Evaluative image 2.0: A web mapping approach to capture people’s perceptions of a city

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Abstract
Evaluative images can help urban planners understand the way citizens perceive their cities. In the seminal article by Jack Nasar, evaluative images were created by means of face-to-face interviews. The present article proposes, implements and evaluates a complementary approach to create evaluative images of cities, namely through web mapping. The approach was implemented in an open-source system called elmage. A user study with 59 participants was conducted in Lisbon, Portugal, to test elmage for usability and usefulness. The study revealed that elmage can help different groups of society quickly voice their opinions on places in their cities that they like/dislike, and that a face-to-face data-collection setting (as opposed to an online one) has a positive influence on the data-collection workflow. The lessons learned in this study may be useful to planners interested in generating composite pictures of how citizens perceive their cities.

1 | INTRODUCTION

The perceived qualities of the urban environment are described as crucial aspects in determining place attachment (Lewicka, 2011) and they are considered a component of what has been called urban cognition (Nasar, 1984), that is, the study of cognitive representation of urban spaces. Moreover, evaluations of the urban environment have been proved to mould behaviours and attitudes related to decisions about walking across the city (Mehta, 2008; Southworth, 2005), getting involved in one’s local neighbourhood, residential choices (Dahmann, 1985; Talen, 2002), and publicly engaging with the urban spaces (Jacobs, 1961; Southworth, 1985). Urban geography
and environmental psychology have been seeking to understand “what is the quality of our public space and how should we evaluate it?” (Mehta, 2014, p. 53) or ‘in what ways do people attach meaning to and organize space and place’ (Tuan, 1977, p. 5). Inevitably, urban planners and decision-makers have been encouraged to take advantage of qualitative research, and there have been debates on how people perceive and remember urban spaces, what they appreciate and what they dislike (Carp, Zawadski, & Shokrkon, 1976; Nasar, 1998).

The Image of the City (Lynch, 1960) was the first attempt to explicitly bring together the discourse about urban form and the mental image resulting from the perception of the urban environment. Lynch’s work comprised an empirical study on how people perceive the urban landscape and how they build a mental image of it. In this view, cities would be characterized by a certain degree of *legibility* (a quality that relates to being recognized, represented mentally, and thus navigated) and *imageability* (the probability of a certain space evoking strong and defined images). These properties can emerge from the interaction of three attributes of urban objects across urban spaces: *identity*, *structure* and *meaning* (Lynch, 1960). A city image requires that its objects are recognizable and distinguishable, among other things (identity), and related to the observer and the surrounding elements (structure).

Urban planners and institutions have recognized the importance of visual quality and people’s perception of the urban environment (Llinares, Page, & Llinares, 2013; Nasar, 1990), and a number of American cities embraced Lynch’s approach in designing imageable places (Mondschein & Moga, 2018). Yet, emphasis has mainly been put on structural and physical properties of the urban environment, neglecting people’s evaluations (Kyttä, Kahila, & Broberg, 2011; Nasar, 1990). Lynch’s research aimed to “influence the physical environment of cities” (Mondschein & Moga, 2018, p. 264), in other words was concerned with cities’ identity and structure. Though Lynch recognized the importance of meaning and evaluation, he “felt that measurement problems and individual differences made them impractical to study” (Nasar, 1990, p. 42). With the aim of capturing the *meaning* constituent of the image of the city, Nasar (1990) readapted Lynch’s method by looking in depth into what people like/dislike in their city, that is, the likeability of a city.

Nasar (1990, 1998) advanced the theory of the *evaluative image of the city* by building on a large body of experimental research in environmental psychology as well as debate on mental imagery. The author claims that collecting evaluations from citizens and visitors provides insights into people’s preferences and experiences with the city quite different from those expressed by planners and architects (see also Carp et al., 1976). His work has been applied, in different forms, in several urban contexts (e.g., Han, 2010; Hanju, 1993; Nasar, 1984) and has influenced research on the assessment of neighbourhood satisfaction (e.g., Al-Kodmany, 2000; Fleury-Bahi, Félonnéau, & Marchand, 2008). Throughout this article, *image of the city* refers to the notion introduced by Lynch (1960), while *evaluative image of the city* denotes Nasar’s concept. An image of the city is an “overlap of many individual images”, namely individual mental representations that support interactions and spatial behaviour within the urban environment. On the other hand, the notion of *evaluative* image refers to a composite map that derives not only from individual images in the Lynchian sense, but also includes people’s explicit evaluations of places in the city.

In Nasar’s work, evaluative images of cities were derived from phone and face-to-face interviews. Although interviews offer rich insights into citizens’ perceptions, they have two key drawbacks. First, accurately delineating the boundaries of areas mentioned by citizens during the interviews is challenging. Second, interviews are arguably time-consuming, involving preparation, appointments with citizens, and qualitative analysis of participants’ inputs. Whereas semi-automated approaches to people’s environment evaluation have been advanced in GIScience, the focus of these works lies only on very specific properties of the environment or on the perception of neighbourhood or local communities. Moreover, these tools are usually designed around the specificity of a certain case study area and therefore offer poor flexibility. Thus, the perception of the urban environment and its elements is not investigated globally, or the tools are flawed in terms of user-friendliness and the flexibility of the system itself.

This work explores the use of web maps to address the drawbacks in Nasar’s original work through automation, while tackling the gaps in existing approaches. The research question of this study concerns how to support
the creation of a city’s evaluative image through a web map. The city of Lisbon, Portugal, was used as a case study area. Section 2 presents in detail the theory of the evaluative image of the city and discusses why we embrace such an approach. Furthermore, it reports on existing quantitative GIS and machine learning approaches advanced to identify the image of the city. Thereafter, the contribution of public participation GIS in collecting evaluations about cities and their neighbourhoods is discussed. Section 3 introduces eImage, an application designed to collect people’s perceptions of their city and automatically generate a community evaluative image of the city. eImage was evaluated through a study in Lisbon: Section 4 presents the study design and Section 5 presents the results. The implications of the results are discussed in Section 6.

2 | BACKGROUND

2.1 | Theoretical grounding

In order to capture the meaning constituent of the image of the city, Nasar (1990) readapted Lynch’s method by looking in depth at people’s “impressions” of the city. He collected around 400 evaluations from inhabitants and visitors in Knoxville and Chattanooga, Tennessee (USA). Each interviewee was asked to indicate five liked and five disliked areas in their city and to explain why. Nasar overlapped the individual maps collected to obtain a global map representing the community appearance of each city, with the most and least appreciated places. Besides observing a significant agreement around the areas which aroused positive sentiments, Nasar noted that most of the negative evaluations referred to commercial development, dirtiness, negligence, industrial areas, or human-made elements. In contrast, green areas, open spaces, and natural landscapes were associated with positive assessments. Overall, Nasar identified five dimensions that contribute to urban preference and shape the evaluative image of the city:

- Naturalness. This property refers to the presence of vegetation, waterbodies, or natural landscapes.
- Upkeep. Clean and well-maintained places are preferred by individuals.
- Openness. This is a sentiment related to the perception of spaciousness available at a location in the city; in other words, the experience of unobstructed views of the environment.
- Historical significance. Locations perceived as meaningful and salient from a historical perspective evoke positive sentiments (Appleyard, 1976; Harrison & Howard, 1972).
- Order. This relates to the organization and structure of a location; chaos and absence of style cause distress and negative sentiment. Consistent, legible and well-defined environments can elicit interest and positive sentiments (Herzog, Kaplan, & Kaplan, 1976), especially if they represent a good compromise between complexity and structure (Kaplan & Kaplan, 1989; Kaplan, Kaplan, & Brown, 1989; Wohlwill, 1976).

The evaluative image of the city emerges from an interplay of these environmental characteristics and an accumulation of individual experiences with the city and its spaces. In other words, it takes shape from associations, processes of abstraction (Rapoport, 1990) and psychological evaluations deriving from what we feel about the environment (Ward & Russell, 1981). “The strictly physical city is rarely seen by its citizens” (Harrison & Howard, 1972, p. 408). Next to its Lynchian roots, Nasar’s work on people’s evaluation of the urban environment draws from and is influenced by research in environmental psychology on the restorative effect of nature on people (Kaplan & Kaplan, 1989; Kaplan et al., 1989; Ulrich, 1986) and preferences for certain landscapes, views or qualities of the environment (Carp et al., 1976; Kaplan, 1987; Kaplan & Kaplan, 1989); theorization and debate around the role of meaning’s attribution processes and individual experiences in the human–environment interaction (Rapoport, 1990, 1993). In a sense, Nasar’s theory was aimed at addressing the lack of systematic models and theories for the evaluation of places (Canter, 1983).
Despite the fact that Nasar’s theory is now 30 years old, we argue that it is still useful to study the likeability of cities. First, its dimensions are grounded in empirical research in environmental psychology and urban theory, besides Nasar's own studies in American cities. Second, it builds on a widely recognized and generalized theory of perception of the physical environment (Lynch, 1960) which still constitutes a fundamental pillar in spatial cognition research and urban theory. Nasar has influenced subsequent research on measuring experiential or perceived qualities of the environment, and this has prompted the design of more specific scales, for example, aimed at the identification of qualities related to walkability (Ewing, Handy, Brownson, Clemente, & Winston, 2016) or physical activities (Day, Boarnet, Alfonzo, & Forsyth, 2006). It has also been incorporated into frameworks developed to assess the quality of public spaces both in relation to likeability, and social dimensions such as inclusiveness, public participation and fairness (e.g., Mehta, 2014; Zamanifard, Alizadeh, Bosman, & Coiacetto, 2019). Finally, the five dimensions identified by Nasar recall and partially overlap with the perceptual qualities identified by Küller (1991)—pleasantness, complexity, unity, enclosedness, potency, social status, affection, and originality—to describe factors that may affect human emotional processes when interacting with the environment.

2.2 | Related work

2.2.1 | Computational approaches to city perception

Several computational approaches have been proposed in GIScience to collect schematic representations of urban spaces. An explicit approach to Lynch’s five elements has been proposed to extract an image of the city computationally, that is, by employing street network techniques and identifying landmarks from building footprints’ attributes (Filomena, Verstegen, & Manley, 2019). Furthermore, geotagged content from social networks has been employed to capture different prototypes of activity patterns (lines, clusters, dense areas, sparse areas) that can be used to characterize the perception of the city and referred to the five elements (Liu, Zhou, Zhao, & Ryan, 2016). Similar methodologies have been described for visualizing ‘crowd-sourced cognitive maps’ (Jang & Kim, 2019) and constellations of memorable places (Meier & Glinka, 2017), or for identifying the Lynchian elements from semantic similarities, from user-generated content (Bahrehdar, Adams, & Purves, 2020). In this direction, Huang, Obracht-Prondzynska, Kamrowska-Zaluska, Sun, and Li (2021) advanced and validated a framework to identify the image of the city using crowd-sourced data; by validating their results with the image of the city emerging from questionnaires, sketch maps and official spatial data sets, the authors found that social media content can confidently be used to identify landmarks, paths and districts (at least in Gdańsk, Sopot and Gdynia, Poland).

Nasar’s theorization has motivated the study of the evaluative image of Melbourne on the basis of pictures shared on social media (Motamed & Mahmoudi Farahani, 2018) and, to some extent, an analysis on inequality, perception of safety, and place associations with social class, from geotagged image processing (Salesses, Schechtner, & Hidalgo, 2013). Zhang et al. (2018) trained a deep learning algorithm using collected human ratings of street images from 56 different cities. The model was used to produce human-like assessments on street view images, for the cities of Shanghai and Beijing (China). Each street view image was assessed in terms of several “perception scores” (safe, lively, boring, wealthy, depressing, beautiful). The authors could finally remap the model’s perceptual scores into the street network so as to obtain an overall picture for each of the indicators, across the case study area. In a similar manner, other studies used machine learning algorithms trained on data sets of pictures to “inform urban renewal” (Ma et al., 2021), predict people’s perception of safety and compare it with actual reported crimes (Zhang, Fan, Kang, Hu, & Ratti, 2021), extract human emotions and relate them to different places (Kang et al., 2019), or estimate perceptions about urban scenes (Yao et al., 2019).
2.2.2 Public participation geographic information systems for collecting people's evaluations

The concept of public participation geographic information systems (PPGIS) has been introduced (Weiner & Daniel, 1996) to describe how applications involving GIS technologies could increase public participation in decision-making processes (Brown & Pullar, 2012; Rambaldi, Kyem, Kyem, & Weiner, 2006). PPGIS is a way to make GIS and mapping practices more inclusive and more digestible to non-official voices such as those of regular citizens (Obermeyer, 1998). It empowers communities by means of flexible and open organizational structures, while still facilitating official policy-making (Kyem, 2000; Tulloch, 2008). Rantanen and Kahila (2009) proposed the concept of softGIS to collect information from people about places. The term "soft" here refers to citizens' local knowledge (opinions and beliefs) and its use in guiding decision-making processes in urban planning. Such a soft layer of information constitutes added value for planners when aiming at improving likeability and user-friendliness of physical settings (Kyttä, Broberg, Tzoulas, & Snabb, 2013).

The softGIS approach was adopted in several studies aimed at extracting perceptions and opinions on several environmental properties of a city. Kyttä et al. (2011) investigated the perceived quality of the urban environment in four Finnish towns, in relation to the density of buildings and the presence of green areas. Subjects would indicate quality factors around their home, first by responding to open-ended questions, and afterwards identifying on a map the location of positive and negative aspects. The quality features described by the subjects were categorized into functional, social, physical and emotional qualities. With a similar approach, Kyttä et al. (2013) conducted a web-based survey for the city of Helsinki (Finland), and collected place experiences. Here also, they investigated the effect of urban structure (building density and land use patterns) in bringing about positive experiences. Talen and Shah (2007) developed an interactive GIS platform that was employed to collect neighbourhood evaluations in Urbana, Illinois (USA). The interviewees were asked to address several questions regarding their activities, distinctive features of the city, where they would like to live within the area, and so forth. Jankowski, Czepkiewicz, Młodkowski, and Zwoliński (2016) used a geoquestionnaire, a combination of questions and sketch maps, to collect citizens' evaluations and preferences in the context of urban development projects. Similar methodologies have been used to map cyclists' experiences (Snizek, Sick Nielsen, & Skov-Petersen, 2013) and the construct of sense of place and social capital (Acedo, Painho, Casteleyn, & Roche, 2018), or to collect perceived qualities associated with green areas (Ives et al., 2017).

Nevertheless, the most genuine implementation of the evaluative image of the city is the work conducted in the neighbourhood of Pilsen, Chicago (USA), by Al-Kodmany (2000). Within a series of workshops meant to support the involvement of the community in design processes, Nasar's approach was also included to investigate the inhabitants' evaluations, in the form of a web-based survey. Citizens would be shown an areal photo superimposed on a grid and asked to indicate five liked and five disliked areas (cells); users could also report on the reasons behind their choices via a free text field. Moreover, photos and slideshows were available to the users for each cell, in case they wanted to be reminded about a specific part of the neighbourhood. Like the community image of the city described by Nasar, a set of interactive maps were obtained as an output of people's preferences to summarize the likeability of the district.

Although not embracing a pure PPGIS approach, a series of studies combined qualitative approaches with GIScience methods. Wridt (2010) used aerial photographs and drawings of participants on these photographs to collect participants’ perception of their neighbourhood regarding urban topics (e.g., food places or "bad" places) in Denver, Colorado (USA). Curtis et al. (2014) collected participants’ perceptions of the environment (i.e., places where they felt afraid) through sketch maps, and performed a subsequent analysis of the data in a GIS. Hur, Nasar, and Chun (2010) found an association between measures of building density and vegetation (computed on Landsat imagery) and people's neighbourhood satisfaction, in relation to openness and naturalness; the study was conducted in Franklin County, Ohio (USA).
2.2.3 | Summary

The studies discussed above feature an interest in people’s perception of place and the use of GIS techniques. Machine learning approaches provide a very powerful tool to assess urban scenes on different dimensions. However, they may overlook the symbolic aspects involved in people's evaluations (Zhang et al., 2018), the pragmatic component of cognitive maps (Haken & Portugali, 2003; Portugali, 2004), cultural and historic meanings (Appleyard, 1969; Rapoport, 1990), not to mention people's actual experiences (Tuan, 1977).

Most of the PPGIS experiences were shaped by the investigation of specific qualities of the urban environment and the corresponding attitudes and beliefs of individuals around such properties; others investigated evaluations of specific parts of the population (e.g., cyclists), or explored residents' neighbourhood satisfaction. The latter studies are indeed interested in understanding whether people are satisfied with their local community and the quality of their residential area. Whereas such evaluations and attitudes are related to the study of the perceived qualities of the environment, “the largest body of this research is focused on connecting residential environs with social-psychological variables such as sense of community, neighbourhood attachment, and sense of place” (Talen, 2001, p. 201). This diverges from Nasar's idea of investigating the meaning layer of one’s image of the city in all its shades and components. Similarly, the work of Curtis et al. (2014) exclusively focused on the perception of “youth fear in Los Angeles gang neighbourhoods”; it presents an approach for obtaining fear heat maps from a series of digitized sketch maps, rather than likeability or combined perceptions of the urban environment.

Besides, the approaches described rarely provide participants with geovisualization information where respondents’ perceptions can be explored dynamically and interactively. This may be due to the tools at the disposal of the researchers—for example, Al-Kodmany’s (2000) study was conducted 20 years ago—but also to the purposes of the systems employed, often designed for the use of planners and experts. As a result, although collecting opinions and emotions regarding urban spaces is of great importance for supporting urban design interventions, citizens cannot completely investigate whether their vision is shared with the remainder of the community or how the information is visualized by decision-makers or other actors. Finally, the PPGIS systems discussed are difficult to use in different case study areas, being closed and poorly flexible systems.

3 | METHOD: GENERATING THE EVALUATIVE IMAGE OF THE CITY COMPUTATIONALLY

eImage is an application designed to collect people's perceptions and evaluations of their city and automatically generate a community evaluative image of the city on the basis of the subjects' responses.

3.1 | Components

eImage was built from scratch based on open-source technologies, both back-end (server-side) and front-end (client-side). PHP was chosen as a programming language, and PostgreSQL and its extension PostGIS were used for the back-end. The front-end consists of two main components: the Canvas and the Viewer (see Figure 1). The Canvas (Figure 1, top) is where users have their first contact with eImage. It is the webpage where the user's city evaluation is collected, in other words, this is the place where each user draws polygons for the areas they like and dislike within the study area. The Viewer (Figure 1, bottom) is where each user is redirected once they have completed the input part. This webpage contains the evaluative image of the city, which is automatically generated while the user completes the drawing part (the Canvas). The front-end was implemented with Leaflet.js. The code for the application is open source and available on GitHub (https://github.com/matheussiba/eimg_lx). The
Canvas is available at http://eimglx.herokuapp.com/ and the Viewer can be accessed at http://eimglx.herokuapp.com/map/eimg_viewer.php.

3.2 | Features

eImage can be accessed from a desktop computer, but also from tablets and smartphones. Since Lisbon was identified as the area of study, eImage is implemented both in Portuguese, to reach locals, and English, to reach visitors and residents who would not speak Portuguese. The process of drawing geometries representing areas users like or dislike was realized through the open-source plugin Leaflet.pm. Any complex shape (convex or concave) can be created using eImage, as long as it does not include self-intersection. The dashed line that follows the user cursor becomes yellow to alert the user to possible self-intersections. Having polygons without self-intersection guarantees the robustness of the data storage in the database, preventing eventual crashes in further calculations.
Another feature of eImage is the displaying of messages to guide participants through the drawing process (see Figure 2).

A consistent colour scheme was used in eImage to avoid misleading the user while using the system. Green was used to represent liked areas and red was used to represent disliked areas. A thumbs-up icon with a green background is added to the sidebar when a liked area is added to the map. On the other hand, a thumbs-down icon with a red background is added to the sidebar when a disliked area is added to the map. Overall, the user can draw a maximum of three areas for each category (liked or disliked). When this limit is reached for one category, the corresponding button for adding a new area is disabled. In order to share their perceptions, participants draw geometries representing the area they want to report about, and then specify why they like dislike that area based on the dimensions originally identified by Nasar. eImage also allows them to specify additional attributes, as Figure 3 shows.

### 3.3 Generating the evaluative image of the city

After each user interaction, a function that is implemented using PostGIS deals with polygon intersections that may occur in eImage. The function splits the polygons at their intersections and sums the number of intersections (see Figure 4). This is a different strategy from the use of hexagonal overlays to summarize polygons contributed by participants (e.g., Pánek, Glass, & Marek, 2020). eImage merges the geometries drawn if they overlap with other geometries, assigns to each geometry a likeability rate, and uses two properties (colour and opacity) to visually communicate the unique features of an area. The colour of a geometry indicates if a region is mostly...
liked, mostly disliked or equally liked/disliked. The intensity of participation (i.e., the number of participants who reported about a specific region) is communicated to users via changes in opacity (see Figure 5). The likeability rate of a region is computed using:

\[
\text{Likeability rate} = \frac{N_{\text{likes}}}{N_{\text{likes}} + N_{\text{dislikes}}}
\]  

(1)

When there are no disliked areas intersecting with a liked area, the likeability rate is equal to 100%. The opposite is also true: when no liked areas intersect a disliked area, the likeability rate is equal to 0%. Then, the equal interval classification based on the likeability rate is used to display the final result. This results in the following three classes:

- most liked areas: colour green, likeability rate from 66.67 to 100%;
- liked/disliked areas: colour yellow, likeability rate from 33.33 to 66.66%;
- most disliked areas: colour red, likeability rate from 0 to 33.32%.

The colour yellow, in this case, means that, statistically, the number of people who disliked an area is about the same as the number of persons who liked it, and vice versa. The colour green means that most people liked that area, and the opposite holds for the colour red. Alternatively, a five-category classification scheme is also available for eImage:

- most liked areas: colour green, likeability rate from 80.01 to 100%;
- liked areas: colour cyan, likeability rate from 60.01 to 80.00%;
- liked/disliked areas: colour yellow, likeability rate from 40.01 to 60.00%;
- disliked areas: colour magenta, likeability rate from 20.01 to 40.00%;
- most disliked areas: colour red, likeability rate from 0 to 20.00%.
To evaluate the approach’s ability to help citizens voice their opinions, eImage was tested in the city of Lisbon. The next sections present the context of the study, the results, and a discussion of their implications. Figure 6 shows the evaluative image obtained during the study.
3.4 | Evaluating the characteristics of the drawn areas

The most liked and disliked areas were examined with regard to the presence of some urban elements included within their boundaries. We used a methodology presented by Filomena and colleagues (Filomena et al., 2019; Filomena, Manley, & Verstegen, 2020) to extract, on the one hand, natural elements such as parks, waterbodies or sea coast, and, on the other hand, human-made elements, or so-called severing barriers. A large body of research in environmental psychology and urban geography, including by Nasar himself, has reported a preference for urban spaces such as parks, green areas and waterfronts or areas featured by the presence of trees, grass, and water (e.g., Kaplan, 1985; Lynch, 1960; Nasar, 1990; Ulrich, 1986). Furthermore, natural elements enhance the perceived walkability of an urban area or a road (Ewing & Handy, 2009; Forsyth, 2015). In contrast, major roads and railway structures, along with other human-made elements, are described as severing barriers that obstruct people’s movement and the perceived quality of the environment (Anciaes & Jones, 2020; Nasar, 1998; van Eldijk, Gil, Kuska, & Sisinty Patro, 2020).

Along these lines, we speculated that the most liked areas are characterized by higher concentrations of natural elements and lower concentrations of human-made ones. Conversely, the presence of human-made elements may be more evident across the most disliked areas. Historical landmarks were also identified given that their symbolic meaning contributes to the likeability of a place (Appleyard, 1976; Harrison & Howard, 1972; Nasar, 1990); see Section 2.1. For each polygon obtained from the overlay of the different areas depicted by the participants (see Figure 4), we therefore computed:

- the number of natural elements within the boundaries of a polygon or, for waterfronts, within 100 m of the polygon’s boundaries;
- the number of parks or green areas larger than 100 m² within the boundaries of a polygon;
- the number of historical landmarks within the boundaries of a polygon.

All natural elements were extracted from OpenStreetMap (OSM; see Open Street Map Contributors, 2020). Historical buildings were identified by selecting buildings whose OSM fields heritage or historic were true or filled. To appraise the relationship between the likeability of urban areas and the presence of such elements, we computed the Pearson product-moment correlation coefficient between:

- the number of natural elements within the boundaries of the polygons and the number of people who liked those polygons (corr_natural);
- the number of historical buildings within the boundaries of the polygons and the number of people who liked those polygons (corr_historical);
- the number of human-made severing elements and the number of people who disliked those polygons (corr_manmade).

4 | THE CASE STUDY AREA: LISBON

The city of Lisbon (Portugal) was chosen as a case study area for this work. The Portuguese capital has often struggled to compete on the European stage as a leading capital. However, the recent economic crisis has pushed urban managers to invest significant resources in territorial rehabilitation, so as to attract both tourists and investors, and thereby revive the urban economy (Ribeiro, 2017). Furthermore, in 2012 the city approved a new Master Plan whose priorities are to "promote an innovative and creative city; affirm the identity of Lisbon in a globalized world; create a participatory governance model and rehabilitation and urban regeneration" (Municipality
of Lisbon, 2012). By engaging citizens in urban governance, the city has aimed to conceptualize and design liveable spaces which may enhance the perceived quality of life (Schaffers et al., 2012).

4.1 | User study

A user study was conducted between December 2018 and January 2019 to test eImage. The study had one independent variable, interaction, with two levels, supervised and unsupervised. Supervised interaction entails that the participants were recruited in public places by word of mouth. Furthermore, the person carrying out the study was next to each participant to help them use eImage, upon request. Unsupervised interaction means that the URL of the eImage platform was sent out through social media groups (Facebook and WhatsApp).

The dependent variables were usability, efficiency, dropout rate, learnability, and usefulness. Data about the variables was collected through the logging system implemented in eImage Canvas to track the users’ interaction with the platform. The System Usability Scale (SUS) was used (Brooke, 1996) to measure perceived usability. A Portuguese version of SUS validated by Martins, Rosa, Queirós, Silva, and Rocha (2015) was employed. Efficiency was measured by the average time people spent drawing an area and indicating its attributes. The dropout rate indicates the number of persons who quit the experiment before finishing it. Learnability was measured by analysing whether the time taken to create an area decreases as the number of drawn areas increases. Finally, usefulness was assessed through participants’ ratings on two statements:

- **Usefulness I** statement: ‘This app helps me say what I like/dislike effectively’.
- **Usefulness II** statement: ‘This app could be an effective way to give feedback to my city council’.

Responses to the two statements had the same range as SUS (from ‘strongly disagree’ to ‘strongly agree’) and were on a five-point Likert scale (strongly disagree = 1, strongly agree = 5). To avoid learning effects, a between-group design was adopted for the user study, whereby one participant performed one type of task (either supervised or unsupervised interaction).

4.2 | Tasks

The participants were asked to perform the following tasks:

- Draw areas they liked and areas they disliked within the study area. The minimum number of drawn polygons was two (one liked and one disliked), and the maximum number was six (three liked and three disliked). The study area comprised four neighbourhoods of Lisbon: Misericórdia, Santo António, Arroios, and Santa Maria Maior (Figure 6).
- Identify an attribute to describe why they liked or disliked the area for each drawn geometry. At least one of five had to be selected (Figure 3, right). The five options are based on the attributes identified by Nasar (1990): naturalness, upkeep, openness, order, and historical significance.

4.3 | Procedure

The duration of each interaction was about 10 min. First, the participant received the eImage web link, which could be accessed from a desktop computer, laptop, smartphone, or tablet. The first page briefly explained the objective of the study and provided a 30-s video showing how to complete a task on the platform. After the
participant had consented to participate, they were redirected to a second page to provide demographic details about themself. Afterwards, the Canvas was accessed (Figure 1, top), and the participant started with the tasks. After drawing all liked/disliked areas, participants filled the usability and usefulness questionnaire, before finally being able to access the Viewer and visualize the results.

A pilot study was conducted before the final data collection to investigate whether the main components of eImage were understandable by a lay person. For that, two male participants of ages 28 and 35, were recruited. The first one was a resident of Lisbon, and the second one was a visitor, who reported having already visited Lisbon many times. The notable issues included: the lack of a searching tool to help users find the locations they want (implemented in the final version, see Figure 1, top); and a description of the attributes to consider while drawing a dis/liked area (also implemented in the final version, see Figure 3).

4.4 | Participants

Table 1 shows the demographic information about the participants who completed the study (N = 68 participants started, nine of whom dropped out). All 59 participants who did not quit the experiment reported that they were residents of Lisbon at the time of the study. For the purposes of the analysis, two types of devices are distinguished: mobile devices (smartphones and tablets) and others (desktop computers and laptops). The significance of associations between the sociodemographic attributes of the participants was tested using Fisher’s exact test. Cramér’s V (strength of the associations) is reported in Table 2 for cases where the correlations are significant. There are a few correlations between the attributes of the participants worth mentioning. Perhaps unsurprisingly, age was correlated with education and income in our sample. The significant correlation between age and devices points to a non-random association between age groups and devices: in each of the groups, the number of participants using mobile devices exceeds the number of participants who did not, except in the 18–24 group where substantially more participants contributed via non-mobile devices. The same goes for the correlation between job and app language: most employed workers and students used the Portuguese version of the app, while the self-employed and freelancers interacted with the English version. Apart from employed workers, who overwhelmingly used mobile devices, the number of participants using each type of device was roughly evenly distributed across all professions. No unemployed, self-employed, or retired persons were present in the online (unsupervised) data. About a third of the participants who used mobile devices interacted with the English version of the app. Exactly the opposite was true for the participants who participated via non-mobile devices (one-third Portuguese, two-thirds English). Finally, about a third of users using non-mobile devices to participate completed the tasks online (one-third unsupervised, two-thirds supervised). The proportions were somewhat different for participants using mobile devices (one in seven unsupervised, six in seven supervised).

5 | RESULTS

Efficiency, usability, usefulness, learnability, and dropout rate are described in this section using data from 59 participants (N = 45, supervised; N = 14, unsupervised) who completed the study. For each of the variables, the average value for the whole study is mentioned, followed by notable significant differences owing to the background of the participants. An overview of the impact of participants’ background on the results is shown in Table 4. The analysis was performed using linear models and linear mixed effects models in R (see Winter, 2013, for an introduction).

As stated above, participants could draw up to six areas they liked or disliked. The mean number of areas drawn during the study was 3 (SD 1.23). Table 3 shows the Kendall’s tau correlation measures between the dependent
variables (Shapiro–Wilk tests of normality confirmed that each variable is non-normally distributed). In general, users who gave high usability scores also gave high scores for Usefulness I and Usefulness II. Moreover, users who rated Usefulness I highly tended to rate Usefulness II highly as well. Users who were fast at drawing the dis/liked area during the study tended to rate Usefulness I and Usefulness II higher. Finally, there was no significant correlation between drawing time and usability ratings, nor was there any significant correlation between drawing time and drawing amount.

| TABLE 1 Demographic information about the participants | Supervised (N = 45) | Unsupervised (N = 14) | Total (N = 59) |
|-------------------------------------------------------|---------------------|-----------------------|---------------|
| Gender                                                |                     |                       |               |
| Female                                                | 18 / 40             | 6 / 43                | 24 / 41       |
| Male                                                  | 27 / 60             | 8 / 57                | 35 / 59       |
| Age                                                   |                     |                       |               |
| 18–24                                                 | 9 / 20              | 4 / 29                | 13 / 22       |
| 25–34                                                 | 25 / 56             | 6 / 42                | 31 / 53       |
| 35–44                                                 | 5 / 11              | 4 / 29                | 9 / 15        |
| 45–54                                                 | 2 / 4               | - / -                 | 2 / 3         |
| 55–64                                                 | 3 / 7               | - / -                 | 3 / 5         |
| >65                                                   | 1 / 2               | - / -                 | 1 / 2         |
| Education                                             |                     |                       |               |
| High school graduate                                  | 1 / 2               | 1 / 7                 | 2 / 3         |
| Professional degree                                   | 2 / 5               | - / -                 | 2 / 3         |
| Bachelor’s degree                                     | 10 / 22             | 5 / 36                | 15 / 26       |
| Master’s degree                                       | 28 / 62             | 7 / 50                | 35 / 59       |
| Doctorate degree                                      | 3 / 7               | 1 / 7                 | 4 / 7         |
| No schooling completed                                | 1 / 2               | - / -                 | 1 / 2         |
| Income                                                |                     |                       |               |
| <1000                                                 | 8 / 18              | 6 / 43                | 14 / 24       |
| 1000–1499                                             | 9 / 20              | 4 / 29                | 13 / 22       |
| 1500–1999                                             | 5 / 11              | - / -                 | 5 / 8         |
| 2000–2999                                             | 3 / 7               | 1 / 7                 | 4 / 7         |
| 3000–3999                                             | - / -               | - / -                 | - / -         |
| 4000–4999                                             | - / -               | - / -                 | - / -         |
| >5000                                                 | 1 / 2               | - / -                 | 1 / 2         |
| NA                                                    | 19 / 42             | 3 / 21                | 22 / 37       |
| Occupation                                            |                     |                       |               |
| Employed worker                                       | 18 / 40             | 1 / 7                 | 19 / 32       |
| Freelance                                             | 3 / 7               | - / -                 | 3 / 5         |
| Self-employed                                         | 2 / 5               | 1 / 7                 | 3 / 5         |
| Retired                                               | 1 / 2               | - / -                 | 1 / 2         |
| Student                                               | 20 / 44             | 11 / 79               | 31 / 52       |
| Other                                                 | - / -               | 1 / 7                 | 1 / 2         |
| Unemployed                                            | 1 / 2               | - / -                 | 1 / 2         |
| Uses mobile device                                    |                     |                       |               |
| No                                                    | 14 / 31             | 9 / 64                | 23 / 39       |
| Yes                                                   | 31 / 69             | 5 / 36                | 36 / 61       |
The average time spent by participants on drawing polygons was 6.1 min during the study (SD 2.63 min). Gender and supervision had significant effects on this (Table 4), with males being significantly faster than females, and participants in the face-to-face condition being significantly faster than online participants. The interaction between the two factors was found to be significant, meaning that the gap between males and females is wider in the online condition than in the face-to-face condition.

5.2 | Usability

The average SUS score was 79 (SD 14.5), which indicates good usability, after Bangor, Kortum, and Miller (2009), and a grade of ‘A–’ on the Sauro–Lewis curved grading scale (Lewis, 2018). Significant differences of SUS ratings were observed according to two factors: app language (users interacting with the application in Portuguese provided significantly higher ratings than those interacting with it in English); and device (users interacting with mobile devices provided significantly higher ratings than those not). The interaction between the two factors (app language and device) was not significant.
5.3 | Usefulness

Question I (‘This app helps me say what I like/dislike effectively’) obtained an average rating of 3.92 (SD 1.19), indicating that the users found eImage useful as a reporting medium for their opinions about places in the city. Here also, device was an important factor: those using mobile devices had significantly higher ratings than those not. Another important factor was supervision: people in the online condition provided significantly lower ratings than those in the face-to-face condition. The interaction between the two factors (device and supervision) was not significant.

Question II (‘This app could be an effective way to give feedback to my city council’) obtained an average rating of 4.4 (SD 0.98), confirming the impression left by the answers to question I. Device remains important: users using mobile devices had significantly higher ratings than those not. Language was important as well: similar to usability, users interacting with the application in Portuguese provided significantly higher ratings than those interacting with it in English. The interaction between the two factors (device and language) was not significant.

5.4 | Learnability

Do users get significantly faster at drawing liked/disliked areas with time? Figure 7 shows the average time spent by the participants on drawing a polygon. As the figure suggests (and the statistical analysis confirmed), the answer to this question is ‘no’. Based on the observations made by one of the researchers during the supervised condition, one reason could be that the participants did not have the liked/disliked places already set in their minds before starting the application. As a result, each time participants wanted to draw a new area, they spent relatively the same amount of time thinking about this new area before drawing it.

5.5 | Dropout rate

There were no dropouts for the supervised (i.e., face-to-face) condition. On the other hand, nine persons dropped out (39%) during the online/unsupervised condition (eight residents, one visitor).
5.6 | Characteristics of the drawn areas

The correlations computed were all weak: between the number of natural elements within the boundaries of the polygons and the number of people who liked those polygons ($\text{corr}_{\text{natural}} = -0.056$); between the number of historical buildings within the boundaries of the polygons and the number of people who liked those polygons ($\text{corr}_{\text{historical}} = -0.019$); and between the number of human-made severing elements and the number of people who disliked those polygons ($\text{corr}_{\text{manmade}} = 0.048$). Hence, there is no linear relationship between the number of elements and the ratings. The relationship is also non-monotonic (Spearman’s correlation coefficients were also close to zero).

Finally, we fitted a logistic regression model to the data to learn about the relationship between the number of elements taken together (historical, natural, human-made) and likeability. Here, likeability was turned into a categorical variable: 0 if disliked or disliked/liked; 1 if liked. The value of McFadden’s pseudo $R^2$ for the model was .106. The regression coefficients of the model were: historical ($-0.606, p > .05$), natural ($= \text{waters} + \text{parks}, 1.3304, p < .001$), and manmade ($= \text{roads} + \text{railway}, -0.1327, p < .001$). That is, in the current scenario, the numbers of natural and human-made features seem to be a good predictor of the overall likeability tendency, in congruence with existing theories. Or put differently, the overall tendency (i.e., positive or not) of the likeability ratings in the scenario may be traced back to the natural and human-made features of the areas drawn. The number of historical features seems not to matter much in the current scenario.

6 | DISCUSSION

We have sought to take advantage of technological progress to partly automate Nasar’s method of generating evaluative images. The novel contribution of this article is an approach to creating evaluative images of cities through web mapping. Our work shares some similarities with Curtis et al. (2014) (see Section 2.2), but there are three key differences. First, the input in the case of Curtis et al. (2014) was a printed map on which participants could report areas where they felt afraid. The printed map was subsequently digitized. Here, the input is a drawing of neighbourhoods on top of a digital map. Second, the output of this study is an evaluative image, whereas fear heat maps were obtained in Curtis’s study. Third, the theme in the current work (places liked/disliked as well as reasons for citizens’ perceptions) covers a much larger ground than fear mapping alone.
Furthermore, as compared to the work of Al-Kodmany (2000), elmage offers technical, design and conceptual enhancements. The first—flexibility, openness of the system and its potential readaption for new case study areas—are a consequence of the current state of the art in web app design, a new impulse towards open science and tools and the availability of spatial data sets. The second, while still connected to the design of the app, pertains to the way the data are collected and aggregated. Citizens in Al-Kodmany’s web application were not only constrained to choose grid cells as liked areas or disliked areas, but also not able to report on the degree of likeability (the evaluation was binary, i.e., liked or disliked). In contrast, in elmage users have the chance to define their own areas, to indicate to what extent they like or dislike a certain area and to choose among different dimensions for motivating their choice. These aspects make our application closer to Nasar’s approach. In particular, they allow us to obtain community evaluative images that really are the result of overlapping individual images. Individual nuances and precision in the definition of the areas are preserved so as to provide more specific and accurate information to decision-makers and planners.

The remainder of this section summarizes takeaways from the user study before highlighting key differences between this and Nasar’s work and pointing towards future work. Lessons learned are divided into two categories: those pertaining to the prototype and those touching on the overall approach.

6.1 | Key takeaways and implications

What we have learned about elmage (i.e., the tool):

- Perceived usefulness positively correlates with perceived usability (Table 3). This is in line with the technology acceptance model (TAM; Marangunić & Granić, 2015), and indicates that the tool would have good chances of acceptance/ adoption, should it be used by city councils to collect participants’ opinions. The TAM posits that perceived ease of use is a determinant of perceived usefulness. The SUS provides a unidimensional measure of perceived usability (Lewis, 2018). The exact relationship between SUS measures and the TAM still needs solid research foundations (Lewis, 2018), but the hypothesis made here, given the relatedness of the concepts of ease of use and usability, is that perceived usability could be a determinant of perceived usefulness.

- Task completion time negatively correlates with perceived usefulness (Table 3). Users faster at completing the tasks also provided higher ratings of the perceived usefulness. The TAM could again prove useful here: it may be that users who were faster at completing the tasks had a greater sense of perceived ease of use of the interface, and consequently of its perceived usefulness. Or, using the TAM2 model (Venkatesh & Davis, 2000), this observation may be in line with the theory that output quality (i.e., how well a system performs tasks relevant to the goal at hand) is a determinant of perceived usefulness.

- Device type mattered during the study. This was quite unexpected, as elmage was not purposefully designed to work better on mobile devices. It was designed as a responsive web application to be used both on desktop and mobile devices. Yet, the fact that users accessing the app through mobile devices consistently rated usability, Usefulness I and Usefulness II higher points at the need for focused efforts to improve the desktop-based version of the tool in future iterations.

- Language mattered. The fact that participants using the Portuguese version of elmage provided higher ratings was also unexpected. Since the study happened in Lisbon, this may just be a consequence of the fact that many participants speak Portuguese. Language was not explicitly controlled for during this study, and these results suggest that it should be in subsequent studies.

- There is a gender gap to bridge. This, too, was a surprising finding. However, the data collected in this study do not provide a basis for solid explanations. It may be that the gender gap observed is a mere feature of our sample, or that there is indeed a gender gap to be bridged in general. Measuring users’ experience with web mapping technologies in replications of the current work will provide a clearer picture regarding this matter.
What we have learned about *evaluative image* 2.0 (i.e., the approach):

- Deep citizen participation. Users provided positive feedback on the perceived usefulness of the tool. Previous work (Degbelo et al., 2016) has highlighted that maps are a promising tool to foster participation of citizens in smarter cities, and the approach offers one instance of how (in addition to the many others that are being currently explored; see Degbelo et al., 2016). That is, city councils may use it in lieu of traditional data-collection procedures (e.g., filling in forms), to get a snapshot of city spaces that should be the focus of further urban development or those that are particularly appreciated by the population. Furthermore, none of age, education, job, and income had a significant impact on the results (i.e., drawing time and drawing amount). This is good news, as it implies transparency of the approach with respect to participant background. In particular, there is reported evidence in the literature that different groups of people have different senses of place (e.g., Carter, Dyer, & Sharma, 2007; Pánek et al., 2020). The fact that the drawing amount is not impacted by participants’ background implies that the elimage approach does not introduce an additional data-collection bias (e.g., a systematic under/over-representation of a particular group’s perspective). The elimage approach can thus help various groups of society (quickly) voice their opinions on the liked/disliked places of their cities.

- Deployment. The good usability ratings of the mobile version are a positive outcome, suggesting that the approach is portable and can be easily deployed. For instance, citizens on the street may be invited to volunteer their time to participate as done during the study. Using elimage, users can participate in opinion polls about liked/disliked places of their city from virtually anywhere on the globe, provided they have internet access.

- Supervision has a positive influence on the results. It gets participants to work faster, has a lower dropout rate, while at the same time not influencing the amount of feedback they provide (Table 4). Moreover, since task completion time correlates with perceived usefulness, this may have been the reason why many who were supervised provided higher ratings to the Usefulness I question (Table 4). Nevertheless, before over-celebrating the supervision condition, there is a need for a more thorough assessment of the bias it may have on the results (e.g., are participants significantly more inclined to provide more liked areas in the face-to-face condition than online?) This is a topic for further investigation in future work.

### 6.2 Comparison with the early work by Nasar

The key steps of the original method for the creation of evaluative maps by Nasar included: (1) questionnaire design; (2) interviews (by telephone or face-to-face); (3) production of one evaluative map per participant; (4) overlay of these evaluative maps to produce the evaluative image; and (5) comparison of cities (liked/disliked places, along with the rationales) based on the evaluative images. The key innovation in the present work is a tool to automate steps (2), (3), and (4) of the process. Through this automation, the amount of time to create evaluative images is substantially reduced, the creation of evaluative images is eased, and this can open the door to several follow-up studies comparing cities. On average, users took 6 min to tell us about their liked/disliked areas (Section 5.1), and this figure rises to 7 min if the 55 s required to fill in background information are included (SD 22 s). That is, the generation of evaluative maps and an aggregate evaluative image occurs with less than 10 min of effort per user, familiarization with the documentation included. As mentioned in Section 2.2, PPGIS devised to collect people’s evaluations about places rarely include a data processing phase and consequent visualization instantly after the participant used their application.

Given that the areas of interest are clearly delineated by the participants themselves, evaluative image 2.0 opens up new possibilities for consolidated hypothesis generation about liked and disliked places. One could, for instance, envision that the data generated by users through elimage are linked to other known facts about the places of interest, providing a more complete picture to urban planners about the places being talked about. Moreover, computational approaches can be developed to automate (or semi-automate) the comparison of
evaluative images across multiple cities, something not possible with the original process (Nasar, 1990), due to the state of the technological evolution back then.

In its original form, the evaluative image of the city was meant to make planners and public organizations more aware of citizens’ perceptions and evaluations. Although we acknowledge the necessity of partly readjusting elmage to meet the needs or interests of possible stakeholders (e.g., specific areas or issues to address), we argue that elmage can inform policy-makers at early stages of urban renovation projects on how people perceive the city and thus guide urban interventions. Furthermore, given its user-friendliness, elmage can offer a real-time picture of people’s opinions and views that public entities can access and consult even prior to actual policy-making. The global results can not only be explored in a straightforward manner, but also be “zoomed in” by analysing specific parts of the cities or individual maps. The tool might thus also strengthen communication processes between citizens and institutions, for example, in the identification of critical issues that should be addressed, degraded areas, and so on.

6.3 Limitations and future work

Compared to Nasar (1990), one limitation of the current work concerns the type of information visualized. Evaluative images were defined as composed of three elements: (1) identity (the salient elements of the city); (2) location (where the salient elements are located); and (3) likeability responses (attributes that account for a strong evaluative response among the public). elmage has first and foremost focused on communicating likeability (e.g., through colour schemes). For now, identity and location are not communicated in the final map. The rationale for this is that the main concern for this work was the involvement of citizens in the production process. The interpretation of the evaluative image \textit{per se} and the evaluation of the quality of evaluative images produced computationally is, for now, deferred to future work. Accounting for identity and location could be done, for example, through an additional map layer in the elmage Viewer.

In addition, participants reported informally that the attributes were not sufficient to express the exact reason why they drew a particular area. This issue points to the expressiveness of the whole approach and was expected, given that a controlled vocabulary was provided in this work (Figure 3). A way of mitigating this could be to design a further field that users can fill in with adjectives related to the drawn area. Text mining techniques can be applied to aggregate these words into groups and conduct further analysis. Another aspect of expressiveness concerns the duality between likeability and dislikeability. This duality could be replaced by a continuum or a larger number of classes (e.g., strongly like/like/dislike/strongly dislike). Furthermore, the approach could be adapted to more specific domains or specific thematic questions. For instance, instead of asking participants about places they like/dislike, they could be asked about areas they perceive as safe/unsafe, clean/unclean, as a slight but perhaps interesting variation in the data-collection process. The current elmage infrastructure would support such questions as well.

Finally, an interesting direction for future work is the integration of the qualitative data generated through elmage with quantitative data relevant for urban planning (e.g., socioeconomic attributes of neighbourhoods). GIScience work on Linked Data (Kuhn, Kauppinnen, & Janowicz, 2014) could be relevant here, as Linked Data support context description (see Scheider, Degbelo, Kuhn, & Przibytzin, 2014). In general, connecting qualitative data sets with others and providing a means to interactively explore their integration could induce planners to make new assessments of the \textit{vertical context} of phenomena taking place in cities, that is, “the context established by other things that are known about the same location” (Goodchild et al., 2012).

7 Conclusion

Evaluative images of cities can help urban planners to understand the way citizens perceive their built environment. This work has proposed, implemented, and evaluated an approach (called evaluative image 2.0) to
digitize and automate the process of creating evaluative images, in the sense of Nasar (1990). The approach was implemented in an open-source system called elmage; Lisbon was chosen as a case-study area. Overall, elmage received positive feedback from users with respect to its usability and usefulness, and can help users, irrespective of their education, age, income, and profession, effectively voice their opinions on liked and disliked areas in their cities.

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CONFLICT OF INTEREST
None.

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ENDNOTES
1. Although for this study the term “mobile devices” covers tablets and smartphones, it is acknowledged that this is an oversimplification: from the perspective of human–computer interaction, the perceived complexity of both types of device is not the same.

2. The introductory video used in the study was less than 30 s long; see https://youtu.be/z8dtaum_Xu0.

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