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Research Paper

The image of the City on social media: A comparative study using "Big Data" and "Small Data" methods in the Tri-City Region in Poland

Jianxiang Huang [a], Hanna Obracht-Prondzynska [b], Dorota Kamrowska-Zaluska [b], Yiming Sun [a], Lishuai Li [c,*]

[a] Department of Urban Planning and Design, Faculty of Architecture, the University of Hong Kong, Pok Fu Lam Rd., China Hong Kong Special Administrative Region
[b] Department of Urban Design and Regional Planning, Faculty of Architecture, Gdańsk University of Technology, 11/12 Gabriela Narutowicza Street, 80-233 Gdańsk, Poland
[c] Department of System Engineering and Engineering Management, City University of Hong Kong, 83 Tat Chee Ave, Kowloon Tong, China Hong Kong Special Administrative Region

HIGHLIGHTS

- The perception of city images in the Tri-City Region of Poland was studied using Geo-coded Social Media, GIS database.
- GSM-based "District", "landmark," "path" were in good agreements with benchmarks, less so for "edge" and "node".
- Instagramability reflected the perception of a place as an architectural landmark and tourist attraction.
- Twitterability reflected the perception of a place being nice and relevance to everyday life of communities.
- Findings have theoretical and practical implications for urban planners.

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ABSTRACT

"The Image of the City" by Kevin Lynch is a landmark planning theory of lasting influence; its scientific rigor and relevance in the digital age were in dispute. The rise of social media and other digital technologies offers new opportunities to study the perception of urban environments. Questions remain as to whether social media analytics can provide a reliable measure of perceived city images? If yes, what implication does it hold for urban planners? This paper describes a study on the perception of city images using a combination of "big data" and "small data" methods in the Tri-City Region in Poland. The aims were to 1) test the hypothesis whether social media analytics can elicit Lynchian elements of city image in consistency with conventional methods, and 2) develop and evaluate social media-based indicators of Imageability for planning practice. Geo-tagged images and texts were collected from Instagram and Twitter, two popular social media platforms in Poland. Text-Mining, Image Processing, Clustering Analysis, Kernel Density Estimation, and Sentiment Analysis were used. Results were compared with benchmarks constructed from official GIS database, questionnaire responses and sketch maps. "District", "landmark", and "path" identified on social media were in good agreements with benchmarks, less so for "edge" and "node". Two social media-based indicators have influenced the perception of a place: Instagramability, the frequency of a place captured on Instagram, was linked to its perception as an architectural landmark and tourist attraction, while Twitterability, the frequency of a place mentioned on Twitter by name, was linked to its perceived niceness and relevance to everyday life of communities. Methods developed in this study have theoretical and practical implications for urban planners.

1. Introduction

"The Image of the City" by Kevin Lynch (1960) is a landmark theory of lasting influence. Lynch outlined three imperative claims: 1) cities have a series of public images held consistently by citizens; 2) city images can be conveniently classified into five elements: "path", "node", "edge", "district" and "landmark"; 3) the ability of the physical urban form to evoke mental images, referred as Imageability by Lynch, offers a

* Corresponding author.

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sense of emotional security and the intensity of human experiences. The city image theory was widely cited by research literature in urban planning, social science, and environmental psychology (Banai & Rapino, 2009; Morello & Ratti, 2009; Pocock, Pocock, & Hudson, 1978). Lynch's work inspired a large body of follow-up studies (de Jonge, 1962; Evans, Marrero, & Butler, 1981; Francescato & Mebane, 1973; Goodey, 1971; Gulick, 1963). The work becomes deeply ingrained in the mental image of generations urban planners and educators, and the legacies of Lynch triggered a resurgent cognitive-environmental approach to planning and design (Mondschein & Moga, 2019; Vale & Warner, 1998).

The scientific rigor of the city image theory was in dispute. Marshall (2012) considered that Lynch's theory has not been tested to a significant degree, and the large number of follow-up studies had simply taken Lynch's claim as a given. Raynsford (2011) argued that the classification of the five Lynchian elements were formulated a priori and could be traced back to civic art traditions, i.e. "avenue," "intersection," "precinct," "wall," and "monument," substituted by Lynch's own terms. Moreover, researchers disagree upon the relative importance of the five elements: some ranked "landmark" as the most important (Golledge & Spector, 1978; Hart, 1973; Siegel & White, 1975), others suggested "path" and "district" (Appleyard, 1970, 1976). An alternative three-element classification consisted of "place", "path", and "domain" was developed by Norberg-Schulz (1971) based on Gestalt psychology, its validity compared with Lynch's five-element classification has yet to be tested.

The advent of digital technologies constitutes both a threat and an opportunity to the study of city images. On the one hand, the relevance of Lynch's work in the digital age was questioned: Al-Ghamdi and Al-Harigi (2015) examined the city image theory in light of the evolution of new technology and argued that location and navigation services such as Google Maps and specific destination applications made moving and steering through the city effortless, thus Lynch's imminent fear of disorientation in the city could have been solved by Google Maps, had he had the means. On the other hand, online and user-generated contents provided new means to study the perception of urban environments. In a pioneering study, Liu (2016) used geo-tagged Panoramio photos from 26 cities to study the perception of city images; findings partially confirmed Lynch's theories and also revealed a gap between subjective perceptions and traditional urban indicators. Jiao, Holmes, and Griffin (2017) studied words and phrases used by Twitter users for navigation during a Super Bowl event held in Indianapolis, USA; reference to Lynchian elements such as "district" and "landmark" were made frequently in tweets, while "edge" was almost non-existent. Questions remain as to whether social media analytics can provide a reliable measure of perceived city images? In other words, can evidence gathered from the virtual world explain public perception of a place in the real world? If yes, what implications does it hold for urban planners?

This paper describes a study on the perception of city images using a combination of "big data," i.e. Geocoded Social Media (GSM), and "small data" methods, i.e. GIS analysis, a questionnaire, and sketch maps. The primary aim is to test the hypothesis whether GSM can be used to elicit city images in consistency with those from conventional methods, i.e. sketch maps and questionnaire. A secondary aim is to develop and evaluate GSM-based indicators of imageability for planning

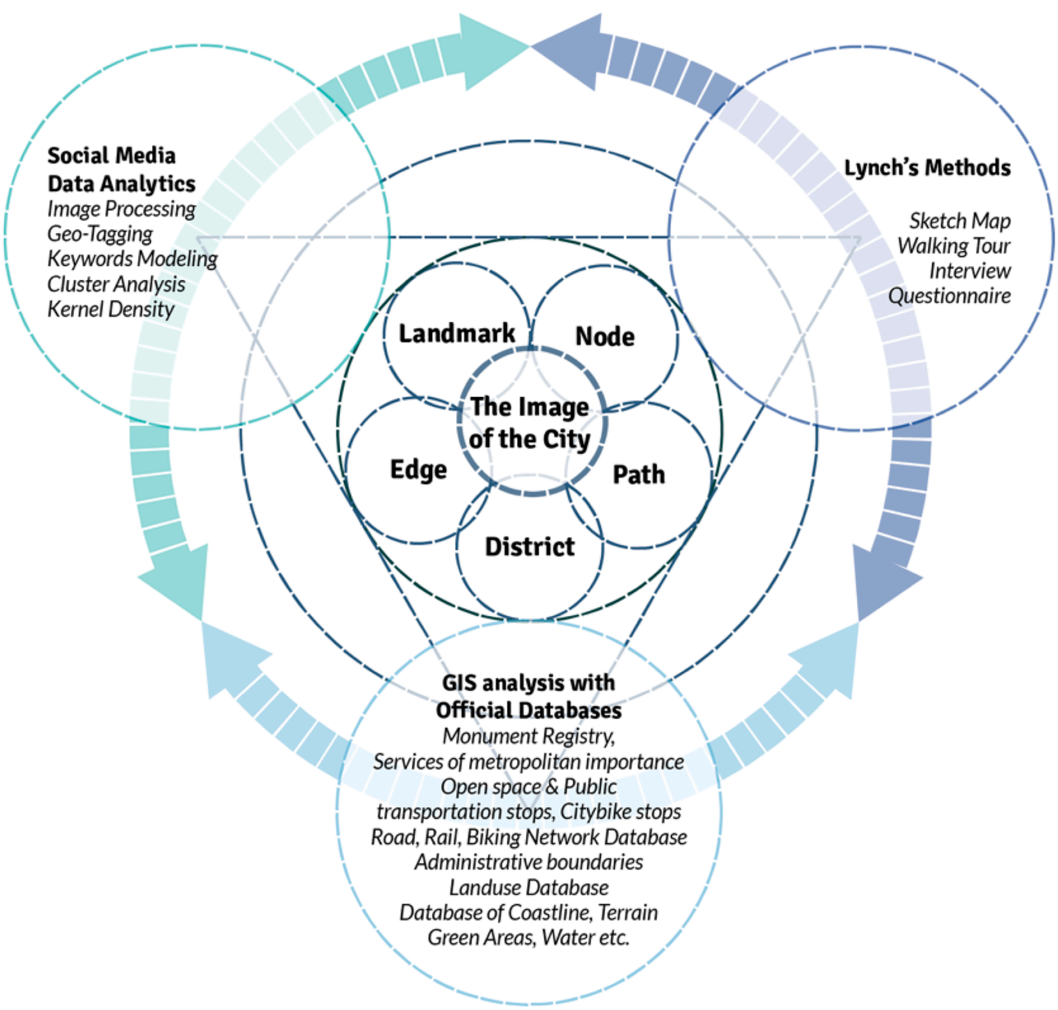

Fig. 1. A conceptual framework of using 1) social media analytics, 2) Lynch's original methods, and 3) GIS analysis to triangulate findings on city image theories.

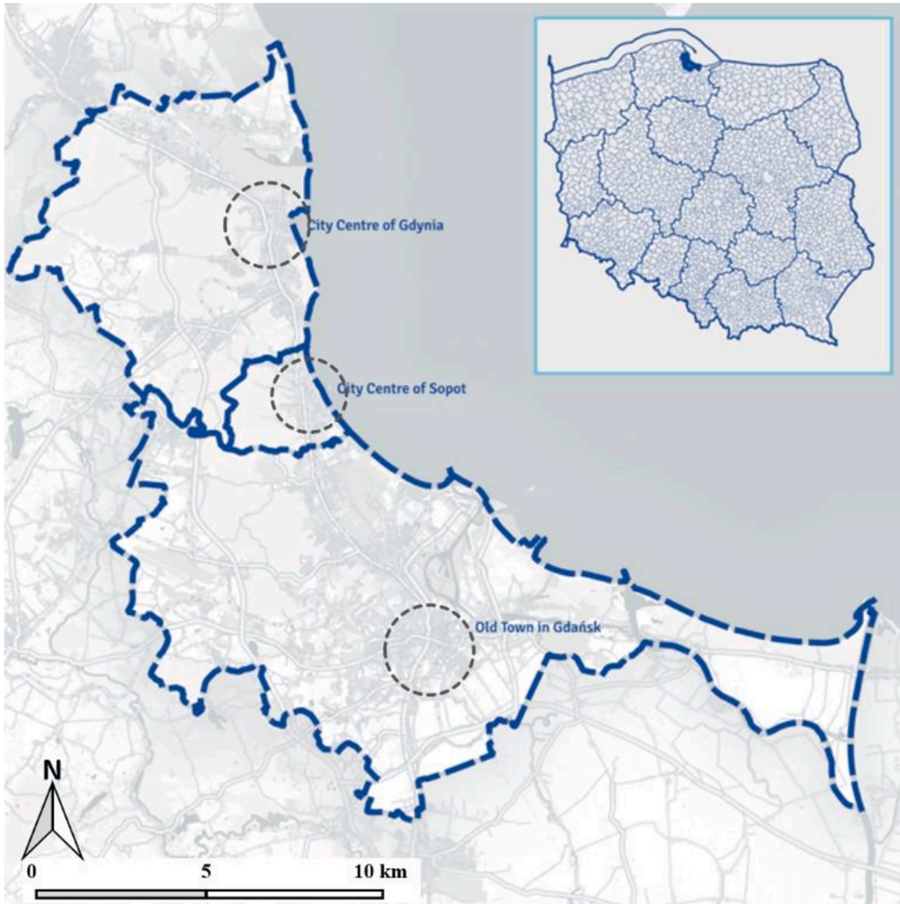

Fig. 2. A map of the Tri-City Region consisted of Gdansk, Sopot and Gdynia in northern Poland.

practice. City images were identified using images and text obtained from Instagram and Twitter, two popular social media platforms; the five Lynchian elements were identified using Image Processing, Clustering Analysis, and Kernel Density Estimations. GSM-based indicators were developed to measure the perceived Imageability of a place, namely Instagramability, Twitterability, and social media sentiment. Comparisons were made between city images based on GSM and those from benchmarks established using the official GIS database, questionnaires and sketch maps.

Revisiting "The Image of the City" has theoretical and practical implications today, 60 years after its publication. GSM-based evidence is expected to reveal the relevance of city image theory in the digital age. Findings can shed new light on existing theoretical disputes over Lynch's original work. Methodologies developed in this paper can offer new means to elicit mental images from the population group active on social media, making a large number of social media dataset into useful tools for urban planning practices.

2. Relevant work

Social media is an accepted component of the 21st century. Platform such as Instagram, Twitter, Flickr, Foursquare, and Facebook generate large quantities of geo-coded photos, videos and text related to users' daily experiences, much of this information were made accessible from the public domain. A large body of research literature has tapped into the rich data source to study human behavior, sentiment, and perception of the urban environment. Bertrand (2013) used geo-coded Twitter data to map user behaviors and sentiment tones in New York. Crandall et al. (2009) analyzed geo-tagged photos collected from Flickr, a photo-sharing website popular with tourists; the results showed that geo-tagged online photos can be used to study the popularity of cities and landmarks. Marti, García-Mayor, and Serrano-Estrada (2019) used Instasights heatmap, a web-based social media mapping tool to monitor the impact of renewed waterfront areas in Spanish cities on perceived functional dynamism and livability, although the data sources and underlying algorithms were undisclosed. Comprehensive studies using social media data to test Kevin Lynch's city image theory are rare.

Social media datasets are essentially volunteered, unstructured information, which are subject to many uncertainties in comparison with the structured datasets obtained from conventional approaches. Expressed behaviors on social media are prone to distortions from commercial incentives, such as exaggerated check-in behaviors (Wang, 2016). Social media data tended to over-represent those that are young, technology-savvy, and male, while the elderly population, and low-incomers may be under-represented (Rost, 2013). It may present distorted pictures of real-world events, according to a previous study on the mismatch between snow events on social media and the precipitation records (Tasse, 2014).

Many recent studies combined social media with structured or semi-structured dataset obtained from interview in order to triangulate findings and to gain a holistic understanding of public perception of landscape characteristics. Johnson (2019) studied the perceived benefits from urban greenspace using both Twitter dataset and semi-structured interview conducted in New York; results revealed the synergies of findings and tradeoffs between both methods, and the authors recommended that social media data to be combined with interview data to expand understandings of the diversity of individual experiences. Another study focused on the perceived attractiveness of the Beijing Olympic Forest Park using both social media and survey data; findings exposed the exaggerated and aggregated bias of the former and

Table 1
Summary of Instagram images and Tweets collected from the Tri-City Region.

	Instagram	Twitter
User IDs	2,001	11,972
Frequent user IDs	601 (30.0%)	3,274 (37.6%)
Infrequent user IDs	1,400 (70.0%)	8,698 (62.4%)
Total Post	9,360	298,465
# with precise coordinates	9,360 (100%)	23,441 (7.9%)
# from long-term residents	6,277 (67.1%)	264,033 (88.5%)
By Language		
• Polish	4,266 (45.6%)	178,247 (59.7%)
• English	3,190 (34.1%)	48,170 (16.1%)
• Portuguese	33 (0.4%)	17,382 (5.8%)
• Spanish	154 (1.7%)	4,417 (1.5%)

Table 2
Instagram posts of the urban environment labelled in consensus by Lynchian element.

Lynchian Elements	Count (%)	Criteria
Path	823 (17%)	Road, railway, pedestrian and bicycle path, etc.
Edge	1,578 (32%)	Seashore, edge of woods
District	207 (4%)	Aerial views
Node	375 (8%)	Open space, train station, bus stop, etc.
Landmark	1,429 (29%)	Iconic building, monuments, sculpture, etc.
Others	459 (9%)	Natural scene such as sky, forest, etc.
Total	4,872 (100%)	

suggested a combined assessment process, in which social media data to be used to establish a framework, and surveys to add supplementary and detailed information (Wang, 2018). Wartmann, Acheson, and Purves (2018) used on-site interview, hiking blogs, and Flickr tags to study the perception of landscape characteristics in Switzerland and concluded that a varied textual sources offers a more holistic view for landscape monitoring and management.

The rise of digital technologies such as the Geographical Information System (GIS), Urban Network Analysis, Imaging Processing, etc. provided new opportunities to study the perception of city images. Filomena, Verstegen, and Manley (2019) developed computational techniques to extract Lynchian elements in a GIS environment, using Boston as a case. Long and Baran (2012) studied the perception of city images using Space Syntax analysis, sketch maps, and surveys; the findings suggested that intelligibility, an objective measured using Space Syntax, influenced subjective experience of the urban environment such as place legibility. Zhang (2018) used Street View imagery and machine learning to measure human perception of a built-up environment in six indicators, namely, safe, lively, beautiful, wealthy, depressing, and boring. Quercia, Hare, and Cramer (2014) used online imagery and a questionnaire to study the perceived aesthetic quality of urban environments. The finding revealed that urban greenery was linked to the perception of beauty, quietude and happiness, while wide streets, fortress-like buildings, and council houses were associated with unattractive qualities. Letenyei and Dobák (2020) developed the Mental Map Editor, a software tool to survey, visualize and analyze participants' mental maps through recall and map allocation.

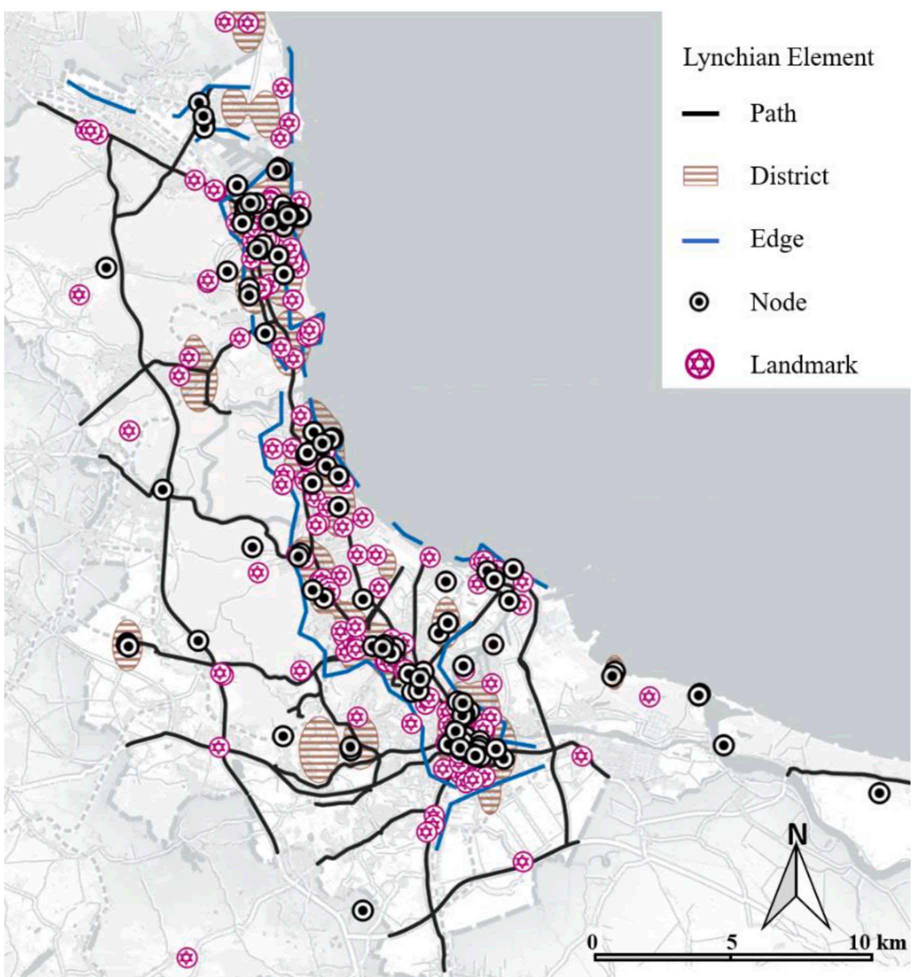

Fig. 3. City images by Lynchian elements elicited using social media analytics.

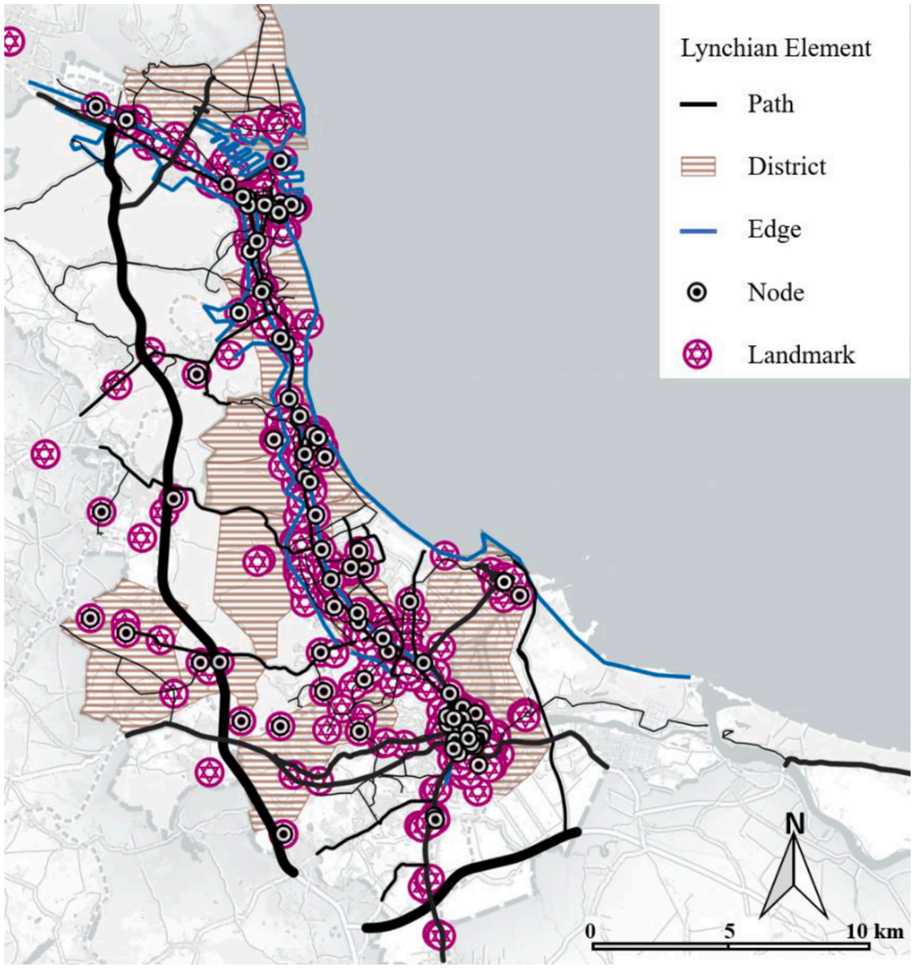

Fig. 4. City images by Lynchian elements elicited using questionnaire, sketch map and GIS database.

Table 3
Agreement between Lynchian elements elicited using "big data" and "small data" methods.

Lynchian Element	"Big Data" Methods (Social Media Analytics)	"Small Data" Methods (Benchmarks)	Agreement
District	• Cluster Analysis using Geo-Tagged Instagram Images • Count of neighborhoods mentioned by name in Twitter text	• Polygons of "mental district" from sketch maps, geospatially corrected using GIS database	91%
Landmark	• Instagram Images identified as "landmark"	• Architectural monuments, significant buildings from official register	65%
Path	• GSM density along the right-of-way of roads	• GIS database of road network by Polish Road Classification	50%
Edge	• Instagram images identified as "edge" • Maximum slope of Twitter kernel density	• Questionnaire and sketch maps	39%
Node	• Instagram images identified as "node"	• Questionnaire and sketch maps	21%

3. Methods

For this study, three parallel methods were adopted in the Tri-City Region in Northern Poland: 1) social media analytics, i.e. Data-Mining, Image Processing, Cluster Analysis, Kernel Density Estimation, Sentiment Analysis, etc.; 2) Lynch's original methods including questionnaire and sketch maps, 3) the official GIS database of urban form, monuments, open space, road network, neighborhood boundaries, etc. The triangulation using "big data" and "small data" methods allow us to test the consistency of findings. A conception the framework is shown in Fig. 1.

3.1. Study area

The study area is the Tri-City Region of Gdansk, Sopot and Gdynia in northern Poland (Fig. 2), a metropolis covering an area of 415 km^2 along the Baltic Sea and home to a population of 750,000 (BDL, 2016). The Tri-City region is considered suitable for this study purpose since it consists of both old and new urban fabric of distinct images, from the medieval Old Town in Gdansk to the modern wide streets and high-rise buildings in Gdynia (Lorens, Kamrowska-Załuska, & Kostrzewska, 2014). The region is known as a popular tourist destination, attracting over 3.1 million visitors annually (Naukowy, 2019). Social media is an active component of daily life in the Tri-City Region and in Poland: 54% of the country's adult population are active social media users (#P2P2, 2019). Instagram has a 24% penetration rate, while Twitter has 18% (Statista, 2018). An up-to-date GIS database can be accessed through the surveyor's office, transport authority, and the monument registry via the Pomeranian Regional Office. Kevin Lynch's idea was echoed by influential Polish town planner Kazimierz Wejchert (1974), who proposed an adapted version of elements as the grammar of urban spatial configurations: street as "path," node as "node," lines and boundaries as "edge," area as "district," and dominants as "landmark."

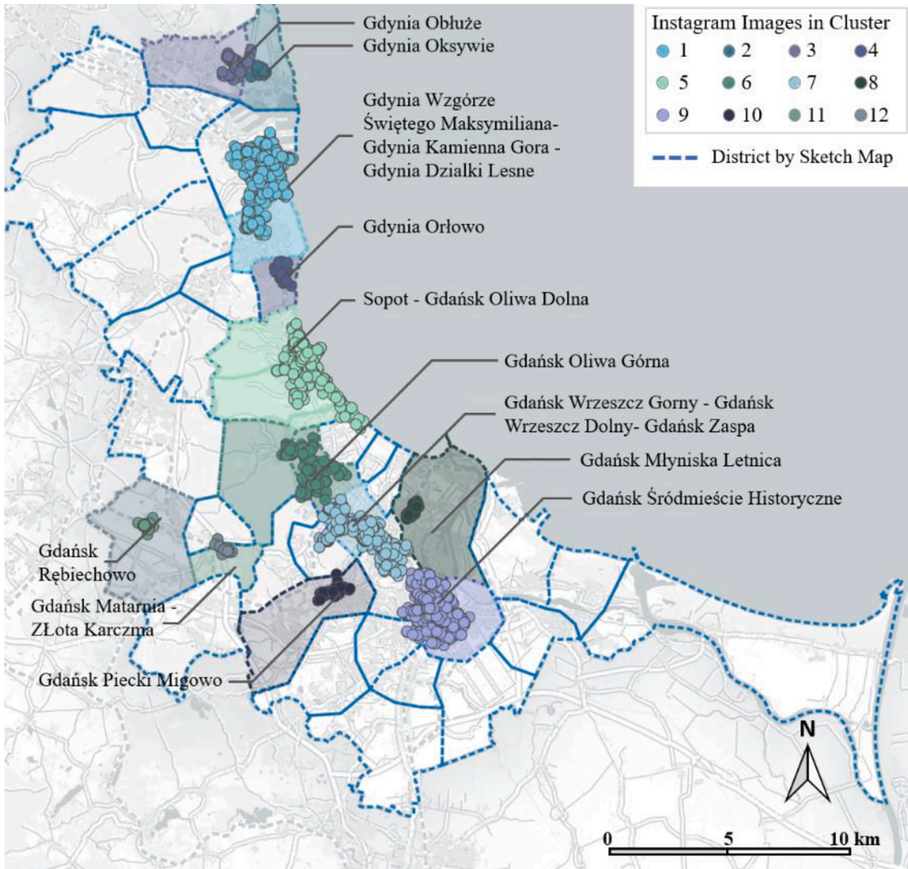

Fig. 5. Identification of "district" using clustering analysis of geo-tagged Instagram posts in comparison with "mental district" by sketch maps.

3.2. Social media analytics

GSM, i.e. images and text information, were collected from two popular social media platforms: 1) Instagram, a photo and video sharing social networking service (Instagram, 2019a), and 2) Twitter, a largely text-based platform allowing users to share short messages typically up to 140-characters long, alternatively known as tweets (Twitter Inc., 2016). The choice of Instagram and Twitter over competing platforms such as Facebook was based on data availability and their appropriateness for the study purposes. By default, Twitter and Instagram made their contents accessible by the public, while Facebook posts are often only visible to chosen groups. The instant, spontaneous nature of Instagram and Twitter posts were said to capture users' perception and experience at a specific location and time, unlike Facebook on which users tended to upload organized and delayed content (Tagtmeier, 2010).

3.2.1. Data-mining and cleaning

Data-mining of text information was conducted using the Twitter Streaming Application Programming Interface (API), a computer program interface allowing continuous acquisition of all publicly accessible Twitter messages within a predefined geographical boundary (Morstatter, 2013). The original dataset consists of text, images/videos if available, time stamp, GPS coordinates, language setting, and user ID, etc. Extensive cleaning was conducted: repetitive posts were removed; the top 1% of high frequency user IDs were manually reviewed in order to filter fake accounts or those affiliated with political or advertisement campaigns. Social media IDs were differentiated as either 1) frequent user IDs or 2) infrequent user IDs. The former refers to an active ID in a period equal to or longer than 2 weeks during the study period, which can be regarded as being owned by a resident. The later were from either short-term visitors or occasional social media users.

Data-mining for Instagram images was conducted through Twitter API. About 3.5% of tweets recorded from the Tri-City Region constitute a URL linked to an Instagram post, presumably by a user who has previously linked the Twitter and Instagram accounts together, so images shared on Instagram will appear on Twitter at the same time (Instagram, 2019c). The URL to Instagram were recorded and activated to download the image content, i.e. a photo or video for analysis. This approach was adopted since access to large quantities of posts on Instagram was limited by the platform's policy (Instagram, 2019b). Therefore, only a proportion of publicly accessible Instagram activities is expected to be sampled from the study area, which is a technical limitation for this research and most Instagram-based studies.

3.2.2. Image processing

Image processing was conducted in order to determine the content of Instagram images and their relevance to perceived Lynchian elements of city images. The first step was to sort Instagram photos and videos related to urban environments using Tensorflow, a machine-learning algorithm (Abadi, 2016) which can label each image with its content, such as "building," "playground," "park," or "street" (Tensorflow, 2019). The images labeled as "posters," "artwork," or indoor settings such as "apartment," "food," "restaurant," or "concert," were excluded from further analysis since they were not directly related to the urban environment. A second step was to manually label each urban environment-related image by Lynchian elements. For instance, if a photo is about an iconic building, it will be labeled "landmark", or "node" if it is about an open space or plaza. In an overlapping case, i.e. the photo contains both an iconic building and a plaza, then the image will be labelled as both "landmark" and "node." Examples of labelling Instagram images by Lynchian elements were provided in Fig. 13 of the

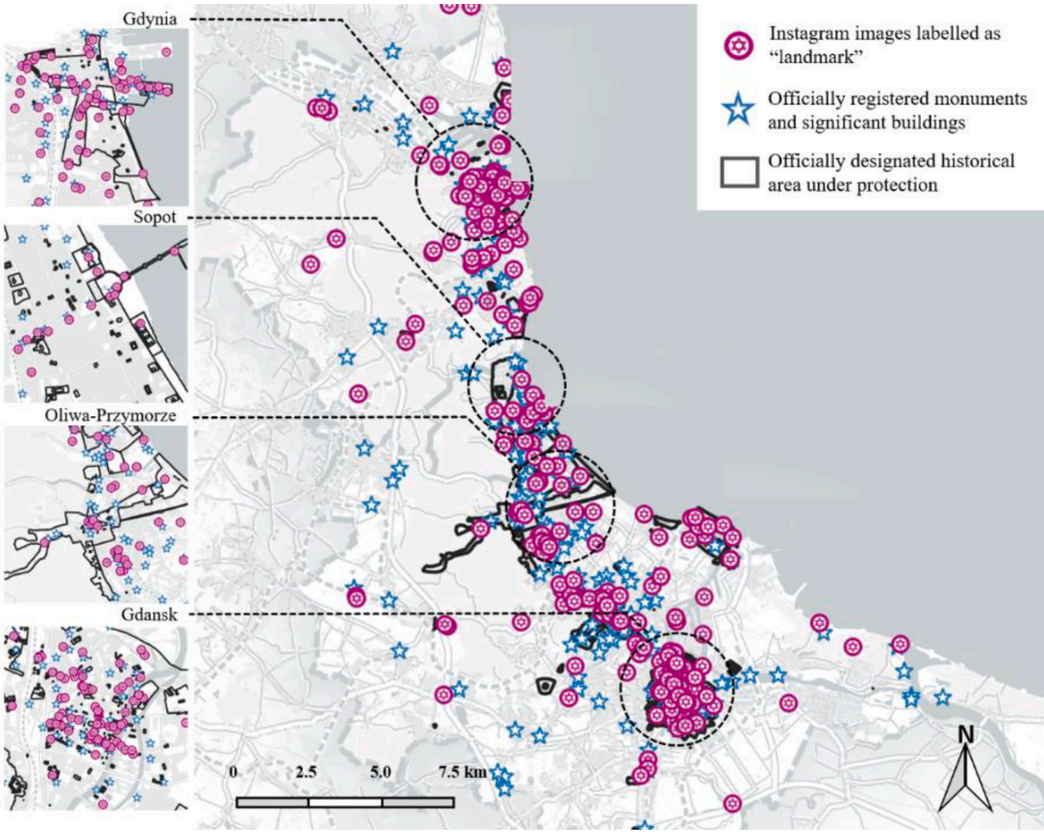

Fig. 6. Instagram images labelled as "landmarks" overlaid on top of officially registered monuments and significant buildings from the metropolitan planning office (stars).

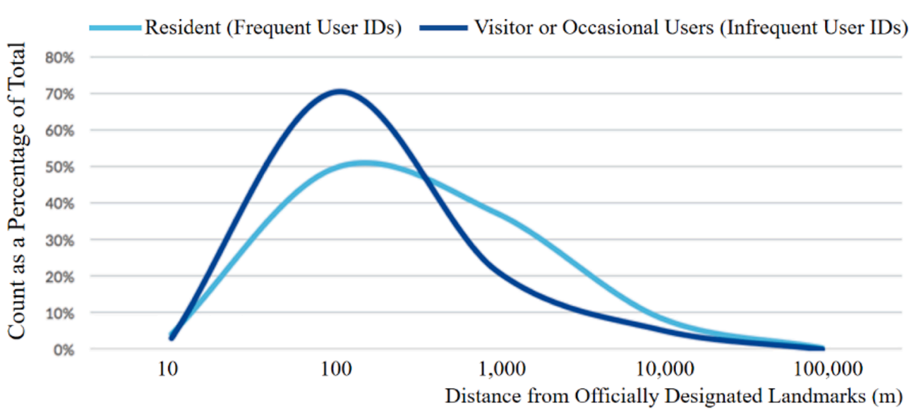

Fig. 7. Distribution of distance of Instagram images labeled as "landmark" to the nearest officially registered monument by frequent and infrequent user IDs.

Appendix. The labeling task was conducted independently by two researchers of urban planning background familiar with Kevin Lynch's work; both were master's students yet were from different institutions.

3.2.3. Cluster analysis

Cluster Analysis was used to assess the spatial continuity and discontinuity of social media activities in order to measure the concept of "district." The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) – a non-parametric, density based clustering technique (Ester et al., 1996) – was used to assess the geospatial proximity of geo-tagged imagery and text. Clusters of Instagram messages and Tweets were identified based on their GPS locations. The two parameters of DBSCAN: minimal points (n) and threshold distance (ε) to form a cluster, were set at 5 and 300 m respectively in this study. Results showed whether a social media post belongs to the core (within a district), the border (at the border of a district) or is an isolated outlier (Noise Point) (He et al., 2011). DBSCAN was considered suitable for this task due to its relative resistance to noise present per the nature of social media platforms and capacity to handle clusters of various shapes and sizes (Tran, Drab, & Daszykowski, 2013).

3.2.4. Kernel density estimation

Kernel Density Estimation (KDE) was used to detect patterns of continuity and discontinuity in social media activities. The purpose was to evaluate the existence of "district" or "edge" in Lynch's theory. A bivariate KDE was used to calculate the density of point features, i.e. geo-tagged Twitter and Instagram, in each output raster cell. The calculation was performed using ArcMap 10.4 software package, which referenced the quadratic kernel function described by Silverman (1986). For each raster cell x centered at coordinates X, Y, the density of social

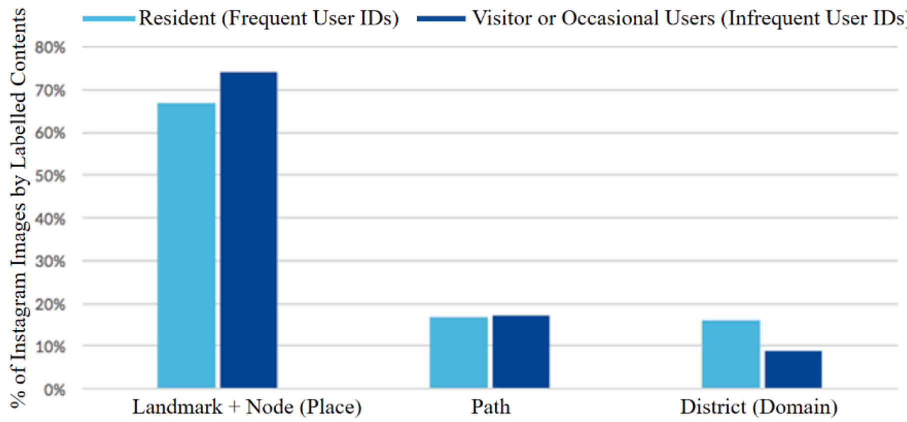

Fig. 8. Percentage of Instagram images from frequent and infrequent user IDs labelled by elements.

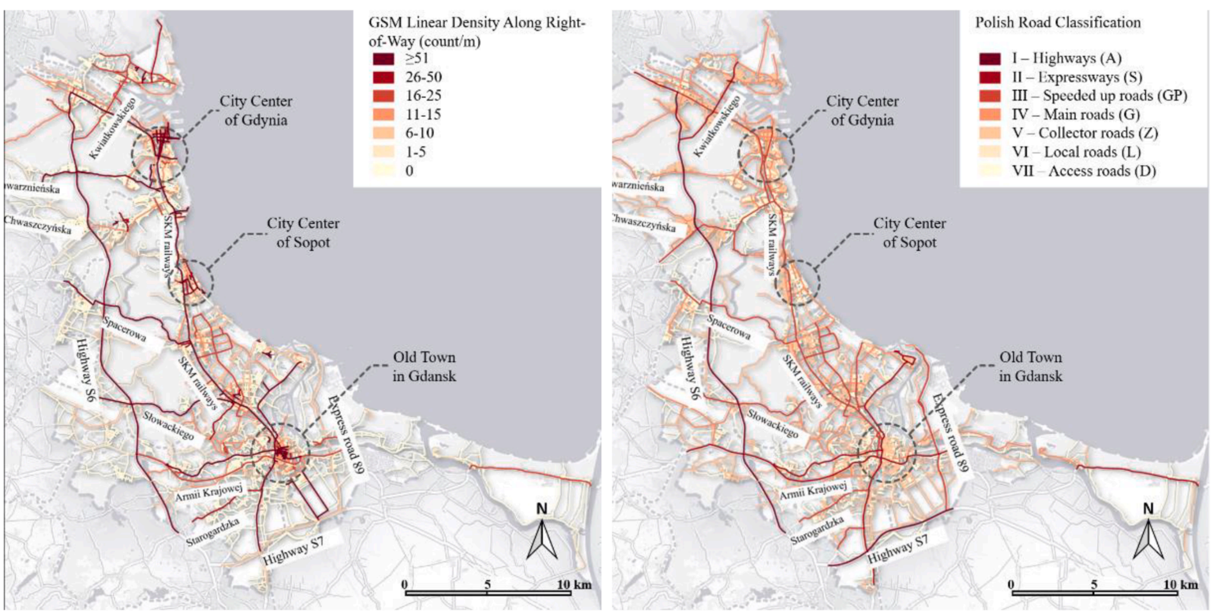

Fig. 9. (Left) Major path identified through social media analytics, i.e. road/rail right-of-way ranked by linear density of GSM. (Right) Major path identified by sketch maps and questionnaires.

media posts $\widehat{f}(x,h)$ under bandwidth h can be expressed in equation (1):

$$\widehat{f}(x) = \frac{1}{nh}\sum\nolimits_{i=1}^{n} K_h(x - x_i) \tag{1}$$

where x_i is the social media dataset containing X, Y coordinates, $x_i = (X_i, Y_i)^T$, and $i = 1,2,3,\ldots$n. h is the bandwidth, also known as the smoothing parameter. K_h is the kernel function which can be expressed in Formula (2) below:

$$K_h(x) = \frac{\exp\left(-\frac{1}{2}x^T, x\right)}{\sqrt{2\pi}h} \tag{2}$$

In order to measure the "edge," or the discontinuity of social media activities, the slope of $\widehat{f_h}$ was calculated to assess the rate of change of social media activities between two neighboring raster cells. A potential "edge" can be identified if $\widehat{f}'(x,h)$ were to reach its maximum value, suggesting a rapid change in the density of social media activities worthy of further verification.

3.2.5. Sentiment analysis & keyword searching

The text of tweets and Instagram posts were measured using sentiment analysis. The aim was to test Lynch's statement (Lynch, 1960, p.5) that "A good environmental image gives its possessor a sense of emotional security". The Linguistic Inquiry and Word Count (LIWC) was used to measure the sentiment tone of the text content from tweets and Instagram posts. LIWC is a lexicon-based analysis tool which reads a given text and counts the percentage of words that reflect emotions, thinking styles, social concerns, and even parts of speech (Kahn, 2007; Tausczik & Pennebaker, 2010). For the text proportion of each Tweet or Instagram post, the LIWC algorithm returns the sentiment tones measured in polarity from −1 to 1 (-1 stands for unhappy and 1 for happy). A random subsample of 5% of the total tweets and Instagram posts were reviewed manually to evaluate the accuracy of sentiment analysis.

Keyword searching was adopted to determine whether a place was mentioned by name in the content of Twitter and Instagram messages. In this study the list of places was derived from a questionnaire to be described in Section 3.3.2. The list was verified and manually matched with their geographical coordinates. The official name nicknames and spelling variations of a specific place were used in the keyword search in order to ensure the robustness of results.

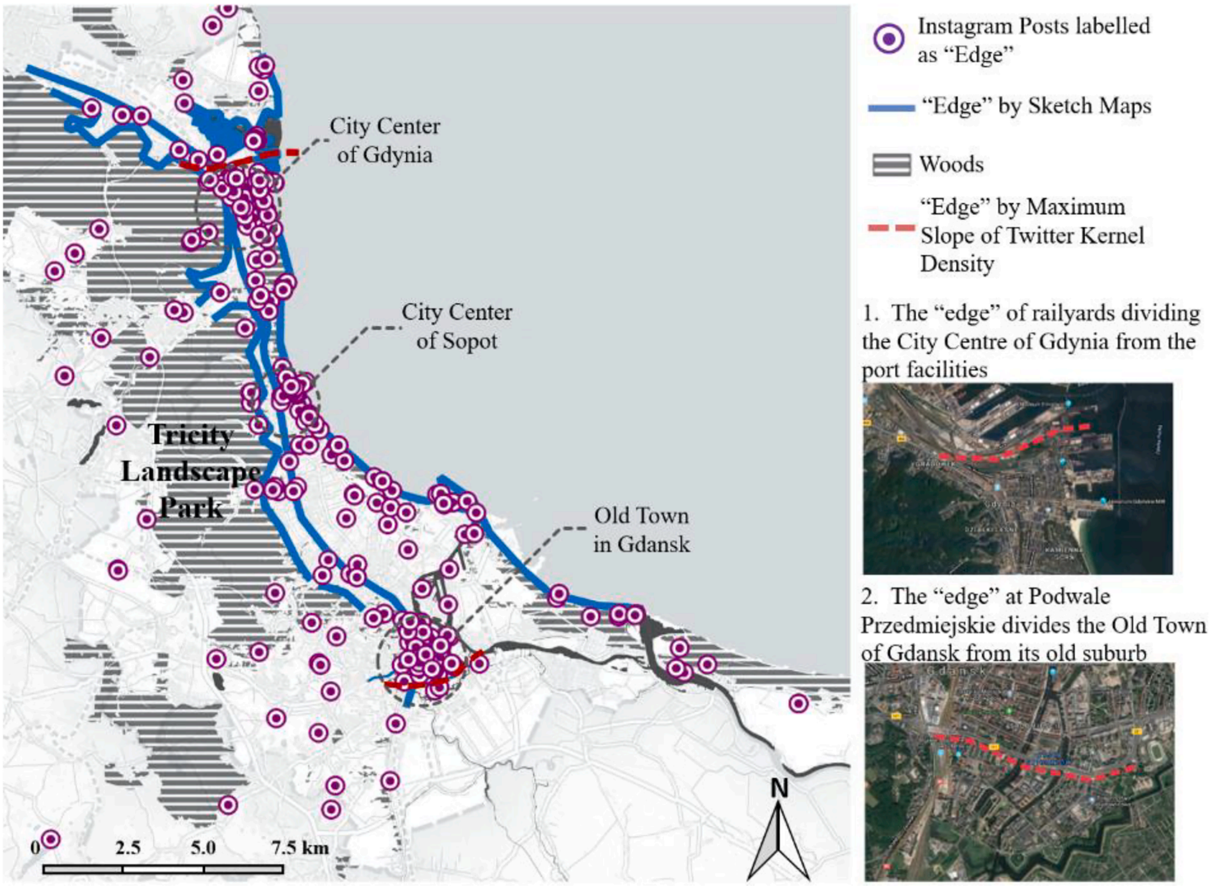

Fig. 10. The "edge" elicited by sketch maps, Instagram posts labelled as "edge", and Twitter kernel density estimation.

3.3. Questionnaire, sketch map and GIS database

A parallel study of city images of the Tri-City Region was conducted using GIS database and Lynch's original methods. The aim was to provide a real-world benchmark to verify GSM-based city images.

3.3.1. GIS database

The GIS database was acquired through government surveying offices, the transport authority, and the monuments and landmarks registry. The purpose was to provide a verified benchmark established via expert review and official procedure. A database was compiled for the registered immovable monuments maintained by the Pomeranian Voivodeship Conservator of Monuments, including the name, address, and geographical coordinates for each monument embodied in the Spatial Development Plan for the metropolitan area of Gdansk-Gdynia-Sopot (MBPV, 2016). Administrative boundary, neighborhood/district polygons, address, road network, open space, and topography information (BDOT10K) were collected from the National Centre for Geodetic and Cartographic Documentation (NCGCD, 2010). Land use and parcel polygons were obtained from the District Geodetic and Cartographic Documentation Centers (Centre, 2010). The coastline, forest cover, highways, public transit such as rail, tram, and bus lines were obtained from the OpenStreetMap database (OSMF, 2016). Census and demographic data were collected from the census bureaus of the three cities, respectively (COGA, 2016; COGD, 2016; COS, 2016).

3.3.2. Questionnaire & sketch map

The questionnaire and sketch map methods were used to measure the perceived Imageability of places from residents of the Tri-City Region. Participants were asked to answer questions on perceived qualities of places after a brief introduction of Kevin Lynch's theory. These questions were designed to measure Imageability as a latent construct using terms understood by the general audience:

1. "Name the top 5 most significant architectural landmarks in the Tri-City Region that you have visited", aimed to capture qualities such as "apparent," "distinct," "remarkable," and "visible" in Lynch's description (1960 p.10).
2. "Name the top 5 most prestigious places in the Tri-City Region that you have visited", intended to capture qualities such as "well formed," "coherent," "legible" (ibid., p.91).
3. "Name the top 5 nicest places in the Tri-City Region that you have visited," aimed to capture qualities related to "the depth and intensity of human experience" (ibid., p.5).

Participants were further asked to draw a cognitive map of their neighborhoods and the daily routes from home to places of work/study, scan the map and send the digital file via the internet. They were also asked to report background information such as age, gender, street address, and length of residence in the area. The questionnaire was administrated online in order to recruit a sample population that are digital-savvy and comparable to social media users on Twitter and Instagram. The full questionnaire is included in Table 5 of the Appendix.

4. Results & discussion

City images elicited by both social media analytics and traditional methods were illustrated and compared with each other. GSM-based indictors, such as Instagramability and Twitterability, were computed to measure the imageability of places. The theoretical and practical implications for urban planners are discussed, along with limitations and the next steps.

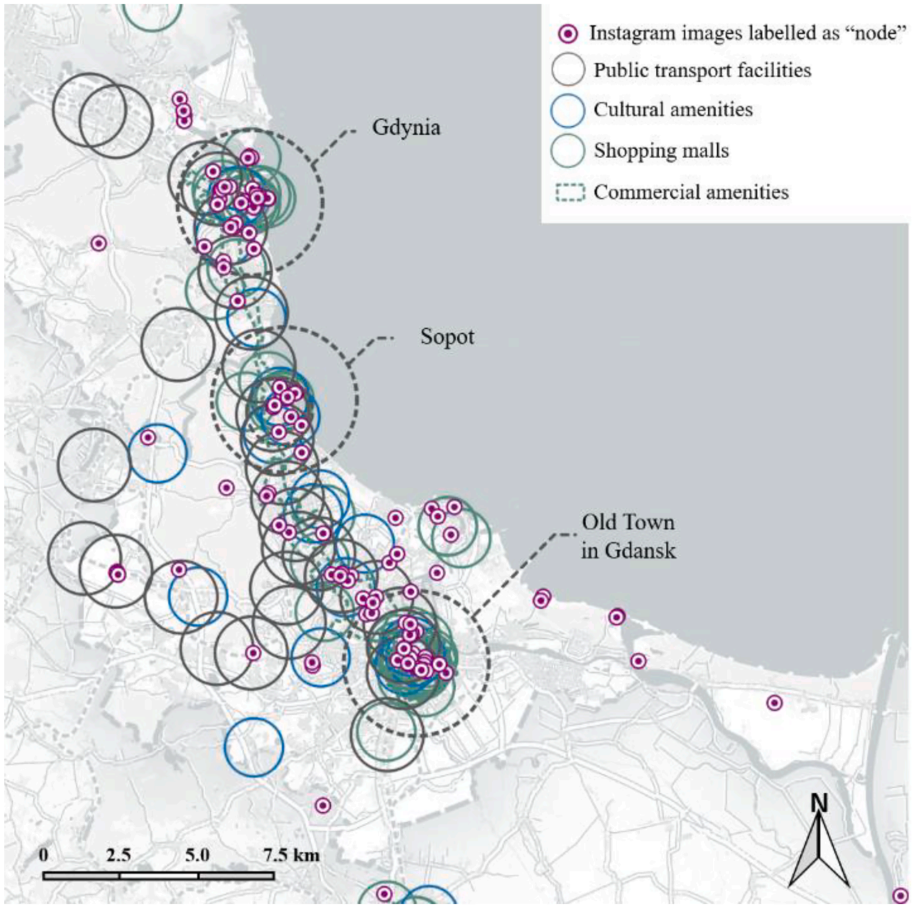

Fig. 11. Instagram images labelled as "node" in comparison with benchmarks by questionnaire and sketch maps (public transport facilities, cultural and commercial amenities).

Table 4
Correlations between web-based measures of Imageability and perception of the quality of place in regression analysis (N = 126).

Regression Coefficient (p-value) (R Squared)		Social Media Indicators of Imageability			Questionnaire Indicators of Place Perception		
		Instagramability[1]	Twitterability[1]	Social Media Sentiment	Nice Score	Landmark Score	Prestige Score
GSM-Based Indicators of Imageability	Instagramability[1]		0.0288 (p = 0.908) (R^2 = 0.000)	**0.014 (p = 0.039)** (R^2 = 0.265)**	0.349 (p = 0.509) (R^2 = 0.061)	**0.010 (p = 0.014)** (R^2 = 0.225)**	**1.510 (p = 0.022)** (R^2 = 0.208)**
	Twitterability[1]			−0.003 (p = 0.698) (R^2 = 0.050)	**0.004 (p = 0.002)*** (R^2 = 0.278)**	0.001 (p = 0.623) (R^2 = 0.045)	**0.007 (p = 0.000)*** (R^2 = 0.388)**
	GSM Sentiment				−11.227 (p = 0.535) (R^2 = 0.081)	3.236 (p = 0.870) (R^2 = 0.021)	0.947 (p = 0.968) (R^2 = 0.005)
Questionnaire-Based Indicators of Place Perception	Nice Score					0.037 (p = 0.710) (R^2 = 0.001)	**0.909 (p = 0.000)*** (R^2 = 0.519)**
	Landmark Score						0.163 (p = 0.127) (R^2 = 0.140)
	Prestige Score						

[1] Values in logarithmic scale ** 95% significance level *** 99% significance level.

4.1. Data characteristics

4.1.1. Social media data

Table 1 summarizes the Instagram and Twitter data recorded between May 1, 2017 and April 30, 2018 from the Tri-City Region. A total of 9,360 Instagram posts were recorded from 2,001 unique user IDs, of which 601 were frequent user IDs used by residents, and 1,400 were infrequent user IDs likely from visitors or occasional Instagram users. A total of 298,465 Tweets, excluding those contains a URL to Instagram posts, were recorded from 11,972 unique user IDs, of which 3,247 were from frequent user IDs, and 8,698 were from infrequent user IDs.

88.5% of tweets retrieved from the Tri-City Region were contributed by frequent user IDs, a majority (59.7%) were in Polish language. In comparison, 67.1% of Instagram posts were contributed by frequent user IDs, while less than half (45.6%) were posted in Polish Language. Given that 97% of Poland's citizens identify Polish as their first language

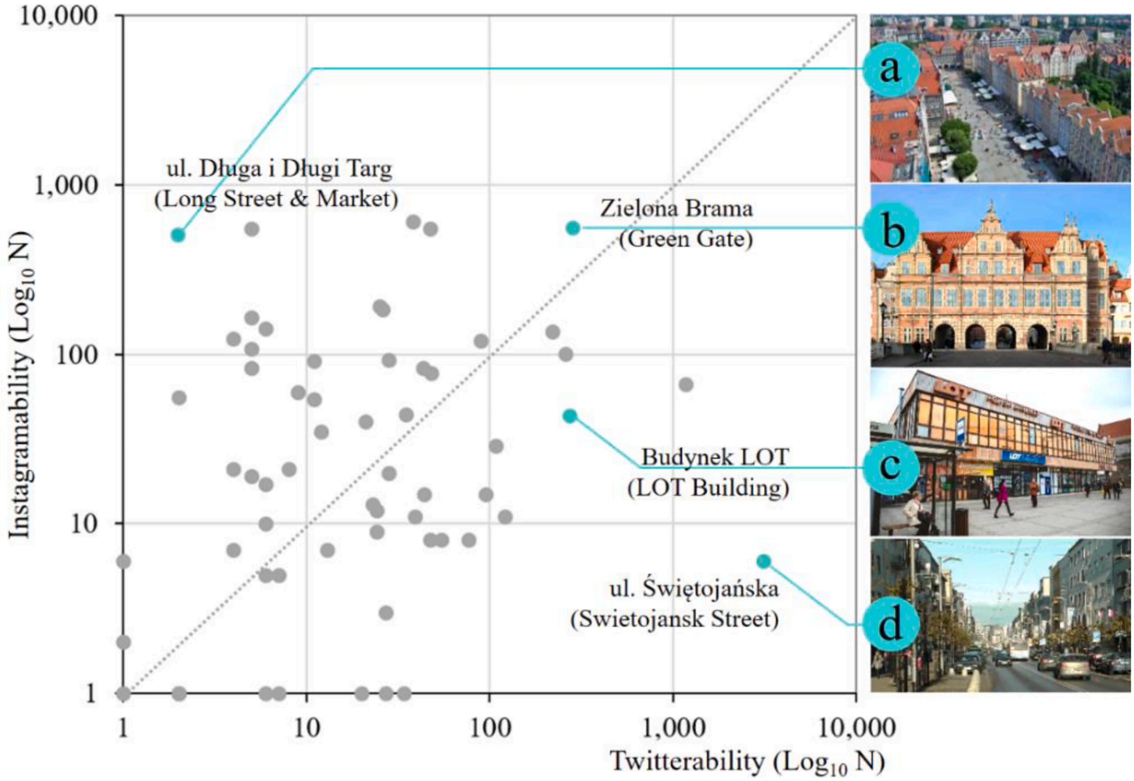

Fig. 12. Scatterplot of places by Instagramability and Twitterability with highlighted cases.

(CSO, 2013), it is reasonable to conclude that local residents dominated Twitter activities in the Tri-City Region, less so for Instagram where visitors or expatriates from outside of Poland were more active.

A total of 9,360 photos and videos were obtained from Instagram in the two categories: 1) the majority (53%) were found to be directly related to the urban environment; 2) the remaining 47% were found to be about food, people, indoor scenes, logos, etc. The former was labelled manually by Lynchian elements by two researchers independently; their labelled results reached an agreement rate of 87%; the remaining 13% in conflict were removed in order to ensure robustness of analysis. Labelled Instagram posts of the urban environment by Lynchian element are summarized in Table 2 below.

4.1.2. Questionnaire and sketch maps

A total of 62 effective responses to the questionnaire were received. Respondents named 126 places from the Tri-City Region as the most prestigious, nicest places or architectural landmarks. 54 places were named at architectural landmarks at least once, 22 of which were located in the historical urban core of Gdansk, 9 at the former Gdansk shipyard, an area under major urban transformation. 57 places were named as the most prestigious places, such as Dluga Street in Gdansk (named by 17% of respondents) and Monte Cassino in Sopot (by 15% of respondents). The list of nominated prestigious place also included many recent developments such as the Olivia Business Center and Alchemia – both are recently constructed high-rise office buildings – and Garnizon, a mixed-use urban regeneration project. 64 places were named as the nicest places, most were in the urban core or recreational area, such as the Seaside Promenade in Gdynia (named by 23% of respondents), Park Regana (by 11% of respondents) and Park Oliwski (by 7% of respondents) in Gdansk.

47 sketch maps were received, the quality of which ranged from a single line for a street to complicated street maps. Depending on the drawing skills of respondents, the information embedded in sketch maps are often represented without geospatially accuracy. The Lynchian elements in sketch maps were extracted and redrawn digitally (Fig. 14), benchmarked with the official GIS database in order to improve the geospatial accuracy of freehand drawings.

4.2. City images by Lynchian elements

The five Lynchian elements of city images were identified using social media analytics (Fig. 3). Results were compared with benchmarks established with GIS database, questionnaire responses and sketch maps (Fig. 4). The agreements between the two were summarized in Table 3. In sum, GSM-based elements such as “district”, “landmark,” and “path,” were in reasonably good agreements with real-world benchmarks, less so for “edge” and “node”. Details are discussed below by element.

District was referred to by Lynch as “sections of the city, … which the observer mentally enters ‘inside of,’ … recognizable … having some common, identifying character” (Lynch, 1960, p.66). “District” was identified using social media analytics, i.e. the aforementioned DBSCAN method applied to geo-tagged Instagram images, and from geospatially corrected sketch maps obtained from questionnaire respondents. Results from both methods are shown in Fig. 5. A reasonably good agreement was observed between the “big data” and “small data” approaches. For the top 12 DBSCAN clusters, each a spatially contiguous district with high levels of Instagram activities, an average of 91% of Instagram posts can be found within a distinct “mental district” identified via sketch maps. Further, these districts were frequently mentioned by name in daily Twitter discussions. A text-based keyword search for the district name in Tweets were summarized in Table 7 of the Appendix. A sensitivity analysis on the input values of threshold distance (ε) used in the DBSCAN analysis is shown in Table 6 of the Appendix, while the procedures of geospatially correction for multiple sketch maps of “mental district” are included in Fig. 14 of the Appendix.

Landmark was defined as the “external reference points, which the observer cannot enter” (Lynch, 1960, p.78). Instagram images labelled as “landmarks,” i.e. an iconic building, monument or sculpture, were found in close proximity to the benchmark of the official list of monuments and significant buildings registered at the Registry of the

Table 5
Questionnaire used to study city images in the Tri-City Region.

Questionnaire of the City Image of the Tri-City Region

This questionnaire is part of a research project on the public perception of city images in the Tri-City Region of Gdansk, Gdynia and Sopot. The research is being jointly conducted by researchers from the Gdansk University of Technology, The University of Hong Kong, and the City University of Hong Kong. You will be asked to answer a few questions and draw two sketch maps. The questionnaire is anonymous, and all information collected will be restricted to research purposes only.

Part 1. Background Information

1. Age □ < 18 □ 18-24 □ 25-30 □ 31-40 □ 41-50 □ 50 <

2. Gender □ Female □ Male

3. Educational Attainment
□ Vocational education □ Secondary education □ Bachelor's degree □ Master's degree or above

4. Employment status
□ Employed □ Unemployed □ Student □ Retired □ Homemaker □ Self-employed

5. City □ Gdansk □ Gdynia □ Sopot □ Outside of the Tri-City

6. Zip Code ____________________

7. Street Name ____________________

8. What type of house do you live in?
□ Single family house □ Semi-detached house or townhouse □ Tenement house
□ Apartment building lower than 5 floors □ Apartment building higher than 5 floors □ Dormitory

9. How long have you lived in this neighbourhood?
□ Less than a year □ 1-2 years □ 2-5 years □ 5-10 years □ over 10 years

10. Rate your neighbourhood on a 1-5 scale (5 is the best)

Part 2. Mental Images

Kevin Lynch, as an American urban planner, worked at MIT where he conducted research into how people find the city they live in, and what impact urban forms have on the way we think about our neighbourhood. His work was based on mental maps. A mental map presents our personal feelings about places, for example: buildings which attract our attention, places which we find to be barriers, such as difficult pedestrian crossings, our aesthetic impressions, e.g. "the square is nice/desolated" etc.

11. Please draw a simple map representing your neighbourhood, scan and upload the map here.

12. Please draw a mental map representing your route from the place you live to the place you work/study/spend most your time, scan and upload the map here.

13. Name five architectural landmarks from the Tri-City Region that you have visited

14. Name the five most prestigious places from the Tri-City Region that you have visited

15. Name the five nicest places from the Tri-City Region that you have visited.

Table 6
Clustering of Instagram posts using various distance thresholds.

Threshold Distance (ε)	200 m	300 m	500 m
# of Instagram posts in cluster	4,932 (92%)	4,790 (89%)	5,152 (96%)
# of Instagram posts outside cluster	446 (8%)	588 (11%)	226 (4%)
# of clusters identified (C)	96	48	55

Voivodship Monument Conservation Office (Fig. 6). In general, 65% of Instagram posts labelled as "landmarks" were found within the 300 m distance from the benchmark (Fig. 7).

A breakdown analysis between by frequent and infrequent user IDs yielded largely consistent results, except that the former were found to identify less with "landmark" compare with the latter. 74% of Instagram images uploaded by infrequent user IDs, meaning visitors or occasional social media users, were found to be about "landmark" and "node". For frequent user IDs (residents), the percentage stood at a lower level of 67% (Fig. 8). Further, Instagram posts uploaded by the former were more concentrated near the benchmarks, about 70% were within a photo-taking distance, while those of the latter were more dispersed, with 50% within a photo-taking distance from benchmarks. The finding is consistent with previous literature on the perceived differences of mental images between newcomers and long-term residents: landmarks was considered to be most important especially for newcomers (Evans et al., 1981) and young children (Siegel & Schadler, 1977).

Path was referred to by Lynch (1960, p.41) as "the channels along which the observer … moves". In general, good agreements were observed between "paths" identified using social media data and benchmarks consisted of road network obtained from the official GIS database. Fig. 9(left) shows paths of the Tri-City Region color coded by

Table 7
Summary of the 20 neighborhoods in the Tri-City Region mentioned in Twitter in relation to their overlapping "districts" identified using DBSCAN cluster analysis.

Neighborhood Name	Alternative Name Used	# of mentions on Twitter	DBSCAN Cluster ID	# Instagram posts in cluster
Gdańsk Zaspa	Zaspa, Rozstaje, Młyniec	22	7	405
Gdańsk Nowy Port	Nowy Port, Westerplatte	96	.	.
Gdańsk Wrzeszcz Dolny	Wrzeszcz Dolny, Strzyża	6	7	405
Gdańsk Brzeźno	Brzeźno, Jelitkowo, Osiedle Tysiąclecia, Osiedle Wejhera	73	.	.
Gdynia Wzgórze Świętego Maksymiliana	Gdynia Wzgórze Świętego Maksymiliana, Wzgórze Nowotki, Wzgórze Świętego Maksymiliana, Wzgórze Maksymiliana	15	1	43
Gdańsk Oliwa Dolna	Oliwa Dolna, Przymorze, Przymorze Małe, Przymorze Wielkie, Żabianka	23	5	15
Gdańsk Śródmieście Historyczne	Śródmieście Historyczne, Główne Miasto, Stare Miasto, Sródmieście, Stare Przedmieście, Ołowianka, Wyspa Spichrzów	45	9	38
Gdańsk Młyniska Letnica	Młyniska Letnica, Letnica, Letniewo, Młyniska	33	8	68
Gdynia Obłuże	Gdynia Obłuże, Pułkownika Dąbka	3	3	694
Gdańsk Klukowo - Rębiechowo	Klukowo - Rębiechowo, Rębiechowo, Klukowo	3	11	12
Gdańsk Oliwa Górna	Oliwa Górna, Uniwersytet, VII Dwór, Oliwa	17	6	376
Gdynia Kamienna Góra	Gdynia Kamienna Góra, Kamienna Góra, Bulwar	46	1	43
Gdańsk Matarnia - ZŁota Karczma	Matarnia - Złota Karczma, Matarnia, Złota Karczma	11	12	34
Sopot Miasto	Sopot - miasto, Sopot, Kamienny Potok, Brodwiono, Monte Cassino, Monciak, Sopot Górny	42	5	15
Gdańsk Piecki Migowo	Piecki Migowo, Brętowo, Piecki Migowo, Migowo, Morena, Siedlce, Matęblewo	28	10	56
Gdynia Działki Leśne	Gdynia Działki Leśne, Działki Leśne, Gdynia Działki	77	1	43
Gdynia Orłowo	Gdynia Orłowo, Klif, Klibki, Redłowo	70	4	22
Gdynia Oksywie		23	2	1155

(continued on next page)

Table 7 (*continued*)

Neighborhood Name	Alternative Name Used	# of mentions on Twitter	DBSCAN Cluster ID	# Instagram posts in cluster
	Gdynia Oksywie, Martnarka Wojenna, Osada Rybacka			
Gdańsk Wrzeszcz Górny	Wrzeszcz Górny, Garnizon, Aniołki	17	7	405
Gdynia Śródmieście	Gdynia Śródmieście, Gdynia Centrum, Skwer Kościuszki, Skwer	93	1	43

comparison between the lists of major paths, identified as the top 20% of road ranked by GSM density in the former and the Level I & II roads in the latter, yielded an overlapping rate of 50%.

A detailed review of Instagram posts on key paths raised cautions: A large number of traffic accident-related Instagram photos were found along highways, such as E28 to the west of the Tri-City Region. These accident photos boosted the GSM density along highways. The density of GSM alone is not a perfect measure of travel behaviours, which, if not carefully discerned, may lead to an exaggerated conclusion of a "path" more important than it was.

Edge was referred to by Lynch (1960, p.63) as "breaks in continuity" or, "linear elements not considered as path". Fig. 10 shows Instagram posts labelled as "edge" (in purple dots) and those identified using by sketch maps, mostly consisted of the seashore and the borders of the Tricity Landscape Park (in blue line). A relatively low agreement was

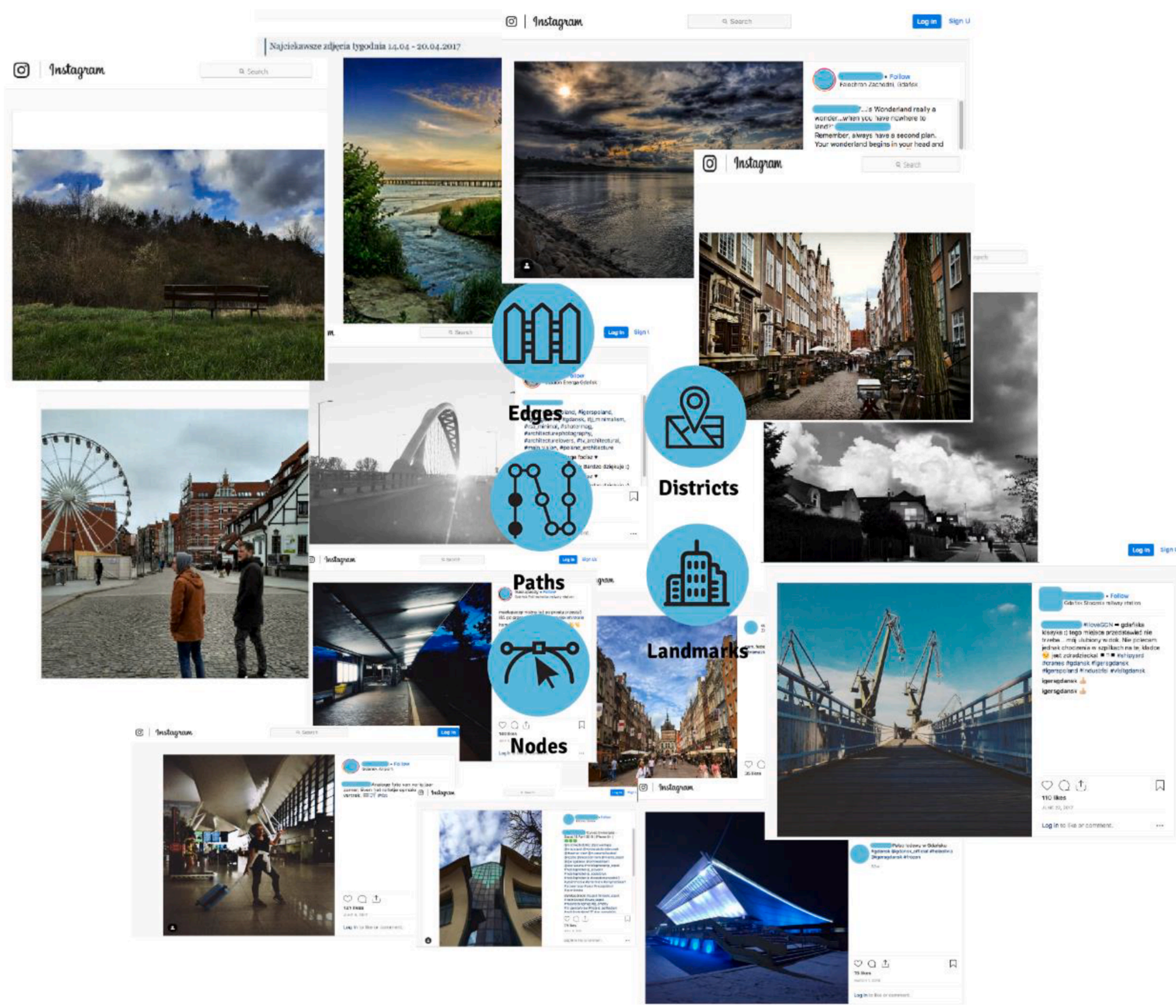

Fig. 13. Examples of Instagram images labelled as "edge", "path", "node", "district" and "landmark" by Lynchian elements.

the linear density of GSM (including tweets and Instagram posts) along the right-of-way[1] of a road, highway or railway line. Fig. 9(right) shows paths color-coded by the Polish Road Classification system (Ministry of Infrastructure, 2016), ranked from I- Highways (A) till VII- Access roads (D). A reasonable agreement can be observed between the two. A

found between the two, only 39% of the "edge" by labelled Instagram posts fell within 100 m from the benchmark by sketch maps. Alternatively, the edge identified by the Kernel Density Estimation method, shown in red dotted line in Fig. 10, also matched poorly with the benchmark. More description on the Kernel Density Estimation is provided in Fig. 15 of the Appendix.

The lack of coherent, agreeable "edge" between "big data" and "small data" methods echoes with a previous study by Jiao et al. (2017). It is possible that the Tri-City Region's sleek, pedestrian-friendly urban

[1] The right-of-way is calculated along the road/railway center line with a buffer distance of 5-10m depending on the width of the corridor.

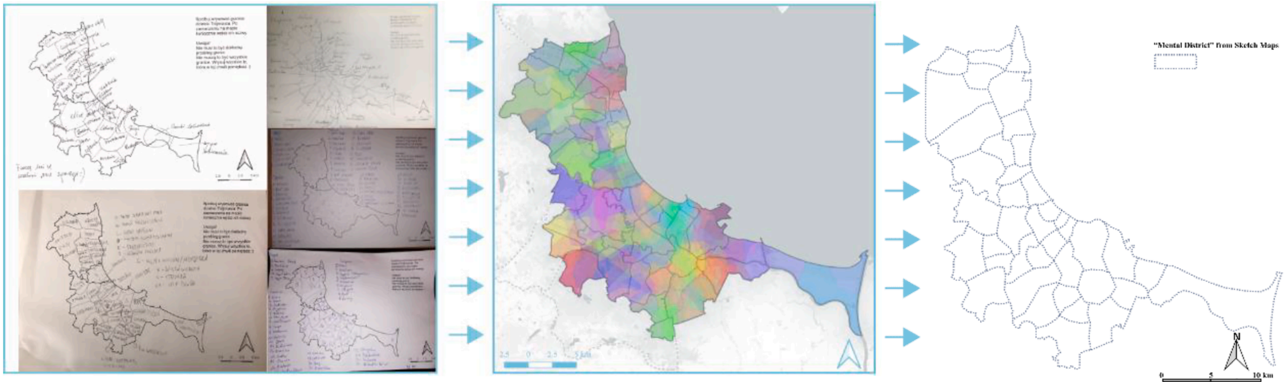

Fig. 14. (left) sketch maps of mental district boundaries obtained from questionnaire respondents; (Middle) Overlapping of multiple sketch maps in reference to administrative district boundary from GIS database; (left) redrawing of the mental district boundaries in GIS space.

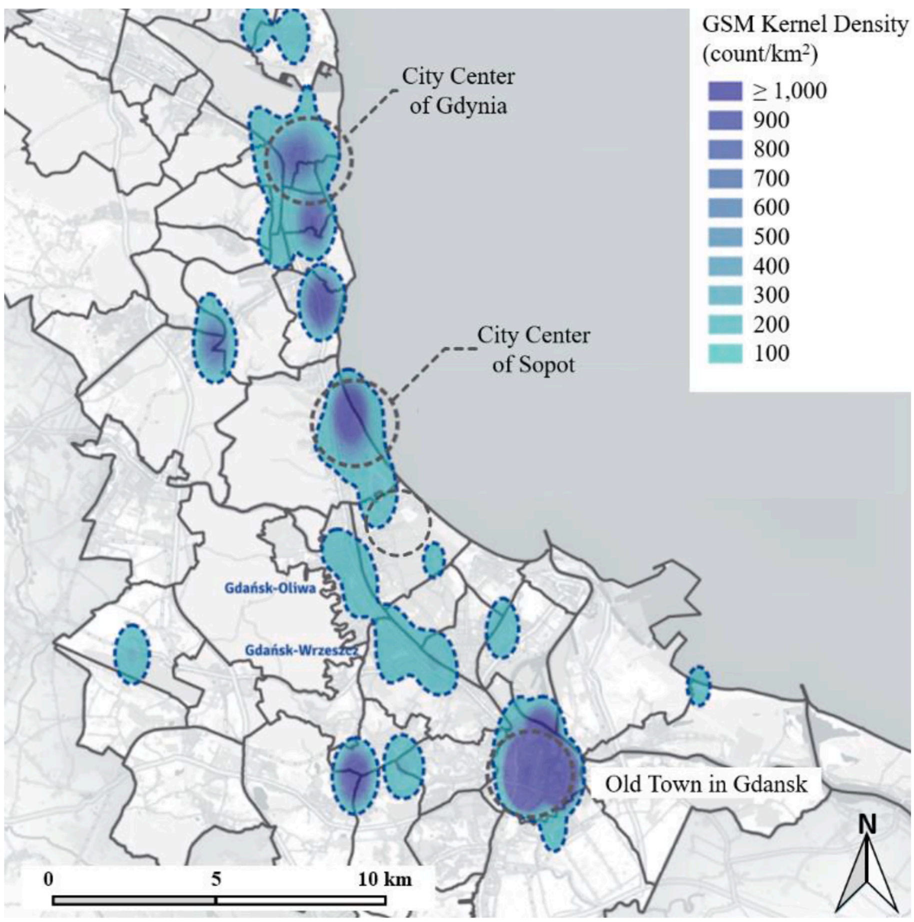

Fig. 15. GSM-based district calculated using the kernel density estimation. The "district" boundary was determined using the contour line of kernel density measured at 100 count/km^{2}.

cores and convenient public transit may not possess as many "edge" described by Lynch for American cities of the 1950s. The region does not have many vacant factories nor run-down neighborhoods of the post-industrial era, unlike many post-industrial cities in Western Europe or North America.

Node was defined as "conceptual anchor points … conjunctions, "strategic (points) in a city into which an observer can enter, and which are the intensive foci to and from which he is traveling" (Lynch, 1960, p.72). Fig. 11 shows Instagram images labelled as "node" (parks, plazas, street intersections, public transit, etc.) and the benchmarks measured by questionnaire and sketch maps (i.e. major public transport facilities, shopping malls, and cultural amenities). 21% of the GSM-based "node" can be found within 100 m from the benchmarks, a relatively poor agreement. This discrepancy between results from the two methods may be explained by the historical structure of Gdansk as a Hanseatic city, which lacks traditional nodes such as the main square or smaller plazas in other medieval European cities. Instead, major public spaces in the Old Town of Gdansk run linear along streets perpendicular to the waterfront, making "nodes" less distinguishable from "paths" or "landmarks".

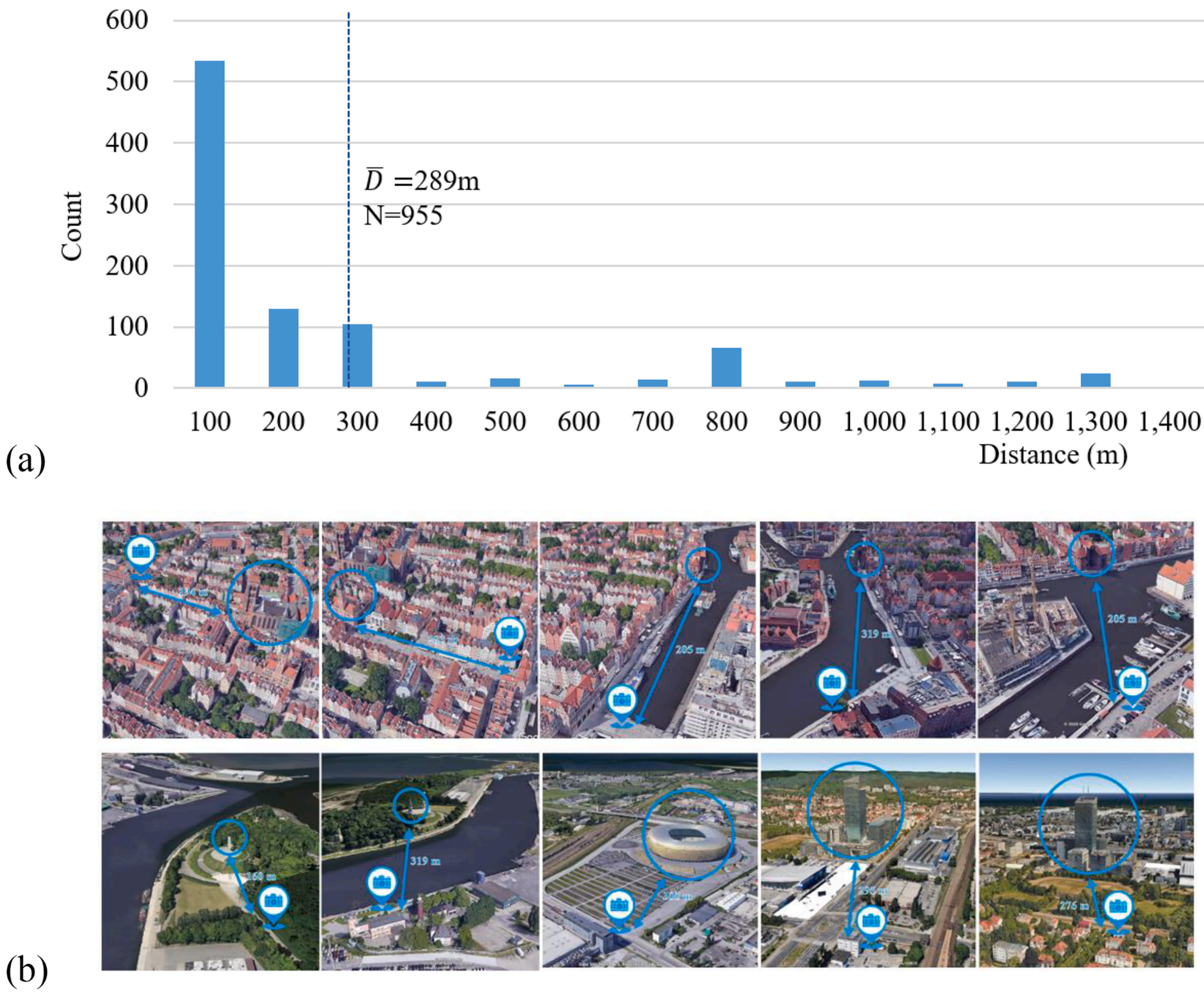

Fig. 16. (a) Distribution of the distance from a landmark to its geo-tagged Instagram photos, for a random sample of 955. (b) Examples of computing the distance from a landmark to its geo-tagged Instagram photos in the Tri-City Region.

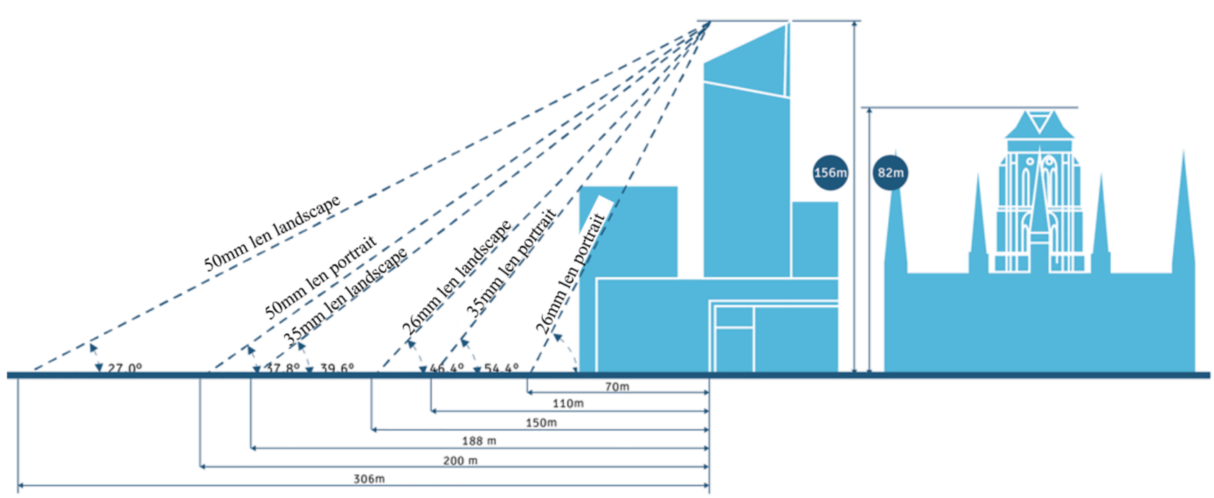

Fig. 17. Estimated photo-taking distance from a typical landmark building using a 26 mm, 35 mm, and 50 mm equivalent lens, the common types of camera lens in smartphones.

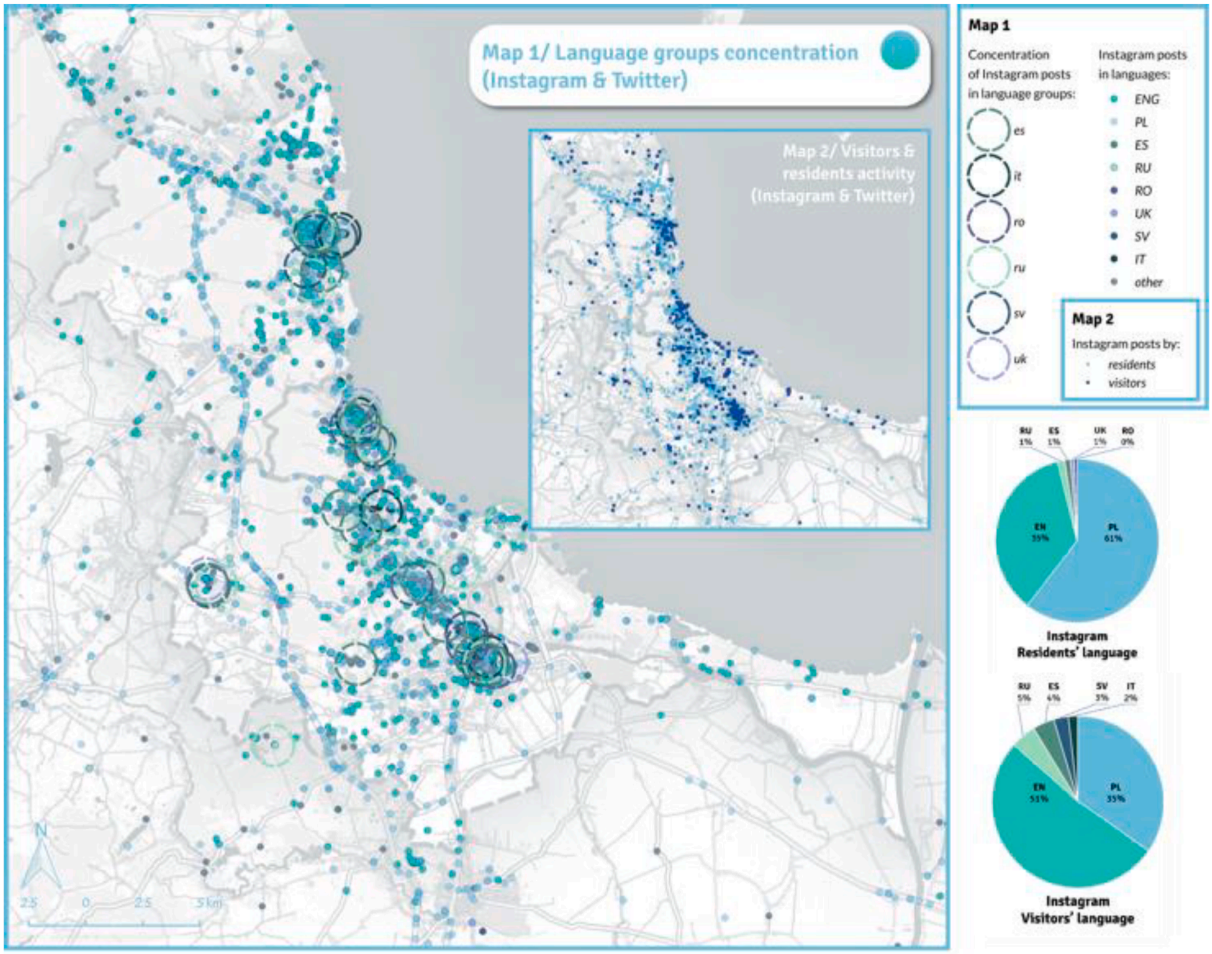

Fig. 18. Geo-tagged Tweets and Instagram Images by language.

4.3. GSM-based indicators of imageability

Three GSM-based indicators were developed to measure the Imageability of a place: Instagramability, Twitterability and GSM Sentiment. Instagramability measures the number of geo-tagged Instagram images found in close proximity of a place (300 m). The concept was previously used as a measure for marketing purposes (Greenwald, 2018) and it was found to have correlated with holiday destination choices for millennials (Schofield, 2017). Twitterability measures the number of times a place was mentioned by name on Twitter. GSM Sentiment measured the average sentiment tones of tweets and Instagram posts within 300 m from the place and those mentioned the place by name; the unit was polarity between −1 (unhappy) and 1 (happy). Places with fewer tweets and Instagram posts (count < 10) were discarded in order to avoid distortion from sparse observations.

Questionnaire data were used as benchmarks to evaluate the above three GSM-based indicators. Based on response to Questionnaire Part 2 question 13–15 (Table 5 in the Appendix), three questionnaire-based indicators were developed to measure the perception of a place: 1) the Landmark Score, the number of times that a place was ranked within top 5 most significant architectureal landmarks; 2) the Prestige Score, the number of times that a place was ranked within top 5 most prestigious places, and 3) the Nice Score, the number of times that a place was ranked within top 5 nicest places. The unit of analysis was the 126 places identified by questionnaire respondents from the Tri-City Region; each place consisted of the geographical coordinates at the center, the official name and several other names known by residents. Bivariate correlation analysis was performed. The p-values of correlations were computed using regression, in which GSM-based indicators served as the dependent variables and questionnaire-based indicators as independent variables. Results are provided in Table 4.

Overall, architectural landmarks and prestigious places were more likely to be featured on Instagram. Instagramability played an important role in explaining the Landmark Score (p-value $= 0.014$, $R^2 = 0.225$) and the Prestige Score (p-value $= 0.022$, $R^2 = 0.208$), but not the Nice Score (p-value $= 0.509$, $R^2 = 0.061$). In contrast, places perceived as nice or prestigious were more frequently discussed on Twitter, less so for landmarks. Twitterability was found to have played an important role in explaining the Nice Score (p-value $= 0.002$, $R^2 = 0.278$) and the Prestige Score (p-value $= 0.000$, $R^2 = 0.388$), but not the Landmark Score (p-value $= 0.623$, $R^2 = 0.045$). The statistical significance of the above observations should not be overly interpreted given the relatively small sample ($N = 126$) of places assessed in this study. We found no evidence on whether the perceived image of a place contribute to emotional security: no significant correlations were found between GSM Sentiment and questionnaire responses. It is possible that GSM Sentiment was influenced by many other factors aside from the perceived image of a place.

The Instagramability relative to Twitterability of a place revealed whether the place was more popular among tourists or local residents. A scatterplot of places by Instagramability and Twitterability is shown in Fig. 12. The upper left half of the graph represents places of high Instagramability relative to Twitterability. A review of these places suggested they were mostly tourist attractions yet less relevant to the daily lives of local communities. Examples included the Long Street & Market (Fig. 12a) and the Green Gate (Fig. 12b), both were historical landmarks at the urban core of Gdansk. This finding is largely consistent with previous literature that most Flickr photos can be found near tourist destinations (Crandall et al., 2009).

In contrast, the lower right half of Fig. 12 constitutes places of higher Twitterability than Instagramability. Most were found to be everyday life venues for communities. An example was the Swietojanska Street (Fig. 12d), a main street in the city of Gdynia and a popular shopping venue for local residents but not for tourists. The place was frequently mentioned on Twitter but hardly captured by Instagram images. Another case was the LOT building (Fig. 12c), the former office building of the Polish Airline (LOT) and a lone modernist building in Gdansk's historical urban core. The LOT building scored low in Instagramability, suggesting it was regarded as less photo-worthy; but the place was frequently mentioned in tweets as a reference point for people to meet, presumably because of its distinct architectural style, perhaps not the most favorable style in contrast to the surrounding historical buildings.

4.4. Discussion

Evidence from this study suggested that social media data can serve as a reliable measure of perceived city images in the digital age. The findings have both theoretical and practical implications. The strength and limitations of the approaches developed from this study are discussed.

The **theoretical implication** of this paper lies three-fold. First, observations made in this study proved the relevance of Lynch's theory in the digital age. The Lynchian elements can still be used to explain expressed urban experiences on social media, suggesting the lasting value of the city image theory amid the prevalence of mobile devices and Google Maps. Further, GSM-based metrics, i.e. Instagramability and Twitterability, have demonstrated potentials to quantitatively measure the imageability of a place, an elusive construct which cannot be conveniently measured previously. This new-found method is essential to the discipline of urban planning, which regard imageability as "a yardstick of good city form and a goal of urban planning practice" (Lynch, 1981). Lastly, the analytical framework developed from this study can be used to evaluate, extend, or even radically rethink classical theory in the digital age. For instance, GSM-based "edge" and "node" matched poorly with those elicited from Lynch's original methods; this discrepancy coincided with Norberg-Schulz (1971) three-element categorization, which consisted of "place", "path" and "domain", yet excluded "edge" and "node". Either GSM were inherently limited in measuring the perception of "node" or "edge" in the study area, or Norberg-Schulz's three-element categorization is a better explanation for GSM-based city images than Lynch's five-element one. More studies are needed in either case.

The **practical implication** of this study lies two-fold: first, the GSM-based city images are valuable supplement to the sketch map method, which are vulnerable to many practical uncertainties: a person may be unable to read a map, unable to manipulate the symbolic languages given, or may react to it as works of art rather than representations of actual places (Canter & Lee, 1974; Downs and Stea, 1973; Pocock et al., 1978). Further, methods developed from this research enables remote measurement of perceived city images at scale. The classification of geotagged Instagram by Lynchian element, although done by manual labelling at this stage, can be automated using machine-learning algorithms in future, reducing the workload of fieldwork required by Lynch's original methods.

The **strength** of this paper lies in evidence collected from multiple sources to triangulate findings. The combination of "big data" and "small data", neither a perfect approach on its own, allows for verifiable inferences to observations in what Lynch suggested: "if a sufficient array of probes is employed, a composite picture develops that is not far from the truth". (Lynch, 1984, p.154).

The **limitation** of this study are many-folds: 1) the GSM dataset may not represent all age and social groups due to the unstructured, volunteered nature of social media data. The Instagram dataset may cover only a partial sample due to limitations associated with the platform itself. 2) findings from this study are drawn from a single city region and it should not be indiscriminately extended to other regions. Location-specific calibrations are due when applying GSM-based metrics in another context. 3) the identification of Lynch's elements using Instagram data relied largely on manual labelling by domain experts, in this case, two researchers well-versed in Lynch's theory. Although labelled results by both agreed reasonably well with each other (87%), it is plausible that the judgement from domain experts differ from those of the general public; uncertainties as a result of such difference are to be investigated in future studies.

5. Conclusion

This paper described a study on the perception of city images using both "big data" and "small data" methods in the Tri-City Region of Poland. Social media analytics were used to measure Imageability and Lynchian elements. The results were evaluated using benchmarks established using official the GIS database, questionnaires and sketch maps obtained from residents. The findings suggested that **1) social media analytics can provide a reliable measure of perceived city images**. Three out of five Lynchian elements including "district", "landmark" and "path" identified on social media were found to be in reasonably good agreement with benchmarks, while "edge" and "node" cannot be verified at the same confidence level. **2) evidence gathered from the virtual world can explain public perception of a place in the real world**. Indicators such as Instagramability and Twitterability were found to play a large role in explaining the perceived Imageability of a place. Instagramability was found to be associated with perceived architectural landmark and tourist attraction, while Twitterability was linked to the place's relevance to everyday life venues for communities. **3) The analytical framework developed in this study have theoretical and practical implications for urban planners**. The analytical framework developed from this study can be used to evaluate and extend classical planning theory in the digital age; the GSM-based city images are valuable supplement to Lynch's original methods. Methods developed from this research enables remote measurement of perceived city images at scale, reducing the workload associated with extensive fieldwork.

CRediT authorship contribution statement

Jianxiang Huang: Conceptualization, Methodology, Validation, Writing - original draft. **Hanna Obracht-Prondzynska:** Visualization, Investigation, Formal analysis. **Dorota Kamrowska-Zaluska:** Conceptualization, Validation, Writing - review & editing. **Yiming Sun:** Software, Data curation. **Lishuai Li:** Supervision, Resources.

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Appendix

Questionnaire and respondent

The 62 participants in the questionnaire is a geographically representative sample of the Tri-City Region, with self-reported residential addresses cover all 20 neighborhoods. The gender divide was 24 males and 38 females. 46 identified themselves as students, 12 employed, 3 self-employed, and 1 retired. 41 were graduate students enrolled in the Faculty of Architecture at Gdansk University of Technology, who possessed sufficient graphic skills and were familiar with Lynch's theory. All participants have lived in the Tri-City Region more than 6 months, 14 less than a year, while 17 lived in the area for 10 + years.

Threshold distance in DBSCAN analysis

In order to determine the appropriate threshold distance (*Eps*), the input parameter governing the minimum distance between "districts" in the DBSCAN analysis, alternative values of 200 m, 300 m, and 500 m were tried to evaluate the clustering results (Table 6). The *Eps* of 300 m, equivalent to the average block size of the Tri-City Region, was considered the appropriate one since it yielded the smallest number of clusters (C = 48) and a majority of city Instagram posts were included in clusters (89.1%).

Geospatial correction of sketch maps

Depending on the drawing skills of respondents, the information embedded in sketch maps are often represented without geospatially accuracy. The Lynchian elements in sketch maps were extracted and redrawn digitally in order to improve the geospatial accuracy of freehand drawings (Fig. 14).

Kernel density estimation results

As an alternative to DBSCAN clustering, the Kernel Density Estimation methods can be used to identify "district". The results are shown in Fig. 15 below. The district boundary was determined using the contour line of kernel density measured at 100 count/km^2

Neighborhoods mentioned in Twitter discussion

Calculation of photo-taking distances

The mean photo taking distance (D^-) from a landmark to its geo-tagged Instagram photos measured at 289 m for a random sample of geo-tagged Instagram photos (N = 955) as it is shown in Fig. 16(a), which is close to the 300 m buffer distance used in the DB scan analysis. The measurement was conducted in GIS space as it is shown in Fig. 16(b).

The existence of a photo-taking distance between an urban element and its Instagram photos can be explained by the angle of view of an optical lens. People need to take the photo from a distance in order to capture the view of the whole element. Fig. 17 shows the distance between a typical landmark building, the Prorem Tower at a height of 80 m, and a possible user taking a picture using a smartphone. The distances were calculated using the three types of camera lens, 50 mm, 35 mm, and 26 mm equivalent, for a portrait and landscape picture respectively. For a 50 mm equivalent lens camera, the user needs to be at least 150 m away in order to capture a portrait view of the whole building, or at least 306 m away for a landscape view.

Discerning City images across demographic groups

Social media data allow a nuanced observation of city images for distinct niche population groups across language and ethnic boundaries (Fig. 18). An alternative breakdown between Polish and English-language users suggest the photo sharing preferences for the two groups differ. The former group were more scattered throughout the city, while the latter concentrated around architectural landmarks. The population of the Tri-City Region consists of a Polish majority (96.7%), and a diversity of German (0.4%), Belarusian (0.1%), and Ukrainian (0.1%) migrant populations.

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