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Measuring the Instantaneous Changes in the Quality of Urban Spaces Based on Big Data Analysis: Case Study of Pakington Street in Australia*

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ABSTRACT

Expansion of digital technologies and wide social networks has caused a change in the understanding of spatial experience. It has also caused a flow of extensive information from the citizens' viewpoints about their experience of urban spaces. Thus, moving towards modern analyses based on big data can cause a paradigm shift in the methods of measuring the quality of urban spaces. In big data analysis, the search process to reveal hidden patterns and unknown correlations can be used for next decisions. Moreover, due to instantaneous changes in various criteria of urban spaces, they are nowadays considered as a dynamic entity. For this reason, their measurement and evaluation should also be presented in the form of methods that can respond to these instantaneous changes. The present study aims to provide a flexible and dynamic method to measure the quality of Pakington Street in Australia as an example of urban spaces based on big data analysis. This measurement has been used due to changes in the urban space in the short term. The main method used in this study is to use the Kalman algorithm model to obtain the moving average graph of the quality of spaces based on the time variable and the rate of the indicators based on the data obtained from the citizens' participation in the Place Score program. After analyzing the big data for the five indicators of the quality of the urban space, it was found that in Pakington Street, the average rate of the two indicators of view and function and uniqueness in the short term is stable, and from the users' viewpoint, the average of the three indicators of safety, things to do, and care of the space varies in the short term of a day and night.

Keywords: Measuring the Quality of Urban Spaces, Smart Tools, Place Score, Big Data.

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1. INTRODUCTION

The quality of urban spaces is one of the important criteria for measuring the desirability of cities (Rafeian et al. 2012, 35). Measurement of the quality of urban spaces, if done comprehensively and correctly, will lead to the creation of sustainable places. In other words, the comprehensive recognition of economic, social and environmental components and their interrelation provides the necessary conditions for guiding urban spaces in the framework of sustainable development model. In this method, the quality of public spaces, which has been widely used in most studies, is evaluated and the quality criteria and components related to the space and finally to measure these components are explained by averages of classical tools such as questionnaires, field visits, etc. An important question raised here is whether these classic methods are responsive in measuring the quality of urban spaces in line with the speed of changes in spaces due to technological advances?

The speed of information exchange, digital communication and easy access to resources that have spread to different aspects of urban life have brought a new type of communication to the area of collective and individual human life (Çukurçayır 2010, 7-12). Due to the expansion of technologies and digital communication in recent years, instantaneous understandings of spatial experience have highlighted weakness of these old methods in spatial analysis. Nowadays, the classic methods of urban design in measuring the state of urban spaces are no longer responsive and consistent with the speed of changes in spaces due to technological advances. The methods of measuring and evaluating the quality of public spaces require fundamental changes and orientation towards information technology and computer science disciplines (Graham and Marvin 2002, 52-19).

With a critical look at the comparison of classic methods and modern methods of measuring the quality of urban spaces, these methods can be evaluated in the two areas of participation and statistical analysis. One of the most important changes that have emerged in the light of technology in the quality of urban spaces is related to participatory areas of citizens in evaluating the quality of spaces. Vast databases of citizens' spatial experiences have led to serious changes in research methods due to the presence of new technologies (Herk et al. 2011). In urban design, the necessity of expanding public opinions on one hand and the need for analyzes in the era of rapid urban changes on the other hand make the use of smart tools in the participatory design necessary.

There are two important differences between the classic methods of measuring the qualities of urban spaces and the modern methods based on big data in the area of statistical analysis. First, in modern methods, due to the large statistical population and the use of mathematical and data mining methods, it is much more possible to discover hidden patterns and unknown correlations, and second, in modern methods, due to receiving data in real time and the possibility of analyzing them simultaneously, it is possible to measure urban spaces in real time. In other words, the effect of intervening factors can be measured instantaneously. Thus, the effect of changes on different qualities can be evaluated in real time. However, it should be noted that in both classical and modern technologies, designers should use their creativity to predict and plan urban spaces that are formed under a participatory process and in a collective context (Ben and Joseph 2011, 277-290). In general, it seems that the desirable future of urban spaces can be created if the three components of people, place and technology are properly and creatively and skillfully integrated (Foth and Marcus 2017, 32). Thus, digital technologies are new ways to deal with the shortcomings of classical participatory processes in measuring and evaluating the quality of urban spaces. Thus, in the urban planning and design, social media and digital tools can be considered as a valid complement to participatory processes to gain insight and facilitate the study of the perceptions, opinions and needs of local communities (Tisma, van der Velde, and Rene 2016). In this regard, the present study aims to provide a flexible and dynamic method to measure the quality of urban spaces based on big data analysis.

Table 1. Comparison of Classical and Modern Methods in Measuring the Quality of Urban Spaces

	Classical Methods of Measuring the Quality of Urban Spaces	Modern Methods of Measuring the Quality of Urban Spaces
The Level of Way of Participation	The concept of participation in primary levels	Active participation of citizens
	Limited statistical population	Receiving a large volume of participation-oriented data
	Has space-time limitations	Removal of space-time limitations
Quality of Statistical Analysis	Weakness in more accurate and deeper detection and measurement of the space due to the limitation of the statistical population	Discovering hidden patterns and unknown correlations due to high statistical population and new mathematical analytical methods
	Impossibility of simultaneous and instantaneous measurement of space due to space-time limitation in receiving data	The capability to instantaneous measurement of spaces using digital tools due to the absence of space-time limitations in receiving data.

2. RSEEARCH BACKGROUND

Using a structured text review, we extracted a large number of studies on topics such as data analysis in smart cities, big data, open data, big data analysis in the city, measuring the quality of urban spaces, and digital tools in smart cities. Since this review focuses on the analysis of big data sources and smart city open data, we limited our search to this topic. In this regard, by searching for relevant words in Google Scholar, Inspire, ScienceDirect and Scopus databases, we first selected 250 recent articles based on their titles and abstracts and filtered these articles by reviewing their abstracts. Finally, 31 articles were selected and the following table was prepared by reviewing the data sources used in them and the methods and analyses applied. According to Table 2 and reviewing past experiences in the area of big data analysis, the methods and sources of each article were reviewed. In general, big data sources include four categories of data, including:

- Sensors and Internet of Things tools such as: sensors for receiving traffic data, environmental data, etc.
- Virtual and social networks such as: data obtained from Twitter, Instagram, and Facebook
- Urban applications such as: place meter, place standard, walk score, place score and...
-GIS and remote images such as: Google street map images, big data from GIS information layers and...

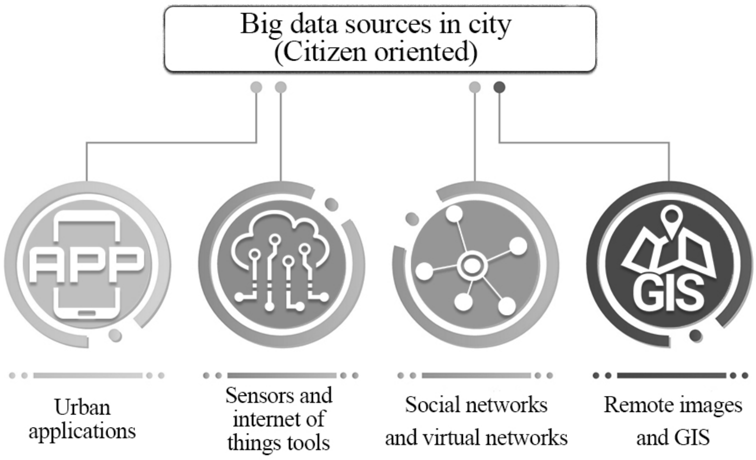

Fig. 1. Classification of Big Data Sources

Table 2. Classification of Studies Conducted in the Area of Big Data Analysis in the City Based on Data Sources

Studies	Data Sources
- Sensor Fusion for Public Space Utilization Monitoring in a Smart City - Role of Big Data and Analytics in Smart Cities - Smart Urban Planning using Big Data Analytics to contend with the Interoperability in Internet of Things - Real Time Analysis of Sensor Data for the Internet of Things by means of Clustering and Event Processing - Quality of Life Palava Smart City:A Case Study - IoT-Based Smart City Development using Big Data Analytical Approach - Real-Time Smart Traffic Management System for Smart Cities by Using Internet of Things and Big Data - Urban Planning and Smart City Decision Management Empowered by Real-Time Data Processing Using Big Data Analytics	Sensors and IOT
- Real-Time Detection of Traffic From Twitter Stream Analysis - Crowdsourcing based Description of Urban Emergency Events using Social Media Big Data - CITYPULSE: A Platform Prototype for Smart City Social Data Mining - Using social media to enhance citizen engagement with local government:Twitter or Facebook? - Activity patterns, socioeconomic status and urban spatial structure:what can social media data tell us? - Real-Time Detection of Traffic From Twitter Stream Analysis - Using Twitter data in urban green space research - Understanding social media data for disaster management - Crowdsourcing functions of the living city from Twitter and Foursquare data - What Your Instagram Feed Has in Common With a Ballot Box	Virtual and Social Networks

Studies	Data Sources
- How Was The Townsville Liveability Study Conducted? - Digital Tools as a Means to Foster Inclusive, Data-informed Urban Planning - Hush City.A new mobile application to crowdsource and assess"everyday quiet areas" in cities. - WeSense: Social Sensing the Quality of Urban Environments - Rating the walkability of cities: a participatory approach - Preliminary Research Project - Active Citizens And Reactive Spaces: How Urban Design Changes With Digital Technologies - James Street Engagement - SpotGarbage: smartphone app to detect garbage using deep learning	Urban Applications
- 'Big data' for pedestrian volume: Exploring the use of Google Street View images for pedestrian counts - OpenStreetMap: User-Generated Street Maps - Automatic Sky View Factor Estimation from Street View Photographs-A Big Data Approach - 'Big Data':Pedestrian Volume Using Google Street View Images - Big Data GIS Analytics towards Efficient Waste Management in Stockholm	GIS and Remote Images

3. THEORETICAL FOUNDATIONS

The continuous expansion of digital technology has resulted in an intellectual paradigm in urban design and planning based on "information input" and networked communication technologies.

Varnelis & Kazys calls this phenomenon "cultural network" (Varnelis and Kazys 2012). In a cultural pattern that operates in the economy, society, public life and at the individual level, everything and everyone are interdependent. Digital technologies are at the heart of these developments. They improve the flow of communication and information and distribute and share data through media and the Internet (Ibid).

Citizens in smart cities are increasingly looking for media. Rich services offered in different media spaces can provide the conditions for citizens' active participation and interaction. Social networks promise to strengthen such participation and interaction, and accordingly, they strengthen participation in cities. However, to have information about the way citizens think, act and talk about their city, it is important to for smart cities to understand their opinions and thoughts about the issues related to their city. Thus, the analysis of citizens' feelings and spatial experience can play a major role. Social media information poses the significant big data challenges (especially for analyzing unstructured data streams), so it will be important to find effective methods for quantitative and qualitative analysis of these data (Psomakelis et al. 2016).

Also, citizens create a constant flow of data within cities using digital tools in the cities. They generate digital information about their activities in the city using applications such as Twitter and Facebook or other programs, which have the potential to provide valuable insights for urban planners. Thus, we can state that the main components required for a smart city program are:

- Abundant sources of data
- Infrastructures, networks, interfaces and architectures
- A wide range of Big Data technologies that support the processing of large volumes of data.
- Sufficient and extensive knowledge of algorithms and toolboxes that can be used to derive effective analyses from big data (Kumar, Prakash, and Anand 2014, 23-12).

Thus, the flow of data produced by citizens from their spatial experiences can be used as a source of big data and open data for accurate spatial analysis to measure the quality of urban spaces. By using big data, it is possible to show hidden correlations beyond the reach of traditional methods to identify correlations between variables, and turn such information into new knowledge, and measure and evaluate urban design and development with qualitative and quantitative analysis. The term "big data" is used to describe a huge volume of structured and unstructured data that is very large and complex and difficult to manage and process using traditional databases and software tools. According to Gartner, "big data" are high-volume, high-speed, and variable assets that require a lot of innovation to process information for advanced analysis and decision-making (Kumar, Prakash, and Anand 2014, 12-23).

Big data analysis is the search process to reveal hidden patterns, unknown correlations and other important information that can be used for further decision making. Big data analysis is made possible by advanced techniques such as prediction modeling, text analysis, machine learning, statistical prediction and analysis, image processing, etc. This helps to identify trends, weaknesses or determine the conditions for better and faster decision making about the future (Kumar, Prakash, and Anand 2014, 12-23) The big data sources can be divided into three categories, including structured, semi-structured and unstructured. In this study conducted to measure the quality of urban spaces using smart tools, urban applications, due to the purposeful and structured nature of their database, they were are used as sources of analysis and receiving data.

4. METHODOLOGY

The present study was an attempt to provide methods to measure the quality of the urban space of Pakington Street, Australia, using smart data and mathematical and statistical methods. In this regard, owing to the presence of the time variable in the database as a dynamic variable, we are trying to provide a method that can measure the changes in the rate of the space indicators from the users' viewpoint in dynamically and instantaneously. Thus, the use of the Kalman filter algorithm to obtain the moving average graph of changes in the quality of indicators from the space users' viewpoint was considered as the main method of plotting the graphs. To present the Kalman algorithm model and the output of the moving average graph of the quality of spaces, two variables as main variables and other variables as sub-branches are needed. Thus, the variables in the received data were examined and the time variable for comment registration (t) along with the rate of the indicators was placed as the main axes of the graph and the rest of the variables were included as sub-branches in quality measurement.

For optimal use of the received database, first the raw data should be separated by precise filters and the outliers (information noises) must be removed. The data preparation for the implementation of computational models was done by two methods of determining the correlation coefficient (R-squared) to detect the level of affectability of variables on each other and Smoothing algorithm was used to control the effect of outliers. Using the R-squared correlation coefficient, the level of effect of the time variable on the rate of the indicators is measured in a short term, and the indicators that have the highest level of affectability are selected as the target indicators and enter the next stage. Indicators that have a weak correlation coefficient during the short-term are not included in the Kalman computation model. The statistical data of the spaces, which were formed as big data, were received from the database of Place Score Company through correspondence with them using smart tools. The research data to measure the quality of Pakington Street, located in the eastern part of Geelong, Australia, were collected by Place Score platform.

Fig. 2. Location of Geelong Region

Fig. 3. Location of Pakington Street Area

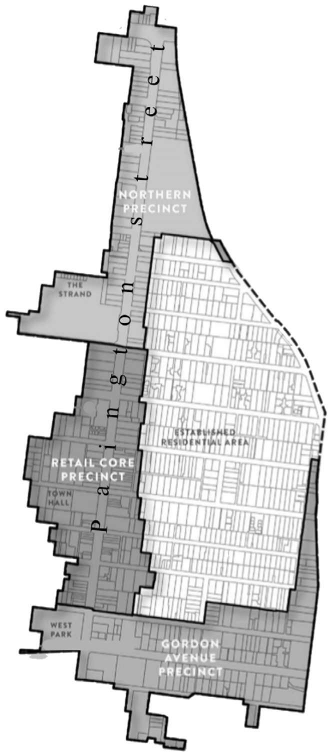

Fig. 4. Spatial Segmentation of Pakington Street Area

It should be noted that the received data are raw and variables such as rate of indicators, gender of participants, the average age and time of submission of opinions were recorded on it, which were not considered given the aim of the study and the information was merged. The desired database was based on collecting the opinions of people using the Pakington Street axis during six consecutive days. A total of 3075 data from users' comments were considered as a database for analysis. This axis is divided into two sections, north and south, with different land uses, and the opinions received from the users of the space in two sections of the street. Also, an attempt was made to provide a method to measure the quality of the north and south space comparatively. Also, the data received in all days were modulated on the axis of time and space rate and considered as the data of one day.

Fig. 5. Images of the Pakington Street Axis

4.1. Kalman Filter Algorithm

Noises generally have high frequency components that remove the noise by using a low-pass filter that passes only the low-frequency components and removes or weakens the high-frequency components. Kalman filter is a low-pass filter that relies on previous and instantaneous data and predicts the data (Huh 2017, 17-29).

The linear Kalman filter is characterized by the following equation:

$$\hat{x}_{\bar{k}} = A\hat{x}_{k-1} + Bu_k$$

In this equation, $\hat{x}_{\bar{k}}$ is the estimate of the current state of the system. A is the previous transfer matrix, $\hat{x}_{k-1}$ is the previous system, B is the identity matrix and uk is the input of the system. Kalman algorithm can plot a moving average graph and can record the movement of variables by removing noises or outliers in real time. Thus, our proposed method to provide an accurate tool to measure the quality of indicators in real time relies on the dynamic variable of time using Kalman' algorithm. Figure 6 shows the Kalman filter algorithm.

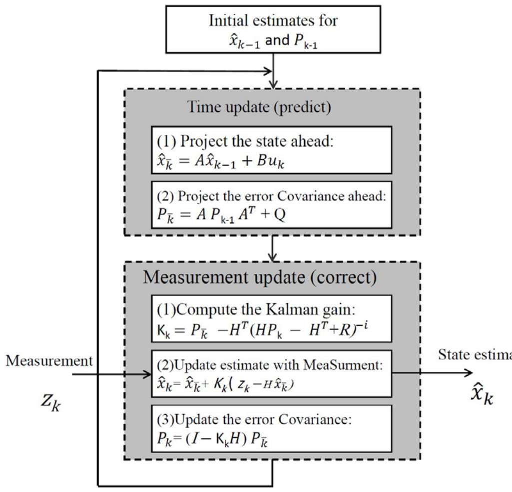

Fig. 6. Kalman Filter Algorithm

(Lee et al. 2016)

4.2. The Correlation Coefficient

R-squared correlation coefficient is a statistical tool to determine the type and degree of relationship of one quantitative variable with another quantitative variable. The correlation coefficient is one of the criteria used to determine the correlation between two variables. This coefficient shows the intensity of the relationship as well as the type of relationship (direct or inverse). It also explains how much the variance of one variable affects the variance of the second variable that its value is between 1 and -1, and it will be zero if there is no relationship between the two variables (Wooldridge 1991, 49-54). The correlation between two random variables of X and y is defined as follows:

$$R^2 = 1 - \frac{\text{Unexplaied Variation}}{\text{Total Variation}}$$

4.3. Smoothing Algorithm

To increase the accuracy and quality of computational models, all data should be normalized so that the effects of outliers (data noises) have the least effect on the computational models. Outliers can change the final result of computations and have a major effect on the average space rate. Therefore, we controlled their effects using the smoothing algorithm, whose formula is as follows:

$$y_s(i) = \frac{1}{2N+1} \times (y(i+N) + y(i+N-1) + \ldots + y(i-N))$$

In this formula, ys (i) is the controlled value, N is the number of neighboring data points on each side of ys (i) and 2N +1.

5. RESULTS

The measurement of the quality of urban space of Pakington Street is according to the data received from the place score application based on the analysis of five indicators in the database, including safety, things to do, look and function, care of the space and uniqueness. After receiving the initial raw data, computational algorithms and quantitative data modeling are implemented. The important point in this section is the preparation of the prerequisites of the used methods. For example, to increase the accuracy and quality of computational models, the data should be first normalized so that the effects of outliers (data noises) have the least effect on the computational models. Therefore, using the smoothing algorithm, the effect of outliers was controlled. Another part of data preparation was the implementation of statistical tests to ensure the affectability of indicators in the two axes of time and rating. Therefore, this affectability was measured using the correlation coefficient (R-squared). In the next step, the correlation of the indicators was evaluated in a peer-to-peer and comparative way in both the northern and southern parts of the street. The important point in this section is to identify the indicators that have the most correlation and affectability in the two axes of time and rating of spaces.

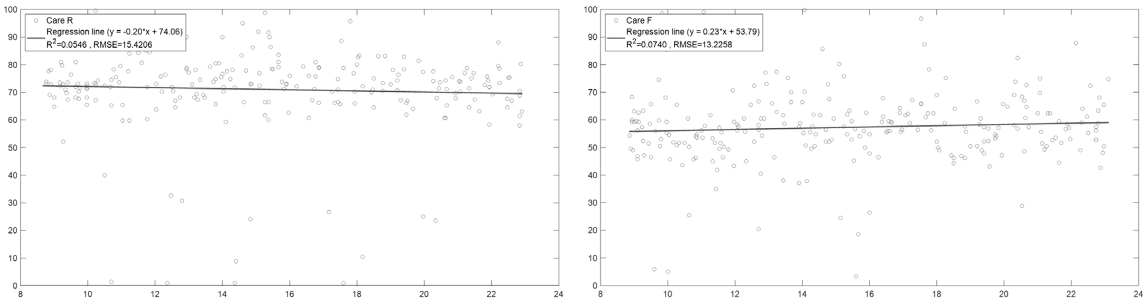

Fig. 7. Measurement of the Correlation Coefficient of the Space Care Indicator in the North and South Spaces of Pakington Street

The above graphs are used to measure the correlation coefficient of the space care indicator. The relatively constant slope of the graph in both spaces shows the minimum effect of users' opinions in different time periods and shows that the space care inicator has followed a stable trend in the short term.

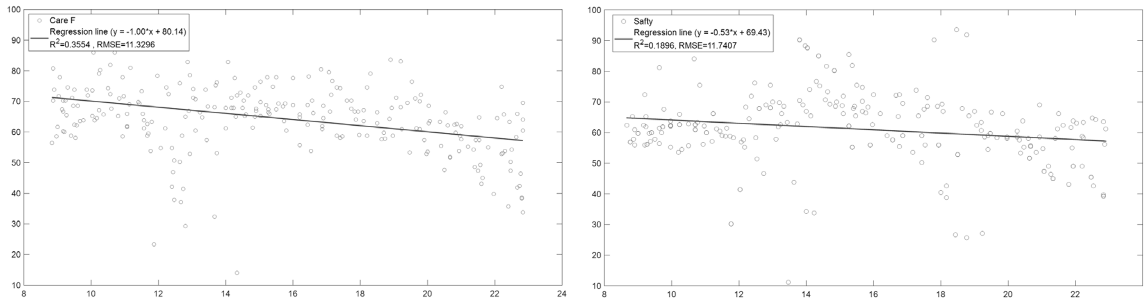

Fig. 8. Measurement of the Correlation Coefficient of the Safety Indicator in the North and South Areas of Pakington Street

The above graphs are used to measure the correlation coefficient of the safety indicator. The slope of the graphs indicates that this indicator has undegone changes in the space rating in the short term from the space users' viewpoint and the downward trend of the graph indicates the relative decrease in the average rating of the space, which is more severe for the northern space than for the southern space.

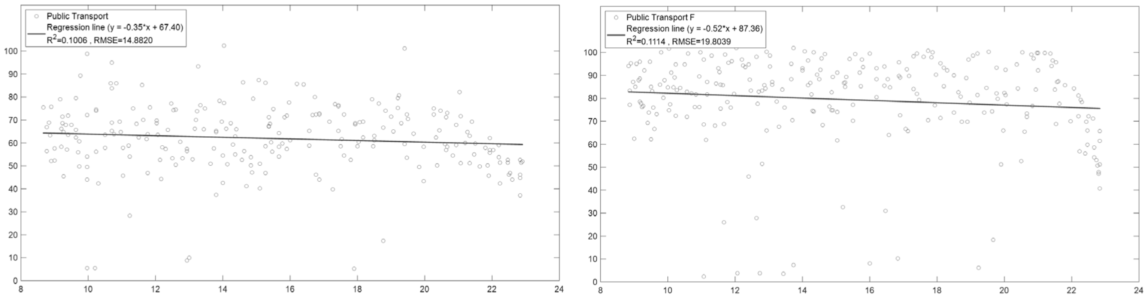

Fig. 9. Measuring the Correlation Coefficient of the Indicator of Things to do in the North and South Spaces of Pakington Street

The above graphs are used to measure the correlation coefficient for the indicator of things to do. The rate of the correlation coefficient and the slope of the graph in this indicator indicate the relative changes in the average opinions of users of the space in the short term, and its downward trend indicates the decrease in the average rating of the space from the users' viewpoint in the short term

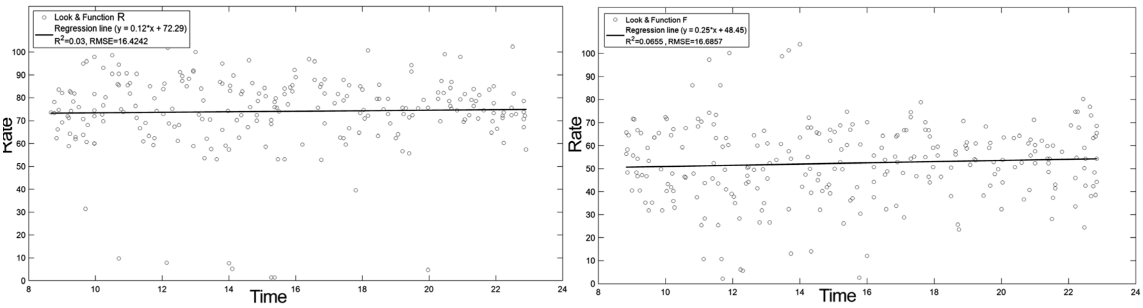

Fig. 10. Measurement of the Correlation Coefficient Look and Function Indicator in the Two Areas of North and South Pakington Street

The above graphs are used to measure the correlation coefficient of the look and function indicator. The absence of a slope in the above graph and the low value of the correlation coefficient in both spaces indicate lack of effect of the space rate variable on time in the short term, and it indicates that the changes in the look and function indicator in the short-term is relatively uniform and within the range of a constant rate from the audiences' viewpoint.

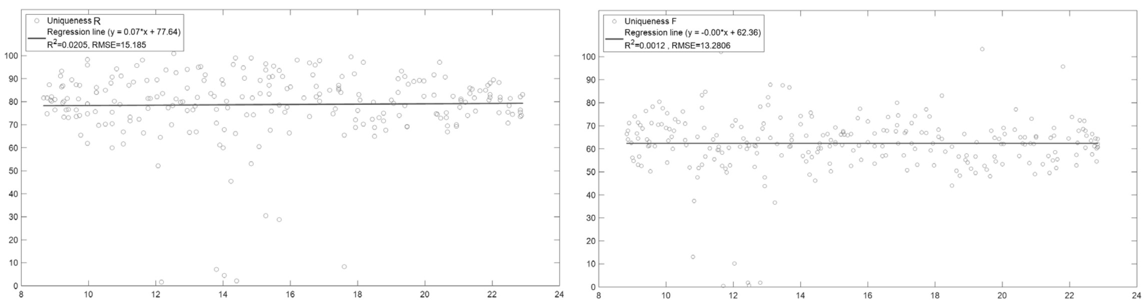

Fig. 11. Measurement of the Correlation Coefficient of the Uniqueness Indicator in the Two Spaces of North and South Pakington Street

The above graphs are used to measure the correlation coefficient of the uniqueness indicator. The absence of slope in the graphs indicates constant changes in short-term and indicates the constant average space rate in the short-term.

In the table below, the correlation coefficient and the degree of slope of the indicators graph in the two spaces of the north and south of the street have been compared with each other in general.

Table 3. Examining the Correlation Coefficient of Indicators Based on Changes in the Time Variable

Indicator / Northern Space	Correlation Coefficient	Graph Slope	Indicator / Northern Space	Correlation Coefficient	Graph Slope
Safety	0.18	-0.53	Safety	0.35	-1.00
Things to Do	0.11	0.52	Things to Do	0.10	0.35
Space Care	0.05	-0.20	Space Care	0.07	0.23
Look and Function	0.03	0.12	Look and Function	0.06	0.25
Uniqueness	0.02	0.07	Uniqueness	0.00	0.00

According to the obtained outputs, three indicators of safety, things to do, and space care were considered as target indicators in the evaluation of the quality of the space based on the moving average on the two axes of time (t) and the rate of the indicators.
In the next step, to increase the accuracy and quality of the Kalman computation model, the data should be normalized so that the effects of outliers (data noise) have the least effect on the computation models. Outliers can change the final result of computations and have a major effect on the average space rate. Thus, we controlled their effects by using the smoothing algorithm. In the graph below, we see an example of applying this filter on one of the space indicators.

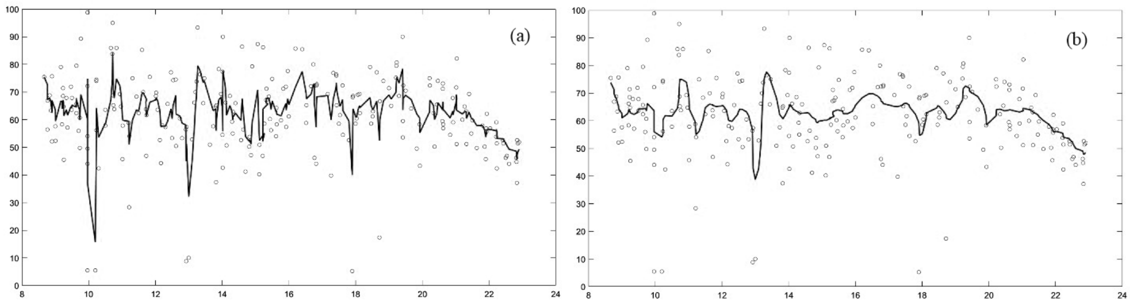

Fig. 12. (a) Effect of Outliers before Applying the Filter, Figure (b) Effect of Outliers After Applying the Filter

In this section, after ensuring the appropriateness of the data structure in the previous section, we consider the normalized data of the previous section as the input of this section and try to plot the graph of the average rate of each indicator in the time axis using the Kalman algorithm model.
The main idea in this method of analysis is to summarize the data in such a way that relationships and patterns can be expressed and introduced better and easier. In short, the Kalman algorithm model seeks to simplify and more easily describe abundant and complex data in the form of a graph, and it can simplify the effectiveness of the rates applied by the space audience and the instantaneous movements in the space rates in different time intervals in two dimensions and on the graph. Then, we evaluate the weaknesses and strengths of using this technique, while examining the outputs of this method on the indicators.

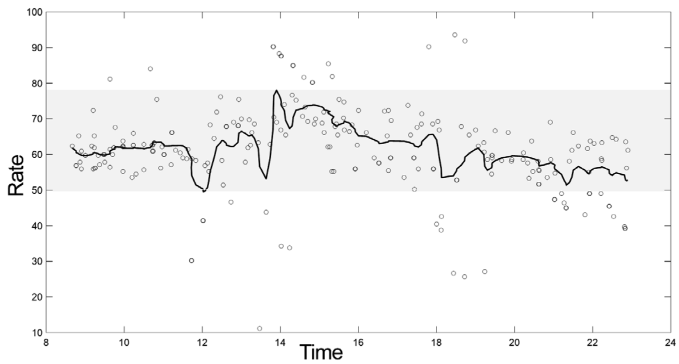

Fig. 13. Kalman Algorithm Model for the Safety Indicator of South Pakington Street

The quality measurement model of safety indicator for the southern area shows the relative stability of this indicator during the morning and night, which is in the 50-60 rate range, and this indicator in the noon and evening, with the higher average rate is in the range of 60-80. In the southern space, this indicator is at its highest in the time range of 14-16.

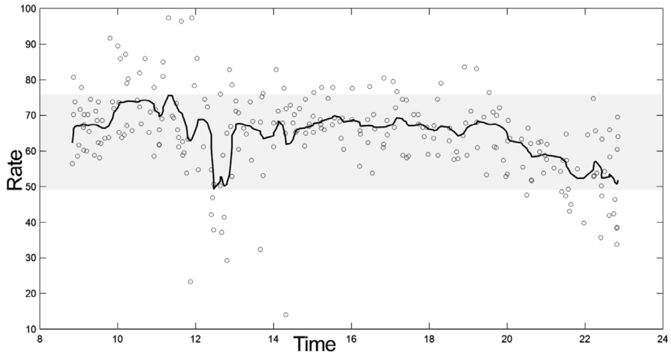

Fig. 14. Kalman Algorithm Model for Safety Indicator of North Pakington Street

The quality measurement model of safety indicator for the northern area is in the range of 60-70 during the day with a relatively constant trend, and it has taken a downward trend towards the end of the night and is in the range of 50-60. This indicator is at its highest level in the rate range of 70-80 in the time range of 10-12.

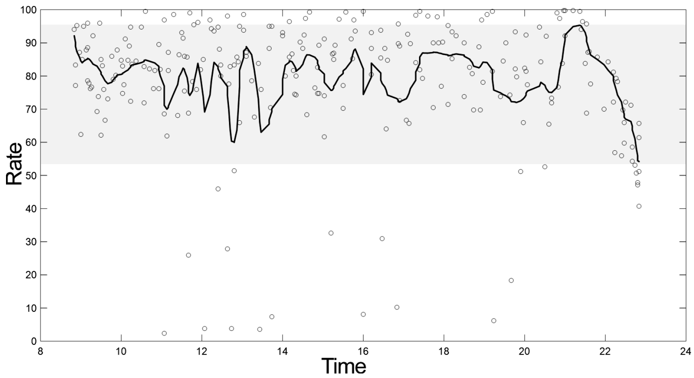

Fig. 15. Kalman Algorithm Model for the Indicator of Things to do in the Southern Space of Pakington Street

The quality measurement model of the indictor of works to do in the southern area varies in the range of 70-90, and in the last hours of the day, it started its downward trend and went down to the rates of 50-60. This indicator was at its highest level on average from morning to evening and was at its lowest level at the end of the night.

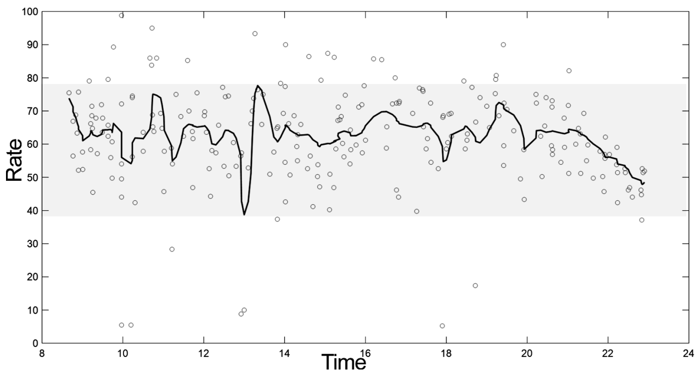

Fig. 16. Kalman Algorithm Model for the Indicator of Works to do in the Northern Space of Pakington Street

The quality measurement model of the indicator of works to do varies in the range of 50-80 for the northern area and during the morning to evening hours; it has started a downward trend with a constant average of 60 and in the final hours of the day.

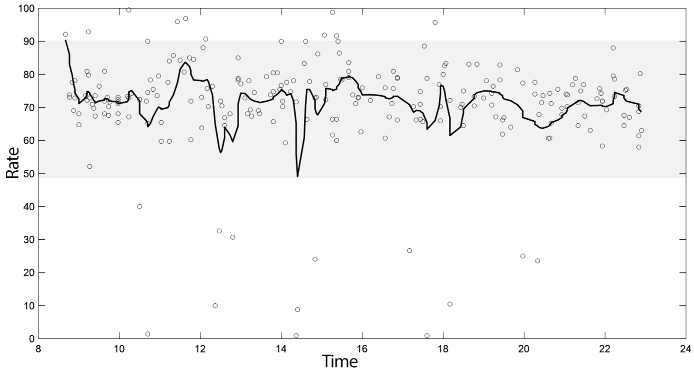

Fig. 17. Kalman Algorithm Model for Space Care Indicator in the South Space of Pakington Street

The quality measurement model of the space care indicator for the southern part of the street shows the relative stability of this indicator in the short-term, the correlation coefficient and the slope of the indicator graph also indicate the absence of serious effects of the space rating in the short-term. However, this indicator is in the range of 60-80, which is a suitable range from the space users' viewpoint for the space care indicator in the southern space.

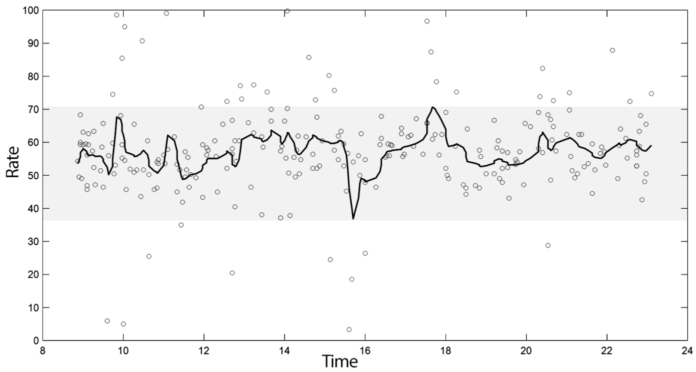

Fig. 18. Kalman Algorithm Model for Space Care Indicator in the Northern Space of Pakington Street

The space care indicator in the northern space of the street, similar to this indicator in the southern space, shows weak changes in the rating of the space on the time axis in the short term with a weak correlation coefficient and a low slope of the graph. In general, this indicator varies from 50 to 70 from the space users' viewpoint.

6. CONCLUSION

The necessity of measuring the quality of urban spaces to achieve the concept of sustainability and aligning this concept with technological changes and the flow of citizens' lives can provide more accurate and deeper results of measuring the quality of urban spaces. This idea, along with concepts such as changing the classic methods of measuring quality to modern methods based on the smart city, as well as concepts such as big data analysis and urban open data can lead to the discovery of hidden and current patterns in the real flow of citizens' lives and their interaction with urban spaces. The necessity of using the modern methods in measuring the quality of urban spaces is access to a database based on big data. Therefore, the data of this study is based on the data bank of Place Score Company from the urban space of Pakington Street, Australia. The changes in urban spaces, including various criteria in short-terms, create the need to create a flexible and dynamic method to measure the quality of urban spaces. Thus, innovation of this study is to provide a method to measure the quality of urban spaces based on the time variable in the short-term. Also, the quality of the urban space of Pakington Street was measured using data preparation methods and the Kalman algorithm. The data obtained from the users' participation was analyzed in the form of a moving average graph based on two variables of time and the rate of the indicators, through which the quality of the evaluated urban space can be analyzed instantaneously and dynamically.

Table 4. The Comparison Table of Measuring the Quality of 5 Indicators for the Northern and Southern Spaces of Pakington Street

Indicator	Northern Space				Southern Space			
	Maximum Range	Minimum Range	Upward Trend	Downward Trend	Maximum Range	Minimum Range	Upward Trend	Downward Trend
Safety	80-70	60-50	Morning	Night	80-70	60-50	Noon	Night
Works to Do	80-70	50-40	Constant from Morning to Evening	Night	100-90	60-50	Constant from Morning to Evening	Night
Space Care	70-60	50-40	Relatively Constant	Relatively Constant	90-80	60-50	Relatively Constant	Relatively Constant
Look and Function	80-70	80-70	Constant	Constant	60-50	60-50	Constant	Constant
Uniqueness	80-70	80-70	Constant	Constant	70-60	70-60	Constant	Constant

By analyzing the data related to the five quality indicators based on the time variable for Pakington Street, it was found that the average score of the look and function indicator and the uniqueness indicator are stable in the short term and time does not act as an intervening variable in their quality. Also, comparing the safety indicator in the northern and southern spaces of Pakington Street shows a higher average rating of the northern space than the southern space. Also, the comparison of the indicator of works with the space care indicator in the northern and southern spaces of Pakington Street shows a higher average rating of the southern space than the northern space in all recorded hours.

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