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Evaluating the risk of accessing green spaces in COVID-19 pandemic: A model for public urban green spaces (PUGS) in London

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ABSTRACT

The pandemic caused by SARS-CoV-2 (COVID-19) at the beginning of 2020 has restricted the human population indoor with some allowance for recreation in green spaces for social interaction and daily exercise. Understanding and measuring the risk of COVID-19 infection during public urban green spaces (PUGS) visits is essential to reduce the spread of the virus and improve well-being. This study builds a data-fused risk assessment model to evaluate the risk of visiting the PUGS in London. Three parameters are used for risk evaluation: the number of new cases at the middle-layer super output area (MSOA) level, the accessibility of each public green space and the Indices of Multiple Deprivation at the lower-layer super output area (LSOA) level. The model assesses 1357 PUGS and identifies the risk in three levels, high, medium and low, according to the results of a two-step clustering analysis. The spatial variability of risk across the city is demonstrated in the evaluation. The evaluation of risk can provide a better metric to the decision-making at both the individual level, on deciding which green space to visit, and the borough level, on how to implement restricting measures on green space access.

1. Introduction

The unexpected SARS-CoV-2 (COVID-19) outbreak has reshaped people’s life and behaviour dramatically. It is considered not simply a health crisis, but a long-term social and economic challenge for the whole world. Social distancing measure, also known as physical distancing, which requires people to keep a distance and reduce interactions from each other (Public Health England, 2020), is seen as the only option to reduce and control virus transmission. This measure has caused a disconnection of social networks in human societies, which in turn established a new norm for social interaction. The evaluation of the short-term and long-term change becomes important. The pandemic has led to a new appreciation of urban nature, since the green spaces can provide a mediation to the depression and anxiety caused by the social disruption. Meanwhile, the socio-economically vulnerable groups are exposed to higher risk of infection and uneven access to natural environment (Frumkin, 2021). How to ensure the safe and even access to green spaces in the pandemic is considered a key issue to be addressed and further considered a potential recovery strategy in the post-pandemic time.

Given the severity of the pandemic, the UK government has responded with three national lockdowns, the risk evaluation system and the introduction of social distancing and travel restriction policies. Until mid-January 2021, there have been over three million cases and nearly 90,000 deaths found in the United Kingdom (UK) since March 2020 (GOV.UK, 2021b). The assignment of risk tiers sets different levels of restriction to different areas, while the national lockdown measure ‘Stay at Home’ requires no leaving from home except when necessary. Two-metres social distancing is required. Non-essential travels are restricted. Social gathering and exercising in open public spaces are allowed with a limitation on the number of people.

The implementation of travel restrictions and social distancing rules in the pandemic have significantly influenced people’s daily life and routine. Public urban green spaces (PUGS) close to homes play a crucial role in the general well-being of people, especially over the lockdown period. The local green spaces provide spaces for outdoor activities and exercise to residents and accommodate some social interactions in the neighbourhood, as one of the several limited places they could visit under the travel restrictions and social distancing. The significance of providing high-quality accessible public open spaces is increasingly aware (Ergen, 2021), while closing the local parks is not recommended (Slater, Christiana and Gustat, 2020). The planning consensus indicates

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that the high green space accessibility is always preferable (Wei, 2017). However, high accessibility encourages visits thus more interactions between people. This could lead to a higher risk of infection during the pandemic. Also, according to the findings in England and Wales (Shoari et al., 2020), though the accessibility around the country is relatively good, there is a potential of overcrowding use in the park, which may deteriorate the social distancing rule. Another study by Nobajas et al. (2020) points out that a majority of urban areas are not sufficiently prepared to respond to the challenge like the pandemic, while the local public spaces can quickly become overwhelmed due to the inadequacy in the public space supply. The uneven distribution of urban nature and limited access to PUGS have exacerbated the risk in the relatively deprived and minority communities. The presence of green spaces is negatively associated with racial disparity in COVID-19 infection rates (Lu et al., 2021). Therefore, a simple and relatively inexpensive strategy to augment the usability of nature without violating the social distancing guidelines is in need (McCunn, 2020). It is important to set up an effective scheme to evaluate the risk of visiting the green spaces and ensure the safety of the local residents when visiting their nearby green spaces. In the long run, the risk assessment system can be integrated to the decision making in green space planning in the future for the pandemic recovery. Also, it can become a part of the long-term PUGS monitoring and evaluation strategy to inform the policy maker (Banchiero et al., 2020; Slater et al., 2020).

This study intends to build a risk assessment model based on the parameters of green space accessibility, local COVID-19 infection rate and deprivation scores, to evaluate the risk of COVID-19 infection when accessing the public green spaces in London (referred as ‘risk’ below). The proposal is developed in the period between the second and third national lockdowns in the UK, following a previous study of the correlation between the accessibility of PUGS and a preliminary risk assessment model based on the Local Moran’s I at the London borough level in May 2020 (Pan et al., 2021). As the previous investigation has demonstrated the spatial distributive effect of the PUGS accessibility and COVID-19 cases, this study aims to measure the risk of every single green space by illustrating its risk exposure and vulnerability. A two-step clustering analysis is conducted to classify the risk level. The model with different levels of risk assigned can be used as a guidance for people to make decisions on what nearby PUGS to visit and a supportive tool for local government to apply restriction rules to PUGS.

Section 2 reviews the literature about the response to the pandemic from the urban environment perspective and the discussion of the link among pandemic, green spaces and urban inequality. Section 3 introduces the data and methods in this study with the introduction of the data-fused risk assessment model. The result and discussion parts (Sections 4 and 5) present and examine the output of the risk assessment model, while the conclusion part provides an overview and points out the limitations.

2. Literature review

2.1. Resilient urban environment as a response to pandemic

The spreading of infectious diseases, such Athens Plague, Black Death and cholera outbreak, have had a vital impact on the shape of the built environment throughout human history (Perdue et al., 2003; Megahed and Ghoneim, 2020; Shenker, 2020). For example, the outbreak of cholera has reshaped the design of modern sewage system in the urban area (Shenker, 2020); the use of openable windows and exhaust fans in low-income housing can reduce the occurrence of tuberculosis (Pardeshi et al., 2020).

The unexpected and crucial influences brought by COVID-19 in 2020 have reinforced the need for constantly updating the knowledge and understanding of the built environment as a response to the large-scale public health crisis. The United Nations Sustainable Development Goal 11 (SDG11) strengthens the importance of ‘make cities inclusive, safe, resilient and sustainable’ (United Nations, 2019b), while this goal seems to become increasingly significant in the pandemic. How to deliver a resilient and safe environment for people through the design and planning approaches remains a field to be explored and developed further.

Literature has illustrated the progress of responding to the changes from the perspective of urban environment scholars. The researchers start from summarising and figuring out the association between the built environment factors and the health risk of the infectious disease at the pandemic context, and gradually move to construct the risk assessment models with multi-aspect indicators. Huang et al. (2020) explain the relationship between the case incidence, case density and the built environment features such as nodal accessibility, population density and land-use diversity. Other features discussed in the correlational studies between the COVID-19 cases and urban environment characteristics include the location and density of hospitals, land use mixture, road density (Li et al., 2020) and the information extracted from the street images like the walkway, dilapidated buildings and non-single family home (Nguyen et al., 2020).

The evaluation of the risk of the contagious disease outbreak has covered a wide range of indicators, such as the demographic and socioeconomic characteristics, travel, housing and environment, and the most important and basic epidemiological value, the number of cases (Acharya and Porwal, 2020; Sangiorgio and Parisi, 2020; Imdad et al., 2021). The simulation modelling and risk assessment tools have a broad application in the analysis and prediction of the virus spreading, thus assisting the policy decision-making and intervention (Spooner et al., 2021). The selection of variables involved in the model depends on the focus, scale and aim of the model. Chang et al. (2021) build the prediction model based on the mobility network data and metapopulation susceptible-exposed-infectious-removed (SEIR) model to estimate the effect of re-opening different points of interest. An assessment model based on the epidemiological and socioeconomic criteria is designed to evaluate the susceptibility and vulnerability to the pandemic at the district level in India (Imdad et al., 2021). Sangiorgio and Parisi (2020) build a multi-criteria model with the infection as the hazard factor, urban district characteristics like population density and crowded places as the vulnerability factor, and age of inhabitants as the exposure factor. A vulnerability index is proposed by Acharya and Porwal (2020) with the variables about socioeconomic status, demography, housing and hygiene, healthcare availability and epidemiology at the district level in India. Another weighted vulnerability index in four large cities in India is composed of the population density, drinking waters and living conditions (Mishra et al., 2020). Moreover, an index integrating the environmental, demographic and health factors is presented with the case of 55 Italian cities (Coccia, 2020).

2.2. COVID-19 and the access to green spaces

The importance of the natural environment in cities for health and well-being has been widely discussed in the academic literature with a range of social, economic and environmental benefits identified (Zhou and Rana, 2012; Konijnendijk et al., 2013; Zhang et al., 2015). Urban green space is defined as the piece of land in an urban area covered by vegetation, varying in size, plant type, facilities and services (Tzoulas et al., 2007; Wolch et al., 2014), such as the urban park, community garden, grassland, forest, street green and green roof (Brauninho et al., 2015). The term ‘public green space’ indicates that the green space can be accessed freely without restrictions or conditions, which differs from the semi-public and private greeneries. In SDG 11, the provision of ‘universal access to safe, inclusive, and accessible, green and public spaces’ (United Nations, 2018b). The significance of offering accessible green spaces is reinforced during the pandemic (Samuelson et al., 2020), especially in the implementation of lockdown measures, as the major spaces for outdoor activities. In addition to SDG 11, the promotion of providing equal and safe access to public green spaces has a significant influence on achieving SDG 3 and SDG 10. The green spaces...
Contribute to the health and well-being improvements in the neighborhood (United Nations, 2019c), while the supply of PUGS in the low-income or minority neighbourhood can reduce the inequality (United Nations, 2019a).

The pandemic demonstrates an urgent need for green spaces, especially for short-distance activities (Kleinschroth and Kowarik, 2020; Ugolini et al., 2020). Scholars are actively engaged in the discussion of new changes in human social behaviour and the use of the public spaces under the containment measures (Geng et al., 2020; Honey-roses et al., 2020; Mehta, 2020; Rodgers, 2020). A large body of studies on the use of green spaces over the pandemic time has been published recently. The exposure to both indoor and outdoor green features has a noticeable association with the well-being of people during the lockdown (Soga et al., 2021). Studies show that the use of green space has increased after the pandemic (Oerks et al., 2020; Geng et al., 2020; Venter et al., 2020; Fagerholm et al., 2021), and urban nature provides resilience to maintain the well-being under the condition of social distancing (Samuelson et al., 2020). The benefits of accessing the green spaces include promoting physical health, recovering stress, feeling of isolation and depression (Samuelson et al., 2020; Soga et al., 2020; Soga et al., 2021), which in turn reduce the vulnerability of people to the disease. Even the presence of a green view through windows can positively affect the mental health of people (Soga et al., 2020). The investigation by Johnson et al. (2021) shows that higher park use is associated with a decrease in case rates after removing the influence of health and mobility variables.

Also, the accessibility and availability of the green spaces are vital in the evaluation of the green space distribution. Accessibility of green spaces is normally measured with a place-based approach, to count the potential for reaching the spatially distributed opportunities (Liu et al., 2021). Availability is commonly represented by the ratio of green spaces within an area and provide an aggregate evaluation of green space provision to a certain number of users (Texier et al., 2018). Distribution refers to the description of spatial pattern. Equal access to green spaces for urban residents would significantly promote public health and well-being (Liu et al., 2021). However, multiple studies have indicated that the current green space distribution is uneven. The spatial assessments of inequality and green space accessibility in Columbus and Atlanta conclude that disparities in green space access are aligned with the income and race distribution, and the economically deprived group has the most constrained access to green spaces (Park and Guldmann, 2020). The examination of the distribution disparity in Chicago also shows that green space accessibility is higher in white-majority areas (Liu et al., 2021). The uneven distribution of PUGS could potentially cause more problems over the pandemic than usual, because the unavailability of local green spaces leads to very limited outdoor activity spaces for residents. Blecic et al. (2020) build a model to evaluate the PUGS walking accessibility with the case of Cagliari in Italy. They underline the fact that the uneven distribution of green spaces can generate socio-spatial inequality and aim to measure the distance-cumulative deficit of PUGS. A study about the accessibility and allocation of parks in England and Wales suggests the necessity of developing relative policies of restricting access to high-risk areas and diverting the visitors to different access time periods, considering the potential overcrowding situation in the parks (Shoari et al., 2020). Rodgers (2020) urges for a response from the planning system to ensure the availability of green spaces and the protection of existing green spaces.

2.3. COVID-19 and social inequality

Moreover, inequality is a key factor that could influence the vulnerability of people in the pandemic. The residents with lower socioeconomic status are more vulnerable in the pandemic, because they have less protection over the infectious disease due to the poorer health condition, overcrowded dwelling, limited access to private gardens, lack of chances to work from home and less access to the high-quality healthcare services (Patel et al., 2020). A proportionally higher impact of COVID-19 on the most deprived area in England is found, and the deaths per 100,000 population is significantly higher in the most deprived area compared to the least deprived ones (Office for National Statistics 2020a, 2020b). The results from the pandemic prediction model directly point to a higher infection rate among the disadvantaged groups because they are not able to reduce their mobility (Chang et al., 2021).

Meanwhile, there has been a lot of studies testing the correlation between socio-economic status and COVID-19 infections directly. The inequality of race, education deprivation and age is discussed in the studies. The research finds that the local built environment factors and the socio-economic features can have a significant impact on virus transmission and incidence (Emeruwa et al., 2020). The socio-demographic inequality and virus infections and testing in New York City is discussed as the spatial analysis case study frequently (Cordes and Castro, 2020; Credit, 2020; Emeruwa et al., 2020; Whittle and Diaz-Artiles, 2020). There is an inverse relationship between the proportion of positive cases and white race, education and income, while the positive association is found between the positive cases and black race, Hispanic ethnicity and poverty at the zip code level in New York City (Cordes and Castro, 2020). The other study, also based on the zip code level in New York City, derives a similar conclusion about the significant association between positive COVID-19 rate and the percentage of young dependents, dense population, low income and black population (Whittle and Diaz-Artiles, 2020). The data analysis of 158 US counties in the large metropolitan area at the community level shows that the poorer and more ethnically and racially diverse areas experience the excess burden of infections and deaths (Adhikari et al., 2020). The index of social vulnerability has been introduced to measure the resilience of communities in the disaster by US Centres for Disease Control and Prevention, which mainly covers the domains of socioeconomic status, household composition and disparity, minority status and language and housing and transportation (Acharya and Porwal, 2020; Dasgupta et al., 2020; Khazanchi et al., 2020). The counties with greater social vulnerabilities have a higher risk of becoming COVID-19 hotspots. Similar findings are reported in UK: A higher average number of cases is found in the most deprived areas (Morrissey et al., 2021); the ICU admission and mortality rates in Wales are associated with the ethnicity and deprivation level of the patients (Baumer et al., 2020). In the less developed countries, like India and Brazil, the socioeconomic disparity in positive COVID-19 cases and deaths is also demonstrated. The results of correlational studies point to the disproportionate impact of the virus spreading on the communities with more vulnerable populations (Buffel et al., 2020; De Souza et al., 2020; Urban and Nakada, 2020).

As a result, the literature review shows that there is no specific risk examination system for PUGS visit in the pandemic time. While the green spaces become the places for socialising and exercising to improve the well-being of residents during the lockdown, the gap for a risk evaluation matrix is identified. The existing studies have demonstrated that the availability and accessibility of PUGS and local deprivation level are associated to the COVID-19 infection. Therefore, the proposed risk assessment system would be derived based on those relevant parameters.

3. Data and methods

In this section, the data and methods applied in this study are presented. A data-fused risk assessment model with three parameters is introduced to evaluate the risk of getting infected when visiting PUGS. This assessment model is demonstrated with the case study in London, while the details of the study area and relevant data are discussed in the following sub-sections.
3.1. Study area

London (51°30′26″N, 0°7′39″W) is the capital of the United Kingdom (UK) with a population of over nine million, also the city that suffers most from the pandemic in the country. There are over 580,000 cases in London in the whole pandemic by the middle of January, which is the top of all regions in England. The number of deaths is about 10,000, which ranks second.

There are a total of 32 boroughs in London, plus the City of London managed by the City of London Corporation. Output areas are the geographical level created for the census data and estimations. Middle-layer super output areas (MSOA) and Lower-layer super output areas (LSOA) are two key levels used in geographical statistics. The 2010 data shows that the average population of an LSOA was 1722 and the average population of an MSOA was 8346 (Greater London Authority, 2011).

According to the data from Greenspace Information for Greater London CIC (GiGL, 2019), London is a green city with a total of 67,541 ha of open spaces occupying 42.36% of Greater London. There is an area of 28,693 ha of public open space occupying 17.995 of the land. Londoners could easily access the public parks with the highest percentage of the population living within a five-minute walking distance to public open spaces among all the regions and counties in the UK. The proportion of the population staying within a five-minute walking distance to a park is 44%, and the figure rises to 58% when playing fields are included. At the same time, there are 21% of households have no access to private or shared gardens during the lockdown (Office for National Statistics 2020a, 2020b). Although some of the facilities are closed due to safety consideration, citizens are still allowed to access the public parks and open spaces around London. Therefore, London is an appropriate case study to understand the risk of PGS access over the pandemic.

3.2. Data-fused risk assessment model

A research framework is presented in Fig. 1, showing the process of data collection, analysis and generation of the risk assessment model. We use the multi-channel data and develop a data-fused multi-level risk assessment with the geo-information tool. This section includes the introduction of major data sources and the application of clustering analysis to understand the features of green spaces.

3.2.1. Data collection

3.2.1.1. COVID-19 cases. The COVID-19 case data in the UK is available at the MSOA level, with a rollover of seven days. The recent seven-days case data in London is extracted on 30 Nov 2020 for analysis (GOV.UK, 2021a), before the large scale winter outbreak of the new variants over the Christmas holiday and the third national lockdown. MSOA level number of cases data is the smallest geographic level of data available due to the disclosure control issues (Department of Health and Social Care, 2020).

3.2.1.2. Green space features. The green space data is collected based on the GiGL dataset, OS Open Green Space from Edina Digimap and green spaces information available on the borough websites. The name, size, use and geographical distribution are extracted for further analysis. The raw green space data is filtered with a set of conditions. According to the London Plan 2016 (Mayor of London, 2016), the green spaces under 2 ha are categorised as the local level green spaces and pocket parks with less people visit and stay. Therefore, the study limits the risk assessment for green spaces with a size larger than 2 ha. The green spaces that are not publicly accessible, such as playgrounds owned by education institutions and sports clubs, are excluded from the list. The major types involved in this study are parks and gardens and natural and semi-natural urban green spaces. There are a total number of 1357 PUGS involved in the analysis.

3.2.1.3. Green space accessibility. The idea of accessibility is defined as ‘the potential for interaction’ (Hansen, 1959, p.73). The availability of public green spaces within walking distance near home is essential in urban life especially over the pandemic due to the movement restrictions (Blecic et al., 2020). The measure of accessibility is one of the key measures in the assessment of urban green space provision. Several frameworks are developed to evaluate the green space accessibility based on various measurements, indicators and geographical analyses at different scales (Comber et al., 2008; Ekkel and de Vries, 2017; Knobel et al., 2019; Zhang et al., 2019; Ergen, 2021).

The green space accessibility in this study is measured based on the network theory (Barabási, 2016). The network is represented in the format of the graph and decomposed to the elements of nodes and links. The spatial network analysis has been suggested to be optimal and effective in the analysis of accessibility in the previous study (Comber et al., 2008). In this case, the input in the analysis is the London road network analysis to understand the features of green spaces.
network extracted from the OS Open Road dataset. The integration and choice values are the measurements of spatial configuration at the urban level. Integration, also known as availability, is defined as the to-movement potential measurement evaluating how integrated the street segment is to the whole network and indicating how many people are likely to be in the space. It measures the potential of the segment to be the desired destination in the defined radius distance. Choice, also known as betweenness, measures the through-movement potential by calculating the possibility of each segment to be selected by the pedestrians as the shortest and simplest route within the radius (Barabási, 2016). A radius of 800 m is chosen for the calculation because the analysis focuses on pedestrian accessibility (Paez et al., 2012; Wei, 2017). In this study, the integration and choice values within 25 m distance from around the green space are summed up as the accessibility value of the green space.

### 3.2.1.4. Index of Multiple Deprivation

The Indices of Multiple Deprivation (IMD) score published by the Ministry of Housing Communities & Local Government (2019) at LSOA level is used as a surrogate of inequality. The IMD score is a composite index of seven domains of deprivation, including income deprivation (22.5%), employment deprivation (22.5%), education, skills and training deprivation (13.5%), health deprivation and disability (13.5%), crime (9.3%), barriers to housing and services (9.3%) and living environment deprivation (9.3%). The higher the score, the more deprived the area is. The study by Morrissey et al. (2021) reports that the most deprived areas in UK had a higher average cases and the infection increased substantially after the ease of lockdown policy.

### 3.2.2. Multi-level risk assessment of PUGS

A conceptual risk assessment model is built to assess the risk of accessing green spaces in the virus outbreak period. Bardhan et al. (2016) define the risk system as a combination of exposure to stresses and inherent resiliency. Following this definition, the risk evaluation in this study is set up with the risk exposure in the physical environment and the internal vulnerability of the local population. Fig. 2 shows the basic structure of the model. Three parameters are proposed to evaluate the risk. The risk exposure is represented by the number of cases and the accessibility to the green spaces, which indicate the concentration of infections and the possibility of transmission separately. The local population vulnerability is measured by the IMD scores. The highly accessible green space located in the area with high local deprivation and a high concentration can be designated with a very high level of risk, while local residents should be advised to avoid visiting that green space.

A two-step clustering analysis is applied to classify the risk level of green spaces. Clustering analysis is an exploratory statistical analysis approach that divides the dataset into several groups with shared common characteristics. The within-group similarity is maximised and the between-group differences are minimised. The clustering analysis in this study aims to understand the characteristic patterns of the green spaces and their neighbourhood with the given datasets and identify the groups of public green spaces with similar features. The classification results contribute to the assignment of risk level in the risk assessment model.

The two-step clustering analysis begins with the pre-clustering stage of conducting a sequential clustering and setting up a Cluster Feature tree, followed by the second step of grouping the leaf nodes with an agglomerative clustering algorithm (Satish and Bharadhwaj, 2010). Two-step clustering is designed to handle large sets of data, which is applicable in this study with 1357 samples. A set of four continuous variables, including the number of cases, the accessibility values integration and choice values of green spaces and their neighbourhood with the given datasets and identify the groups of public green spaces with similar features. The classification results contribute to the assignment of risk level in the risk assessment model.

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While the clustering results characterise the features of the PUGS around London based on the three variables, the next step is to translate the clusters to a risk assessment system and determine the level of risk. Fig. 3 presents the process of assessing the risk level for each cluster. There are three input parameters, the number of new cases, PUGS accessibility (composed of the integration and choice values) and IMD score. The existence of cases around the local neighbourhood is the essential condition for virus transmission, so the number of cases takes priority in the assessment. The level of each parameter is classified to ‘high’ and ‘low’ by comparing to the mean value of the parameter. For example, the cluster with a high risk of exposure (high in both the number of new cases and green space accessibility) indicates that it has a high level of risk, regardless of its internal vulnerability; The high number of cases and high IMD scores also lead to the assignment of high-risk level; The green spaces with low exposure to risk and high vulnerability are classified as medium. As a result, all the clusters are assigned with different levels of risk from ‘high’ to ‘medium’ to ‘low’ based on this risk identification system, while the results are discussed in the following section.
4. Results

4.1. Clustering results: variability of risk factors

The basic clustering result is described in this part. A total of 1341 samples are involved in the classification, while 16 data records are outliers. The clustering quality is ‘fair’ with an average silhouette value of 0.3. The number of clusters performed in the analysis is determined automatically in the two-step clustering procedure. Eight clusters are generated by the analysis. Table 1 presents the distribution of clusters and their size, as well as the descriptive data of each cluster with the mean value and the standard deviation. Cluster 6 is the largest cluster with 334 cases, while the smallest cluster, cluster 1, has only 21 cases. The input importance distributes equally among the four features. The size of other clusters lies between 117 and 250.

In cluster 1, the accessibility values are the highest among all groups, while the IMD score is around the average and the number of cases is slightly lower than the average. Cluster 2 has the second-highest accessibility values, but not as high as cluster 1. The deprivation level presented in cluster 2 is relatively high compared to the average value and the value of the new cases is slightly higher than the mean. Cluster 3 shows the second-lowest IMD score and new cases, while the
accessibility values are much higher than the mean value. Cluster 4 is the most deprived cluster with the highest IMD rate with the accessibility lower than the average and new cases above the average. In cluster 5, the IMD score is the second-highest, whilst both the accessibility and the new cases are below the average. All of the parameters for cluster 6, which is the biggest cluster, are the lowest among all clusters, and the standard deviation values in this cluster are relatively low as well. The green spaces in cluster 7 is featured by a high new case, low accessibility and medium deprivation score. This cluster is the second largest cluster. Cluster 8 exhibits the highest number of new cases, with an IMD score slightly higher than the average and accessibility lower than the average.

4.2. Risk assessment: spatial variability of risks among London boroughs

Based on the clusters generated in the clustering analysis, the public green spaces are divided into groups exhibiting similar accessibility features with a similar level of new cases and deprivation in the neighbourhood. The integration and choice values share the same pattern among all the clusters, which are combined as ‘accessibility value’. The level for each parameter and the corresponding risk levels are summarised in Table 2.

The risk level is assigned based on the listed results and the identification system outlined in Fig. 3, Section 3.2.2. The eight clusters are reclassified into three levels, which are ‘high risk’, ‘medium risk’ and ‘low risk’. As a result, cluster 2, cluster 4 and cluster 8 are classified as ‘high risk’. The clusters with ‘medium risk’ include cluster 1, cluster 3, cluster 5 and cluster 7. Cluster 6 are noted as ‘low risk’.

Fig. 4 shows the spatial distribution of PUGS at each risk level around London.

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**Table 1**
Descriptive data of clustering analysis results.

| Cluster | Size | Number of new cases | Integration value | Choice value | IMD Score |
|---------|------|---------------------|-------------------|--------------|-----------|
|         |      | Mean (SD)           | Mean (SD)         | Mean (SD)    | Mean (SD) |
| 1       | 21   | 13.00 (6.28)        | 2,528,087.62 (1,428,714.68) | 38,258.38 (19,202.44) | 19.35 (7.24) |
| 2       | 117  | 16.41 (7.73)        | 948,696.13 (326,153.10)  | 13,577.85 (46,10.10)  | 25.63 (8.34) |
| 3       | 127  | 10.02 (3.84)        | 456,569.46 (196,938.87) | 7,295.29 (2,572.96)  | 12.65 (4.49) |
| 4       | 144  | 19.97 (3.62)        | 167,027.71 (146,758.35) | 3194.68 (2428.84)  | 33.97 (5.40) |
| 5       | 233  | 10.02 (2.92)        | 141,088.72 (148,714.27) | 2697.80 (2,079.38)  | 27.86 (5.88) |
| 6       | 334  | 9.98 (3.30)         | 57,055.36 (63,784.02)  | 1525.79 (1307.81)  | 10.72 (3.45) |
| 7       | 250  | 18.97 (3.25)        | 91,423.72 (111,720.71) | 1931.03 (1736.62)  | 16.48 (4.67) |
| 8       | 115  | 32.10 (8.38)        | 118,494.09 (141,092.09) | 2395.23 (1962.70)  | 22.56 (5.81) |
| Combined Average | 15.25 (8.03) | 249,467.94 (448,026.98) | 4231.90 (6398.83) | 19.90 (9.57) |

**Table 2**
Level assigned for each cluster.

| Cluster | Number of new cases | PUGS Accessibility | IMD Score | Risk Level |
|---------|---------------------|-------------------|-----------|------------|
| 1       | Low                 | High Low          | Low Medium | Medium    |
| 2       | High                | High High         | Low High Low | High     |
| 3       | Low                 | High Low          | Low Medium | Medium    |
| 4       | High                | Low Low           | High Medium | Medium    |
| 5       | Low                 | Low Low           | Low Low Medium | Low    |
| 7       | High                | Low Low           | Low Medium | Medium    |
| 8       | High                | High Low          | High High Medium | Medium    |

Fig. 4. Spatial distribution of the PUGS risk levels around London.
London. We discuss the implications of risk levels at the borough level, because the London borough authorities are the administrative unit that owns and manages most green spaces. Fig. 5 summarises the distribution of risk levels at the borough level. All of the 32 local authority districts and the City of London are included.

4.2.1. High-risk clusters: cluster 2, cluster 4, cluster 8
There are a total of 375 green spaces noted as ‘high risk’ and marked in red in the distribution map. They mainly distribute around central London and Northeast London. Most of the group member has a high number of new cases, with either deprivation index or green space accessibility relatively higher than the average. The boroughs, like Barking and Dagenham, Newham and Hackney, have over 60% of PUGS classified as ‘high risk’. A number of 24 PUGS in Barking and Dagenham are high-risk green spaces, which accounts for 92% of the total number in the borough. The boroughs of Enfield, Hammersmith and Fulham, Islington, Redbridge, Tower Hamlets and Waltham Forest have over 50% of green spaces at high-risk level. Ealing has the biggest number of high-risk PUGS, at 38, though they only occupy 46% in the borough. At the same time, Bromley and Croydon, as the two boroughs with the largest total PUGS number, have a very low proportion of high-risk PUGS.

4.2.2. Medium-risk clusters: cluster 1, cluster 3, cluster 5 and cluster 7
This group has 631 green spaces, shown in yellow on the map and located across the whole of London. It is the biggest risk level group among all of the three levels. Croydon in outer London has the highest number of medium-risk PUGS, at 51, which occupies about 57% of the green spaces in the borough. Lewisham has the biggest proportion of medium-risk PUGS among all, with 30 taking 78% of all PUGS in the borough. The only green space identified in the City of London is also assigned with a middle risk.

4.2.3. Low-risk clusters: cluster 6
There are 334 green spaces in cluster 6 noted as ‘low-risk’, and most of them distribute around the west and south London, represented by the blue colour in the map. There are seven boroughs with no PUGS at low risk, including the City of London, Barking and Dagenham, Brent, Hackney, Hammersmith and Fulham, Islington and Newham, while four boroughs have only one low-risk PUGS, which are Kensington and Chelsea, Lambeth, Tower Hamlets and Waltham Forest. Over 70 low-risk green spaces are found in Bromley, which accounts for 61% of PUGS in the whole borough. Croydon is the borough with the second-highest number that 36 low-risk PUGS occupies 40% of the total of 90 green spaces.

5. Discussion
The risk of accessing green spaces has proved to be lower than the other activities like visiting shops and offices (Johnson et al., 2021). The need for micromanagement of public spaces to prevent the spread of the virus is highlighted in the pandemic (Nobajas et al., 2020). The clustering analysis presented in this study has built an effective character of the green space and its surrounding area, while the combination of
The application of this model is expected to give guidance to both the individuals and local government. The PUGS in high-risk clusters require more attention and more responding measures. For example, this model has the potential to be used as a dynamic system that is updated with the number of cases to inform the local residents. The residents could be suggested to avoid visiting the green space with higher risk and shift to using the lower-risk places. Also, if they find the nearby green spaces are all with a high number of cases, they could choose the green spaces with lower accessibility or lower IMD score. People who live in the area with a high IMD-score could visit the spaces in the neighbourhood with lower IMD score, while people who usually go to the high-accessibility spaces could switch to those with lower accessibility. Furthermore, residents could avoid accessing the high-risk green spaces over a busy time to get rid of the overcrowding situation.

We further analyse the implications of risks for boroughs by normalising the data in each risk group. The values of the number of PUGS at different levels in each borough are normalised to a scale between 0 and 1, with 0 indicating no risk and 1 indicating high risk. This allows for a comparison of risks across different boroughs and helps in identifying areas with higher or lower risk levels.

| Inner London boroughs | High | Medium | Low | Outer London boroughs |
|-----------------------|------|--------|-----|-----------------------|
| City of London        | 0    | 0      | 0   | Barking and Dagenham  |
| Camden                | 0.06 | 0.14   | 0.08| Barnet                |
| Greenwich             | 0.53 | 0.86   | 0.08| Bexley                |
| Hackney               | 0.32 | 0.12   | 0   | Brent                 |
| Hammersmith and Fulham| 0.21 | 0.06   | 0   | Bromley               |
| Islington             | 0.16 | 0.08   | 0   | Croydon               |
| Kensington and Chelsea| 0.03 | 0      | 0.01| Ealing                |
| Lambeth               | 0.21 | 0.16   | 0.01| Enfield               |
| Lewisham              | 0.13 | 0.58   | 0.04| Haringey              |
| Southwark             | 0.18 | 0.24   | 0.04| Harrow                |
| Wandsworth            | 0.08 | 0.16   | 0.07| Havering              |
| Westminster           | 0.08 | 0.14   | 0.03| Hillingdon            |

Fig. 6. Heat map of risks among London boroughs.
0 and 1. The normalised values are formatted in the colour scale (shown in Fig. 6). The darker colour indicates the larger number. In general, compared to the inner London boroughs, the outer London boroughs have a higher PUGS risk level, mainly because they have a larger number of green spaces. The boroughs like Ealing, Havering and Hillingdon require immediate responses because both the high risk and medium risk values are high, while the situation will become worse if the spreading continues and the medium-risk PUGS turn into high-risk. For the boroughs with a relatively large medium-risk PUGS group and relatively smaller high-risk group (such as Greenwich, Bexley and Barnet), attention needs to be paid on controlling the case development in the middle-risk areas. Harrow, Bromley, Richmond upon Thames and Croydon are identified as the boroughs with a majority of PUGS at medium or low-risk level, thus they should focus on maintaining the current safety situation. While the inadequate provision of public spaces and the increasing amount of local visitors lead to an overwhelming situation in the pandemic (Nobajas et al., 2020), the local government could deliver the different containment rules based on the identified risk levels, especially in the public parks owned and managed by the borough. The relevant restriction measures include limiting access to the high-risk spaces, controlling the number of people in the park, diverting the use of green spaces to different periods for different groups with various levels of vulnerability (Shoari et al., 2020). Compared to the borough-level risk assessment model developed in the previous study (Pan et al., 2021), the model proposed in this study locates the high-risk PUGS directly and enables the delivery of the intervention to the scale of green spaces.

6. Conclusion

In conclusion, the presence of this pandemic has exposed the inherent vulnerability of the urban system (Milner et al., 2021) and reinforced the significance of increasing the general resilience of the built environment regarding the unknown crisis in the future. Given the benefits of accessing the green spaces, especially at the background of the global pandemic, it is important to make sure that people can visit the public green spaces in their neighbourhood safely. Also, the necessary policy adjustment about the use of green spaces at the borough level can be implemented by the local government.

This study sets up a data-fused model to assess the risk of COVID-19 infection during PUGS visits over the pandemic time. As the previous studies have proved a spatial correlation between the green space accessibility and the emergence of COVID-19 cases (Pan et al., 2021), and the people in poverty are more vulnerable to this contagious disease, the risk assessment is conducted based on the growth of new cases at MSOA level, the accessibility of each green space and the IMD score at LSOA level. London is taken as the case study to illustrate the application of the model. While some research evaluates the risk at the urban district level, this study focuses specifically on the green spaces and demonstrates the risk of every single green space. Also, the novelty of the study is the integration of the clustering analysis to the risk assessment model. The clusters of PUGS are classified based on their features, then assigned to different levels of risks.

However, this study has several limitations. Firstly, the data is collected at the end of November, before the winter outbreak caused by the new variants and the third national lockdown. The cluster analysis only reflects the clustering pattern over the seven days period before 25 November 2020. When the significant growth of cases is observed over December 2020 and January 2021, the geographical pattern of new cases growth could have changed. The clustering result could change when the distribution of new cases is different. At the same time, as the current situation of transmission is changing rapidly, the data from the earlier time frame could result in a more representative clustering pattern. Also, compared to the model of adding up weighted value, the clustering analysis captures the characteristics of green spaces more accurately. The classification of risk level would not be influenced by the immediate rise of the new cases. Furthermore, the public green spaces considered in this research is those with a size of over 2 ha, while the smaller public spaces can also be chosen by local residents as the place to relax and exercise. The omission of the small size may cause bias in the accessibility evaluation, especially for those inner London boroughs with very limited space to hold large-size PUGS.

Overall, PUGS are a significant urban element that can contribute to sustaining physical and mental health and general well-being over the pandemic. Both a policy-level response to the control of PUGS access and use and an individual-level awareness of the risk of PUGS visits can help to ensure safe access to the green spaces. While the creation of more public parks and changes in landscape design will become the lasting impacts of the pandemic (Frumin, 2021), the urban greening system is expected to be more resilient in the future to face the extending challenges of the pandemic and the rising challenges like climate change and flooding (Fagerholm et al., 2021; Milner et al., 2021). Further study is expected to turn the risk assessment model into a real-world application to give effective instructions to the green space users. The application system can be updated according to the instant data and send out warnings to high-risk areas. This system can lower their risk of being infected when visiting the green spaces. The development of a comprehensive risk assessment method will ensure the safe and equal access to local green spaces and contribute to the improvement of resiliency in the urban system when facing the next ‘black swan’ event.

CRediT authorship contribution statement

Jiayu Pan: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. Ronita Bardhan: Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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