Geography and Sustainability 1 (2020) 284–294

Contents lists available at ScienceDirect

Geography and Sustainability

journal homepage: www.elsevier.com/locate/geosus

Article

Using multi-source data to assess livability in Hong Kong at the community-based level: A combined subjective-objective approach

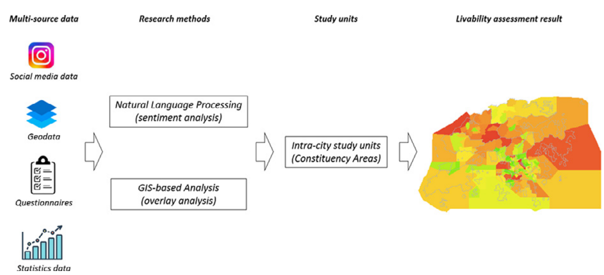
Jianxiao LIU, Han BI, Meilian Wang*

Department of Land Surveying and Geo-Informatics, Hong Kong Polytechnic University, Hong Kong, China

HIGHLIGHTS

- An evaluation index system about the intra-city livability of Hong Kong is developed.
- Multiple datasets such as statistic data, geo-data, and social media data are used.
- Personal emotions on Instagram are extracted for measuring the intra-city livability.
- The relationship between personal sentiment and intra-city livability is discussed.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 23 September 2020
Received in revised form 2 December 2020
Accepted 2 December 2020
Available online 5 December 2020

Keywords:
Habitability
Social media data
Instagram
Urban informatics
Spatial analysis
Sentiment analysis

ABSTRACT

With the emergence of new types of data (e.g. social media data) and cutting-edge computer technology (e.g. Natural Language Processing), the shortcomings of traditional methods (subjective and objective ways) for detecting urban livability can be overcome by an integrated approach. This study aims to develop a comprehensive approach to measure urban livability based on statistic data, geo-data (e.g. points of interest), questionnaires survey, and social media data (Instagram), from both objective and subjective angles. Hong Kong, as a city with a high level of urbanization and contrasting urban environments, is chosen as the study area in this research. Through this study, the question "which area of Hong Kong is more suitable for living" is answered by the visualization of GIS-based analysis. Also, the correlation between livability scores and individuals' sentiment scores are explored. Specifically, the results show that central areas of Hong Kong with a higher level of urbanization are relatively more livable than suburban regions. However, through sentiment analysis, individuals who post Instagram in suburban areas of Hong Kong usually express more positive content and happier emotion than those who post Instagram in central urban areas. The study could offer useful information for the policy action of authorities as well as the residential location choices of citizens.

1. Introduction

Progressive urbanization will lead to 60% of the population living in urban settlements by 2050 (Habitat, 2016), but urban regions normally are places of increasing inequality and segregation of residents (Saitluanga, 2014). For this reason, measuring and monitoring the quality of urban citizens become increasingly important for diverse actors. Urban livability measurement (ULM), which could reveal the spatial justice that concerns the question of "who gets what, where and how" (Smith, 1979), is conducive to providing useful feedback information for authorities to adjust or formulate opportune policies so that urban regions can continuously meet the needs of current citizens as well as to attract investment and future inhabitant taxpayers (Scott, 1998). Consequently, ULM has become an effective and essential way to determine urban sustainable development as well as residents' quality of urban life. Currently, due to the diversified definitions of livability, the measurement of urban livability has received no consensus. However, from the existing literature, there are two paths to evaluate urban livability in general, which are the subjective approach and objective approach. The subjective one focuses on capturing personal subjective life quality such as happiness and satisfaction, while the objective approach aims to

* Corresponding author: Tel.: +852 5449 0364
E-mail address: meilianp.wang@connect.polyu.hk (M. Wang).

https://doi.org/10.1016/j.geosus.2020.12.001

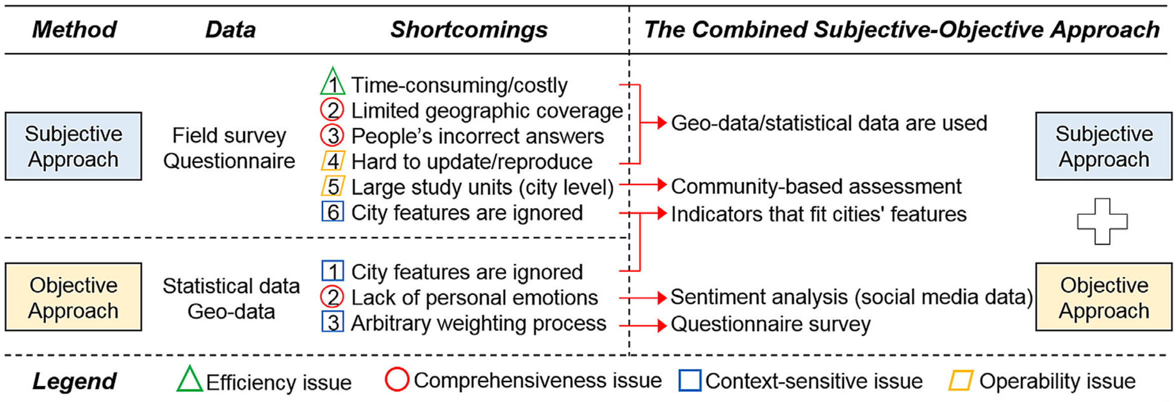


Fig. 1. Summary of the shortcomings of subjective- or objective-based livability approach

assess objective life quality such as convenience. These two approaches were usually applied separately in practice.

The subjective approach based on livability measurement involves making subjective assessments of individuals' satisfaction with their living conditions based on questionnaires survey, and it is a preferred way for sociologists to study livability before the emergence of various location-based services. For example, Wang et al. (2019) assessed the features of the satisfaction level of rural livability and then applied a structural equation model to examine the effects of livability-related determinants in 12 towns of China. Lee (2008) surveyed subjective resident assessments of the quality of life (QOL) and revealed the causal relationships among the variables affecting QOL in Taipei city. Zhan et al. (2018) applied the geographic detector model at a large-scale level to explore the features of satisfaction with urban livability and the effect of its determinants. On the other hand, most of the geographical inquiries on livability are based on objective measures (Pacione, 1990). The objective approach captures tangible and objective life quality represented by material well-being such as infrastructure, crime levels, and social welfare, usually relying on socioeconomic statistical data or geo-data like points of interest. Previous studies have also made many efforts on this topic. For instance, Fu et al. (2019) applied a principal component analysis-based method to assess the urban livability in Changchun Proper, in the People's Republic of China, based on GIS and remote sensing data. Deng et al. (2019) developed a quick assessment approach to evaluate the sustainability of the urban built environment of four large-sized cities in China based on data from statistical yearbooks. Paul and Sen (2018) evaluated the livability variations in the Kolkata Metropolitan Area of India based on the impact of Integrated Urban Geographic Factors on clustering urban centers. Similarly, Shamsuddin et al. (2012), Kyttä et al. (2016), and many other researchers have evaluated livability based on the objective approach.

Nevertheless, both abovementioned approaches, typically applied separately, have their shortcomings so that they fail to reflect the overall well-being (subjective and objective) of citizens in a quick, reproducible, and updateable way (Fig. 1), relevant to operationalize important evaluation outcomes in practice through local policies. Specifically, the subjective approach has four types of drawbacks. First, lacking operability. Prior studies usually set a whole city as the study unit, comparing and ranking various cities' livability score. But 'livability is best defined at the local level' (AIA, 2005), so the city-level measurement of livability is more like conveying an overall impression and feeling of a city to people, but such measurement is not conducive to implement pragmatic local policies. Second, lacking efficiency. The questionnaire survey of citizens' satisfaction is time-consuming, costly, and hard to update with changes of the situation. Moreover, surveys are of a strong contextual component, which makes it difficult to reproduce the research into another study area (Liu et al., 2020). Third, lacking comprehensiveness. Research materials acquired from questionnaires are often covering limited urban areas and population size. Most importantly, questionnaire respondents might provide incorrect or perfunctory answers. Last, lacking context-sensitive. There is a lack of consideration for the characteristics of different cities and the personal preferences of different individuals (e.g. emotions, feelings, and values). On the other hand, the objective approach has two of the above shortcomings, comprehensiveness, and context-sensitiveness. The existing issues of two approaches in livability measurement have adverse effects on the policy action and planning purposes, as well as residential location choices and decisions of citizens.

In this context, including multi-source data in this study absorbs the advantages of the current two research paradigms, proposing a combined subjective-objective way to evaluate urban livability, which can moderate most of the shortcomings in previous studies. To be specific, firstly, the research scale can be narrowed down to the community/neighborhood level (inner city) so that local elements of livability can be revealed, and then policymaking can be more specific and targeted. Secondly, as a supplement of field survey data, the availability of geo-data greatly saves the cost of research. At the same time, the complete coverage of geo-data and more samples improve the comprehensiveness of research. Thirdly, new entry points and opportunities for research have emerged with the emergence of new types of data such as social media data (e.g. Instagram, Facebook) and computer technology such as Natural Language Processing (NLP). Therefore, intangible qualities such as personal emotions and feelings can be obtained from social media data, which are important elements in urban livability but have been less considered in previous studies. Besides, as noted by Marans and Stimson (2011), the quality of any entity has subjective dimensions that are perceptual as well as having objective realties, including not only material well-being (standard of living or livability) but also non-material elements (Okulicz-Kozaryn, 2013), so the subjective indicators of livability do not replace but complement the objective ones (Stiglitz et al., 2009). Accordingly, an integrated approach may be a good way to better understand spaces of cities (Bao et al., 2002) and to find out the pattern of urban livability (Milbrath, 1979).

This study seeks to measure community-based urban livability and to uncover the inequity of livability components within cities based on multiple datasets. We choose Hong Kong as our study area not merely due to the availability of data, but also because of its relatively low livability ranks when compared with its urbanization degree (Ng et al., 2011). Compared with previous studies, the primary contribution of this paper is concentrated on the following aspects. 1) Shortcomings of previous studies are overcome due to the combined subjective-objective approach based on multiple datasets. 2) Measurement of community-based livability is beneficial to the implementation and formulation of local policies as well as the detection of geographic livability inequity.

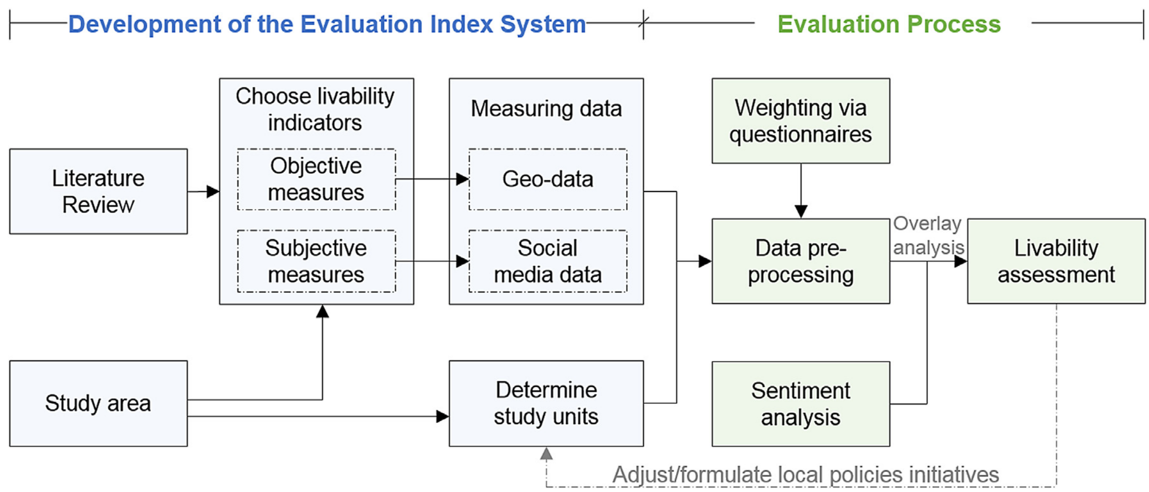


Fig. 2. Summary of the combined subjective-objective approach for measuring livability

3) To the best of our knowledge, personal emotions, and feelings acquired from social media data are the first time applied in livability studies. This study is helpful for authorities to adjust or formulate the local land-use policies, and for citizens and companies to invest in the city.

2. Materials and methods

As Fig. 2 illustrates, the combined subjective-objective approach for measuring urban livability is composed of two parts: the development of the evaluation index system and the evaluation process.

2.1. Development of the Evaluation Index System

2.1.1. Definition of (Urban) Livability

The concept of livability embraces cognate notions such as sustainability (Miller et al., 2013), quality of life (McCann, 2007), habitability (Veenhoven, 2000), the 'character' of place, and the health of communities. It is the sum of economic, social, and physical attributes (Saitluanga, 2014), the living environment of safety, health, convenience, and amenity (Higasa and Hibata, 1977). According to Crowhurst Lennard and Lennard (1995), livability is reflected by the performances of three main areas: environmental quality, neighborhood amenity, and individual well-being. Newman (1999) regarded livability as the quality of the urban environment that offers 'human requirement for social amenity, health, and well-being' at the community and individual level. Chazal (2010) pointed out that livability is 'desires related to the contentment of life in a specific location'. Pacione (1990) defined it as the 'behavior-related function of the interaction between environmental characteristics and personal characteristics'. Obviously, livability is a fluid, multifaceted and broad concept with no precise or universally agreed-upon definition, and the "standards for livability varying not only from country to country, but from city to city" (Ruth and Franklin, 2014), so precise definition of livability relies upon the time, place, and the assessment purpose (Pacione, 2003). Therefore, the measurement indicators of livability currently involve a lack of consensus.

However, we consider the following intrinsic values of livability as important in our study. 1) Definition of livability may differ from one culture to another and from time to time, so it only can be specified in a certain "….place, time and purpose of the assessment and on the value system of the assessor" (Pacione, 2003). 2) An important but usually ignored point is that livability comprises both subjective and objective measures. Since livability is a holistic paradigm (Jomehpour, 2015), it is not merely physical settings but also social interactions (Hankins and Powers, 2009). 3) Livability is a concept that tends to highlight a relatively small geographic area such as communities and neighborhoods (Pacione, 1990; Pacione, 2003; Portney, 2013), as it is important to community well-being (Tilaki et al., 2014), representing issues of local concern. Following the above principles, our selection of livability indicators will be introduced in section 2.1.3.

2.1.2. Study area

Hong Kong, officially the Hong Kong Special Administrative Region of the People's Republic of China, is an autonomous territory in China, to the south of the mainland Chinese province of Guangdong and east of the former Portuguese colony and fellow Special Administrative Region of Macao. Known to be "Asia's World City", Hong Kong is also one of the world's most significant financial centers, with the highest Financial Development Index score and consistently ranks as the world's most competitive and freest economic entity (WEF, 2012). Besides, Hong Kong is the world's most popular international travel destination, and the home to the world's most frequently traveled citizens (Yau et al., 1990). Hong Kong currently is the eighth most densely populated region in the world, with about 7.5 million residents of various nationalities in a territory of 1,107 km^2 . Hong Kong comprises three geographical regions, which coincide with its historical expansion by the British colonial government: Hong Kong Island, Kowloon (1860), and the New Territories and Outlying Islands (1898). In 1999, Hong Kong became a unitary territory subdivided into 18 districts (Fig. 3).

2.1.3. Dimensions, indicators, and datasets of livability

1) Dimension. Livability is a multi-dimensional and hierarchical concept, although the dimension may vary a little between different studies, while from a macro view of the selection of livability indicators, three dimensions of livability are often explicitly or implicitly covered in many previous studies, including the social dimension, economic dimension, and physical and environmental dimension. These three dimensions could reflect the overall living conditions of urban citizens. In 2016, the Ministry of Construction of the People's Republic of China released the Habitable Community Scientific Evaluation Index System (HCSEIS), which covered the above three dimensions. HCSEIS aimed to build livable cities through actions at the community level. It is the evolution and adaptation version in China of the living environment notion of "convenience, amenity, health, and safety" proposed by WHO in the 1970s (Fu et al., 2019). In the present study, since we intend to measure livability at a local level as well, and there exist close socio-economic, cultural, and demographic ties and similarities between mainland cities and Hong Kong, therefore, we follow the livability dimensions of the HCSEIS in this study. The five dimensions are "peace and harmony", "com-

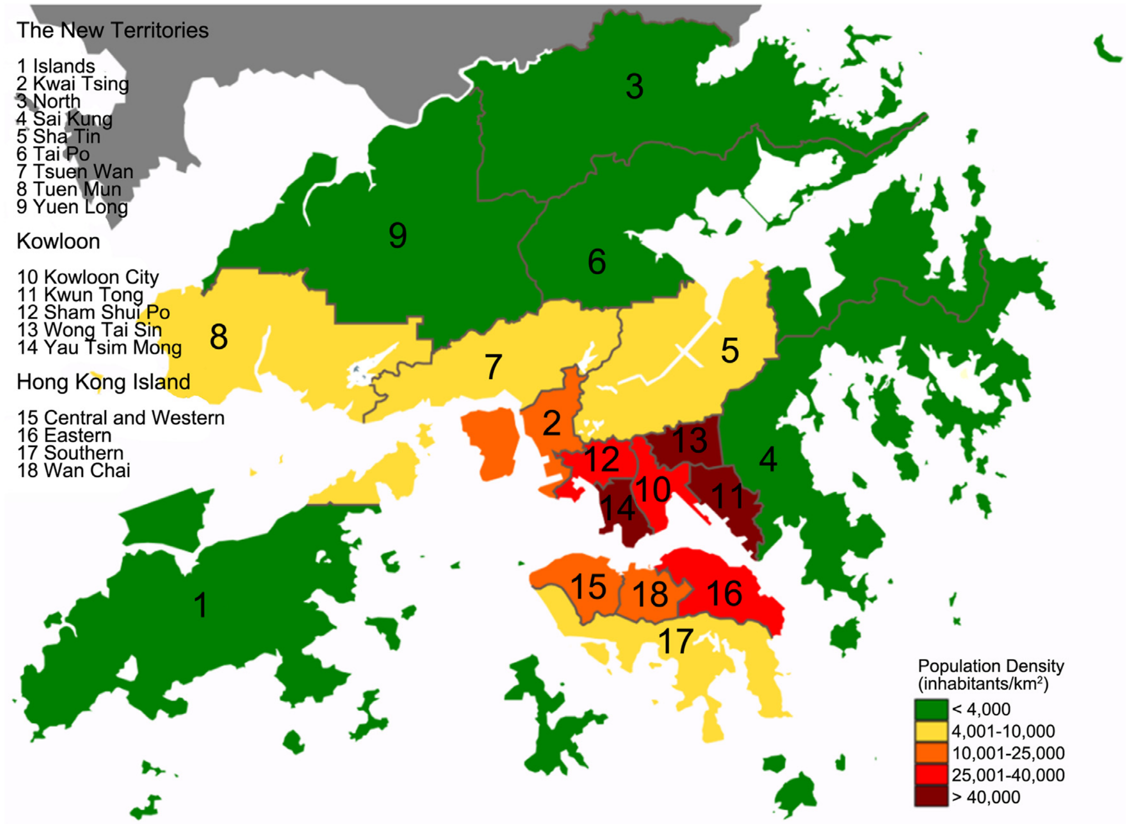


Fig. 3. The 18 territory sub-divisions of Hong Kong (Edit based on https://www.wikiwand.com/en/Districts_of_Hong_Kong)

plete services", "comfortability", "well-equipped facilities", and "residents' satisfaction".

2) Indicators. For each defined dimension, indicators should be included as the impact factors that may affect the evaluation from many perspectives. The livability indicators for Hong Kong are selected based on previous studies (e.g. Ghasemi et al., 2018; Paul and Sen, 2018; Zhan et al., 2018; Liu et al., 2020) and their weights are determined by questionnaires described in section 3.2. Commonly used indicators like crime and safety, transportation (accessibility), education, health, natural environment, and service facilities are considered. Besides, indicators that can reflect urban features of Hong Kong are also incorporated such as housing prices (Yang et al., 2019, 2020a, 2020b), demographic information (e.g. population density, age level), and medical facilities (especially for the elderly). Details of these indicators and their match with the standard of the HCSEIS (2016) can be checked in Table 1. Various studies have noted some common and promising indicators for assessing urban livability, while the normative quality of life is regarded as models of what specialists expect a good life (Ahmed et al., 2019). In this sense, the commonly selected livability indicators from previous studies could be counted as a kind of normative measure for assessing livability. Meanwhile, the objective quality of life depicts the objective features and qualities of cities, such as the population density, income of citizens, and the number of elderly centers, which are also included in this study. On the other hand, the subjective quality of life represents the feeling and emotions of citizens when they live in their city and community, and we capture such an intangible feature by the social media dataset as well. Therefore, we believe our chosen indicators could be regarded as "normative, objective, and subjective" (Okulicz-Kozaryn, 2013) measures to assess the livability of Hong Kong.

3) Datasets. The datasets used to establish the evaluation index system for quantitative analysis of urban livability could be divided into three types: statistics data from authorities, geospatial data, and social media data. The geospatial data sources include the Hong Kong government open data websites, some commercial data websites, real estate websites, and census statistics websites from 2016 or 2017 (see details in Table 1). The social media data used in this study was crawled from Instagram for the whole year of 2015, aiming to extract the subjective living emotions of local citizens. The spatial range of social media data is the whole Hong Kong area. Each piece of data in this dataset is the textual part of a post on Instagram including the username, content, hashtags, coordinates, and time, and they are in point data format. Each piece of the data is georeferenced as the poster added a locational check-in tag with the post. The volume of the Instagram data is approximately 2,000,000 pieces. The elaborate datasets and indicators, descriptions are summarized in Table 1.

2.1.4. Division of Study Units

As mentioned early, livability assessments were mostly at a comprehensive and global level to present cities' livability ratings and rankings, for example, the Mercer Quality of Living Survey (Mercer, 2003), Most Livable Cities Index (Giap et al., 2014), and the Economist Intelligence Unit's Livability Ranking (EIU, 2015). However, large-scale livability assessment cannot determine how livability is distributed across the city (Ahmed et al., 2019), and due to the requirement of behavior change, implementation of livability policy in a large geographic unit would not be efficient and effective (Gough, 2015). Intra-city disparities in facilities provision would only be revealed through a fine-grained spatial scale (local level) analysis, thereby delivering livability for all the citizens as well as assessing intra-city inequality in livability. Accordingly, evaluation at a spatial scale smaller than a city is required, where study units play a vital role in this process. Besides, intra-city study units, especially community-based units, are ideal spatial units to reflect and collect issues of local concern (Miller et al., 2013), which also provide targeted and specific information for various stakeholders such as planners and policymakers to take appropriate actions.

Table 1
Description of the datasets and indicators used in this study

Dimension	Indicators	Sub-indicators
Peace and harmony	Safety*	- crime intensity value
Complete services	Service facilities**	- parking - fuel station - bank/ATM - fire station - police station - library - post office/box - administrative offices - place of worship
Comfortability	Natural environment/views**	- peak - coastline
Well-equipped facilities	Leisure facilities**	- sports area - eating & drinking places - #community halls & community centers - children playroom - #parks - museum - theatre
	Transportation***	- highway/main road - subway stations - bus stops - ferry
	Hospitality**** (health)	- #hospital - #clinic - child assessment center - #elderly center - dental office
Well-equipped facilities	Education****	- kindergarten - government primary school - government high school - private primary school - private high school - #international primary school - #international high school - higher educational institutes
Residents satisfaction	Housing price*****	- #average housing price (HKD/sqft)
	Demographic information (including Employment)******	- #population density - #income level (household income/month) - #age level (age median) - education level (percentage of over secondary education level)
	Residents' emotion	- sentiment score

Data sources:
* Hong Kong Crime Map, http://hongkongcrimemap.com/charts/
** http://www.mapcruzin.com/
*** DATA.GOV.HK, https://data.gov.hk/en/
**** GovHK-GeoInfo Map, http://www1.map.gov.hk/
***** Centamap, http://hk.centamap.com/gc/home.aspx
****** 2016 demographic statistics, http://www.bycensus2016.gov.hk/
Note: The red sub-indicators are those considering the feature of Hong Kong.

Based on the 18 districts (see Fig. 3), the whole land and sea areas of Hong Kong can be further divided into 431 Constituency Areas. The Constituency Areas of Hong Kong are the unit scale of the analysis performed in the current study. However, as the Constituency Areas are unevenly divided and too detailed for developing the research, the 431 Constituency Areas are merged into 174 districts and assumed as the study units (Fig. 4). The reference substance of the merge and the naming of each study unit refers to the district's division standard of Google Maps. Overall, applying 174 intra-city units, the intra-urban livability of Hong Kong can be measured and monitored at a community-based level.

2.2. Evaluation Process

2.2.1. Data Pre-processing

Before data analysis, some data preprocessing is required to unify the data format, the projection coordinate system, and the numeric magnitude. The data processing software used in this study is ArcGIS. After the data is exported as shapefile data in ArcGIS, the projection coordinate system needs to be unified with the study area's data frame to perform further spatial analysis. Then, the data would be overlaid with each study unit by the spatial joint tool in ArcGIS. The joint results contain the joint number of the point or the length of the polyline data of each study area. Since the area of each study area is uneven, the data needs to be normalized by dividing the study unit area.

On the other hand, since the numeric magnitude of the data differs the overlay cannot be calculated. For example, the index 'transportation' contains highway/main road (polyline) and subway station (point). In order to make all the sub-indicators or the indexes in the same comparable classification system for the overlay analysis, the original normalized data needs to be reclassified and a new value assigned to each class. Hence, the original data is reclassified as 10 classes by the natural break method and the assigned values range from 0 to 10. Generally, the value 0 represents a poor state of certain attributes such as "there are no schools in this region'. However, in this study, some of the sub-indicators' assigned value range is inversed as 10 to 0, because their attribute is that the higher the value, the more disadvantageous for the evaluation system, like crime intensity value and housing price. The reclassified value of each sub-indicator is referred to as Ri, where i refers to the category of sub-indicators.

2.2.2. Questionnaire and Weighing

Although the HCSEIS (2016) has pre-defined weights for each livability domain based on different lifestyles, values, and perceptions, the citizens' understanding of livability varies between individuals and groups. Therefore, the purpose of the questionnaire is to determine the importance of each (sub-) indicator towards the local residents about the urban livability of Hong Kong, and the results can be converted into weighting values of the evaluation index system. The questionnaires were responded by 102 residents currently living in Hong Kong, and 75% of them were born in Hong Kong and can be considered as local citizens. Since the study is about the local living environment of Hong Kong, the majority of the respondents of this questionnaire should be local residents. Therefore, the first question of the survey is to ask if the respondent is a local Hong Konger to ensure accuracy. The second question is to ask the age of the respondent to make sure the survey outcomes are from various age levels. The questionnaire consists of a combination of the following questions:

- How important do you feel about having educational institutes (kindergartens, primary schools, high schools, and universities) in your living neighborhood?
  - ☐ Not very important ☐ Normally important
  - ☐Very important ☐ extremely important
- Please rank the importance level you think about having the following educational institutes in your living neighborhood. Pick the four most important ones and put the ranking number in front of them.
  - ☐ Kindergartens
  - ☐ Government-owned primary schools
  - ☐ Government-owned high schools
  - ☐ Private primary schools
  - ☐ Private high schools
  - ☐ International primary schools
  - ☐ International high schools
  - ☐ Higher educational institutes

The first question above is to determine the importance of each index, and the second one is to determine the importance of sub-indicators. The results of the questionnaire would be used to calculate the weight value by mathematical methods. For each of the indicators, there is a similar question pair for it. Therefore, there are 7 pairs of them,

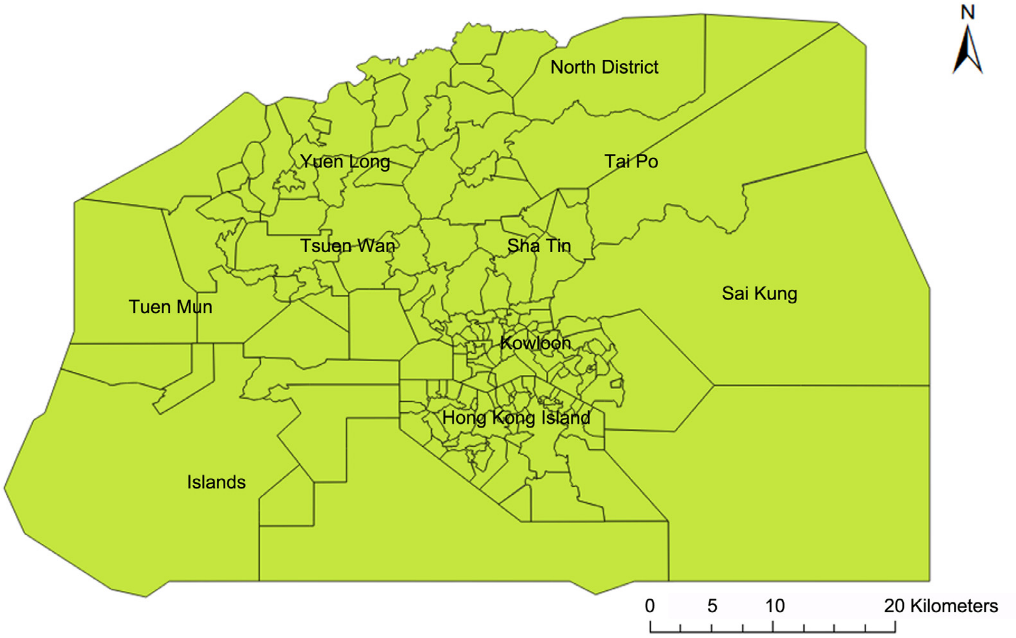


Fig. 4. The 174 study units in Hong Kong

and 19 questions in total including two basic personal information (10 indicators in total and 3 indicators do not have sub-indicators, so the total number of questions is 2+7×2+3=19). For the sub-indicators, the percentage value of each of them is selected as the first, second, third, fourth important and no ranking from the second question is recorded as p_{i1}, p_{i2}, p_{i3}, p_{i4} and p_{i5}. The weight value of each sub-indicator is referred to as $\mathrm{w_i}$. The $\mathrm{w_i}$ is calculated by the following formula:

$$wi = p_{i1} \times 0.4 + p_{i2} \times 0.3 + p_{i3} \times 0.2 + p_{i4} \times 0.1 + p_{i5} \times 0$$

0.4, 0.3, 0.2, 0.1, and 0 are the weight value multiplied by the percentage values of ranking to distinguish the importance. Based on the same principle, the weight value of indexes is determined by the result of the importance level options in the first question. P_{i1}, P_{i2}, P_{i3} and P_{i4} are the percentage values of the index, classified as "extremely important", "very important", "normally important" and "not very important". The weight value Wi of each index is calculated as:

$$W_i = \frac{P_{i1} \times 0.4 + P_{i2} \times 0.3 + P_{i3} \times 0.2 + P_{i4} \times 0.1}{\sum_{i=1}^{n} P_{i1} \times 0.4 + P_{i2} \times 0.3 + P_{i3} \times 0.2 + P_{i4} \times 0.1}$$

The reason why the calculation of $\mathrm{W_i}$ needs to be divided by the sum is that, unlike sub-indicators, the weight of the index is evaluated by rating other than ranking. Otherwise, the sum of weight value would be over 100%.

2.2.3. Overlay Analysis

As long as the weight values are obtained, overlay analysis can be done by the raster calculation tool of ArcGIS. Overlay analysis is a group of GIS-based methodologies applied in optimal site selection or suitability modeling. It is a technique for applying a common scale of values to diverse and dissimilar inputs to create an integrated analysis. Suitability models identify the best or most preferred locations for a specific phenomenon. Overlay analysis often requires the analysis of many different factors. Before the weighted overlay calculation, the normalized data value of sub-indicators should be transformed from vector to raster value as the algorithm of the overlay calculation tool on ArcGIS is based on the raster data format. Then, the weighted outcome of each index would be calculated by using w_i value. The formula is:

$$o = \sum_{i=1}^{n} s_i \times w_i$$

In which, o refers to the outcome of indexes, and s_i refers to the normalized data value of sub-indicators. Afterward, O value, the outcome of the urban livability evaluation system is acquired by the second overlay calculation using o_i and W_i. o_i refers to the o value of each index generated from the first overlay calculation. The formula is:

$$O = \sum_{i=1}^{n} o_i \times W_i$$

2.2.4. Text Mining of Instagram

Text mining also referred to as text data mining, roughly equivalent to text analytics, is the process of deriving high-quality information from text. In document analysis, an important task is to automatically find keywords that best describe the subject of the document, which is an essential material for doing the sentiment analysis. One of the most widely used techniques for keyword detection is a technique based on the term frequency-inverse document frequency (TF-IDF) heuristic (Havrlant and Kreinovich, 2017). TF-IDF is a numerical statistic method intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in searches of information retrieval, text mining, and user modeling. The TF-IDF value increases proportionally to the number of times a word appears in the document but is often offset by the frequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general. Nowadays, TF-IDF is one of the most popular term-weighting schemes, and about 83% of text-based recommender systems in the domain of digital libraries use TF-IDF (Beel et al., 2013). For the Instagram dataset, there are two main steps for mining the text in this research.

1) Data filtering. To make sure the text content was extracted from the local users of Instagram in each study unit in Hong Kong, the first step of data filtering is to roughly filter out the non-local people of each study unit. Because the study is about the livability of local Hong Kongers, the social media opinions of non-local people who are just temporarily in Hong Kong are not representative at all. Therefore, the filtering condition of a local user is defined as *the same user ID posts at least 3 times in a year in the same study unit.* It is assumed that a local Instagram user will at least post 3 times in the same region for a year, and most tourists' check-in post will have high mobility since if they travel in Hong Kong, they must do check-in posts for many places of attraction all over Hong Kong, and will not geographically check several times for the same place. Before the filtering, the dataset is a spatial joint with the study unit data to make each piece of post data have a field that refers to a location.

2) Key term filtering. The second step is to find the hot topics of each study unit by detecting the key terms used in the study unit over a year. TF-IDF is used as the algorithm to sort out the high frequency mentioned terms with an inverse document frequency (IDF) weighing, which are the terms that are highly used in one document but rarely used in other documents. The value of TF-IDF is calculated as:

$$TF-IDF(t,d,D)=TF(t,d)\times\ IDF(t,D)={f_{t,d}}/{\sum_{t'\in d} f_{t',d}}\times log\frac{N}{n_t}$$

where TF(t,d) refers to the frequency, which is the number of times that term t occurs in document d out of all the terms of d. In this study, the Instagram posts geographically from one study unit are considered as a document. And the term frequency is calculated as:

$$TF(t,d)={f_{t,d}}/{\sum_{t'\in d} f_{t',d}}$$

The inverse document frequency (IDF) is the logarithmically scaled inverse fraction of the study unit that contain the term, obtained by dividing the total number of study units (N) by the number of study units containing the term (n_t), and then taking the logarithm of that quotient. IDF weight is calculated as:

$$IDF(t,D)=log\frac{N}{n_t}$$

The TF and IDF values are calculated for each term of the dataset and timed together afterward. The inputs of terms here are the hashtags of each post, which are the topic generated by users for their posts. This is more convenient for this study because the content of the posts is already summarized as key terms by users before the filtering. Therefore, the field “tags” from the dataset were selected to run the filtering command.

After calculating the TF-IDF value of each term (hashtag) of the dataset, a table of terms with corresponding TF-IDF values from high to low are created, and the top 50 high TF-IDF values are saved. The result may contain 50% of undefined codes since hashtags can be written in Chinese or other languages, and thus need to be deleted. Therefore, the result is used to further identify the top 25 high TF-IDF value terms, which can be considered as the top 25 hot topics people talk about for the year 2015 about each study unit in Hong Kong.

2.2.5. *Sentiment Analysis*

The sentiment analysis is used to extract subjective information usually from a set of documents, often using online reviews to determine "polarity" about specific objects. It is especially useful for identifying trends of public opinion in social media, for the purpose of marketing. In addition, it can extract information, for example, about people, places, and events mentioned in text documents, and understand sentiments about them. The inclusion of sentiment analysis in this study is because livability, as a multifold concept, is more than the availability degree of public facilities in a certain region, and it is not necessarily expressed and depicted by authoritative and conventional data. Rather, an important feature of livability is that it has close relation with human perception, feeling, and desire, so traditional data combined with ephemeral data such as questionnaires and social media data can capture the dynamics of space more effectively. In this view, social media check-in data, one type of crowdsourcing open data about individual activity-related choices, provides a new perspective to sense people’s spatial and temporal preferences in urban places (Shen and Karimi, 2016). Services such as YouTube, Facebook, Flickr, Twitter, and FourSquare contain a wealth of information about peoples’ spatiotemporal behavior that is often disaggregated and is being continuously updated in real-time. Therefore, the Instagram data was used to do the sentiment analysis in this study to capture the overall emotional feeling (positive or negative) of local people about a place (study unit).

The key terms can be quantified by the sentiment extent of the texts to show the emotion and feelings of people from each study unit. The sentiment extent can be rated as a sentiment score by NLP technology. Currently, there are plenty of mainstream natural language processing application program interfaces that can do the sentiment analysis.

Table 2
Indexes and associated Weight Values used in this study

Indexes	Weight values	Names in the formula
Leisure	0.09	leisure_facilities
Transport	0.13	transportation.tif
Education	0.09	schools.tif
Hospitality	0.10	medical_facilities
Services	0.11	services_facilities
View/natural environment	0.04	view
Safety	0.12	crime_rate
Demographics	0.11	population_info
Housing price	0.11	housing_price
Residents’ emotion	0.10	residents’ emotion

Table 3
Eight most and least urban livable study units in Hong Kong

Most Livable Study Units		Least Livable Study Units	
Study Unit Name	**Livability Score**	**Study Unit Name**	**Livability Score**
Wong Tai Sin	6.09	Kai Tak	2.22
Lok Fu	5.19	Jardine’s Lookout	2.33
Sai Ying Pun	5.17	Shek Kong	2.46
Cheung Sha Wan	5.13	Lau Fau Shan	2.50
Choi Hung	5.00	Stubbs Road	2.52
Tai Wo	4.97	Stonecutters Island	2.55
Sheung Wan	4.95	Sai Kung	2.55
Shaukeiwan	4.93	West Kowloon	2.64

Google Cloud Natural Language API (https://cloud.google.com/natural-language#natural-language-api-demo) is one of them, and it reveals the structure and meaning of the text by offering powerful machine learning models in an easy to use REST (Representational State Transfer) API. On this platform, the top 25 key terms can be uploaded, and a sentiment score will be generated after analyzing if the textual content is overall relatively positive or negative emotionally. The sentiment score value of the Google natural language processing tool ranges from -1 to 1. The value closer to 1 means more positive, and closer to -1 means more negative. The result of the sentiment extent could be applied in two aspects. First, it will be used as one of the affecting factors of the livability measurement. The other application is to compare it with the livability assessment result to analyze if the local citizens actually feel happy while their living condition is good, or if inhabitants from less lively areas express negative emotions on social media.

3. Results

3.1. *The Outcome of Livability Assessment*

According to the questionnaires and weighting process, the weight values of each index were calculated (Table 2) and then used for the calculation of livability. Therefore, based on the questionnaire, an outcome map was generated by the overlay raster calculator on ArcGIS (Fig. 5). The formulas of the overlay calculation are as follows:

O="crime_rate"×0.12+"view"×0.04+"transportation.tif"×0.13+
"service_facilities"×0.11+"schools.tif"×0.09+"leisure_facilities"×0.09+
"medical_facilities"×0.10+"population_info"×0.11+"housing_price
"×0.11 +"residents’ emotion"×0.10

The outcome map representing the urban livability scores of the study units ranges from 0 to 10, shown through a red-green color scheme. The redder means less and greener means more livable. From the illustration of the map of the outcome (see Table 3), the most livable study units in this study mainly distribute at the Northern and Southwestern part of Hong Kong Island, Southern Kowloon, Kwun Tong, and Wong Tai Sin District. The livable areas can be regarded as some small clusters which are scatteredly locate at the central part of the whole Hong Kong territory. Moreover, the Northwestern (mainly Tuen Mun

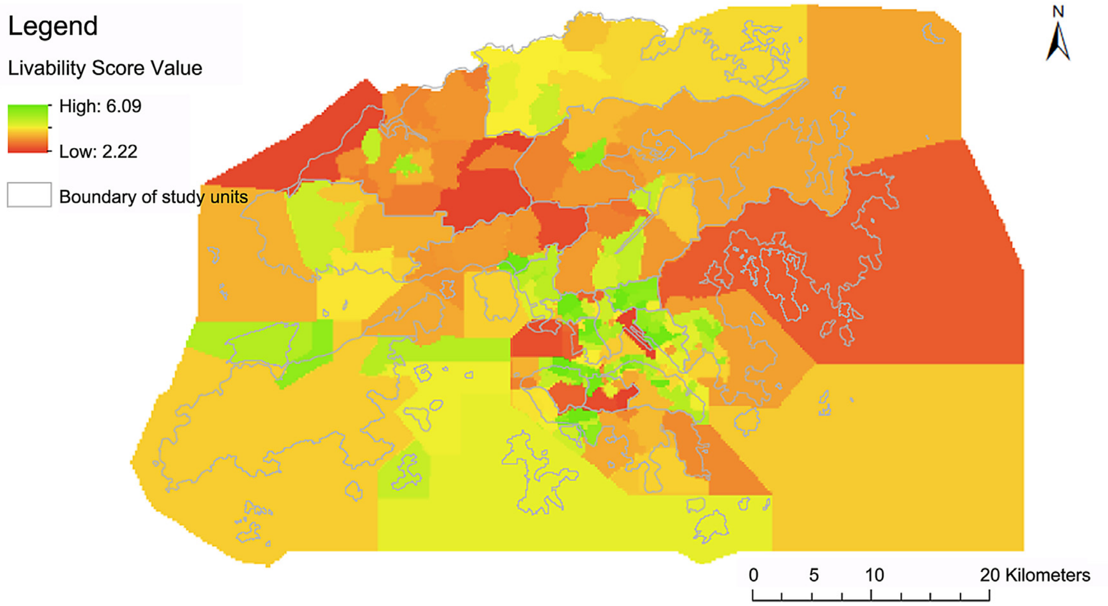


Fig. 5. The Urban Livability Evaluation Index System-Outcome in Hong Kong study area

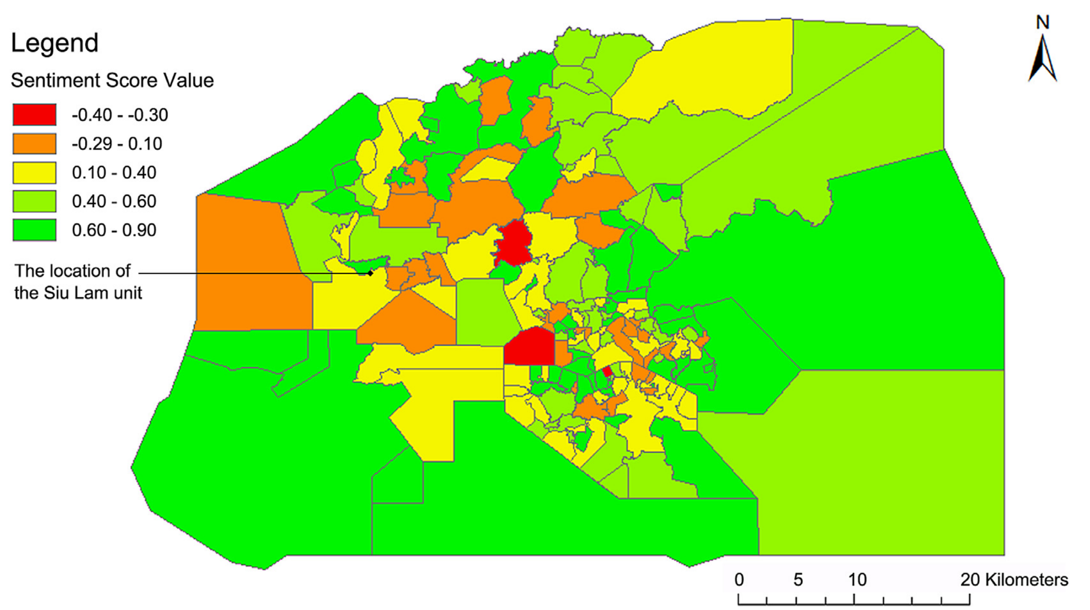


Fig. 6. The sentiment score distribution in the study units of Hong Kong

and Yuen Long area), Western (mainly Sai Kung District) part of Hong Kong, and some areas at the Hong Kong Island are reflected as relatively less-livable. Focusing on which the livable and unlivable study units are in Hong Kong, the rankings of livability value are as bellow. For the most livable study unit, Wong Tai Sin is suitable for living in every aspect. For the ranking list of less-livable study units, Jardine's Lookout, Shek Kong, Lau Fau Shan, and Stubbs Road are the units, which do not have an ideal living environment from the angle of residents' opinion.

3.2. Local Sentiment Analysis

The Google natural language processing tool generates a sentiment score for each study unit based on the top 25 key terms, and Fig. 6 shows the sentiment score distribution map. The map demonstrates that there is a small cluster of study units where the sentiment scores are relatively lower than others in the Northwest-central part and in the very central part of Hong Kong. Correspondingly, the suburban area of Hong Kong obviously has a higher sentiment score than the central urban area, which means individuals who post Instagram in the suburban areas usually express more positive textual content or happier emotion than the people who post in the central urban areas.

We randomly selected a study unit called Siu Lam to make sure it lies a reasonable correlation between sentiment scores and text contents of the Instagram post. The sentiment score of Siu Lam is 0.4, which reflects that people posting Instagram in Siu Lam have a relatively positive emotional feeling. To explore the reason behind the relatively positive emotion, a list of key terms (extracted from Instagram by TF-IDF for sentiment analysis) is included in Table 4. Since Siu Lam is located in the coastal area of southern Hong Kong, hashtag terms of coastal views sceneries such as 'beach', 'gold coast', golden beach', 'sunset' are the most frequently posted on Instagram. In the Google natural language processing platform, these textual contents have a relatively higher sen-

Table 4
List of key terms posted on social media by inhabitants from Siu Lam study unit

Ranking	Key terms	TF-IDF	Interpretation of key terms
1	gold coast	0.0373	Nature/views
2	gold coast hongkong	0.0366	Nature/views
3	beach	0.0293	Nature/views
4	goldenbeach	0.0293	Nature/views
5	ccr	0.0249	Celerity (Band Name)
6	cat lover	0.0205	Pet
7	before sunset	0.0204	Nature/views
8	this is now	0.0200	Nature/views
9	catstagram	0.0199	Pet
10	cross	0.0168	Retail (brand name)

Note: ccr: Creedence Clearwater Revival (a rock band)

timent score, since by people's life experience and intuition in real life individuals commonly link these words of sceneries with good things and positive feelings. This explains why Siu Lam got such a positive sentiment score with a value of 0.4.

A possible reason for such a higher sentiment score is that suburban regions normally have beautiful natural sceneries, which may relieve people's pressure of living a fast pace of life in an international metropolis like Hong Kong. Thus, no matter if people live there or just go there for recreation, once they post Instagram in suburban areas they usually feel emotionally positive. After all, people's perceptions and behaviors are not merely influenced by their residential environment, but also by the activities provided by the spaces, e.g., where they shop and perform recreation, so life experiences in residential and non-residential environments are both related to people's satisfaction with livability (Wang et al., 2019). Further explanations about the correlation between sentiment and livability will be introduced in the following sub-sections.

3.3. Livability vs Sentiment

Since the Google natural language processing tool generates a sentiment score for each study unit with a value ranging from -1 to 1, the sentiment scores and the livability score values need to be reclassified to the same magnitude by reclassifying them into 10 classes and values from 1 to 10 to enabling comparison analysis. Then a further analysis to identify where these two results differ (errors) and the spatial pattern of the correlation between people's sentiment and the local livability was done by making a residuals distribution map. The residual distribution result of sentiment score deducting livability score is shown in Fig. 7. The residuals are generated by the difference of livability and sentiment values, so the more positive (red) residuals mean the people of the area are emotionally positive but the living environment is unideal, and the more negative (blue) residuals mean the people of the area are not very happy but the condition there is very suitable for living. The spatial pattern of the residual distribution shows a cluster of study units in the central part of Hong Kong with negative residuals, while the study units locate at boundary areas, like the very Northwest, Southwest, and East areas, have very positive residuals.

Choosing Sai Kung as a representative study unit for a further detailed study, it can be seen that the residual value between sentiment and livability scores is 9 and that the key terms of Instagram hashtags of 2015 are mainly "beach", "hiking", "boattrip" and "summer". This reveals that the users who post Instagram posts enjoy the beauty and nature there. However, some aspects closely related to individuals' life are not satisfactory. For example, the average household income per month of this study unit is 37,020 HKD, which is lower than the average level of all the study units (37,576 HKD) and is only half of the income level in Olympic (75,000 HKD), and 1/4 of Peak (132,250 HKD). However, the housing price in Sai Kung turns to be 15,907 HKD/ft^2, which is well above the average price of all study units in Hong Kong (10,816 HKD/ft^2).

The spatial pattern of the residual distribution might reveal that the objective and subjective aspects of life quality are opposite to some extent in a large metropolitan city. Hong Kong, as a city with a high level of urbanization, might have very complete objective facilities for people's daily life in the highly urbanized area, which is the central part of Hong Kong (Northern Hong Kong island and Southern Kowloon area), but the crowded volunteered data do not represent the equivalent level of positive sentiment in this way. On the contrary, the people from the suburban area of Hong Kong with a low level of urbanization, and basically formed by the natural environment and light human activities, expressed more optimistic emotion through social media and seems to enjoy their life there, even though the living environment is not very qualified for urban livability criteria from the aspect of the objective condition.

To further examine the correlation of livability scores and people's sentiment scores, a regression test was applied, and the test result is summarized in Table 5. However, it shows that the adjusted R^2 is around 0.08, which means there is barely any correlation between sentiment scores and livability scores. The opposite objective and subjective aspects of life quality are a partial result only recorded in certain urban areas. Overall, the phenomenon does not have any statistical support. On the other hand, the week relationship between objective indicators and subjective ones has been also identified by previous studies (e.g. Okulicz-Kozaryn, 2013; Saitluanga, 2014).

4. Discussion

4.1. Livability assessment result and its correlation with emotion

The spatial pattern of urban livability in Hong Kong indicates that the central part, with a high level of urbanization, is more livable than the suburban area. The finding is consistent with previous studies that claimed 'the overall level of livability will be diminished from the central business district of the city to peripheral areas' (Saitluanga, 2014). On the other hand, the study demonstrates a poor correlation between livability and personal emotion, which is in line with the findings of Saitluanga (2014) and Okulicz-Kozaryn (2013) regarding a weak correlation between the objective measure of the quality of life and subjective measures. There may be three reasons to explain this poor correlation. Firstly, like livability, individuals' feelings and emotions are also complicated and multidimensional concepts that include various influence factors. Therefore, not only the quality of the living environment but also many other factors may have an impact on people's emotions. For instance, whom people interact with may affect individual emotions. Fowler and Christakis (2008) found that happy people make others happy, and living in places where most people are happy is likely to make a person happy as well. Similarly, Florida (2010) argued that people feel most happy if they live among open, tolerant, and curious people. Secondly, people sometimes may have conflicting minds about their inner feelings and living conditions. For example, New York is a city with great creativity and innovation, and New Yorkers are proud to live there. But at the same time, they are also unhappy to live in New York because they have to pay a lot for an old and small house, and they have to face congestion and noise in the city (Balducci and Checchi, 2009). Thirdly, emotional feelings vary from person to person, and sometimes they are not related to the quality of living conditions. One may live in a so-called livable region but still has a bad emotional feeling due to his/her unfortunate personal circumstances such as unemployment, loneliness, and illness.

4.2. Implications for urban planning and policy

The results from this study could be taken into account when considering how to improve individuals' well-being through urban planning policy. Livability tends to highlight a relatively small geographic area (Pacione, 1990; Pacione, 2003; Portney, 2013), and it refers to a degree

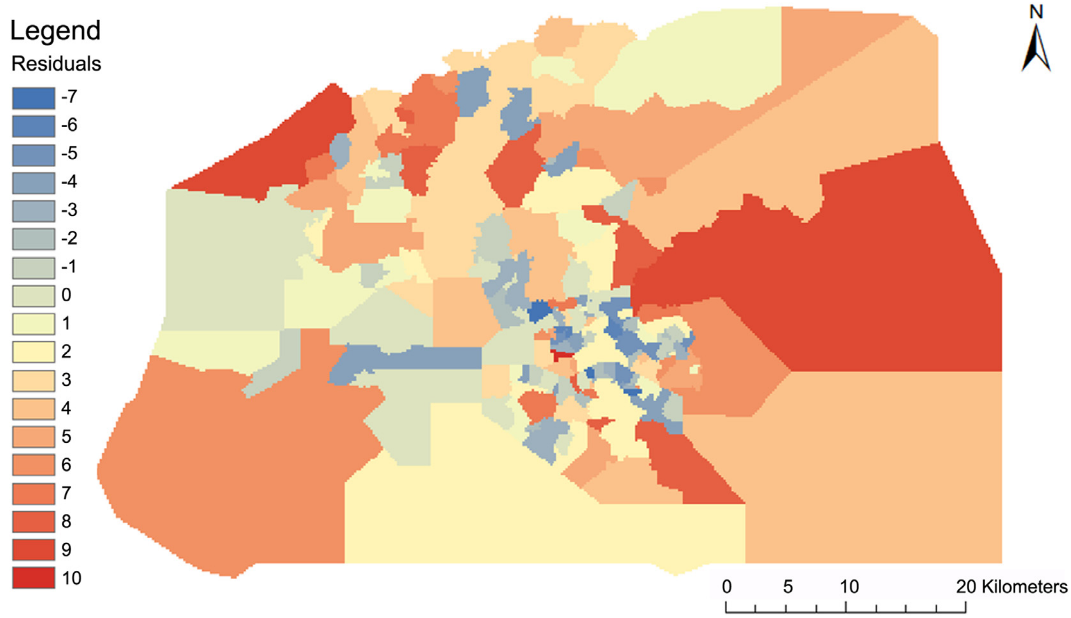


Fig. 7. The Residuals Distribution Map between Sentiment and Livability in Hong Kong

Table 5
Summary of Residual Spatial Autocorrelation (SA)

SA	AdjR^2	AICc	JB	K(BP)	VIF	Model
0.412025	0.080449	792.014712	0.039044	0.041063	1.000000	+RECLASS_LI***

AdjR2: adjusted R-Squared; AICc: Akaike information criterion; JB: the value of Jarque–Bera test; K(BP): the value of Breusch–Pagan test; VIF: variance inflation factor.

of interactions between residents and their surroundings (Kim, 2002; Pacione, 2003), so community-based livable components affect individuals' lifestyles, actions, perceptions, values, and feelings, reflecting their overall subjective well-being and satisfaction (Bishop, 2009; Senlier et al., 2009). Through community-based livability assessment, local governments could have a clear direction on how to improve the livability elements when formulating planning policy in corresponding study units such as increasing the number of schools and hospitals. Besides, adjustment of planning policies or decision-making processes is also actionable and effective based on the intra-city study units. For example, in our study, we choose constituency areas as the basic study units. The constituency areas are developed for district administration and election purposes, therefore, they are convenient and representative to reflect residents' concerns in terms of livability related issues through legislative council candidates, and then the planning policy could further consider these residents' requirement.

4.3. Limitations and uncertainties

This study has some limitations which require further research. Firstly, the data process filtering requires a more accurate sub-division with a higher level of technology, like machine learning. For example, the separation of tourists and local residents from the dataset used in this study is too rough, based on solely distinguishing if they post in an area more than 3 times a year. A more accurate user portrait algorithm can be used to do this. If so, individuals' sentiments extracted from the social media platform could be more precise. Secondly, the data indicators of the evaluation index system are not comprehensive due to data availability limitations in this study. Besides, some sub-indicators may contain both positive and negative effects on livability, while the negative ones were not included in this study. For example, shopping malls and industrial areas might generate toxic waste, and this can be taken into consideration for further studies. Lastly, the samples of the questionnaire survey used to determine the weight of livability indicators are still relatively small. This may restrict the cover of individuals from different social backgrounds, and therefore, their opinions about livability may be neglected. Furthermore, the social media data used in the study may have some potential bias because the product attribute of Instagram is partial to life-sharing by image posting and the textual part is the description of the corresponding image. Therefore, there may be more positive content than negative comments on Instagram. This may impair the detection of critical feelings from users through social media data. Future work to narrow the bias can integrate the mining process with data from alternative social media platforms like Twitter, because Twitter is more a comment expression platform that can detect more diversified emotions and opinions.

5. Conclusions

In this study, an evaluation index system about urban livability of Hong Kong is developed, and the question "which area of Hong Kong is suitable for living" is answered by the visualization of GIS-based overlay analysis, supported by traditional Geo-data and social media data. Besides, the correlation between livability scores and individuals' sentiment scores are discussed. Based on the study results, the following conclusions can be drawn for this study. 1) The basic spatial pattern of the urban livability is the central part of Hong Kong (including, for example, Sai Ying Pun, Wong Tai Sin, and Sheung Wan), demoting that a high level of urbanization is more livable than the suburban area (for example, Shek Kong and Sai Kung). Such a phenomenon about livability diminishing from central areas of the city to the periphery has been found in India as well (Saitluanga, 2014). 2) However, through sentiment analysis, individuals who post Instagram in suburban areas of Hong Kong usually express more positive content and happier emotions than those who post Instagram in central urban areas. A possible reason for this is that there are many natural sceneries in suburban areas which could make people feel relaxed and free from the stress of work. 3) The residuals distribution map between sentiment and livability shows that the sentiment of the local people and the actual livability situation are mismatching in some areas of Hong Kong. However, the regression test result shows that there is barely a correlation between sentiment and livability, and this finding could be supported by previous studies.

Declaration of Competing Interest

The authors declare no conflict of interest.

Author Contributions

Han BI conceived the presented idea. Jianxiao LIU wrote the manuscript. Meilian WANG further edited the language of the manuscript. All the authors have approved the final version of this manuscript.

References

Ahmed, N.O., El-Halafawy, A.M., Amin, A.M., 2019. A Critical Review of Urban Livability. Eur. J. Sustain. Dev. 8 (1), 165 -165.

American Institute of Architects (AIA), 2005. Livability 101. AIA, Washington, DC.

Balducci, A., Checchi, D., 2009. Happiness and quality of city life: The case of Milan, the richest Italian city. Int. Plan. Stud. 14 (1), 25–64.

Bao, S., Chang, G., Sachs, J.D., Woo, W.T., 2002. Geographic factors and China's regional development under market reforms, 1978–1998. China Econ. Rev. 13 (1), 89–111.

Beel, J., Langer, S., Genzmehr, M., Gipp, B., Breitinger, C., Nürnberger, A., 2013. Research paper recommender system evaluation: a quantitative literature survey. In: RepSys '13: Proceedings of the International Workshop on Reproducibility and Replication in Recommender Systems Evaluation. Hong Kong.

Bishop, B., 2009. The big sort: Why the clustering of like-minded America is tearing us apart. Houghton Mifflin Harcourt, Boston.

Chazal, J.d., 2010. A systems approach to livability and sustainability: Defining terms and mapping relationships to link desires with ecological opportunities and constraints. Syst. Res. Behav. Sci. 27 (5), 585–597.

Deng, W., Peng, Z., Tang, Y., 2019. A quick assessment method to evaluate sustainability of urban built environment: Case studies of four large-sized Chinese cities. Cities 89, 57–69.

Economist Intelligence Unit (EIU). 2015. Global liveability ranking. http://www.eiu.com/public/topical_report.a–spx?campaignid=Liveability2015 (accessed 7 March, 2016).

Florida, R., 2010. Who's your city?: How the creative economy is making where to live the most important decision of your life. Vintage, Canada. Toronto.

Fowler, J.H., Christakis, N.A., 2008. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. Bmj. 337, a2338.

Fu, B., Yu, D., Zhang, Y., 2019. The livable urban landscape: GIS and remote sensing extracted land use assessment for urban livability in Changchun Proper. China. Land Use Pol. 87, 104048.

Ghasemi, K., Hamzenejad, M., Meshkini, A., 2018. The spatial analysis of the livability of 22 districts of Tehran Metropolis using multi-criteria decision making approaches. Sustain. Cities Soc. 38, 382–404.

Giap, T.K., Thye, W.W., Aw, G., 2014. A new approach to measuring the liveability of cities: the Global Liveable Cities Index. World Rev. Sci. Technol. Sustain. Dev. 11 (2), 176–196.

Gough, M.Z., 2015. Reconciling livability and sustainability: Conceptual and practical implications for planning. J. Plan. Educ. Res. 35 (2), 145–160.

Habitat, U., 2016. Urbanization and Development: Emerging Futures. World Cities Report 3 (4), 4–51.

Hankins, K.B., Powers, E.M., 2009. The disappearance of the state from "livable" urban spaces. Antipode 41 (5), 845–866.

Havrlant, L., Kreinovich, V., 2017. A simple probabilistic explanation of term frequency-inverse document frequency (tf-idf) heuristic (and variations motivated by this explanation). IJGS 46 (1), 27–36.

Higasa, T., Hibata, Y., 1977. Urban Planning. Kioritz Corporation Press, Tokyo.

Jomehpour, M., 2015. Assessing the livability of the new and old parts of Tehran, municipality districts 22 and 10 of Tehran. OIDA Int. J. Sustainable Development. 8 (09), 87–96.

Kim, K., 2002. The effects of tourism impacts upon quality of life of residents in the community. Virginia Polytechnic Institute and State University, Virginia, p. 61.

Kyttä, M., Broberg, A., Haybatollahi, M., Schmidt-Thomé, K., 2016. Urban happiness: Context-sensitive study of the social sustainability of urban settings. Environ. Plann. B. 43 (1), 34–57.

Lee, Y.J., 2008. Subjective quality of life measurement in Taipei. Build. Environ. 43 (7), 1205–1215.

Liu, J., Shi, W., Chen, P., 2020. Exploring Travel Patterns during the Holiday Season—A Case Study of Shenzhen Metro System During the Chinese Spring Festival. ISPRS Int. J. GeoInf. 9 (11), 651.

Liu, J., Wang, M., Yang, L., 2020. Assessing Landscape Ecological Risk Induced by Land-Use/Cover Change in a County in China: A GIS-and Landscape-Metric-Based Approach. Sustainability 12 (21), 9037.

Marans, R.W., Stimson, R., 2011. An overview of quality of urban life. In: Marans, R.W., Stimson, R.J. (Eds.), Investigating quality of urban life: Theory, methods, and empirical research. Springer Science & Business Media, pp. 1–29.

McCann, E.J., 2007. Inequality and politics in the creative city-region: Questions of livability and state strategy. Int. J. Urban Reg. Res. 31 (1), 188–196.

Mercer, W., 2003. Quality of living survey. http://www.mercer.com/qualityofliving (accessed 24 March, 2010).

Milbrath, L.W., 1979. Policy relevant quality of life research. Ann. Am. Acad. Pol. Soc. Sci. 444 (1), 32–45.

Miller, H.J., Witlox, F., Tribby, C.P., 2013. Developing context-sensitive livability indicators for transportation planning: A measurement framework. J. Transp. Geogr. 26, 51–64.

Newman, P.W., 1999. Sustainability and cities: extending the metabolism model. Landsc. Urban Plan. 44 (4), 219–226.

Ng, C.N., Xie, Y., Yu, X., 2011. Measuring the spatio-temporal variation of habitat isolation due to rapid urbanization: A case study of the Shenzhen River cross-boundary catchment. China. Landsc. Urban Plan. 103 (1), 44–54.

Okulicz-Kozaryn, A., 2013. City life: Rankings (livability) versus perceptions (satisfaction). Soc. Indic. Res. 110 (2), 433–451.

Pacione, M., 1990. Urban liveability: A review. Urban Geogr. 11 (1), 1–30.

Pacione, M., 2003. Quality-of-life research in urban geography. Urban Geogr. 24 (4), 314–339.

Paul, A., Sen, J., 2018. Livability assessment within a metropolis based on the impact of integrated urban geographic factors (IUGFs) on clustering urban centers of Kolkata. Cities 74, 142–150.

Portney, K.E., 2013. Taking Sustainable Cities Seriously: Economic Development, The Environment, and Quality of Life in American Cities. MIT Press, Massachusetts.

Ruth, M., Franklin, R.S., 2014. Livability for all? Conceptual limits and practical implications. Appl. Geogr. 49, 18–23.

Saitluanga, B.L., 2014. Spatial pattern of urban livability in Himalayan Region: A case of Aizawl City. India. Soc. Indic. Res. 117 (2), 541–559.

Scott, A.J., 1998. Regions and The World Economy: The Coming Shape of Global Production, Competition, and Political Order. Oxford University Press, Oxford Oxfordshire.

Senlier, N., Yildiz, R., Aktaş, E.D., 2009. A perception survey for the evaluation of urban quality of life in Kocaeli and a comparison of the life satisfaction with the European cities. Soc. Indic. Res. 94 (2), 213–226.

Shamsuddin, S., Hassan, N.R.A., Bilyamin, S.F.I., 2012. Walkable environment in increasing the liveability of a city. Procedia-Social Behavioral Sciences 50, 167–178.

Shen, Y., Karimi, K., 2016. Urban function connectivity: Characterisation of functional urban streets with social media check-in data. Cities 55, 9–21.

Smith, D.M., 1979. Where The Grass Is Greener: Geographical Perspectives on Inequality. Croom Helm, London, p. 77.

Stiglitz, J. E., Sen, A., Fitoussi, J. P., 2009. Report by the commission on the measurement of economic performance and social progress. http://www.stiglitzsen-fitoussi.fr/documents/rapport_anglais.pdf (accessed Sept 27, 2013).

Tilaki, M.J.M., Abdullah, A., Bahauddin, A., Marzbali, M.H., 2014. The necessity of increasing livability for George Town World Heritage Site: An analytical review. Mod. Appl. Sci. 8 (1), 123.

Veenhoven, R., 2000. The four qualities of life. J. Happiness Stud. 1 (1), 1–39.

Wang, Y., Zhu, Y., Yu, M., 2019. Evaluation and determinants of satisfaction with rural livability in China's less-developed eastern areas: A case study of Xianju County in Zhejiang Province. Ecol. Indic. 104, 711–722.

World Economic Forum (WEF). 2012. The Financial Development Report 2012. Geneva. Switzerland.

Yang, L., Zhou, J., Shyr, O.F., Huo, D.D., 2019. Does bus accessibility affect property prices? Cities 84, 56–65.

Yang, L., Chau, K.W., Szeto, W.Y., Cui, X., Wang, X., 2020a. Accessibility to transit, by transit, and property prices: Spatially varying relationships. Transp. Res. D Transp. Environ. 85, 102387.

Yang, L., Chu, X., Gou, Z., Yang, H., Lu, Y., Huang, W., 2020b. Accessibility and proximity effects of bus rapid transit on housing prices: Heterogeneity across price quantiles and space. J. Transp. Geogr. 88, 102850.

Yau, O.H., Chan, C.F., 1990. Hong Kong as a travel destination in South-East Asia: A multidimensional approach. Tourism management 11 (2), 123–132.

Zhan, D., Kwan, M.P., Zhang, W., Fan, J., Yu, J., Dang, Y., 2018. Assessment and determinants of satisfaction with urban livability in China. Cities 79, 92–101.