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A room with a (re)view. Short-term rentals, digital reputation and the uneven spatiality of platform-mediated tourism[1]

Abstract – The article investigates how users' reviews on digital accommodation platforms represent the city and mediate urban tourism practices. Drawing upon research on user-generated contents, digital reputation, platform capitalism, and the spatiality of short-term rentals, the aim is to show the performative power of the reviewing mechanism in enhancing visibility, building trust and distributing value unevenly in the city. We show how such unevenness is constructed through the layering of different meanings conveyed by guests' reviews, each having its own specific spatiality. In order to detect and map these meanings, we develop a textual analysis of the content of reviews and a spatial analysis of the distribution of their most salient topics in the city of Florence (Italy), based on a dataset of 491,379 reviews left by guests on Airbnb.com. Platform users - we argue - display an overtly calculative rationality and portray the city as an abstract space where the choice of the accommodation is aimed at minimizing travel distances from an access point to a few top attractions. Distance and centrality override any other concerns about the characteristics of the apartment, the host, the service, and even the price. Peripheral listings are not evaluated negatively; they are almost invisible. This "tyranny of distance" is co-produced by users and amplified by the platform's algorithms and interface: it contributes to the further shrinking of the tourist city into a few privileged neighbourhoods, and raises questions about the selectiveness and increasing pervasiveness of platform-mediated tourism practices.

Keywords: Airbnb, Platform capitalism, Digital reputation, Online reviews, Topic Modelling, Florence (Italy).

Introduction

In the last few years, the short-term rental market has expanded rapidly, along with the spread and success of digital accommodation platforms like Airbnb.com (Guttentag, 2019). Similarly to other online marketplaces, the intermediation provided by those platforms relies crucially on digital reputation systems based on ratings and reviews voluntarily contributed by users (Bridges and Vasquez, 2018; Tussyadiah and Park, 2018; Ert and Fleischer, 2019). Through ratings, guests can provide a score for the accommodation and service according to several pre-defined criteria. Reviews are short written commentaries that provide future guests with information about the lodging and its qualities (e.g. cleanliness, convenience, etc.), and about the interaction with the host[2]. This information is crucial for the platform, as we will discuss further in the paper: it builds trust, helps regulate the

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[2] https://www.airbnb.co.uk/help/article/13/how-do-reviews-work-for-stays?

market, and assists users in deciding whether or not to make a transaction. As such, the review system is by no means harmless, nor it is neutral: it influences decisions, impacts prices, provides signals to the platforms' algorithms, creates value and distributes such value unevenly with remarkable consequences for individuals and places.

In order to show the performative power of digital reputation systems in enhancing visibility, building trust and distributing value unevenly in the city, the paper presents a textual and spatial analysis of Airbnb reviews. It explores and maps the distribution of the two main signals that digital platforms use to rank and assign value to their contents: the volume of reviews received by each listing, and their valence - i.e. the positive or negative attributes users associate with those listings (Purnawirawan et al., 2015). Contrary to the claim that short-term rentals contribute to spreading tourism more evenly within cities[3], we aim to show how Airbnb users' choices are extremely selective, and that digital platforms risk amplifying this selectiveness and the unevenness that characterizes the tourist city. The analysis permits us moreover to see how such unevenness is constructed through the layering of different meanings associated with listings and their locations, each having its own specific distributional pattern. In order to detect and map these meanings, we perform a Topic Modelling analysis (Steyvers and Griffiths, 2007) that highlights the main subject matter categories which orchestrate reviews. The idea is that an analysis of the spatial distribution of reviews and of their textual content can shed light, on the one hand, on the selective functioning of digital platforms and on the other, on the peculiar spatialities of platform-mediated tourism practices.

Previous research has already explored the spatial distribution of short-term rentals advertised through accommodation platforms (for a review see Guttentag, 2019). Airbnb and similar platforms, as has been shown, contribute substantially to the over-touristification of already highly touristified city centres (Arias Sans and Quaglieri Domínguez, 2016; Picascia et al., 2017; Benìtez-Aurioles, 2018), as well as to the 'invasion' of less touristified neighbourhoods (Gravari-Barbas and Guinand, 2017; Ioannides et al., 2019). Analyses that compared the spatial distribution of Airbnb listings to that of hotels found in fact that the former are more widespread in the city; they may extend to some near-central zones but also to central areas that are less well served by hotels (Gutiérrez et al., 2017; Celata, 2017; Gyòdi, 2017). The effect is that – on average – short-term rentals are relatively closer to the city's main attractions compared to traditional accommodation facilities. The attractiveness of short-term rentals, consequently, may have little to do with guests' desire to "live like a local" or explore less touristified neighbourhoods, as is often claimed by the platform[2]; it may be more simply due to a more convenient location in proximity to the city's main tourism hotspots.

At the same time, scholars have explored how user-generated content and digital reputation systems regulate online multi-sided markets (Floyd et al., 2014; Tadelis, 2016), sustain emerging forms of "platform capitalism" (Srnicek 2017; Langley and Leyshon, 2017), and feed the computational and algorithmic machinery set up by the platforms (Hearn, 2010; Leoni and Parker, 2019; Minca and Roelofsen, 2019). This paper is situated at the intersection of those lines of inquiry, and aims to answer to the following questions: how does the reviewing mechanism influence the distribution of tourists and

[3] https://www.airbnb.com/economic-impact

accommodation facilities in the city? How are accommodation listings and their location in the city represented by platforms' users, and what are the consequences? What is the spatiality of digital reputation and of tourism practices mediated by digital platforms?

The paper focuses predominantly upon written reviews that, compared to ratings, offer a larger amount of information and include subjective and qualitative evaluations of the accommodation and its location. The meanings that reviews convey have received some attention (on Airbnb, see: Bridges and Vasquez, 2016; Cheng and Jin, 2019), but their spatial dimension remains largely unexplored. In line with critical approaches to the Geoweb (Kelley, 2013; Graham et al., 2013), we consider reviews as a selective informational filter that does not merely represent places, but influences the form and content of such representation, matching places with meaning and value, with the risk of reinforcing or altering pre-existing socio-spatial patterns.

The case study is Florence, Italy, one of the world's main tourist cities, with 10 million arrivals per year and 379,000 inhabitants in 2018[4]. Tourism is concentrated predominantly in the city's historic centre, an area that covers 5% of the municipal area and hosts 17.6% of its population[5]. Florence is also one of the most attractive Airbnb destinations. Previous research highlights that the percentage of the city centre's residential housing stock for rent on Airbnb increased from 18% in 2016, to 22% in 2017 (Picascia et al., 2017) and 25% in October 2018 (Romano, 2018).

The paper is organized as follows. The next section discusses the key functions of digital reputation and the review system in Airbnb and other similar platforms, in order to provide both an overview of research on the topic and a framework for the subsequent analysis. We then describe the data and analytical tools used to explore the spatial distribution and textual content of Airbnb reviews, and present the results: the distributional patterns of Airbnb ratings and reviews in the city, and the meaning and spatiality of the most important qualities guests assign to Airbnb listings. The paper closes with a discussion of the main findings and some suggestions for further research.

The economy and politics of digital reputation

In order to understand the relevance of Airbnb reviews, it is useful to explore some of the key functions that digital reputation systems perform in accommodation platforms.

The first of those functions is to provide information in order to facilitate guests' decisions. The same applies to hosts' evaluations of their guests, thanks to the Airbnb reciprocal reviewing system (Bridges and Vasquez, 2016), but this paper will focus only on guests' reviews. Some argue that ratings are more important than reviews, while others show that both have the same power to influence (Hong and Park, 2012), even if people read only a few of the most recent messages. Evidence suggests, moreover, that on Airbnb ratings and reviews are overwhelmingly positive (Bridges and Vasquez, 2016). Nevertheless, negative reviews exert a stronger influence than positive ones (Purnawirawan et al., 2015); even just one negative review may therefore have serious consequences.

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[4] http://www.cittametropolitana.fi.it/turismo/

[5] http://opendata.comune.fi.it/

The crowdsourcing and online distribution of user-generated content replaces both word-of-mouth communication and traditional intermediaries, such as travel guides or travel agencies. While word-of-mouth communication tends to deteriorate with scale and requires pre-existing social ties, the information provided online is potentially unlimited in terms of reach and volume (Dellarocas, 2003). Compared to traditional intermediaries the system may also be perceived as more impersonal and 'objective', given that it is based on the crowdsourcing of a greater quantity of independent evaluations. However, such a huge amount of data must be carefully ordered, filtered, and hierarchized, and such operations are by no means neutral (Kitchin, 2017). Digital platforms replace the expert-based selection of a few 'recommended' transactions with an algorithm-driven ranking of potentially infinite sets of alternatives based on the extraction, coding and sorting of user-generated information. The second function of ratings and reviews is in fact to provide signals that feed the search and ranking algorithms arranged by the platform.

The third key function of digital reputation is to enhance trust. Digital intermediation platforms have the advantage of allowing for a much richer and more direct flow of information between users but, at the same time, entail problems of trust, reliability, certification and safety, as they reduce the possibility of hierarchical control and quality assurance (Celata et al., 2017). The efforts devoted by accommodation platforms to enhancing and communicating a feeling of trust is indeed considerable, and the object of a great deal of research. Digital reputation systems act as confidence and responsibility builders (Tussyadiah and Park 2018; Ert and Fleischer 2019); they provide both an augmentation and a certification of the information provided by hosts through their listings. In terms of valence, as mentioned above, research shows that 97-98% of Airbnb reviews are positive (Fradkin, 2015; Bridges and Vasquez, 2016), and that negative experiences are often not reported (Fradkin et al., 2018). Because of this, and given that many platform users do not fully trust the content of reviews (Bae and Koo, 2018), their volume may be more important than their valence. Having many reviews certifies that the host is not an occasional player and, besides other things, implies that he/she has more incentives not to cheat the guest, even if their relationship is a one-time deal (Dellarocas, 2013).

A corollary – and the fourth key function of the review system – is that such a system is a means through which the platform 'captures' its users: the 'reputational capital' users accumulate there cannot be transferred to other competing platforms. In this respect, the competitive advantage of a platform like Airbnb lies not only in having the best algorithms or the nicest interface, but also and predominantly in having accumulated a large stock of information, and consequently users (Srnicek, 2017). The biggest and forerunner digital platforms, in other words, can exploit substantial network effects that give them monopolistic advantages: the more users they have, the more information they accumulate, the more attractive they are for other users, and so on.

Airbnb has indeed become the world leader in short-term rentals by acting almost exclusively like a "network orchestrator" (Libert et al., 2014), based on a 'lean' business model which may be regarded as an extreme frontier of post-fordism (Srnicek, 2017). Users are not only the owners and managers of the assets that are traded on the platform, but they are also crucial for regulating the market, which is the fifth key function of ratings and reviews. Such an open and decentred business model exists, paradoxically, in parallel with the capacity of digital platforms to concentrate and retain huge market power by capturing a socially produced economic value (Rossi, 2019). The appropriation of such a stock of information has been equated to a "primitive accumulation" and also to a new "enclosure" (Pasquinelli, 2009; O'Regan and Choe, 2017), given that the resource that platforms accumulate – information – is a common good produced freely by users for the benefit of their 'peers'.

The sixth key function of digital reputation is that it enforces a system of indirect controls and sanctions for users, which is informal, 'lean' and extraordinarily cheap (Leoni and Parker, 2019). The 'threat' of a negative review encourages hosts and guests to behave well, since being reviewed positively is essential to surviving on the platform. From this perspective, a platform like Airbnb may well be considered part of an emerging "surveillance capitalism" (Zuboff, 2019), that constantly monitors and extracts information from users' interactions not only to monetize them, but also to elicit certain behaviour (Minca and Roelofsen, 2019; Cheng and Foley, 2019). The accommodation and the host are induced to conform to users' expectations and benchmarks, with the effect that listings and profiles all seem very similar, despite the variety of contexts they refer to. Reviews also "comprise a very restricted set of linguistic resources, establishing the site's norm of highly positive commentary, which in turn makes Airbnb reviews, on the surface, appear to be quite similar to one another" (Bridges and Vasquez, 2016, p. 2057). These standards have to do with the characteristics of the accommodation at least as much as with the behaviour of the host, as exemplified by the "Superhost" label (Roelofsen and Minca, 2018).

The seventh key function of reviews is to contribute to 'personalizing' the transaction and the digital market for short-term rentals. What is peculiar about Airbnb, even with respect to other similar platforms, is that the object that is exchanged – the accommodation – seems to be equally as important as the subject of this exchange, i.e. the host (Celata et al. 2017), who must portray him/herself as a trustworthy, 'open' individual (Ronzhyn, 2013, Tussyadiah and Park 2018). Indeed, the host's personal photo may be even more important than his/her review score (Ert et al., 2016). Such personalization performs various related functions: it enhances trust; induces users to feel like part of a 'community' of "collaborative consumption"; motivates them to contribute voluntarily to such a community through advice and recommendations; enables the platform to promise an experience that is neither standardized nor anonymous, but 'authentic', 'local', etc. Such personalization may also explain why negative reviews are rare (Bridges and Vasquez, 2016).

In short, reviews and ratings represent a crucial source of value. Having many (positive) reviews contributes, as already mentioned, to users' "reputational capital"; an old concept that in the age of digital platforms has become more relevant, measurable and even somehow material (Hearn, 2010). For the platform, reviews are one of the main means through which value is managed, since the attribution of value to an object is by definition inter-subjective (Baka, 2015). Such a source of value, as already mentioned, is made available to the platform for free, since it is co-produced by users and distributed online at nearly zero marginal costs. For this reason, digital platforms have been equated to rent-seekers who extract – rather than produce – value (Rossi, 2019), while users' voluntary contribution of information has been interpreted as a source of "free" or "affective labour" (Terranova, 2000; Hearn, 2010). Arun Sundararajan has defined such accumulation systems as "crowd-based capitalism": "a shift in the primary institutions that organize economic activity, away from the quintessential twentieth century managerial hierarchy" (Sundararajan, 2017 p. 489). In this context, Airbnb has created a "genuinely decentralized" system (ibidem) because pricing, positioning, and merchandizing are carried out by hosts, who are building their micro-business on the platform. This content is then assigned value by guests through their ratings or search patterns, while the platform triggers and filters users' activity through interfaces and algorithms.

This information is always geolocalized and transferred to map-based interfaces that are pervasive on the platform and are crucial facilitators of users' decisions. The meaning and value assigned to the listings, consequently, influence their visibility (or invisibility) in the ranked list of search results on the website, as well as how those results are presented (or not) in the web-map. Those values are therefore immediately assigned to the places where the listing is located, and may affect those places enormously and unevenly. Previous research showed, for example, how online restaurant reviews (Zukin et al., 2015), postings on (geo)social media (Kelley, 2013; Boy and Uitermark, 2017), user-generated repositories like Wikipedia (Graham et al., 2014), or (geo)web search patterns (Graham et al., 2013; Frith, 2017), may both reflect and enforce existing socio-spatial processes and inequalities. This is because user-generated content may disproportionally focus on the most 'popular' locations, be biased by preconceptions, is cumulative and self-reinforcing, and is an increasingly important mediator of our relationship with space. The "where" of user-generated content is therefore pivotal to understanding their functioning and its consequences (Capineri et al., 2016). In the next sections we will explore first what guests say about Airbnb listings, and then what are the implications for the places where those listings are located.

Data and methodologies

In the paper, we develop two related analytical steps: a spatial analysis of the distribution of reviews in comparison to the distribution of Airbnb listings, and a textual analysis of the ontology built on reviews' contents and their spatial patterns. We first explore guests' reviews quantitatively, in order to extract the main positive and negative qualities guests associate with Airbnb listings, and see how those are distributed in the city. The results are then explored qualitatively in order to interpret these topics and how they associate various attributes and values to the different parts of the city.

The analysis is based on data about 11,361 listings that were active on Airbnb.com in October 2018 in the municipality of Florence. The source of the data is Insideairbnb.com. The dataset includes the textual content of 491,379 reviews left by guests about those listings in the period 2008-2018. Each review is attached to a unit of accommodation that is spatially located. Data on a listing's location provided by Airbnb may be imprecise, but such imprecision, we believe, does not affect the results of the analysis.

In Airbnb, ratings give a grade of the perceived quality of the accommodation based on six evaluation criteria: cleanliness (was the space clean and tidy?); accuracy (how accurately did the listing page represent the space?); value (did the listing provide good value for money?); communication (how well did the host communicate with the guest?); arrival (how smoothly did the check-in go?); and location (how did the guest feel about the listing's neighbourhood?). Reviews, as already mentioned, are written commentaries of a maximum of 1,000 words submitted within an average of four days after checkout

(Fradkin et. al., 2018). According to Airbnb, reviews are left by approximately 70% of guests. Their number can be taken as a proxy for the number of guests each listing has accommodated.

The first set of analyses deals with the overall spatial distribution in the city of both the average number of reviews per year and the average ratings of those listings. The aim is to understand how much place matters by highlighting the granularity and intensity of the spatial pattern in the distribution of those variables. Distributions reveal patterns. A core-periphery pattern, for example, would indicate that not only are listings predominantly concentrated in the city centre (which is obvious), but that central listings are also relatively more attractive to guests, more reviewed and more positively evaluated, which in turn produces better rankings on Airbnb, greater trust from future potential guests, etc.

In order to perform the analysis, listing data were aggregated using a uniform spatial partition – a 50x50 metre spatial grid – in order to reduce the variability of the data in locations with a high density of listings. At the same time, the analysis was performed at a high degree of spatial resolution in order to account also for 'local' variations. The grid split the municipality of Florence into 73,872 cells, of which 4,476 contained listings and were considered for further analyses. In order to measure and map the spatial distribution of reviews, a local spatial autocorrelation analysis was performed using the local Getis-Ord Gi statistics. A positive, high and significant spatial autocorrelation indicates that nearby grid cells have similar, high values, and is useful for revealing the degree of clustering of listings with high intensities in certain parts of the city, as well as for mapping the resulting "hot spots". Nearby cells have been considered within a fixed distance band of 640 metres, i.e. a "peak clustering" scale identified thanks to an assessment of the degree of clustering at increasing distances. To test the significance of the results, we considered p-values and z-scores, and applied a false discovery rate correction (Caldas de Castro and Singer, 2005). The software used was ArcGIS.

Next, a textual data analysis was performed on the 31 million word corpus of the 491,379 reviews to identify not only the main topics highlighted by reviewers, but also their place-related features. Textual analysis is a process used to find implicit, otherwise unobservable, and 'meaningful' semantic patterns from a large text repository. Instead of a simple extraction of the most commonly recurring terms, which is frequent in geographical analyses of user-generated content (Derungs and Purves, 2016), a Topic Modelling analysis was performed (Steyvers and Griffiths, 2007). Topic Modelling consists of extracting k topics that capture the most salient semantic nuclei within the corpus, each including a ranked list of strongly-associated terms. In contrast to other similar textual analysis tools, e.g. cluster analysis, each document (in our case each review) can be linked to more than one topic. Moreover, Topic Modelling is more accurate, as it employs a Bayesian approach based on iterative and probabilistic techniques.

The analysis identified 12 topics based on Non-Negative Matrix Factorization and Factor Analysis. The software used was Wordstat. Furthermore, in order to assess the most influential topics, the *eigenvector centrality* was calculated for each topic. The eigenvector centrality is a method of computing the centrality of each node in a graph, where the node here is represented by a topic. The method was employed to highlight the nodes/topics that had high correlations with other nodes/topics that were themselves central in the network. The assumption is that each node's centrality is the sum of the

centrality values of the nodes that it is connected to. The analysis permits us not only to highlight the most important topics but also how they relate to each other and how content in reviews is structured.
The innovative aspect of the analysis was to link the topics to their (i.e. the listing's) spatial location, in short to know *what* people say about *where*. We then measured and mapped the spatial autocorrelation of the frequency of each topic in the listings' reviews over the total number of reviews. Therefore we analysed the relative frequency of each topic in the reviews' textual corpus, rather than merely the spatial distribution of those topics, which is obviously denser in the city centre. Data were aggregated again using a 50x50 metre spatial grid. We performed both a global spatial correlation analysis, using the Moran's I index, and a local spatial autocorrelation analysis using the Getis-Ord Gi statistics, adopting the same method as described above. The "peak clustering" fixed distance band in this case was 344 metres. Moran's I is a commonly used indicator of the overall degree of spatial clustering, and its values range from −1 to +1, where 1 means perfect spatial autocorrelation or maximum clustering. The Moran's I index may seem to highlight a low degree of clustering, as it ranges from +0.01 to +0.4 (Tab. 1), but this is natural at such a high degree of spatial resolution; however, the statistics return highly significant results, always above a 99% confidence level.

Digital reputation in space: the power of centrality and the tyranny of distance

Airbnb listings, similarly to other types of accommodation, tend to be concentrated around the city's main attractions and transport facilities. In the case of Florence, as in most (art) cities, the majority of attractions are within the centre, which in the maps that follow is identified based on the delimitation of the UNESCO area, i.e. the area within the medieval walls. The centre is also the most accessible in term of transport facilities. This area includes 62% of all Airbnb listings, and 77% of all hotels; the supply of short-term rentals is therefore more dispersed compared to traditional accommodation facilities, as mentioned in the introduction, but the demand is highly concentrated.
In terms of the spatial distribution of reviews per listing, a strong core-periphery pattern emerges. Average reviews per year decline in relation to how far the listing is from the city centre: it is above 15 in the UNESCO area, and less than 8 at 4 km from the city centre.
A similar decay is shown by the average ratings, not only when it comes to evaluating the listings' "location", which is naturally associated with a central location. Even the rating for "value for price", on average, decreases with increasing distance from the city centre (figure 1), even though one of the parameters behind such a criterion (price) provides a strong counterbalance to the advantages of centrality, as prices decline steadily as the distance from the city centre increases.

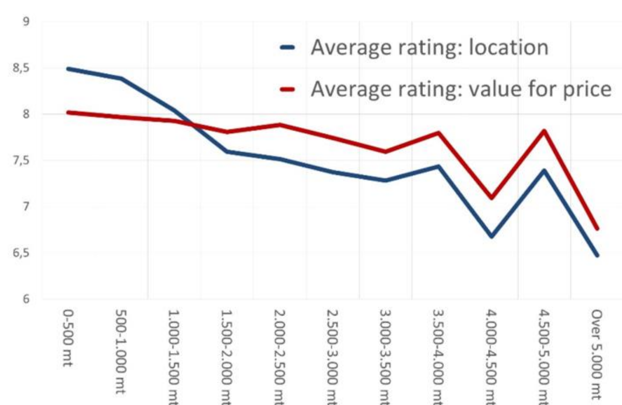

Fig 1. Average rating of Airbnb listings per distance from the city centre, Florence (Italy), 2018

The local spatial autocorrelation analysis of the average reviews per listing (Figure 2) provides a confirmation and some additional evidence about this core-periphery pattern. Hot spots cluster almost exclusively in a central area that covers basically the whole historic centre and extends towards the main railway station. Cold spots are rare, indicating that while ‘success’ in the market is heavily dependent upon location, ‘failure’ is more randomly distributed.

It is worth noting that a similarly skewed distribution can be observed in the distribution of reviews per listing: the number of reviews per listing has a mean value of 43, but 15% of those listings received no reviews and 50% have less than 20; on the other hand a mere 10% of ‘top’ listings capture approximately 43% of reviews. Such figures indicate a high degree of unevenness in the distribution of reviews and, consequently, how the attractiveness and value of Airbnb listings is perceived by guests and distributed in the city.

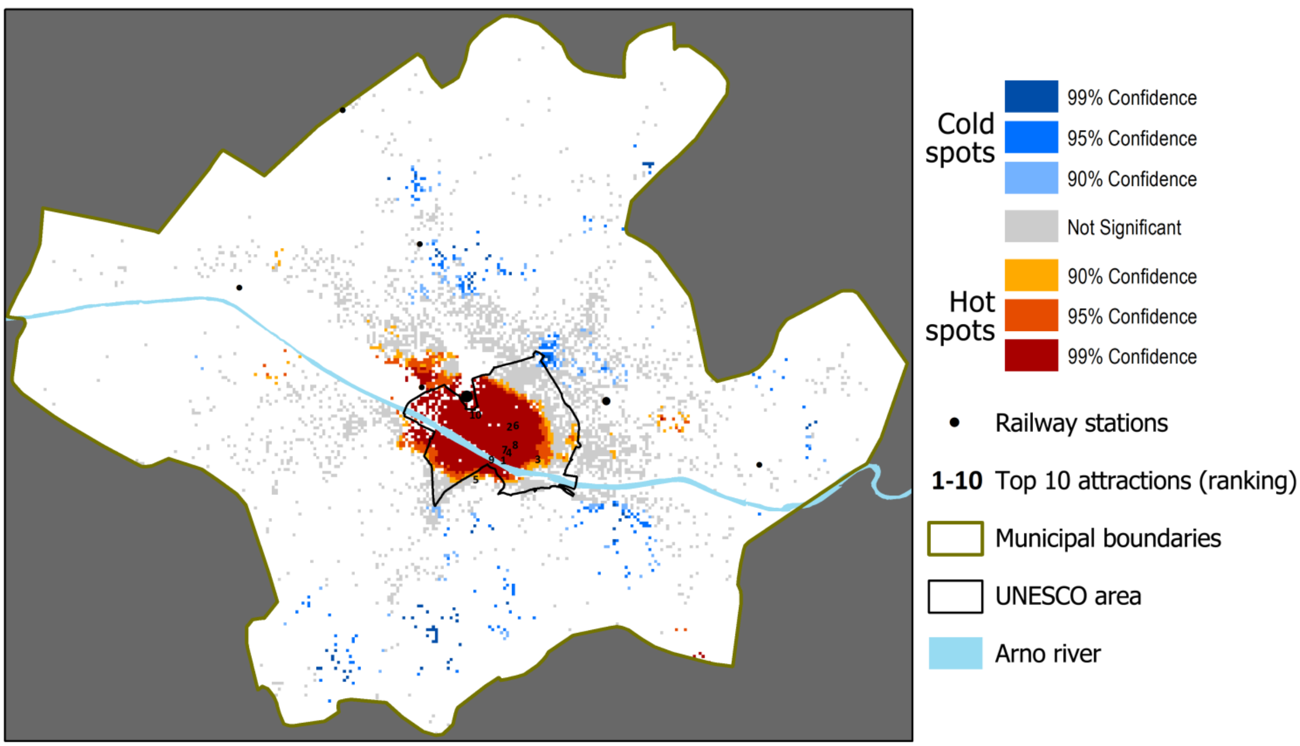

Fig 2. Local spatial autocorrelation of the average yearly reviews per Airbnb listing in Florence (Italy), 2018, at a 50x50 metre grid aggregation (Getis-Ord Gi* statistics)

The meanings and spatiality of Airbnb reviews

If the value assigned to Airbnb listings through reviews and ratings displays a strong core-periphery pattern, it is interesting to see how such value is a summation of different, overlapping meanings conveyed by the reviews and what the spatial distribution of their main ‘topics’ in the city is. The results of the textual analysis are synthesized in Table 1, where the 12 salient topics identified by the Topic Modelling are ranked according to their (eigenvector) centrality. Each topic is associated with several associated terms (keywords) that highlight the topic's main meaning. The degree of global spatial autocorrelation, as already mentioned, measures how strongly the relative frequency of those topics reveals a spatial pattern in the city.

Table 1. Main topics in Airbnb reviews, description, keywords, category, centrality and degree of spatial clustering (autocorrelation) in Florence (Italy), 2008-2018

Topic	*Description*	*Main keywords*	*Category*	*Eigenvector centrality*	*Spatial autocorrelation*
Distance	Short distance from the main attractions	Distance; walking; major; attractions	Influencer	1	0.092
Transport	Need for transport to visit the city	Bus; stop; center; city; centre; minutes	Influencer	0.71	0.113
Train station	Proximity to the main railway station	Train station; minute walk; close to the train station; walk from the train station; short walk; main train station	Influencer	0.49	0.068
Services	Availability of basic functions nearby	Restaurants; bars; shops; nearby	Facilitator	0.33	0.116
Landmarks	Proximity to attractions and landmarks	*Duomo,*; *Ponte Vecchio*; *Uffizi*	Facilitator	0.22	0.400
House facilities	Availability of facilities and equipment in the accommodation	Shower; living; bedroom; comfortable; elevator; floor; stairs; luggage; washing machine; bathroom; kitchen	Scaffolder	0.14	0.015
Recommend	Expressions of appraisal	Highly recommended; recommend staying; recommend this place; recommend this apartment	Outsider	0.087	0.027
Feel at home	Atmosphere and care	Home; felt; feel; safe; kind; map; provided; recommendations; information; visit	Scaffolder	0.049	0.016
Complaints	Negative aspects	Noise; windows; street; open; noisy; sleep	Outsider	0.026	0.038
Welcome gift	Welcome gift by the host	Wine; bottle; left	Scaffolder	0.012	-
Centrally located	Central position	Centrally located; perfectly; located	Scaffolder	0.004	-
Apartment	Quality of the accommodation	Apartment; clean; excellent; home; cozy; villa; lodgement; accueil	Scaffolder	0	-

Figures 3a and 3b show the results of the local spatial autocorrelation analysis of relative frequency of the nine most central topics, namely where the topics cluster in different parts of the city.

The most salient topic is labelled "distance" and highlights a prevailing pedestrian scale of short/walking distances from the listing to tourist attractions and, secondarily, transport facilities. The hot spots for "distance" cover basically the whole UNESCO area.

The second topic – "transport" – is in some ways complementary to the previous one. The topic has a reversed core-periphery spatial pattern: it indicates that transport services (bus, taxi, etc.) are needed to reach the city centre. A few peripheral hot spots cluster in locations that are well served by public transport, e.g., around bus stops or secondary railway stations.

The third most central topic refers to the main station (Santa Maria Novella), and secondarily to other stations. Hot spots cluster predominantly around Santa Maria Novella, but also along the railway lines. Cold spots cluster where the main city's attractions are located, i.e. where other topics prevail (the analysis highlights what is peculiar for reviews in different locations, relative to the frequency of the other topics).

The fourth most central topic – "services" – indicates proximity to restaurants, shops, bars, etc. Hot spots cluster in several central locations that surround the parts of the city centre where the main attractions are located. Reviews here focus on the liveability of those zones and the density of services, as complementary attractions with respect to the city's landmarks.

The fifth topic – "landmarks" – is mainly associated with a few 'top' attractions, such as the *Duomo*, *Ponte Vecchio*, *Uffizi*. Hot spots mostly cluster where the city's attractions are located, along the river Arno, within the historic centre. This is also the topic that shows by far the highest degree of spatial autocorrelation. The relative frequency of this topic decreases very fast as we move outside this area, as indicated by the large cluster of cold spots located north of the city centre.

The next topic – labelled "house facilities" – refers to the quality of the apartment and its equipment/furnishings. The topic refers to the quality of the accommodation and does not depend on location. Consequently, the topic shows a certain degree of clustering, but no clear spatial pattern: hot spots are few, isolated and randomly distributed within the city, while the degree of global spatial autocorrelation is by far the lowest compared to the other topics.

The next topic – "recommend" – shows a low degree of autocorrelation, but also an interesting localized hot spot in a specific area of the city centre: near the *Duomo*. Recommendations are expressions of appraisal that have a strong persuasive power because they synthesize and emphasize a positive review. Our analysis reveals that 75% of reviews that include this topic are concentrated within the UNESCO area. However, in terms of the analysis, the topic is not directly relevant nor meaningful *per se*, but rather in association with the specific features to which the recommendations refer: the accommodation, its location, the quality of the apartment, the host, etc. Each of these features has its own spatial pattern, which explains the low overall degree of spatial autocorrelation of the "recommend" topic.

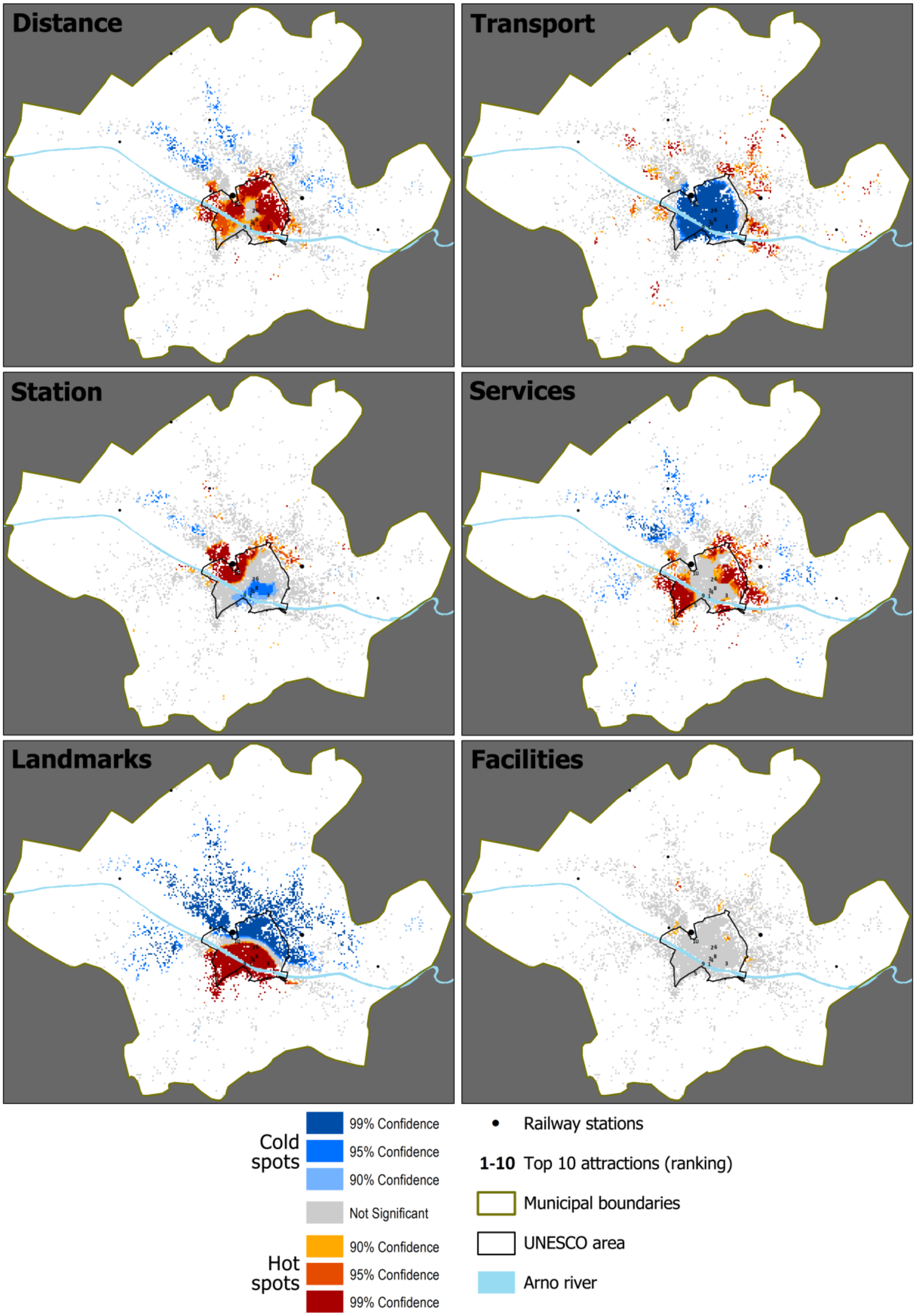

Fig 3.a. Local spatial autocorrelation of the average recurrence of the topics per number of reviews, at a 50x50 metre spatial grid aggregation (Getis-Ord Gi* statistics)

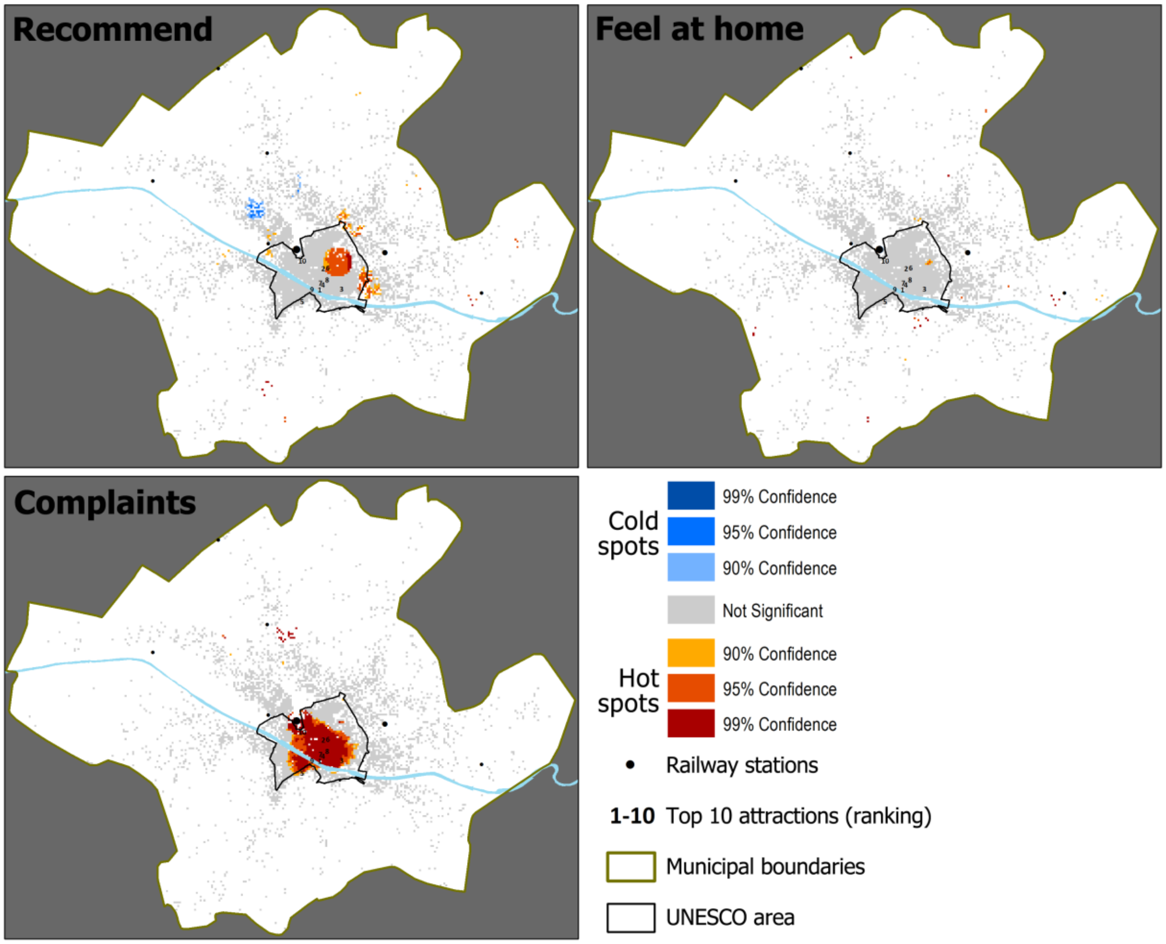

Fig 3.b. Local spatial autocorrelation of the average recurrence of the topics per number of reviews, at a 50x50 metre spatial grid aggregation (Getis-Ord Gi* statistics)

The topic "feel at home" shows a spatial pattern similar to that of "house facilities": a few randomly distributed hot spots. While "house facilities" refers to specific objects, appliances, etc., here guests refer to the subject: the host, his/her performance, kindness, care, availability, willingness to provide information and guidance.

The ninth topic – "complaints" – is the only topic that refers explicitly and exclusively to negative aspects, and particularly noise (see also Cheng and Jin, 2019). The topic shows a big cluster of hot spots in the inner city centre, indicating that despite all the advantages, this location also implies some disadvantages (e.g., "convenient location although weekend nights may have a little noise due to tourists"). This topic, however, shows a low degree of global spatial autocorrelation, indicating that these disadvantages are not only mentioned with reference to the city centre.

The remaining three topics refer to a "welcome gift" offered by the host, a "central location", the quality of the "apartment"; these topics are not relevant for the analysis, because they have a low degree of centrality and their meaning overlaps with that of other more central topics.

Topic Modelling also permits us to outline the structure of the narratives conveyed by the reviews in terms of the direction and intensity of the relationships among topics (figure 4). Based on this topology, it is possible to deduce the role topics play in the communication performed by reviews. "Distance", “train station” and “transport” are the topics which most of the other topics converge around, and may be defined as ‘influencers’, as they strongly affect the review’s content. “Services” and “landmarks” are defined as ‘facilitators’ since they refer to aspects that facilitate but do not substantially influence the choice of the accommodation. “House facilities”, “feel at home”, “welcome gift”, are defined as ‘scaffolders’ since they play a secondary role in supporting the listing’s positive review. “Recommend” and “complaints” are defined as ‘outsiders’: they are ‘extreme’ issues that may either positively or negatively subvert the review’s content.

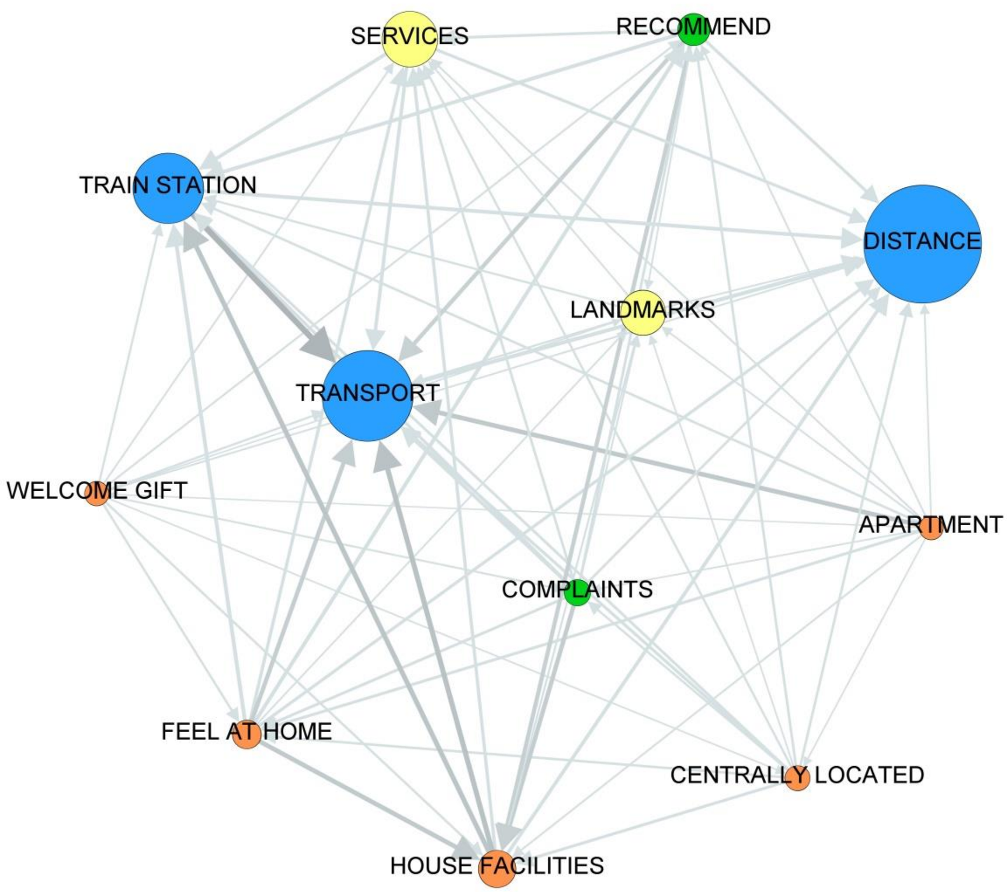

Fig 4. Network of the main topics in Airbnb reviews. Node size is proportionally to the eigenvector centrality; edges indicate the direction and frequency of the topics relationship; colours indicate categories: influencers (blue); facilitators (yellow); scaffolders (orange); outsiders (green).

Discussion and conclusions

The article presented a systematic analysis of the content of reviews posted by users on the digital accommodation platform Airbnb. Compared with previous research (Bridges and Vasquez, 2016; Cheng and Jin, 2019), we added a spatial dimension, which provides a better understanding both of the meanings assigned to Airbnb listings and how the reviewing mechanism represents and produces space.

Previous analyses already showed the high degree of concentration of short-term rentals in central locations and around attractions and transport facilities (Guttentag, 2019). However, as mentioned in the introduction, when compared to hotels and traditional accommodation facilities Airbnb listings are more widespread in the city. The spread of short-term rentals could therefore, on the one hand, potentially favour more peripheral locations, but on the other allows a further concentration of the accommodation capacity in proximity to the city's main attractions.

In this article, we used spatial analysis techniques that enable us to obtain a very accurate representation of how the demand for Airbnb listings is distributed in the city, based on the volume of reviews, and showed that such demand is much more concentrated and sloped than the supply of short-term rentals, i.e. the distribution of listings. The demand activated by non-central listings is indeed minimal as is, consequently, the income those listings produce.

In the article we also highlighted what produces such unevenness, i.e. how it is constructed through the layering of the different meanings or review 'topics', each having its own specific spatiality. Conversely to the mission of Airbnb, which insists on 'placeness'[6], platform users seem to be obsessed with space. The tourist city is predominantly portrayed as an abstract space made of distances, where the choice of the accommodation is driven by minimizing travel times from the access point (the main railway station) and the centre of gravity: a very small set of 'top' attractions. Those topics that have to do with the accommodation's location are not only those that – unsurprisingly – display a more pronounced (centre-periphery) spatial pattern, but also are the most salient for guests. On the other hand, those topics that have to do with the quality of the accommodation and of the service are not only more randomly distributed, but also less relevant in the reviews and secondary in guests' choices. Distance and proximity, in short, override any other concerns about the characteristics of the apartment, the host and even the price (see also Benìtez-Aurioles, 2018; Cheng and Jin, 2019). In a city like Florence, similarly to many others, this process translates into a strong core-periphery pattern. In any case, short-term rental platforms contribute to the further shrinking of the tourist city to a few privileged neighbourhoods.

Reviews are predominantly positive, but their volume decreases very fast as distance increases and plays an important role in enhancing visibility and trust. Even a negative connotation, such as being distant from the city centre, is somehow made positive by describing such a location as "well connected" to the centre thanks to public transport. This qualifies the location as "ok", but inferior to those "highly recommended" listings that are inside the centre of gravity. The only topic that shows a truly clustered spatial pattern, rather than a purely core-periphery pattern, refers to the proximity to services such as restaurants or shops. But those services and their clusters are once again associated with a central location. And even the only explicitly negative connotation – noise – is also associated with the historic centre, which obviously suffers from overcrowding. At the same time other reviewing criteria that may counterbalance the advantages of centrality – e.g. "value for price" – also show decreasing ratings as we move away from the city's barycentre.

[6] https://blog.atairbnb.com/belong-anywhere/

Such a spatial pattern is not only typical of tourist accommodation advertised through digital platforms. What platforms do is to amplify such patterns, increasing the scale and power of the mechanisms by which value is ascribed to certain locations and aspects. Reviews in this sense may be considered visibility catalysts whose effects are cumulative and self-reinforcing. Similarly to the "network effects" that permit the leading platforms to enjoy monopolistic advantages (Srnicek, 2017), a better location attracts more guests, leading to more and better reviews, which in turn produce better rankings, more guests, more reviews, etc. This mechanism is further amplified by the search ranking algorithms used by digital platforms and by the pervasiveness of map-based interfaces that direct users' attention towards the most 'popular' and central locations.

Peripheral listings are not valued negatively and their ratings are only slightly lower than those of more central listings: rather, they are rendered largely invisible; they simply do not appear in the search results and in the maps users view once they access and use Airbnb or similar websites. Such a strongly differential functioning of digital platforms is disguised by an apparently neutral mechanism that is open, crowd-based, where every review is somehow positive, and everything is, in theory, equally visible (Kelley, 2013; Graham et al., 2013; Frith, 2017). In these circumstances, even the most diligent host can do little to subvert the tyranny of distance – i.e. the advantages of location – aside from trying to avoid the consequences of a negative review, conforming to the expectations of users, adapting to how the platform translates those expectations into rankings, or lowering prices to compete in an increasingly overcrowded market.

The 'power' of reviews is in no way a new phenomenon. Contemporary tourism has been shaped from its very beginning by the chronicles and suggestions of earlier travellers (Baka, 2015). Digital platforms have only increased the volume, immediacy and reach of these 'recommendations', by decentring the production of tourism-related information while centralizing the infrastructure through which this information is gathered, codified and distributed. Airbnb reviews may not be crucial in guests' choices (Ert et al., 2016; Bae and Koo, 2018), but they are certainly a key resource to understanding the logics behind such choices and, consequently, key signals that short-term rentals platforms use to sort and rank listings.

Critical research about the 'tyranny' of algorithms (in the case of Airbnb, see O'Regan and Choe, 2017; Minca and Roelofsen, 2019; Cheng and Foley, 2019; Leoni and Parker, 2019) has extensively explored how platform users are shaped by these socio-technical assemblages and, occasionally, try to resist, subvert or rework them (Kitchin, 2017). Focusing on reviews posted voluntarily online allows us to appreciate how users are also the platforms' best allies. This is not only because they contribute freely to regulating the online market and many of them actually enjoy being "incorporated into the grand metrics of the platform" (Minca and Roelofsen, 2019, p. 18), but because the platforms' obsession with metrics and computability is somehow mirrored by the calculative rationality of users and in how they represent the city. Guests' feedback overlooks the particular feature of the listing and its specific location, and refers instead to some 'universal' standards; a certification rather than a description. These standards are partly engineered by the platform and partly produced inter-subjectively by the 'community' of users. This precious source of free labour is carefully elicited by the platform, as it is crucial to its lean and extractive accumulation system, to monitor, sanction or reward hosts and guests.

Our research has a number of limitations. First, we focused on one case study only; a comparison with other similar or dissimilar cities may provide additional and more generalizable evidence. Second, data from platforms is fluid, and the digital short-term rentals market is evolving rapidly; more importantly, our analysis is static, while the effects platforms produce are dynamic. Third, in terms of data modelling, we used univariate spatial autocorrelation techniques that could be complemented with other methods, such as spatial interpolation, multi-variate and regression analyses. Finally, a full appreciation of the 'power' of digital reputation requires going beyond the quantitative analysis presented in the paper with more in-depth, qualitative inquiries about the meaning and practice of reviewing and being reviewed.

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