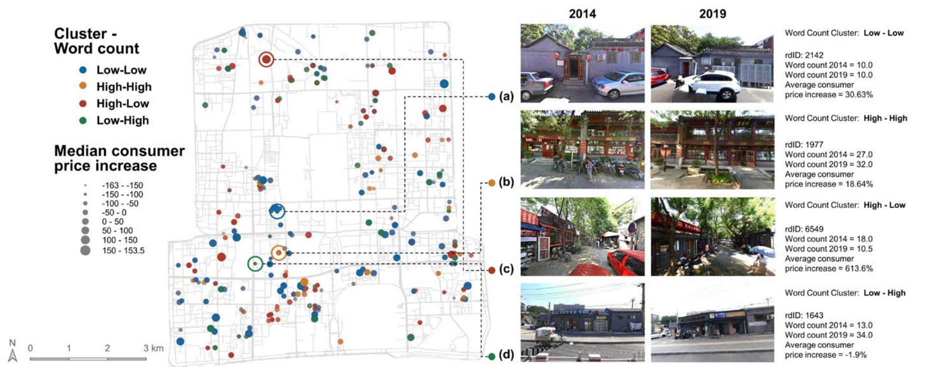

Figure 9. Street sample images of word count clustering result. Source: Authors.

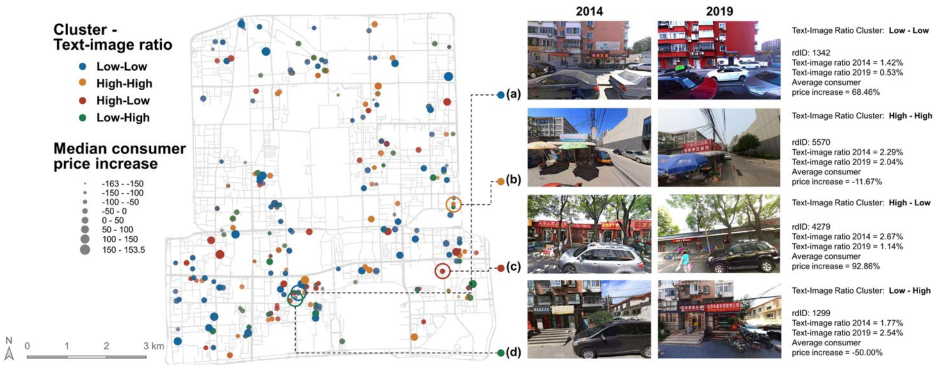

Figure 10. Street sample images of text-image ratio clustering result. Source: Authors.

Furthermore, this study can provide urban planners with a more intuitive cognitive perspective and design insight. By continuously monitoring the linguistic landscape of street businesses over time, areas in need of urban renewal can be identified. Subsequently, urban renewal efforts may intervene in the linguistic landscape by incentivizing the introduction of specific business types. Additionally, urban street interface design guidelines serve as an effective intervention method. During the guideline formulation process, it is essential to match linguistic landscape designs with the target business types and consumption levels, avoiding the over-gentrification of linguistic landscapes. For example, to improve the city's streetscape, Beijing conducted campaigns to clear shops that unlawfully removed street-facing building walls. However, this has led to a mismatch between commercial supply and consumer demand after the renovation of certain streets, highlighting the potential loss of street vitality when emphasizing tidiness over commercial viability.

Our research has limitations. Firstly, due to data constraints, the street view and consumption data are restricted to specific time periods. Secondly, further improvement in detection accuracy is possible. With the advancement of machine learning, future models may enhance the precision of identification, especially for low-resolution images. Additionally, linguistic landscapes may be related to broader socioeconomic factors. For instance, streets near greenfield parks exhibited lower word counts, while streets with lower road grades displayed higher ones. These findings might suggest connections between linguistic landscapes and land use, POIs, road grades, etc. A further focus of specific units may help urban researchers uncover deeper patterns in cities.

5 Conclusion

The linguistic landscape of streets contributes to explaining the commercial and economic attributes, and employing various indicators for quantification can effectively describe the commercial consumption levels on streets. We employ pixel-based measures for text-image and native language ratios, which, compared to count-based indicators, closely align with human observations and better capture linguistic landscape impressions within a given scene.

This study confirms the overall trend of linguistic landscape changes from the perspective of large-scale urban data. From 2014 to 2019, the overall distribution of shop sign word count, text size, and local language proportion on streets has decreased. Furthermore, precise and comprehensive quantitative methods are employed to explore the relationship between linguistic landscape and commercial consumption. Specifically, in residential roads, it confirms a significant negative correlation between the native language ratio on shop sign and the consumer levels, and discusses the negative correlation between changes in the number and size of texts with changes in consumer price. This implies that de-localization, simplicity and abstraction of linguistic signage may contribute to higher consumption as facets of urban renewal and gentrification.

While linguistic landscape indicators may not directly reflect consumption prices, they serve as essential information about urban streets and implicitly convey levels of commercial consumption. They can provide urban planners with an intuitive understanding and design guidance. By employing appropriate intervention measures, linguistic landscapes can be aligned with consumption levels. This research offers an evidential perspective on linguistic landscapes, contributing to the economic development and refined street design of cities.

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Reference

Backhaus, P. (2005). Signs of multilingualism in Tokyo—a diachronic look at the linguistic landscape.

Backhaus, P. (2006). Multilingualism in Tokyo: A look into the linguistic landscape. *International Journal of Multilingualism*, *3*(1), 52-66.

Backhaus, P. (2007). Alphabet ante portas: How English text invades Japanese public space. *Visible Language*, *41*(1).

Biljecki, F., & Ito, K. (2021). Street view imagery in urban analytics and GIS: A review. *Landscape and Urban Planning*, *215*, 104217. https://doi.org/https://doi.org/10.1016/j.landurbplan.2021.104217

Landry, R., & Bourhis, R. Y. (1997). Linguistic landscape and ethnolinguistic vitality: An empirical study. *Journal of language and social psychology*, *16*(1), 23-49.

Leeman, J., & Modan, G. (2009). Commodified language in Chinatown: A contextualized approach to linguistic landscape 1. *Journal of Sociolinguistics*, *13*(3), 332-362.

Liu, L., & Wang, H. (2019). Application of computer vision in urban studies: review and prospect. *City Plan. Rev*, *43*, 117-124.

Long, Y., & Tang, J. (2019). Large-scale Quantitative Measurement of the Quality of Urban Street Space: The Research Progress (in Chinese). *City Planning Review*, *43(06)*, 107-114.

Long, Y., & Zhou, Y. (2017). Pictorial Urbanism: A New Approach For Human Scale Urban Morphology Study (in Chinese). *Planners*, *33(02)*, 54-60.

Lou, J. J. (2010). Chinatown transformed: Ideology, power, and resources in narrative place-making. *Discourse Studies*, *12*(5), 625-647. http://www.jstor.org/stable/24049860

Ma, R., Wang, W., Zhang, F., Shim, K., & Ratti, C. (2019). Typeface Reveals Spatial Economical Patterns. *Scientific Reports*, *9*(1), 15946. https://doi.org/10.1038/s41598-019-52423-y

Manan, S. A., David, M. K., Dumanig, F. P., & Channa, L. A. (2017). The glocalization of English in the Pakistan linguistic landscape. *World Englishes*, *36*(4), 645-665. https://doi.org/https://doi.org/10.1111/weng.12213

Manan, S. A., David, M. K., Dumanig, F. P., & Naqeebullah, K. (2015). Politics, economics and identity: mapping the linguistic landscape of Kuala Lumpur, Malaysia. *International Journal of Multilingualism*, *12*(1), 31-50. https://doi.org/10.1080/14790718.2014.905581

Meng, Y., Xing, H., Yuan, Y., Wong, M. S., & Fan, K. (2020). Sensing urban poverty: From the perspective of human perception-based greenery and open-space landscapes. *Computers, Environment and Urban Systems*, *84*, 101544.

Papen, U. (2012). Commercial discourses, gentrification and citizens' protest: The linguistic landscape of Prenzlauer Berg, Berlin. *Journal of Sociolinguistics* *16*(1), 56-80. https://doi.org/10.1111/j.1467-9841.2011.00518.x

Shcherbakov, O., & Bagirova, A. (2020). Linguistic Landscapes of Gentrified Localities: A Case Study of China. 2020 the 5th International Conference on Education Science and Development.–2020.–In print.

Trinch, S., & Snajdr, E. (2017). What the signs say: Gentrification and the disappearance of capitalism without distinction in Brooklyn. *Journal of Sociolinguistics*, *21*(1), 64-89.

Yin, L. (2017). Street level urban design qualities for walkability: Combining 2D and 3D GIS measures. *Computers, Environment and Urban Systems*, *64*, 288-296. https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2017.04.001