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An Assessment of Neighborhood Disaster Resilience in Tehran Metropolis

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ABSTRACT

There is growing interest in how local communities could become more resilient to the adverse effects of disasters. Identifying baseline indicators and establishing a methodology for evaluating community disaster resilience (DR) at a finer scale (neighborhood) is of utmost importance. This article (1) adapts the Baseline Resilience Indicators for Communities (BRIC) framework to identify baseline resilience indicators, (2) utilizes the hybrid Factor Analysis and Analytic Network Process (F'ANP) model to assess DR, and (3) uses discriminant analysis to validate the applicability of the proposed methodology at the neighborhood level of the Tehran Metropolis. Guided and inspired by the BRIC framework, 35 baseline DR indicators are chosen from the literature. Using the F'ANP model, the seven extracted DR subdomains are reorganized to align with the BRIC structure. A composite DR index is computed and classified into five categories, using K-Means cluster analysis. The results are validated by discriminant analysis and spatial autocorrelation. Employing the BRIC-F'ANP model allows for the restructuring of identified disaster resilience subdomains to form the necessary resilience structure. The obtained results indicate that higher DR neighborhoods are concentrated in the northern parts of the city, whereas those with lower DR are clustered in the southern parts of the Tehran Metropolis. The adaptation of the BRIC-F'ANP model has resulted in the development of a robust methodology for measuring DR at the neighborhood level that could be replicated for assessing the neighborhood DR in other cities.

1. INTRODUCTION

With growing awareness of the potential severity of human-caused climate change and rapid urban growth, particularly in the major cities and metropolises of the Global South (Joerin et al., 2014), there is increasing interest in how local communities and neighborhoods can become more resilient to withstand their corresponding negative impacts (Rendon et al., 2021). The issue has gained importance due to rising concern over the dramatically increasing number of disasters (Khan et al., 2023). The impact of disasters is influenced by several factors, including the severity of the disaster, the resilience of the urban population, available support systems, and the level of preparedness (Bakic and Ajdukovic, 2021). When an adverse event occurs in a resilient community, it does not necessarily escalate into a full-blown disaster. Conversely, even in developed countries, vulnerable residential areas can face serious consequences generated by disasters. Thus, a system's resilience determines its capacity to withstand stress and mitigate significant physical and economic losses during climatic or sociopolitical stresses (Abdul and Yu, 2020). Accordingly, resilience has gained considerable attention and has become a cornerstone for risk management and disaster mitigation initiatives (Graveline and Germain, 2022).

Being a polysemic concept, resilience is defined in numerous ways that vary from one discipline to another. The United Nations Office for Disaster Risk Reduction (UNDRR) defines resilience as "the ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management" (UNDRR, 2024, p. 1). Consequently, the concept of community disaster resilience and its assessment has garnered considerable attention in recent years. However, the effective operationalization of CDR assessment frameworks presents significant challenges (Manyena et al., 2019). A central challenge lies in the definition and identification of indicators for accurately measuring resilience, as well as in determining suitable analysis units and mapping methods. Without a solid conceptual framework that enables the definition and measurement of resilience, there is a risk that this concept will be ineffective for properly assessing the community's resilience capacities and unsuitable for informing policy actions in this area (Mayunga, 2007). Several community disaster resilience assessment frameworks have been developed and widely used at various scales and settings. The Baseline Resilience Index for Communities (BRIC) framework (Cutter et al., 2010; Cutter, 2014) is one of the most replicated, mature (Camacho et al., 2023) and cited frameworks (Qiang et al., 2023), originally designed and applied at the county level in the USA. The BRIC framework uses the Disaster Resilience of Place (DROP) model (Cutter et al., 2008) as a theoretical basis for indicator selection and has been validated with the Social Vulnerability Index (Derakhshan et al., 2022; Bronfman et al., 2024). It has mostly been applied at the county (Cutter et al., 2016; Derakhshan et al., 2022), district (Csizovszky and Buzási, 2023; Bronfman et al., 2024), municipality (Scherzer et al., 2019), and census tract levels (Derakhshan et al., 2022). Hence, the BRIC framework is primarily a county-level disaster assessment framework and "does not reflect the variations of resilience at the sub-county scale" (Derakhshan et al., 2022, p. 2). Camacho et al. (2023), reviewing the geographical locations, types of communities and disasters in which the BRIC framework has been applied, find that, of the 32 worldwide applications of the BRIC framework for CDR assessment, only one study has taken place at the neighborhood level. This indicates that the BRIC framework's applicability at the neighborhood level is very scant and remains uncertain. To fill this gap, the current study uses the BRIC framework combined with the F'ANP model to assess disaster resilience at the neighborhood level in a Global South metropolis, its findings demonstrating the suitability of the BRIC framework for evaluating CDR at the neighborhood level. The F'ANP model is a hybrid approach that merges exploratory factor analysis (FA) with the analytic network process (ANP) to compute the relative weights of individual variables representing a multidimensional concept and aggregates them to construct a composite index. The model leverages the inherent advantages of FA to address the limitations of the ANP (Zebardast, 2013; Zebardast, 2022). The F'ANP model has been applied in various fields of research to compute weights for indicators that represent the phenomenon under examination and for constructing composite indices.

This paper attempts to: (1) identify BRIC-based baseline indicators for neighborhood-level disaster resilience assessment in the city of Tehran, (2) present an augmented BRIC-F'ANP model to evaluate the disaster resilience at the neighborhood level, and (3) validate the results of applying the proposed BRIC-F'ANP model. The article is organized as follows: after the introduction, the study area and the methodology of the paper are explained; the results of the study are then presented, followed by a discussion and conclusion in the latter parts of the paper.

2. COMMUNITY DISASTER RESILIENCE FRAMEWORKS

Numerous CDR frameworks are available in the literature. Most CDR frameworks utilize an indicator-based approach, incorporating both quantitative and qualitative methods to evaluate resilience. CDR indicators are elements that can be employed to assess and compare resilience levels across different spatial and temporal scales (Cutter et al., 2008). Cutter (2016) classifies the CDR frameworks into three categories: indices, scorecards and tools. According to her, the following eight frameworks measure CDR "with specific identifiable concepts and variables" (Cutter, 2016, p. 749): BRIC – Baseline Resilience Indicators for Communities (Cutter et al., 2010; Cutter et al., 2014); CRI – Community Resilience Index (Sherrieb et al., 2010; Bergstrand et al., 2015); CART – Communities Advancing Resilience Toolkit (Sherrieb et al., 2012; Pfefferbaum et al., 2013); RCI – Resilience Capacity Index (Pendall et al., 2010); CDRI – Community Disaster Resilience Index (Yoon et al., 2016); and ResilUS – a community-based disaster resilience model (Miles and Chang, 2011). Other noteworthy CDR frameworks are (Asadzadeh et al., 2017; Tariq et al., 2021): CDRI- Community Disaster Resilience Index (Parsons et al., 2016); CDRI –

Community Disaster Resilience Index (Prashar et al., 2012); and CRI – Community Resilience Index (Norris et al., 2008). The main reasons for selecting the BRIC framework (Cutter, 2010; Cutter, 2014) to inspire and guide the neighborhood-level CDR assessment in the Tehran metropolis, are as follows: (1) it is purely objective, multifaceted and covers all hazards; (2) it is the most replicated and mature approach for measuring CDR and has been widely applied at different spatial levels, especially in recent years (Camacho et al., 2023).

3. METHODOLOGY

3.1. Study area

Tehran Metropolis, with a population of 8.9 million in 2022, is the most populous city in Iran. As the national capital, the city hosts high levels of administrative, service, and manufacturing activities and covers an area of approximately 730 square kilometers. It is divided into 22 districts and 354 neighborhoods (Fig. 1).

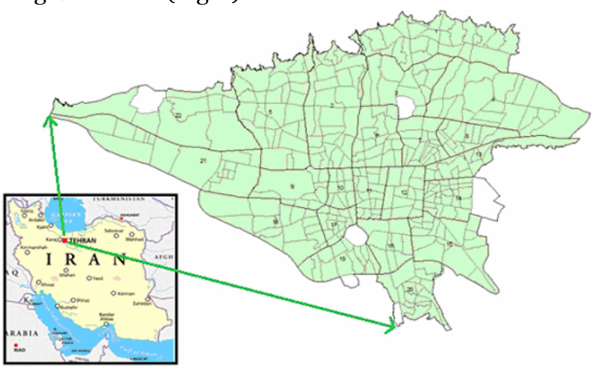

Fig. 1. Location of the Tehran Metropolis in Iran *(source: Zebardast, 2022, p. 6).*

The city is located in the southern foothills of the Alborz Mountains and is surrounded by several active seismic faults (Ashtari et al., 2005). The city is also prone to severe flash floods. During the 1920-2021 period, Tehran Metropolis and its surrounding provinces of Alborz, Qazvin, Qom, and Markazi have experienced 28 natural disasters, resulting in about 55 thousand casualties and US$ 22 billion in economic damages (Farzanegan et al., 2024). These facts and figures indicate the vulnerability of Tehran city to natural disasters.

3.2. Data and methods

The flowchart of the proposed methodology is presented in Figure 2. The data needed for the selected indicators are obtained from the Population and Housing Census data conducted by the Statistical Center of Iran in 2016 (SCI, 2016) and different layers of Tehran Map obtained from the Municipality of Tehran Information and Communication Technology Organization (MTICTO, 2024).

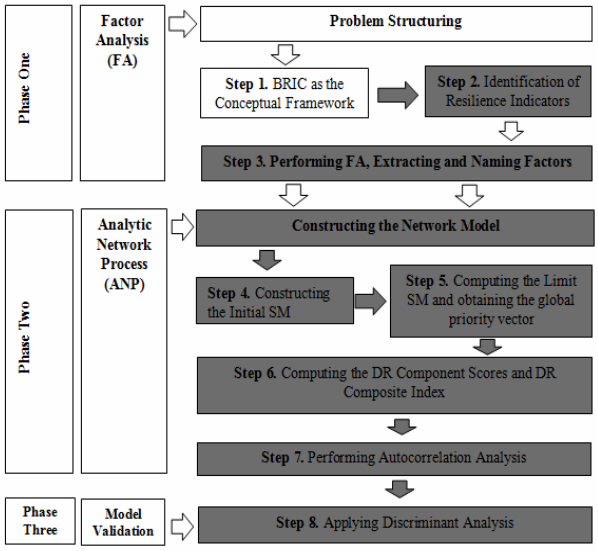

Fig. 2. Flowchart of the proposed methodology.

This study adapts the BRIC framework for neighborhood disaster resilience assessment. The BRIC framework is composed of six sub-dimensions: social, economic, institutional, housing and infrastructure, community capital, and environmental (Cutter et al., 2014). Utilizing the BRIC as a conceptual framework, the F'ANP model is applied to assess disaster resilience and obtain a composite DR index at the neighborhood level within the Tehran Metropolis. The proposed F'ANP model is composed of three phases: factor analysis, analytic network process, and model validation. Each of these three phases and steps involved in applying them is shown in Figure 2 and the processes of their application are shown in the results section of the paper.

4. RESULTS

4.1. Problem structuring

In the first phase of the F'ANP model (Fig. 2), factor analysis is used for problem structuring.

Step 1. BRIC as the Conceptual Framework. The first step in the F'ANP application is developing a conceptual framework based on which the relevant indicators of the phenomenon at hand are chosen. The BRIC framework is chosen as the conceptual framework for this study.

Step 2. Identification of Resilience Indicators. To select the relevant DR resilience indicators at the neighborhood level, the original BRIC indicators were not translated; instead, from among the existing BRIC adaptations and disaster resilience literature, those indicators that were (a) sensible and justifiable in the Iranian context, (b) applicable at the neighborhood scale, (c) accessible in terms of data, and (d) reliable and simple for replication were selected. Each of the proposed BRIC indicators was checked for suitability at the neighborhood level. Due to data unavailability for some of the BRIC-institutional subdomain indicators, such as: "ten-year average per capita spending for mitigation projects", and "the percentage of the housing units covered by the National Flood Insurance Program" (Cutter et al., 2014, p. 69), along with non-applicability of other indicators at the neighborhood level, like, "the governments and special districts per 10,000 persons," "proximity of the county seat to the nearest county seat within a Metropolitan Statistical Area," and "proximity of the county seat to the state capital" (Cutter et al., 2014, p. 69), the institutional dimension of the BRIC resilience was omitted from the study, as done by Aksha and Emrich (2020), Javadpoor et al. (2021), and Csizovszky and Buzási (2023). Initially, 41 indicators were selected and they were checked for possible collinearity. Using Statistical Package/Program for Social Sciences (SPSS Version 26), Pearson's correlation coefficients for the 41 selected indicators were computed to examine the possible multicollinearity between them. Six indicators, namely, access to cultural centers, housing tenure diversity, access to recreation areas, access to health centers, percent unskilled laborers, and per capita urban green space were found to be highly correlated *(Pearson's r>0.7)* were omitted from the study. The final 35 baseline indicators, their data sources, computation procedures and effects on resilience are presented in Table 1.

Table 1. Selected baseline resilience indicators.

No.	Resilience subdomains	Indicators	Acronym	Data provider (Scoring procedure)	Effect on resilience	Justification/ Inspiration
1	Social	% Non-elderly population	NEP	Statistical center of Iran-SCI	Positive	Cutter et al., 2014
		% Households with disabled persons	DIS	SCI	Negative	Cutter et al., 2010
		Ratio of men to women	MTW	SCI	Positive	Cutter et al., 2010
		% Housing units (HUs) with telephone	TEL	SCI	Positive	Cutter et al., 2014
		% Population with health insurance	HIN	SCI	Positive	Cutter et al., 2010
		Ratio of the % population with college education to % illiterate population	COL	SCI	Negative	Cutter et al., 2010
		Single-parent households	SPH	SCI	Negative	Parsons et al., 2021
		Number of rooms per HU	RMH	SCI	Positive	Chen et al., 2013
		Number of households per HU	NHH	SCI	Negative	Zebardast et al., 2024
		Number of widowed women per 1000 population	NWP	SCI	Negative	Kwan, 2020
		% Households owning cars	CAR	SCI	Positive	Cutter et al., 2010
		Household size	HHS	SCI	Negative	Henly-Shepard et al., 2015
2	Economic	% Owner-occupied HUs	OWN	SCI	Positive	Cutter et al., 2010
		Ratio of employed to population	EMP	SCI	Positive	Cutter et al., 2014
		% Employed females	FEM	SCI	Positive	Cutter et al., 2010
		Access to retail and/or commercial establishments	ARC	(a)	Positive	Parsons et al., 2021
		Employment diversity	EMD	(b)	Positive	Derakhshan et al., 2022
3	Community	Satisfaction with neighborhood relations	NRE	(c)	Positive	Ostadtaghizadeh et al., 2016
		Sense of belonging	SBE	(c)	Positive	Cutter et al., 2014
		Satisfaction with participation in neighborhood decisions	PAR	(c)	Positive	Ostadtaghizadeh et al., 2016
		Sense of security	SOS	(c)	Positive	Derakhshan et al., 2022
		Social Capital	SOC	(c)	Positive	Cutter et al., 2014
		Cultural heritage (Ratio of cultural land use (LU) to population)	CLU	Municipality of Tehran ICT Organization (MTICTO), SCI	Positive	Derakhshan et al., 2022
4	Infrastructure	Number of public schools per 1000 population	NPS	SCI	Positive	Derakhshan et al., 2022
		Ratio of health LU to population	HLU	MTICTO, SCI	Positive	Scherzer et al., 2019
		Access to fire stations	AFS	(a)	Positive	Scherzer et al., 2019
		Access to hospitals	ATH	(a)	Positive	Scherzer et al., 2019
		Ratio of sports and recreational LU to population	SLU	MTICTO, SCI	Positive	Opach et al., 2020

		Land use diversity	LUD	(b)	Positive	Suárez et al., 2016
		Housing unit size diversity	HUS	(b)	Positive	Tiwari and Shukla, 2024
		Ratio of open space LU to area	OLU	MTICTO, SCI	Positive	Derakhshan et al., 2022
5	Environment	% Permeable surface	PER	MTICTO	Positive	Cutter et al., 2014
		Ratio of green space to area	GSA	MTICTO, SCI	Positive	Derakhshan et al., 2022
		Green space satisfaction	GSS	(c)	Positive	Rus et al., 2018
		Access to public green spaces	AGS	(a)	Positive	Derakhshan et al., 2022

(a)- In ArcGIS, spatial buffer functions are used on Tehran Metropolis Land Use (2015) to identify service catchment areas within a 1000-meter radius for hospitals and fire stations, and 650 meters for health centers. Service catchment areas for these facilities in each neighborhood is divided into the neighborhood area to obtain each neighborhood's access to these facilities.

(b)- Simpson's diversity index is used to calculate the land use and housing size diversity in the neighborhoods.

(c)- MTICTO has used a multistage sampling for data collection. Using self-administered questionnaires, a total of 34,700 households have been surveyed. Questions for each indicator have been based on a five-point Likert scale (never = 1 to completely = 5). The mean score for each indicator has been computed for each neighborhood.

Source of data: The Statistical Center of Iran (SCI, 2016) and the Municipality of Tehran Information and Communication Technology Organization (MTICTO, 2024).

All indicators were standardized through min-max transformation. Positive indicators were standardized using Equation (1) and negative indicators using Equation 2:

$$tx_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad (1)$$

$$tx_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad (2)$$

where:

- tx_i is the transformed indicator x_i in neighborhood i;

- x_{max} and x_{min} are the maximum and minimum value of indicator x_i, respectively.

Step 3. Performing FA, extracting and naming factors. Exploratory factor analysis (EFA) is performed using the SPSS 26 software and the selected 35 baseline indicators (Table 1).

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were computed to control data suitability for FA. The KMO value (0.815) and Bartlett's test of sphericity (sig. = 0.0001) indicate that the data is suitable for FA. Applying the Kaiser criterion (eigenvalues greater than or equal to 1), the scree plot, and the percentage of variance criterion, which recommends retaining factors that cumulatively explain at least 60% of the data variance, while also considering the interpretability of the factors, seven factors are extracted. These cumulatively explain 63.61% of the data variance. Varimax rotation is utilized to obtain simple and interpretable factors. The varimax rotated component matrix is presented in Table 2.

Table 2. Varimax rotated component matrix.

No.	Indicators	Acronym	F1	F2	F3	F4	F5	F6	F7
1	% Households owning cars	CAR	**0.868**	-0.314	0.019	0.094	0.171	0.007	0.056
2	% HUs with telephone	TEL	**0.821**	0.107	0.285	-0.108	-0.017	0.035	0.117
3	Ratio of the % population with college education to % illiterate population	COL	**0.785**	-0.132	0.404	-0.019	0.031	-0.113	0.002
4	% Employed females	FEM	**0.696**	0.078	0.525	-0.092	-0.218	-0.081	-0.011
5	Number of rooms per HU	RMH	**0.667**	-0.203	0.297	0.000	0.391	-0.304	-0.008
6	% Households with disabled persons	DIS	**-0.657**	0.117	0.122	-0.005	0.044	0.085	-0.023
7	Ratio of men to women	MTW	**-0.625**	-0.242	-0.372	0.029	-0.143	-0.001	-0.038
8	Number of households per HU	NHH	**-0.584**	-0.135	0.179	-0.035	0.049	-0.315	-0.070
9	Number of public schools per 1000 population	NPS	0.103	**0.848**	0.157	-0.016	-0.001	-0.130	0.029
10	Access to retail and/or commercial establishments	ARC	-0.355	**0.783**	0.103	-0.126	-0.067	-0.040	-0.058
11	Ratio of sports and recreational LU to population	SLU	0.000	**0.770**	0.096	-0.351	0.058	0.012	0.002
12	Land use diversity	LUD	-0.085	**0.663**	0.159	-0.126	-0.082	0.264	-0.090
13	Single-parent households	SPH	0.043	0.342	**0.835**	-0.190	0.093	-0.133	0.047
14	Number of widowed women per 1000 population	NWP	0.172	0.019	**0.799**	-0.116	0.030	0.060	-0.008
15	Household size	HHS	-0.308	-0.293	**-0.732**	0.143	0.078	-0.083	-0.108
16	Ratio of green space to area	GSA	-0.074	-0.053	-0.104	**0.838**	0.143	0.067	0.028

17	Access to public green spaces	AGS	-0.065	-0.210	-0.249	**0.819**	-0.024	0.109	-0.024
18	% Permeable surface	PER	-0.051	-0.575	-0.228	**0.670**	0.023	0.033	-0.024
19	Green space satisfaction	GSS	0.327	-0.135	0.019	**0.530**	-0.007	-0.050	0.359
20	% Non-elderly population	NEP	0.130	-0.169	0.398	-0.006	**0.716**	-0.127	0.038
21	Ratio of employed to population	EMP	-0.005	0.228	0.359	-0.119	**-0.661**	0.013	-0.005
22	% Owner-occupied HUs	OWN	0.565	0.075	0.091	0.013	**0.606**	0.055	0.013
23	Employment diversity	EMD	0.109	0.303	0.013	0.046	**0.509**	0.013	0.123
24	% Population with health insurance	HIN	0.249	-0.012	-0.002	-0.033	**-0.406**	0.193	0.001
25	Ratio of health LU to population	HLU	-0.090	0.108	-0.050	0.068	-0.061	**0.751**	0.049
26	Ratio of open space LU to area	OLU	-0.108	-0.442	0.227	-0.093	0.052	**0.595**	-0.108
27	Housing unit size diversity	HUS	0.125	-0.120	0.425	-0.195	0.299	**-0.572**	0.073
28	Ratio of cultural LU to population	CLU	0.176	0.124	0.186	0.080	-0.209	**0.521**	0.156
29	Access to hospitals	ATH	0.036	0.320	0.477	-0.176	-0.025	**-0.478**	0.055
30	Access to fire stations	AFS	-0.059	0.221	0.153	0.087	-0.262	**-0.354**	-0.041
31	Social capital	SOC	-0.274	0.013	-0.125	-0.007	0.074	0.085	**0.756**
32	Satisfaction with participation in neighborhood decisions	PAR	-0.097	0.102	0.021	0.097	-0.168	0.010	**0.724**
33	Sense of security	SOS	0.227	-0.097	0.091	-0.050	0.078	-0.080	**0.628**
34	Sense of belonging	SBE	0.488	0.006	0.091	0.002	0.063	0.011	**0.501**
35	Satisfaction with neighborhood relations	NRE	0.200	-0.040	0.057	0.049	0.128	0.075	**0.468**
Percent variance each factor explains			***15.49***	***10.90***	***10.60***	***7.11***	***6.63***	***6.58***	***6.30***

Source of data: The Statistical Center of Iran (SCI, 2016) and the Municipality of Tehran Information and Communication Technology Organization (MTICTO, 2024).

Factor 1 (F1) has positive loadings with the percentage of households owning cars (0.868), the percentage of housing units (HUs) with telephone (0.821), the ratio of the percentage of the population with college education to the percentage of the illiterate population (0.785), the percentage of employed females (0.696), and the number of rooms per HU (0.667). It also presents negative loadings with the percentage of households with disabled persons (-0.657), the ratio of men to women (-0.625), and the number of households per HU (-0.584). This factor is composed of seven indicators from the social subdimension and one indicator (the percentage of employed females) from the economic subdimension of the BRIC model.

Factor 3 (F3) has loadings with single-parent households (0.835), the number of widowed women per 1000 population (0.799), and household size (-0.732). This factor is composed of three indicators from the social subdimension of the BRIC model.

Although factors 1 (F1) and 3 (F3) are extracted as two distinct DR components, all except one of their indicators (the percentage of employed females) belong to the social subdimension of the BRIC framework. Therefore, as done by Wang (2007), they are named "social resilience 1" (F1) and "social resilience 2" (F3), respectively.

Factor 2 (F2) is loaded by the following indicators: the number of public schools per 1,000 people (0.848), access to retail and/or commercial establishments (0.783), the ratio of sports and recreational land use (LU) to the population (0.770), and land use diversity (0.663). All four indicators of this factor belong to the housing and infrastructure subdimension of the BRIC framework.

Factor 6 (F6) reveals loadings with the ratios of health LU to population (0.751), open space LU to neighborhood area (0.595), housing unit size diversity (-0.572), cultural LU to population (0.521), access to hospitals (-0.478), and access to fire stations (-0.354). Except for one indicator (the ratio of cultural LU to population), which belongs to the community capital resilience subdimension, the remaining indicators are part of the housing and infrastructure subdimension of the BRIC framework.

Similar to factors 1 and 3, factors 2 (F2) and 6 (F6) are named "Housing and Infrastructure Resilience 1" (F2) and "Housing and Infrastructure Resilience 2" (F6), respectively. Factor 4 (F4) has significant positive loadings on the ratio of green space to the area (0.838), access to public green spaces (0.819), the percentage of permeable surfaces (0.670), and green space satisfaction (0.530). This factor encompasses all the indicators of the environmental subdimension of the BRIC model. It is, therefore, named environmental resilience. Factor 5 (F5) consists of five indicators with significant loadings for the percentage of the non-elderly population (0.716), the ratio of employed individuals to the population (-0.661), the percentage of owner-occupied housing units (0.606), employment diversity (0.509), and the percentage of the population with health insurance (-0.406). Except for the percentage of the population with health insurance variable, which belongs to the social subdimension, the remaining indicators of this factor are placed in the category of the economic subdimension of the BRIC framework. Therefore, this factor is named economic resilience. Factor 7 (F7) shows positive loadings with social capital (0.756), satisfaction with participation in neighborhood decisions (0.724), sense of security (0.628), sense of belonging (0.501), and satisfaction with neighborhood relations (0.468). All of these indicators belong to the community capital resilience subdimension of the BRIC framework. Therefore, this factor is referred to as community capital resilience.

4.2. Constructing the network model

In the second phase of the F'ANP model, the results obtained from the FA are used to construct the ANP network model (Fig. 3a).

Step 4. Constructing the Initial super-matrix (SM). The ANP network model (Fig. 3a) is used to construct the initial SM (Fig 3b).

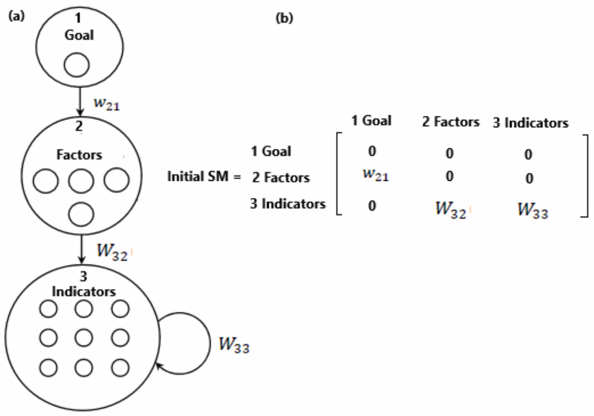

Fig. 3. The ANP network model (a) and its initial SM (b).

Step 5. Computing the Limit SM and obtaining the global priority vector. To compute the limit SM, first, the elements of the initial SM (Fig. 3b; [w_{21}], [w_{32}], [w_{33}]) are calculated. The priority vector [w_{21}] represents the effects of "goal" on "extracted factors". It is calculated by normalizing the amount of variance explained by each extracted factor (Table 3).

Table 3. Computing the priority vector [w_{21}].

Factor	%Variance explained	Normalized
Factor 1	15.49	0.243
Factor 2	10.90	0.171
Factor 3	10.60	0.167
Factor 4	7.11	0.112
Factor 5	6.63	0.104
Factor 6	6.58	0.103
Factor 7	6.30	0.099
Sum	63.61	1.000

$$[w_{21}] = \begin{bmatrix} 0.243 \\ 0.171 \\ 0.167 \\ 0.112 \\ 0.104 \\ 0.103 \\ 0.099 \end{bmatrix}$$

Source: Authors' computations based on factor analysis results obtained using SPSS software.

Sub-matrix [w_{32}] which represents the impact of "factors" on their respective "indicators", is computed by normalizing the absolute value of the factor loadings presented in the rotated components matrix (Table 4).

Table 4. Computing the [w_{32}] sub-matrix.

(a) Absolute value of rotated component matrix

Variable	F1	F2	F3	F4	F5	F6	F7
ATH	0.036	0.320	0.477	0.176	0.025	0.478	0.055
HHS	0.308	0.293	0.732	0.143	0.078	0.083	0.108
NPS	0.103	0.848	0.157	0.016	0.001	0.130	0.029
ARC	0.355	0.783	0.103	0.126	0.067	0.040	0.058
SPH	0.043	0.342	0.835	0.190	0.093	0.133	0.047
NWP	0.172	0.019	0.799	0.116	0.030	0.060	0.008
NHH	0.584	0.135	0.179	0.035	0.049	0.315	0.070
SOS	0.227	0.097	0.091	0.050	0.078	0.08	0.628
HUS	0.125	0.120	0.425	0.195	0.299	0.572	0.073
AGS	0.065	0.210	0.249	0.819	0.024	0.109	0.024
GSA	0.074	0.053	0.104	0.838	0.143	0.067	0.028
LUD	0.085	0.663	0.159	0.126	0.082	0.264	0.090
GSS	0.327	0.135	0.019	0.530	0.007	0.05	0.359
NEP	0.13	0.169	0.398	0.006	0.716	0.127	0.038
DIS	0.657	0.117	0.122	0.005	0.044	0.085	0.023
MTW	0.625	0.242	0.372	0.029	0.143	0.001	0.038
TEL	0.821	0.107	0.285	0.108	0.017	0.035	0.117
HIN	0.249	0.012	0.002	0.033	0.406	0.193	0.001
COL	0.785	0.132	0.404	0.019	0.031	0.113	0.002
OWN	0.565	0.075	0.091	0.013	0.606	0.055	0.013
RMH	0.667	0.203	0.297	0.000	0.391	0.304	0.008
CAR	0.868	0.314	0.019	0.094	0.171	0.007	0.056
EMP	0.005	0.228	0.359	0.119	0.661	0.013	0.005
FEM	0.696	0.078	0.525	0.092	0.218	0.081	0.011
NRE	0.2	0.04	0.057	0.049	0.128	0.075	0.468
CLU	0.176	0.124	0.186	0.080	0.209	0.521	0.156
SBE	0.488	0.006	0.091	0.002	0.063	0.011	0.501
PAR	0.097	0.102	0.021	0.097	0.168	0.010	0.724
SOC	0.274	0.013	0.125	0.007	0.074	0.085	0.756
HLU	0.09	0.108	0.050	0.068	0.061	0.751	0.049

[w_{32}] =

(b) Normalized

F1	F2	F3	F4	F5	F6	F7
0.003	0.038	0.056	0.032	0.004	0.082	0.011
0.030	0.035	0.087	0.026	0.013	0.014	0.022
0.010	0.101	0.019	0.003	0.000	0.022	0.006
0.035	0.093	0.012	0.023	0.011	0.007	0.012
0.004	0.041	0.099	0.035	0.016	0.023	0.010
0.017	0.002	0.095	0.021	0.005	0.010	0.002
0.057	0.016	0.021	0.006	0.008	0.054	0.014
0.022	0.012	0.011	0.009	0.013	0.014	0.130
0.012	0.014	0.050	0.036	0.050	0.098	0.015
0.006	0.025	0.029	0.151	0.004	0.019	0.005
0.007	0.006	0.012	0.154	0.024	0.011	0.006
0.008	0.079	0.019	0.023	0.014	0.045	0.019
0.032	0.016	0.002	0.098	0.001	0.009	0.074
0.013	0.020	0.047	0.001	0.120	0.022	0.008
0.064	0.014	0.014	0.001	0.007	0.014	0.005
0.061	0.029	0.044	0.005	0.024	0.000	0.008
0.080	0.013	0.034	0.020	0.003	0.006	0.024
0.024	0.001	0.000	0.006	0.068	0.033	0.000
0.077	0.016	0.048	0.004	0.005	0.019	0.000
0.055	0.009	0.011	0.002	0.101	0.009	0.003
0.065	0.024	0.035	0.000	0.065	0.052	0.002
0.085	0.037	0.002	0.017	0.029	0.001	0.012
0.001	0.027	0.042	0.022	0.110	0.002	0.001
0.068	0.009	0.062	0.017	0.036	0.014	0.002
0.020	0.005	0.007	0.009	0.021	0.013	0.097
0.017	0.015	0.022	0.015	0.035	0.089	0.032
0.048	0.001	0.011	0.000	0.011	0.002	0.103
0.010	0.012	0.003	0.018	0.028	0.002	0.150
0.027	0.002	0.015	0.001	0.012	0.015	0.156
0.009	0.013	0.006	0.012	0.010	0.128	0.010

SLU	0.000	0.770	0.096	0.351	0.058	0.012	0.002	0.000	0.092	0.011	0.065	0.010	0.002	0.000
OLU	0.108	0.442	0.227	0.093	0.052	0.595	0.108	0.011	0.053	0.027	0.017	0.009	0.102	0.022
PER	0.051	0.575	0.228	0.670	0.023	0.033	0.024	0.005	0.068	0.027	0.124	0.004	0.006	0.005
EMD	0.109	0.303	0.013	0.046	0.509	0.013	0.123	0.011	0.036	0.002	0.009	0.085	0.002	0.026
AFS	0.059	0.221	0.153	0.087	0.262	0.354	0.041	0.006	0.026	0.018	0.016	0.044	0.061	0.008

Source: authors' computations based on factor analysis results obtained using SPSS software.

Sub-matrix [w_{33}] represents the inner dependence among the indicators of the CDR and is computed by normalizing the absolute value of the columns of the "correlation matrix" of the indicators in the model. Then, the computed priority vector and sub-matrices are input into the initial SM to obtain the weighted SM (Appendix, Table A1). To obtain the limit SM, the weighted SM is raised to the power of a large number, here 60, using MATLAB software (Appendix, Table A2). The relative importance of the DR indicators is obtained from the goal column of the limit SM (Zebardast, 2022) and is presented in Table 5.

Table 5. The ANP driven weights for the DR indicators (W_{ANP}).

No.	Indicators	Acronym	Relative importance (W_{ANP})
1	% Households owning cars	CAR	0.0416
2	% HUs with telephone	TEL	0.0428
3	Ratio of the % population with college education to % illiterate population	COL	0.042
4	% Employed females	FEM	0.0428
5	Number of rooms per HU	RMH	0.0402
6	% Households with disabled persons	DIS	0.0247
7	Ratio of men to women	MTW	0.0387
8	Number of households per HU	NHH	0.0229
9	Number of public schools per 1000 population	NPS	0.0302
10	Access to retail and/or commercial establishments	ARC	0.0343
11	Ratio of sports and recreational LU to population	SLU	0.031
12	Land use diversity	LUD	0.0265
13	Single-parent households	SPH	0.0402
14	Number of widowed women per 1000 population	NWP	0.0313
15	Household size	HHS	0.0403
16	Ratio of green space to area	GSA	0.0234
17	Access to public green spaces	AGS	0.0307
18	% Permeable surface	PER	0.0346
19	Green space satisfaction	GSS	0.0255
20	% Non-elderly population	NEP	0.0283
21	Ratio of employed to population	EMP	0.0258
22	% Owner-occupied HUs	OWN	0.0322
23	Employment diversity	EMD	0.0181
24	% Population with health insurance	HIN	0.0143
25	Ratio of health LU to population	HLU	0.0198
26	Ratio of open space LU to area	OLU	0.0164
27	Housing unit size diversity	HUS	0.0308
28	Ratio of cultural LU to population	CLU	0.019
29	Access to hospitals	ATH	0.0329
30	Access to fire stations	AFS	0.0152
31	Social capital	SOC	0.0187
32	Satisfaction with participation in neighborhood decisions	PAR	0.0152
33	Sense of security	SOS	0.0229
34	Sense of belonging	SBE	0.0285
35	Satisfaction with neighborhood relations	NRE	0.0183

Source: the 'Goal' column in the limit super-matrix presented in the Appendix Table A2.

Step 6. Computing the DR Component Scores and DR Composite Index. In the EFA, in order to enhance theoretical coherence or to simplify the interpretation and naming of the extracted factors, it is customary to combine extracted similar factors into a new composite subdomain (Howard, 2016), even if they are extracted separately in the EFA (Costello and Osborne, 2005). The application of the F'ANP model to the baseline 35 DR indicators resulted in the extraction of seven DR subdomains that differ from the original BRIC structure. However, a closer examination of the F'ANP - extracted subdomains reveals that by regrouping four of the seven extracted DR subdomains, a BRIC structure could be achieved (Table 6). Factors one (social resilience 1) and three (social resilience 2) are combined to represent the social resilience subdimension. Factors two (housing and infrastructure resilience 1) and six (housing and infrastructure resilience 2) are regrouped to constitute the housing and infrastructure resilience subdimension. The remaining factors are in accordance with the BRIC structure.

Table 6. Regrouping the F'ANP extracted DR subdomains.

F'ANP extracted factors		BRIC-adapted	Indicators in conformity with BRIC subdomains	
			No.	Percent
Factor 1	Social Resilience 1	Social Resilience	11 out of 12	91.67
Factor 3	Social Resilience 2			
Factor 2	Housing and infrastructure resilience 1	Housing and infrastructure resilience	7 out of 8	87.50
Factor 6	Housing and infrastructure resilience 2			
Factor 4	Environmental resilience	Environmental resilience	4 out of 4	100.00
Factor 5	Economic resilience	Economic resilience	3 out of 5	60.00
Factor 7	Community capital resilience	Community capital resilience	5 out of 6	83.33
Overall DR			30 out of 35	85.71

Source: authors' computations based on factor analysis results obtained using SPSS software.

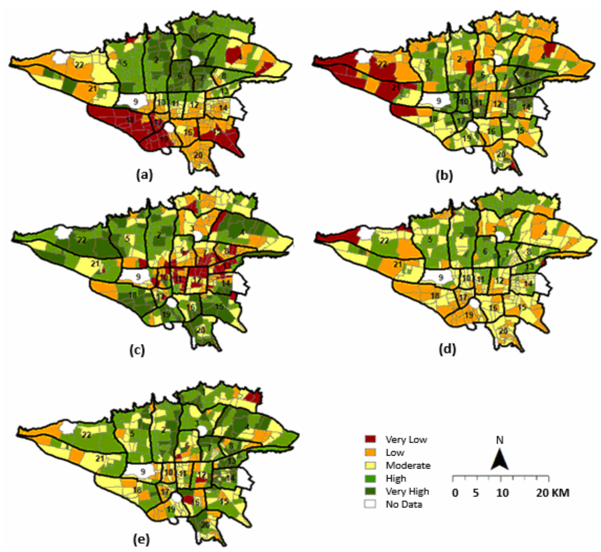

Fig. 4. The spatial distribution of the five DR factors in Tehran Metropolis: **(a)** social resilience, **(b)** housing and infrastructure resilience, **(c)** environmental resilience, **(d)** economic resilience, and **(e)** housing and infrastructure resilience *(source: prepared by authors using ArcMap software).*

The five regrouped disaster resilience subdomains are checked for conformity with the BRIC structure. The regrouped F'ANP subdomains resemble BRIC subdomains, wherein 30 out of 35 indicators (85.71%) fall under the BRIC-based subdomains (Table 6). To obtain the factor scores for the five DR subdomains, a weighted aggregation of the indicators of each factor is applied (Zebardast, 2022):

$$DRF_{ik} = \sum_{j=1}^{5} W_{ANP_{jk}} SDRI_{ijk} \quad (3)$$

where:

- DRF_{ik} is the *DR* factor score in neighborhood *i* for factor *k*;

- $W_{ANP_{jk}}$ is the *ANP* driven weight for indicator *j* of the factor *k* (Table 5);

- $SDRI_{ijk}$ is the standardized value of *DR* indicator *j* of factor *k* in neighborhood *i*.

The spatial distribution of the five *DR* factors is classified into five groups of very low, low, moderate, high, and very high *DR* using *K*-means cluster analysis and are shown in Figure 4.

The computed factor scores for the five BRIC-based DR subdomains are summed to obtain the composite disaster resilience index (CDRI). The neighborhood DR composite index is obtained by summing the factor scores of the seven extracted DR factors:

$$CDRI_i = \sum_{k=1}^{5} DRF_{ik} \quad (4)$$

where:

- $CDRI_i$ is the composite *DR* index for neighborhood *I*;

- DRF_{ik} is the *DR* score in neighborhood *i* for factor *k*.

K-means cluster analysis, using SPSS 26 software, is employed to the CDRI to classify the city's neighborhoods into five groups: very low, low, moderate, high, and very high DR (Fig. 5).

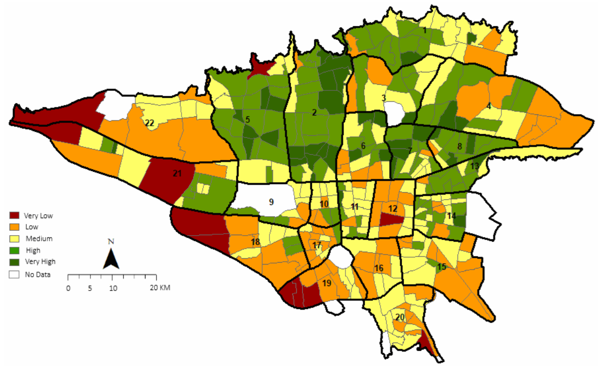

Fig. 5. Composite DR index for neighborhoods in the Tehran Metropolis.

Step 7. Performing autocorrelation analysis. Spatial autocorrelation statistics, using ArcMap 10.8.2 software, are computed to further examine the spatial features of the composite DR index. The global Moran's I for the composite DR index *(Moran's I = 0.298, p-value = 0.0000)* shows that the DR in the Tehran Metropolis is spatially clustered (Fig. 6a). Hot spot analysis, using ArcMap 10.8.2 software, is performed to identify areas of spatial hot spots, cold spots, outliers, and areas with no statistical significance (Anselin, 1995). With a significance level higher than 95%, about 18.8% of neighborhoods are identified as spatial cold spot, 21% are identified as spatial hot spots and the remaining 60.2% are identified as having no statistical significance (Fig. 6b).

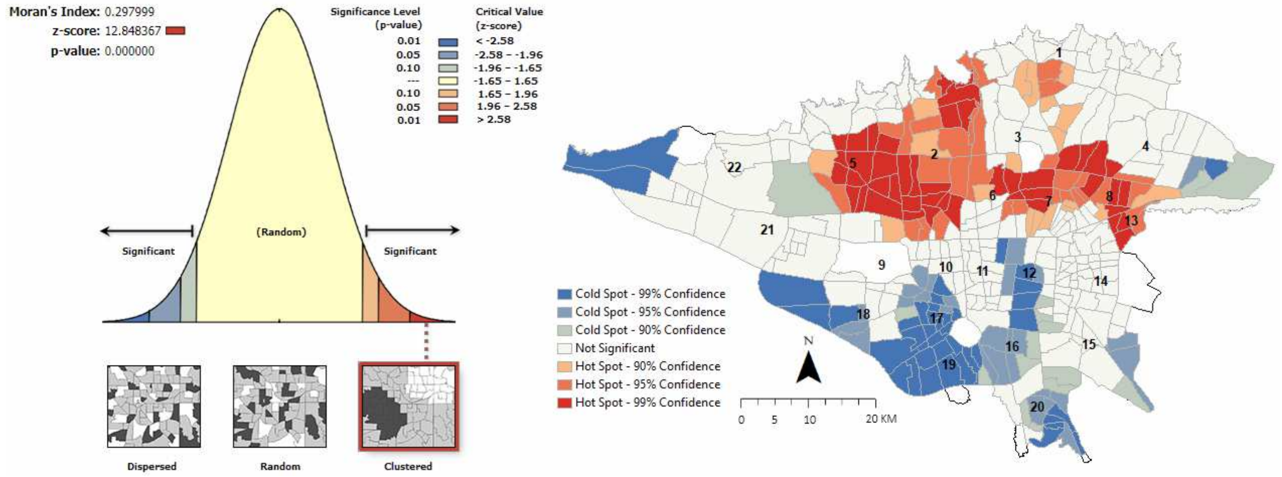

Fig. 6. The Global Moran's I (a) and Hot spot analysis (b) for composite DR index for neighborhoods in the Tehran Metropolis *(source: prepared by authors using ArcMap software).*

4.3. Model validation

The outcomes achieved by utilizing the BRIC-F'ANP model require validation. Discriminant analysis (DA), using SPSS 26 software, is used to validate the results obtained by adapting the BRIC - driven F'ANP output. DA is a multivariate statistical technique commonly used to construct a discriminant function to distinguish a set of observations according to predefined groups (Klecka 1980).

Step 8. Applying Discriminant Analysis. DA is used to evaluate how accurately the neighborhoods are classified as a result of applying BRIC and F'ANP, as well as the performed K-means cluster analysis. In the DA, the K-means clustering results for each RD subdimension serve as the dependent variable, while the indicators of the corresponding subdomains are considered independent variables. The DA classification accuracy results for the five RD subdomains are shown in Table 7.

Table 7. The DA classification accuracy for the five BRIC-adapted resilience subdomains.

No.	Resilience subdomains	Dependent variable	Independent variables (Indicators)	Acronym	DA Classification accuracy (%)	
					Original	Cross-validated
1	Social Resilience	K-means classification result for combined factor scores of Factor 1 (Social resilience 1) and Factor 3 (Social resilience 2)	% Households owning cars	CAR	92.1	89.6
			% HUs with telephone	TEL		
			Ratio of the % population with college education to % illiterate population	COL		
			% Employed females	FEM		
			Number of rooms per HU	RMH		
			% Households with disabled persons	DIS		
			Ratio of men to women	MTW		
			Number of households per HU	NHH		
			Single-parent households	SPH		
			Number of widowed women per 1000 population	NWP		
			Household size	HHS		
2	Housing and infrastructure resilience	K-means classification result for combined factor	Number of public schools per 1000 population	NPS	94.3	92.4
			Access to retail and/or commercial establishments	ARC		

		scores of Factor 2 (Housing and infrastructure resilience 1) and Factor 6 (Housing and infrastructure resilience 2)	Ratio of sports and recreational LU to population	SLU		
			Land use diversity	LUD		
			Ratio of health LU to population	HLU		
			Ratio of open space LU to area	OLU		
			Housing unit size diversity	HUS		
			Ratio of cultural LU to population	CLU		
			Access to hospitals	ATH		
			Access to fire stations	AFS		
3	Environmental Resilience	K-means classification result for factor scores of Factor 4 (Environmental Resilience)	Ratio of green space to area	GSA	**95.6**	**94.0**
			Access to public green spaces	AGS		
			% Permeable surface	PER		
			Green space satisfaction	GSS		
4	Economic Resilience	K-means classification result for factor scores of Factor 5 (Economic Resilience)	% Non-elderly population	NEP	**95.4**	**95.1**
			Ratio of employed to population	EMP		
			% Owner-occupied HUs	OWN		
			Employment diversity	EMD		
			% Population with health insurance	HIN		
5	Community capital resilience	K-means classification result for factor scores of Factor 7 (Community capital resilience)	Social capital	SOC	**95.9**	**93.2**
			Satisfaction with participation in neighborhood decisions	PAR		
			Sense of security	SOS		
			Sense of belonging	SBE		
			Satisfaction with neighborhood relations	NRE		
6	Composite DR index	K-means classification of CDRI	All 35 BRIC indicators		**92.6**	**87.5**

Source: results obtained from discriminant analysis using SPSS software.

The very high DA classification accuracy rates for each of the BRIC-adapted DR subdomains and the composite DR index (ranging from 92.1% to 95.9% for the original grouped cases, and from 87.5% to 95.1% for cross-validated grouped cases - Table 7) show that the indicators belonging to the DR subdomains, their weights, and final scores, characterize the groupings derived from the K-means classification method, thereby validating the results of the F'ANP-determined subdomains of the BRIC framework.

5. DISCUSSION

This paper examined the applicability of the BRIC framework at the neighborhood level in a Global South metropolis, using the F'ANP model. Guided and inspired by the BRIC framework, 35 baseline indicators are identified. These indicators are not exact translations of the BRIC indicators, but are chosen from the disaster resilience literature to be sensible, justifiable, applicable at the neighborhood level, and accessible in terms of data. The application of the F'ANP model to these 35 indicators resulted in the extraction of seven disaster resilience subdomains that have a different composition from those of the BRIC framework. In alignment with the BRIC framework, the seven extracted subdomains were regrouped into five disaster resilience subdomains. By summing the factor scores of the five subdomains, a composite RD index at the neighborhood level is obtained. A K-Means cluster analysis is used to classify the Composite DR index into five categories.

Discriminant analysis validated the findings of the study. This finding of the study confirms that applying F'ANP with a set of sensible neighborhood-level BRIC-based indicators could yield to BRIC-conformed subdimensions and a composite resilience index. Moreover, it also aligns with the results of Scherzer et al. (2019), Csizovszky and Buzási (2023), and Camacho et al. (2024), who adapted the BRIC-based indicators at the district level and used Principal Component Analysis (PCA) to investigate the similarity of the PCA-extracted components with those of the BRIC framework in Chile, Norway, and England, respectively.

In contrast, the results of this research disagree with those of Derakhshan et al. (2022), who utilized exploratory factor analysis on BRIC indicators and discovered that the obtained factor structure did not align with the original BRIC framework. Employing the BRIC-F'ANP model allows for the reorganization of identified disaster resilience subdomains to form the necessary resilience framework. Validation of the model through DA indicated that the rearranged subdomains, which reflected the BRIC structure, demonstrated high accuracy.

The global Moran's I for the composite DR index indicates that the DR in the Tehran Metropolis is spatially clustered (Fig. 6a). Neighborhoods of similar resilience are located near one another, and the hotspot analysis reveals that the hotspot clusters of neighborhoods with significantly high resilience scores are situated in the northern parts of the city (except for some neighborhoods located in the extreme northwest and northeast) (Fig. 6b). The spatial distribution of CDRI scores (Fig. 5) also demonstrates that most of the neighborhoods in the northern parts of the city belong to the very high and high resilience categories. In contrast, the majority of the neighborhoods in the southern parts of the city fall under the very low and low resilience categories. This finding aligns with the results of Haghighi Fard and Doratli (2022), who showed that "the resilient areas (of Tehran City) are often in two areas: (a) the northern part of the city center, and (b) the eastern zones"; and that the "non-resilient neighborhoods" of Tehran city are predominantly located in "the southern part of the city" (Haghighi Fard and Doratli, 2022, p.15).

The prevalence of neighborhoods with high resilience in the northern parts of the city and low resilience in the southern parts supports the earlier assertions of the north-south divide in the Tehran Metropolis (Zebardast, 2022; Ziari and Zebardast, 2024). Adapting the BRIC framework for neighborhood-level disaster resilience assessment has been very limited. The proposed adaptation of the BRIC framework, combined with the F'ANP model and validation of its results in the applied case study paves the way for its application in disaster resilience assessment at the neighborhood level in other cities and contexts.

5.1. Limitations of the proposed BRIC-F'ANP model

The proposed BRIC-F'ANP model has two limitations. Firstly, in the original BRIC model, every indicator within the resilience subdomains and all sub-indices are assigned equal weights (Scherzer et al., 2019). By incorporating the F'ANP model into BRIC, the indicators receive data-driven weights, which means the resulting composite resilience index will differ from the BRIC-only model. While over half of the research utilizing the BRIC framework has assigned weights to indicators, whether through multivariate or multicriteria decision methods (Camacho et al., 2023), this could be viewed as a limitation. Additionally, the F'ANP model employs FA for problem structuring purposes, and FA requires relatively large sample sizes to yield more accurate outcomes (Costello and Osborne, 2005). Consequently, the suggested BRIC-F'ANP model is not appropriate for small sample sizes.

6. CONCLUSIONS

This study has adapted the BRIC framework with the F'ANP model to assess neighborhood-level disaster resilience in the Tehran Metropolis. The proposed model has transformed 35 baseline DR indicators into seven subdomains. The seven extracted DR components are regrouped to align with the BRIC's five subdomain structure. The K-Means cluster analysis is used to depict the spatial distribution of the DR components and the composite DR index at the neighborhood level of Tehran city. Discriminant analysis and autocorrelation analyses have validated the results of the study. The results indicate that the disaster resilience at the neighborhood level in Tehran city follows a north-south divide, wherein the majority of the neighborhoods located in the northern parts of the Metropolis belong to the very high and high-resilient categories, while, conversely, the majority of neighborhoods located in the southern parts of the city fall into the very low and low categories of resilience. This study has proposed and validated an innovative methodology that can easily be replicated for disaster resilience assessment at the neighborhood level in cities worldwide. The results of the study could also be used by both urban planners and city officials to set up disaster reduction strategies and policies.

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APPENDIX: Table A1. The weighted supermatrix.

	Goal	F1	F2	F3	F4	F5	F6	F7	ATH	HHS	NPS	ARC	SPH	NWP	NHH	SOS	HUS	AGS	GSA	LUD	GSS	NEP	DIS
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F1	0.243	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0.171	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0.167	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4	0.112	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F5	0.104	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6	0.103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F7	0.099	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ATH	0	0.003	0.038	0.056	0.032	0.004	0.082	0.011	0.120	0.039	0.049	0.036	0.056	0.036	0.022	0.011	0.056	0.047	0.038	0.023	0.018	0.019	0.006
HHS	0	0.030	0.035	0.087	0.026	0.013	0.014	0.022	0.048	0.098	0.044	0.022	0.076	0.075	0.028	0.029	0.035	0.045	0.041	0.045	0.003	0.019	0.022
NPS	0	0.010	0.101	0.019	0.003	0.000	0.022	0.006	0.045	0.033	0.130	0.076	0.042	0.014	0.001	0.000	0.014	0.033	0.021	0.083	0.008	0.000	0.004
ARC	0	0.035	0.093	0.012	0.023	0.011	0.007	0.012	0.037	0.019	0.086	0.115	0.035	0.006	0.022	0.027	0.010	0.034	0.024	0.076	0.053	0.023	0.047
SPH	0	0.004	0.041	0.099	0.035	0.016	0.023	0.010	0.069	0.076	0.055	0.041	0.098	0.090	0.013	0.020	0.055	0.057	0.046	0.044	0.018	0.045	0.011
NWP	0	0.017	0.002	0.095	0.021	0.005	0.010	0.002	0.034	0.058	0.015	0.005	0.070	0.126	0.010	0.017	0.035	0.041	0.031	0.015	0.005	0.050	0.008
NHH	0	0.057	0.016	0.021	0.006	0.008	0.054	0.014	0.016	0.016	0.001	0.015	0.007	0.008	0.172	0.023	0.020	0.006	0.005	0.005	0.021	0.013	0.041
SOS	0	0.022	0.012	0.011	0.009	0.013	0.014	0.130	0.007	0.016	0.000	0.018	0.011	0.012	0.022	0.172	0.025	0.008	0.002	0.011	0.041	0.027	0.029
HUS	0	0.012	0.014	0.050	0.036	0.050	0.098	0.015	0.053	0.027	0.014	0.009	0.042	0.034	0.027	0.034	0.128	0.036	0.029	0.015	0.001	0.064	0.011
AGS	0	0.006	0.025	0.029	0.151	0.004	0.019	0.005	0.043	0.034	0.033	0.030	0.044	0.040	0.008	0.011	0.036	0.128	0.108	0.035	0.053	0.017	0.002
GSA	0	0.007	0.006	0.012	0.154	0.024	0.011	0.006	0.027	0.024	0.016	0.016	0.027	0.024	0.005	0.002	0.022	0.083	0.168	0.023	0.046	0.005	0.003
LUD	0	0.008	0.079	0.019	0.023	0.014	0.045	0.019	0.018	0.029	0.073	0.059	0.029	0.013	0.006	0.013	0.013	0.030	0.026	0.148	0.021	0.018	0.025
GSS	0	0.032	0.016	0.002	0.098	0.001	0.009	0.074	0.014	0.002	0.007	0.040	0.012	0.004	0.023	0.046	0.001	0.044	0.050	0.020	0.154	0.017	0.029
NEP	0	0.013	0.020	0.047	0.001	0.120	0.022	0.008	0.016	0.013	0.000	0.019	0.032	0.045	0.016	0.034	0.059	0.016	0.006	0.019	0.018	0.139	0.008
DIS	0	0.064	0.014	0.014	0.001	0.007	0.014	0.005	0.004	0.014	0.004	0.034	0.007	0.006	0.044	0.032	0.009	0.001	0.003	0.024	0.028	0.007	0.160
MTW	0	0.061	0.029	0.044	0.005	0.024	0.000	0.008	0.033	0.056	0.034	0.000	0.048	0.046	0.063	0.027	0.033	0.024	0.020	0.017	0.018	0.029	0.056
TEL	0	0.080	0.013	0.034	0.020	0.003	0.006	0.024	0.027	0.049	0.030	0.019	0.032	0.047	0.076	0.049	0.025	0.030	0.030	0.007	0.035	0.030	0.064
HIN	0	0.024	0.001	0.000	0.006	0.068	0.033	0.000	0.005	0.008	0.003	0.002	0.001	0.004	0.026	0.004	0.017	0.004	0.014	0.007	0.004	0.027	0.006
COL	0	0.077	0.016	0.048	0.004	0.005	0.019	0.000	0.029	0.048	0.009	0.038	0.033	0.053	0.050	0.036	0.045	0.019	0.019	0.019	0.042	0.040	0.074
OWN	0	0.055	0.009	0.011	0.002	0.101	0.009	0.003	0.014	0.018	0.018	0.015	0.018	0.022	0.045	0.028	0.026	0.005	0.000	0.009	0.029	0.072	0.046
RMH	0	0.065	0.024	0.035	0.000	0.065	0.052	0.002	0.030	0.027	0.005	0.045	0.022	0.032	0.016	0.040	0.071	0.015	0.005	0.027	0.041	0.078	0.065
CAR	0	0.085	0.037	0.002	0.017	0.029	0.001	0.012	0.012	0.014	0.020	0.066	0.011	0.019	0.070	0.049	0.026	0.008	0.013	0.040	0.062	0.044	0.090
EMP	0	0.001	0.027	0.042	0.022	0.110	0.002	0.001	0.031	0.041	0.033	0.029	0.025	0.029	0.003	0.008	0.009	0.029	0.035	0.040	0.014	0.046	0.002
FEM	0	0.068	0.009	0.062	0.017	0.036	0.014	0.002	0.040	0.057	0.031	0.008	0.049	0.073	0.048	0.033	0.033	0.034	0.036	0.008	0.024	0.022	0.056
NRE	0	0.020	0.005	0.007	0.009	0.021	0.013	0.097	0.003	0.013	0.002	0.011	0.005	0.004	0.019	0.026	0.011	0.006	0.009	0.011	0.024	0.018	0.016
CLU	0	0.017	0.015	0.022	0.015	0.035	0.089	0.032	0.007	0.021	0.011	0.002	0.008	0.018	0.039	0.019	0.030	0.001	0.003	0.021	0.012	0.015	0.000
SBE	0	0.048	0.001	0.011	0.000	0.011	0.002	0.103	0.008	0.024	0.013	0.020	0.012	0.019	0.042	0.047	0.019	0.011	0.003	0.005	0.051	0.022	0.043
PAR	0	0.010	0.012	0.003	0.018	0.028	0.002	0.150	0.009	0.008	0.010	0.007	0.003	0.001	0.007	0.054	0.005	0.004	0.012	0.001	0.039	0.012	0.001
SOC	0	0.027	0.002	0.015	0.001	0.012	0.015	0.156	0.007	0.008	0.001	0.007	0.006	0.017	0.008	0.051	0.010	0.010	0.013	0.008	0.016	0.006	0.023
HLU	0	0.009	0.013	0.006	0.012	0.010	0.128	0.010	0.036	0.002	0.006	0.007	0.016	0.008	0.017	0.011	0.051	0.015	0.015	0.032	0.000	0.023	0.008
SLU	0	0.000	0.092	0.011	0.065	0.010	0.002	0.000	0.037	0.030	0.084	0.068	0.036	0.020	0.000	0.009	0.004	0.058	0.050	0.079	0.035	0.002	0.017
OLU	0	0.011	0.053	0.027	0.017	0.009	0.102	0.022	0.027	0.004	0.047	0.027	0.009	0.005	0.002	0.010	0.016	0.008	0.001	0.000	0.010	0.011	0.006

PER	0	0.005	0.068	0.027	0.124	0.004	0.006	0.005	0.050	0.040	0.067	0.059	0.049	0.037	0.002	0.001	0.024	0.090	0.097	0.073	0.050	0.002	0.009
EMD	0	0.011	0.036	0.002	0.009	0.085	0.002	0.026	0.012	0.022	0.018	0.009	0.016	0.009	0.026	0.023	0.008	0.011	0.011	0.000	0.001	0.030	0.003
AFS	0	0.006	0.026	0.018	0.016	0.044	0.061	0.008	0.031	0.009	0.030	0.026	0.015	0.004	0.019	0.002	0.018	0.008	0.014	0.010	0.003	0.007	0.009

Table A1. continued

	MTW	**TEL**	**HIN**	**COL**	**OWN**	**RMH**	**CAR**	**EMP**	**FEM**	**NRE**	**CLU**	**SBE**	**PAR**	**SOC**	**HLU**	**SLU**	**OLU**	**PER**	**EMD**	**AFS**
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ATH	0.029	0.021	0.011	0.023	0.014	0.025	0.010	0.039	0.031	0.005	0.013	0.009	0.019	0.013	0.060	0.039	0.053	0.048	0.023	0.066
HHS	0.059	0.047	0.021	0.046	0.023	0.027	0.014	0.064	0.054	0.029	0.045	0.034	0.022	0.017	0.005	0.039	0.010	0.047	0.049	0.023
NPS	0.027	0.021	0.006	0.006	0.016	0.004	0.014	0.039	0.022	0.004	0.017	0.013	0.020	0.002	0.009	0.081	0.087	0.059	0.029	0.059
ARC	0.000	0.015	0.005	0.031	0.016	0.038	0.055	0.038	0.007	0.022	0.004	0.025	0.015	0.013	0.012	0.075	0.056	0.058	0.016	0.059
SPH	0.050	0.030	0.002	0.031	0.022	0.022	0.011	0.039	0.046	0.011	0.017	0.017	0.009	0.014	0.032	0.047	0.022	0.057	0.035	0.039
NWP	0.037	0.034	0.008	0.040	0.021	0.025	0.014	0.036	0.054	0.007	0.030	0.021	0.001	0.028	0.012	0.020	0.010	0.034	0.015	0.008
NHH	0.037	0.041	0.042	0.027	0.032	0.009	0.039	0.003	0.026	0.024	0.047	0.034	0.010	0.010	0.020	0.000	0.003	0.002	0.033	0.029
SOS	0.016	0.026	0.007	0.020	0.020	0.023	0.027	0.007	0.018	0.032	0.023	0.038	0.082	0.062	0.013	0.006	0.015	0.001	0.029	0.003
HUS	0.026	0.018	0.037	0.033	0.025	0.055	0.019	0.011	0.024	0.019	0.049	0.021	0.010	0.016	0.080	0.004	0.031	0.022	0.014	0.036
AGS	0.019	0.022	0.009	0.014	0.005	0.011	0.006	0.034	0.024	0.010	0.001	0.012	0.008	0.017	0.024	0.058	0.014	0.080	0.018	0.017
GSA	0.012	0.017	0.023	0.010	0.000	0.003	0.007	0.032	0.020	0.012	0.004	0.003	0.019	0.017	0.018	0.038	0.001	0.065	0.014	0.022
LUD	0.012	0.004	0.013	0.012	0.007	0.018	0.026	0.041	0.005	0.016	0.030	0.005	0.001	0.011	0.043	0.067	0.000	0.056	0.001	0.017
GSS	0.012	0.021	0.007	0.025	0.023	0.026	0.038	0.014	0.014	0.033	0.016	0.046	0.065	0.022	0.001	0.028	0.015	0.037	0.002	0.005
NEP	0.022	0.020	0.053	0.027	0.063	0.055	0.030	0.050	0.015	0.028	0.022	0.022	0.022	0.009	0.032	0.002	0.019	0.002	0.047	0.014
DIS	0.035	0.037	0.010	0.043	0.035	0.040	0.053	0.002	0.032	0.022	0.000	0.037	0.002	0.030	0.010	0.014	0.009	0.006	0.004	0.015
MTW	0.102	0.055	0.010	0.058	0.055	0.045	0.041	0.007	0.050	0.042	0.043	0.046	0.003	0.031	0.028	0.024	0.020	0.029	0.044	0.003
TEL	0.061	0.092	0.071	0.063	0.063	0.056	0.066	0.020	0.071	0.045	0.042	0.059	0.003	0.029	0.007	0.012	0.013	0.027	0.032	0.011
HIN	0.004	0.024	0.276	0.012	0.007	0.005	0.010	0.014	0.026	0.000	0.029	0.004	0.011	0.001	0.026	0.006	0.015	0.002	0.035	0.013
COL	0.063	0.062	0.036	0.094	0.056	0.073	0.071	0.010	0.066	0.041	0.033	0.057	0.017	0.053	0.037	0.001	0.005	0.008	0.006	0.000
OWN	0.046	0.048	0.016	0.043	0.122	0.059	0.050	0.055	0.031	0.041	0.007	0.037	0.031	0.007	0.010	0.005	0.002	0.008	0.064	0.030
RMH	0.047	0.053	0.015	0.070	0.074	0.098	0.073	0.025	0.052	0.026	0.016	0.052	0.031	0.039	0.053	0.008	0.001	0.002	0.036	0.002
CAR	0.045	0.064	0.028	0.070	0.065	0.075	0.095	0.023	0.052	0.040	0.018	0.059	0.013	0.037	0.014	0.026	0.020	0.021	0.025	0.038
EMP	0.005	0.012	0.025	0.006	0.044	0.016	0.014	0.153	0.034	0.008	0.029	0.000	0.021	0.017	0.013	0.031	0.001	0.034	0.028	0.041
FEM	0.055	0.071	0.078	0.067	0.041	0.055	0.054	0.056	0.092	0.016	0.034	0.044	0.001	0.050	0.022	0.017	0.018	0.030	0.005	0.022
NRE	0.020	0.019	0.000	0.018	0.023	0.012	0.017	0.005	0.007	0.216	0.022	0.073	0.021	0.043	0.004	0.012	0.003	0.004	0.015	0.007
CLU	0.021	0.019	0.039	0.015	0.004	0.008	0.008	0.022	0.015	0.022	0.207	0.021	0.033	0.004	0.058	0.013	0.032	0.009	0.013	0.004
SBE	0.034	0.039	0.008	0.039	0.033	0.037	0.041	0.000	0.029	0.114	0.031	0.138	0.034	0.033	0.003	0.005	0.013	0.007	0.006	0.006
PAR	0.001	0.001	0.012	0.006	0.015	0.012	0.005	0.012	0.000	0.017	0.026	0.018	0.258	0.102	0.019	0.010	0.021	0.001	0.015	0.002
SOC	0.015	0.013	0.002	0.023	0.004	0.018	0.017	0.012	0.022	0.044	0.003	0.022	0.125	0.211	0.021	0.002	0.002	0.003	0.016	0.016

HLU	0.014	0.003	0.036	0.018	0.006	0.026	0.007	0.010	0.010	0.004	0.061	0.002	0.025	0.022	0.199	0.011	0.090	0.002	0.005	0.024
SLU	0.019	0.009	0.014	0.001	0.005	0.006	0.020	0.037	0.013	0.021	0.021	0.006	0.020	0.003	0.017	0.127	0.058	0.083	0.049	0.038
OLU	0.008	0.005	0.018	0.002	0.001	0.000	0.008	0.001	0.007	0.002	0.028	0.008	0.023	0.002	0.074	0.031	0.240	0.018	0.031	0.029
PER	0.026	0.022	0.005	0.007	0.009	0.002	0.018	0.045	0.024	0.007	0.016	0.009	0.003	0.006	0.003	0.093	0.038	0.114	0.018	0.035
EMD	0.020	0.013	0.045	0.003	0.036	0.016	0.011	0.020	0.002	0.015	0.012	0.004	0.018	0.016	0.005	0.029	0.035	0.009	0.218	0.011
AFS	0.001	0.004	0.013	0.000	0.014	0.001	0.014	0.024	0.008	0.006	0.003	0.003	0.002	0.013	0.019	0.019	0.027	0.015	0.009	0.259

Source: authors' computations based on F'ANP results obtained using MATLAB software.

APPENDIX: Table A2. The limit supermatrix.

	Goal	F1	F2	F3	F4	F5	F6	F7	ATH	HHS	NPS	ARC	SPH	NWP	NHH	SOS	HUS	AGS	GSA	LUD	GSS	NEP	DIS
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ATH	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
HHS	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403
NPS	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302
ARC	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343
SPH	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402
NWP	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313
NHH	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229
SOS	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229
HUS	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308
AGS	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307
GSA	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234
LUD	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265
GSS	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255
NEP	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283
DIS	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247
MTW	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387
TEL	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428
HIN	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143
COL	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
OWN	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322
RMH	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402
CAR	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416
EMP	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258
FEM	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428
NRE	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183

CLU	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
SBE	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285
PAR	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152
SOC	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187
HLU	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198
SLU	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031
OLU	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164
PER	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346
EMD	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181
AFS	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152

Table A2. continued

	MTW	TEL	HIN	COL	OWN	RMH	CAR	EMP	FEM	NRE	CLU	SBE	PAR	SOC	HLU	SLU	OLU	PER	EMD	AFS
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ATH	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
HHS	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403	0.0403
NPS	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302	0.0302
ARC	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343	0.0343
SPH	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402
NWP	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313
NHH	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229
SOS	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229	0.0229
HUS	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308	0.0308
AGS	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307
GSA	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234	0.0234
LUD	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265	0.0265
GSS	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255	0.0255
NEP	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283	0.0283
DIS	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247
MTW	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387	0.0387
TEL	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428
HIN	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143
COL	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
OWN	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322	0.0322
RMH	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402	0.0402
CAR	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416

EMP	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258	0.0258
FEM	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428	0.0428
NRE	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183	0.0183
CLU	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
SBE	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285
PAR	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152
SOC	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187	0.0187
HLU	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198	0.0198
SLU	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031
OLU	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164	0.0164
PER	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346	0.0346
EMD	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181
AFS	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152

Source: authors' computations based on F'ANP results obtained using MATLAB software.