The Influence of Perceived Landscape Qualities on Economic Vitality: A Case Study of a Retail Coffee Chain

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Abstract: As a crucial aspect of vitality, the economic facets of vitality at the store level have yet to be investigated in greater detail, and its relationship with micro-level perceived landscape qualities in the public realm requires further examination. The recent advancements in big data and Machine Learning (ML) have presented an exceptional opportunity to empirically investigate vitality and its association with the urban built environment. This research aims to comprehensively gather various dimensions of economic vitality for retail coffee chain, using Starbucks stores in Hong Kong as a case study. The study incorporates the previously under-researched dimension of customer sentiment, which is interpreted through the Natural Language Processing (NLP) model. Additionally, the study collects both subjectively measured landscape perceptions and objectively extracted visual features from street view imagery (SVI) using ML algorithms and crowdsourced surveys. Results indicate that micro-level perceived landscape qualities, such as scale and signage, have a greater impact on economic vitality than conventional macro-level planning characteristics. The findings of this research have the potential to inform and support a successful and economically dynamic retail model at the neighbourhood scale, further emphasizing the economic significance of human-scale landscape design in the public realm.

Keywords: Economic vitality, coffee retail, Machine Learning, perceived landscape quality, Street View Imagery

1 Introduction

Urban vitality has long been considered a critical aspect of successful cities in place making, contributing to resilience, creativity, and innovation for sustainable development (CHEN et al. 2022, MONTGOMERY 1998). First introduced in JACOBS (1961)' seminal book, and initially defined as the presence of active street life, the concept of vitality has evolved into a multi-faceted connotation that encompasses various dimensions, with economic vitality being regarded as a critical component (HUANG et al. 2020).

Quantifying vitality remains a challenge due to its complex nature, encompassing both social and economic aspects. Previous studies have used macro-scale indicators, such as the number of entertainment facilities within a city, to measure vitality. However, with the rise of big data, new opportunities have emerged to quantify vitality. Despite this, researchers have pointed out that some big data sources, such as cell phone records, have relatively low data quality. Therefore, researchers have shifted to using the intensity of geo-tagged catering businesses from POIs to measure economic aspects of vitality (XIA et al. 2020, YE et al. 2018). Alternatively, LONG & HUANG (2019) compared economic vitality across hundreds of cities in China using crawled numbers of reviews from popular social media websites that collects

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ratings for restaurants. More recently, researchers have proposed more complex frameworks that utilize information available from online service evaluation platforms, such as incorporating service quality and scale in addition to popularity (LI et al. 2022). In conclusion, the spatial organization of small food establishments plays a significant role in reflecting human activity patterns. Utilizing customer reviews to gather information about economic vitality has also proven to be a valuable approach. However, these methods fail to consider the emotions and sentiments of user groups, which play a crucial role in the human-environment interaction and contribute to the economic and social aspects of individual businesses at a micro-level (LIU et al. 2020). Additionally, calculating an overall vitality index using certain weighting methods for each dimension may be inexorably subject to bias, as different businesses may provide different types of services and target distinct demographic groups with varying economic statuses.

In view of these factors, exploring the economic vitality of chained catering services, specifically coffee retail, can provide an innovative approach for comparison across different stores. Coffee retail is often considered a crucial type of "third place," where people gather for socializing without an obligation to stay. It creates a sense of place, a key aspect of promoting vitality (OLDENBURG 1989). The success of coffee retail is influenced by various factors such as the environment, service quality, context, and food and beverage offerings. However, literature in the hospitality industry suggests that chained coffee shops often use standardization and intra-regional diversification strategies based on 'portfolio theory' to reduce costs, providing a tactical advantage and greater survival rates over single-location franchises (PARK & JANG 2022). As a result, the differences in services and food offerings between stores within the same chained business can be largely ignored when comparing their economic vitality, offering a solution to the limitations of previous methods.

On the other hand, previous research has shown that the design of the built environment can affect vitality. For instance, building morphology, density, typology, and land use mix have all been linked to vitality (HUANG et al. 2020, LONG & HUANG 2019, XIA et al. 2020, YE et al. 2018). However, these studies focused merely on objective environment factors at a macro and planning scale, but neglected the nuances of daily life experience and the micro-level perceived landscape qualities which can be critical in promoting vitality.

Perceived landscape qualities can be measured objectively, subjectively, or through a combination of the two measures. Advancements in Computer Vision (CV) technology have allowed for more efficient and high-throughput methods like using emerging urban data such as SVI to measure perceived qualities (DUBEY et al. 2016, ITO & BILJECKI 2021, ZHANG et al. 2018). In a nutshell, the perceived landscape qualities can be largely categorized into subjectively measured design perceptions and objectively measured visual elements (QIU et al. 2022). These human-centric perceived qualities, which can proxy how people perceive the environment when walking down the street, have been used to examine the impact of micro-level perceived landscape qualities on walking behaviour or housing prices (BASU & SEVTSUK 2022, SONG et al. 2023, SONG et al. 2022).

Though several recent studies have sought to reveal the correlation between perceived landscape qualities and street vitality (CHEN et al. 2022, JIANG et al. 2022), they mainly focused on pedestrian volume as a representation of vitality and only studied a limited number of perceived landscape qualities. Further research is needed to investigate how perceived environment qualities contribute to the economic vitality of coffee retail at a micro-scale. Addi-

tionally, due to differences in measurement methods, subjectively measured perceptions have been shown to exhibit different spatial heterogeneity patterns in comparison with their objective counterparts (SONG et al. 2022). Thus, their separate impacts on economic vitality warrant further understanding.

In conclusion, our research endeavours to address the existing knowledge gaps by integrating the human-environment interaction into the measurement of economic vitality across chained coffee stores, and examining how economic vitality is influenced by quantifiable micro-level perceived landscape qualities measured through both subjective and objective methods. Our research offers new insights in the following aspects:

1) It sheds light on the multiple dimensions of economic vitality of chained coffee shops at the store level and incorporates customer sentiment using advanced Natural Language Processing (NLP) techniques.
2) The study measures both subjectively measured perceptions and objectively measured visual elements from SVI with ML tools.
3) The relationship is disclosed between the perceived landscape qualities within the walking radius around each store and the various dimensions of economic vitality, by the comparison of the perceived landscape qualities with macro-level factors in relation to economic vitality.

2 Data and Methods

2.1 Study Area and Data Source of Economic Vitality

The study area is Hong Kong, a high-density city that is one of the world's largest financial centres with over 7 million residents. To control for factors that could impact the economic vitality of different services, chained coffee stores were selected for our investigation using big data. By choosing stores from a single brand, the research can mitigate the influence of food quality, service, and interior design and focus instead on other key factors such as the quality of the outdoor street environment and macro-level spatial qualities such as accessibility to transportation and points of interest (POI). This approach offers a straightforward research design, which provides a clearer understanding of the economic vitality of these stores compared to previous studies that have utilised a more broad-brush approach, observing citywide vitality in a coarser grid. Specifically, Starbucks coffee is chosen, a global market leader with over 150 stores in our study area. The analytical framework of this study can be seen in Fig. 1.

The search results were finalised using the Google Map API, which returned information for 158 Starbucks stores (Fig. 2) located throughout Hong Kong after initial data cleansing. It is worth mentioning although data was also obtained from the local restaurant evaluation platform 'Open Rice', the number of reviews for Starbucks Coffee on this platform was insufficient, so this data was not included in the study. Information gathered from the web crawl for each store comprised its geographic coordinates, address, and, most importantly, information on reviews, including the number of reviews, the number of review images, overall review score, review score distribution, and detailed review text (the 20 most recent reviews after January 2017).

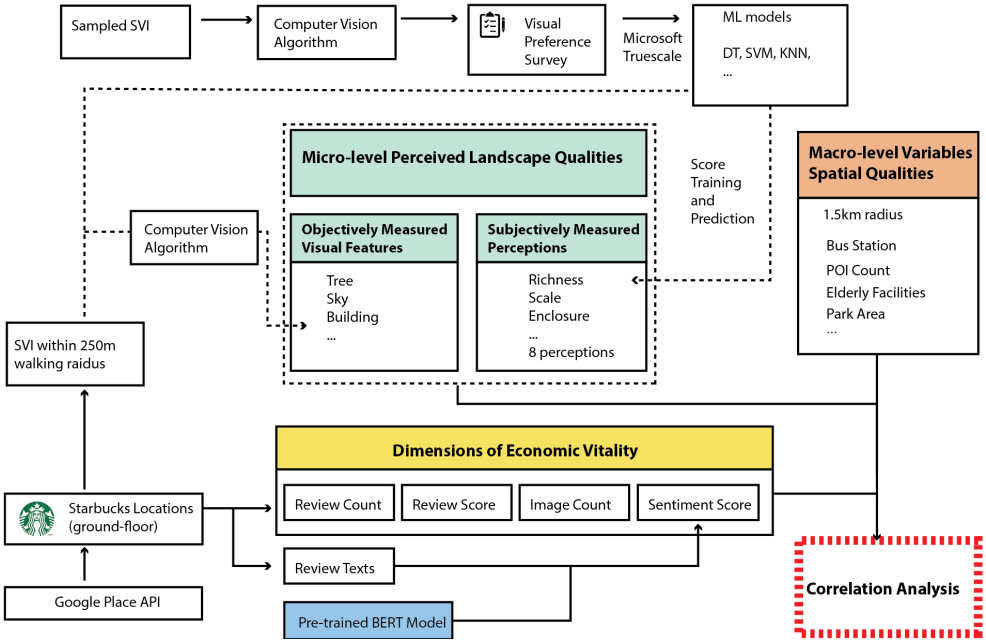

Fig. 1: Analytical Framework Diagram

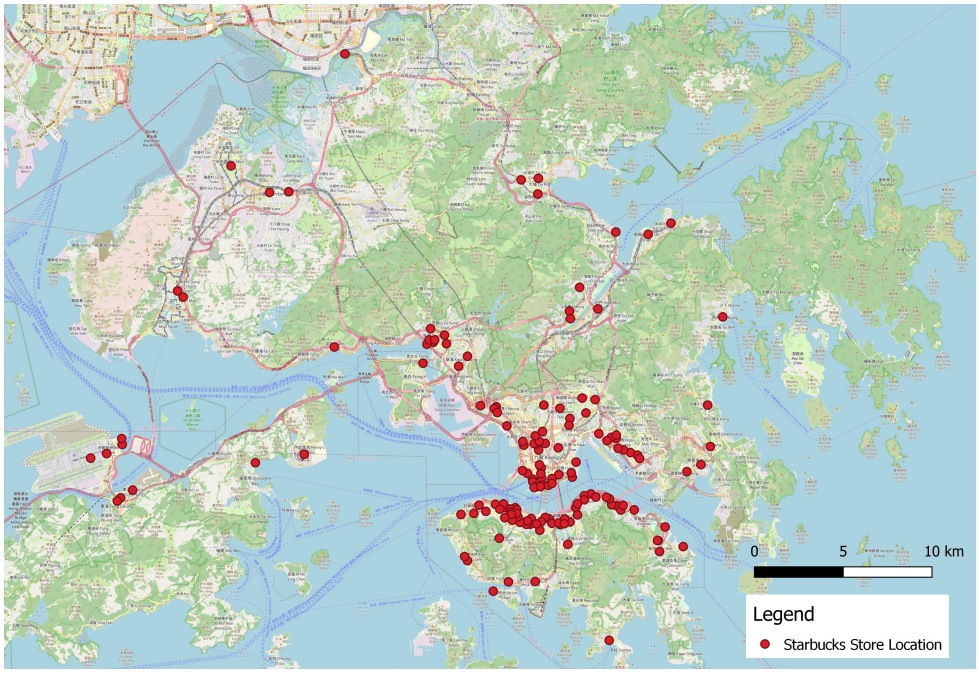

Fig. 2: Locations of the 158 Starbucks coffee shops in Hong Kong

NLP is a field of Artificial Intelligence and computational linguistics concerned with the interactions between computers and human (natural) languages. It enables the interpretation of the human language in a meaningful way, for instance, to understand the emotions. Sentiment scores were calculated for each store based on its review texts using the state-of-the-art Bidirectional Encoder Representations from Transformers (BERT) model, an NLP technique that uses a self-attention mechanism and eliminates biases from left-to-right momentum which was used in previous models. The use of BERT has been increasing in recent studies (ALAPARTHI & MISHRA 2021). The model was pre-trained on a review dataset containing 150k reviews and reported to achieve an exact prediction accuracy of 67% and an off-by-1 score prediction accuracy of 95% for reviews in English. The sentiment score for each store was calculated as the average of the sentiment scores interpreted from its crawled reviews, with a score between 1 and 5, where 3 represents a neutral sentiment, 5 represents the most positive sentiment, and 1 represents the most negative sentiment.

2.2 Measuring Micro-level Perceived Landscape Qualities

The street network for this study was obtained from OpenStreetMap and points along the Hong Kong road network were sampled every 50m using the QGIS platform (ZHANG et al. 2018). To examine the correlation between perceived landscape qualities and economic vitality, points were selected within the 250m walking radius around each of the chained coffee stores located on the ground floor. Points located on highways were excluded as they do not reflect the pedestrian experience. The coordinates of points were fed into the Google Street View Static API and street view images (SVI) were obtained (heading = 0, field of view = 90, image size = 800 x 400 pixels). After discarding grey or indoor images, 2,110 SVIs were left and used for further analysis.

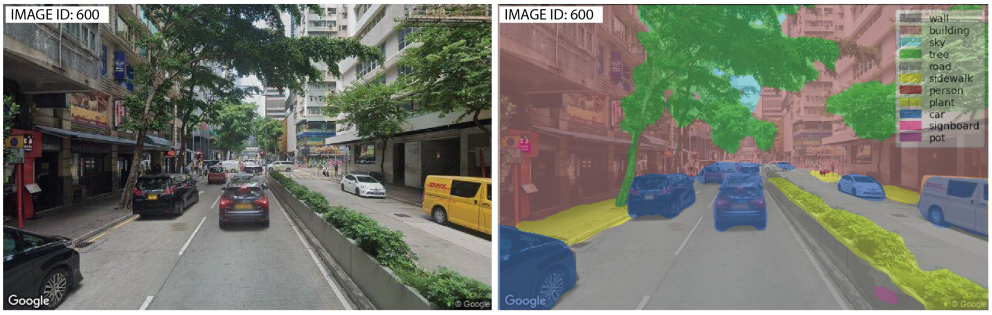

Fig. 3: Example of Raw SVI and Segmented result

To extract objectively measured visual features from SVIs, the widely used ML algorithm PSPNet pre-trained on the ADE20K cityscape dataset was adopted. Around 20 streetscape elements, such as sky, sidewalk, trees, buildings, etc., were successfully extracted from each SVI. The view index of each visual feature (i. e., the percentage of an element within the entire image) was calculated and the average value of each element within the walking radius was used as the perceived objective feature quality for each store. A randomly sampled SVI and its semantic segmentation result using the PSPNet algorithm are shown in Fig. 3.

Meanwhile, in accordance with previous studies, we aimed to quantify eight subjectively measured design perceptions: typology, order, ecology, enclosure, aesthetics, accessibility,

richness and scale (EWING et al. 2006, SONG et al. 2022; TIAN et al. 2021). To achieve this, we utilised perceived quality scores obtained from 300 SVIs, with 80% used for training and 20% for testing, gathered from crowdsourcing surveys in a previous study (TIAN et al. 2021). These scores served as the dependent variables, while the view indices of key street elements served as the independent variables for the prediction task.

Eight ML algorithms were used and compared for prediction performance: K-Nearest Neighbours (KNN), Support Vector Machines (SVM), Random Forest (RF), Decision Tree (DT), Gaussian Process (GP), Voting Selection (VS), ADA Boost (ADAB) and Bagging Regression (BR). The ML models were evaluated by using R-squared (R2) and Mean Absolute Error (MAE). The best-performing model for each subjectively measured landscape quality was then selected to predict the scores for the entire SVI dataset in Hong Kong.

2.3 Macro-level Conventional Planning Qualities and Correlation Analysis

In addition to the micro-level perceived landscape qualities, macro-level planning factors were also computed to evaluate their impact on vitality. A 1.5 km buffer was created around the centre of each store location, and the relevant variables were obtained from the Hong Kong Geodata Store (https://geodata.gov.hk/gs/) and processed in QGIS. The variables included ‘number of POIs’, ‘number of hotels’, ‘number of Airbnb’, ‘number of elderly facilities’, ‘number of bus stops’, ‘distance to metro station’, and 'size of park area', which have been reported to contribute to street vitality. For example, accessibility to transportation facilities such as the distance to metro stations and the number of bus stops can impact the potential crowds around the station. The accumulation of destinations (number of POIs) can attract people and promote vitality. Meanwhile, park size represents the neighbourhood-scale environmental quality, which contributes to subjective well-being and often attracts people. Additionally, Airbnb can attract tourists and is essential to vitality.

The study conducted further statistical analysis to determine the correlations between the different dimensions of economic vitality of ground-floor stores and various groups of built environment qualities. Pearson correlation analysis was applied to provide a comprehensive comparison between macro and micro-level factors and their relationship with economic vitality.

3 Results

3.1 Comparison of Economic Vitality

The 158 Starbucks Coffee outlets in Hong Kong are dispersed throughout various regions of the city. Among these outlets, about 13 stores are located in the ‘Central’, which is its most concentrated area, 91 stores of them on the ground floor and 67 stores on other floors ranging from -1st to 9th level. Because the intent of this research is to assess the economic vitality and its relationship with the surrounding context and integrates the Sentiment analysis based on reviews, those review numbers were excluded if they were less than 30 times, and 127 stores were left. And because the stores located on the ground level have more direct interactions with the built environment, the stores on other levels were further removed, and 79 stores located on the ground level left. The detailed statistics are demonstrated in Table 1.

Table 1: Statistics of Economic Vitality of Stores on the ground floor

Variable	Score (mean)	Review Count (min)	Review Count (max)	Review Count (mean)	Image Count (min	Image Count (max)	Image Count (mean)	Senti-ment Scores (mean)
Starbucks Stores	3.82	34	1189	250	12	3466	187	3.67

Although only ground-floor stores were utilized for further analysis, a preliminary comparison was performed with stores located on other floors to identify potential biases. And the statistics revealed similar results. In summary, ground-floor stores make up approximately 60% of the total stores analysed. The average rating for these stores is slightly higher compared to those on other floors. The image count suggests that customers are more likely to take and post photos in stores located on the ground floor, which may be due to the surrounding built environment. With regards to sentiment scores, it can be concluded that stores received overall positive sentiment scores, as a neutral emotion is rated as 3.0 on the scale used.

3.2 ML Model Performances

Multiple ML algorithms were used to determine the most effective models for predicting subjectively measured perceptions. As shown in Table 2, while four out of eight variables (Typology, Order, Aesthetics and Richness) had low R-squared (R2) values and were excluded from further analysis, the qualities of Access, Ecology, Enclosure, and Scale achieved R2 values ranging from 0.40 to 0.53. These prediction accuracies are deemed acceptable

Table 2: Performances of ML Algorithms

	KNN		SVM		RF		DT		GP		VS		ADAB		BR	
ML Models	**R^2**	MAE	**R^2**	MAE	**R^2**	MAE	**R^2**	MAE	**R^2**	MAE	**R^2**	MAE	**R^2**	MAE	**R^2**	MAE
Q1_ Typol-ogy	0.18	1.16	0.31*	1.04*	0.28	1.07	-0.18	1.13	0.2	1.27	0.27	1.09	0.23	1.25	0.31	1.06
Q2_ Order	0.08	0.16	0.13	0.15	0.06	0.16	0.19*	0.15*	0.16	0.15	0.16	0.15	0.1	0.16	0.09	0.15
Q3_ Access	0.13	0.17	0.33	0.16	0.35	0.16	-0.01	0.19	0.4*	0.15*	0.39	0.15	0.34	0.16	0.32	0.16
Q4_ Aes-thetics	0.05	0.17	0.13*	0.16*	0.09	0.17	0.11	0.16	0.13	0.17	0.11	0.17	0.04	0.17	0.11	0.17
Q5_ Ecol-ogy	0.38	0.14	0.45	0.13	0.37	0.14	0.22	0.16	0.45	0.13	0.45	0.13	0.44	0.13	0.46*	0.13*
Q6_ Enclo-sure	0.46	0.12	0.44	0.12	0.43	0.12	0.37	0.13	0.53*	0.11*	0.46	0.11	0.4	0.11	0.43	0.12
Q7_ Rich-ness	-0.01	0.16	-0.01	0.15	0.02*	0.16*	-0.2	0.17	-0.08	0.16	-0.06	0.16	-0.04	0.16	-0.0	0.15
Q8_ Scale	0.3	0.14	0.37	0.13	0.41	0.13	0.17	0.15	0.41	0.12	0.46*	0.12*	0.42	0.12	0.4	0.12

* denotes the best-performed model

given the size of the training sample, and they partially outperformed results from previous studies (DUBEY et al. 2016, ITO & BILJECKI 2021, SONG et al. 2022). Therefore, the four selected perceived landscape qualities were predicted for all SVIs using the best-performing models (i. e., Gaussian Process, Voting Selection, and Bagging Regression). After determining the qualities of each street view, we linked them to the corresponding Starbucks store locations and obtained the mean value for each store as the neighbourhood's subjectively measured perceptions.

3.3 Correlation Analysis and Discussion

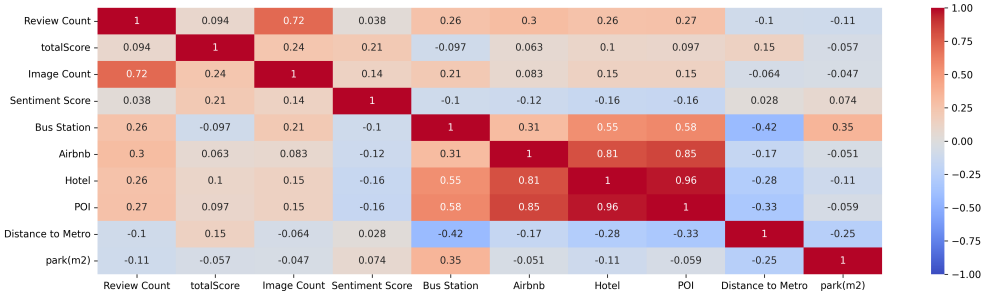

Fig. 4: Pearson Correlation coefficients between economic vitality dimensions and macro-level variables

The Pearson Correlation analysis was conducted to investigate the correlation between the four dimensions of economic vitality and selected macro-level spatial attributes (Fig. 4). The results indicate that many macro-level factors had a moderate to weak positive correlation with the review count. For instance, besides the most prominent impact of Airbnb (0.3), bus stops, POIs, and hotels also showed a similar positive association with the review count (0.26 to 0.27). The image count showed a weak positive relationship with bus stops (0.21). However, the correlations between the overall score and sentiment score and macro-level planning factors were negligible. Despite this, POIs (-0.16) and hotels (-0.16) had the highest strengths in correlation coefficients with the sentiment score, suggesting that they may have a potentially negative impact on visitors' emotions, which in turn may negatively affect the economic vitality of the stores.

We conducted a separate analysis for the micro-level perceived landscape qualities (Fig. 5). On the one hand, out of the four subjective perceptions, the quality of Scale, showed a moderate positive correlation with the review count (0.35), while its correlation with the image count was weaker (0.23). Additionally, the review count demonstrated a weak positive correlation with Enclosure (0.27) and a weak negative correlation with Ecology (-0.27). The overall review score showed a positive correlation with Ecology (0.2). Similar to the macro-level spatial qualities, the correlations between sentiment and subjective landscape qualities were statistically negligible. However, Ecology reported the highest positive impact (0.15) on sentiment.

On the other hand, the correlations between the objectively measured visual features and economic vitality dimensions were similar in strength to the subjectively measured perceptions. The review count demonstrated a strong positive correlation with signboard (0.42).

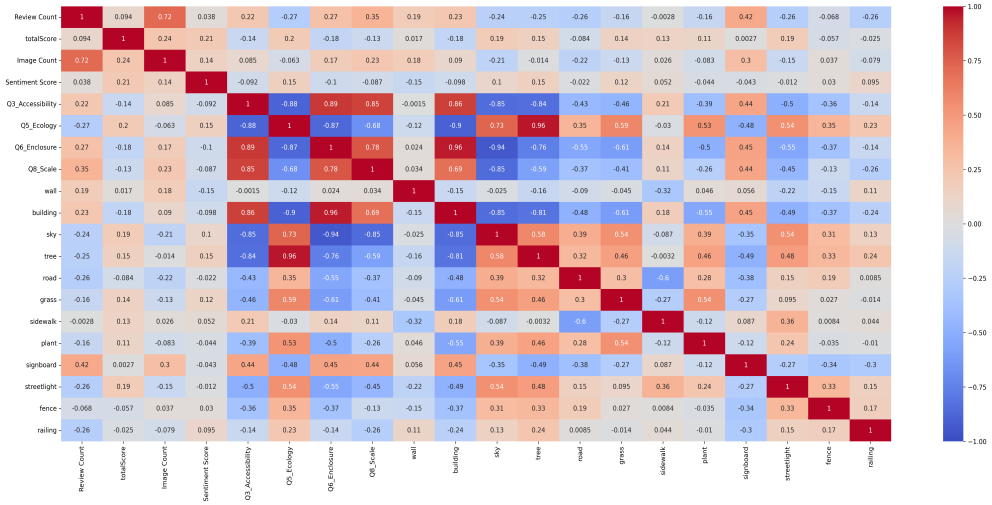

Fig. 5: Pearson Correlation coefficients between economic vitality and micro-level perceived landscape qualities (including subjectively measured perceptions and objectively measured visual elements)

Additionally, the review count showed comparable weak positive correlations with several other visual elements, including sky (-0.24), tree (-0.25), road (-0.26), streetlight (-0.26), and railing (-0.26). It also reported a weak positive correlation with building (0.23). The image count exhibited a moderate positive association with signboards (0.3) and weak negative relationships with the sky (-0.21) and road (-0.22). The sentiment demonstrated a positive correlation with trees, showing its consistency of correlation with the Ecology perception (0.15), though the correlation strength is statistically insignificant.

Our study provides a brand-new insight into the hitherto poorly understood relationship between store-level economic vitality and built environment factors. Most importantly, it was observed that compared to macro-level variables, micro-level perceived landscape qualities exhibit stronger correlations with economic vitality dimensions. Additionally, objectively perceived visual features were found to complement subjectively measured perceptions. For example, signboard was found to have the highest impact among all perceived landscape qualities, offering meaningful design suggestions for enhancing future economic vitality. It proves that the wayfinding system is essential in the urban built environment. Conversely, sky, railing, and a few other visual elements had a negative impact, whereas building was found to have a positive impact, potentially reflecting a different interpretation of enclosure quality, which supports walkability for pedestrians on the streets. This result is inconsistent with the results of previous research that found sky and sidewalk to be positively related to vitality using SVI (LI et al. 2022), which could be caused by differences in geographical context. It was also found that review count was negatively correlated with Ecology, which might stem from a lack of available space in the public realm for street planting. This result contradicts prior research, which suggests that street greenery has a positive impact on walking behaviours in Hong Kong (LU 2019) and that vegetation enhances street vitality (JIANG et al. 2022). However, it did provide similar result which aligns with the findings of Y. LI et al. (2022), who found the greenery seem to show a degree of negative correlation when fo-

cusing on a commercial complex site in Japan. This may suggest that poorly positioned greenery may obstruct key commercial areas, potentially negatively affecting the economic vitality of stores. Future research should aim to conduct a more comprehensive analysis of the relationship between street greenery and store-level economic vitality in Hong Kong.

The quality of Scale, Enclosure, and Access was all found to be positively related to review intensity, highlighting the importance of human-scale design quality in enhancing pedestrians' experience and street vitality and supporting the benefits of appropriate street planning and design. Lastly, sentiment score was found to have a positive relationship with both greenery and ecology perception, albeit with relatively low strengths. This is in line with previous research that greenery can provide psychological benefits. Nevertheless, no statistically significant correlations were established with other variables, suggesting the need for further research. The sentiments reported in reviews can be complex and might yield mixed results compared to review intensity.

Regarding macro-level factors, access to transportation was found to have a positive impact on the dimensions of economic vibrancy, which is in line with previous research that suggests public transportation facilities improve accessibility for non-local communities (HUANG et al. 2020). Additionally, the presence of visitor-oriented urban functions, such as hotels and Airbnb, were positively associated with economic vibrancy at the store level. The number of Points of Interest (POIs) was found to have a relatively high impact among the macro-level variables, which is consistent with earlier findings that land use density and functional mix affect economic vitality (LONG & HUANG 2019, XIA et al. 2020). However, our study surprisingly did not find significant correlation between park size and economic vitality, probably because park accessibility does not necessarily equate to increased economic activity in retail or commercial stores. Although increasing pedestrian volume can increase vitality, other driving forces, like perceived landscape qualities or urban micro-level amenities, are necessary for attracting people to stay and linger so as to promote urban economic vitality.

4 Conclusion

This study offers several important contributions to the existing literature. Firstly, it provides a unique perspective on quantifying the dimensions of economic vitality at the individual store level, using a case study of chained coffee shops in Hong Kong. The study employs data mining and NLP techniques to measure users' sentiment scores from reviews, offering a novel approach to this area of research. Secondly, the dimensions of economic vitality are statistically evaluated in relation to both macro-level planning variables and micro-level perceived landscape qualities, including subjectively measured perceptions and objectively measured visual elements based on SVI dataset. This can help derivation of quantifiable design strategies and implementable guidelines to enhance the economic vitality of neighbourhoods. Our preliminary data analysis suggests that compared to macro-level characteristics, subjectively measured perceptions such as Scale, and objective visual elements, such as signboards, can have a significant impact on economic vitality. The objective visual elements in the streetscape can complement the subjectively measured perceptions and vice versa. Thirdly, although no statistically strong associations were found between sentiment scores and built environment factors, the study suggests that visual greenery and Ecology perception could play a positive role in affecting sentiment scores, which is beneficial in promoting

economic vitality. Lastly, this research adds to our knowledge of future recommendations for retail store location selection, and provides actionable insights for landscape architects on the design of streetscapes, with the goal of creating economically vibrant cities through meaningful placemaking.

Nevertheless, this research has several limitations. Firstly, the dataset could be enhanced by including comparison with other brands, such as Pacific Coffee, which holds a similar market share to Starbucks in terms of coffee outlets in Hong Kong. This would help reduce any biases in the conclusion. Secondly, recent studies have shown that people's walking behaviour has a non-linear relationship with the built environment, and therefore, the vitality of an area may be influenced in a similar way. In future research, multiple walking radii could be employed to gain deeper insights into this phenomenon. Thirdly, Thirdly, the accuracy of predictions of subjectively measured landscape perceptions could be improved by either increasing the size of the training set or by employing more advanced machine learning algorithms such as Convolutional Neural Networks. Lastly, it would be beneficial to further explore other perceived landscape qualities or psychological perceptions, such as safety, in future studies.

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