An evaluative model for assessing pandemic resilience at the neighborhood level: The case of Tehran

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ABSTRACT

The spread of the COVID-19 virus, which has caused abundant mortalities in human settlements, has drawn the attention of urban planners and policy-makers to the necessity of improving resilience to future pandemics. In this study, a set of indicators related to pandemic resilience were identified and used to develop a composite multi-dimensional pandemic resilience index for Tehran's neighborhoods. The physical, infrastructural, socio-economic, and environmental dimensions of pandemic resilience were defined considering the conditions of 351 neighborhoods through the exploratory factor analysis method. Accordingly, the pandemic resilience (PR) score of the neighborhoods was calculated. Furthermore, the Pearson correlation analysis was used to validate the PR scores by examining the correlation between the neighborhood PR scores and the number of confirmed cases. For this purpose, we used a sample consisting of 43,000 confirmed COVID-19 patients in the first five months of its spread. The test shows a statistically significant negative correlation between neighborhoods' resilience score and the cumulative number of confirmed patients in the neighborhoods (r= -.456, P<0.001). This study also tries to develop a new model to better understand health determinants of pandemic resilience. The proposed model can inform planners and policymakers to take appropriate measures to create more pandemic-resilient urban neighborhoods.

1. Introduction

Urban planning and design are inextricably linked with public health. Traditionally, cities have always evolved to effectively and efficiently confront public health and other security threats (Lai et al., 2020). For instance, the bubonic plague that happened in the 18th century facilitated the emergence of Renaissance cities in Europe; the last cases of Cholera epidemics that occurred in the 19th century contributed to global efforts to improve the health conditions of colonial cities; and the Spanish flu, which emerged in the 20th century highlighted that non-pharmacological interventions could play a very significant role in controlling epidemics and pandemics in cities (Göran & Whitehead, 1991). COVID-19 is claimed as one of the most severe public health crises in human history. Historically, non-pharmacological considerations, including the design and planning of urban environments, have been considered pivotal factors in preventing and managing epidemics and pandemics (Lai et al., 2020).

Pandemics can have significant socio-economic and environmental impacts. Enhancing urban resilience to pandemics requires a new understanding of the human-environment relationships and using socio-ecological models that can help identify the necessary context for building environments that are suitable for health, well-being, and comfort of urban residents during pandemics (Bates et al., 2020). In this regard, identifying various ecological, physical, social, and economic dimension of the environment as well as their relationships is needed (Göran & Whitehead, 1991). It is argued that dimensions of the built environment at the micro-and meso-scales (i.e., the neighborhood and public open spaces levels) can affect the exposure and spread dynamics of the disease and should, therefore, be considered in efforts aimed at combating the pandemic (Hu et al., 2020).

While a considerable amount of research has been published on the pandemic in urban contexts, there is still limited research on the dynamics of the pandemic at the neighborhood level (Hu et al., 2020; Li et al., 2021). Studying neighborhood-related features is essential as most people spend a significant share of their time in their homes and surrounding neighborhoods. This warrants further focus on the effects of

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the built environment and neighborhood features on public health during pandemics to facilitate better-informed urban design and policymaking. This study focuses explicitly on examining the relationship between neighborhood-related features and the pandemic to fill this gap.

The study also contributes to the ongoing discourses on urban resilience. Although this field has expanded rapidly over the past decade, there is very limited research on urban resilience to pandemics (Lak et al., 2020; Tang et al., 2020). A better understanding of factors which can contribute to pandemic resilience can lead to better-informed and more effective interventions that can improve the planning, absorption, recovery, and adaptation capacities of cities (Sharifi & Khavarian-Garmsir, 2020). Chen and Quan (2021) utilized economic, ecological, infrastructural, and social indicators to assess the overall level of resilience in the Yangtze River Delta under the COVID-19 pandemic. They have acknowledged the availability of frameworks and indicators for assessing resilience against various hazards such as natural disasters, accidents, economic shocks, and social security, with natural disasters receiving the most attention (Chen & Quan, 2021:831). They emphasized the necessity of accurate risk assessment methods to enhance urban resilience to pandemics and facilitate better prevention and control of future pandemics.

Various definitions have been provided for the term 'resilience' in the literature. Common to most definitions is the emphasis on the abilities to plan and prepare for, absorb, and recover from shocks (Walker & Salt, 2006). Chen & Quan (2021) have discussed resilience into three scales: region, city, and community (neighborhood). They have emphasized the importance of resilience-building activities at the neighborhood scale. Despite this, there is limited research on pandemic resilience at the neighborhood level. Accordingly, in this study we endeavor to further elaborate on the characteristics of pandemic resilient neighborhoods. In fact, COVID-19 provides an unprecedented opportunity to understand what characteristics are needed to make a neighborhood more resilient.

It should be mentioned that, as shown in Figure 1, resilience building should be an iterative process focused on enhancing the four abilities mentioned above (i.e., planning, absorption, recovery, and adaptation). The figure shows that improving resilience has multiple dimensions and entails taking different efforts. Assessment of baseline conditions and also assessment following adverse events are important for building resilience as they can highlight areas that need more actions and/or should be prioritized in resilience building efforts. An important step for building resilience assessment frameworks is identifying indicators. A lot of work has been done on resilience indicators, but not in the context of pandemic resilience. As a step towards filling this gap, we use a connective factor analysis approach (Asadzadeh et al., 2015) to develop a set of composite indicators of assessing neighborhood pandemic resilience. Having a list of relevant indicators can contribute to resilience building efforts, particularly those related to planning and preparation as shown in Figure 1. The focus is on Tehran (351 neighborhoods), the capital city of Iran. After defining the indicators related to the urban form of neighborhoods, their resilience scores are determined. Finally, correlation analysis is conducted to examine the relationship between neighborhood resilience scores and the rates of COVID-19 infections during the first five months of its spread.

2. Influential factors

Resilience in the context of adverse events can be defined as the ability to resist, absorb, and recover in a timely and efficient manner (Asadzadeh et al., 2015). One of the major features of pandemics is the way they spread spatially, and this is influenced by various factors such as the dynamic mechanisms of the pandemic, individual patterns of mobility, and management and control plans and policies (Franch-Pardo et al., 2020). Understanding the underlying mechanisms of spatial spread is essential, particularly to plan for and absorb the shocks (i.e., to contain the spread of the virus). In this regard, conducting spatial analyses, finding spatial correlations with other variables, and identifying the factors influential in the spread of diseases are crucial and can contribute to developing strategies to control pandemics (Liu et al., 2020).

Previous studies have contributed to understanding factors that contribute to the spatial spread of diseases at the urban level. However, there has been limited success in providing granular examinations at the neighborhood level (Hu et al., 2020). A study of the spread of COVID-19 in Wuhan showed that human-to-human transmission was common among close contacts (Li et al., 2020). Similar findings have been reported elsewhere, highlighting the need to take appropriate measures to control the spread of the disease at the local level by understanding the determinants of health (Tang et al., 2020). To identify factors that may influence the spatial spread of the disease, a brief literature review is presented in the remainder of this section. As can be seen, multiple factors could be influential and should be considered. In their study on the determinants of health during the pandemic, Hu et al.(2020) argued that a combination of social, economic, and environmental factors should be considered. These include factors such as income level, the
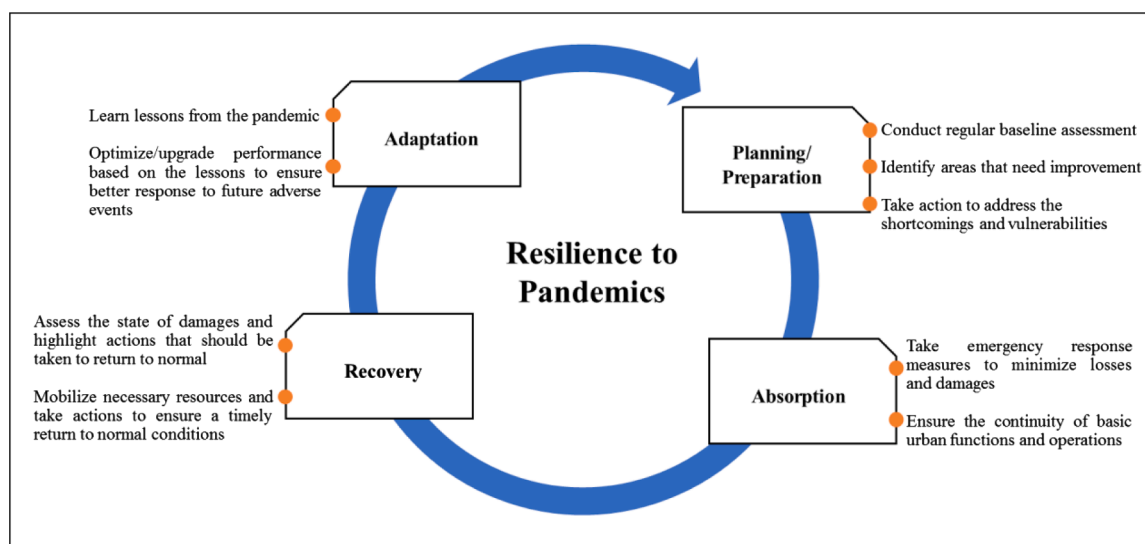

Fig. 1. A conceptual framework to understand resilience and its multiple stages (adapted from (Sharifi et al., 2021)).

density of the built environment, education level, levels of crime and violence in the neighborhood, and availability and access to healthcare services. These factors can have direct and indirect impacts on human health. For instance, poverty can limit access to healthy food and in the long run can lead to diseases such as diabetes that may increase vulnerability to infectious diseases. Or, high-density and crowded urban environments may increase the risk of exposure to viruses in the absence of measures that can ensure social distancing (Khavarian-Garmsir et al., 2021).

Influential factors have also been explored in other studies. Mollalo et al. (2020) introduced multiple explanatory factors that may influence the spread of COVID-19. These are related to various dimensions such as social (e.g., justice), demographic (e.g., ethnicity and gender), economic (e.g., employment status and insurance), environmental (e.g., levels of pollution and temperature), behavioral (e.g., smoking habits), and topographical (e.g., slope and altitude). Analysis of these factors using spatial regression and autoregressive models showed that the impacts of environmental factors on the incidence of COVID-19 are not significant. Similar findings have been reported elsewhere (Franch-Pardo et al., 2020). However, this may not always be the case. In fact, a review of the impacts of environmental factors shows that existing evidence is mixed (Sharifi & Khavarian-Garmsir, 2020). The same study indicates that socio-economic factors may have more significant effects. This is corroborated by Mollalo et al. (2019). They show that four factors, namely, 'average household income', 'income inequality', 'percentage of nurse practitioners', and 'percentage of black women', are particularly significant and are the main reasons behind the high variability of the pandemic spread in the United States of America (Mollalo et al., 2019).

Other factors related to the built environment have also been discussed in the literature. Bouffanais & Lim (2020) concluded that infectious diseases spread faster in places where people spend much time in close and face-to-face contact with each other, such as nursing homes, hospitals, and restaurants. However, it is necessary to consider other factors such as the extent of contacts and interactions. Other high-risk places in terms of the spread of the disease include recreation centers, religious conferences and gatherings, workplaces, densely populated dormitories, and places where people interact with those with weak immune systems. In addition, the movement of people within cities and urban environments occurs in dynamic spaces such as airports, public transport stations, restaurants, coffee shops, and cinemas. Based on this, it has been argued that modeling the movement of people in cities via intelligent monitoring systems and subsequently preparing maps to represent the main directions for the movement of people in cities, especially in crowded places such as shopping malls, subway stations, and nursing homes are essential. Also, such maps should consider other places where people interact in closed and crowded spaces, such as schools, libraries, and airports (Bouffanais & Lim, 2020).

Factors related to the urban form and physical characteristics of the built environment are also argued to influence the spread dynamics of the pandemic. Noteworthy factors are density, accessibility, design, and configuration of urban infrastructures such as street and transportation networks, location of jobs and services, and location and distribution patterns of other urban services such as recreational facilities, hospitals, restaurants, supermarkets, shopping malls, places of worship, etc. (Lai et al., 2020; Lak et al., 2020; Megahed & Ghoneim, 2020; Mollalo et al., 2020).

Overall, it is evident that multiple factors can influence the spread patterns of the pandemic. Accordingly, we have selected indicators related to various dimensions of pandemic resilience (PR) in the previous studies (Table 1). As will be discussed later, we will use connective factor analysis to explore these indicators' effects on PR.

The indicators extracted from the literature were used as a basis for the construction of an index system to define an evaluative model for neighborhood pandemic resilience. Chen & Quan (2021) indicated that the quantitative resilience assessment principally consists of "evaluation based on the system function curve" and "evaluation based on the index

Table 1
Indicators for developing a Neighborhood Pandemic Resilience Index (NPRI).

References	Indicators	Sub-dimensions	Dimensions
(Sharifi & Khavarian-Garmsir, 2020; Wilkinson, 2020)	Quality of residential area	Built environment characteristics	Physical Dimension
(Wilkinson, 2020)	Average housing area in neighborhoods		
(Wilkinson, 2020)	Building density		
(Brito et al., 2020; Franch-Pardo et al., 2020; Lai et al., 2020; Liu et al., 2020; Mollalo et al., 2019; Sangiorgio & Parisi, 2020)	Land use mix	Land use	
(Franch-Pardo et al., 2020; Ren et al., 2020)	Number of neighborhood centers (Supermarkets, Bakery, Grocery, and ….)		
(Franch-Pardo et al., 2020; Pourghasemi et al., 2020; Ren et al., 2020)	Number of Banks		
(Franch-Pardo et al., 2020; Ren et al., 2020)	Number of Chain stores		
(Franch-Pardo et al., 2020; Liu et al., 2020; Sharifi & Khavarian-Garmsir, 2020)	The ratio of non-built-up areas		
(Franch-Pardo et al., 2020; Ren et al., 2020; Sangiorgio & Parisi, 2020)	The ratio of the areas of educational, cultural and religious centers		
(Franch-Pardo et al., 2020; Lak et al., 2020; Sangiorgio & Parisi, 2020)	Number of Drugstores		
(Ren et al., 2020)	Number of hospitals designated to dealing with the pandemic		
(Franch-Pardo et al., 2020; Ren et al., 2020)	Access to public transportation	Access and Infrastructure	
(Brito et al., 2020; Franch-Pardo et al., 2020; Lai et al., 2020; Mollalo et al., 2019, 2020; Ren et al., 2020)	Access to plots and blocks		
(Brito et al., 2020; Lai et al., 2020; Liu et al., 2020; Mollalo et al., 2019; Ren et al., 2020)	Access to health centers		
(Sharifi & Khavarian-Garmsir, 2020)	Percent of population with higher education degrees		Demographic Dimension
(Franch-Pardo et al., 2020; Kim & Bostwick, 2020; Wilkinson, 2020)	Percent of population with pre-existing chronic diseases and health conditions (e.g., diabetes, asthma,		

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Table 1 (*continued*)

References	Indicators	Sub-dimensions	Dimensions
(Franch-Pardo et al., 2020; Kiaghadi et al., 2020; Lai et al., 2020; Liu et al., 2020; Mollalo et al., 2019; Ren et al., 2020; Wilkinson, 2020)	obesity & hypertension) Percent of the elderly population (over 65)		
(Franch-Pardo et al., 2020; Lai et al., 2020; Liu et al., 2020; Peng et al., 2020; Ren et al., 2020; Sharifi & Khavarian-Garmsir, 2020; Wilkinson, 2020)	Population density		
(Peng et al., 2020; Wilkinson, 2020)	Household size		
(Franch-Pardo et al., 2020; Mollalo et al., 2019, 2020; Sharifi & Khavarian-Garmsir, 2020)	The average number of polluted days in a year		Environmental Dimension
(Franch-Pardo et al., 2020; Mollalo et al., 2019, 2020; Sharifi & Khavarian-Garmsir, 2020)	Average levels of environmental pollution (air, water, soil)		
(Sharifi & Khavarian-Garmsir, 2020)	Temperature, wind speed and humidity		
(Sharifi & Khavarian-Garmsir, 2020; Wilkinson, 2020)	Average state of environmental cleanness (the amount of waste in neighborhood and water cycle)		
(Lai et al., 2020; Mollalo et al., 2019; Wilkinson, 2020)	The ratio of land uses related to health		Infrastructural Dimension
(Mollalo et al., 2019; Wilkinson, 2020)	The ratio of educational land uses		
(Mollalo et al., 2019)	The ratio of cultural-religious places		
(Franch-Pardo et al., 2020; Lai et al., 2020; Mollalo et al., 2019; Sannigrahi et al., 2020)	Percent of employed population		Economic Dimension
(Sharifi & Khavarian-Garmsir, 2020; Wilkinson, 2020)	The ratio of the population above the poverty line		
(Lai et al., 2020; Liu et al., 2020; Wilkinson, 2020)	Place attachment to the neighborhood		Social Dimension
(Glover et al., 2020; Lai et al., 2020; Liu et al., 2020; Wilkinson, 2020)	Level of social capital		

system". Accordingly, the NPR evaluation model introduced in this study is based on the index system that can evaluate the resilience level neighborhoods to the pandemic. However, it should be noted that "the index system's formulation and factor weight assignment are subjective" (Chen & Quan, 2021: 831).

3. Materials and methods

3.1. Case study: Tehran's characteristics

Tehran is the capital and the most important and populous city of Iran. It is located at 35° 41' N - 51° 25' E, and its altitude ranges from 1000-1800 meters. In the north, it borders the southern slopes of the Alburz Mountain, and in the south, it borders the Varamin plain. Tehran's climate is mild and temperate. Its average maximum temperature is 29° C, and its average minimum temperature is 0.1 °C (Municipality, 2020).

The city is one of the most polluted cities in the Middle East and even the world. It is now experiencing growing environmental problems related to air, water, and land (Ramyar, Ramyar, et al., 2019; Ramyar, Zarghami, et al., 2019). During the last forty years, Tehran's population has grown at a high rate, and, as a result, its area has expanded significantly (Municipality, 2020). In recent years, local authorities have tried to control and manage the quality of the built environment and improve microclimatic conditions in the city (Ramyar, Ramyar, et al., 2019).

More than 8,600,000 people live in 22 districts and 351 neighborhoods of Tehran (Fig. 2) (Municipality, 2020). District 4, with a population of 920,000, is the most populated one; and District 9, with about 174,000 people, is the least populated. The most densely populated district of Tehran is District 10, with 399 people per hectare (Fig. 3). In contrast, with 30 people per hectare, District 22 is the least densely populated one (Municipality, 2020). A previous study by Akhoundi et al. (2014) showed that, in general, the quality of life is higher in neighborhoods located in Districts 4 and 20 and lower in neighborhoods located in Districts 19 and 16. According to Sadeghi & Zanjari (2017), recently, the highest urban development rate belongs to Districts 3 and 1, and the lowest rate of urban development belong to Districts 17, 19, 18, 15, 16, and 20. Districts 3, 1, 2, and 6 are the most wealthy districts. In contrast, Districts 18, 15, 16, 19, and 17 are the most underdeveloped and most impoverished (Municipality, 2020).

3.2. Methods

To better understand the pandemic resilience status of Tehran's neighborhoods, the process of composite indicator development is explained below. This process will facilitate understanding the resilience level of the neighborhoods.

The indicators of Neighborhood Pandemic Resilience (NPR) (Table 2) were analyzed based on the 2017 population and housing census data of Tehran (Municipality, 2020), the 2015 spatial information of Tehran's land use and activities (Municipality, 2020), the outputs of the Urban Heart Research Project in Tehran (Asadi-Lari et al., 2016), as well as the outputs of the research project on Measuring Quality of Urban Life in Tehran (Akhoundi et al., 2014). According to the available indicators and data, out of the 351 neighborhoods of Tehran, four were excluded due to special conditions and lack of information on most indicators. The meteorological data of the districts, particularly heat island, were gathered from Landsat data (Rousta et al., 2018). Also, the addresses of all the 43,000 COVID-19 cases used in this study were gathered from the Medical Care Monitoring Center (MCMC), and the Hospitals' Information Management (HIM) system based on the factsheets that contain daily situation reports (Gholamzadeh et al., 2020).

Developing a set of composite indicators is well recognized as an accurate way to evaluate levels of resilience. A composite indicator combines individual indicators and offers an aggregate measure of a complex and multi-dimensional phenomenon such as pandemic resilience (Lak et al., 2020). The step-by-step processes of indicator selection and development are introduced based on previous studies (Asadzadeh et al., 2015; Daneshvar et al., 2019).

To be more specific, the model which is used for the evaluating NPR includes the following phases:

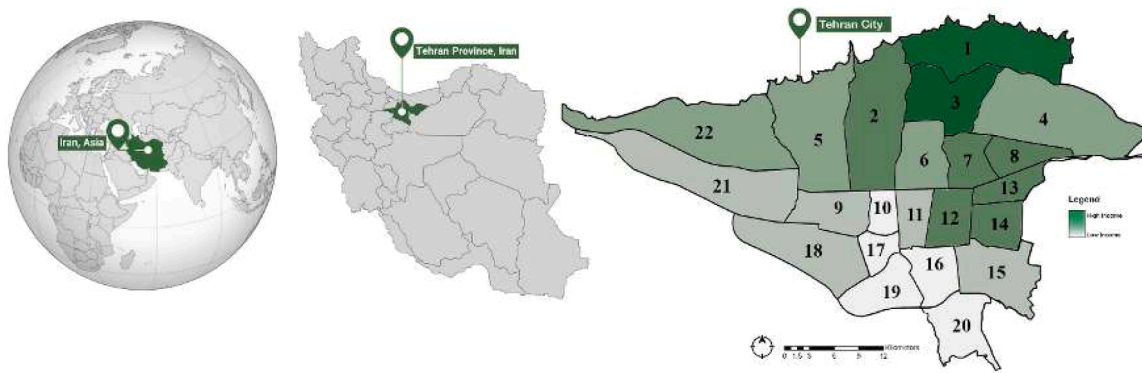Phase 1: Theoretical framework for indicator selection

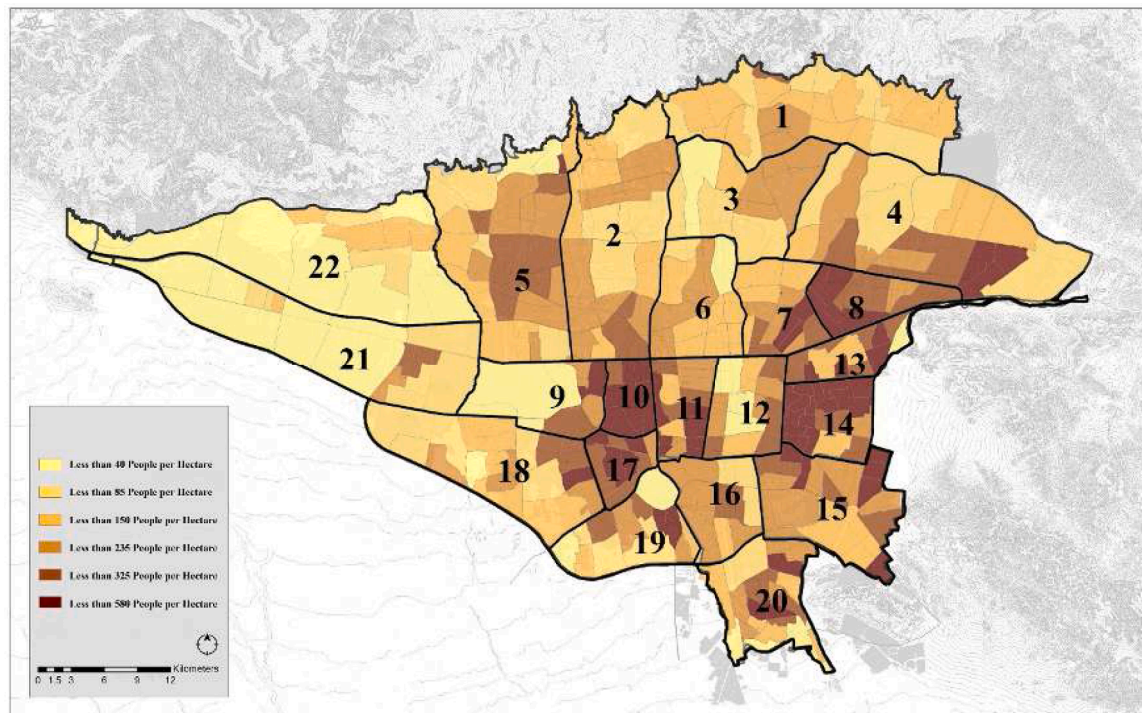**Fig. 2.** Urban districts of Tehran, the capital city of Iran.

Fig. 3. Population density of Tehran's neighborhoods. Adapted from (Lak, Sharifi, et al., 2021; Lak et al., 2021).

Developing a composite indicator should begin with examining and reviewing relevant literature and theoretical frameworks. This will facilitate elaborating on the concept and allows clarifying the structure of the analysis framework. Indicators extracted for this study are shown in Table 1.

Phase 2: Choosing relevant indicators and data normalization

The next phase in developing a composite indicator is the identification of appropriate indicators. One of the functions of a composite indicator is to measure a multi-dimensional concept. The multi-dimensional concept in this study is resilience to infectious diseases. After identifying a set of indicators, they should be synthesized into a composite indicator (E. Zebardast, 2013). As these indicators have various ranges or scales, the next step should be to normalize the data. For this purpose, the min-max normalization method was used in this study (Asadzadeh et al., 2015; E. Zebardast, 2013).

Phase 3: Factor analysis to reduce data and identify latent dimensions

After the indicators of pandemic resilience are selected, the next step is to perform factor analysis (FA) to determine the indicators' association with each other and find out how they change in relation to one another (Asadzadeh et al., 2015). In factor analysis, correlations among variables are examined, and correlated variables are sorted into clusters (Fabrigar et al., 1999; Khanaposhtani et al., 2016). The purpose is to reduce the number of variables and classify them (Asadzadeh et al., 2015). In this study, factor analysis is used to determine the correlation patterns among indicators and reduce them to specific factors known as pandemic resilience dimensions in the neighborhood scale.

Phase 4: Visualization and validation of the model

After the weights of the neighborhood-scale pandemic resilience indicators are identified, the next step is to calculate their scores. These scores are calculated using the mean and the standard deviation values. In other words, the 351 urban neighborhoods of Tehran are classified based on their standard deviation from the mean. In the next step, ArcGIS is used to visualize the results. Finally, the results are validated to verify their adequacy.

After the scores of the pandemic resilience dimensions and the composite NPRI (Neighborhood Pandemic Resilience Indicators) are calculated, in the next step, the results are visualized to get a better understanding of the pandemic resilience of Tehran's neighborhoods. Finally, cross-validation is performed to determine whether the

Table 2

The selected indicators for assessing NPR.

Effect	Abb.	Indicators	Sub-dimensions	Dimensions
+	QRA	The quality of the residential area	Built environment characteristics	Physical Dimension
+	AHA	Average housing area in the neighborhoods		
-	BD	Building density		
-	LUM	Land use mix	Land use	
-	NNC	The number of centers in the neighborhood (supermarket, bakery, grocery, etc.)		
-	NCS	Number of chain stores		
+	RBA	The ratio of non-built-up areas		
-	RCC	The ratio of the areas of educational, cultural and religious centers		
-	NDR	Number of drugstores		
+	NIH	Number of designated hospitals dealing with the pandemic		
-	APT	Access to public transportation	Access and Infrastructure	
-	NPT	Number of stations (subway and bus)		
-	ACC	Access to plots and blocks		
+	AHC	Access to health centers		
-	REP	The percentage of the elderly population (over 65)		Demographic Dimension
-	PD	Population density		
+	NPD	The average of non-polluted days in the neighborhood		Environmental Dimension
-	EP	The amount of environmental pollution		
+	EC	The average state of environmental cleanness		
-	MS	Temperature, wind speed, and humidity status (especially Heat Island and low wind speed)		
+	RH	The ratio of land uses related to health		Infrastructural Dimension
+	RE	The ratio of educational land uses		
+	RC	The ratio of cultural-religious spaces		
-	PEP	The percentage of unemployed population in the neighborhood		Economic Dimension
-	RP	The ratio of the population above the poverty line in the neighborhood		
-	PA	Place attachment to the neighborhood		Social Dimension
-	SC	Social capital in the neighborhood		

developed composite indicators accurately represent the real world (i.e., the results are compared with those of other validated models) (Asadzadeh et al., 2015; Daneshvar et al., 2019).

In the last step of developing a composite indicator, the model should be examined and verified. The purpose of the model examination is to determine the reliability of the underlying assumptions and determine whether the proposed model accurately represents the real world (Asadzadeh et al., 2015). In this study, the model examination aims to examine the correlation between the composite pandemic resilience indicators and the number of confirmed COVID-19 patients in Tehran's neighborhoods to determine whether it is a suitable measure of the overall pandemic resilience. To this end, the Pearson correlation coefficient, suitable for discrete data through parametric test (King & Eckersley, 2019), is used to determine the correlation between neighborhood pandemic resilience scores and the number of the confirmed patients. SPSS V. 25 is used to calculate the Pearson correlation coefficient.

4. Results

4.1. The theoretical framework for choosing indicators

Table 1 provides the theoretical framework and is used for choosing indicators in this study. After reviewing the relevant literature, 30 indicators related to the six domains were chosen, including: physical indicators (15), social indicators (2), economic indicators (2), environmental indicators (3), infrastructural indicators (3), and demographic indicators (5).

4.2. Selecting neighborhood pandemic resilience indicators and data normalization

Among the 30 indicators of the NPR model (Table 1), 27 indicators were regarded as suitable for measuring pandemic resilience in the specified context of Tehran (Table 2), as the updated data for three indicators were not accessible for further analysis.

The chosen indicators were then normalized and transformed (see Table 2). The indicators with positive associations with pandemic resilience were normalized using Eq.(1), and those with negative associations with pandemic resilience were normalized using Eq.(2) (Asadzadeh et al., 2015).

$$TX_i = \frac{X_i - X_{iMin}}{X_{X_{iMax} - X_{iMin}}} \quad (1)$$

$$TX_1 = 1 - \frac{X_i - X_{iMin}}{X_{X_{iMax} - X_{iMin}}} \quad (2)$$

Where, TX_t is the normalized value and X_{tmax} and X_{tmin} are, respectively, the maximum and minimum values of the original variable X_i.

4.3. Applying factor analysis to reduce data and identify latent dimensions

In the next step, Exploratory Factor Analysis (EFA) was conducted in order to determine the main and the latent dimensions to generate the model (Asadzadeh et al., 2015). The purpose of using EFA was to reduce the data and to determine various dimensions of pandemic resilience based on the neighborhood characteristics.

4.3.1. Assumptions of the technique

For the EFA to be acceptable, the sample size should be greater than 200, and the ratio of cases to variables should be equal to or larger than 5 (Asadzadeh et al., 2015). The sample size of this study is 351 (the number of neighborhoods) and the ratio of cases to variables is greater than 5. Therefore, both necessary conditions for the exploratory factor analysis to be acceptable are met.

As mentioned, the purpose of EFA is to identify the number of common factors describing the pattern of correlations among the measured variables and eventually to get a better conceptual understanding of them (Asadzadeh et al., 2015; E. Zebardast, 2013). The second step is to extract uncorrelated factors. For this purpose in this study, the principal components analysis (PCA) was used as a method for factor extraction (Zhong et al., 2014).

To check the appropriateness of data for factor analysis, the Kaiser's Measure of Sampling Adequacy and the Bartlett's Test of Sphericity were

used (Sarkkinen & Kässi, 2013). The Bartlett's Test (X^2: 2438, 042; df = 153; p < 0.0001) and Kaiser Test (0.721 > 0.50)) proved the suitability of the factor analysis.

4.3.2. Performing PCA and extracting dimensions of neighborhood pandemic resilience

After identifying the less important indicators using the communalities table and excluding them from the analysis, the latent dimensions of pandemic resilience were extracted. The communalities table determines the ratio of each variable's variance that is explainable by the principal components. Higher values of communality indicate that an indicator correlates with more items (Asadzadeh et al., 2015). In contrast, lower values (smaller than 0.4) mean that results may be substantially distorted, and thus, they should be excluded (Asadzadeh et al., 2015; A. Zebardast, 2010; E. Zebardast, 2013). Accordingly, nine indicators, namely, 'the number of stations (subway and bus)', 'access to plots and blocks', 'the average number of non-polluted days in the neighborhood', 'the average state of environmental cleanness (waste)', 'the ratio of land uses related to health', 'the ratio of educational land uses', 'the ratio of cultural-religious spaces', and 'the ratio of the areas of educational, cultural and religious centers' were excluded from the analysis due to their low values.

The number of the indicators used in the PCA is equal to the number of the extracted components. We used Kaiser's criterion (eigenvalues ≥ 1) to decide how many factors should be extracted from the dataset. Based on this rule, only the factors with an eigenvalue equal to or greater than 1.0 can be retained. Accordingly, four factors were extracted from the dataset. To develop the rotated component matrix and eventually develop a clear factor structure of pandemic resilience, Varimax rotation was used. This rotated component matrix is the critical output of principal components analysis. It contains the correlations between the variables and the estimated components. These variables play an essential role in interpreting the dimensions as they show the number of factors that explain variables in the process of factor analysis (Table 3).

In the rotated component matrix, variables are assigned to factors depending on the loading between variables and factors. Thus, based on factor analysis results, the initial set of 19 pandemic resilience variables (indicators in Table 3) were reduced to four underlying factors (dimensions in Table 3). The variables related to each factor can refer to a different dimension of pandemic resilience. We also decided to exclude variables with factor loadings less than 0.4 so that the pattern correlations of variables and components are increased. The rotated component matrix is generally aimed at transforming correlated indicators into a new set of uncorrelated components. These components (dimensions) are the best linear combination of considered indicators, explaining the most variance in the dataset than other linear combinations (Asadzadeh et al., 2015). Therefore, the first component here is the best linear combination among the data and captures most of the variance. The second component is the second-best combination and extracts the maximum variance from the residual variance.

In the next step, these components should be labeled. This labeling process is subjective and inductive (A. Zebardast, 2010). Considering that systematic factor analysis aims to find the dimensions that explain most of the responses, the dimensions shown in the first column of Table 3 were labeled based on the contents of their underlying indicators. The extracted dimensions include physical dimension (D1), infrastructural dimension (D2), socio-economic dimension (D3), and environmental dimension (D4).

The four components representing the urban form have values greater than one and capture 56.269% of the variance. Table 3 shows the percentage of the variance explained by each dimension and its associated indicators. Relying on the scores of the relevant indicators in each dimension, it is possible to interpret and label the relevant dimensions.

Table 3

The new dimensions of NPR and their primary indicators after PCA.

Dimensions	Variance %	Indicators	Abb.	Loading Factor
Physical Dimension (D1)	22.277	Average housing area in neighborhoods	AHA	.744
		The number of neighborhood centers (supermarkets, bakery, grocery, and ….)	NNC	-.607
		Number of chain stores in the neighborhood	NCS	-.501
		Number of drugstores	NDR	-.724
		Number of hospitals and clinics	NIH	.595
Infrastructural Dimension (D2)	14.247	Access to public transportation	APT	-.530
		Access to health centers	AHC	.624
		Population density	PD	-.722
Socio-economic Dimension (D3)	10.402	Quality of residential area	QRA	-.456
		Land use mix	LUM	-.529
		The percentage of the elderly population (over 65)	REP	-.426
		The percentage of unemployed population in the neighborhood	PEP	-.464
		The ratio of the population above the poverty line in the neighborhood	RP	.453
		Social capital	SC	.431
		Place attachment	PA	.470
Environmental Dimension (D4)	9.343	Average levels of environmental pollution	EP	.463
		Building density	BD	-.410
		The ratio of non-built-up areas	RBA	.524
		Temperature, wind speed, and humidity status (Heat Island and low wind speed)	MS	-.401
Aggregate	56.269			

4.4. Visualization and validation of the model

We first developed the composite indicators to measure neighborhood pandemic resilience and calculated the scores for the four dimensions of pandemic resilience and the composite NPR index. Next, we visualized the obtained results to better understand neighborhood pandemic resilience for 351 urban neighborhoods of Tehran. Finally, we validate the obtained results.

4.4.1. Mapping the neighborhood pandemic resilience scores

The ArcGIS software was used to visualize the composite indices for the neighborhoods. Furthermore, standard deviations from the mean were extracted to specify the urban neighborhoods with the highest and the lowest scores in terms of their pandemic resilience and determine the spatial pattern of pandemic resilience in the study area. Fig. 4 shows the spatial distribution of pandemic resilience for Tehran's neighborhoods.

This visualization facilitates better understanding of the variations in the levels of pandemic resilience. Examining the results shows significant differences between the northern and southern parts of the city. Nevertheless, the most important result is that only a few neighborhoods are highly resilient. The level of resilience in most of Tehran's neighborhoods is moderate or relatively low (Table 4). Based on the obtained results, the northern neighborhoods have relatively better conditions. In sum, neighborhoods in Districts 1, 3, 6, and 7 perform better in terms of pandemic resilience, and neighborhoods in Districts 2, 4, 5, 15, 16, and 18 show lower levels of resilience.

We also mapped the physical, socio-economic, infrastructural, and environmental dimensions separately to show variations across different
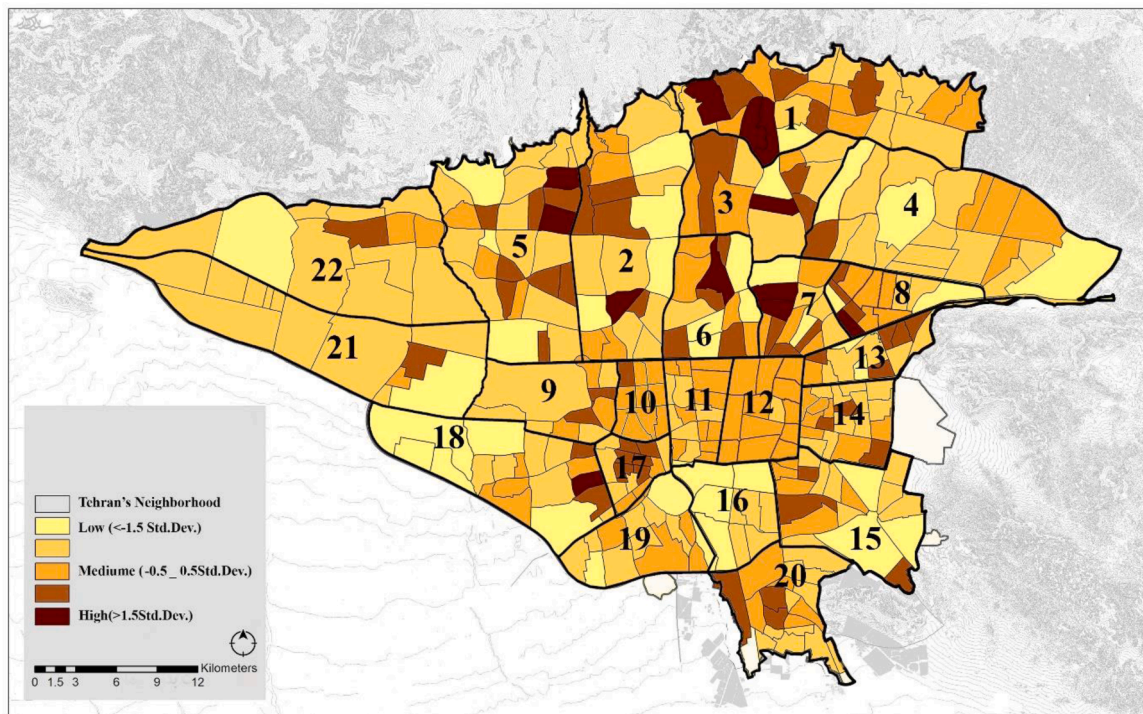
Fig. 4. The spatial distribution of pandemic resilience for neighborhoods of Tehran.

Table 4
The degree of pandemic resilience for the urban neighborhoods of Tehran.

Pandemic resilience degree	Urban neighborhoods	Percentage (%)
High	10	3
Relatively high	80	23
Moderate	116	33
Relatively low	91	26
Low	54	15
Total	351	100

underlying dimensions of pandemic resilience (Fig. 5).

Several important points can be highlighted based on this figure. The neighborhoods in districts 1, 2 and 3 have better performance in terms of physical dimension (Fig. 5a). In terms of the socio-economic dimension (Fig. 5c), approximately 50% of the neighborhoods have moderate levels of resilience, and the neighborhoods in districts 1, 2, 3 and 6 have relatively better conditions compared with other districts.

In contrast, neighborhoods in districts 14, 15, 10 and 11 have higher levels of buildings and population density, and thus, they could be more vulnerable to pandemics than the southern and eastern ones (Fig. 5b). Regarding the environmental dimension (Fig. 5d), neighborhoods in districts 21, 22 and 4 have higher levels of pandemic resilience than other parts, and regarding the infrastructural dimension (Fig. 5b), the neighborhoods in districts 7 and 12 have better conditions.

Overall, the spatial variation among different resilience dimensions shows that we need to deal with a multi-dimensional concept, and only paying attention to some indicators may not be enough. Instead, mapping resilience by focusing on its different dimensions is necessary and can help city officials better understand the underlying dynamics and influential dimensions of pandemic resilience.

4.4.2. Associations between resilience scores and the number of confirmed cases

The Pearson correlation coefficient was employed to measure the correlation between the neighborhood pandemic resilience scores and the number of the confirmed patients in the neighborhoods. The Pearson

correlation coefficient (r= -.456, P<0.001) showed a statistically significant negative correlation between the pandemic resilience scores and the number of confirmed patients in the neighborhoods (Fig. 6).

Fig. 6 shows that there are correlations between the number of disease cases and D1, D3, and D4. The correlation is significant for D1 at the confidence level of 0.01 with r=0.157 and for D3 and D4 at the confidence level of 0.05 with r=-0.106 and r=-0.105, respectively. D2 is statistically significantly correlated with case rate (r=-0.141) at the confidence level of 0.01 and D3 is statistically significantly correlated with death rate (r=0.154) at the confidence level of 0.01. NPR score is statistically significantly correlated with case rate and case fatality rate at the confidence level of 0.01 (P-Value=0.000) with r=0.304 and r=-0.243, respectively. Further, the correlation values of case rate with mortality rate and case fatality rate, at the confidence level of 0.01, are r=-0.407 and r=-0.157, respectively. Also, the two variables mortality rate and case fatality rate correlate with each other (r=0.165) at the confidence level of 0.01.

5. Discussion

5.1. The prediction of the vulnerable neighborhoods to the pandemics

This study provided a framework for measuring pandemic resilience in urban neighborhoods. This framework is based on four dimensions (i. e., physical, socio-economic, infrastructural, environmental) and 19 indicators. It can be used to assess neighborhood pandemic resilience and the results can highlight major intervention areas that should be prioritized and necessary preparation, response, and adaptation measures that should be taken (Connolly et al., 2020).

The spatial distribution of pandemic resilience scores in Tehran shows that nearly 41 percent of the neighborhoods (145) have unfavorable conditions and 33 percent have moderate levels of pandemic resilience (Table 4). Neighborhoods with favorable conditions in terms of pandemic resilience are in Districts 1, 3, 6, and 7. In these districts, after the infrastructural dimension, the socio-economic dimension had the most significant effect on pandemic resilience. However, the environmental dimension had the least effect.
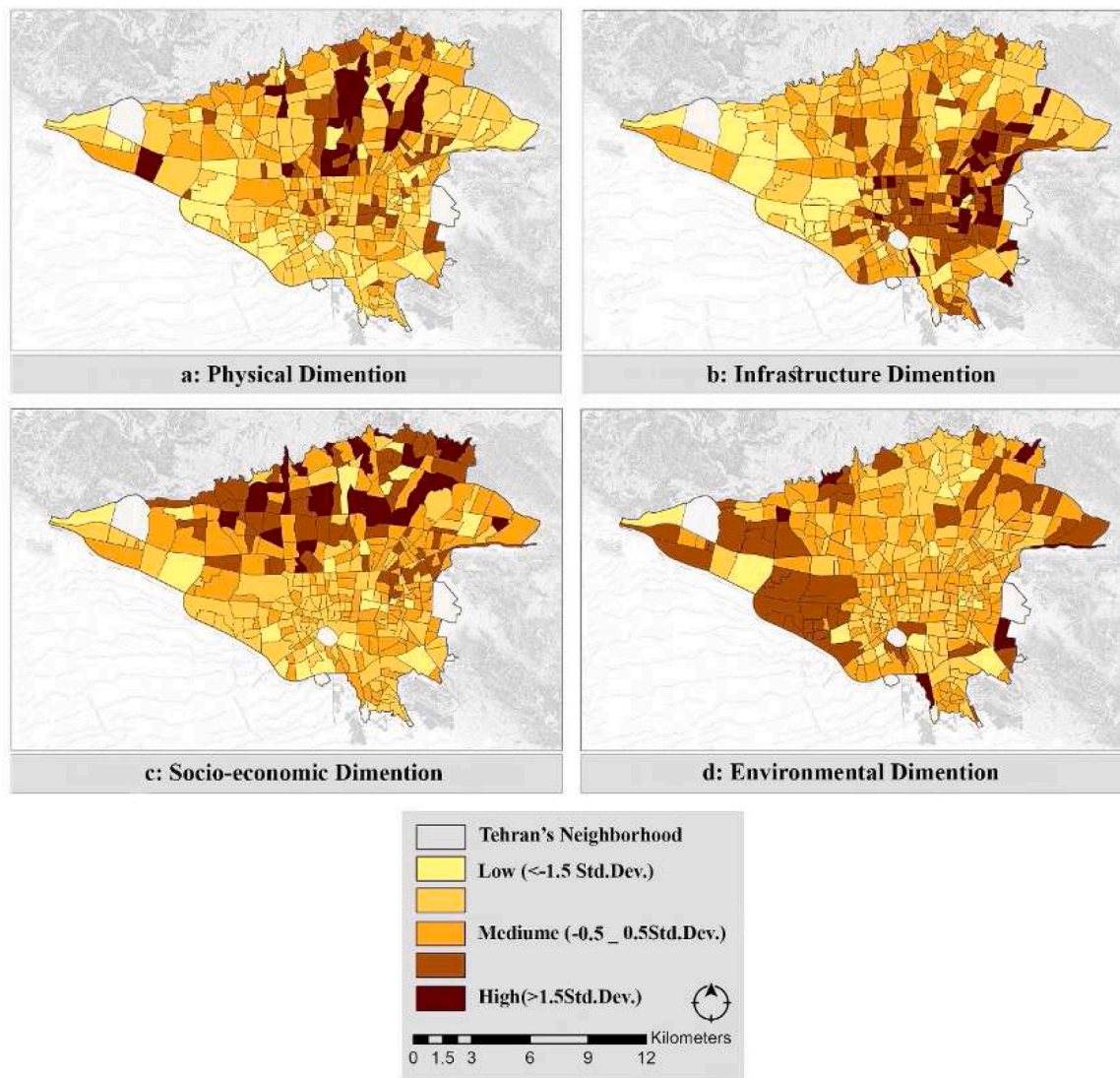
Fig. 5. Performance in terms of various dimensions of pandemic resilience.
a: Physical dimension, b: Infrastructure dimension, c: Socio-economic dimension, d: Environmental dimension.

Results showed that neighborhoods in Districts 2, 4, and 5 in the northern part and Districts 10, 15, 16, and 18 in the southern part of the city are less resilient to pandemics. Although Districts 2, 4, and 5 have favorable physical and socio-economic conditions, their larger number of COVID-19 cases can be related to more social contacts of residents due to high population density and the diversity of economic activities in the neighborhoods (Akhoundi et al., 2014). Moreover, neighborhoods in Districts 10, 15, 16, and 18 had lower resilience scores. Although these districts have relatively suitable conditions in terms of providing infrastructure and access to medical care, their lower scores show that non-infrastructural factors such as socio-economic conditions may significantly affect the outbreak and the spread of pandemics. The significance of socio-economic conditions has also been confirmed in other studies (Hu et al., 2020).

The correlation between the pandemic resilience score of neighborhoods and the number of the confirmed patients during the first five months of the pandemic indicates the validity of the proposed evaluative model and the composite indicator framework. Therefore, the NPR model is able to show the level of neighborhood vulnerability to virus spread in future pandemics. Here, it should be mentioned that in this study we have only examined correlation, and this should not be interpreted as causation. Therefore, further testing is needed to find out

if higher neighborhood resilience can lead to better abilities to control the spread of pandemics.

One of the main contributions of this study is mapping the spatial distribution of pandemic resilience in urban neighborhoods. While there are some differences between the neighborhoods in terms of resilience levels, only a few neighborhoods have high scores of pandemic resilience. This shows that the pandemic can affect different parts of the city irrespective of socio-economic status.

5.2. The proposed model of pandemic resilient neighborhood

Based on the indicators explored in this study, the proposed evaluative framework seeks to assess neighborhood pandemic resilience based on various determinants of health. This framework includes the physical (average housing area in neighborhoods, number of neighborhood centers, number of chain stores, number of drugstores, number of hospitals and clinics), infrastructural (access to public transportation, access to health centers, population density), socio-economic (quality of residential area, land use mix, the percentage of the elderly population (over 65), the percentage of the unemployed population, the ratio of the people above the poverty line, social capital, place attachment) and environmental (average levels of environmental pollution, building

Fig. 6. The coefficient matrix and scatter plot of correlations between the NPR scores (physical dimension (D1), infrastructural dimension (D2), socio-economic dimension (D3), environmental dimension (D4) as well as the overall NPR score), and the outcome variables, including case rate (COVID-19 rates), morality rate, case fatality rates as well as the cumulative number of patients and deaths.
Significance levels of p-values (* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$)

density, the ratio of non-built-up areas, climatic parameters (especially Heat Island and low wind speed)) dimensions.

The most critical evaluating factors are the built environment attributes of neighborhoods. Their importance in the outbreak of the COVID-19 pandemic has also been mentioned in other studies. For example, (Li et al., 2020) show that built environment attributes have played an important role in the spread of the COVID-19 disease in urban regions. Factors such as housing density, spatial distribution of chain stores and local shopping centers, quality and spatial distribution of transport infrastructure (bus and metro stations), quality and spatial distribution of medical facilities (hospitals, clinics, and drugstores), and also housing prices which indicate the social-economic situation of residents have played critical roles.

Some other characteristics of the proposed evaluation model are aslo confirmed in the literature. For example, Das et al. (2021) discovered that socio-economic status was a major determinant of the spatial clustering of COVID-19 hotspots in the Kolkata megacity. Other studies (Coşkun et al., 2021; Hassan & Soliman, 2021) mentioned the role of environmental factors such as air pollution, and meteorological and social parameters in the spread of the Covid-19 outbreak. Harris (2020) showed that socio-demographic characteristics such as age, deprivation, and ethnicity could be associated with higher COVID-19 death rates.

It should be noted that the dimensions and indicators extracted for this study explained 56 percent of the variance related to the characteristics of neighborhoods and their performance against pandemics. Therefore, we can consider the COVID-19 Determinants of Health Model (Liu et al., 2020) to identify factors affecting the outbreak and the spread of pandemics in neighborhoods. This model has adapted the influential factors in the Social Determinant of Health Model and has introduced a combination of significant individual, social, and environmental factors. It is adapted from the Kaiser Family Foundation model (Foundation, 2020) created by the PHOEBE Laboratory (University of Maryland, Public Health Outcomes and Effects of the Built Environment), and discussed in Hu et al., (2020).

According to the proposed model, factors such as healthcare (living in poor health conditions), poor nutritive conditions (food shortage), and residents' health misbehaviors, including the consumption of poor-quality food (food environment), or factors such as suffering from type II diabetes due to unhealthy diets, lack of physical activity, inadequate healthcare, or genetic characteristics (individual determinant) are very influential. In line with the PHOEBE Laboratory model, our model also states that observing health protocols such as using masks and maintaining social distancing helps prevent diseases that spread due to direct contact between individuals (Fig. 7). Also, (Li et al., 2020) emphasized: "the importance of residents' behavior in controlling human-to-human transmission risk and highlights the need to understand better the high-risk behaviors in specific urban spaces" in encountering infectious diseases.

The collective impact of these factors can have major implications for people's health in the conditions of epidemics and pandemics. While one factor may not be sufficient to jeopardize people's health in these conditions, the collective force of these determinants may lead to fatal outcomes.

To be "anti-pandemic", cities and neighborhoods must provide different responses, through emergency management and the reorganization of services, social welfare, and healthcare system, based on "tailor-made" responses (Moraci et al., 2020).

The health crisis can affect urban daily life, including" health access, education accessibility, public space, economic activity, connectivity, and social inequalities" (Martínez & Short, 2021:2). It could also lead to sudden shocks, for instance, the lockdown of the economy, and closure of retail stores and educational facilities (Litman, 2020). A pandemic resilient neighborhood can respond positively to the effects of health shocks and has the capacities to maintain its basic functions and return to normal conditions in a timely manner. Resilient neighborhoods need to have particular characteristics such as diversity, efficiency, strength, adaptability, and collaborative capacities to be able to control pandemics (Moraci et al., 2020:29). The model introduced in this study includes attributes that could contribute to enhancing such characteristics. Further research is, however, needed to better explore how such characteristics can be enhanced through the attributes introduced in this study. The developed evaluative model for NPR is able to identify and
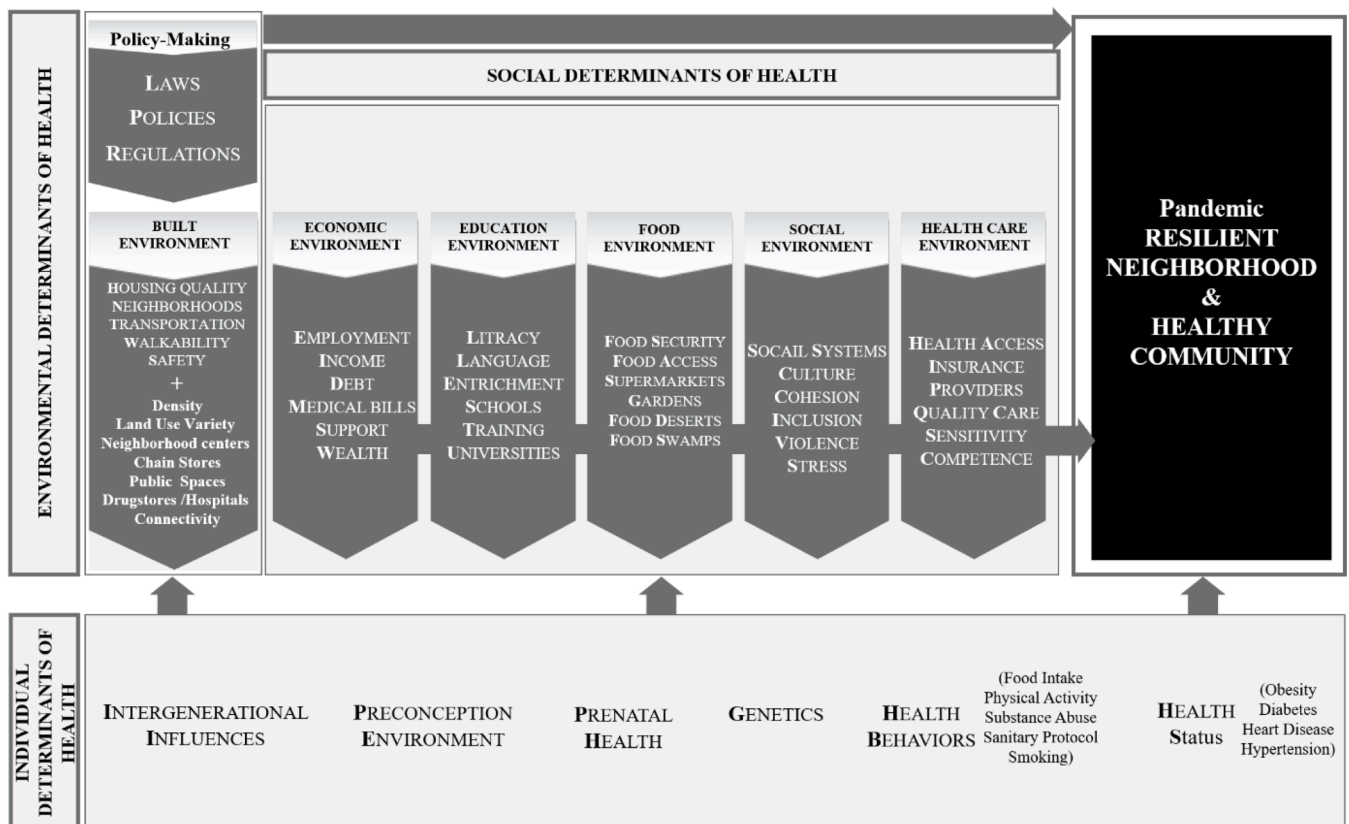
Fig. 7. Determinants of neighborhood pandemic resilience.

improve the factors that can contribute to reducing neighborhood vulnerability to pandemics by developing strategies based on the determinants of neighborhood pandemic resilience. Attention to these factors could also, in the long run, strengthen adaptation capacities at the neighborhood level. The attributes highlighted in the NPR model could be linked to preparedness, mitigation, and response phases (Afrin et al., 2021). The model can be used for identifying the resilience scores of neighborhoods and for highlighting the areas that need improvement and should be prioritized. Accordingly, better informed decisions can be made to strengthen planning, mitigation, and response capacities in terms of different physical, infrastructural, socio-economic, and environmental dimension. Enhancing such capacities could also, indirectly, contribute to better recovery to normal conditions as, for instance, the overall damages could be minimized and less efforts and resources would be needed for recovery.

This study has some limitations that should be mentioned. One important issue is related to the limited availability of data related to the residents' pre-existing health conditions (e.g., chronic diseases such as diabetes, hypertension, obesity, respiratory diseases, etc.) at the neighborhood level. Therefore, future research should also consider these factors. Another limitation is that only the overall conditions between February and July 2020 were examined, and temporal changes were not explored. Moreover, recovery and adaptation are two major underlying characteristics of resilience, and their analysis requires evaluation of temporal changes. Such temporal analysis will also allow a better understanding of the effectiveness of planning and response measures taken during the pandemic. Examining recovery capacities requires analyzing temporal changes and such changes should be explored when data related to different phases of the pandemic in Tehran becomes available. Due to such data availability constraints in evaluating the recovery of neighborhoods against COVID-19 during the pandemic, this model could be tested for the recovery phase in post-COVID era in the future. Therefore, analysis of temporal changes is highly recommended.

Despite these limitations, this study can be considered as a starting point for evaluating resilience through a mixture of quantitative and qualitative methods.

6. Conclusion

This study's primary purpose was to enhance our understanding of the factors affecting pandemic resilience at the neighborhood level in Tehran. After reviewing the literature to identify potential indicators and selecting important indicators using the exploratory factor analysis, a composite indicator framework was developed, and resilience scores for different neighborhoods were calculated. This allowed us to understand the relative performance of different neighborhoods and highlight those areas that need further attention. Also, examining the correlation between the calculated resilience scores of neighborhoods and the number of confirmed COVID-19 patients showed that the pandemic had spread more in the neighborhoods with lower resilience scores. This indicates that resilience score could be a predictor of vulnerability to pandemics. As correlation does not necessarily mean causation, however, further testing is needed to better understand how resilience scores and the abilities to deal with and control pandemic are related. Overall, the results show that different city neighborhoods are not performing well in terms of pandemic resilience. However, conditions are less favorable in some districts. This highlights issues related to socio-economic justice and other issues related to the availability and accessibility of resources and services needed to combat adverse events such as pandemics. The NPR evaluation process can be adopted to aid future pandemic response in cities. It can also contribute to more effective organization and management processes, leading to better pandemic resilience.

It is hoped that planners and policymakers will use the results to develop appropriate intervention plans and policies to overcome vulnerabilities and inequalities and ensure better preparation for future

pandemics. We also hope that the suggested method will be used in other cities in Iran and elsewhere to identify potentially vulnerable neighborhoods and take necessary actions towards creating cities and neighborhoods that are more just and resilient.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

References

Afrin, S., Chowdhury, F. J., & Rahman, M. (2021). COVID-19 pandemic: rethinking strategies for resilient urban design, perceptions and planning. *Frontiers in Sustainable Cities, 3*, 32.

Akhoundi, A. A., Barakpur, N., Khalili, A., Sedaghatnia, S., & Safiyari, R. (2014). Measuring Quality of Urban Life in Tehran Metropolitan. *HOnar - ha - ye - ziba Memari - va - shahrsazi, 6*(58), 5–22. https://www.magiran.com/paper/1458143. LK - https://www.magiran.com/paper/1458143.

Asadi-Lari, M., Khosravi, A., Nedjat, S., Mansournia, M. A., Majdzadeh, R., Mohammad, K., Vaez-Mahdavi, M. R., Faghihzadeh, S., Mehrizi, A. A. H., & Cheraghian, B. (2016). Socioeconomic status and prevalence of self-reported diabetes among adults in Tehran: results from a large population-based cross-sectional study (Urban HEART-2). *Journal of Endocrinological Investigation, 39*(5), 515–522.

Asadzadeh, A., Kötter, T., & Zebardast, E. (2015). An augmented approach for measurement of disaster resilience using connective factor analysis and analytic network process (F'ANP) model. *International Journal of Disaster Risk Reduction, 14*, 504–518.

Bates, L. C., Zieff, G., Stanford, K., Moore, J. B., Kerr, Z. Y., Hanson, E. D., Barone Gibbs, B., Kline, C. E., & Stoner, L. (2020). COVID-19 Impact on Behaviors across the 24-Hour Day in Children and Adolescents: Physical Activity, Sedentary Behavior, and Sleep. *Children, 7*(9), 138.

Bouffanais, R., & Lim, S. S. (2020). *Cities—Try to predict superspreading hotspots for COVID-19*. Nature Publishing Group.

Brito, P. L., Kuffer, M., Koeva, M., Pedrassoli, J. C., Wang, J., Costa, F., & Freitas, A. D. (2020). The Spatial Dimension of COVID-19: The Potential of Earth Observation Data in Support of Slum Communities with Evidence from Brazil. *ISPRS International Journal of Geo-Information, 9*(9), 557.

Chen, X., & Quan, R. (2021). A spatiotemporal analysis of urban resilience to the COVID-19 pandemic in the Yangtze River Delta. *Natural Hazards, 106*(1), 829–854.

Connolly, C., Keil, R., & Ali, S. H. (2020). *Extended urbanisation and the spatialities of infectious disease: Demographic change, infrastructure and governance*. Urban Studies, Article 0042098020910873.

Coşkun, H., Yıldırım, N., & Gündüz, S. (2021). The spread of COVID-19 virus through population density and wind in Turkey cities. *Science of the Total Environment, 751*, Article 141563.

Daneshvar, M. R. M., Rabbani, G., & Shirvani, S. (2019). Assessment of urban sprawl effects on regional climate change using a hybrid model of factor analysis and analytical network process in the Mashhad city, Iran. *Environmental Systems Research, 8*(1), 23.

Das, A., Ghosh, S., Das, K., Basu, T., Dutta, I., & Das, M. (2021). Living environment matters: Unravelling the spatial clustering of COVID-19 hotspots in Kolkata megacity. *Sustainable Cities and Society, 65*, Article 102577.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272.

Foundation, K. F. (2020). KFF health tracking poll—June 2020. KFF,Henry J. Kaiser Family Foundation, June. http://files.kff.org/attachment/Topline-KFF-Health-Tracking-Poll-September-2020.pdf.

Franch-Pardo, I., Napoletano, B. M., Rosete-Verges, F., & Billa, L. (2020). Spatial analysis and GIS in the study of COVID-19. A review. *Science of The Total Environment, 739*, Article 140033. https://doi.org/10.1016/j.scitotenv.2020.140033

Gholamzadeh, S., Mohammadi, G., Looha, M. A., Akrami, F., Zarean, E., Vafaee, R., Maher, A., & Khodadoost, M. (2020). Baseline Characteristics and Associated Factors of Mortality in COVID-19 Patients; an Analysis of 16000 Cases in Tehran. *Archives of Academic Emergency Medicine, 8*(1). e70–e70.

Glover, R. E., van Schalkwyk, M. C., Akl, E. A., Kristjannson, E., Lotfi, T., Petkovic, J., Petticrew, M. P., Pottie, K., Tugwell, P., & Welch, V. (2020). A framework for identifying and mitigating the equity harms of COVID-19 policy interventions. *Journal of Clinical Epidemiology*. https://doi.org/10.1016/j.jclinepi.2020.06.004

Göran, D., & Whitehead, M. (1991). Policies and strategies to promote social equity in health.

Harris, R. (2020). Exploring the neighbourhood-level correlates of Covid-19 deaths in London using a difference across spatial boundaries method. *Health & Place, 66*, Article 102446.

Hassan, S. B., & Soliman, M. (2021). COVID-19 and repeat visitation: Assessing the role of destination social responsibility, destination reputation, holidaymakers' trust and fear arousal. *Journal of Destination Marketing & Management, 19*, Article 100495.

Hu, M., Roberts, J. D., Azevedo, G. P., & Milner, D. (2020). *The role of built and social environmental factors in Covid-19 transmission: A look at America's capital city*. Sustainable Cities and Society, Article 102580.

Khanaposhtani, H. F., Nikabadi, M. S., Eftekhari, H., & Aslani, A. (2016). A new decision making model based on factor analysis (FA), F-ANP, and F-ARAS for selecting and ranking maintenance strategies. *International Journal of Business Analytics (IJBAN), 3*(4), 41–63.

Khavarian-Garmsir, A. R., Sharifi, A., & Moradpour, N. (2021). Are high-density districts more vulnerable to the COVID-19 pandemic? *Sustainable Cities and Society, 70*, Article 102911.

Kiaghadi, A., Rifai, H. S., & Liaw, W. (2020). *Assessing COVID-19 Risk, Vulnerability and Infection Prevalence in Communities*. MedRxiv.

Kim, S. J., & Bostwick, W. (2020). *Social Vulnerability and Racial Inequality in COVID-19 Deaths in Chicago*. Health Education & Behavior: The Official Publication of the Society for Public Health Education, 1090198120929677–1090198120929677.

King, A. P., & Eckersley, R. J. (2019). Descriptive Statistics II: Bivariate and Multivariate Statistics (A. P. King & R. J. B. T.-S. for B. E. and S. Eckersley (eds.); pp. 23–56). Academic Press. https://doi.org/10.1016/B978-0-08-102939-8.00011-6.

Lai, K. Y., Webster, C., Kumari, S., & Sarkar, C. (2020). *The nature of cities and the Covid-19 pandemic*. Current Opinion in Environmental Sustainability.

Lak, A., Shakouri Asl, S., & Maher, A. (2020). Resilient urban form to pandemics: Lessons from COVID-19. *Medical Journal of The Islamic Republic of Iran (MJIRI), 34*(1), 502–509. https://doi.org/10.34171/MJIRI.34.71

Lak, A., Sharifi, A., Badr, S., Zali, A., Maher, A., Mostafavi, E., & Khalili, D. (2021). *Spatio-temporal Patterns of the COVID-19 Pandemic, and Place-based Influential Factors at the Neighborhood scale in Tehran, 103034*. Sustainable Cities and Society. https://doi.org/10.1016/j.scs.2021.103034

Lak, A., Zali, A., Badr, S., Mostafavi, E., Baradaran, H. R., Hanani, K., Toomanian, A., & Khalili, D. (2021). A description of spatial-temporal patterns of the novel COVID-19 outbreak in the neighbourhoods' scale in Tehran. *Medical Journal of The Islamic Republic of Iran (MJIRI), 35*(1), 954–961.

Li, B., Peng, Y., He, H., Wang, M., & Feng, T. (2020). Built environment and early infection of COVID-19 in urban districts: A case study of Huangzhou. *Sustainable Cities and Society, 102685*. https://doi.org/https://doi.org/10.1016/j.scs.2020.102685.

Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., Ren, R., Leung, K. S. M., Lau, E. H. Y., & Wong, J. Y. (2020). *Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia*. New England Journal of Medicine.

Li, S., Ma, S., & Zhang, J. (2021). *Association of built environment attributes with the spread of COVID-19 at its initial stage in China*. Sustainable Cities and Society, Article 102752.

Litman, T. (2020). *Pandemic-resilient community planning*. Victoria Transport Policy Institute.

Liu, S., Qin, Y., Xie, Z., & Zhang, J. (2020). The Spatio-Temporal Characteristics and Influencing Factors of Covid-19 Spread in Shenzhen, China—An Analysis Based on 417 Cases. *International Journal of Environmental Research and Public Health, 17*(20), 7450.

Martínez, L., & Short, J. R. (2021). The Pandemic City: Urban Issues in the Time of COVID-19. *Sustainability, 13*(6), 3295. https://doi.org/10.3390/su13063295

Megahed, N. A., & Ghoneim, E. M. (2020). Antivirus-built environment: Lessons learned from Covid-19 pandemic. *Sustainable Cities and Society, 61*, Article 102350.

Mollalo, A., Mao, L., Rashidi, P., & Glass, G. E. (2019). A GIS-based artificial neural network model for spatial distribution of tuberculosis across the continental United States. *International Journal of Environmental Research and Public Health, 16*(1), 157.

Mollalo, A., Vahedi, B., & Rivera, K. M. (2020). GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. *Science of The Total Environment*, Article 138884.

Moraci, F., Errigo, M. F., Fazia, C., Campisi, T., & Castelli, F. (2020). Cities under pressure: Strategies and tools to face climate change and pandemic. *Sustainability, 12*(18), 7743.

Municipality, T. (2020). *Atlas of Tehran Metropolis*. Tehran, 2018.

Peng, Z., Wang, R., Liu, L., & Wu, H. (2020). Exploring urban spatial features of COVID-19 transmission in Wuhan based on social media data. *ISPRS International Journal of Geo-Information, 9*(6), 402.

Pourghasemi, H. R., Pouyan, S., Farajzadeh, Z., Sadhasivam, N., Heidari, B., Babaei, S., & Tiefenbacher, J. P. (2020). *Assessment of the outbreak risk, mapping and infestation behavior of COVID-19: Application of the autoregressive and moving average (ARMA) and polynomial models*. MedRxiv.

Ramyar, R., Ramyar, A., Kialashaki, Y., Bryant, M., & Ramyar, H. (2019). *Exploring reconfiguration scenarios of high-density urban neighborhoods on urban temperature–The case of Tehran (Iran), 44*. Urban Forestry & Urban Greening, Article 126398.

Ramyar, R., Zarghami, E., & Bryant, M. (2019). *Spatio-temporal planning of urban neighborhoods in the context of global climate change: Lessons for urban form design in Tehran, 51*. Iran. Sustainable Cities and Society, Article 101554. https://doi.org/10.1016/j.scs.2019.101554

Ren, H., Zhao, L., Zhang, A., Song, L., Liao, Y., Lu, W., & Cui, C. (2020). Early forecasting of the potential risk zones of COVID-19 in China's megacities. *Science of The Total Environment, 729*, Article 138995.

Rousta, I., Sarif, M. O., Gupta, R. D., Olafsson, H., Ranagalage, M., Murayama, Y., Zhang, H., & Mushore, T. D. (2018). Spatiotemporal analysis of land use/land cover and its effects on surface urban heat island using Landsat data: A case study of Metropolitan City Tehran (1988–2018). *Sustainability, 10*(12), 4433.

Sadeghi, R., & Zanjari, N. (2017). The inequality of development in the 22 districts of Tehran metropolis. *Social Welfare Quarterly, 17*(66), 149–184.

Sangiorgio, V., & Parisi, F. (2020). A multicriteria approach for risk assessment of Covid-19 in urban district lockdown. *Safety Science*, Article 104862.

Sannigrahi, S., Pilla, F., Basu, B., Basu, A. S., & Molter, A. (2020). Examining the association between socio-demographic composition and COVID-19 fatalities in the European region using spatial regression approach. *Sustainable Cities and Society, 62*, Article 102418.

Sarkkinen, M., & Kässi, T. (2013). Strategic innovation development based on systems research in a rural region. *Nternational J. Ind. Eng. Manag, 4*, 57–67.

Sharifi, A., & Khavarian-Garmsir, A. R. (2020). The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. *Science of The Total Environment*, Article 142391.

Sharifi, A., Khavarian-Garmsir, A. R., & Kummitha, R. K. R. (2021). Contributions of Smart City Solutions and Technologies to Resilience against the COVID-19 Pandemic: A Literature Review. *Sustainability, 13*(14), 8018.

Tang, J., McNabola, A., & Misstear, B. (2020). *The potential impacts of different traffic management strategies on air pollution and public health for a more sustainable city: A modelling case study from.* Dublin, Ireland: Sustainable Cities and Society, Article 102229.

Walker, B. H.(Brian H., & Salt, D.(David A. (2006). *Resilience thinking : sustaining ecosystems and people in a changing world.* Island Press.

Wilkinson, A. (2020). Local response in health emergencies: key considerations for addressing the COVID-19 pandemic in informal urban settlements. *Environment and Urbanization*, Article 0956247820922843.

Zebardast, A. (2010). The application of analytic network process (ANP) in urban and regional planning. 79–90 ,(41)2 ,شهرسازی و معماری‌ـهای زیبا هنر نشریه.

Zebardast, E. (2013). Constructing a social vulnerability index to earthquake hazards using a hybrid factor analysis and analytic network process (F'ANP) model. *Natural Hazards, 65*(3), 1331–1359.

Zhong, S., Clark, M., Hou, X.-Y., Zang, Y., & FitzGerald, G. (2014). Validation of a framework for measuring hospital disaster resilience using factor analysis. *International Journal of Environmental Research and Public Health, 11*(6), 6335–6353.