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A Citizen-Sensing System for Measuring Urban Environmental Quality: A Case Study Carried out in Taiwan

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Featured Application: This research describes a prototype of a system that extracts data from a social network for the purposes of urban environment analysis and that can transform subjective citizen feelings into quantifiable data via machine learning.

Abstract: Urban planning is usually dependent on urban analysis and tends to use data from sensor networks collected over a long period time. However, in recent years, due to increased urbanization and the rapid growth of transport, a gap has developed between urban environments and citizen feelings. Rebuilding urban infrastructure or making urban planning changes require a lot of time and resource costs. The hardware in a city cannot be easily changed, but citizen activities change all the time. Distributing city space according to a software-based recommendation, such as arranging different locations for citizen activities or traffic, is a method that can be implemented to improve city environments and to avoid resource waste. In this paper, citizens were used as sensors to extract environmental information collected using a social network service (SNS), and the information was analyzed to turn subjective feelings into objective environmental phenomena. The research focused on how to collect citizens' feelings regarding urban environments and to develop a citizen-sensing system to bridge the gap between citizen feelings and sensor networks. The results prove that citizens who sense the city environment create small-sized data that are suitable for small-scaled, high-density cities.

Keywords: data analytics; smart city; deep learning; citizen sciences; urban science

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1. Introduction

Smart city management is dependent on data collected from urban analyses, with most information being recorded by sensor networks in cities. There is a large amount of information required for analyzing a smart city. For the requirement of a data source, a wide variety of covering sensor networks is basic equipment for a smart city. According to a speech by Hamilton (2015) [1], there are several methods of urban analysis: satellite photographs; global fine-scale information; multi-sensors; sustainable information production; information democratization; open, public, and reproducible information. However, those data need to be collected over a long period of time, with extensive recording and analysis through general investigations or device sensing. As cities expand, the population increases, and industry becomes more complex, so such data cannot represent the urban conditions after a short period of time. Moreover, due to the lack of databases, a series of data may be less reflective of value and may be unable to be analyzed. Urban analysis has shown that urban construction is not always suitable for users. Unsuitable infrastructure in a city causes waste in terms of time, space, money, and resources. To avoid these kinds of problems in smart city development, we suggest one method to acquire environmental information for urban analysis: citizen feelings. In the information age, people share their opinions on the Internet all the time. This information includes description of surrounding environments. Citizen feelings directly illustrate urban planning performance, and the more people who sense urban spaces, the more support there is for policies and strategies. Citizen science has become increasingly important to urban analysis in recent years. Blaschke et al. (2011) [2] reinterpreted how a "city" is not only a place, but a massive aggregate composed of construction, buildings, the local population, and information. Citizens are a part of urban life. Gabrys (2014) [3] proposed that "citizenship" focuses on monitoring and managing data in urban planning. As a type of information, citizen feelings are open, public, low-cost, and reproducible when collected through social networks. This kind of data reflects trends in the geographical environment and infrastructure, transportation, and industrial activities and has an important meaning for urban development. Santos et al. (2016) [4] developed a crowdsensing platform for smart city environment sensing, which was easily reconfigurable and was carried out by more than 600 participants. Dutta et al. (2017) [5] presented an air quality monitoring device (AQMD) to collect information about air quality through smartphones. The AQMD is a lightweight, low-power, and low-cost environmental sensor for a smart city. In this experiment, the information about city activities collected from citizen feelings was extracted for urban analysis to reinforce the sensor networks. Therefore, using human beings as sensors to collect information is the foundation of an extraction system for citizen feelings. However, citizen feelings are complicated and have no specific standards. For the analysis of specific, subjective citizen feelings, we used the information in several machine learning methods to convert the subjective citizen feelings into objective data. Saralioglu and Gungor (2022) [6] built a website for users to label pictures to refine image classification training in a CNN and achieved high accuracy results. Using experimental data extracted from cities in Taiwan, SNSs are used widely in this country. As Taiwan has a high population density and small living area, it is suitable for this study.

2. Related Works

2.1. Information for Urban Spatial Element Development: From Sensor Networks to Social Media

Most of the information about urban development is data acquired from general investigations. City managers typically use this information to evaluate regional development policies for the coming decade. Development based on city information is also the main idea in smart cities. Information about urban infrastructure operation is not only acquired over long investigations but also by sensor networks. The physical data extracted from an information environment using sensor networks are wide-reaching and can be acquired more quickly than through general investigations. Research on complexity in future cities shows that urban infrastructure systems (UISs) will gain complexity through analyzing the elements of urban infrastructure. In *The Image of the City* (Lynch, 1960) [7], it is suggested that the structure of a city is inseparable from its development. The image of a city depends on citizens' views of the appearance of the city, while the city has a positive effect on the development and environmental quality of its residents. In *Happy City: Transforming Our Lives Through Urban Design* (Montgomery, 2013) [8], several studies show that the distribution of urban transportation modes and public areas affects the quality of the environment, which is evident in citizens' feelings. In recent years, citizen-sensing information has been collected via social networks and has been accumulated in many databases, which is used to enhance urban development. Sui, Goodchild, and Elwood (2013) [9] proposed a methodology of collecting volunteered geographic information (VGI) to enforce a geographic information network through user sensing. In research by Crooks et al. (2017) [10], several experiments were utilized, such as recording the activity areas and staying times of citizens and visitors, by using Bluetooth and sensor networks to understand their usage habits and to improve the transportation system. Ramsay, Paradiso, and Hamburg (2018) [11] identified several methods (from open data to standardization) to improve environmental quality. They sought to encourage other researchers to extend environmental quality data to improve the living environment and to protect citizens from pollution. Di Dio et al. (2018) [12] involved citizens in smart cities through a mobile game. The players gained rewards from sustainable companies by using green-energy transportation. This research shows that involving citizens in urban policy planning helps to improve the urban environment. Saralioglu and Gungor (2020) [13] proposed several example using crowdsourcing to reinforce a sensor network that was collecting geographical data.

2.2. Citizen Sensing of the Urban Environment

Lynch (1960) [7] theorized that the ideal city plan can be described by the images of residents. Arranging these images creates the elements and rules of city construction and generates the features of the ideal city plan. This construction rule of applying ideal city features can be used by city planners when generating and improving cities. Research by Costa, Noble, and Pendeleton (1991) [14] referenced the development of three old cities that used new urban planning suggestions, spatially dividing each field of society in cities to discover problems that may occur during city development and to search for solutions to social issues. Taking the social field as an information source for city planning and collecting effective data are useful ways to improve cities. Bonney et al. (2009) [15] crowdsourced citizen-sensing data to observe the environment for ornithological research. Citizens can sense aspects of a field that sensor networks cannot; thus, citizen science is a suitable method for researching city phenomena. Following the work of Wiggins and Crowston (2011) [16], several studies have applied citizen science, as algorithms are suitable for processing data extracted by crowdsourcing. In *Decoding the City: Urbanism in the Age of Big Data*, Offenhuber and Ratti (2014) [17] proposed that social media information can be useful for the development of smart service in smart cities. This information is effective for upgrading service efficacy and for solving environment problems arising from urbanization. In the Senseable City Project (MIT Media Lab, 2017) [18], many experiments have been conducted to study the information collected from cities as well as to search for solutions to urban problems. There are several forms of data extraction, including sensor networks, general investigations, and the collection of data from social media. In *Sentient City: Ubiquitous Computing, Architecture, and the Future of Urban Space*, Shepard (2011) [19] proposed that a city can "sense" local phenomena. City designers can learn about the phenomena and problems of the city through this type of sensing. According to this research, social activity information can be collected through social media. This begs the question of whether public transportation systems, stations, roads, and regional division plans in cities impact the activity patterns of citizens differently and affect the quality of the environment. Spyratos and Stathakis (2018) [20] collected citizen satisfaction from Foursquare to determine the real feelings of citizens regarding urban facilities and services. Keramitsogloun et al. (2017) [21] provided a series of services and tools to citizens in high-temperature areas to reduce the risks of elevated urban temperatures through a mobile app. The service protected people from heatwaves and reduced the urban thermal risk by changing citizen activities. Navarrete-Hernandez et al. (2019) [22] used subjective well-being (SWB) measures to find that the greener an individual's local environment is, the higher the levels of happiness and the lower the levels of stress are that citizens feel. In this paper, we explored the urban spatial structure using information obtained directly from social network users. We assumed that how citizens moved was affected by urban transportation facilities and compared the relationship between urban transportation and environmental quality by collecting information about citizen feelings. This research shows that people put their footsteps on social media and present their current spatial status on the Internet. This is in line with the work of Chen, Mahmassani, and Frei (2018) [23], who analyzed a series of information on social media (such as the distance between the check-in marks of specific users over a long-term period), concluding that people's travel behavior correlates with how many friends they have. The presentation of social network service (SNS) information can reveal activity in a city and some phenomena that cannot be sensed with sensor devices. Analyzing the activity of a city by extracting this kind of information can solve city problems and offer recommendations for improvement.

2.3. Optimizing Cities Using Social Media

In Cranshaw et al.'s work (2010) [24], mobile entropy was calculated using social media to determine the high-entropy field of each city. The higher an entropy field is, the more crowded together people are. This experiment is useful for social network designers when planning the installation and maintenance of a city's information infrastructure and interaction devices. Baptiste, Foley, and Smardon (2015) [25] conducted surveys to examine citizen knowledge and citizen willingness to implement green infrastructure technologies within two neighborhoods in Syracuse, New York, USA. Additionally, this research indicated that city managers can take on a targeted approach for implementing green infrastructure measures to optimize quality. Berntzen, Johannessen, and Florea (2016) [26] presented a research design in smart cities and smart users, which was based on a serial data-collecting system by citizens to help with smart city development. Sullivan, Brian L. et al. (2017) [27] and Lopez, Minor, and Crooks (2020) [28] used open data from social network services on people's observations of birds, to determine where people observe birds in the cities, to protect bird habitats. In Hsu et al.'s work (2017) [29], crowd sensing was used as a sensor tool. A social network platform was developed for users to publish bad air positions, and data were collected as evidence of air pollution due to local factories emitting exhaust gas. This research resulted in local factories moving away from the town. To understand the activities of residents in a city, we can acquire information from social media through our extraction system. Thus, citizens' feelings directly show phenomena within a social dimension and provide information for development suggestions.

3. Research Issues

3.1. Gap between Sensory Extraction and Citizen Feelings

Data-extraction methods (such as satellite photographs, global fine-scale information, and multi-sensors) all derive data from sensor networks, and the information extracted from sensor networks is the only data they use (see Figure 1). For example, air-quality sensors only sense the component of air and the subjects in their location. In contrast, citizens are complicated, diverse, and nearly everywhere. The continuous expansion of both the urban environment and the Internet means that numerous activities occur simultaneously within a city. Thus, once a gap occurs between sensory extraction and citizen feelings, problems arise (such as traffic jams, air pollution, global warming, power overloads, and confined living spaces). How to distribute city resources (such as street space or seating on transportation) is extremely important, especially in the post-pandemic era. Ideal urban planning can solve these kinds of problems. To address the information gap, we suggest considering citizen feelings as part of urban analysis.

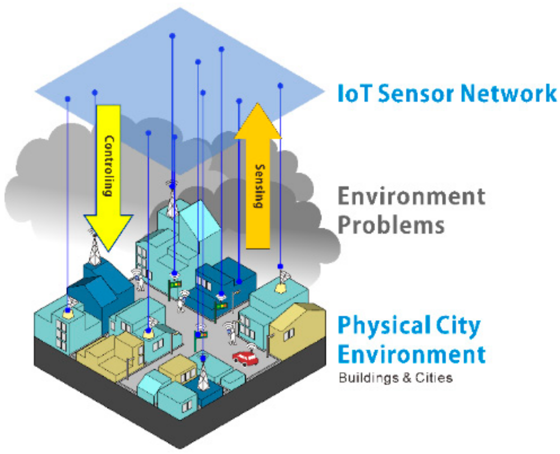


Figure 1. The information gap between the sensor network and citizen feelings. The IoT sensor network only senses the information type and where it is. The gap will appear in locations without sensors.

3.2. Unexpected Citizen Activities Cause by City Problems

The gap between sensor networks and citizen feelings can be understood by the way people who live in a city easily acquire their living-zone information (such as where the good restaurants are and which shopping mall is having a big sale), enabling citizens to come together in a short period of time. However, when people congregate in a zone unexpectedly, the space may not be able to accommodate that many people. Urban physical environments can be built according to the urban planning method, which references sensor networks. In contrast, information about unexpected citizen activity is incomplete, short-term, and not integrated with the urban physical environment. This information gap is likely to be because of environmental problems in the city and can lead to issues such as an increased spread of disease.

To solve this kind of problem, the information collected from the physical environment and social activities was analyzed and integrated (see Figure 2). After presuming and verifying the information, the relationship between social phenomena and the urban environment was inferred to exist, and then solutions for the social problems caused by the social phenomena were proposed. In this paper, we chose several districts for data collection and analysis to find the activity zones in a city.

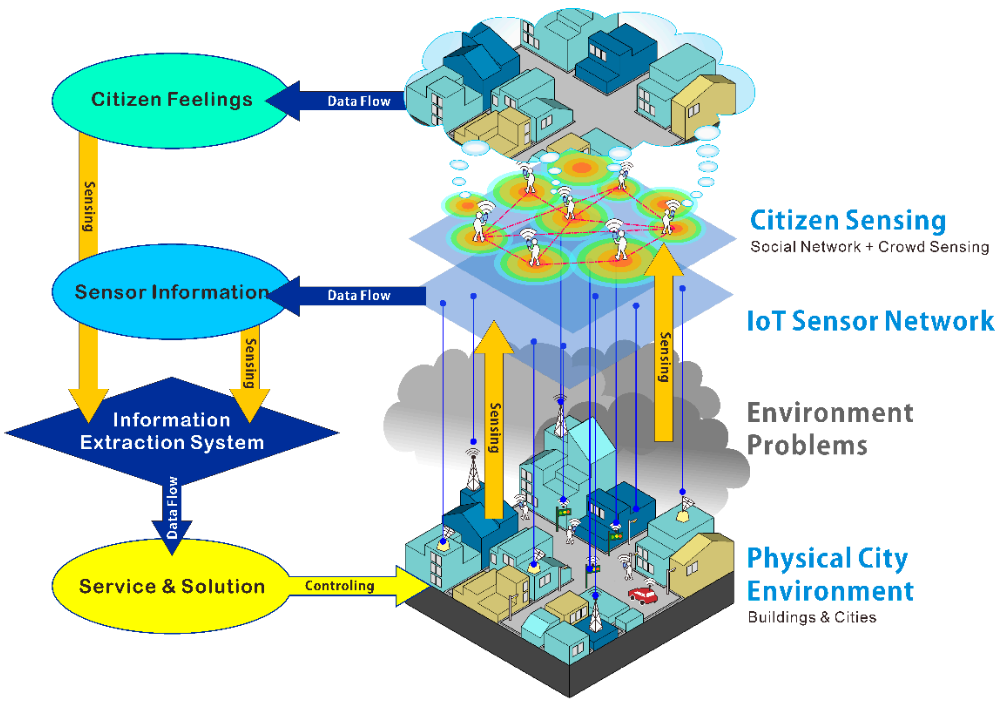


Figure 2. Importing the social-activity information layers to connect the gap between the information layer and physical environment layer in a city. Citizens are used as sensors to fill-in the gap between the physical environment and the sensor network.

4. Research Process

The purpose of collecting citizen feelings is to elucidate the effects of the city environment on social activity. The methods include putting the subjective commons together, quantifying them effectively, and developing a methodology that extracts social activity information from which a statistical analysis can be conducted. To derive information on social activities in a city, analyze the data, and solve problems in the urban environment, this research was conducted in three steps: (1) classification of city information using the data source, (2) data extraction by classification, and (3) utilization of an algorithm comprising social activity information and the city's environment data.

The first step is data classification. We sorted the information into two classifications: psychological and geographic. These two main types of information were extracted from citizen sensing and sensor networks. Psychological information about the city environment refers to the evaluation of citizens collected through the extraction system. The psychological information sensed by citizens was classified into three indexes of city environments: urbanization, traffic accessibility, and personal feelings. Geographic information refers to the coordinates of the marks where users check in on the extraction system. We combined psychological and geographic information to intensify the focus of citizen sensing. In the second step, data extraction was conducted by classification using questionnaires. Thus, citizen feelings were transformed into countable values. The citizens provided information about their location and feelings about the quality of local environments by grading the evaluation (using a range of levels). To analyze the obtained results as accurately as possible, website registration was open to anyone, and the users were invited through an SNS (e.g., Facebook). After data classification, the data were divided into three quality indexes to determine the characteristics of the environment. Then, the data were sorted according to the indexes in the third step, by using data algorithms to verify the accuracy of the indexes and the sensibility of the citizen feelings toward the environment (see Figure 3).

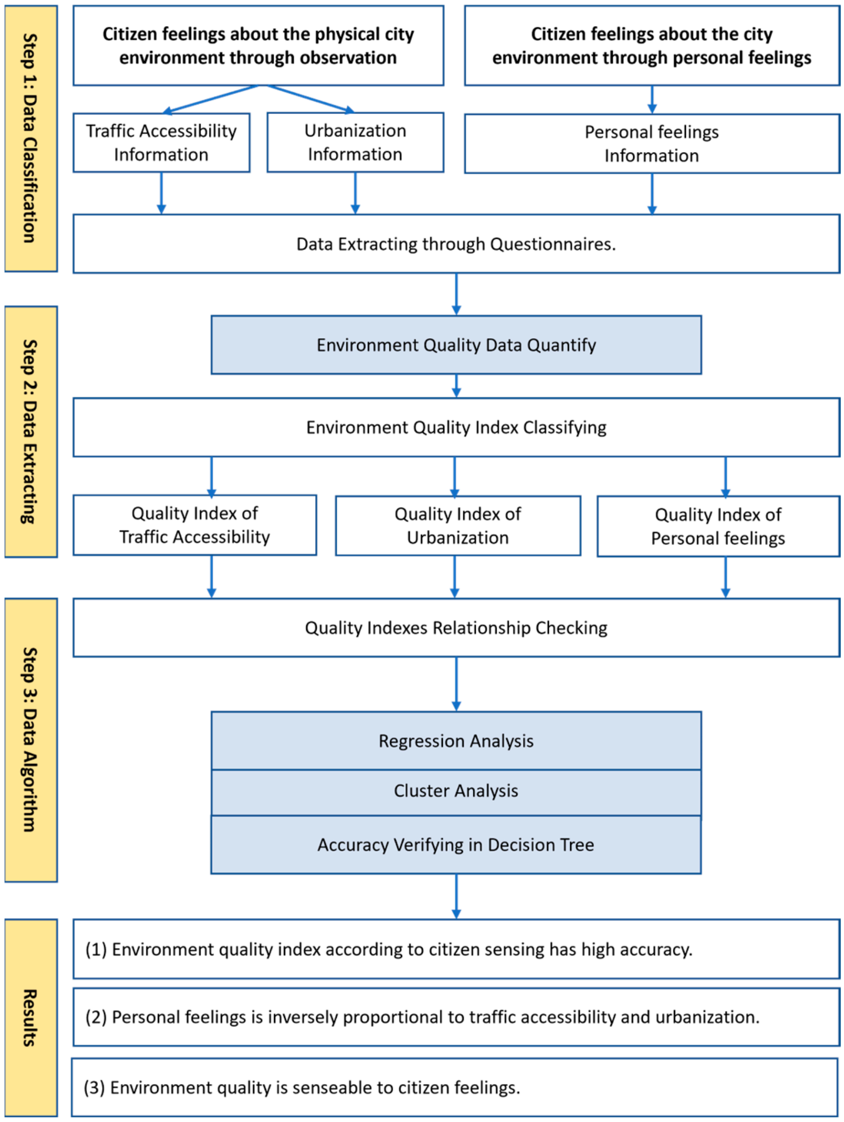


Figure 3. System flowchart of experiment. The data are extracted according to the information sources separately and are quantified into numbers for classifying and analyzing, to obtain the indexes of environment quality. The indexes are used for measuring environment quality.

4.1. Classification of City Information according to Data Source

City information can be classified as either physical environment information or social activity information. In urban planning, physical environment information includes the buildings, streets, infrastructure, and any hardware data. Hardware data include information regarding the coverage rate, plot ratio, road configuration, signal arrangement, and administrative area. This is confirmable at the city planning stage and makes up the city hardware plan. Most social activity information (referred to as "software") is derived from the activities of people in a city. Population, industrial structures, vehicle flow, electricity consumption, water consumption, and waste are examples of software information. Obtaining this type of information requires a sensor network and general investigation or any other data collection method. We can understand the effect of social activities due to environmental development by classifying this information into several layers and by analyzing them individually.

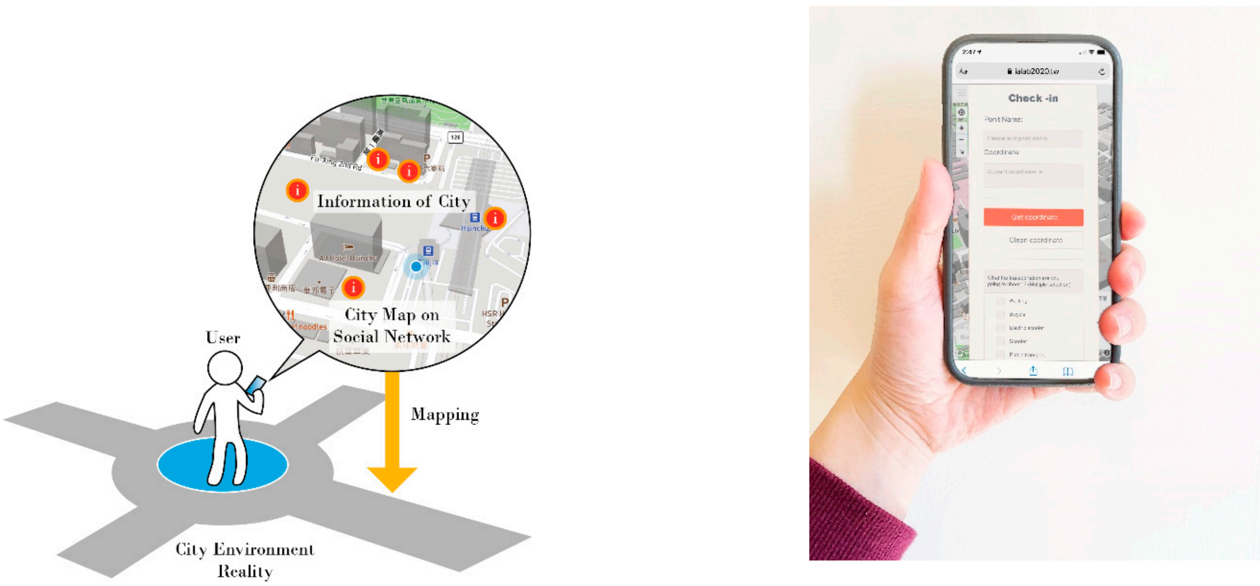
In the first step of data classification, the psychological information was sorted into three indexes: urbanization, traffic accessibility, and information about personal feelings. The urbanization index refers to information about an urban space. The traffic infrastructure index refers to the paths and the edge of an urban space. We combined these two indexes with citizens' personal feelings about the environment because the city sources were usually distributed according to the population density, which was determined during urban planning. If an urban planner decided to place some sources in certain places, but citizens do not agree with the policy or location, then the sources are wasted. However, feelings are complex and can change throughout the day. To elucidate the factors of urban phenomena, qualified feelings were sorted during data collection. Citizens sense the city environment through the buildings and streets. The questionnaires asked citizens about their views of buildings, streets, and infrastructure instead of about their views on urbanization or traffic accessibility. People may feel that a location is good because of the weather, the food, or other reasons that have nothing to do with the physical environment. Buildings and roads are designed in ways to guide users to have certain feelings toward their environment. Table 1 presents the classifications of citizen feelings into several categories. The value from citizen feelings was exported to the three selected classifications. The system collected the citizen feelings that were simpler and directed toward the environmental phenomena in the city, in the second step after data classification. For example, citizen feelings toward "urbanization" vary from person to person. Some people think that high levels of urbanization are good, while others think the opposite. Some people may consider high levels of urbanization to be good in a specific place, but, when the place or time changes, they may then think differently. Therefore, the questionnaires were designed to turn personal feelings into calculable data within the extraction system.

Table 1. Rules for classifying citizen feelings into calculable data. It shows the process of data quantification, because the data formats of environmental problems are totally different from one another.

Extraction Methodology		Data Classification		
		Urban Physical Environment Information	Citizen Feelings Information	
			Subjective	Objective
Sampling Area	(a) Global Environment	IoT Sensor Network	Few	Few
	(b) District	IoT Sensor Network	Interview or Questionnaire	Personal Device Sensing
	(c) Zone	Few	Interview or Questionnaire	Personal Device Sensing

4.2. Data Extraction by Classification

Data obtained from social activity information can be classified as objective or subjective information. Objective information describes the physical environment, such as how tall the buildings are or how many lanes the road has. We can also find this type of data in urban planning. Subjective information varies from person to person and includes feelings about the environment, opinions on urban problems, and the reason for choosing a district to settle down in. This kind of information cannot be collected directly using a sensor network; therefore, the citizens acted as sensors for data extraction. The description of the environment in our system was quantified for analysis. To quantify citizen feelings, we overlapped them on the physical environment, applying location check-ins and a questionnaire. By extracting citizens' feelings, quantifying them, and analyzing them, we determined the causes of city problems that are unable to be determined by sensor networks. In the next step of the experiment, the system collected the citizens' feelings about the urban phenomena according to data classification. (The data-extraction method was a system in which users checked-in on a website). The system collected information regarding citizen feelings using questionnaires and coordinated them when the citizens checked-in, as shown in Figures 4 and 5.



(a) (b)

Figure 4. Prototype display of the citizen-sensing system: (**a**) checking-in on the social network and obtaining current location information on a mobile device; (**b**) collecting citizen feelings through questionnaire after marking location coordinates.

4.2.1. Citizen Sensing by User Check-In

The extraction system used for citizen feelings was a website designed via a responsive web design (RWD) that could operate on a desktop, laptop, or mobile device. To indicate how the citizens felt about the quality of their location in the city, they only had to check-in and answer a questionnaire on the system. The system collected the coordinates and evaluations obtained from the users' check-in marks. The questionnaire was designed to describe the urban planning of a specific zone and to quantify it with countable levels. There were five levels to score how citizens felt regarding the quality of the environment (with zero being the lowest level, and four being the highest level: excellent). When describing a city's physical environment, the more infrastructure there is, the higher the score for the check-in is. In this way, we can acquire the scores of citizen feelings toward the environment as well as their location coordinates, at the same point in the raw data. In the next step, the hypothesis that traffic accessibility is related to the urbanization was verified, and users were asked about their feelings for both of these factors in the questionnaire through the algorithm.

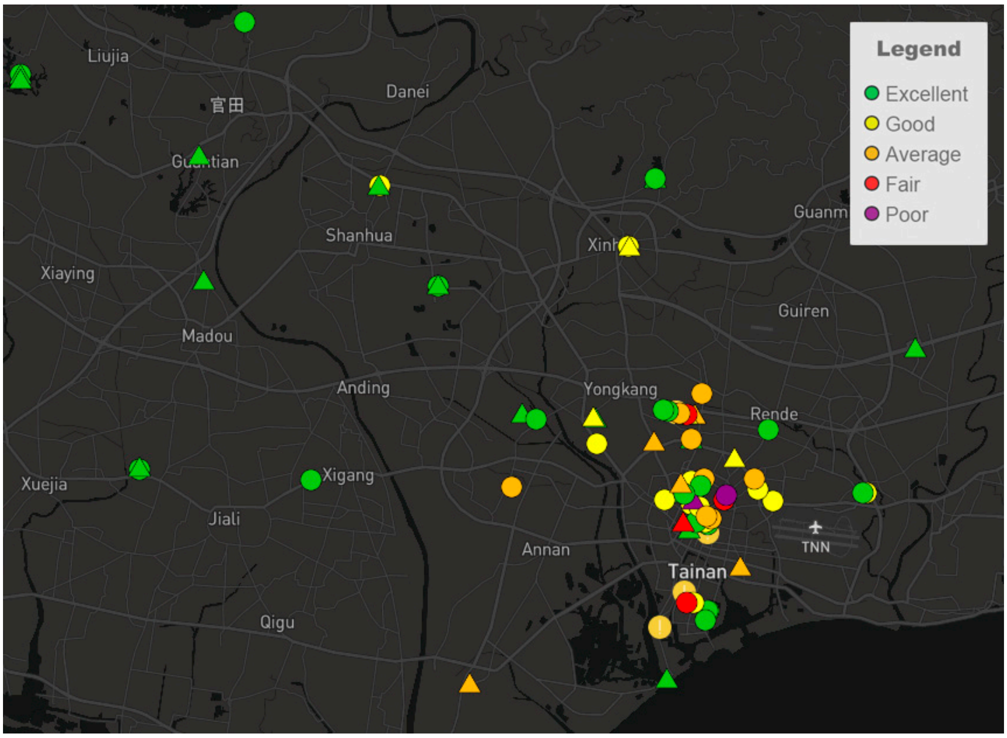


Figure 5. Check-in marks on the map on the website. The spots show how the users feel regarding the environment.

4.2.2. Quantifying Urban Spatial Data: Turning Citizens' Feelings into Values through the Questionnaire

According to *The Image of the City* (Lynch, 1960) [3], the elements of the urban spatial structure are classified as paths, edges, districts, nodes, and landmarks. We referenced this rule to classify the elements of the urban spatial structure, which enabled us to design the questionnaire and to sort the information obtained from the user check-ins. The raw data from the completed questionnaires was analyzed to build the urban appearance through citizens' feelings, according to the description of their locations. The questionnaire quizzes included several levels to rate the environment: traffic, buildings, and general feelings. For effective data analysis, the questionnaire was designed to quantify the descriptions of feelings about the environment. Several examples of questions taken from the questionnaire are shown in Table 2.

Traffic accessibility is an index of the urban spatial elements and is connected to the urban physical environment. In the experiment, we supposed that citizens' feelings about the urban environment change with the spatial construction and traffic. Accordingly, the questionnaire requested the bulk and traffic infrastructure details of the users' locations. We took the information from the questionnaire and compared it to the evaluation between the urban spatial construction and the citizens' feelings. Therefore, according to the quantification rules, the higher the traffic accessibility of a facility was, the higher the score it received. For example, for the transportation choices, bicycles received one point, scooters received two points, and public transport and motorized vehicles received three points. The users gave a score according to their feelings.

Table 2. Questionnaire used in extraction system to determine citizen feelings. This is the questionnaire implemented in the check-in system on the website. Each selection sends a number to the database. For example, in Q7, when the user feels better in the environment, the number is bigger. All of the numbers are integers.

No.	Please Provide the Traffic Detail of Your Mark	Options
Q1	What the transportation are you going to choose? (Multiple selection)	Walking/Bicycle/Electric scooter/Scooter/Public transport/Vehicle/Others____
Q2	Do you see any of the facilities as below at your location? (Multiple selection)	Sidewalks/Pedestrians signs/Barrier-free facilities/Bicycle lanes /Bike rental station/Scooters parking spaces/Electric scooters swap stations/Gas stations/Bus stations/MRT stations/Escalators/Car parking spaces/Others___ (Self-input)
Q3	How many lines is the street or road in? (Single selection)	Six-lane road/Four-lane road/Two-lane road/Single-lane road/One-way road/Unplanned road/Hard to determine
Q4	How convenient is it to move in the direction of your choice? (Single selection)	Quite convenient/Convenient/Acceptable/Inconvenient/Quite inconvenient
Q5	How do the buildings look like at your position? (Single selection)	Many tall buildings/Flat buildings/Less buildings/Others__ (Input description)
Q6	Is there any clearly landmark?	No/Yes (Input description)
Q7	How is your evaluation to this environment? (Single selection)	Excellent/Good/Average/Fair/Poor

Table 3 presents the functional server-side definitions for the seven questions given to users. Q1 refers to the traffic level selected by the user when checking in. Q2 to Q4 are descriptions of traffic accessibility, Q5 and Q6 are descriptions of urbanization, and Q7 examines the subjective feelings of the user. The system recorded the user number (ID), check-in time (Time), IP address (IP), and the position of the mark (Coordinate) when the users checked-in. Each mark annotated the location, time, identity, and value each user provided. We then analyzed the data of citizen feelings. According to the definition of a linear equation, if the single variable y has a linear relationship with variable x, then the function of y and x is:

$$y = ax + b \tag{1}$$

Table 3. Functional definitions of questionnaire answers. Briefly, the questionnaire answers are converted into algebra and functions.

No.	Description	Algebra	Function	Information Classification
Q1	Transportation Kind	c_0	$F(c)$	Personal Feelings/Selection
Q2	Traffic Facility	a_2	$T(a)$	Traffic Accessibility
Q3	Lines of Roads	a_3		Traffic Accessibility
Q4	Convenience	a_4		Traffic Accessibility
Q5	Buildings	e_5	$U(\mathrm{e})$	Urbanization
Q6	Landmarks	e_6		Urbanization
Q7	Environment	c_7	$F(c)$	Personal Feelings/Selection

The hypothesis of this experiment is that if an index of a city environment, for example, $F(c)$, has a linear relationship with citizen feelings, then the function of $F(c)$ is:

$$y = F(c),\ x = c_n F(c) = ac_n + b,\ a\ and\ b\ are\ constants \tag{2}$$

According to the check-in data acquired from the extraction system used to organize citizen feelings, the algebra and functions were set as seen below (Table 3). Besides the constitution of the citizen feeling functions, the relationship of the environment indexes is also verified by a linear equation.

There were seven questions included in the questionnaire, and Questions 1 and 7 concerned citizens' personal feelings about how and why they were in their present location. These questions were classified as personal feelings and selections with a functional codename of $F(c)$. Questions 2, 3, and 4 were about traffic construction in the location and had a functional codename of $T(a)$. Questions 5 and 6 were about the urban buildings in the location and had a functional codename of $U(\mathrm{e})$. Although the traffic construction and buildings are objective facts of the urban environment, we asked the users to confirm if construction was conspicuous enough for citizens to "sense" it in the environment. In this experiment, if the urban construction was not built obviously enough for citizens to sense it, then the levels of traffic accessibility and urbanization were low for citizens.

4.3. Data Algorithm of Check-In Information

We hypothesized that citizens have a sense of the environment by carrying out certain behavior patterns, as classified by the environmental quality index. After the check-in marks were obtained and quantified effectively, we used the data algorithm to verify our hypothesis. Since citizen feelings are different from the sensor network, the results of the problems cannot be exported directly. Three scenarios for the algorithm were drafted: (1) citizen feelings about the city environment are relevant to urbanization, (2) citizen evaluations of the environment have a positive (or negative) correlation with traffic accessibility, and (3) citizen feelings can be used to find the best location in a city. Urbanization and traffic accessibility are indexes of urban planning. Most urban spatial construction references traffic plans, and, in addition to the streets, the density of the buildings is a characteristic of urbanization. In the data-extraction step, citizens were asked about their feelings regarding the city environment, specifically how they felt about traffic accessibility and the buildings' density, to turn their subjective feelings into objective descriptions. Therefore, the relationship between urbanization, traffic accessibility, and citizen feelings was verified by our algorithm (e.g., a linear regression analysis, as detailed in Section 5). We also determined the optimized urban plan according to the citizens' feelings. For example, we reviewed whether the ideal location that was determined according to citizen feelings reflects the more (or less) urbanized areas within the city. In addition, we suggest optimizing the urban plan or using it as a reference when conducting mass-gathering activities in a city.

5. Implementation

Although the website is open to everyone, considering the regional differences in citizen feelings, the users were invited to participating using a specific language (Mandarin) and using the specific SNS that people Taiwan tend to use (Facebook) as the specific data source. Thus, until we started to analyze the data, there were 47 users registered in the system, and 147 check-in marks were received in total. All of the marks were located in Taiwan. Each mark was a sequence that included seven numbers, several texts, and one pair of coordinates. A seven-integer sequence was used to present user scores. Several of the text inputs were user comments about the locations. The one pair of coordinates was the latitude and longitude of the check-in mark's position. The coordinates were evidence of the seven-integer sequence and the comments pointing to the same position. We analyzed the dataset using algorithms to determine why citizens felt a certain way about the city environment and to check the accuracy of the indexes sorting the check-in marks, given the small-scale database.

5.1. Information Quantification for Analysis

We asked users to answer questionnaires when checking-in on the website. Citizens were invited to participate in a satisfaction survey using the website to determine the environmental quality. The answers were quantified according to three functions: $F(c)$, $T(a)$, and $U(e)$ (see Table 3), and their relevance and distribution were analyzed using an algorithm. Therefore, we obtained a seven-integer sequence of each check-in mark. The dataset is shown in Table 4.

Table 4. Cleaned dataset of questionnaire answers from check-in marks. Every answer was turned to an integer for comparison using a data-cleaning process.

Data SN	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	2	9	5	3	2	1	2
2	11	22	5	3	0	1	3
3	3	6	3	2	1	0	4
4	4	12	5	4	2	0	4
5	4	1	4	3	1	0	3

5.2. Citizen Feelings Data Classifying

To classify the marks using the questionnaire answers, statistics were used to count every score in each question to observe the dataset (see Figure 6). Since the values obtained in the questionnaires were different, the statistics chart is presented in percentages. If there were similar percentage distributions, those factors were determined to be relevant.

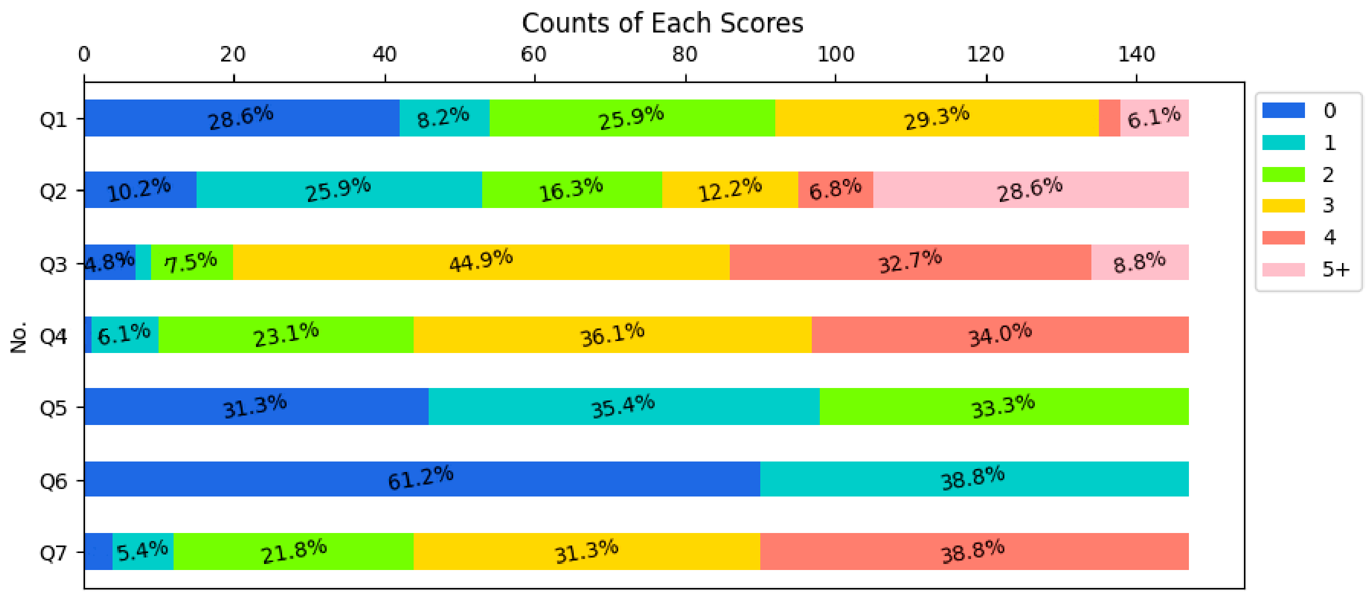


Figure 6. Statistics of each score count. The x-axis is the sum of the total numbers of check-in marks (total 147), and the y-axis lists the question numbers (from Q1 to Q7). The bars present the percentage of answers (from 0 to 5+). Since the maximum for each answer is not the same, this bar chart shows the statistics in percentages.

Figure 6 presents the statistics for Questions 1 to 7, for which each score ranges from 0 to 5+ (some questions had a score of more than 5, but in this chart, they were all grouped as 5+). According to this statistic, as a rough overview, the percentage distributions of Q1 and Q5 were determined to be similar: one-third of each score. The percentage distribution for Q1 shows that the users' choices of transportation were average and demonstrated no explicit factors in the city environment. Furthermore, the percentage distribution of Q1 shows that Q1 had no explicit factor with Q2 to Q4, meaning that Q1 had a low relevance to traffic accessibility. Users chose the transportation, to target the location, according to their free intentions and not according to the physical infrastructure. Therefore, the function of personal feelings, $F(c)$, was able to be determined two ways using the algorithms (see Table 3 for algebra codename definitions):

$$F_0(c) = c_7 \tag{3}$$

$$F_T(c) = c_1 + c_7 \tag{4}$$

The functions of traffic accessibility and urbanization, $T(a)$, and $U(\mathrm{e})$, were:

$$T(a) = a_2 + a_3 + a_4 \tag{5}$$

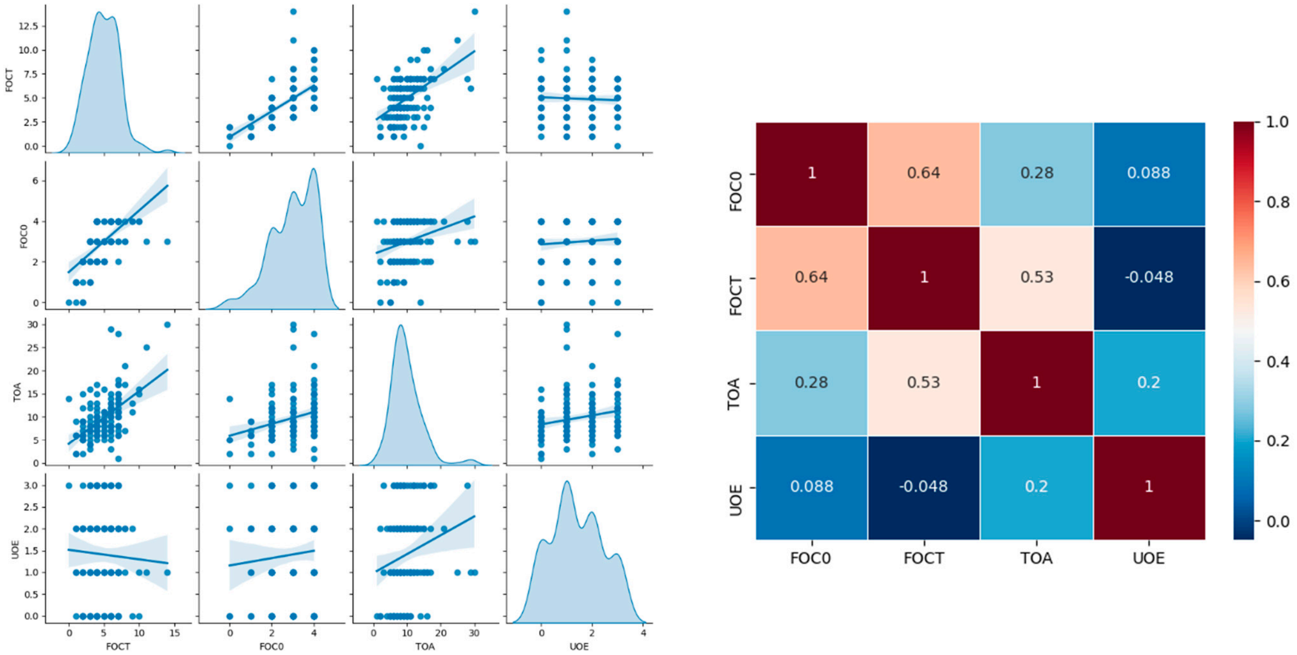
$$U(\mathrm{e}) = e_5 + e_6 \tag{6}$$

In the third stage of the experiment, we used three algorithm scenarios to analyze the data obtained from citizen feelings through the three indexes—$F(c)$, $T(a)$, and $U(\mathrm{e})$—to verify the relevance between the three types of citizen feelings and the urban environment.

5.3. Regression Analysis between Personal Feelings, Traffic Accessibility, and Urbanization

In the first scenario of the algorithm, we used regression analysis to verify the hypothesis that citizens' personal feelings about the urban environment are correlated with the physical construction, by again comparing the linear relevance of the citizens' feelings indexes—$F_0(c)$, $F_T(c)$, $T(a)$, and $U(e)$—using a pair plot (see Figure 7a). Through the pair plot, we found that $F_0(c)$ and $F_T(c)$ also had a linear relevance to $T(a)$ and $U(e)$. The oblique line (fitted by four functions in the pair plot) illustrates the linear relevance between them. The linear relevance in this pair plot can be seen more clearly than that of the questionnaire answers (see Figure 7a). However, the evidence is not sufficient to confirm the functional relationship via a pair plot comparison alone, because four functions—$F_0(c)$, $F_T(c)$, $T(a)$, and $U(e)$—have to be compared. The current linear regression only compares two of them simultaneously. In addition, the values of the dataset were integers in fixed ranges, so regardless of the calculation being compared, the difference will be in integers; therefore, we applied Pearson correlation algorithms to obtain a more specific comparison (Figure 7b). The Pearson correlation is used to compare the alternative relationship between two functions when the difference is between 1 and 0. We took the differences in the Pearson correlation as the percentage of relevance (1 = 100%), where a higher percentage meant a higher relevance between the two functions. In the Pearson correlation, the relational value r is the contrast between two different values with a unified standardization. The reference values of r in the Pearson correlation are $r < 0.3$ for a low correlation, $0.3 \leq r < 0.7$ for a medium correlation, and $r \geq 0.7$ for a high correlation. In Figure 7b, for the function of citizens' personal feelings regarding traffic selection—$F_T(c)$—the r to $T(a)$ was 0.53, which is the highest correlation in this algorithm. The r between the traffic accessibility function $T(a)$ and urbanization $U(e)$ was 0.2, which shows that the linear relevance between $T(a)$ and $U(e)$ was low and had a negligible relevance. The function $F_0(c)$, which represents the pure personal feelings of citizens about the urban environment, had a correlation of r = 0.28 with the function of traffic accessibility $T(a)$, which is even higher than the correlation between $T(a)$ and $U(e)$. However, the r between $F_0(c)$ and $U(e)$ was only 0.088, revealing a very low relevance between the two functions. According to the Pearson correlation comparison, users' feelings about the environment (either positive or negative) are not dependent on urbanization and are only slightly related to traffic accessibility.

To avoid confusion during programming, the labels in the chart are displayed as $FOC0 = F_0(c)$; $FOCT = F_T(c)$; $TOA = T(a)$; and $UOE = U(\mathrm{e})$.



(**a**) (**b**)

Figure 7. Regression analysis between personal feelings, traffic accessibility, and urbanization: (**a**) pair plot of citizen feelings in valuable functions; (**b**) heatmap of citizen feeling indexes of Pearson correlation. The heatmap turns the pair plot into quantified values for more accurate comparison. The correlation value is between 0 and 1. When the value is bigger, the correlation between the two functions is higher.

5.4. Defining Environmental Quality Indexes through Cluster Analysis

To define the environmental quality indexes, we conducted a linear correlation analysis of the values obtained from the questionnaires in the system. If citizens are able to sense the urban environment and respond to the information in the system, we can determine the quality of the urban environment objectively using citizen feelings. The variation influencing citizens' personal feelings to the environment $F(c)$ is still $T(a)$ and $U(\mathrm{e})$ in this step of the algorithm. Therefore, there are at least four relative relevancies for $F(c)$ between $T(a)$ and $U(\mathrm{e})$:

$F(c)$ is proportional to $T(a)$ and $U(\mathrm{e})$;
$F(c)$ is proportional to $T(a)$ and inversely proportional to $U(\mathrm{e})$;
$F(c)$ is inversely proportional to $T(a)$ and proportional to $U(\mathrm{e})$;
$F(c)$ is inversely proportional to $T(a)$ and $U(\mathrm{e})$.

To classify the four relative relevancies, we defined the class IDs from 4 to 1 according to their correlation. The class IDs are defined in Table 5.

Table 5. Class ID definitions of check-in marks. This table presents the definitions of the class IDs of the check-in marks. The check-in marks are classified into four types to define the variation between $F(c)$, $T(a)$, and $U(\mathrm{e})$.

	$\boldsymbol{T(a)}$	$\boldsymbol{U(\mathrm{e})}$	**Class ID**
$F(c)$	+	+	4
	+	−	3
	−	+	2
	−	−	1

Symbols: proportional: +; inversely proportional: −.

Since the dataset for each check-in mark was a seven-integer sequence, we transformed the functions $F(c)$, $T(a)$, and $U(\mathrm{e})$ in the algorithm analysis into percentages:

$$F_T(c) = (Q_1 + Q_7)/15 \tag{7}$$

$$T(a) = (Q_2 + Q_3 + Q_4)/31 \tag{8}$$

$$U(\mathrm{e}) = (Q_5 + Q_6)/3 \tag{9}$$

The denominators 15, 31, and 3 are the maximum values of the sums of the questionnaire evaluations. In this calculation, we only took $F_T(c)$ as the citizens' personal feelings and did not include $F_0(c)$ because $F_T(c)$ contains personal feelings about both traffic accessibility and the physical environment. The denominator of each formula is the maximum of the scores from each question. In this way, the functions $F(c)$, $T(a)$, and $U(\mathrm{e})$ were converted into a percentage between 0% and 100% and were able to be compared. Therefore, the check-in marks in the class ID were sorted according to their definition, using the following data-classifying equation:

$$\text{Define class ID} = i \tag{10}$$

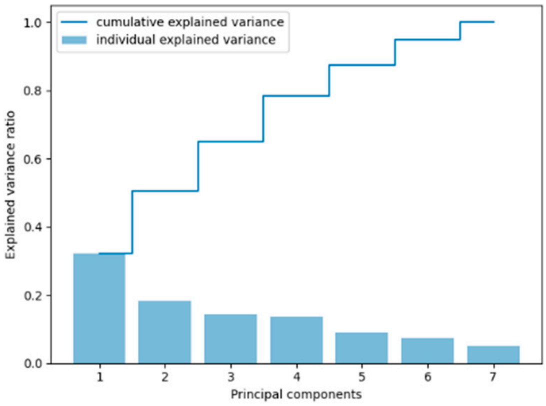
$$\text{if } F_T(c) - T(a) \geq 0 \text{ and } F_T(c) - U(\mathrm{e}) \geq 0,\ \mathrm{i} = 4 \tag{11}$$

$$\text{if } F_T(c) - T(a) \geq 0 \text{ and } F_T(c) - U(\mathrm{e}) < 0,\ i = 3 \tag{12}$$

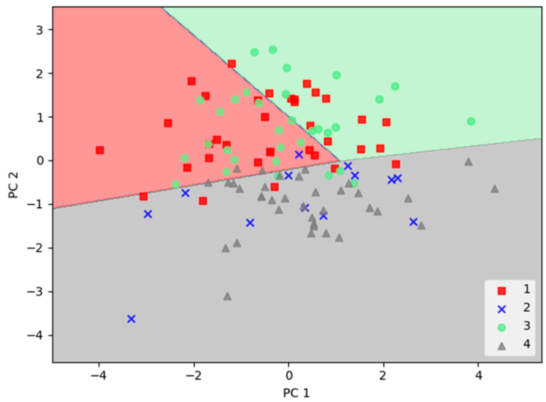
$$\text{if } F_T(c) - T(a) < 0 \text{ and } F_T(c) - U(\mathrm{e}) \geq 0,\ \mathrm{i} = 2 \tag{13}$$

$$\text{if } F_T(c) - T(a) < 0 \text{ and } F_T(c) - U(\mathrm{e}) < 0,\ \mathrm{i} = 1 \tag{14}$$

We defined the index functions $F(c)$, $T(a)$, and $U(\mathrm{e})$ as percentages between 0% and 100% as follows: $F(c) = 100\%$ (meaning that the environment is "very good"); $T(a) = 100\%$ (traffic accessibility is "high"); $U(\mathrm{e}) = 100\%$ (urbanization is "high"). The functions "$F_T(c) - T(a) \geq 0$" and "$F_T(c) - U(\mathrm{e}) \geq 0$" mean "The citizen feeling is better/higher than traffic accessibility and urbanization". Thus, the four possible situations were defined into four class IDs, as shown in Table 5. Through the classifying equation for the class IDs, each check-in mark obtained from the extracted data was assigned a class ID. We calculated the eigenvalues of the check-in marks and conducted a principal component analysis (PCA) to verify whether each class ID had been classified effectively. The PCA results are shown in Figure 8a,b. The principal component shows the regular pattern of the dataset. The factors of citizen feelings about the city environment are complicated; therefore, we supposed that the index factors have a relationship with traffic accessibility and urbanization and, thus, classified the check-in marks according to the indexes. A PCA was used to confirm the classification. If the classification does not result in a correct dataset, then the explained variance ratio of the principal component will not be high enough. The PCA results show that the principal components of the dataset (according to the classification) are representative and have a resolution, as shown in Figure 8. Figure 8a is a draft of the explained variance ratio of each principal component, where PC1 is 0.36 (36%) and PC2 is 0.19 (19%) for all of the principal components in this dataset. PC1 and PC2 include nearly 55% of all of the components, so we considered them to be sufficiently representative for definition. Figure 8b is a scatter plot of all of the check-in marks of the two principal components (PC1 and PC2) and includes a decision distribution map of the component plot. The symbols from 1 to 4 represent the class IDs that we previously classified, and the decision distribution map clearly divides the class IDs into pairs: 4 and 2; 1 and 3. According to the definition of the class ID (Table 5), ID 4 indicates that the percentage of $F_T(c)$ is stronger than the percentages of $T(a)$ and $U(\mathrm{e})$, while ID 2 indicates that the percentage of $F_T(c)$ is stronger than the percentage of $U(\mathrm{e})$ but weaker than the percentage of $T(a)$. IDs 4 and 2 were sorted into the near area, which shows that citizens feel that an environment is good when there are lower levels of traffic and construction in an urban location. This inference can also logically explain why IDs 3 and 1 were sorted into the near area. In this experiment, we concluded that people are more likely to feel comfortable in urbanized environment areas with low traffic. High urbanization usually means high traffic accessibility, which means that a high $T(a)$ results in a high $U(e)$, and our users usually did not like such locations.



(**a**)



(**b**)

Figure 8. Data classification according to the environmental quality indexes determined according to PCA: (**a**) explained variance ratio of each principal component. This statistical chart presents the proportions of principal component PC1 and PC2 to certify that they are effective. If the proportion of the sum of PC1 and PC2 is lower than 0.3 (30%), then the principal component cannot certify that the classification is accurate; (**b**) decision-distribution map of component scatter plot. This scatter plot presents the check-in marks distributed according to the four class IDs on the 2D vector graphs constituted by PC1 and PC2. If the classification is accurate, then the scatter points should come together under the same class ID. This plot presents the classification output of at least three effective blocks on the PC1–PC2 graphics.

5.5. Accuracy Verifying Environmental Quality Indexes through Decision Tree

In the third scenario, we verified the accuracy of the environmental quality indexes using decision tree analysis. The dataset was divided into two variables ("Q1–Q7" and "Class ID") to split the data for training and testing. Then, we built a decision tree model using Scikit-learn. The decision trees show the sorting method of the class ID in the internal nodes. The sorting methods for the decision trees represent the most ideal path to classify each class ID. Decision tree analysis is a method for checking classification accuracy. In Figures 9 and 10, the starting root nodes are Q5, "How do the buildings look at your position?", which shows that Q5 is an index for the determination of this classification. Two criteria to carry out classification in Scikit-learn are Gini and entropy. Figure 9 is a visualization of a decision tree with the Gini criterion for classification, and the highest classification rate is 72.73%, which is quite accurate. Figure 10 is a visualization of a decision tree with the entropy classification criterion, for which the classification rate is 61.36%, which is still high. The method of the data splitter in both trees is "best". Another splitter is "random". Since the quantity of the dataset was less than 1000 until we started the algorithm, the random splitter was not selected in this experiment. Since the sampling data were random, the classifying rates were not all the same. We trained the decision tree several times, as shown in Table 6, and all of the classification rates are higher than 60%, with the highest value obtained being 72.73% and the highest entropy rate being 68.82% for the Gini index. Training the decision tree verified the hypothesis that how citizens feel about the urban environment is recognizable and extractable by this system.

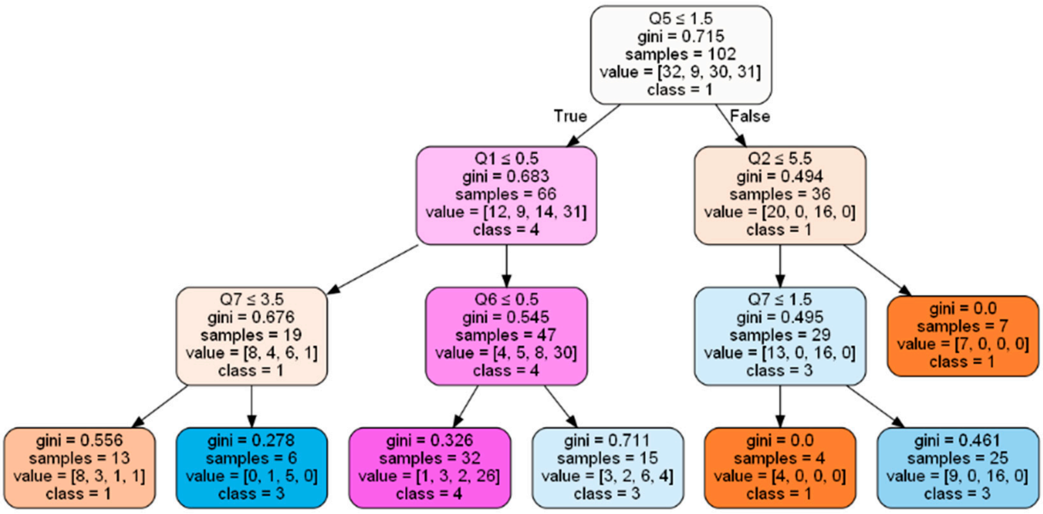


Figure 9. Decision tree of sorting class IDs in Gini criterion (depth = 3).

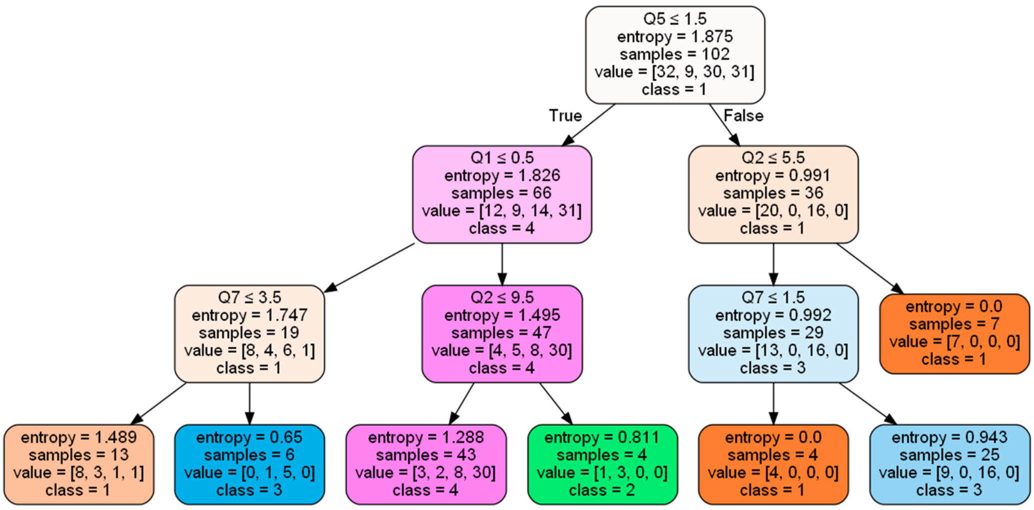


Figure 10. Decision tree of sorting class IDs in entropy criterion (depth = 3). Figures 9 and 10 are two methods to decide nodes of the decision tree. The decision tree may be overfitting when the amount of data is too small. To obtain a higher accuracy, two splitting methods are carried out. The result of the decision tree shows that two sorting methods have high accuracy (higher than 60%).

Table 6. Accuracy of the classification rate of the two criterion methods.

Criterion	Classifying Rate					
Gini Index	72.73%	70.45%	68.19%	65.91%	65.91%	70.45%
Entropy	61.36%	63.64%	63.64%	63.64%	65.91%	68.82%

6. Conclusions

In this paper, we implemented a system that could extract information from citizen feelings in order to collect information corresponding to the quality of the urban environment. The results of this practice show that citizens sense, feel, and share information in an objective way. We discovered that people tend to feel more comfortable in areas with lower levels of urbanization and in areas with low traffic accessibility. According to this data-extraction system, three indexes can be used to determine how citizens feel about the environmental quality of a city. This experiment proved that personal feelings toward city environments are inversely proportional to traffic accessibility and urbanization. Regardless of urban planning and development, people still prefer locations with low levels of development. This may mean that the volume of urban construction should be controlled or equally distributed to increase citizen satisfaction. Although only 147 check-in marks could be observed on the map, the algorithms, data regression, clustering, and decision tree analysis were still able to classify them effectively. The results show that algorithms can be applied to process small amounts of data. Therefore, we can also analyze urban data obtained over a short period of time or from a small area via citizen sensing and clustering algorithms. There are significant differences between the methodology used in this experiment and previous urban analysis studies. In addition, this methodology is also suitable for small, high-density cities. Increases in the population mean that urbanization is certain, though urbanization and traffic loads put pressure on citizens. Extracting information through a citizen-sensing system without a social network allows for adaptation of the city environment, representing a long-term process that does not require any extra cost. It is a sustainable method to help urban development. We suggest that urban planners use our tool to attend to the feelings of citizens while pursuing urban development strategies. While allowing for reflections on citizen feelings, sensor networks cannot sense phenomena with lower data requirements, representing another advantage of citizen sensing. This prototype extraction system can be extended for use in other aspects of urban planning. Emotionally, it is also good to involve citizens in urban development, considering that the feelings of citizens enrich urbanization. When we have more information, urban planning can be better supported. A reasonable allocation of urban construction is better than comprehensive construction.

In the post-COVID-19 era, finding a new lifestyle is an important issue in the field of urban planning. In past urban-planning strategies, the feelings of citizens have rarely been considered. As a result of this experiment, if citizens "feel good" about a location, it means that the location is "sparsely populated", as urbanization causes crowded and low-quality environments. Urbanization is helpful for human progress and should not be repressed, even in the post-COVID-19 era. In this context, algorithms represent effective methods for transforming subjective opinions into objective phenomena. In the upcoming era, urban planners may investigate new design requirements for balancing urban growth and for increasing the population in urban areas. Urban planners can, thus, consider the feelings of citizens as a factor of urban development. This goal can be implemented through training an algorithm-based social media system that "learns" how citizens feel by means of citizen sensing and data analysis.

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