EVALUATION OF ADMINISTRATIVE DIVISION-LEVEL ROAD SAFETY INDICES

by
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To my wife, Sanam, and in memory of my father, Ali Ahmadpur.

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ABSTRACT

EVALUATION OF ADMINISTRATIVE DIVISION-LEVEL ROAD SAFETY INDICES

Inadequate regional road safety studies have been conducted in developing countries such as Iran, Egypt, and Türkiye. Also, despite the existence of various regional road safety indices (RSIs), the associations between these rates rarely have been studied. Besides, there are limited studies regarding crash severity indices in the literature. Despite high road fatalities in developing countries, little attention has been given to road safety performance in these countries. Additionally, the differences between developed and developing countries regarding road safety performance rarely have been discussed. Thus, it was aimed to evaluate the regional RSIs in Iran, Türkiye, the UK, Egypt, and the USA, using correlation and regression analysis. Also, the distribution patterns of administrative divisions of these countries were assessed. Data on regional road safety and socioeconomic rates of these countries were collected. The associations between the variables were evaluated using correlation and regression analysis. Using Moran's I, local Moran indices, and Jenks natural breaks method, administrative division’s spatial distributions were evaluated. Hot spot analysis was used to identify road safety deficient regions. Significant correlations between the variables were detected. Vast local clusters in terms of RSIs were detected in the countries. The distribution patterns of subdivisions regarding RSIs were cluster-like. Variable groups influencing road safety performance in regions were identified. Generally, crashes were severe in underdeveloped and remote regions. Increasing income and education levels make it possible to reduce crash severity indices in these countries. Higher exposure rates mean higher fatalities in regions. There is a nonlinear and significant association between motorization rates and TR indices of regions, and fatality risk decreases as the motorization rate increases. There is a considerable gap between developed and developing countries regarding regional RSIs. Findings suggest using the fatality per number of motor vehicles index instead of the fatality per population rates in regional road safety studies. Using distinct exposure measures in calculating RSIs leads to the inverse local cluster maps.

ÖZET

İDARİ BÖLÜM SEVİYESİ YOL GÜVENLİĞİ ENDEKSLERİNİN DEĞERLENDİRİLMESİ

İran ve Türkiye gibi gelişmekte olan ülkelerde yetersiz bölgesel karayolu güvenliği çalışmaları yapılmıştır. Ayrıca, çeşitli bölgesel karayolu güvenliği endekslerinin (KGE'ler) varlığına rağmen, bu oranlar arasındaki ilişkiler nadiren incelenmiştir. Ayrıca literatürde kaza şiddet indeksleri ile ilgili sınırlı sayıda çalışma bulunmaktadır. Gelişmekte olan ülkelerdeki yüksek karayolu ölümlerine rağmen, bu ülkelerde karayolu güvenliği performansına çok az ilgi gösterilmiştir. Ek olarak, gelişmiş ve gelişmekte olan ülkeler arasındaki karayolu güvenliği performansına ilişkin farklılıklar nadiren tartışılmıştır. Böylece İran, Türkiye, İngiltere, Mısır ve ABD'deki bölgesel KGE'lerın korelasyon ve regresyon analizi kullanılarak değerlendirilmesi amaçlanmıştır. Ayrıca bu ülkelerin idari bölümlerinin dağılım örüntüleri değerlendirilmiştir. Bu ülkelerin bölgesel karayolu güvenliği ve sosyoekonomik oranlarına ilişkin veriler toplanmıştır. Değişkenler arasındaki ilişkiler korelasyon ve regresyon analizi kullanılarak değerlendirildi. Moran's I, yerel Moran indeksleri ve Jenks doğal kırılma yöntemi kullanılarak idari bölünmenin mekânsal dağılımları değerlendirilmiştir. Karayolu güvenliği açısından yetersiz bölgeleri belirlemek için sıcak nokta analizi kullanılmıştır. Değişkenler arasında anlamlı korelasyonlar tespit edildi. Ülkelerde KGE'ler açısından geniş yerel kümeler tespit edildi. KGE'lere ilişkin alt bölümlerin dağılım modelleri küme benzeriydi. Bölgelerde yol güvenliği performansını etkileyen değişken grupları belirlenmiştir. Genel olarak, kazalar az gelişmiş bölgelerde şiddetliydi. Artan gelir ve eğitim seviyeleri, bu ülkelerde kaza şiddeti endekslerinin düşürülmesini mümkün kılmaktadır. Daha yüksek maruz kalma oranları, bölgelerde daha yüksek trafik kaza ölümleri anlamına gelir. Bölgelerin motorizasyon oranları ile risk indeksleri arasında lineer olmayan ve anlamlı bir ilişki vardır ve motorizasyon oranı arttıkça ölüm riski azalmaktadır. Bölgesel KGE'ler konusunda gelişmiş ve gelişmekte olan ülkeler arasında önemli bir fark vardır. Bulgular, karayolu güvenliği çalışmalarında nüfus başına ölüm oranları yerine motorlu taşıt sayısı başına ölüm indeksinin kullanılmasını öneriyor.

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Adj. R^2	Adjusted coefficient of determination
B	Unstandardized beta
C_0	Observed value
C_E	Expected value
e	Euler's number (2.7182)
F	F statistic
HR	Health risk
I	Moran’s I
k	Kilo or thousands
MR	Motorization rate
n	Number of regions
p	p-value
R^2	Coefficient of determination
RMV	Registered motor vehicles
RTF	Road traffic fatalities
S_0	Sum of the weights
SD	Square root of variance
t	t-value
TR	Traffic risk
W_{ij}	Element of the spatial weight matrix
x	Independent variable, x axe value
x_i	A value of an index in region i
y	Dependent variable, y axe value
Z_i	Deviation of x_i from its mean
Z_j	Deviation of x_j from its mean
$\overline{X}$	Average value of an index in regions
$	US dollar

LIST OF ACRONYMS/ABBREVIATIONS

ASEAN	Association of Southeast Asian Nations
CAPMAS	Central Agency for Public Mobilization and Statistics
COORD	Coordination
COVID	Coronavirus Disease of 2019
CRF	Crash per fuel consumption
CRP	Crash per population
CRV	Crash per vehicle
EB	Emergency base
EL	Education level
FHWA	Federal Highway Administration
FPC	Fatality per crash
FPI	Fatality per on-fatal road crash injury
FPNF	Fatal crash per non-fatal crash
FRTC	Fatal crash
FRTI	Female non-fatal road traffic crash injury
GDP	Gross domestic product
GDPC	Gross domestic capita per capita
GIS	Geographic information system
HB	Hospital bed
HBPP	Hospital bed per population
HC	Health center
HH	High-high
HL	High-low
HR	Health risk
ICU	Intensive care units
ICUHB	Intensive care units hospital bed
ILMO	Iranian legal medicine organization
IPP	Non-fatal road traffic crash injury per population
IRTC	Non-fatal road traffic crash

ITF	International Transport Forum
LH	Low-high
LISA	Local Indicators of Spatial Association
LL	Low-low
LR	Literacy ratio
MENA	Middle East and North Africa
MR	Motorization rate
MRTI	Male non-fatal road traffic crash injury
NFRTC	Non-fatal road traffic crash
NHTSA	National Highway Traffic Safety Administration
NIORDC	National Iranian Oil Refining and Distribution Company
OECD	Organization for Economic Co-operation and Development
ONS	Office for National Statistics
PCC	Pearson correlation coefficient
PP	Per population
RMV	Registered motor vehicles
RSI	Road safety index
RTC	Road traffic crash
RTF	Road traffic fatality
RTI	Non-fatal road traffic injury
SD	Standard deviation
SPA	Fatality at crash scene per fatality after crash
TR	Traffic risk
TUIK	Türkiye İstatistik Kurumu
VIF	Variance Inflation Factor
WHO	World health organization

1. INTRODUCTION

Land transportation systems aim to move humans, life forms, and goods from A to B in a fast, sustainable, and safe manner. However, for various reasons, the transportation systems have failed to provide fatality-less road transport for humans. Each year, authorities declare high road traffic fatalities and non-fatal injuries because of road traffic crashes. Even in a developed country such as the United Kingdom, 1500 individuals lose their lives because of road crashes. According to the literature, part of these crashes is preventable when precise and efficient road safety policies are implemented in countries.

Each country has administrative divisions, and there is a considerable difference between these subdivisions regarding road safety performance indices. These indices are integer type indices, such as the number of fatalities, or ratio type ones, such as fatality risk rates, such as the number of fatalities per population of regions. Road safety experts use these rates and indices to compare the road safety performance of regions inside a country or continent. One of the initial steps in a road safety study in a country is to conduct spatial analysis to investigate the spatial distribution of regions and detect hot spots regarding various road safety performance indicators. The literature review shows that preliminary studies have been conducted regarding this issue in developing countries, and most studies are about developed ones. Also, road crash severity indices are ignored in the literature. Additionally, there is no study regarding the similarity and differences between developed and developing countries regarding regional road safety indicators. Also, there is no study on various regional RSIs' relationships, similarities, and differences.

This dissertation intends to fill a considerable gap in the literature by exploring various countries' regional road safety indicators for understanding road safety issues with a comprehensive review. Although many studies in the literature address regional road safety performance of countries, theories, and approaches, this dissertation is the first attempt to use the “multiple road safety indicator approach”.

1.1. Purpose of Dissertation

The main objective of this dissertation is to explore the regional road safety indicators and their attributes for understanding road safety issues with a comprehensive review of macro-level road safety literature. This dissertation aims to extend the discussion of the importance of selecting RSIs in road safety studies. It will also attempt to extend the empirical applications of hot-spot, regression, and spatial analysis in road safety studies. The dissertation will shed new light on regional road safety discussions by presenting the similarities and differences between various RSIs in developed and developing countries. The insights and results from Iran, Türkiye, the United States, Egypt, and England will be particularly relevant for developing road safety policies in various countries. The dissertation aims to provide novel approaches, frameworks, and solution sets for road safety problems. The dissertation comprises four papers, each of which constitutes one section of the dissertation. All sections aim to provide an institutional lens through which regional road safety problems can be conceptualized and contextualized. They examine the issue of regional road safety in various countries.

The first paper in section three aims to conduct spatial analysis and evaluate province-level RSIs of Türkiye between 2015 to 2019 using spatial, clustering, correlation, and regression analysis. The second paper in section four aims to provide road safety-related knowledge, detect significant associations between socioeconomic variables and province-level RSIs in Iran, and model regional RSIs by considering the studied socioeconomic variables. The third paper in section five aims to examine associations between variables, including 19 regional RSIs and 82 socioeconomic, transport, and geographic indices, identify hot spots, and assess the distribution of Iranian provinces regarding road safety performance. The aim of the fourth paper in section six is to evaluate the country- and subdivision-level RSIs and related indices of four countries, including two developed (USA and England) and two developing (Egypt and Türkiye) ones, to illustrate the differences and similarities between the countries regarding regional road safety performance.

1.2. Literature Review

In this dissertation, three different literatures of the same time are examined to seek out the previous regional road safety studies in Iran, Türkiye, and developed countries. For the literature on regional road safety studies in Iran and Türkiye, the recent literature is focused on staying within the literature of the last ten years as much as possible. An inadequate number of studies regarding regional road safety studies in developed countries have been found.

Road traffic crashes (RTCs) and related fatalities (RTFs) significantly adversely impact countries. 1.35 million RTFs and 50 million yearly injuries have been reported (World Health Organization [WHO], 2018). Published reports indicate that a considerable number of RTFs (approximately 80%) in the world occur in middle-income countries, and RTFs in low-and middle-income countries are higher than in high-income countries (Haghani et al., 2022). The middle-income countries own 59% of motor vehicles in the world, and despite the low motorization rates (MRs), excessive numbers of RTFs have occurred in developing countries (WHO, 2018a). The average mortality rate (RTFs per 100,000 population) in developing countries is 27.5, 3.3 times greater than in developed countries (WHO, 2018b). These numbers indicate the considerable gap between developed and developing countries regarding road safety performance.

A developed country such as the USA spends considerable socioeconomic resources because of RTCs and related issues (Ali et al., 2021). Also, it was reported that because of RTCs and related issues, approximately 3% of each country's gross domestic product (GDP) is wasted (Wachnicka et al., 2021). Published reports indicate that it is possible to reduce these negative impacts of RTCs, and substantial growth in income level could be achieved by preventing and decreasing the number of RTCs (World Bank, 2017).

Almost all countries comprise administrative divisions, such as provinces, with different governance laws and socioeconomic and geographic characteristics than other regions. Conducting spatial analysis and determining hot spots regarding road safety performance is one of the initial steps toward a precise road crash avoidance program in a country. By conducting spatial analysis, it is possible to prevent crashes and reduce their adverse effects. Additionally, conducting regional road safety studies provides a superior awareness of road safety performance in a country. This awareness could aid national road safety managers and local authorities in authorizing sustainable and precise road safety management systems. Previous studies have reported considerable differences between regional road safety indicators (RSIs) of countries and the existence of local clusters of subdivisions with similar RSIs (Ahmadpur and Gokasar, 2021; Erdogan, 2009; Huang et al., 2010; Truong et al., 2016; Wachnicka et al., 2021a).

The annual road safety reports of institutes, such as WHO, provide high-detailed knowledge regarding country-level RSIs. However, these reports and studies ignore road safety conditions in countries' subdivisions. Also, empirical examples of spatial analysis of road traffic crashes are mainly concerned with black spot analysis in local areas, and with a few exceptions, regional data are neglected. It is usual to compare subdivisions of a country according to their RSIs (Adeleke et al., 2021; Erdogan, 2009; Iyanda, 2019; Tortum and Atalay, 2015). Regional areas (counties, cities, states, provinces) have been implemented in the spatial approaches in road traffic safety studies. Some studies have evaluated road safety in one specific state or province (Atubi, 2012; Bolakar et al., 2015; Bu et al., 2018; Cai et al., 2017; Huang et al., 2010; Li et al., 2013), and some in all administrative-divisions of a country (Adeleke et al., 2021; Erdogan, 2009; Iyanda, 2019; Osayomi, 2013; Truong et al., 2016; X. Wang et al., 2019).

Given the higher rate of RTFs in developing countries than in developed ones (World Health Organization, 2018a) and the limited resources to improve road safety conditions in developing countries (Abdolmanafi and Karamad, 2019), conducting spatial analysis regarding regional RSIs in developing countries is vital. Unfortunately, most regional road safety studies have been conducted about developed countries, and despite the high RTF levels in developing countries, little attention has been given to regional road safety issues in those (Ziakopoulos and Yannis, 2020). Also, despite high RTF levels in low- and middle-income countries, only 10% of studies have evaluated road safety issues in these countries (Haghani et al., 2022). Therefore, further regional road safety studies in developing countries like Türkiye and Iran are needed.

Various studies have used different RSIs to evaluate road safety performance in countries. These RSIs are the backbones of regional road safety studies. However, it was observed that inadequate attention had been given to the associations between these indices. These associations rarely have been discussed in the literature, and the significance of these associations in other countries is unknown. Therefore, it is necessary to evaluate these associations in other countries using statistical techniques like regression analysis and correlation. Additionally, most regional road safety studies adopted limited numbers of RSIs to evaluate road safety performance in regions, and there is little knowledge about regional RSIs. A few studies have evaluated and compared various countries' RSIs (Chen et al., 2017; Elvik et al., 2009; Lassarre and Thomas, 2005; Wachnicka et al., 2021). We are unaware of a study that has used several RSIs and has evaluated and compared regional RSIs in countries with different backgrounds. Thus, there is a need for in-depth studies to understand the nature of the regional RSIs.

Regional RSIs could be divided into crude- and ratio-type indices. In the literature, different integer or crude RSIs, such as the number of fatalities (Adeleke et al., 2021; X. Wang et al., 2019), and ratio-type RSIs, such as fatalities per population (Ahmadpur and Gokasar, 2021; Erdogan, 2009), have been adopted for the evaluation of road safety performance in geographic regions. Each RSI has its advantages and disadvantages, and using all available RSIs in the same study could reveal their attributes in more detail. In addition, there is limited knowledge regarding crash severity indices, such as the fatality per the number of nonfatal injuries, and a limited number of studies have evaluated them (Ahmadpur and Gokasar, 2021; Iyanda, 2019).

1.3. Contributions

The main contributions of this dissertation can be summarized as follows:

- Several RSIs have been assessed, and two crash severity indices have been proposed.
- The spatial distributions of subdivisions of 5 countries, including Iran, Türkiye, the USA, England, and Egypt, regarding multiple RSIs are evaluated, and road safety deficient regions are identified.
- The associations between the studied RSIs are evaluated, and similar RSIs are categorized. Similarities and differences between various RSIs are described.
- Influencing socioeconomic factors on the road safety performance of developing countries are revealed.
- It is proved that the presence of heavy vehicles, rural population, income rate, and

education level of people significantly impact road safety performance in developing countries.

- The significant relationship between the total number of detected hot and cold spots and Moran's I index is revealed.
- A Hot spot analysis method is introduced to discover the factors influencing regional RSIs.
- The regional road safety performance of developed and developing countries is compared, and their similarities and differences regarding road safety are discussed.
- A significant negative relationship between motorization rate and crash risk is detected.
- It has been proved that the fatality per number of registered vehicles or fuel consumption index provides more accurate fatality risk rates than the fatality per population, especially in developing countries.
- It is shown that road crashes tend to be severe in underdeveloped regions of developing countries.
- A comprehensive literature review regarding regional road safety studies and revealing the gap in the literature regarding crash severity indices and associations between RSIs.

1.4. Organization of This Dissertation

In section one, the introduction of the dissertation is presented. In section two, the methodology and data collection method are described. Each of the papers in sections three to six is associated with a country or countries and explains regional road safety conditions and RSIs in that country. The flowchart of the dissertation structure is illustrated in Figure 1.1. Whereas evaluating regional road safety indices in Türkiye (section 3) provides knowledge regarding road safety conditions in a developing and middle-income country, section six, regarding four studied countries, explicitly addresses differences between developed and developing countries regarding regional road safety indicators. Therefore, sections gradually explain regional road safety conditions in developed and developing countries.

This dissertation is structured as follows. In section 2, the methods for conducting spatial and statistical analysis are described. In section 3, the evaluation of province-level RSIs of Türkiye is presented. In section 4, detected significant associations between socioeconomic variables and province-level RSIs of Iran are described. Section 5 presents the spatial analysis of Iranian provinces. Section 6 presents the evaluation of country- and subdivision-level RSIs and related indices of four countries, including the USA, England, Egypt, and Türkiye. Section 7 concludes the dissertation by summarizing the results of this dissertation.

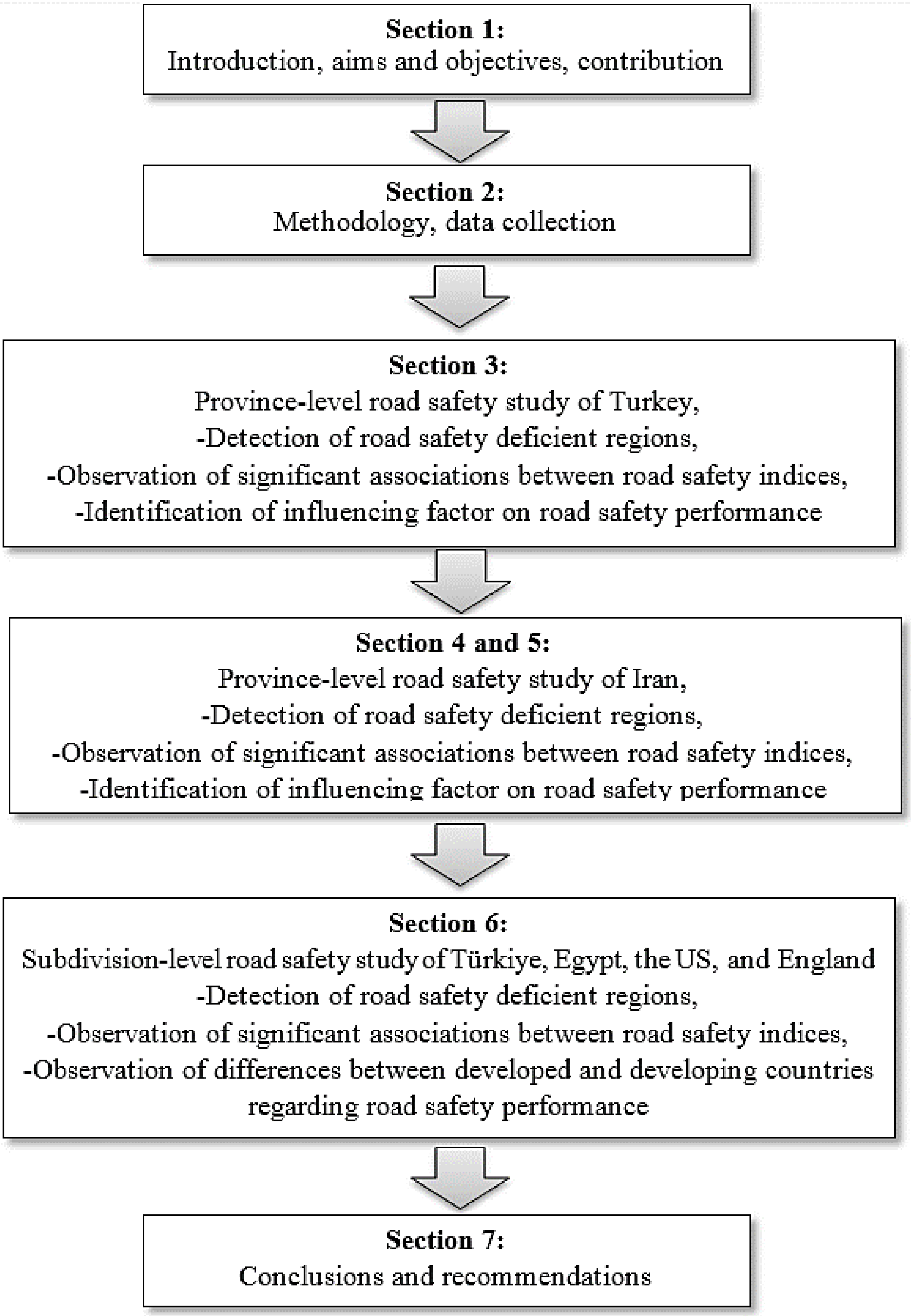


Figure 1.1. The flowchart of dissertation structure.

2. METHODOLOGY

This dissertation comprises four papers presented in sections 3 to 6. In section 3, province-level RSIs of Türkiye are evaluated using spatial, correlation, and regressions analysis. In section 4, province-level RSIs of Iran are assessed using correlation and regression analysis. Using spatial analysis methods, province-level RSIs of Iran are evaluated and presented in section 5. In section 6, administrative division-level RSIs of four countries, including Egypt, England, Türkiye, and the USA, are evaluated using correlation, regression, and spatial analysis methods. Since the same spatial and statistical analysis methods have been used in these papers, these methods are described in this section.

Because of the availability and differences of administrative-division level data in each country, the collected data of the countries and adopted RSIs are slightly different; therefore, each country's data collection and collected data are described in the related section.

2.1. Data

Administrative division-level data is needed to conduct subdivision-level spatial analysis in a country. The data of countries were collected from government websites and databases. It was observed that each country has different regional datasets. Thus, the data and collecting methods of each country are explained in each chapter. The general data collection steps in this dissertation are as follows:

- Downloading and collecting annual regional road safety and socioeconomic data of administrative divisions of countries from government websites.
- Compiling the data set of each country in MS Excel.
- Calculating ratio-type road safety and socioeconomic indices by using the gathered road safety and socioeconomic data.

Data collection and related information about Türkiye are provided in section 3.2.1. Data collection and related information on Iran is provided in sections 4.2.1 and 5.2.1. Data collection and related information from the USA, England, and Egypt are provided in sections 6.2.1.

2.2. Road Safety Indicators

Road safety performance and conditions of geographic regions have been assessed using road safety indices. These indices are integer-type values, such as the number of road fatalities in regions, or ratio-type ones, such as fatality per population. The ratio-based RSIs can be further categorized into two groups. The first group includes risk rates, such as fatality rates per population, which provide insights into the likelihood of fatalities occurring on roads. The second group comprises severity indices, such as the number of fatalities per crash, reflecting the seriousness of crashes in different regions. The risk indices show the probability of being killed, injured, or involved in a road crash in a region. These risk indices are calculated by dividing a crude RSI, such as the RTF index, by an exposure measure, such as the region's population. A higher RTC severity index means that RTCs are more severe and catastrophic. Also, these indices indicate the inadequacy of resources to secure road users from fatal injury or provide rapid medical treatment for severe injuries. Based on the data available in the studied countries, various RSIs were used to evaluate road safety conditions in these countries. Further explanations regarding the RSIs of each country are provided in sections 3 to 6.

2.3. Spatial Analysis and Spatial Autocorrelation

Spatial analysis refers to the examination and interpretation of geographic patterns, relationships, and processes using spatial data. It involves analyzing data linked to specific locations or spatial units, such as points, lines, polygons, or grids. Spatial analysis aims to understand the spatial characteristics, distributions, and interactions of various phenomena. Using Moran’s I, local Moran indices, and Jenks natural breaks method, the spatial distribution of administrative divisions of the countries was evaluated. These methods are used in sections 3, 5, and 6. In this dissertation, GeoDa software, which is a free software, was used for conducting the spatial analysis. Figures and maps illustrating the geographic distribution of studied indices and clustering results were produced using GeoDa software.

2.3.1 GeoDa Software

In this dissertation, the GeoDa software was used for conducting clustering and producing choropleth maps. Also, this software was used for conducting spatial analysis, including calculating Moran's I to assess the spatial distribution of regions and using local Moran indices to identify hot and cold spots. GeoDa is a free software package that has been used for conducting spatial data analysis, clustering, spatial autocorrelation, and spatial modeling. This software facilitates new insights from various data sets of regions by exploring and modeling spatial patterns. GeoDa was developed by Luc Anselin through the Center for Spatially Integrated Social Science at the University of Illinois (Anselin, 2005). The program provides a functional graphical interface to exploratory spatial data analysis methods, such as spatial autocorrelation statistics and fundamental spatial regression analysis for point and polygon data.

2.3.2 Moran's I and Local Moran

Each country comprises administrative divisions, and each region has unique values regarding a target index, such as the motorization rate. When the values of the target variable that are spatially adjacent to each other are correlated, a strong autocorrelation occurs. If the administrative divisions or the values of variables related to them are randomly distributed in the space, there must be no relationship between them. One of the indicators of spatial autocorrelation in spatial analysis is Moran's I index, proposed by Moran (1950) and popularized by Cliff and Ord (1973). This index was adopted in numerous regional road safety studies in countries (Adeleke et al., 2021; Cai et al., 2017; Erdogan, 2009; Iyanda, 2019; Lassarre and Thomas, 2005; Moradi et al., 2016; Osayomi, 2013; Truong et al., 2016; X. Wang et al., 2019).

Moran's I, with a value between -1 and 1, indicates the spatial distribution of regional data in terms of a target variable. A positive Moran's I indicates that regions with similar target variable rates tend to have a nonrandom distribution pattern in space, and a negative index shows that geographic regions' distribution pattern is arbitrary. Figure 2.1 illustrate attributes of Moran's I index in more detail. When regions with similar target values are clustered in space, Moran's I is positive and high. A non-random distribution means that some phenomena or influencing factors led to the clustering of regions with similar values.

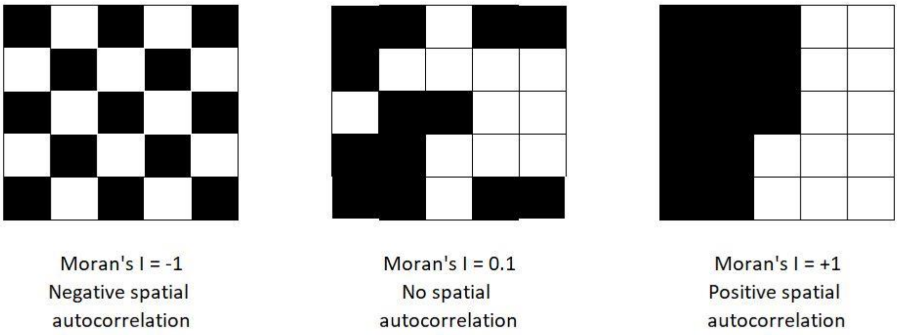


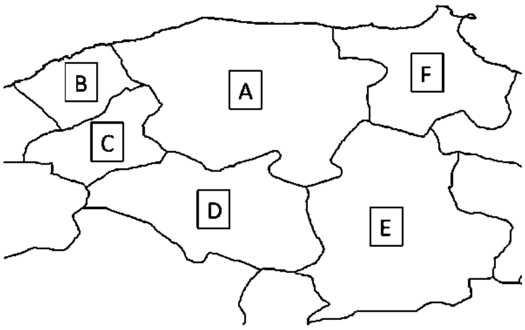
Figure 2.1. Moran’s I index and distribution of regions. When Moran’s I approach -1, the white and black square distributions are random. If the blocks are clustered, Moran's I approach +1.

Moran’s I is a cross-product statistic between a variable and its weighted average of neighboring values. The mathematical formulation of Moran’s I index is expressed as

$$I = \frac{\sum_i \sum_j \left(\frac{W_{ij} Z_i Z_j}{S_0}\right)}{\sum_i \frac{Z_i^2}{n}}, \tag{2.1}$$

where I is Moran’s index, i is a region, X_i is a value in region i, $\overline{X}$ is the average value of regions, Z_i is the deviation of X_i from its mean (X_i-$\overline{X}$), W_{ij} is the element of the spatial weight matrix (a matrix that indicates the region's neighbors), S_0 is the sum of the weights ($\sum_i \sum_j W_{ij}$), and n is the number of regions.

Spatial weights or weight matrices are critical in constructing spatial autocorrelation statistics such as Moran's I. These weights represent the neighbor structure between observations. In this dissertation, spatial contiguity weights were adopted, and contiguity means that two administrative divisions share a common border of nonzero length. Figure 2.2 presents an example of a weight matrix for a country with six regions. When two regions have a common border, the corresponding element in the weight matrix equals 1.



	A	B	C	D	E	F
A	0	1	1	1	1	1
B	1	0	1	0	0	0
C	1	1	0	1	0	0
D	1	0	1	0	1	0
E	1	0	0	1	0	1
F	1	0	0	0	1	0

Figure 2.2. Map of a country with six administrative divisions (left) and related weight matrix (right). In contiguity weight matrices, if two regions have a common border, the corresponding element in the weight matrix is equal to one, and other elements are equal to zero.

A z-score testing method for assessing the significance of the results of Moran's I is used, and the mathematical formula of the z-score is expressed as

$$Z_C = \frac{C_O - C_E}{SD_{CE}}, \tag{2.2}$$

where C_O is the observed value, C_E is the expected value, and SD is the square root of variance.

The process of creating a global, whole-map metric such as Moran's I is frequently not what analysts are most interested in. Understanding which specific local aspects of the data contribute most to the overall pattern can be more crucial. The localized phenomena of relevance in the context of spatial autocorrelation are those areas of the map that contribute particularly significantly to the general trend, which is often positive autocorrelation. Local Indicators of Spatial Association refer to techniques such as Local Moran that allow an analyst to pinpoint specific map areas where data values are significantly positively or negatively correlated. By conducting hotspot analysis and identifying local hot or cold spots, it is possible to detect road safety deficient regions of countries and come up with more precise and feasible road safety policies.

Anselin (2010) proposed the Local Moran index as a method to identify local spatial clusters and outliers. The local Moran index was used in several regional road safety studies in various regions (Erdogan, 2009; Iyanda, 2019; Lassarre and Thomas, 2005; Tortum and Atalay, 2015). Mathematical formulas of the Local Moran index and associated z-score are expressed as

$$I_i = \frac{(X_i - \overline{X})}{m_2} \sum\nolimits_j W_{ij} \left(X_j - \overline{X}\right), \tag{2.3}$$

where I_i, X, X_i, W_{ij}, and X_j, are as defined before, and m_2 can be computed as

$$m_2 = \frac{\sum_i \left(X_i - \overline{X}\right)^2}{n}, \tag{2.4}$$

where $\overline{X}$, X_i, and n, are as defined before. The associated z-score of Local Moran's I is expressed as

$$Z(I_i) = \frac{I_i - E(I_i)}{\sqrt{Var(I_i)}}, \tag{2.5}$$

where I_i is the local Moran index of region i, $Z(I_i)$ is the z-score of I_i, $E(I_i)$ is the expected value of I_i, and $Var(I_i)$ is the variance of I_i.

Using the GeoDa software's Cluster Maps tool, local cluster maps were produced, and significant provinces were categorized as significant high-high (HH) and low-low (LL) spatial clusters and high-low (HL) and low-high (LH) spatial outliers. When a region is marked as HH local cluster, it means that regions with high and similar rates surround this region. In addition, LL location means that the region with a low target rate is surrounded by regions with similar and low values. High-low means a region with a high target value is surrounded by areas with low target value. When a region is HH regarding road fatality index, it means that there is a spatial pattern in the country, and some unknown factors cause an abnormal and high number of fatalities in that specific region, and immediate regional policies and interference are needed. An example of GeoDa output is illustrated in Figure 2.3. Regions in the east of Türkiye have high traffic risk rates, and in the west of the country, provinces with high-risk rates are side by side, forming a vast local HH cluster.

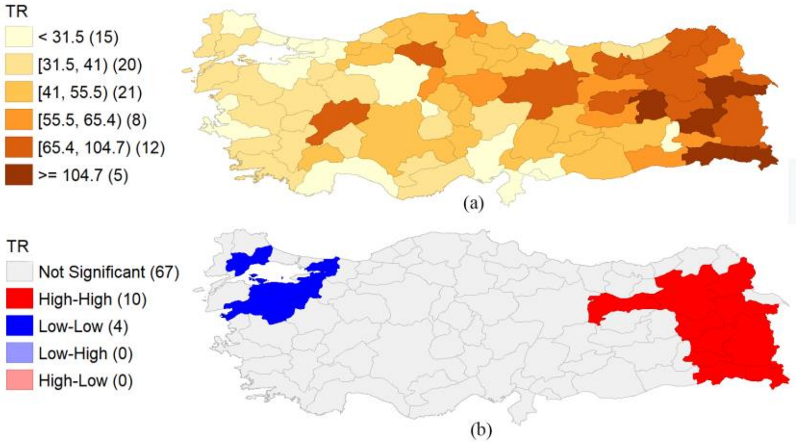


Figure 2.3. Choropleth map (a), and high-high and low-low local clusters map (b) regarding the traffic risk index of Türkiye.

2.3.3 Spatial Analysis Steps

The steps of the conducted spatial analysis are expressed in Figure 2.4. A geospatial vector or shape file is a vector data file format commonly used for geospatial analysis. Shape files store the location, geometry, and attribution of point, line, and polygon features, such as the internal borders of countries.

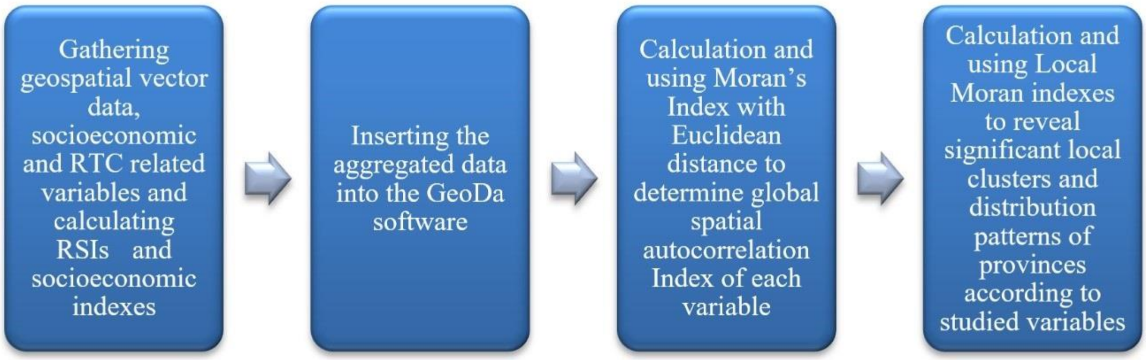


Figure 2.4. Steps of the conducted spatial analysis.

A screenshot of the software during the calculation of Moran's I index is provided in Figure 2.5. Steps for calculation of the Moran's I of countries regarding target variables are as follows:

- Regional data of subdivisions were collected, and the database was compiled in Excel.
- The shape file of the target country was obtained and inserted into the software.
- Then, the weight matrix of the target country was defined using the contiguity concept.
- Using the Moran Scatter Plot tool of the software and the selection of Univariate Moran’s I, the Moran’s I index of each variable was calculated and extracted.

Hot spot identification analysis using GeoDa software was conducted in the following steps:

- Regional data of regions were collected, and the dataset was compiled in Excel.
- The shape file of the target country was obtained and inserted into the software.
- The weight matrix of the target country was defined using the contiguity concept.
- Then, the local cluster maps were produced and extracted using the Univariate Local Moran’s I tab of the Moran Cluster Map tool of the software. In this step, the p-value of cluster maps was set to 0.01.
- Cluster maps were extracted from the software.

Identified significant regions by GeoDa software were significant at p-value <0.01. In the local spatial autocorrelation calculation process, selecting an appropriate p-value is crucial. The conventional choice of 0.05 might create many false positives (Anselin, 2005). Therefore, the p-value was set to 0.01 to decrease the false positives in assessing Local Moran indices. A screenshot of the software during hotspot analysis steps is provided in Figure 2.6.

Hot spot analysis in Iran was conducted by comparing extracted hot spot maps from GeoDa software to identify variables that affect RSIs. The hot and cold spot maps of all studied socioeconomic indices were produced and evaluated, and indices with significant hot and cold spots were identified. Then, the locations of hot and cold spots regarding RSIs and the other variables were compared, and variable pairs with similar or opposite significant cluster types (HH or LL) and locations were paired.

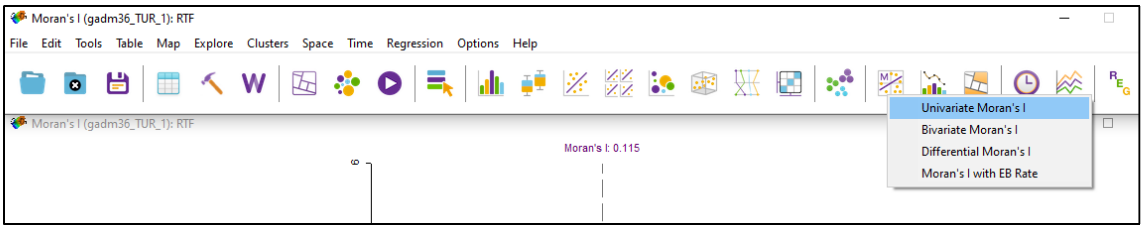


Figure 2.5. Screenshot of GeoDa software, calculation of Moran's I for RTF index of Türkiye.

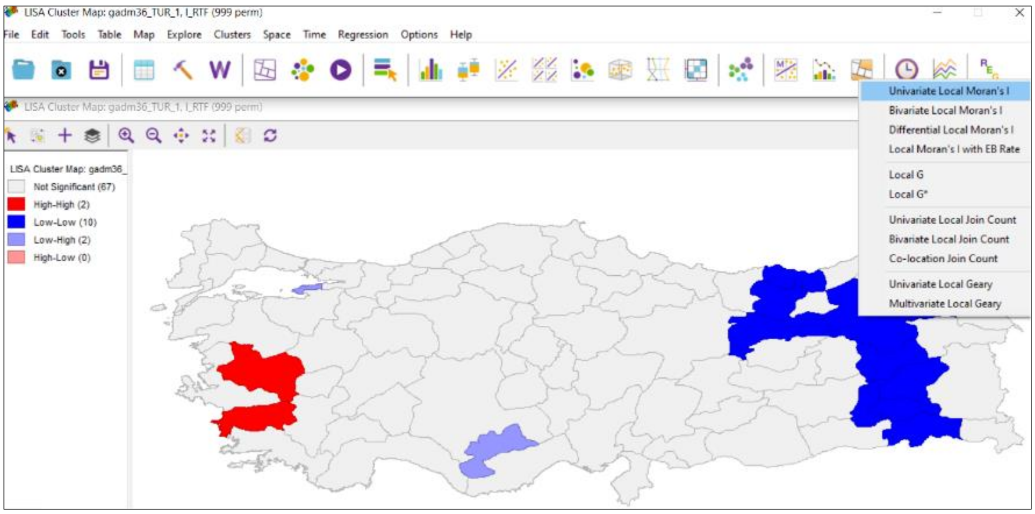


Figure 2.6. Screenshot of GeoDa software, conducting hotspot analysis for RTF index of Türkiye.

2.3.4 Jenks Natural Break Method

Jenks natural breaks classification is one of the well-established classification techniques in making choropleth maps and has been adopted in several road traffic safety studies (Erdogan, 2009; Lassarre and Thomas, 2005; Tortum and Atalay, 2015). Jenks natural breaks execute a nonlinear algorithm to cluster observations such that the within-group homogeneity is enlarged, following the comprehensive studies of Fisher (1958) and Jenks (1977). By adopting the Jenks natural breaks classification method and regarding the studied variables, the administrative divisions of countries were clustered into seven groups. In similar studies, the numbers of clusters in choropleth maps were equal to 5,6 or 7 (Adeleke et al., 2021; Erdogan, 2009; Iyanda, 2019; Lassarre and Thomas, 2005; Tortum and Atalay, 2015; Truong et al., 2016). With the increase in the number of classes, it is possible to reduce data generalization, but this action could decrease the map's legibility and increase the risk of map reading errors. Thus, considering the literature, the number of clusters was set to 7. An example of Jenks natural breaks method for grouping regions based on their road fatality index is illustrated in Figure 2.7. A screenshot of the software during the clustering steps is provided in Figure 2.8. This figure provides the natural breaks map of Turkey (left) regarding the road fatality index, and the clustered frequency distribution of target values of subdivisions (right) is illustrated. Clustering analysis using Jenks natural breaks method in GeoDa software was conducted in the following steps:

- Regional data of regions were collected, and the database was compiled in Excel.
- The shape file of the target country was obtained and inserted into the GeoDa software.
- Then, using the Maps and Rates tool of the software, the Natural Breaks or choropleth maps of countries were produced and extracted.

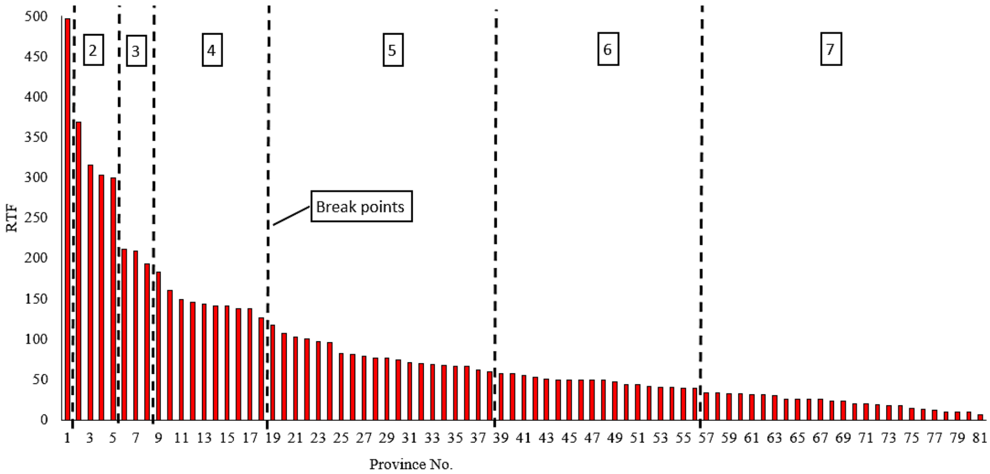


Figure 2.7. The road traffic fatality rates of provinces of Turkey are clustered with Jenks natural breaks method. The cluster numbers and breakpoints are illustrated in the figure.

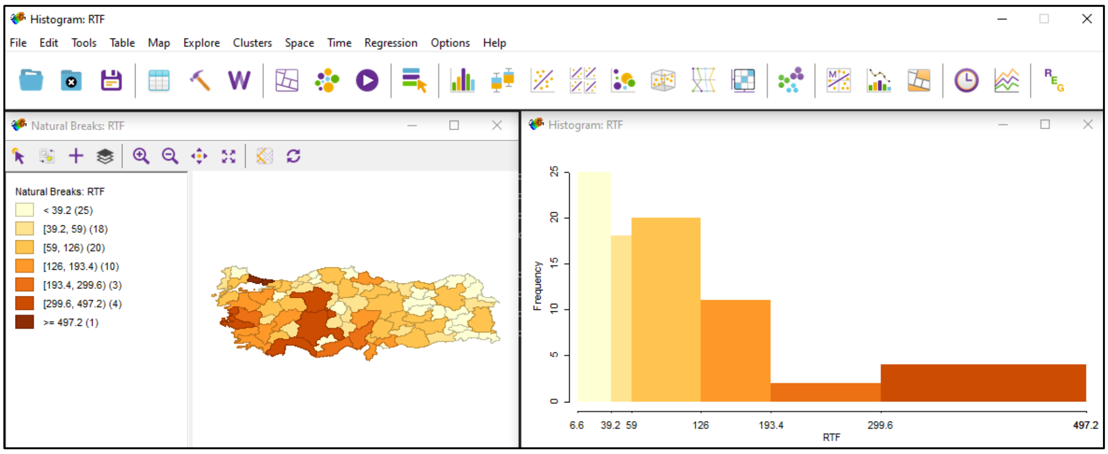


Figure 2.8. Screenshot of software, natural breaks map for RTF index of Türkiye (left) and related histogram (right).

2.4. Correlation and Regression Analysis

2.4.1 Correlation

The Pearson correlation index, also known as Pearson's correlation coefficient or Pearson's r, is a statistical measure that quantifies the strength and direction of the linear relationship between two continuous variables. It is widely used to assess the degree of association between variables. The Pearson correlation coefficient ranges from -1 to 1, where:

- A value of -1 indicates a perfect negative linear relationship, meaning that as one variable increases, the other decreases in a perfectly predictable manner.
- A value of 1 indicates a perfect positive linear relationship, meaning that as one variable increases, the other also increases in a perfectly predictable manner.
- A value of 0 indicates no linear relationship, suggesting that the variables are not correlated or are weakly correlated.

In this dissertation, the Pearson correlation coefficient (PCC) was used to measure the linear correlation between the studied variable pairs. Correlation analysis has been applied in numerous administrative division-level road safety studies in developing countries to explore the possible relationships between variables. Considering the calculated correlations, indices not significantly associated with RSIs were removed from the analysis. It is well known that calculated high PCC measures do not imply causation. Therefore, after calculating PCC values for pairs of studied variables, scatter plots of variable pairs were visually inspected to confirm the detected significant relationships between them.

Correlation analyses were conducted using SPSS software in the following steps:

- Regional data of regions were collected, and the database was compiled in Excel.
- Then, these indices were inserted into SPSS software.
- Using the Analysis>Correlate tool of software, the variables for calculating correlations were selected.
- The software provided the correlation table and significance rates of each correlation value for pair of variables.
- Insignificant correlations removed from tables
- After visual inspections, correlations because of outliers were removed from tables.

2.4.2 Regression

After calculating correlation values, the association between studied variables was examined by visual inspection. Then, linear and nonlinear regression methods were used to estimate the equation of the line that best describes the relationship between independent and dependent variables. Several non-linear regression models, including rational, logarithmic, inverse, quadratic polynomial, cubic polynomial, power, compound, S, logistic, growth, and exponential, were adopted, and the most appropriate one was selected for pairs of variables. Logarithmic, power, linear, and exponential regressions were conducted using SPSS software in the following steps:

- Collected data sets were inserted into SPSS software.
- Using the Analysis>Regression>Curve estimation tool of software, the dependent and independent variables were introduced. Models for conducting the fit were selected, and analysis commenced.
- Results were extracted from the software, and the suitable regression model was selected by visual inspection and checking the R2 values, F statistics, and standard error values.

Rational regression was conducted using MATLAB software's Curve Fitting tool in the following steps:

- Collected data sets were inserted into MATLAB software.
- Using the APPS>Curve Fitting tool of software, the dependent and independent variables were introduced. A rational model for conducting the fit was selected, and analysis commenced. The numerator and Denominator degrees were set to 1.
- Results were extracted from the software, and by visual inspection and checking the R^2 and standard error values, the suitable regression model was selected.

Multiple regression analysis was used to detect essential factors that influence regional RSIs and model the RSIs in Iran by using studied socioeconomic indices. These models' coefficient of determination (R^2), F-statistic, R^2 change, and variance inflation factor (VIF) coefficients were used to evaluate the fitted models. Multiple regression was conducted using SPSS software. This analysis was conducted in the following steps:

- Collected data sets were inserted into SPSS software.
- Using the Analysis>Regression>Linear tool of software, the dependent and independent variables were defined. Since there are many variables, and some of them are correlated, the stepwise method was used. Also, under the Statistics tab, the collinearity diagnostic was actuated.
- The software provided several models, and variables with high correlations were removed automatically.
- The best model was selected considering the F statistics and variance inflation factor. Models whose independent variables had VIF less than five were selected. Generally, a VIF value of 1 indicates no multicollinearity, while values above 1 suggest increasing levels of multicollinearity. There is no universally agreed-upon threshold for an acceptable VIF value, as it depends on the specific context and research field. However, a common guideline is to consider VIF values above 5 or 10 as indicative of high multicollinearity.
- Results extracted from the software.

3. SPATIAL ANALYSIS AND EVALUATION OF ROAD TRAFFIC SAFETY PERFORMANCE INDICES ACROSS THE PROVINCES OF TÜRKIYE FROM 2015 TO 2019[1]

3.1. Introduction

Road traffic crashes and related fatalities are a serious and growing public health problem in countries. According to the World Health Organization's annual road safety report, approximately 1.35 million people die yearly because of RTCs. The RTC issue is worsening; approximately 3,700 people die on the roads daily because of RTCs (WHO, 2018a). It is noteworthy that hospitals and emergency responses also impose significant price pressure on the country's economy. Reduction in RTCs and related road traffic fatalities could raise countries' GDP and GDP per capita (GDPC) and improve the quality of life (World Bank, 2017).

Road safety reports indicate that almost 80% of worldwide RTFs occur in middle-income countries. Moreover, from 2013 to 2016, 60 middle-income countries' RTF levels increased (WHO, 2018b). The middle-income countries own 59% of motor vehicles in the world. Consequently, despite the lower motorization rate in middle-income countries, most of the RTF occurs in these countries. Most of the population in middle-income countries is young; unfortunately, road traffic injury is the leading cause of death for children and young adults aged between 5-29 years (World Health Organization, 2018a). Thus, further attention should be given to road safety issues in middle-income countries such as Türkiye.

Türkiye is a developing, transcontinental country located mainly on the Anatolian peninsula in Western Asia. This middle-income country is subdivided into 81 provinces with an efficient RTF registration system (WHO, 2018a). Turkish Statistical Institute (TUIK) publishes datasets of population, registered motor vehicles (RMVs), RTFs, road traffic

[1] This section is based on the paper "Ahmadpur and Gokasar, (2021). Spatial Analysis and Evaluation of Road Traffic Safety Performance Indices across the Provinces of Türkiye from 2015 to 2019." DOI:10.1080/17457300.2021.1925923.

injuries (RTIs), and annual traffic police reports of Türkiye. Some socioeconomic and road safety-related information about Türkiye is summarized in Table 3.1.

Table 3.1. Various socioeconomic and road traffic-related information about Türkiye (TUIK, 2021).

Variable (2019)	Population	RMVs	RTFs	RTIs	RTCs	Fatal-RTC	Non-fatal RTC
	83,154,997	23,156,975	5,473	283,234	1,168,144	993,248	174,896
Cause of RTCs (2019)	Driver fault	Passenger faults	Pedestrian fault	Road defects	Vehicle defects	-	-
	89%	1%	9%	1%	1%	-	-
Cause of driver faults (2019)	Not adapting vehicle speed to the conditions	Right of way violation	Unsafe lane change	Rear-end collision	Other		Driving under the influence of alcohol
	39%	14%	9%	8%	11%		1%

According to Table 3.1, driver faults were the primary cause of high RTF rates. Road transportation is Türkiye's most preferred transportation mode, and most RTCs happen due to non-compliance with traffic rules (Kuşkapan et al., 2021). From 1980 to 2016, a dramatic increase in GDP, vehicle ownership, and vehicle-kilometer travel occurred in this country. At the same time, RTCs were decreased by 17%. Despite that, the country-level RTF of Türkiye was higher than most of the European Union countries (ÖZEN, 2018). The provided data in the annual road safety report of the International Transport Forum (ITF) and Organization for Economic Co-operation and Development (OECD) point out that in 2018, the RTF-per-100k population ratio of Türkiye (8.14) was higher than the same rate of most European countries such as Norway (with that of 2) (ITF and OECD, 2019). Türkiye's high RTF rates indicate that reducing RTCs and related fatalities should be a priority in this country.

One of the initial steps in a comprehensive road traffic safety program in a country is to distinguish and group road safety-deficient regions. The spatial analysis could effectively detect hazardous regions and hot spots regarding road safety performance. Regional areas (counties, cities, states, provinces) have been implemented in the spatial approaches in road traffic safety studies. These areas are administrative divisions of countries with different governance laws than other regions. Some studies have evaluated road safety in one specific state or province (Atubi, 2012; Bu et al., 2018; Cai et al., 2017; Huang et al., 2010; Li et al., 2013; Tortum et al., 2015), some in all administrative-divisions of a country (Adeleke et al., 2021; Erdogan, 2009; Iyanda, 2019; Osayomi, 2013; Truong et al., 2016; X. Wang et al., 2019), or some of them at the city-level (Moradi et al., 2016; Soltani and Askari, 2017; S. Wang et al., 2020). It is usual to compare the administrative divisions of a country according to their road safety performance indices (Adeleke et al., 2021; Erdogan, 2009; Iyanda, 2019; Tortum and Atalay, 2015). In literature, various ratio-type RSIs have been adopted for comparing geographic regions.

Six of the widely used ratio-type RSIs in literature are pointed out in the following:

- The mortality rate (RTF per population) or health risk (HR) (Besharati, Tavakoli Kashani, and Washington, 2020; Elvik et al., 2009; Erdogan, 2009; Lassarre and Thomas, 2005; World Bank, 2017; World Health Organization, 2018a).
- The fatality risk (fatality per distance traveled) (ITFand OECD, 2019; Truong et al., 2016).
- The RTF per RMV rate or traffic risk (TR) (Elvik et al., 2009; Erdogan, 2009; ITF and OECD, 2019; World Bank, 2017).
- The RTF per RTC rate (FPC) as a crash severity index (Iyanda, 2019; Tortum and Atalay, 2015).
- The fatal-RTC per population rate or crash rate standardized by population (CRP) (Erdogan, 2009).
- The fatal-RTC per RMV rate or crash rate standardize by the number of RMVs (CRV) (Erdogan, 2009).

The risk value of being killed in an RTC in a region is calculated as RTF per measure of exposure in the road network of the geographic region (Elvik et al., 2009). HR and TR are rates of the risk of being killed in RTCs in a region. Distance travel or mobility is one of the best exposure measures in road traffic safety studies. However, in the lack of distance traveled data, alternative exposure measures such as the population or the number of RMVs in the investigated region could be adopted as the exposure values (ITFand OECD, 2019).

Most spatial analysis-based road safety studies have been conducted in developed countries (especially the USA). Contrarily, a few considerations have been paid about the same issues in developing countries (Ziakopoulos and Yannis, 2020). Several studies have focused on the road safety issues of administrative divisions in developing countries. In these studies, regression or correlation analysis has been applied to determine the effect of specific socioeconomic variables on administrative division-level RSIs. Additionally, spatial analysis has been applied to evaluate the geographic patterns of regions regarding the selected RSIs, and in some others, both regression and spatial analysis were applied. In some investigations, local clusters of problematic regions in terms of RSIs have been identified by using local spatial autocorrelation indices. Also, researchers have used clustering techniques such as natural breaks to produce choropleth maps and group similar regions corresponding to their RSIs. These studies are outlined in Table 3.2.

Table 3.2. Reviewed studies regarding road safety analyses primarily conducted in developing countries.

Author(s) (year)	**Studied region, regional level**	**Method(s)**	**Spatial analysis statistics**	**Study Period**	**Adopted RSPI(s)**	**Dependent variable**
Lassarre and Thomas (2005)	Western Europe, country, region, and groups of counties	Mean, variance, and autocorrelation analyses, analysis of deviance, regression, and correlation	Moran’s I, Geary G, local Moran I	1998, except for Italy (1999) and Norway (1997)	HR	HR
Erdogan (2009)	Türkiye, province	Regression analysis, spatial autocorrelation analyses	Moran's I, Geary's c, local Moran's I, Getis-Ord Gi*	2001-2006	HR, TR, CRP, CRV	RTCs, RTFs
Osayomi (2013)	Nigeria, states and federal territory	Regression analysis	Moran’s I	2003-2007	RTC	RTC
Tortum and Atalay (2015)	Türkiye, province	Spatial analysis, factor analysis, regression analysis	Local Moran’s I	2012	SI, 1k RTF per length of roads	RTCs in uninhabited areas
Truong et al. (2016)	Vietnam, province	Spatiotemporal model, correlation analysis	Moran’s I	2012-2014	RTF, RTFs per million passenger km travel	RTF
Soltani and Askari (2017)	Shiraz city, traffic analysis zonal level	Spatial autocorrelation, comap method	Local Moran’s I, Moran’s I, local Getis-Ord Gi*	2010-2014	RTF, RTI, RTC, property damage RTCs, severity index	RTFs, RTIs, property damage RTC
Iyanda (2019)	Nigeria, states and federal territory	Geographic analysis	Local Moran's I	2012-2016	FPC	FPC
Adeleke et al. (2020)	Nigeria, state	Spatial-, regression- and correlation analysis	Moran’s I	2017-2019	RTC, RTF, RTI, HR, RTCs per 100k population, RTIs per 100k population	RTC, RTI, RTF
Besharati et al. (2020)	Iran, province	Comparative analysis- panel analysis	-	2005-2015	HR	HR

Several road safety-related spatial analyses of the provinces of Türkiye were conducted (Erdogan, 2009; Tortum and Atalay, 2015), and in terms of studied RSIs, spatial diversities among provinces of Türkiye were observed. Also, the spatial distributions of provinces regarding studied RSIs were defined as non-random and clustered. These studies revealed that RTCs and related RTFs were a public health problem in Türkiye.

The primary goal of this section is to conduct spatial analysis and evaluate the province-level RSIs of Türkiye between 2015 to 2019 using spatial, clustering, correlation, and regression analysis. In this section, fourteen integer- and ratio-type RSIs and nine socioeconomic indicators were adopted. These high numbers of RSIs have rarely been used in previous regional road safety studies in developing countries. Using selected RSIs in the same dataset helps to reveal the differences and similarities of RSIs in further detail. In addition, by applying correlation and regression analysis, the potential associations between selected province-level RSIs were examined. Notably, this examination of relationships between RSIs was not conducted in previous studies. The correlation and regression analysis were employed to declare variables that influence the RTF or RTC rates of provinces. Regarding the insufficient number of administrative-division-level road safety studies in Türkiye, this dissertation bridges this gap and contributes to knowledge on RTCs and related RSIs in the provinces of a developing country, namely Türkiye.

3.2. Data and Method

Selected methods and data for conducting analysis are described in this section. Aggregating the selected variables and RSIs for five years leads to stability in the province-level road safety data (Erdogan, 2009; Lassarre and Thomas, 2005). Hence, the study period was set between 2015 and 2019, and selected RSIs were averaged across five years of data.

3.2.1 RSIs and Socioeconomic Indices

Obtained socioeconomic variables from TUIK's website were divided into integer and ratio-type variables. Selected integer-type socioeconomic variables are population, GDP, education level (EL) (number of graduates above primary school), number of hospital beds (HBs), and number of RMVs. TUIK provides province-level RTC data as annual reports and regularly publishes them on its website. These annual reports include the number of RTFs, RTIs, RTCs, non-fatal RTCs (property damage only), fatal RTCs (RTCs cause RTF or RTI), RTF-at-RTC-scene, and number of RTF-after-RTC (within 30days after RTC) (TUIK, 2021). RSIs were divided into crude and ratio-type indices. Selected crude RSIs are defined in Table 3.3. The ratio-type socioeconomic variables were calculated using the integer-type socioeconomic variables and crude RSIs. These indices are represented in Table 3.4.

Table 3.3. Selected province-level crude RSIs.

RSI
RTC (including fatal and non-fatal RTC)
Fatal RTC
RTF at RTC scene
RTF after RTC (within 30 days after RTC)
RTF (Include RTF at RTC scene and after RTC)
RTI

Table 3.4. Calculated ratio-type RSIs and socioeconomic indices of provinces.

Index	**Equation**
HR	RTFs / (population / 100k)
TR	RTFs / (RMVs / 100k)
CRP	Fatal RTCs / (population / 100k)
CRV	Fatal RTCs / (RMVs / 100k)
FPC	RTFs / (100k RTCs)
FPI	RTFs / (1k RTIs)
FPNF	Fatal RTCs / Non-Fatal-RTCs
SPA	RTFs at RTC scene / RTFs after RTC (within 30 days)
HBPP	HBs / 100k population
LR	EL/population over the age of 15
GDPC ($)	GDP / population
MR	RMVs / 1k population

Unfortunately, the data on traveled distance by RMVs in provinces between 2015 and 2019 were unavailable. Thus, population and RMV rates of provinces were adopted as exposure measures to calculate the risk of being killed in RTCs. HR assesses the risk of being killed in RTC of the entire population in a region. This index is macroscopic and more epidemiological. In calculating the TR as a transport-oriented risk rate, the number of RMVs was used as the exposure index. CRP and CRV indices indicate the risk of fatal RTC per unit of exposure in a province, and a larger index reveals poor road safety performance in a region. Regarding the exposure indices, TR and CRV are based on the RMV measure, and HR and CRP are based on the population rate of provinces.

Several RTC severity indices were employed in this section of the dissertation. The FPC, RTF per RTI (FPI), fatal-RTC per non-fatal RTC (FPNF), and RTF-at-RTC-scene per RTF-after-RTC (SPA) were used to measure the severity of RTCs in provinces. The FPC index shows, on average, how much RTF occurs in RTCs. If RTCs be more severe, the FPC index should be higher. A higher FPI index indicates that the ratio of RTF to RTI is higher, and RTCs are more drastic. The higher measure of FPNF shows that the number of fatal RTCs is higher than the number of property-damage-only RTCs, and crashes are more fatal in a region. A high SPA index shows that more individuals lose their lives in the RTC scene, and RTCs are more catastrophic in a province. The GDPC index in this section equals the average GDPC rates between 2017 and 2018. Also, the hospital bed per population (HBPP) is the average HBPP value for the years between 2015 and 2019. The LR index is the average value of LR measures between 2015 and 2019.

3.2.2 Spatial Analysis and Spatial Autocorrelation

Moran’s I, local Moran indices, and Jenks natural breaks method were used to evaluate the spatial distribution of regions in Türkiye. These methods are explained in section 2.3.

3.2.3 Relationships between Variables

Pearson correlation coefficient and regression analysis were used to evaluate associations between variables. These methods are explained in section 2.4.

3.3. Results and Discussion

This section presents a comprehensive province-level analysis of RSIs in a developing country using spatial, clustering, correlation, and regression analysis. Regarding studied RSIs and variables, substantial differences between the provinces of Türkiye were observed. The country was not homogenous in terms of studied RSIs. In the study period, country-level RSIs of Türkiye decreased. Distribution patterns of provinces in terms of several RSIs, such as the TR, were cluster-like and non-arbitrary. Hot spots in terms of ten distinct RSIs were identified. Significant linear and non-linear associations between studied variables were detected.

The statistical summary of the evaluated province-level variables is presented in Table 3.5. The most significant statistical dispersion (regarding coefficient of variation) was in non-fatal-RTC, GDP, RTC, EL, and RMV indices.

Table 3.5. Descriptive statistics of province-level variables.

Variable	Min	Max	Mean	Standard Deviation	Standard Error	Coefficient of Variation
RTC	453	331,386	15,052	40,707	4,523	2.70
Non-fatal-RTC	265	315,203	12,800	38,129	4,237	2.98
Fatal-RTC	157	16,184	2,252	2,720	302	1.21
RTF-at-RTC-scene	4	195	41	37	4.11	0.90
RTF-after-RTC	2	302	44	51	5.67	1.16
RTF	7	497	85	88	9.78	1.04
RTI	326	22,619	3,701	3,974	442	1.07
HR	1.67	23.39	10.86	4.27	0.47	0.39
TR	12.5	135.99	49.43	23.42	2.60	0.47
CRP	68	487	258	81	9.00	0.31
CRV	407	3459	1182	495	55	0.42
CRV	407	3459	1182	495	55	0.42
FPC	150	2251	1150	498	55	0.43
FPI	7.06	34.97	23.7	5.46	0.61	0.23
FPNF	0.05	0.47	0.39	0.2	0.02	0.51
SPA	0.47	4.1	1.3	0.69	0.08	0.53
Population	83,248	15,015,554	998,828	1,812,439	201,382	1.81
RMV	8,713	3,978,513	269,943	513,075	57,008	1.90
HB	161	36,874	2,732	4,668	519	1.71
EL	43,616	8,329,072	509,762	1,003,682	111,520	1.97
GDP (million $)	487	256,269	10,144	29,606	3,290	2.92
HBPP	129	522	270	82	9.11	0.30
LR	53	77	65	4	0.44	0.06
GDPC ($)	3,351	17,278	7,602	2,648	294	0.35
MR	33	500	252	107	12	0.42

3.3.1 Country-level RSIs and Socioeconomic Variables

Country-level variables, RSIs, and the percentage changes of these variables are expressed in Table 3.6. The FPNF, population, RMV, and MR levels of Türkiye were raised by 9, 6, 16, and 10%, respectively. The sharpest increase was in the RMV level, and the steepest decrease was in the TR index. Compared to other indices, the decrease percentages of the fatal-RTC and the RTI indices were smaller than other variables.

Table 3.6. Country-level variables of Türkiye between 2015 and 2019 and related percentage change values in the same period.

Variable	2015	2016	2017	2018	2019	Percentage change from 2015 to 2019 (%)
Population (millions)	78.74	79,81	80,81	82,00	83,15	6
RMV (millions)	19.99	21.09	22.21	22.86	23.15	16
MR	254	264	275	279	278	10
RTC (millions)	1.313	1.182	1.202	1.229	1.168	-11
Non-fatal-RTC (millions)	1.13	0.99	1.02	1.04	0.99	-12
Fatal RTC	183,011	185,128	182,669	186,532	174,896	-4
RTF at RTC scene	3,831	3,493	3,534	3,368	2,524	-34
RTF after RTC	3,699	3,807	3,893	3,307	2,949	-20
RTF	7,530	7,300	7,427	6,675	5,473	-27
RTI	304,421	303,812	300,383	307,071	283,234	-7
HR	9.56	9.15	9.19	8.14	6.58	-31
TR	37.66	34.61	33.43	29.19	23.63	-37
CRV	915	878	822	816	755	-17
FPC	573	617	618	543	469	-18
FPI	24.7	24.0	24.7	21.7	19.3	-22
FPNF	0.16	0.19	0.18	0.18	0.18	9
SPA	1.04	0.92	0.91	1.02	0.86	-17

Despite the rise in the population, RMV, and MR indices in the study period, almost all country-level RSIs decreased. An overview of Table 3.6 affirms that the road authorities of Türkiye successfully managed to reduce the country-level RSIs in the study period. Considering the leading cause of RTCs in Türkiye (driver faults), an increase in drivers' education (especially young drivers) about road safety and a rise in Traffic law enforcement could lessen the number of RTCs and related RTFs in Türkiye.

3.3.2 Correlation and Regression Analysis

Calculated correlation rates for pairs of variables are given in Table 3.7, and significant correlations at the 0.01 level are marked. The integer-type socioeconomic variable pairs were highly correlated (PCC > 0.96), and visual inspections confirmed the presence of significant linear relationships between these variables. All crude RSI variable pairs, such as the RTC-RTF pair, were highly correlated (PCC>0.75). Visual inspections and strong positive correlation coefficients (PCC > 0.95) proved the existence of significant linear relationships between the fatal-RTC, RTF-in-RTC-scene, RTF-after-RTC, RTF, and RTI indices. Also, the RTC and Non-fatal-RTC relationship was significant and linear (PCC > 0.98). The calculated PCCs of ratio-type RSI and crude RSI pairs were low. Among calculated PCCs for ratio-type RSI pairs, the correlation coefficients of TR-CRV, HR-CRP, TR-FPC, FPNF-FPC, and FPI-HR variable pairs were the largest ones (PCC > 0.62). Ratio-type socioeconomic variables were not correlated with crude RSIs. On the other hand, the crude RSIs were highly correlated with the integer-type socioeconomic variables (PCC > 0.71). HR, TR, CRP, and CRV indices correlated highly with the MR index (PCC > 0.64).

Table 3.7. Calculated Pearson correlation coefficients for the studied variable pairs.

Variable	**Crude RSIs**							**Ratio-type RSIs**							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. RTC	-														
2. Non-fatal-RTC	0.99*	-													
3. Fatal-RTC	0.99*	0.85*	-												
4. RTF-in-RTC-scene	0.77*	0.75*	0.96*	-											
5. RTF-after-RTC	0.82*	0.80*	0.96*	0.95*	-										
6. RTF	0.81*	0.79*	0.97*	0.98*	0.99*	-									
7. RTI	0.84*	0.82*	1.00*	0.97*	0.96*	0.98*	-								
8. HR								-							
9. TR	-.34*	-.33*	-.47*	-.44*	-.42*	-.43*	-.47*		-						
10. CRP								0.73*	-0.37*	-					
11. CRV	-.30*	-.29*	-.40*	-.43*	-.43*	-.44*	-.40*	-.37*	0.77*	-.37*	-				
12. FPC	-.44*	-.43*	-.56*	-.48*	-.46*	-.47*	-.56*	0.39*	0.74*		0.32*	-			
13. FPI								0.66*			-.33*	-.58*	-		
14. FPNF	-.37*	-.36*	-.46*	-.47*	-.44*	-.46*	-.47*		0.44*		0.48*	0.62*		-	
15. SPA			-.32*	-.30*	-.43*	-.38*	-.31*	-.31*	0.30*	-.32*	0.44*		-.33*		-
14. Pop	0.99*	0.98*	0.88*	0.80*	0.84*	0.83*	0.86*	-.31*	-.34*		-.29*	-.45*		-.37*	
15. RMV	0.98*	0.97*	0.93*	0.86*	0.90*	0.89*	0.91*		-.41*		-.37*	-.47*		-.40*	
16. HB	0.98*	0.97*	0.91*	0.83*	0.87*	0.87*	0.89*		-.37*		-.32*	-.48*		-.42*	
17. EL	0.99*	0.99*	0.88*	0.79*	0.84*	0.83*	0.86*	-.29*	-.35*		-.30*	-.45*		-.38*	
18. GDP	0.99*	0.99*	0.81*	0.71*	0.77*	0.75*	0.78*		-.31*			-.40*		-.34*	
19. HBPP											-.30*	-.29*		-.38*	
20. LR	0.41*	0.40*	0.42*	0.29*	0.35*	0.33*	0.40*		-.38*			-.59*	-.34*	-.29*	
21. GDPC	0.59*	0.58*	0.60*	0.54*	0.55*	0.56*	0.59*		-.58*		-.55*	-.59*		-.59*	-.31*
22. MR			0.31*	0.37*	0.36*	0.37*	0.31*	0.66*	-.64*	0.80*	-.75*				-.47*
**. Correlation is significant at the 0.01 level (2-tailed).*															

Figures 3.1, 3.2, and 3.3 illustrate the modeled significant relationships between studied variable pairs. By applying linear and nonlinear regressions, these relationships were modeled. Estimated equations and R^2 of the lines that best represent the significant relationships between the independent and dependent variables are displayed in Figures 3.1, 3.2, and 3.3. Figure 3.1 represents the relationship between two crude RSIs and exposure rates (population and RMV). Crude RSIs are highly correlated with all integer-type socioeconomic indices, and for simplification, only the exposure rates were expressed in

Figure 3.1. This figure illustrates that regions with higher exposure levels tend to have higher RTF and RTC measures. The relationship between RMV and RTF indices are non-linear and meaningful, indicating that as RMV levels increase, the rate of increase in RTF levels slows down. The observed significant linear relationship between population and the RTC index implies that provinces with larger populations tend to have more RTCs. Atubi (2012) achieved comparable results in Nigeria. Regression and correlation analysis results revealed a significant linear relationship between integer-type socio-economic indicators and the RTC measure of provinces. It was noticed that the population, EL, HB, GDP, GDPC, and RMV indices of provinces are highly correlated with the RTF rates of regions. These results are in accordance with X. Wang et al. (2019) conclusions about RTF levels in China. Therefore, a higher exposure rate means higher road fatality in regions. With a larger population or vehicles on roads, there is more exposure to crashes on the roads, which can lead to a higher number of crashes and, consequently, more fatalities.

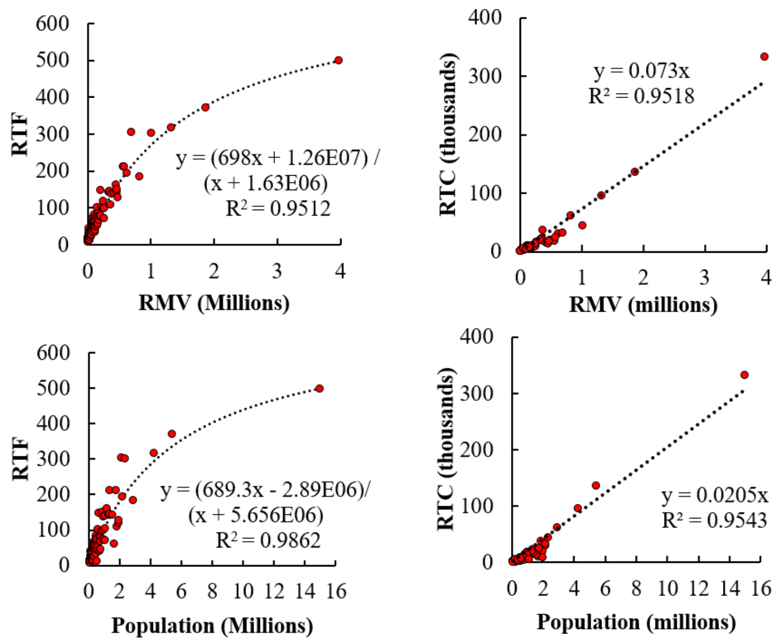


Figure 3.1. Significant relationships between integer-type RSIs and exposure values of provinces and estimated regression lines imposed on the scatter diagrams.

Figure 3.2 depicts the scatter plots of ratio-type RSIs, socioeconomic variables, and fitted regression lines. According to Figure 3.2, regions with higher MR tend to have higher HR and CRP indices. Also, provinces with larger MR had lower TR or CRV measures.

Besides, regions with higher GDPC tend to have lower TR, CRV, FPC, and FPNF indices. Thus, income level significantly influences road safety performance in Türkiye, and higher income in regions means higher motorization rates and road safety performance in this country. This finding is in accordance with the report of the World Bank (2017) about the link between income rates and road safety levels. Regions with higher MR rates have higher HR and CRP indices; however, regions with higher MR have lower TR and CRV rates.

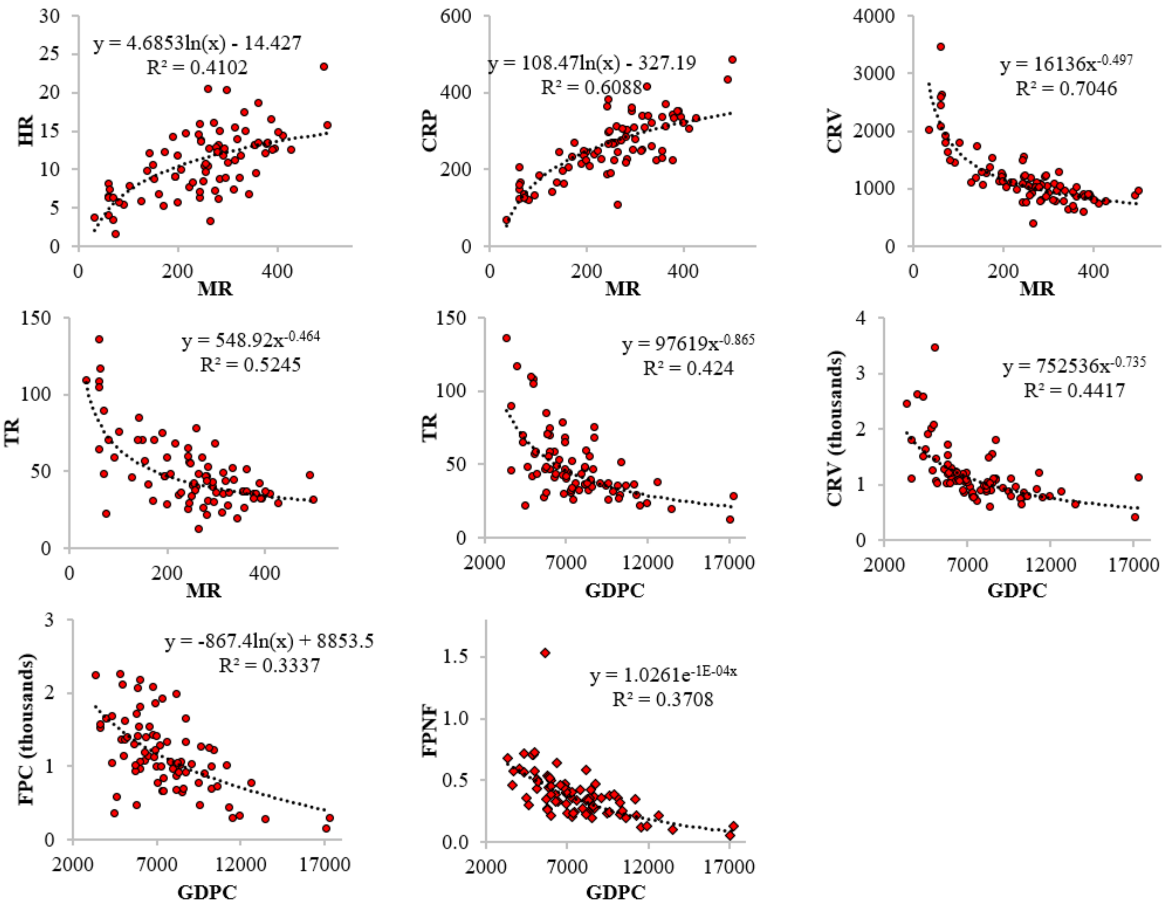


Figure 3.2. Significant relationships between integer-type RSIs and exposure values of provinces, and the related regression lines embedded on the scatter diagrams.

The association between MR and TR makes sense since higher MR levels show higher income and development in regions, and when a region is more developed, the crash risk is lower. However, the association between HR and MR is positive. This can occur when the growth in the number of vehicles outpaces the implementation of safety measures, infrastructure improvements, and traffic regulations. As more vehicles enter the road network, there can be congestion, an increased likelihood of accidents, and a higher risk of fatalities. According to Elvik et al. (2009), countries with higher MR levels tend to have lower TR indices, and a nonlinear relationship exists between TR and MR rates. Comparing the scatter plot of TR and MR in Figure 3.2 and provided information by Elvik et al. (2009) reveal the similarity between province-level TR-MR in Türkiye and the country-level TR-MR graph of the world.

Figure 3.3 exhibits the scatter plots and the fitted significant linear and nonlinear regression lines for RSI pairs.

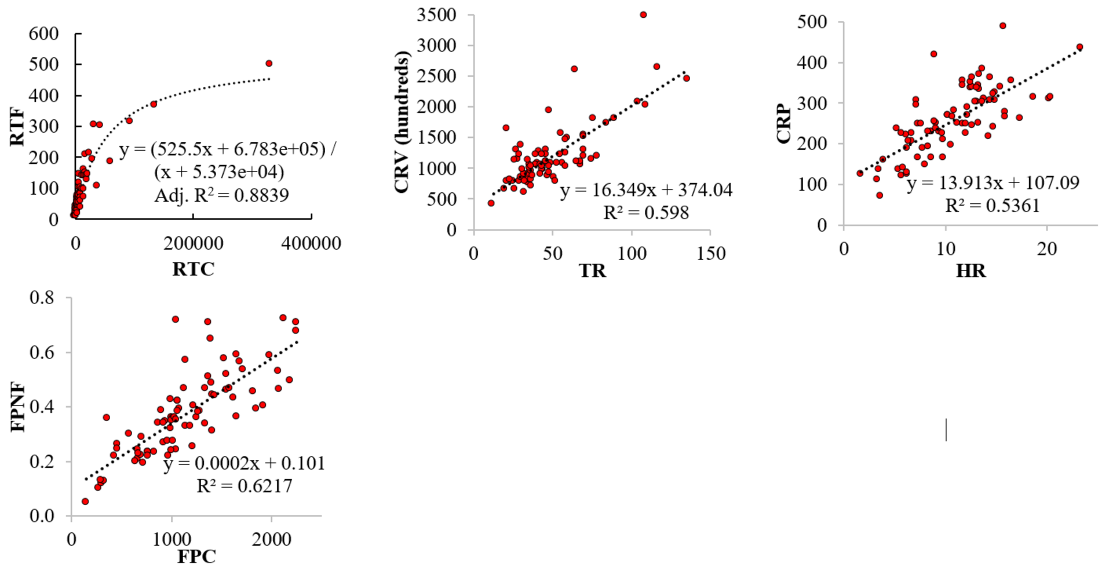


Figure 3.3. Significant relationships between RSIs and corresponding regression lines.

The non-linear association between RTC and RTF rates suggests that as the number of crashes increases, the likelihood of fatalities also increases, but at a decelerating rate. Thus, fatalities per crash or FPC rates are lower in regions such as Istanbul and Ankara. Various reasons, such as better road quality in developed regions and higher road safety awareness, could cause this pattern. Significant linear associations exist between fatality risk indicator pairs, including TR-CRV and HR-CRP. These graphs prove that there are significant associations between RSIs and similarities between them. In the computation of HR and CRP indices, the population of provinces was adopted as the denominator or exposure measure. The number of RMVs was used as the exposure index in calculating TR and CRV indices. The significant relationships between these variables suggest that RSIs with the same exposure measure (such as HR and CRP) had significant and linear relationships. On the other hand, the relationship between RSIs with different exposure indices (such as HR and TR) was insignificant.

The FPC and FPNF indices (as RTC severity indices) had a significant nonlinear relationship. This positive relationship implies that regions with higher FPC indices tend to have larger FPNF rates. The strong linear correlation between FPNF and FPC suggests a similarity between these indices. This positive relationship indicates that when one severity index increases, the other severity index also tends to increase. This suggests a positive correlation or simultaneous occurrence between the two risk factors being measured.

The detected significant linear and nonlinear associations between RSIs could also be valid in other developing countries. In most developing countries, the exposure data, such as the number of RMVs or RTCs, is unavailable. Therefore, the findings of this dissertation (especially the detected significant associations between RSIs) could be used in road safety studies in other developing countries.

3.3.3 Global Spatial Autocorrelation

The studied variables had positive Moran's I indices, and the distribution patterns of regions in terms of these variables were cluster-like. Calculated Moran's I indices are illustrated in Figure 3.4. The Moran's I index of the MR was the highest (0.82). Among socioeconomic variables, MR, GDPC, and LR indices had the highest Moran's I, respectively. The Moran Indices of CRP, CRV, TR, and HR were above 0.5. Also, the crude RSIs, including the fatal-RTC, RTF, RTF-in-the-RTC-scene, RTF-after-RTC, and RTI, had a positive and considerable Moran's I index (Moran's I > 0.18). Moran's I index of all RTC severity measures was positive and above 0.14. These discoveries prove the existence of systematic spatial variation in province-level RSIs. Spatial analysis in terms of RMV, GDPC, MR, HR, TR, CRP, and CRV indices led to the recognition of large LL and HH clusters. Also, the high Moran index of RSIs revealed substantial differences between geographic regions of Türkiye in terms of these indices. Large LL or HH clusters regarding RSIs indicate that the RTCs and related RTFs are a public health problem in Türkiye.

Numerous studies also pointed out the substantial difference between regions regarding the HR index (Adeleke et al., 2021; Besharati, Tavakoli Kashani, and Washington, 2020; Erdogan, 2009; Lassarre and Thomas, 2005; X. Wang et al., 2019). Besharati et al. (2020) reported a negative effect of HBPP on the HR index of provinces in Iran. The dissertation indicates that no significant relationship exists between the HR and HBPP indices of provinces in Türkiye.

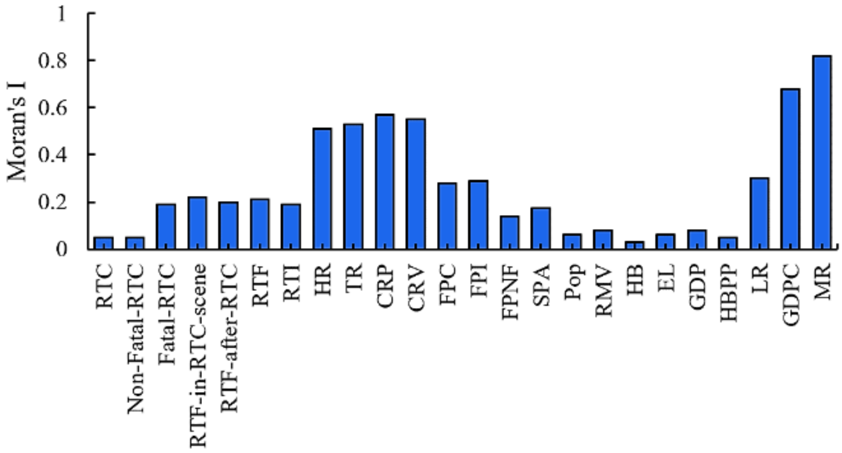


Figure 3.4. Moran’s Index of studied province-level variables of Türkiye in the study period.

3.3.4 Local Spatial Autocorrelation and Clustering

The cluster maps of the RTC, RTF, and socioeconomic variables of provinces are illustrated in Figure 3.5, and substantial differences between provinces were observed. Significant local HH, LL, HL, and LH clusters are illustrated in dark-red, dark-blue, light-red, and light-blue colors, respectively. In the significance maps, referring to the p-value, two types of regions are represented, with dark green (p-value<0.001) and light green (0.01<p-value<0.001). In significance and local cluster maps, non-significant regions are colored in light grey. In the natural breaks maps, regions with the smallest and largest values are grouped in clusters one and seven, respectively. There were massive LL or HH clusters regarding some variables such as MR, GDPC, and RMV. The RTC, population, RMV, EL, and GDP indices had similar significant local cluster maps. The problematic regions (HH clusters) location regarding eight RSIs are illustrated in Figure 3.5 and Figure 3.6.

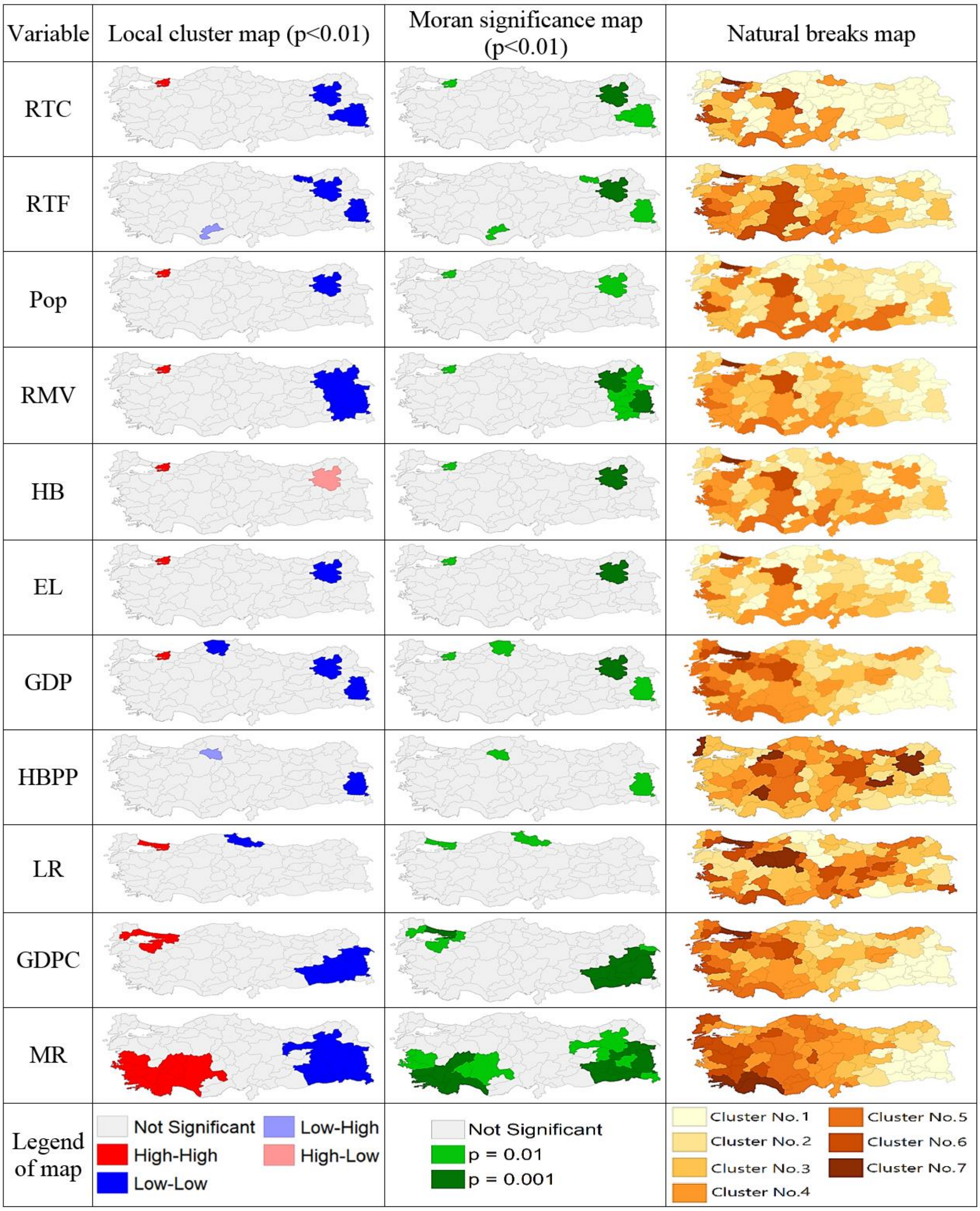


Figure 3.5. Local cluster, significance and natural breaks maps of province-level RTC, RTF and socioeconomic variables of Türkiye in the study period.

Figure 3.6 demonstrates that most regions in the east and southeast of Türkiye had low HR levels. Also, Istanbul and its surrounding provinces had a low HR index, and the LL cluster in the southeast of Türkiye was massive. On the other hand, a big HH cluster in the southwest of Türkiye was identified. Regions with higher HR indices surrounded Ankara province, which was classified as an LH cluster. Also, Kocaeli (in the northwest) and Çorum (in the north) were identified as the core of LL and HH clusters, respectively. Most provinces in the east of Türkiye had high TR levels. Contrarily, the TR levels of western regions were low. The HH cluster regarding the TR index in the east of Türkiye was enormous. Also, a scattered LL cluster was observed in the country's northwest.

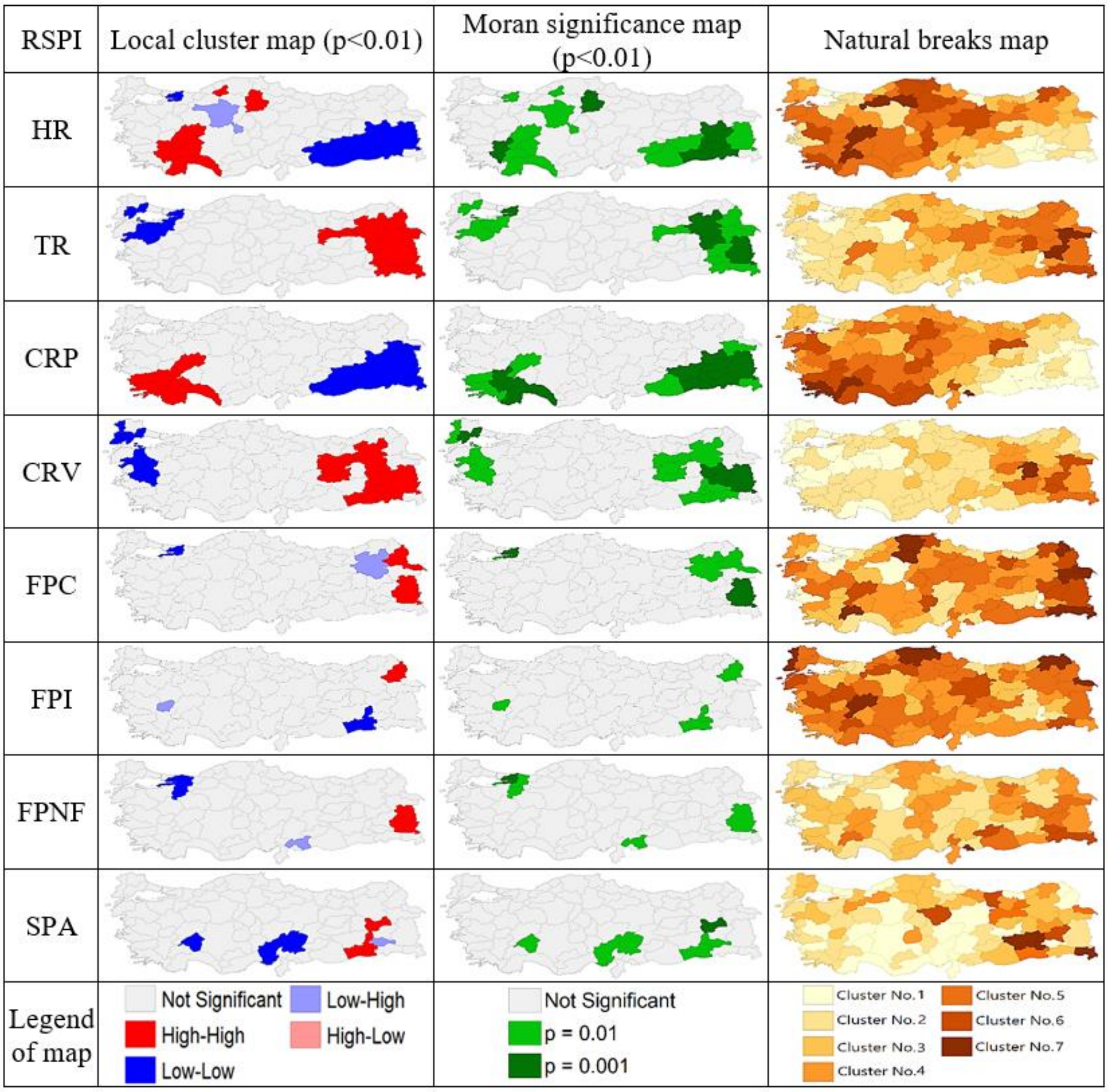


Figure 3.6. Local cluster, significance and natural breaks maps of ratio-type RSIs of provinces of Türkiye in the study period.

The produced maps of the CRP index were analogous to the HR index, with a vast LL cluster in the southeast and a large HH cluster in the southwest. South-eastern provinces had extremely low CRP indices. The CRV indices in the eastern provinces were larger than in the western and central provinces. Also, HH and LL clusters were in the east and west of Türkiye, respectively. Accordingly, the HH cluster in the east was more significant than the scattered LL cluster in the west. Local clusters, Moran significance, and natural break maps of ratio-type RSIs are illustrated in Figure 3.6. Legends of maps in Figure 3.5 and Figure 3.6 are the same.

Figure 3.6 demonstrates that all border provinces east of Türkiye had high FPC levels. Also, the FPC index in Burdur (southwest) and Cankiri (north) was huge. In addition, a HH cluster was in the east of Türkiye, and the significant LL cluster core was in the country's northwest. FPI indices of several provinces in the northwest and northeast of Türkiye were large. Regarding the FPI index, HH and LL clusters were identified in the northeast and southeast of the country, respectively. The FPNF measures of regions in the southeast and east of Türkiye were large. Regarding the FPNF index, the HH and LL clusters were recognized in the southeast and northwest of the country, respectively. According to Figure 3.6, the SPA indices of eastern regions were high, and the HH cluster was detected in the country's southeast. In addition, a significant LL cluster was observed in the south and southwest of Türkiye.

According to spatial maps, the position of HH and LL clusters in terms of MR, HR, and CRP indices were analogous. The results of correlation analysis revealed high correlations between these variables (PCC>0.65). Also, the local cluster maps of GDPC, TR, and CRV indices were comparable, and these variables were highly correlated (PCC>0.58). These similarities in cluster maps of RSIs seem to happen because of employing the same exposure indices in the computation of RSIs. When the number of RMVs was used as the exposure indicator, eastern provinces were diagnosed as problematic regions. On the other hand, adopting the population as the exposure index led to disclosing problematic regions in the country's southwest. It was interesting to identify some of the least developed regions (such as Hakkari in the southeast) and most developed provinces (such as Istanbul in the northwest) in the same cluster with minor rates in terms of HR index. On the other hand, the clustering results regarding the TR index indicated that road safety performance was low in the least developed regions in the east of Türkiye. We cannot say which group of RSIs (based on the adopted exposure measure) are more appropriate for comparing the performance of provinces, but the result of spatial analysis and clustering in terms of the RTC severity indices and RMV-based RSIs (such as TR) reveals that eastern regions had poor road safety performance. These findings reveal that various RSIs produce different hot spots and cluster maps. Other studies also reported this issue (Erdogan, 2009; Tortum and Atalay, 2015; Ziakopoulos and Yannis, 2020). Thus, selecting appropriate RSI for comparing the traffic safety performance of geographic regions is extremely important, and region comparisons according to RSIs should be interpreted with the highest care.

Erdogan (2009) demonstrated that provinces with the highest CRV and TR indices were scattered throughout Türkiye from the east to the country's northwest. This dissertation reveals that regions with the highest CRV and TR indices were situated frequently in eastern regions, which differs from the discoveries of Erdogan (2009). Additionally, the location of most regions with the largest HR indices was analogous to the conclusions of Erdogan (2009). However, the dissertation illustrates that in one decade, some regions in the northeast and south of Türkiye moved to the higher ranks in cluster number, and the HR rates of these regions increased. These discoveries prove that in one decade, the location of regions with the highest RSIs in a country could be altered, and the spatial autocorrelation and clustering analysis should repeat periodically to report problematic regions in a country.

FPC levels in eastern regions were large, and the HH cluster in terms of FPC was discovered in the country's east. Also, the HB, HBPP, GDP, and EL indices in most of the eastern provinces were smaller than in other provinces. This finding suggests that the shortage of emergency response, the number of hospital beds, and lower GDP lead to a higher FPC index in these regions. The findings of the dissertation are in accordance with the findings of Iyanda (2019), which disclosed that the FPC index was larger in regions with insufficient emergency response care and hospitals.

This section reveals the location of problematic regions in terms of studied RSIs. Also, the relationships between studied variables and RSIs are described. This section of the dissertation points out some variables (such as the RMV level) that affect the province-level RSIs. As a developing country, the many RTFs and distribution patterns of RSIs in Türkiye prove the need for further and intense road safety studies in these countries. Further studies could concentrate on identified problematic regions to discover the variables that affect RSIs negatively or positively. More detailed road safety analysis in problematic regions could contribute to achieving further information about road safety issues in the provinces of Türkiye as a developing country.

4. EVALUATING ROAD SAFETY STATISTICS AND INFLUENCING FACTORS ON SUBDIVISION-LEVEL ROAD SAFETY INDICES ACROSS PROVINCES OF IRAN

4.1. Introduction

Almost every day, 3,700 people die because of RTCs, and approximately 3% of each country's gross domestic product is wasted because of RTCs and related issues (Wachnicka et al., 2021). Due to limited economic resources in developing countries, the optimal use of insufficient resources in road safety programs in these countries is of immense importance (Abdolmanafi and Karamad, 2019). In addition, previous studies showed that RTCs and related fatalities in low-and middle-income countries are higher than in high-income countries (Haghani et al., 2022). Therefore, more in-depth road safety studies in developing countries are needed.

Regional road safety studies in developing countries must be conducted to uncover influencing factors on RSIs. For conducting province-level and regional road safety studies in developing countries, these countries RTC-related information and socioeconomic data are needed. Iran is among the developing countries with a sound RTC data collection system (WHO, 2018) and has a statistical center that provides various socioeconomic regional data. Iran is a middle-income and developing country that comprises 31 provinces. This country is in the Middle East and bridges West, Central, and Southern Asia. Unfortunately, between March 2014 and March 2019, RTCs caused 81,989 RTFs, and 1,661,126 non-fatal road traffic injuries in Iranian provinces' intercity, urban and rural roads (Iranian Legal Medicine Organization [ILMO], 2021). The high RTF level indicates that decreasing the number of RTCs and related issues should be a priority in this country.

RSIs are the backbones of regional road safety studies, but little attention has been given to the associations between these indices. Most road safety studies have used a limited number of RSIs to evaluate road safety conditions in developing countries, and the knowledge about regional RSIs in these countries is little. Thus, there is a need for in-depth studies to understand the nature of the regional RSIs. Regional RSIs could be categorized into crude- and ratio-type indices. Several studies used crude RSIs, such as the number of RTFs, to evaluate road safety in geographic regions (Adeleke et al., 2021; X. Wang et al., 2019). Some others used ratio-type RSIs, such as the traffic risk index that equals the RTFs per number of registered motor vehicles.

A limited number of road safety studies have examined regional RSIs in Iran (Alizadeh et al., 2015; Besharati, Tavakoli Kashani, Li, et al., 2020; Hasani et al., 2019; Shavaleh et al., 2018). These studies detected considerable differences between Iranian provinces regarding regional RSIs, such as RTF levels, indicating province-specific features and regional diversity within the country. In addition, regions were compared based on a limited number of RSIs in these studies, and the relationships between these indices and other variables were neglected. In most of these studies, the overall RTF measure of regions was used to conduct the dissertation, and the composition of RTFs and the occurrence environment of the RTC were ignored.

Several studies used statistical methods to investigate the influencing factors on RSIs. These studies showed significant associations between RSIs and socioeconomic or transport-related variables, including population or population density (Ahmadpur and Gokasar, 2021; Besharati, Tavakoli Kashani, and Washington, 2020; Erdogan, 2009; Osayomi, 2013; Tortum and Atalay, 2015; Truong et al., 2016; X. Wang et al., 2019), road-related variables such as road length (Besharati, Tavakoli Kashani, and Washington, 2020; Erdogan, 2009; Osayomi, 2013; Tortum and Atalay, 2015), number of health care institutions or related indices such as the number of hospital beds (Ahmadpur and Gokasar, 2021; Besharati, Tavakoli Kashani, and Washington, 2020; Truong et al., 2016), and education status of people (X. Wang et al., 2019). Thus, by considering the literature, various variables were gathered to evaluate their associations with RSIs of Iranian provinces and detect influencing factors using statistical methods.

In this section of the dissertation, 19 RSIs were adopted to evaluate road safety conditions in subdivisions of Iran. Also, relationships between 82 socioeconomic variables and selected RSIs were examined to assess the influencing factors of studied RSIs. Multiple regression was used to model major regional RSIs to reveal attributes of RSIs in more detail.

This number of variables and RSIs rarely were used in previous regional road safety studies in developing countries. Evaluation of the high number of RSIs in this dissertation aids in illustrating the similarities and differences between regional RSIs in more detail and could benefit future road safety studies in other countries. Worthy of note, each country's subdivision-level RTC data set is distinct, and an evaluation of Iran's RTC data could provide insights applicable to other countries.

Given the inadequate macro-level road safety studies in Iran, preliminary studies related to associations between regional RSIs in this country, and limited knowledge regarding variables that affect road safety indices in Iran, this section dissertation comes forward to fill this gap and provide reliable road safety-related knowledge. These prompted us to apply the correlation and regression analysis to detect significant associations between socioeconomic variables and province-level RSIs in Iran. In addition, multiple regression was used to model subject RSIs by considering the studied socioeconomic variables. The following objectives were aimed to evaluate the RSIs of Iranian provinces in the study period: 1) collecting data and creating a dataset, 2) producing regional RSIs, 3) calculating the Pearson correlation coefficient between studied variables, 4) using regression analysis to model the RSIs based on studied variables, 5) organizing and grouping similar RSIs based on correlation and regression results, 6) modeling the studied major RSIs using multiple regression.

4.2. Data and Methodology

The collected data and adopted methods of this dissertation section are explained in this section.

4.2.1 Data and RSIs

Aggregating RSIs for five years yields the advantage of stability in the province-level rates (Erdogan, 2009). Also, after the spread of COVID-19, substantial fluctuation in RTC data in a developing country was reported (Ahmadpur, 2022). Also, the Iranian calendar starts on 21 March; thus, the selected 5-year study period was set between 21 March 2014 and 20 March 2019. The majority of the collected socioeconomic variables, including transportation, education, demography, and income-related data, are represented in Table 4.1. These variables were obtained from the annual census and the website of the Statistical Center of Iran (Statistical Center Of Iran, 2021).

Table 4.1. Gathered socioeconomic and transportation-related data and rates of Iranian provinces.

Category	Variable
Population	Urban and rural population, overall population
Income	Rural family income, urban family income, GDP of the province
Education and literacy	Number of people above six and with a university, high school, middle school, and primary school degrees, literacy ratio
Health care	The number of healthcare institutions and related variables, including hospitals, hospital beds, ICU beds, pharmacies, clinics, health bases, health houses, and emergency bases.
Roads	Length of rural roads, intercity roads, highways, freeways
RMVs	Number of newly registered RMVs
Fuel consumption	Gasoline and diesel fuel consumption by RMVs

In addition, the associations between RSIs and healthcare institution-related variables, including health base (HBase), health center (HC), emergency base (EB), hospital (H), clinics, pharmacies, active hospital bed, and health house (HH), were evaluated. A health center provides vaccination and medical services. In urban or rural HB, health care service is provided for the urban or rural population. A health house is a village unit with an average population of 1,500 people in the main village and neighboring villages, and health care is provided for the rural population. Urban emergency bases (urban EB) are located in cities with universities or colleges of medical sciences or a population of more than fifty thousand people. Road emergency base (road-EB) is situated on busy or accident-prone roads and at the entrance of cities with a population of fewer than fifty thousand people.

The annual fuel consumption information of provinces was obtained from the website of the National Iranian Oil Refining and Distribution Company (NIORDC) (National Iranian Oil Refining and Distribution Company [NIORDC], 2021). In this country, diesel fuel is only consumed by heavy vehicles, and higher diesel fuel consumption indicates the presence of more heavy vehicles in regions. Using the gathered data, ratio-type socioeconomic variables such as the number of hospitals per population were calculated, and their relationships with RSIs were examined.

Iranian provinces' crude- and ratio-type RSIs were collected or calculated using the literature and available exposure measures (such as population). The crude RSIs of regions were obtained from the Iranian Legal Medicine Organization’s (ILMO's) website (ILMO, 2021) and the Statistical Center of Iran (Statistical Center Of Iran, 2021). These RSIs are represented in Table 4.2. Iranian Legal Medicine Organization provides road fatality data by road type, including urban, rural, and intercity road fatalities. Therefore, evaluating the RTFs in various road types in this developing country is possible. This evaluation could provide insights that could be applicable in other countries and could provide high-detail knowledge regarding road fatalities in a country. These detail in road fatality data is not available in Türkiye. The ratio-type RSIs comprise the risk and severity indices in this section. The risk indices show the probability of being killed, injured, or involved in an RTC in a region. HR is the risk index of being killed in an RTC, considering an area's entire population. TR is the ratio of RTFs per consumed one-billion-liter fuel by RMVs. The CRP and CRV indices are the risks of a fatal RTC in regions. Injury per population (IPP) shows the risk of being injured in RTCs for the entire population. RTC severity indices include the fatality per crash index, RTF per RTI, and fatal crash (FRTC) per non-fatal crash (NFRTC).

Table 4.2. Formula and definition of the Crude and ratio-type RSIs of Iranian provinces in the study period.

Index	**Type**	**Equation or Description**	**Resource**
RTF	Crude	RTF in roads of province	ILMO
Urban RTF	Crude	RTF in urban roads of the province	ILMO
Rural-RTF	Crude	RTF in rural roads of province	ILMO
Intercity RTF	Crude	RTF in intercity roads of province	ILMO
RTI	Crude	RTI on the roads of province	ILMO
Female RTI	Crude	Number of injured females in RTC	ILMO
Male RTI	Crude	Number of injured males in RTC	ILMO
RTC	Crude	RTCs in province	Statistical Center of Iran
NFRTC	Crude	Property damage only RTCs	Statistical Center of Iran
FRTC	Crude	Fatal RTCs	Statistical Center of Iran
IRTC	Crude	RTCs lead to non-fatal injury	Statistical Center of Iran
HR	Ratio, Risk index	RTFs / (population / 100k)	Authors
TR	Ratio, Risk index	RTFs / (Fuel usage / 1bn)	Authors
CRP	Ratio, Risk index	Fatal RTCs / (population / 100k)	Authors
CRV	Ratio, Risk index	Fatal RTCs / (Fuel usage / one bn)	Authors
IPP	Ratio, Risk index	RTIs / (population / 100k)	Authors
FPC	Ratio, RTC severity index	RTFs / (100k RTCs)	Authors
FPI	Ratio, RTC severity index	RTFs / (1k RTIs)	Authors
FPNF	Ratio, RTC severity index	Fatal RTCs / non-fatal-RTCs	Authors

4.2.2 Statistical Analysis

Pearson correlation coefficient and regression analysis were used to evaluate associations between variables. These methods are explained in Section 2.4 of the dissertation.

4.3. Results

During the study period, the total number of RTFs in provinces was stable, but the total number of RTIs increased by 20.68% from 304,485 in the first year of study to 367,451 in the last year. In addition, 66%, 27%, and 5% of RTFs occurred in provinces' intercity, urban and rural roads, respectively.

4.3.1 Correlation and Regression Analysis

The calculated PCCs between studied RSIs are represented in Table 4.3.

Table 4.3. The correlations between regional road safety indices of Iran.

Indices	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. RTF																		
2. Urban RTF	**.81**[a]																	
3. Rural-RTF	**.60**[a]																	
4. Intercity RTF	**.90**[a]	**.48**[a]	**.69**[a]															
5. RTI	**.89**[a]	**.95**[a]		**.64**[a]														
6. Female RTI	**.87**[a]	**.92**[a]		**.64**[a]	**.99**[a]													
7. Male RTI	**.89**[a]	**.96**[a]		**.64**[a]	**1.00**[a]	**.98**[a]												
8. RTC	**.73**[a]	**.97**[a]		.39	**.91**[a]	**.88**[a]	**.92**[a]											
9. NFRTC	**.63**[a]	**.93**[a]			**.84**[a]	**.81**[a]	**.85**[a]	**.98**[a]										
10. FRTC	**1.00**[a]	**.80**[a]	**.59**[a]	**.90**[a]	**.89**[a]	**.88**[a]	**.89**[a]	**.72**[a]	**.62**[a]									
11. IRTC	**.84**[a]	**.96**[a]		**.55**[a]	**.96**[a]	**.94**[a]	**.96**[a]	**.95**[a]	**.87**[a]	**.83**[a]								
12. HR		-.43			-.44	-.44	-.44	-.46	**-.47**[a]		-.39							
13. CRP		-.41			-.40	-.39	-.40	-.43	-.45		-.37	**.98**[a]						
14. TR		-.43			-.37	-.37	-.37	-.42	**-.46**[a]			**.47**[a]	.44					
15. CRV		-.40						-.40	-.44			.45	.45	**.98**[a]				
16. IPP			-.42									.39	.43					
17. FPNF			.44			-.37		-.43	**-.47**[a]									
18. FPC		-.37	.42		-.42	-.44	-.41	**-.49**[a]	**-.51**[a]		-.43						**.87**[a]	
19. FPI			**.55**[a]			-.36						**.49**[a]	.44			**-.52**[a]	**.63**[a]	**.67**[a]
a) Correlation is significant at the 0.01 level (2-tailed).																		

Table 4.3 shows that several pairs of crude RSIs, such as the RTF and intercity-RTF, RTF and FRTC, and RTI and IRTC, are highly correlated (PCC>0.90). Positive significant linear relationships were detected between TR and CRV (PCC=0.98) and HR and CRP pairs

(PCC=0.98). Positive and significant correlations were observed between the studied severity indices, including FPNF, FPC, and FPI (PCC>0.63). The urban-RTF, RTC, and NFRTC variables have strong linear relationships (PCC>0.93). According to Table 4.3, most of the crude RSIs are highly correlated with each other except for the rural-RTF and intercity-RTF indices. The associations between crude and ratio-type RSIs are weak. Interestingly the rural-RTF is the only index correlated positively with three severity indices.

Based on the calculated correlation coefficients and similarity between studied RSIs, they were categorized into six groups which are represented in Table 4.4.

Table 4.4. Grouped road safety indices based on calculated Pearson correlation coefficients between them.

Group No.	Indices	Pearson Correlation coefficient
1	RTF, FRTC, and intercity-RTF	> 0.90
2	urban-RTF, RTC, NFRTC, RTI, and IRTC	>0.93
3	Rural-RTF	-
4	HR and CRP	>0.98
5	TR and CRV	>0.98
6	FPNF, FPC, and FPI	>0.64

Several variables were selected and used as proxies for simplification for others because of their detected high correlations. These proxies are represented in Table 4.5.

Table 4.5. Adopted proxies and related variables of Iranian provinces.

Proxy	Variables
EL	University-, high school-, middle school-, and primary school-degree holders
H	HB, ICUHB, pharmacies, clinics, health bases, urban health bases
Fuel	Consumed gasoline
Road	The length of the main intercity, side intercity, intercity, asphalt rural, and rural roads
Rural health houses	Road-EB, rural HC
Urban EB	Urban HC
EB	Health center
RTI	FRTI, MRTI, and IRTC
Urban-RTF	RTC
RTF	FRTC
HR	CRP
TR	CRV

The calculated correlations between major RSIs and studied socioeconomic variables are presented in Table 4.6.

Table 4.6. Calculated Pearson correlation coefficients between province-level road safety indices and studied variables of Iran.

Variable	RTF	RTI	Urban RTF	Rural -RTF	Intercity RTF	HR	TR	FPNF	FPC	FPI
Urban population	0.72	0.91	0.98			-0.53				
Rural population	0.79	0.61		0.78	0.82					
Population	0.81	0.94	0.98		0.48	-0.51				
GDP	0.60	0.78	0.89			-0.47	-0.47			
EL	0.75	0.92	0.98			-0.51				
H	0.80	0.94	0.98		0.48					
EB	0.91	0.80	0.68	0.64	0.86					
Urban-EB	0.88	0.90	0.79		0.74					
Rural health base	0.71	0.76	0.79		0.46					
Rural health houses	0.64	0.46		0.69	0.77					
Highway length	0.73	0.56	0.49		0.74					
Rural gravel road length				0.47				0.48		0.51
Road length	0.69			0.76	0.82					
Diesel fuel consumption	0.88	0.84	0.81	0.46	0.72		-0.50			
Fuel consumption	0.84	0.93	0.98		0.53		-0.51			
Distance from capital				0.70				0.60	0.51	0.71
Area	0.50			0.71	0.59					0.50
X coordination of the center				0.56				0.55		0.49
Y coordination of the center										-0.58
Urban per rural population							-0.56			
Urban family income			0.64			-0.61	-0.54			
Rural family income				-0.53		-0.59	-0.58			-0.63
Urban per rural family income				0.61				0.50		0.66
LR							-0.66		-0.46	
% with a university degree				-0.60				-0.54	-0.53	-0.53
% with a high school degree							-0.58	-0.48		
% with a primary school degree								0.56		
Urban HBase Per Urban Pop.	-0.53	-0.54			-0.52					
Highway length per pop.						0.65				
Intercity road length per pop.						0.48				
Rural gravel road per rural pop.		-0.50	0.47							

Pairs of variables with low PCCs (between -0.46 and +0.46) were removed from Table 4.6. Also, several correlation values that were large because of outliers were removed from the table after visual inspections. This table shows that the RTF and RTI indices are higher in provinces with higher population, GDP, EL, and fuel consumption measures. Also, the RTF, intercity-RTF, and rural-RTF values are larger in regions with longer intercity and rural roads. It was observed that Urban-RTF is higher in areas with a higher urban population, overall population, GDP, EL, H, highway length, diesel fuel consumption, and fuel consumption. According to Table 4.6, the intercity-RTF and rural-RTF rates are higher in regions with larger areas, rural population, and diesel fuel consumption rates. Also, these RSIs are larger in regions with long roads. The HR and CRP indices are also lower in regions with a higher urban population, population, GDP, urban family income, and EL rates. According to Table 4.6, the HR index is higher in regions with higher highway length per population rates. The TR and CRV indices negatively correlated with the urban per rural population, urban family income, GDP, LR, number of high school degree holders, and fuel consumption measures. The FPNF and FPI indices are higher in regions with longer rural gravel roads. Also, RTC severity indices are higher in areas far from the Tehran province (where the capital city is located). In addition, the FPI index is higher in vast provinces and regions with high urban-per-rural family income.

The rural-RTF, HR, TR, and FPI indices are larger in areas with lower rural family income. Provinces with a higher percentage of university degree holders tend to have low rural-RTF, FPNF, FPC, and FPI indices. In regions with a high percentage of primary degree holders, the RTC severity indices are higher. According to Table 4.6, the H, urban-EB, EB, rural-HBase, and rural health house measures have significant and positive associations with RTF, RTI, and intercity-RTF indices. Also, the EB and rural health house measures were highly correlated with the rural-RTF index. A significant relationship between healthcare institution-related variables and RTC severity indices was not observed. Also, negative associations were observed between the urban-HBase per urban population and the RTF, RTI, and intercity-RTF indices.

The fitted linear and non-linear regression lines describe the significant associations between integer-type RSIs, scatter plots, embedded regression lines, and related R^2 of some variable pairs with significant relationships are represented in Figure 4.1. These results indicate that there are significant and positive linear relationships between RTF-RTI, HR-CRP, and TR-CRV variable pairs. The association between RTC and RTF suggests that road traffic crashes influence the number of road traffic fatalities. The logarithmic transformation indicates that this relationship is not linear, meaning that small changes in RTC may have a larger impact on the number of road traffic fatalities at some values of RTCs than others. Also, this relationship shows that regions' RTF per RTC rate or HR index tends to be lower in more populated and developed regions. This phenomenon could occur because of better road safety conditions, such as higher awareness, better cars, and roads in more developed regions. A similar non-linear association between RTC and RTF rates was observed in Türkiye.

There is a significant linear association between RTF and RTI rates in this country. When road injuries occur, there is a greater likelihood of road fatalities happening as well. The severity of road injuries can directly impact the number of fatalities. Higher rates of road injuries generally lead to higher rates of road fatalities. Therefore, regions with a higher occurrence of road injuries are more likely to experience a greater number of road fatalities. The RTF-RTI graph shows that in the crashes, there is approximately one road fatality per 21.4 injuries in Iran. The IRTC-FRTC scatter plot is similar to the RTC-RTF plot, and there is a logarithmic association between IRTC and FRTC indices. This graph indicates that with the increase in the number of non-fatal crashes, there is an increase in fatal crashes, with a decreasing rate. Therefore, the ratio of FRTC per IRTC is lower in developed and populated regions; consequently, road safety conditions are better in developed areas of this country.

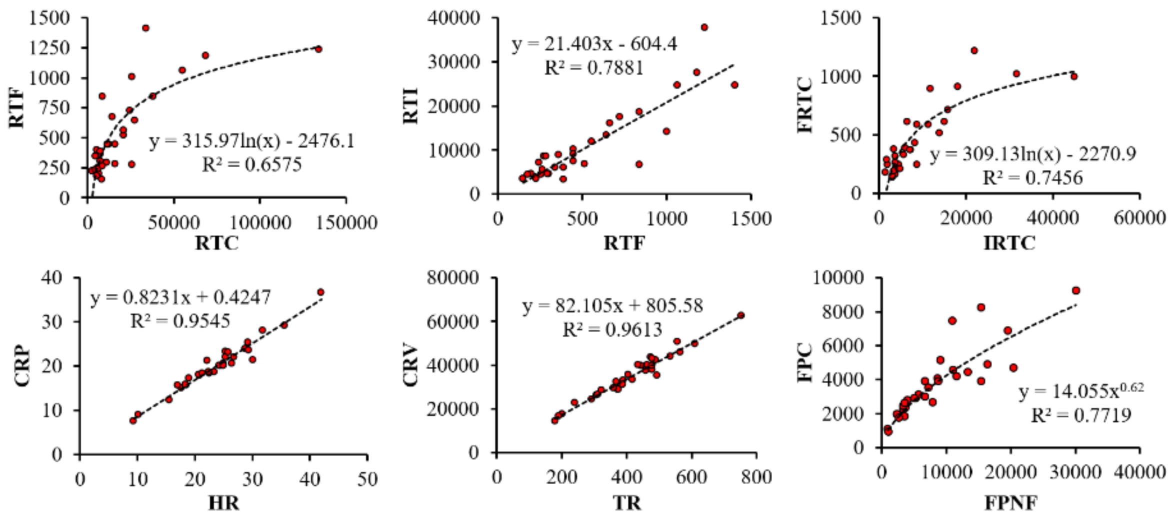


Figure 4.1. The significant relationships between province-level RSIs of Iran.

The significant and positive linear association between HR-CRP and TR-CRV was also observed in Türkiye. Thus, these findings indicate that these associations could be valid in other developing countries, and CRP and CRV indices could be used as proxies for HR and TR rates. When studying a phenomenon or developing models, knowing the significant linear association between variables can guide the selection of relevant predictors or explanatory variables. The non-linear and significant association between FPNF and FPC indicates that these indices have some similarities between them. This positive relationship between FPNF and FPC implies that as one severity index increases, the other severity index tends to increase as well. This suggests a positive correlation or co-occurrence between the two risk factors being measured, and these indices have similar attributes.

The significant associations between some of the crude RSIs and socioeconomic indices are represented in Figure 4.2, including scatter plots, embedded regression lines, and related R^2.

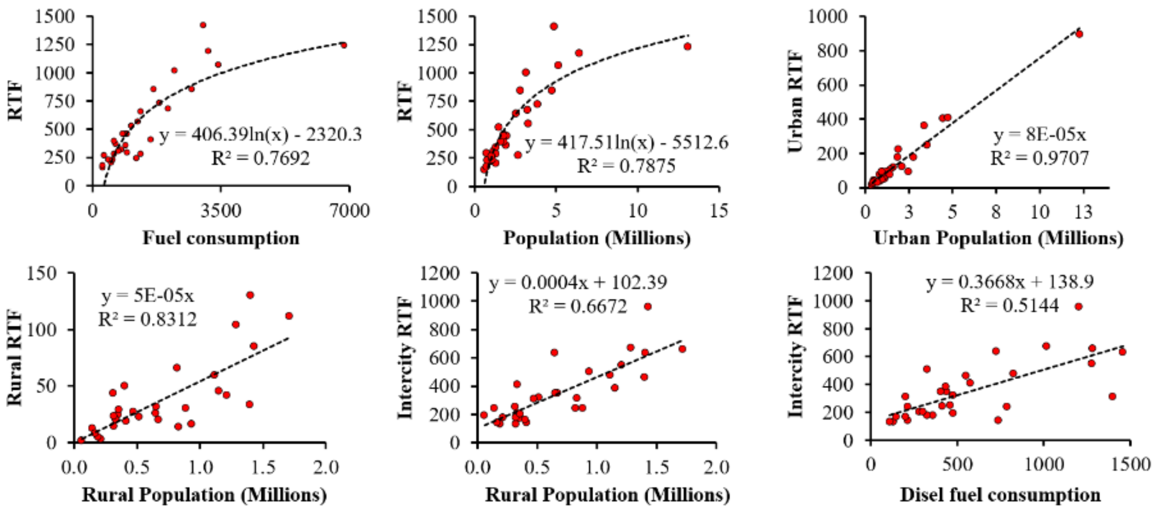


Figure 4.2. Associations between crude province-level road safety indices of Iran.

Figure 4.2 shows a logarithmic relationship between exposure measures (fuel consumption and population) and road fatalities. Thus, higher fuel consumption and population mean higher road fatalities on roads. However, since this association is nonlinear and positive, the ratio of fatality per exposure measures or fatality risks tends to be lower in more populated and developed regions, such as the capital province Tehran. These associations are occurring for several reasons, including allocating more resources to developed regions, lower law enforcement in underdeveloped and remote regions, public transportation systems in developed regions, and inefficient safety policies in remote provinces. Similar associations between RTF and exposure measures were observed in Türkiye. The linear and significant association between the urban population and Urban-RTF indicates that there is not a considerable difference between fatality risk in urban regions of provinces. Thus, road safety-related infrastructure and awareness seem to be similar in urban areas of this country. Like the urban-population and urban-RTF pair, the

Rural-RTF and rural-population rates have linear and significant associations. Regions with higher rural populations tend to have higher levels of traffic activity. This can increase the exposure to road risks and the likelihood of accidents, resulting in higher road fatality rates in rural areas. Thus, the fatality risk in rural regions of provinces of Iran seems to be similar.

The significant association between the rural population and the number of RTFs on intercity roads indicates the significant impact of the rural population on RTFs on intercity roads. Since the majority of fatalities in Iran occur on intercity roads, this finding is significant. The rural population is higher in underdeveloped and remote regions, where the urbanization rate is lower, and road infrastructure is in bad condition. Also, among the rural population, road safety-related education is inadequate. These could be reasons for the significant impact of the rural population on intercity fatalities. In addition, the presence of more heavy vehicles (diesel fuel consumption) is another factor influencing fatalities on intercity roads since there are linear and positive relationships between these indices. Due to their size, weight, and longer stopping distances, heavy vehicles can pose a higher risk of accidents. When these vehicles are more prevalent on intercity roads, the likelihood of accidents involving heavy vehicles increases, which can result in a higher number of fatalities. Also, collisions involving heavy vehicles can often be more severe due to their size and mass. Intercity roads often have different characteristics than urban or local roads, including higher speeds, longer distances, and potentially challenging driving conditions. When heavy vehicles are present in greater numbers on these roads, it may contribute to an increased likelihood of accidents and subsequent fatalities. Another factor could be the outdated design of vehicles, since in this country, the average age of heavy vehicle fleet is high because of sanctions and various socioeconomic issues.

The significant associations between major ratio-type RSIs and socioeconomic indices are represented in Figure 4.3, including scatter plots, embedded regression lines, and related R^2 rates.

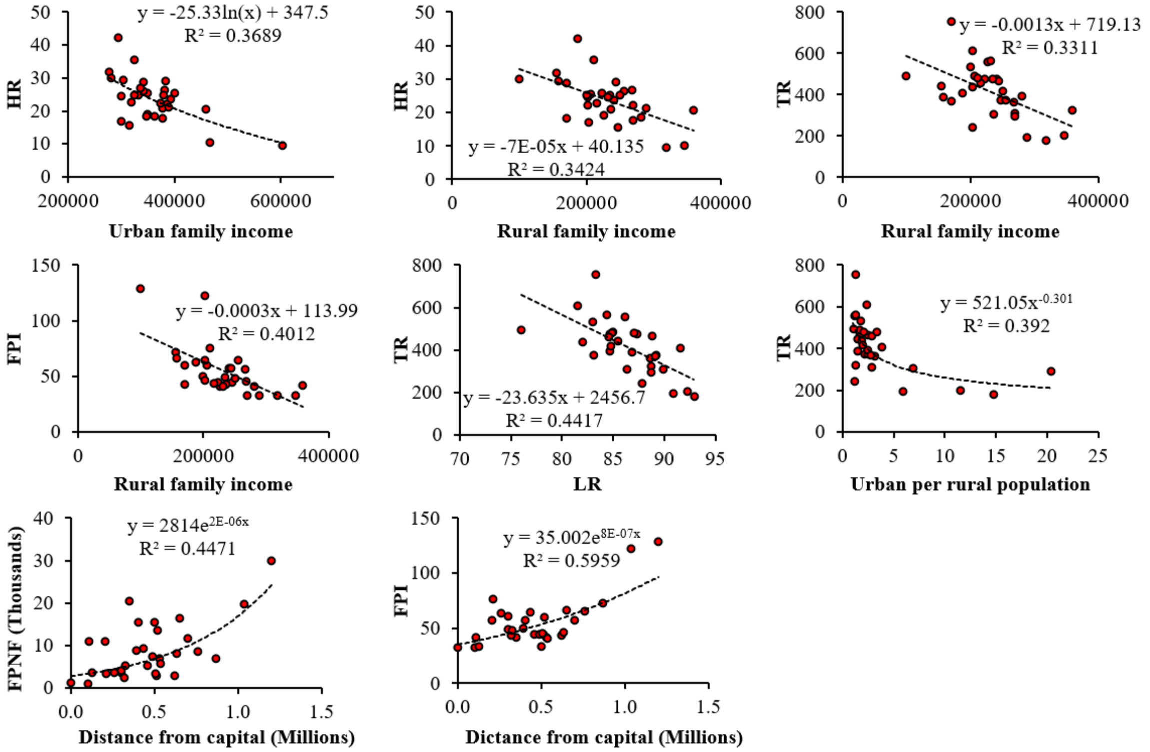


Figure 4.3. Associations between ratio-type province-level Road safety indices of Iran.

According to Figure 4.3, there are negative and significant associations between the income levels of rural families and RSIs, including HR, TR, and FPI. Also, the income rates of families in urban areas have negative associations with the HR index. Thus, families' income level significantly influences regions' road safety performance. Regions characterized by lower income levels may experience a higher fatality risk due to factors such as substandard road quality, limited vehicle safety features, inadequate access to healthcare systems, and lower levels of road safety education among road users. These circumstances contribute to an elevated likelihood of fatalities. The negative associations observed between the literacy ratio and the TR index demonstrate the positive impact of education levels on road safety performance within the country. A higher literacy ratio indicates increased awareness, knowledge, and comprehension of road safety information, effective communication, and understanding of road signs, enhanced decision-making abilities, and access to road safety education. These factors collectively contribute to improved road safety outcomes.

As presented in Figure 4.3, urbanization rate or urban per rural population is another factor negatively associated with TR or crash risk in regions. The negative relationship means the crash fatality risk tends to decrease as the urbanization rate increases. However, the relationship is nonlinear, indicating that the decrease in crash fatality risk is not strictly proportional to the increase in urbanization rate. Urban areas generally have more developed infrastructure, better access to emergency medical services, offer diverse transportation options (such as public transportation systems), and experience higher traffic congestion, leading to lower average vehicle speeds. These factors could be reasons for lower crash fatality risk in regions with higher urbanization rates. Another factor influencing RSIs in Iran is the geographic characteristics of areas since there are positive and significant associations between crash severity indices and the distance from the capital index. This association shows that crashes tend to be severe in remote regions of this country, and road safety conditions are better in regions closer to the capital city. This is happening because regions closer to the capital city generally have better road infrastructure, better road conditions, and better emergency response systems.

4.3.2 Multiple Regression

The results of multiple regression analysis are represented in Table 4.7; the adjusted R^2 and F statistics of crude RSI models were high, indicating that the regression models fit the data well. On the other hand, the same indices were low for ratio-type RSIs, especially RTC severity indices. The equations of the regression models are represented in this table.

Results of multiple regression indicate that modeling ratio-type RSIs except the HR index is challenging. Also, the gathered socioeconomic data may not be adequate for estimating ratio-type RSIs such as the FPC index. In addition, it was observed that geographic indices such as distance from capital play an essential role in modeling regional RSIs. These models indicate that geographic, population, fuel consumption, education, and income-related variables considerably influence regional RSIs.

Table 4.7. Results of multiple regression analysis of Iranian province-level RSIs.

Dep. variable	Ind. variable	B	St. error	St. coefficient	t	p	F statistic and p-value	Adj. R^2	VIF
RTF	(Constant) Diesel fuel consumption Rural population	1.866 0.549 0.000	42.25 0.069 0.000	 0.631 0.417	0.04 7.94 5.25	0.965 0.000 0.000	108.093-0.00	0.877	 1.54 1.54
RTI	(Constant) Population Highway length Coordination Y (province center)	-3974.79 0.003 5.871 0.004	1479.81 0.000 0.935 0.001	 0.809 0.320 0.171	-2.68 17.38 6.27 3.64	0.012 0.000 0.000 0.001	183.7-0.00	0.948	 1.25 1.49 1.27
Urban RTF	(Constant) Education level Highway length	-39.63 9.38E-05 0.061	6.74 0.000 0.010	 0.925 0.159	-5.87 36.50 6.27	0.000 0.000 0.000	877.07-0.00	0.984	1.144 1.144
Rural RTF	(Constant) Rural population Distance from capital Coordination X (province center) Urban family income Intercity road per population	55.00 3.76E-05 3.56E-05 2.94E-05 0.000 -0.053	19.77 0.000 0.000 0.000 0.000 0.024	 0.537 0.296 0.337 -0.255 -0.202	2.78 6.28 2.96 3.97 -3.03 -2.23	0.010 0.000 0.007 0.001 0.006 0.035	38.718-0.00	0.863	 1.59 2.18 1.57 1.54 1.78
Intercity RTF	(Constant) Length of all roads Intercity road per population Rural gravel road per population Distance from capital Area (km2)	206.70 0.043 -0.544 -0.372 0.000 0.001	30.50 0.005 0.159 0.165 0.00006 0.00045	 0.870 -0.327 -0.182 -0.226 0.258	6.77 9.00 -3.41 -2.25 -2.83 2.23	0.000 0.000 0.002 0.033 0.009 0.034	53.786-0.00	0.898	 2.74 2.69 1.91 1.85 3.91
HR	(Constant) Highway length per population Rural family income Population	32.928 0.158 -4.95E-05 -7.32E-07	3.529 0.038 0.000 0.000	 0.480 -0.408 -0.269	9.33 4.21 -3.61 -2.34	0.000 0.000 0.001 0.027	19.7 – 0.00	0.652	 1.11 1.10 1.14
TR	(Constant) Literacy ratio Diesel fuel consumption Highway length	2268.34 -20.887 -0.203 0.125	395.04 4.661 0.062 0.054	 -0.587 -0.641 0.452	5.74 -4.48 -3.27 2.32	0.000 0.000 0.003 0.028	13.5 – 0.00	0.557	 1.16 2.58 2.54
IPP	(Constant) University degree holder % Urban family income Dist. from capital	580.68 21.832 -0.001 -0.00015	121.96 4.762 0.000 0.000	 0.706 -0.711 -0.351	4.76 4.58 -4.78 -2.37	0.000 0.000 0.000 0.025	14.0 – 0.00	0.566	 1.64 1.52 1.51
FPNF	(Constant) Distance from capital Primary degree %	-14604.39 0.011 696.05	7667.18 0.004 316.834	 0.429 0.351	-1.90 2.68 2.19	0.067 0.012 0.036	11.6 – 0.00	0.455	 1.31 1.31
FPC	(Constant) University degree % Coordination Y (province center) Diesel fuel consumption	12522.92 -262.58 -0.003 -1.661	1646.66 72.084 0.001 0.697	 -0.484 -0.485 -0.331	7.60 -3.64 -3.49 -2.38	0.000 0.001 0.002 0.024	9.9 – 0.00	0.473	 1.00 1.09 1.09
FPI	(Constant) Dist. from capital Urban per Rural family income	-6.264 4.07E-05 26.376	14.509 0.000 10.436	 0.491 0.374	-0.43 3.32 2.52	0.669 0.002 0.017	20.3 – 0.00	0.563	 1.50 1.50

4.4. Discussion

The socioeconomic, transport, and geographic variables with significant associations with the studied regional RSIs were detected using correlation and regression analysis. Similar regional RSIs were identified and categorized into six groups. Since 66% of RTFs occurred on intercity roads in Iran, this country's major road safety problem is the high number of RTFs on intercity roads. Most of the studied socioeconomic indices were similar, and several indices were used as proxies for others.

Similar findings regarding the positive relationships between province-level RSIs in Türkiye were reported in previous studies (Ahmadpur and Gokasar, 2021). The majority of crude RSIs were higher in regions with higher population, GDP, income, EL, number of hospitals, urban-EB, EB, rural-HBase, highway length, and fuel consumption measures. These findings are in accordance with the literature (Ahmadpur and Gokasar, 2021; Atubi, 2012; Erdogan, 2009; Tortum and Atalay, 2015; Truong et al., 2016; X. Wang et al., 2019). Also, similar results regarding the detected positive relationship between fuel consumption and RTF levels in provinces were reported in previous studies (Besharati, Tavakoli Kashani, Li, et al., 2020).

The rural-RTF index was higher in regions with higher diesel-fuel consumption, distance from the capital, area, and urban-per-rural-family-income indices. In addition, lower rural-RTF in regions with higher rural-family-income and %-of-university-degree-holders indicate the negative relationship between education and income level measurements with road fatalities on rural roads. The rural-RTF index was higher in the country's east, south, and southeast, except for South Khorasan province. In Razavi-Khorasan province, most people live in urban areas (73%), but the rural-RTF index of the province was one of the highest ones in the country. On the other hand, the Golestan province, with a high rural population (47% of the population), had one of the lowest rural-RTF indices in this country. Similar causations seem to lead to high rural-RTF levels in Iran's eastern and south-eastern border provinces. Another interesting finding is the positive and robust linear relationship between the rural population index and all studied crude RSIs. In addition, the rural population measure has a significant relationship with the intercity-RTF index among all studied socioeconomic indices. Thus, the rural population index substantially affects this country's RTF and RTI levels of all types of roads. Previous studies indicated the positive effect of the number of road crossings on the rural-RTF index in Iran (Kashani et al., 2012). Therefore, it is urgent to give special attention to regions where the rural populations live near intercity roads, main roads, and road crossings and intersections that connect rural roads to the main roads of provinces. Also, improving road safety-related education in regions with a high rural population could lessen the number of RTFs on the entire road network of Iran. Tehran and its neighboring provinces are more developed and have the lowest rural population, and as a result, the rural-RTF index was lower in this region. As mentioned, south-eastern provinces, including Hormozgan, are less developed and have higher rural-

RTF levels. It seems that the location of these border regions is associated with the high number of RTFs on rural roads.

The intercity-RTF index was higher in regions with high rural population, highway length, road length, area, and diesel-fuel consumption measures. Similar findings regarding the intercity RTF rates in Iranian provinces were expressed in previous studies (Alizadeh et al., 2015). The high diesel fuel consumption and the presence of more heavy vehicles on roads positively affected the intercity RTF levels of regions. The presence of more heavy vehicles could cause more drastic RTCs and more RTFs on roads. Thus, special attention should be given to regions with high diesel fuel consumption, rural populations, and longer roads and highways. Implementing enforcement policies such as speed control, road safety education programs in such regions, and increasing road safety-related knowledge in rural regions could be beneficial in the reduction of intercity RTF levels in Iran.

The HR and CRP indices are lower in more developed provinces with higher income and education levels, and roads are safer than in underdeveloped regions. Previous studies reported similar findings regarding the negative and significant relationship between the HR and socioeconomic indices, such as regions' income levels (Erdogan, 2009; Tortum and Atalay, 2015; Wachnicka et al., 2021). Also, the detected relationships between education and economic measures with the RTF and RTI indices are in accordance with the literature (Sánchez González et al., 2020).

The TR and CRV indices were higher in provinces with lower income levels, fuel consumption, urban per rural population, LR, and % of high school degree holder measures. These findings indicate that TR is higher in underdeveloped provinces. Similar results regarding road safety conditions in underdeveloped regions of developing countries were reported in previous studies (Ahmadpur and Gokasar, 2021; Erdogan, 2009). According to the results, income level is vital in evaluating TR and HR indices because all studied income level indicators, including GDP, urban family income, and rural family income, have negative relationships with TR and HR indices. Also, education-related indices, including EL, LR, and % of high-school-degree-holders, have negative and significant relationships with TR and HR indices.

The result of this section indicates that RTCs are more drastic in vast and remote provinces, especially in south-eastern border provinces. Also, RTCs are severe in regions with considerable income gaps between urban and rural families, as indicated by the urban-per-rural family income index. An interesting finding was the relationship between RTC severity indices and people's education level in the studied regions. The severity indices were lower in provinces where people pursue their studies and have a higher education degree (such as a university or high school degree). On the other hand, the severity indices were higher in regions where more people left school and held lower education degrees. These findings indicate the direct effect of education level on the RTC severity indices in a developing country.

The identified high FPI index in underdeveloped and border provinces shows that RTC severity is a significant health problem in these regions. The existence of areas with high RTC severity indices in border and remote areas was reported in previous studies (Ahmadpur and Gokasar, 2021; Iyanda, 2019). For example, the Sistan-and-Baluchestan province in the southeast is one of the least developed provinces in Iran, and the literacy rate in the province is one of the lowest (Statistical Center Of Iran, 2021). Previous studies on road safety conditions in Sistan-and-Baluchestan province showed a significant correlation between the location of RTFs (pre-hospital and hospital) and the site location of related RTCs. Also, low seat belts and helmet use were observed in this province. Accordingly, this province's primary cause of RTFs was head and face trauma. In addition, this province is vast, its cities are far from each other, and the majority of the RTFs occurred on the intercity roads of this province. Therefore, it is highly potential that the delay of the police and emergency services at the scene of the occurred crashes led to drastic RTCs in this province (Taravatmanesh et al., 2015). The presented facts related to road safety conditions in the Sistan-and-Baluchestan province could be causes of high RTC severity indices in underdeveloped provinces of Iran.

Results illustrate a considerable diversity in terms of RSIs among Iranian provinces. The RTCs are drastic in underdeveloped areas. Road safety is a social problem, and the adverse effects of RTCs on public health could be lessened by taking specific and feasible RTC preventative policies. These policies could include identifying road safety deficient regions and detecting the variables that affect road safety performance in sub-divisions.

The findings of this section could be used by road authorities and policymakers who decide about budget allocations and intervention policies to reduce RTCs and related RTFs in countries. Reviewed literature shows that seat belt and helmet usage ratios are low in various areas of this country, and a considerable part of RTFs and RTIs were preventable. High correlations between the rural-population index and other studied crude RSIs indicate that rural population significantly influences these indices, and policymakers should give special attention to this issue. Results suggest that several provinces need immediate revisions in road safety programs on urban roads, others need road safety improvements on intercity roads, and some need modifications in rural road safety policies. Hence, regarding the limited economic resources in developing countries, selecting a general macro-level index, such as the overall RTF measure of regions to allocate funds for road safety prevention policies in these regions, is not logical.

5. EVALUATION OF INFLUENCING FACTORS ON REGIONAL ROAD CRASH SAFETY AND SEVERITY INDICES: INSIGHTS FROM IRAN

5.1. Introduction

It is possible to prevent crashes and reduce their adverse effects by implementing precise strategies, such as conducting spatial analysis regarding road safety performance indices, identifying areas with low safety performance, and detecting the influencing factors of these indices. Considering the higher rate of road fatalities in developing countries than in developed ones and the limited resources to improve road safety conditions in developing countries, conducting spatial analysis regarding regional RSIs in developing countries is of immense importance. Despite higher mortality rates in developing countries, inadequate regional road safety studies have been conducted regarding developing countries such as Iran, and further studies are needed. Conducting regional road safety studies and focusing on regional units such as provinces provides a superior awareness of road safety conditions in a country. This awareness could aid national road safety managers and local authorities in authorizing feasible and precise road safety management systems and efficiently deciding on developing effective area-based RTC avoidance programs.

With 31 provinces and a middle-income status, Iran is a developing country located in the Middle East and neighboring Central- and West-Asian countries. Evaluating Iran's road safety data could provide insights into the road safety conditions of other developing countries in this region. Iran is among the developing countries with a sound and reliable road crash data collection system (World Health Organization, 2018a), and its regional socioeconomic data is available. In comparison to other countries, road fatalities in Iran are excessive.

Several studies have examined regional RSIs in Iran (Alizadeh et al., 2015; Besharati, Tavakoli Kashani, Li, et al., 2020; Hasani et al., 2019; Shavaleh et al., 2018). These studies indicate significant differences between Iranian provinces regarding RSIs, the existence of province-specific features, the regional diversity within the country, and the possibility of the existence of hot or cold spots with similar RSIs. Regarding the strategic location of this country, lack of regional road safety studies in this region, high road fatality rates, and availability of regional data in detail, Iran is a perfect case for evaluating regional road safety conditions in a developing country.

In the literature, various integer or crude RSIs, such as the number of fatalities (Adeleke et al., 2021; X. Wang et al., 2019), and ratio-type RSIs, such as fatalities per population (Ahmadpur and Gokasar, 2021; Erdogan, 2009), have been used for the evaluation of road safety conditions in geographic regions. In addition, the majority of regional road safety studies adopted limited numbers of RSIs to evaluate road safety conditions in various countries. Additionally, previous studies have rarely discussed the associations between these indices and their attributes (Ahmadpur and Gokasar, 2021). Each RSI has its advantages and disadvantages, and using all available RSIs in the same study could reveal their attributes in more detail. In addition, there is limited knowledge regarding crash severity indices, such as the fatality per the number of nonfatal injuries, and a limited number of studies have evaluated them (Ahmadpur and Gokasar, 2021; Iyanda, 2019).

Moran's I, as a well-established indicator of spatial autocorrelation, measures the overall clustering of the spatial data. This index has been widely used to evaluate the distribution pattern of geographic regions regarding road safety performance (Adeleke et al., 2021; Ahmadpur and Gokasar, 2021; Hasani et al., 2019; Shabanikiya et al., 2020; Tokey, 2021). In addition, local Moran statistics have been used to detect hot or cold spot regions regarding road safety indicators (Ahmadpur and Gokasar, 2021; Hasani et al., 2019; Iyanda, 2019). We are unaware of a study in developing countries that used local cluster analysis to investigate the reasons behind the existence of significant hot spots regarding RSIs.

Various variables could influence regional RSIs, and previous studies reported significant associations between RSIs and other variables, such as population and related variables. Given the literature, in this section, regional socioeconomic and transport-related variables potentially influencing Iran's regional RSIs were collected and evaluated.

Considering the preliminary regional road safety and hotspot analysis studies in developing countries and limited knowledge regarding the attributes of regional RSIs and their influencing factors, this section aims to fill this gap and provide in-depth and detailed road safety knowledge. In this section, hot spot and spatial analysis were conducted to identify hot spots and assess the distribution of provinces regarding road safety performance in Iran.

To achieve the primary goal of this section of the dissertation, the following objectives were met: 1) collecting regional data, 2) producing RSIs, 3) assessing the spatial distribution of provinces using Moran's I, 4) identifying hot and cold spots using the local Moran index, 5) calculating the correlations between the variables, 6) clustering provinces and producing choropleth maps, and 7) conducting hot spot analysis.

5.2. Material and Methods

The collected data and adopted methods are described in this section.

5.2.1 Data and RSIs

The study period was set between 21 March 2014 and 20 March 2019. Iran's regional socioeconomic and transport-related variables were collected, including the length of roads, fuel consumption, population, income, education status, and the number of healthcare facilities. Road crash, socioeconomic and transportation-related variables were obtained from the website of the Statistical Center of Iran (Statistical Center Of Iran, 2021). The collected crash data include the number of crashes that lead to fatality, crashes that lead to nonfatal injury (IRTCs), and the number of nonfatal crashes. The fuel consumption data were collected from the website of the National Iranian Oil Refining and Distribution Company (National Iranian Oil Refining and Distribution Company, 2021). Ratio-type indices such as road length per population were calculated using the collected data. The regional road fatality on various road types (urban, rural, and intercity) and nonfatal injury data were extracted from the annual road fatality reports provided on the website of the Iranian Legal Medicine Organization (Iranian Legal Medicine Organization, 2021).

The ratio-type RSIs include the risk and severity indices. The risk ratios indicate the probability of being killed, injured, or involved in RTCs in regions. These rates are calculated by dividing crude RSIs by exposure measures such as fuel consumption in the region. The selected and calculated RSIs of this dissertation section are represented in Table 5.1.

Table 5.1. The adopted regional crude and ratio-type RSIs of Iran.

RSI	Type	Equation or Description
RTF	Crude	Road fatalities occurred on all roads
Urban-RTF	Crude	RTF on urban roads
Rural-RTF	Crude	RTF on rural roads
Intercity RTF	Crude	RTF on intercity roads
RTI	Crude	Nonfatal road traffic injuries on all roads
Female RTI	Crude	Number of injured females in RTC
Male RTI	Crude	Number of injured males in RTC
RTC	Crude	Road crashes in province
NFRTC	Crude	Property damage only RTCs
FRTC	Crude	Fatal RTCs
IRTC	Crude	RTCs lead to nonfatal injury
HR	Risk index	RTFs/(population/100k)
TR	Risk index	RTFs/(bn. liter Fuel usage)
CRP	Risk index	Fatal RTCs/(population/100k)
CRF	Risk index	Fatal RTCs/(bn. liter Fuel usage)
IPP	Risk index	RTIs/(population/100k)
FPC	Severity index	RTFs/(100k RTCs)
FPI	Severity index	RTFs/(1k RTIs)
FPNF	Severity index	Fatal RTCs/nonfatal-RTCs

5.2.2 Clustering and Choropleth Maps

Jenks natural breaks method was used to categorize provinces into seven groups. Considering the literature, the provinces were grouped into 7 clusters. This method is described in section 2.3.4.

5.2.3 Correlation Analysis

The Pearson correlation coefficient was used for the evaluation of associations between variables. This method is explained in section 2.4.1.

5.2.4 Spatial Analysis

Moran’s I and local Moran indices were used to evaluate the spatial distribution of regions in Türkiye. These methods are explained in Section 2.3.

5.3. Results

The total nonfatal injuries increased by 20.68% in the study period. Additionally, 66%, 27%, and 5% of fatalities occurred on intercity, urban and rural roads, respectively.

5.3.1 Correlation Analysis

The calculated correlations between the RSI pairs with positive Moran's I index are illustrated in Table 5.2. Positive and significant correlations were observed between the severity indices, including the FPNF, FPC, and FPI (PCC>0.63). Since the TR and crash per fuel consumption (CRF) indices were highly correlated (PCC=0.98), the TR index was used as a proxy for the CRF index.

Table 5.2. The correlation analysis results of the regional road safety indicators of Iran.

Indicator	Rural-RTF	IPP	FPNF	FPC
IPP	-0.42[a]			
FPNF	0.44[a]	-		
FPC	0.42[a]	-	0.87[b]	
FPI	0.55[b]	-0.52[b]	0.63[b]	0.67[b]

a) Correlation is significant at the 0.05 level (2-tailed).
b) Correlation is significant at the 0.01 level (2-tailed).

The significant correlations for pairs of RSIs and socioeconomic variables with a positive Moran's I index are presented in Table 5.3. The rural-RTF index is larger in regions with a higher rural population, diesel fuel consumption, distance from the capital, area, x-coordination of province center, and urban per rural family income. Additionally, this index is larger in regions with longer rural gravel roads and all types of roads. The Rural-RTF index negatively correlates with rural family income and the percentage of university graduates indices. The TR index is lower in regions with higher GDP, diesel fuel consumption, fuel consumption, urbanization rate (urban per rural population), urban family income, rural family income, literacy ratio, and % of high school graduates. The FPNF and FPI indices are higher in regions with longer rural gravel roads, distance from the capital, x-coordination of the region's center, and urban per rural family income. FPI and the rural family income index have a significant negative correlation. A negative correlation was observed between the percentage-of-university-graduates index and the rural-RTF, FPNF, FPC, and FPI indices.

Table 5.3. Significant correlations between the regional road safety indices and socioeconomic and transport-related variables of Iran.

Variables	Rural-RTF	TR	IPP	FPNF	FPC	FPI
Rural population	0.78					
GDP		-0.47				
Rural gravel road length	0.47			0.48		0.51
Road length (all road types)	0.76					
Diesel fuel consumption	0.46	-0.50				
Fuel consumption (Gas and diesel)		-0.51				
Distance from capital	0.70			0.60	0.51	0.71
Area	0.71					0.50
X coordination of the region's center	0.56			0.55		0.49
Y coordination of region's center						-0.58
Urbanization rate		-0.56				
Urban family income		-0.54				
Rural family income	-0.53	-0.58				-0.63
Urban per rural family income	0.61			0.50		0.66
Literacy ratio (LR)		-0.66			-0.46	
% of university graduates	-0.60		0.51	-0.54	-0.53	-0.53
% of High school graduates		-0.58		-0.48		
% of Primary school graduates				0.56		

5.3.2 Spatial Analysis

The Moran's I indices of the RSIs are given in Figure 5.1. The FPI index has the largest Moran's I index among the RSIs, and the distribution patterns of Iranian provinces in terms of the rural-RTF, TR, IPP, FPNF, FPC, and FPI indices are cluster-like.

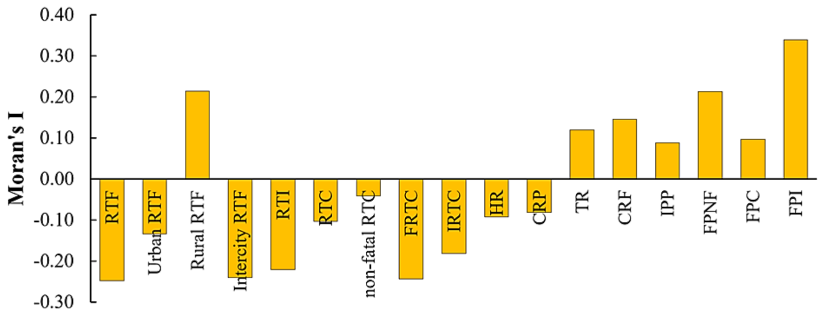


Figure 5.1. Moran's I index of regional RSIs of Iran.

The choropleth maps of provinces in terms of the major RSIs with negative Moran's I are represented in Figure 5.2.

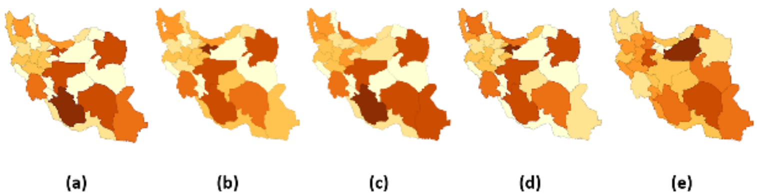


Figure 5.2. Choropleth maps of Iranian provinces according to road traffic fatalities (a), road fatalities on urban roads (b), fatalities on intercity roads (c), nonfatal road traffic injuries (d), and health risk or mortality rate (e).

The rural-RTF, IPP, FPNF, FPC, and FPI are the RSIs with significant hot and cold spots (P-value <0.01). The cluster maps regarding these RSIs are illustrated in Figure 5.3.

The association between Moran's I indices and the total number of detected hot and cold spots (sum of LL and HH cluster cores) are represented in Figure 5.4. It was observed that variables with a positive and high Moran's I index, including urban-per-rural-income and urban-family-income, did not have significant ($p<0.01$) hot and cold spots. On the other hand, none of the indices with a negative Moran's I index had a hot or cold spot region. A significant linear association between positive Moran's I and the total number of significant cluster cores was also detected ($R^2=0.68$). The fitted line's equation and coefficient of determination are represented in Figure 5.4.

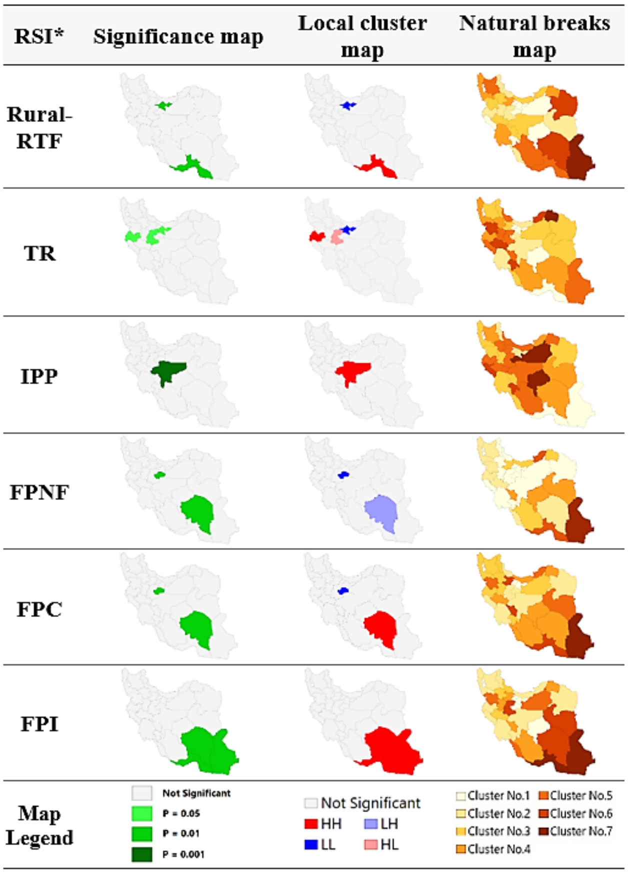


Figure 5.3. Cluster maps of Iranian provinces in terms of the road safety indices with significant local clusters in the study period.

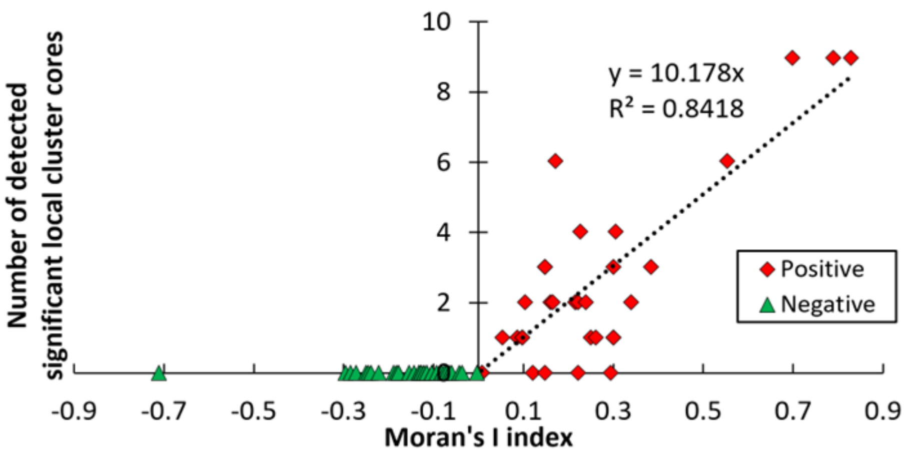


Figure 5.4. The relationship between the total number of detected hot and cold spots (including low-low and high-high, P <0.01) and negative and positive Moran's I index of the province-level variables of Iran.

The hotspot analysis results are represented in Table 5.4. For example, the cold spot locations in terms of rural-RTF and the socioeconomic and transport-related indices, including intercity-side-road, rural-gravel-road, and intercity-main-road, were identical. The hotspot locations regarding the rural-RTF and the other indices, including the area, intercity-side-road, and intercity-road, were the same. In addition, regions that are cold spots regarding the rural-RTF index are hot spots regarding the literacy ratio, urbanization rate, and percentage of university graduates.

Table 5.4. Hot and cold spot analysis table showing variable pairs that have similar or opposite cluster types and locations.

Road safety index		**Socioeconomic and transport-related index and cluster type**	
Index	**cluster type**	**Cold spot (LL)**	**Hot spot (HH)**
Rural-RTF	**Cold spot (LL)**	Intercity side road, rural gravel road, main intercity road	LR, urbanization rate, % of university graduates
	Hot spot (HH)	-	Area, intercity side road, intercity road
TR	**Cold spot (LL)**	Intercity side road, rural gravel road, main intercity road	LR, urbanization rate, % of university graduates
	Hot spot (HH)	-	-
FPNF	**Cold spot (LL)**	Rural gravel road	LR, % of university graduates
	Hot spot (HH)	-	-
FPC	**Cold spot (LL)**	-	LR, % of university graduates
	Hot spot (HH)	Population density	Area, intercity side road, intercity road, intercity road length per population, roads
FPI	**Cold spot (LL)**	-	-
	Hot spot (HH)	Rural Family Income, urbanization rate, population density	Area, intercity side road, urban per rural income, intercity road, intercity road length per population, roads

The hotspot analysis results also are represented in Figure 5.5. A limited number of socioeconomic and transport-related variables' hotspot locations were observed to be precisely the same as the RSIs. These indices include literacy-related variables (literacy ratio, % of university graduates), population-related indices (urbanization rate, population density), road length-related variables (including the roads, intercity, intercity side, main intercity, and rural gravel roads), and income-related variables (rural family income, urban per rural income).

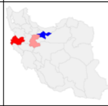
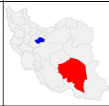
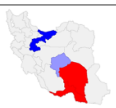
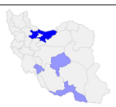
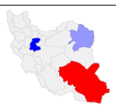
			Road safety indices				
			Rural-RTF	TR	FPNF	FPC	FPI
		Cluster Maps					
Socioeconomic and transport-related variables	Literacy ratio		LL-HH	LL-HH	LL-HH	LL-HH	-
	Percent of university graduates		LL-HH	LL-HH	LL-HH	LL-HH	-
	Area		HH-HH	-	-	HH-HH	HH-HH
	Urbanization rate		LL-HH	LL-HH	-	-	HH-LL
	Population density		-	-	-	HH-LL	HH-LL
	Rural family income		-	-	-	-	HH-LL
	Urban per rural family income		-	-	-	-	HH-HH
	Roads		-	-	-	HH-HH	HH-HH
	Intercity road		HH-HH	-	-	HH-HH	HH-HH
	Intercity side road		LL-LL HH-HH	LL-LL	-	HH-HH	HH-HH
	Rural gravel road		LL-LL	LL-LL	LL-LL	LL-LL	-
	Main intercity road		LL-LL	LL-LL	-	-	-
	Intercity road length per population		-	-	-	HH-HH	HH-HH

Figure 5.5. Hot and cold spot comparison results showing variable pairs that have similar or opposite cluster types and locations.

5.4. Discussion

Using spatial and correlation analysis, the spatial distributions of the administrative division of Iran were evaluated, road safety-deficient locations were detected, and variables influencing RSIs were identified. Since, in this country, a considerable portion of road fatalities (66%) occurred on intercity roads, further studies must be done regarding this issue. According to maps of the intercity-RTF-index, the distribution of regions in terms of this index is arbitrary, and the Fars province in the south has the highest intercity road fatality. Regarding the urban-RTF and RTI indices, it was observed that the frequency of road fatalities in regions with a high urban population, including Tehran province (the capital is located in this province) in the north of the country, was considerable.

Significant correlations between regional RSIs, such as the CRP and HR indices, were observed, and the results suggest that some RSIs had similar attributes. Similar findings regarding correlations between these RSIs in Türkiye were reported (Ahmadpur and Gokasar, 2021). These findings suggest that some regional RSIs could also be used as a proxy for other RSIs in other countries. Most of the studied crude RSIs, such as the number of road fatalities, were high in regions with a large population, GDP, income, education level, highway length, and fuel consumption indices. These findings are in line with previous studies (Ahmadpur and Gokasar, 2021; Atubi, 2012; Erdogan, 2009; Osayomi, 2013; Tortum and Atalay, 2015; Truong et al., 2016; Wang et al., 2019). Additionally, significant and positive correlations were observed between exposure variables (including population and fuel consumption) and crude RSIs, such as the number of fatalities. A previous study has reported similar findings (Besharati, Tavakoli Kashani, Li, et al., 2020). Thus, more road fatalities should be expected in regions with higher exposure rates, such as the population.

A previous study (using only one RSI) argues that no concrete evidence exists that income has improved traffic safety (Wachnicka et al., 2021). Since several RSIs in parallel are used in this section of the dissertation, more insights regarding this association could be provided. The results suggest negative and significant associations between several RSIs (including TR, HR, and FPI) and income-based variables (including GDP and family income rates). These findings are in line with previous research (Sánchez González et al., 2020). On the other hand, positive correlations between some crude RSIs (including RTF, urban-RTF, RTI, and RTC) and income-related indices were observed. These results indicate that researchers may prefer to use a crude RSI, such as the RTF index, and conclude that higher income means higher fatality and less road safety performance in regions. On the other hand, if the same study selects a risk rate such as TR, it may conclude the opposite. Therefore, one of the reasons for the ambiguity regarding the effect of income on road safety could be the selected RSI for conducting the study.

Similar results to our findings regarding a positive correlation between education level and the number of fatalities in China and Türkiye (Ahmadpur and Gokasar, 2021; Wang et al., 2019) and negative and significant associations between education-related indices and ratio-type RSIs, such as the TR index (Ahmadpur and Gokasar, 2021) have been reported I previous studies. Similar to the conclusion regarding the associations between RSIs and income-related variables, the crude and ratio-type RSIs have opposite relationships with education-level indices. These findings again reveal the importance of selecting an RSI for evaluating road safety performance in geographic regions.

Elvik et al. (2009) argue that the number of RTCs depends on many variables, including several socioeconomic indices, such as education and income. Our findings regarding the effect of income and education on RTCs are in accordance with this book. However, in their arguments, Elvik et al. (2009) only refer to the effect of education and income on the number of RTCs. Our findings suggest that education and income factors affect the number of RTCs and significantly correlate with other types of RSIs, including TR and crash severity indices.

The result suggests that the positive Moran's I regarding an RSI did not necessarily guarantee the existence of hot and cold spots when the p-value is less than 0.01. Additionally, when Moran's I is negative, it is highly potential that there will not be a cold or hot spot in terms of the subject index. In addition, variables with Moran's I greater than 0.5 were observed to have numerous hot or cold spot regions. The authors are unaware of any study that evaluated this association between Moran's I and the number of significant local cluster cores. Many variables could influence the detected association, such as the shape and size of geographic regions or the weight matrix type in the spatial study. Thus, further studies related to this association are needed.

5.4.1 Road Fatalities on Rural Roads

The spatial distribution of the provinces in terms of the rural-RTF was cluster-like, and the hot spot (Hormozgan province) and cold spot (Tehran province) were located in the south and north central of the country, respectively. The capital located province (Tehran) and its neighboring provinces are more developed and have a low rural population, and as a result, the rural-RTF index was lower in this region. The southeastern provinces, including Hormozgan, are less developed and have higher rural-RTF levels. The rural-RTF index is highly correlated with several variables, including rural-population, road-length, distance-from-capital, area, %-of-university-graduates, and urban-per-rural-family-income. Similar findings regarding the significant and positive correlation between the length of roads and road fatalities in rural areas were reported in previous research (Osayomi, 2013).

The rural-RTF index was larger in the country's east, south, and southeast, except for the South Khorasan province. Similar causations seem to lead to high rural-RTF levels in Iran's eastern and southeastern border provinces. These border regions' locations appear to be associated with the number of RTFs on rural roads. Regions that are hot spots in terms of rural RTF are also hot spots regarding the area, intercity road, and intercity-side-road indices. Additionally, cold spot regions in terms of the same RSI are cold spots in terms of intercity-side-road, rural-gravel-road, and intercity-main-road indices. In addition, regarding the rural-RTF index, cold spot regions are hot spots regarding literacy ratio, urbanization rate, and percentage of university graduates. These results suggest that the length of the intercity road, urbanization rate, and education level of people significantly influence the number of road fatalities on rural roads.

A higher length of intercity roads in areas means there is a greater extent of road infrastructure connecting different regions or cities. This increased road network can result in higher exposure to potential road hazards. More exposure rates on these roads can increase the risk of accidents and subsequent fatalities. A lower urbanization rate indicates less urban development and a lower population density. The road infrastructure may be less developed in such areas compared to urban regions. The lack of proper road infrastructure, including safety features such as lighting, signage, and well-maintained roads, can contribute to a higher risk of road crashes and fatalities. Also, regions with lower urbanization rates may have limited access to emergency services such as hospitals, ambulances, and well-trained emergency personnel. These factors can contribute to increased fatalities and crash severity in these regions.

A lower education level among the population can impact road safety awareness and emergency response knowledge. Individuals with lower education levels may be less exposed to formal road safety education and less aware of safe driving practices, traffic regulations, and emergency response on crash scenes. This lack of knowledge and awareness can lead to more hazardous driving behaviors, such as speeding, reckless driving, or non-adherence to traffic rules, increasing the likelihood of road crashes and fatalities. Also, this lack of awareness can lead to late responses to injured individuals on the crash scene, resulting in higher crash severity indices and fatalities on roads. Additionally, lower education levels can lead to lower awareness about road safety practices and, consequently, lower usage of seat belts and helmets. These issues can lead to a higher likelihood of fatality risk in regions.

5.4.2 Traffic Risk or Road Fatality per Fuel Consumption

The TR index is larger in underdeveloped regions with low urbanization, education, and income levels. These findings are in line with previous studies regarding the TR index in Türkiye, a neighboring country of Iran with similar income and development levels (Ahmadpur and Gokasar, 2021; Erdogan, 2009). Provinces have a cluster-like distribution in terms of the TR index, and this rate is higher in the west and south of the country. The cold spot (Tehran province) and hot spot (Kermanshah province) are located in the country's center and west, respectively. The hot spot analysis result was identical to the rural-RTF result, and similar variables, including road length, urbanization rate, and education level of people, influence this index in cold spot regions. There may be limited resources and safety measures in underdeveloped regions with low urbanization rates. Additionally, there may be a lack of public transportation alternatives, leading to a higher dependence on individual motor vehicles. The combination of these factors can increase the risk of fatalities on roads. In regions with low-income levels, there might be limited access to quality healthcare and emergency services. Prompt medical attention after a crash is crucial for reducing fatalities. If the availability and quality of emergency medical services are compromised due to limited resources, the fatality rate may increase. Additionally, regions with lower income levels may have limited resources for replacing outdated and unsafe vehicles with high-standard ones, road infrastructure improvements, traffic safety measures, and efficient emergency response systems. Consequently, lower income levels can increase crash severity and fatality risk in regions.

5.4.3 Severity Indices

Road crash severity indices have rarely been evaluated in regional road safety studies. The FPNF and FPI indices significantly correlate with high numbers of socioeconomic and transport-related variables. On the other hand, the FPC rate is only correlated with three indices. All three severity indices are correlated with the distance-from-capital and %-of-university-graduate indices. Additionally, the FPNF and FPI indices are significantly correlated with the rural-gravel-road-length, x-coordination of the province center, and urban-per-rural-family-income levels. In addition, these indices have negative correlations with income and education level-related indices. These findings suggest that road crashes are more severe and fatal in remote and underdeveloped regions. Similar findings were reported regarding road crash severity indices in Türkiye and Nigeria (Ahmadpur and Gokasar, 2021; Iyanda, 2019; Tortum and Atalay, 2015).

According to choropleth maps, RTCs are drastic in vast southeastern provinces. The identified massive hot spot regarding the FPI index (Figure 5.3) shows that RTC severity is a significant health problem in southeast Iran. Regions in this hot spot are some of the least developed provinces in the country. The existence of local clusters in terms of RTC severity indices in border and remote regions was reported in previous studies (Ahmadpur and Gokasar, 2021; Iyanda, 2019). For example, the Sistan-and-Baluchestan province is one of the least developed provinces in Iran, and the literacy rate in the province is one of the lowest (Statistical Center Of Iran, 2021). Previous studies on road safety conditions in this region showed a significant correlation between the location of RTFs (pre-hospital and hospital) and the site location of related RTCs. Provinces in southeastern Iran are vast, their cities are far from each other, and most RTFs occur on intercity roads in this region. Therefore, the delay of the police and emergency services at the crash scene may have led to drastic RTCs in this province (Taravatmanesh et al., 2015). These could be some causes of high RTC severity indices in southeastern Iran.

The cold spot region in terms of FPNF and the rural-gravel-road index was identical. Additionally, cold spot regions regarding both FPNF and FPC indices were hot spots regarding the literacy ratio and %-of-university-graduate indices. In addition, the hot spot regions regarding FPC and population density were precisely the same. The hot spot regions in terms of the FPC index were hot spots in terms of the area, intercity-side-road, intercity-road, intercity-road-length-per-population, and road indices. Regarding the FPI index, hot spots were cold spots in terms of the rural-family-income, urbanization rate, and population density. Additionally, hot spots in terms of this index were hot spots regarding the area, intercity-side-road, urban-per-rural-income, intercity-road, intercity-road-length-per-population, and road indices. These findings indicate that socioeconomic and transport-related variables, including the length of intercity roads, area, income level, population density, urbanization rate, and people's education level, significantly influence crash severity indices in problematic regions. Larger areas and longer roads often correspond to diverse road conditions, varying traffic patterns, potentially longer travel distances, and longer response times to crashes from emergency and police forces. These factors can contribute to higher severity when crashes occur. The impact of income and education level on severity are discussed in sections 5.4.1 and 5.4.2. The results suggest that increases in development levels could lead to less road crash severity in administrative divisions of this country.

6. EVALUATION AND COMPARISON OF REGIONAL ROAD TRAFFIC SAFETY INDICES OF EGYPT, ENGLAND, TÜRKIYE, AND THE UNITED STATES

6.1. Introduction

Road traffic crashes result in significant injuries, leading to 1.35 million road traffic fatalities annually (Ali et al., 2021). Additionally, developed countries such as the USA spend considerable resources due to road traffic crashes and related fatalities, which disturb traffic flow on roads (Ali et al., 2021). Despite the low motorization rates, excessive RTFs have occurred in developing countries (World Health Organization [WHO], 2018a). The average fatality per 100,000 population rate in developing countries equals 27.5, which is 3.3 times greater than that in developed ones, indicating that the road fatality risk in developing countries is considerably high (WHO, 2018b). Therefore, further and precise road crash prevention programs are needed in developed and developing countries to reduce fatalities and prevent fluctuations in traffic flow.

Almost all countries comprise administrative divisions such as provinces. Previous studies have reported considerable differences between road safety performances of administrative divisions of countries. Also, local clusters of administrative divisions with similar RSIs within countries or counties have been reported (Ahmadpur and Gokasar, 2021; Erdogan, 2009; Huang et al., 2010; Truong et al., 2016; Wachnicka et al., 2021a). One of the initial steps in a precise road crash prevention program in a country is conducting spatial analysis to identify the spatial distribution of administrative divisions of the country and identify hotspots regarding regional RSIs. The annual road safety reports and literature provide high-detailed information on country-level RSIs. However, these studies pay limited attention to road safety conditions in countries' subdivisions. Empirical examples of spatial analysis of road traffic crashes are mainly concerned with black spot analysis in local areas, and with a few exceptions, regional data are neglected. Most of the studies on subdivision-level RSIs are concentrated in developed countries, and only a few have evaluated the same indices in developing countries (Haghani et al., 2022; Ziakopoulos and Yannis, 2020). In addition, there is limited knowledge regarding the similarity and differences between developed and developing countries regarding subdivision-level RSIs. A few studies have evaluated and compared various countries' RSIs (Chen et al., 2017; Elvik et al., 2009; Lassarre and Thomas, 2005; Wachnicka et al., 2021). However, these studies used limited numbers of RSIs or provided limited knowledge regarding administrative-division level RSIs in the selected regions. We are unaware of a study that has used several RSIs and has evaluated and compared regional RSIs in countries with different backgrounds. A previous study reported significant correlations between regional RSIs and exposure variables in Türkiye and identified their influencing factors (Ahmadpur and Gokasar, 2021). These associations rarely have been discussed in the literature, and the significance of these associations in other countries is unknown. Therefore, it is necessary to evaluate these associations in various countries.

These prompted us to evaluate the country- and subdivision-level RSIs and related indices of four countries, including two developed (USA and England) and two developing (Egypt and Türkiye) ones, to illustrate the differences and similarities between the countries regarding regional road safety performance. In addition, the attributes of the RSIs are evaluated, and an index is suggested, which could briefly indicate the road safety conditions in subdivisions of countries. The Pearson correlation coefficient and regression analysis were used to detect significant relationships between the variables to reach the primary goal of this section. Moran's I, local Moran indices, and the Jenks natural breaks method were used to evaluate the spatial distributions of regions.

To reach the primary goal of this section of the dissertation, the following objectives were met: a) collecting subdivision-level data of the countries, b) calculating subdivision- and country-level RSIs, c) checking the existence of spatial autocorrelation in terms of RSIs by using Moran's I index, d) identifying significant local clusters with high or low RSIs by using local Moran indices, e) calculating correlations between studied variables, f) evaluating descriptive statistics of studied variables to reveal the differences and similarities between countries in terms of RSIs, g) producing choropleth maps by using the Jenks natural break method.

6.2. Method

Two developed and two developing countries, including Egypt, Türkiye, England, and the USA, were selected for the study. These countries were selected because of their available and reliable RTC registration system (WHO, 2018a). Data and geographical information about these countries were collected from the statistical center of each country. Using statistical and spatial analysis methods, the spatial and statistical attributes of the regional RSIs of these countries were evaluated and compared. Using spatial analysis, hot or cold spots of countries in terms of regional RSIs could be identified, and the spatial distribution of administrative divisions could be evaluated. These assessments provide insights and knowledge regarding the regional RSIs in developed and developing countries. Additionally, similarities and differences between these countries regarding regional RSIs could be identified. Previous studies reported considerable fluctuations in countries' road safety data after the COVID-19 outbreak (Ahmadpur, 2022). Thus, to reduce the noise and increase the reliability of the results, a 5-year study period between 2015 and 2019 was set, and the average data value of the variables for this period was utilized.

6.2.1 Data and RSIs

The regional population, the number of registered motor vehicles, and RTF data of the countries were gathered to calculate their regional RSIs and motorization rates. Egypt comprises 27 subdivisions (Governorates), has a large population, and is located in the Middle East and North Africa (MENA) region. This country is highly urbanized, and most people live along the Nile River. Central Agency for Public Mobilization and Statistics (CAPMAS) is Egypt's official statistical agency, providing regional data of Egypt as annual reports on their website (Government of Egypt, 2022). The data from Egypt was obtained from CAPMAS's website. Türkiye, a middle-income and developing country, has 81 provinces, and according to the Turkish Statistical Institute, nearly three-quarters of its population lives in towns and cities (TUIK, 2022). The annual data of Türkiye was collected from the website of the Turkish Statistical Institute. This institute provides detailed data regarding road traffic fatalities in this country. With 48 geographical (ceremonial) counties, England has one of the lowest RTF rates globally. In this section, geographical divisions or ceremonial counties of England were adopted as subdivisions of this country. The data of

England was collected from the website of the Office for National Statistics (ONS), which provides regional statistics of England's population, RMV, and RTFs (Office for National Statistics, 2022). The USA comprises 48 contiguous states located in North America. The population data of the USA was obtained from the website of the United States Census Bureau, and according to this data, the population of the US in 2019 was around 328.24 million (United States Census Bureau, 2021). The number of RMV data was obtained from the Federal Highway Administration (FHWA) website, and according to gathered data, in 2019, there were 276.49 million RMVs in the US (Federal Highway Administration, 2022). In addition, the country-level RTF of the US in 2019 was 36,355 (National Highway Traffic Safety Administration, 2022). RTF data of the USA was obtained from the website of the National Highway Traffic Safety Administration. The descriptive statistics of the regional indices of the countries are presented in Table 6.1.

Table 6.1. Descriptive statistics of the regional registered motor vehicles, road traffic fatalities, and population of Egypt, England, Türkiye, and the USA in the study period and 2019.

Country	Variable	Annual in 2019	Average[1]	Min[1]	Max[1]	St. deviation[1]
Egypt	Population	98.9 million	3,467,948	130,003	9,552,090	2,640,092
	RMV	10.57 million	344,175	30,632	2,373,032	456,733
	RTF	6,721	255	19	1158	256
England	Population	56.28 million	1,182,715	39,280	8,826,332	1,270,833
	RMV	32.94 million	682,421	26,928	3,071,428	479,934
	RTF	1,489	32	3	124	19
Türkiye	Population	83.15 million	1,111,066	83,248	15,015,554	2,222,498
	RMV	23.15 million	310995	9301	3,978,513	624787
	RTF	5,473	87	10	497	98
USA	Population	328.24 million	5,313,460	341,688	30,541,957	5,508,152
	RMV	276.49 million	6,370,071	581,078	39,326,177	7,211,434
	RTF	36,355	721	27	3,725	794
1) Calculated based on annual data between 2015 and 2019						

In this section of the dissertation, the number of RTFs and two ratio-type RSIs, including health risk and traffic risk indices, were used. The TR and HR indices are risk rates that indicate the probability of road fatality by considering the number of RMVs and the population of areas, indicating how safe road travel is in geographic regions (Elvik et al., 2009). The HR and TR indicators have been used widely in previous macro- and micro-level road safety studies and were adopted in different annual road traffic safety reports to compare regions according to their road safety performance (Ahmadpur and Gokasar, 2021; Erdogan, 2009; International Transport Forum [ITF] and Organisation for Economic Co-operation and Development [OECD], 2019; World Bank, 2017; WHO, 2018a). The mathematical formulation of the HR rate of a region is expressed as

$$HR = RTF / (Population / 100{,}000), \tag{6.1}$$

where *RTF* is the number of deceased individuals because of road crashes in the region, and the *population* is the number of individuals living in the same area. The mathematical formulation of the TR index of the region is expressed as

$$TR = RTF / (RMV / 100{,}000), \tag{6.2}$$

where *RTF* is as defined before, and *RMV* is the number of registered motor vehicles in the region. Additionally, the MR index, which equals the number of RMVs in a subdivision per 1000 individuals who live in the same area, was used to illustrate vehicle ownership status in the regions. Using equations (6.1) and (6.2) and the equation of the MR index, the HR rate could be expressed as

$$HR = TR * (MR / 1000), \tag{6.3}$$

where *TR* is the TR index of the same region, and *MR* is the MR index of the region. According to equation (6.3), the line slope in an MR-HR scatter plot, which connects the origin to each data point, indicates that data point's MR index. Therefore, regions with a high HR index and low MR index tend to have a large TR index.

6.2.2 Correlation, Regression

Pearson correlation coefficient and regression analysis were used to evaluate associations between variables. These methods are explained in Section 2.4.

6.2.3 Spatial Analysis and Spatial Autocorrelation

Moran’s I and local Moran indices were used to evaluate the spatial distribution of regions in Türkiye. These methods are explained in Section 2.3.

6.3. Results

The result of correlation, regression, and spatial analysis of the selected countries are provided in this section.

6.3.1 Variation Patterns of Country-Level Indices

The country-level indices and their variation patterns are represented in Figure 6.1. The USA's RTF level was the highest among the countries.

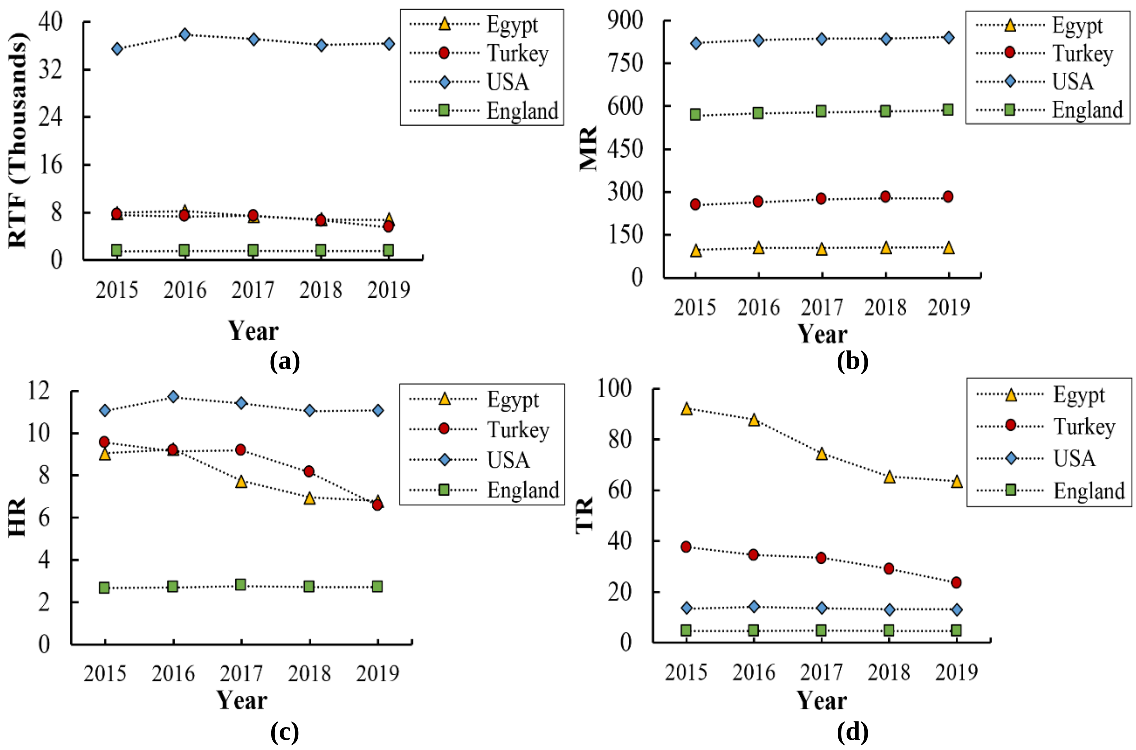


Figure 6.1. Annual country-level RTF (a), MR (b), HR (c), and TR (d) indices of England, the USA, Egypt, and Türkiye between 2015 and 2019.

From 2015 to 2019, the % change in RTF levels in Egypt, Türkiye, England, and the USA were -19, -27, +2, and +2, respectively. A steady rise in the MR index of the countries was observed. The MR index of the USA, England, Türkiye, and Egypt increased by 2.6%, 3.3%, 9.7%, and 8.9%, respectively. During the study period, the HR index of England remained almost the same, the same index of the USA increased, and the HR index of both developing countries significantly decreased. In addition, small changes in the TR index of the developed countries and sharp decreases in the same index of developing ones were observed.

6.3.2 Regional RSIs and Variables

The modeled relationships between the variables are represented in Figure 6.2.

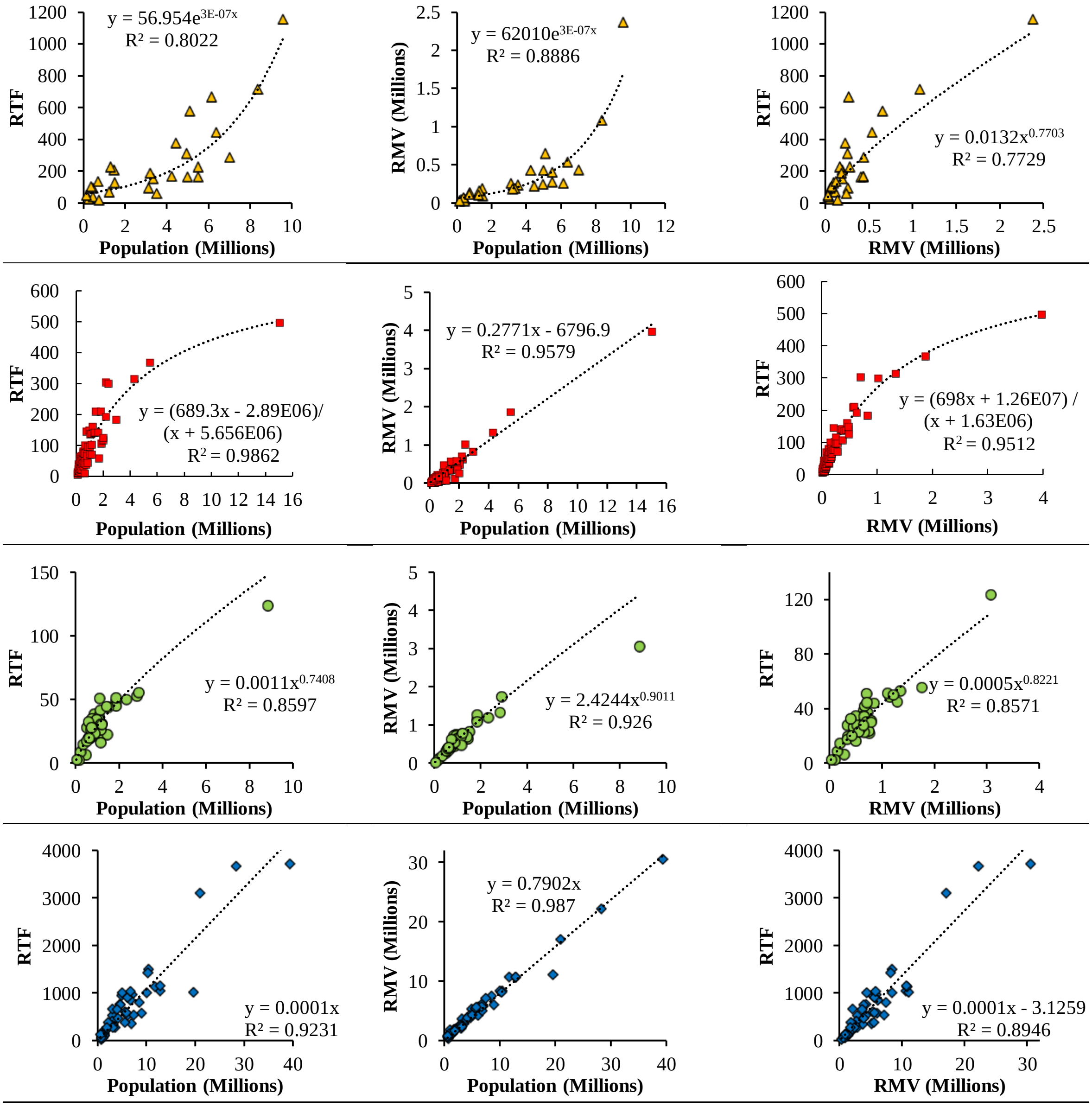


Figure 6.2. Scatter plots of regional RTF, population, and RMV indices of Egypt (row 1), Türkiye (row 2), England (row 3), and the USA (row 4).

The line equation describing the significant relationship between variable pairs and the related R^2 index of the fitted line is embedded in each scatter plot. Figure 6.2 shows that the relationships between the USA's RTF, population, and RMV indices are significant and positive. The associations between the same indices in Egypt are nonlinear and significant. The visual inspection and high R^2 rates indicate that the models replicate the observed outcomes suitably. The correlation analysis result is represented in Figure 6.3. High correlations between regional population (Pop)-RTF, Pop-RMV, and RTF-RMV variable pairs of the countries were observed. On the other hand, the associations of Pop-TR, RMV-HR, and RTF-MR variable pairs were weak and non-significant in the countries. The correlation of HR-TR variable pairs was high for developed countries.

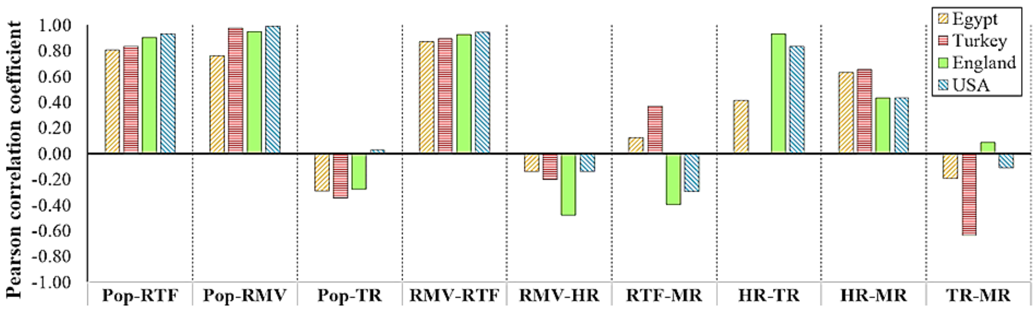


Figure 6.3. Pearson correlation coefficient for pairs of regional variables of Egypt, England, Türkiye, and the USA.

Scatter plots of the regional variables are represented in Figure 6.4. Most regions in developing countries had low MR and similar HR to subdivisions of developed countries. Additionally, in the MR-HR diagram (Figure 6.4a), a considerable gap between the subdivisions of developing and developed countries was observed. As presented in Figure 6.4b, subdivisions of both developing countries have low TR and high MR rates, and most regions in Türkiye have intermediate MR and TR indices. In addition, some areas of Egypt have extreme TR indices and low MR rates. The modeled association between the regional TR and MR rates is presented in Figure 6.4b. High R^2 values and visual inspection confirmed the nonlinear and significant association between the subdivisions' regional MR and TR indices. A significant and linear relationship was observed between developed countries' TR and HR indices (Figure 6.4c). The same association was not meaningful in developing countries. The regional TR indices of Türkiye were closer to those of developed countries, and the differences between subdivisions of Egypt in terms of HR and TR indices were excessive. The detected significant linear relationship between the developed countries' regional HR and TR indices is represented in Figure 6.4d. Both fitted lines' slopes were positive and high, and the R^2 measures of fitted lines were considerable (above 0.67). Compared to the USA, the TR and HR indices of subdivisions of England were lower. One reason for this phenomenon could be the lower RTF levels in regions of England despite similar MR levels with states of the USA. Another reason could be the two countries' transportation systems since England's public transportation system is more developed than the US.

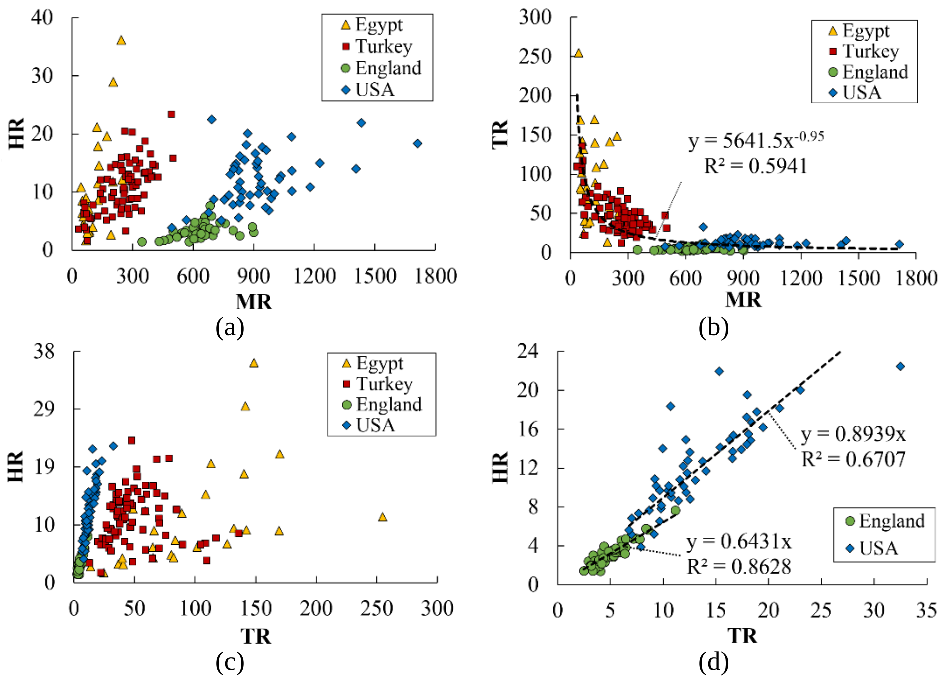


Figure 6.4. Scatter plots of administrative-division level MR-HR (a), MR-TR (b), and HR-TR (c) variable pairs of Egypt, England, Türkiye, and the USA. The significant nonlinear association between regional TR and MR indices (b), and the significant association between regional HR and TR indices of England and the USA (d).

Descriptive statistics of subdivision-level RSIs of studied countries are presented in Figure 6.5. According to Figure 6.5, the USA had the highest statistics regarding the regional RTF index. In addition, the range statistic of Egypt in terms of both HR and TR indices was very high. The USA and Türkiye's calculated statistics in the HR rate were similar. Compared to other countries, the descriptive statistics of RSIs in England were the lowest.

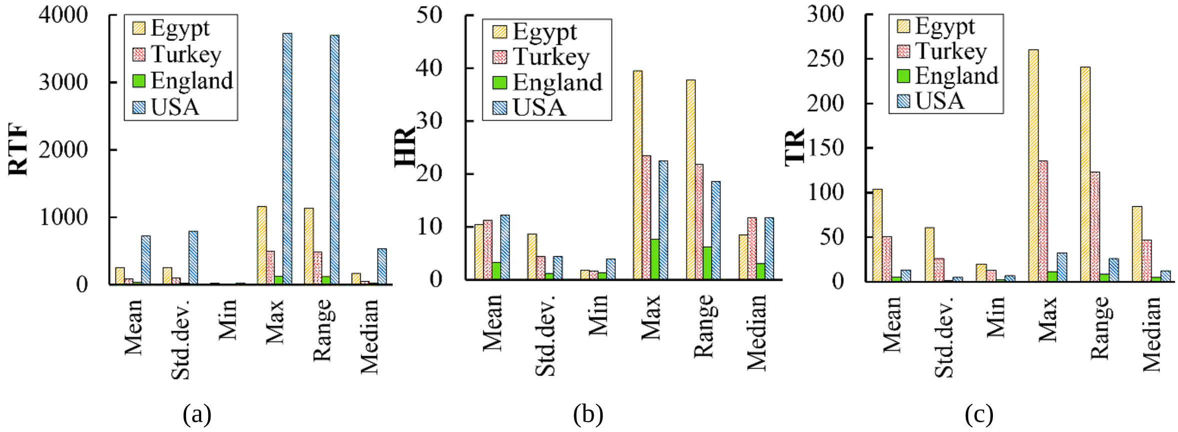


Figure 6.5. Descriptive statistics of the administrative-division level RTF (a), HR (b), and TR (c) indices of Egypt, England, Türkiye, and the USA.

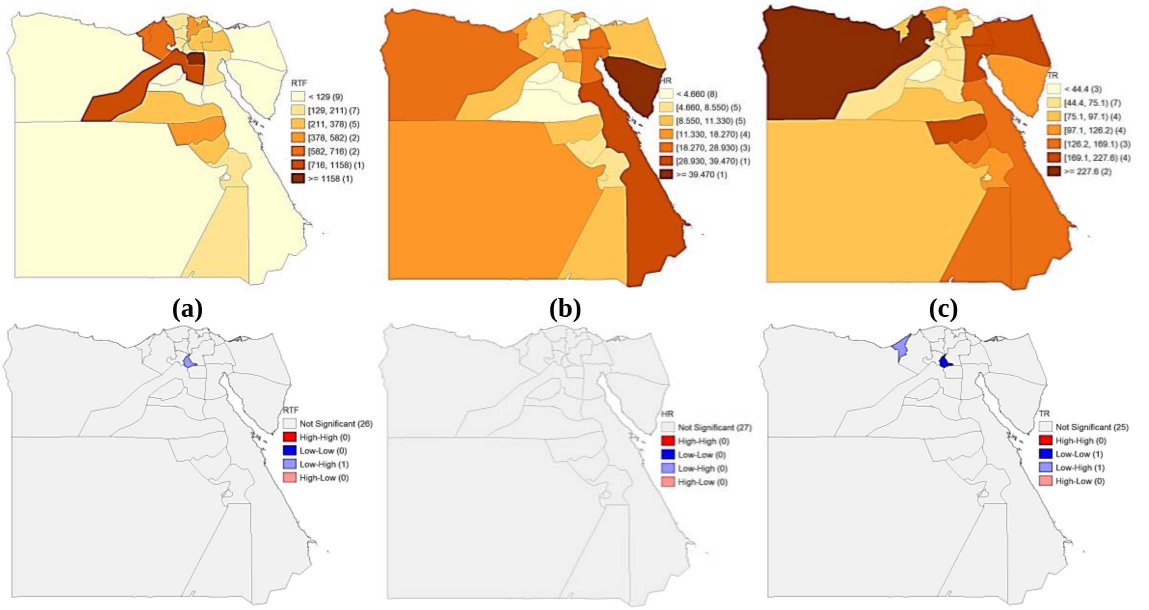
6.3.3 Spatial Analysis

The calculated Moran's I index of regional RSIs is represented in Table 6.2. All the regional RSIs have positive Moran's I indices, and the subdivisions had non-arbitrary spatial distributions. Moran's I index of TR indices of the countries (except Egypt) was positive and considerable (above 0.2).

Table 6.2. Calculated Moran's I index of the regional road safety indices of Egypt, England, Türkiye, and the USA.

Country		Egypt	Turkiye	England	USA
RSI	RTF	0.04	0.21	0.06	0.15
	HR	0.10	0.51	0.18	0.48
	TR	0.06	0.53	0.24	0.55

The clustering results of Egypt's RTF, HR, and TR indices are illustrated in Figures 6.6a, 6.6b, and 6.6c. Figures 6.6d, 6.6e, and 6.6f depict the spatial analysis results. Regions with the highest RTF measures were around the capital city (Figure 6.6a). Regions around the capital city had lower TR and HR indices than other regions, and remote and border regions had higher TR and HR rates (Figure 6.6b and 6.6c). In terms of the TR rate, one significant LL cluster core (Qalyubiyya) next to the capital city Cairo and one outlier (Alexandria) were identified (Figure 6.6f).

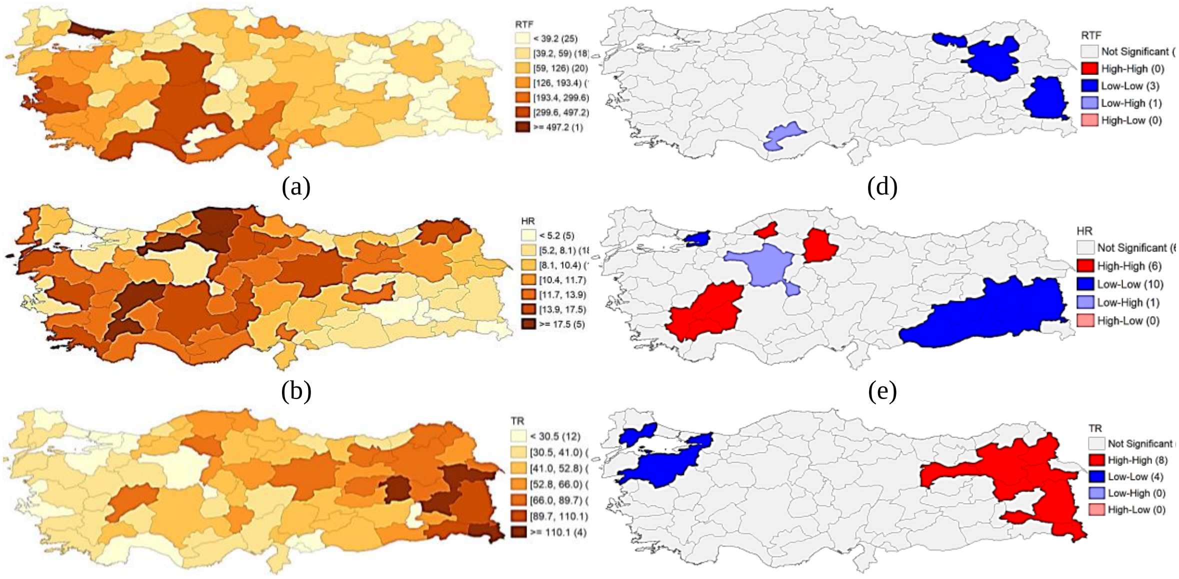


(a) **(b)** **(c)**

(d) **(e)** **(f)**

Figure 6.6. Choropleth maps of RTF (a), HR (b), and TR (c) indices. Spatial cluster maps based on the regional RTF (d), HR (e), and TR (f) indices of Egypt.

Cluster maps and the result of the spatial analysis of Türkiye are illustrated in Figure 6.7.



(a) (d)

(b) (e)

(c) (f)

Figure 6.7. Natural break maps of RTF (a), HR (b), and TR (c) indices and spatial cluster maps based on the regional RTF (d), HR (e), and TR (f) rates of Türkiye.

Most regions with high and low RTF indices were in western and eastern Türkiye, respectively (Figure 6.7a). Regions with the lowest HR indices are located southeast and northwest of this country (Figure 6.7b). Most areas in southwestern and northern Türkiye had high HR rates. Regarding the TR index, most provinces in eastern Türkiye had high TR rates, and the same index in western regions was low (Figure 6.7c). Regarding the RTF index, there were three LL cluster cores in the east (Figure 6.7d). Regarding the HR index, the LL regions were located in the southeast and northwest (Figure 6.7e), and significant HH cluster cores were detected in the southwest and north. Regarding the TR index, significant HH and LL regions were located east and northwest of the country, respectively (Figure 6.7f).

Cluster maps of England are represented in Figure 6.8.

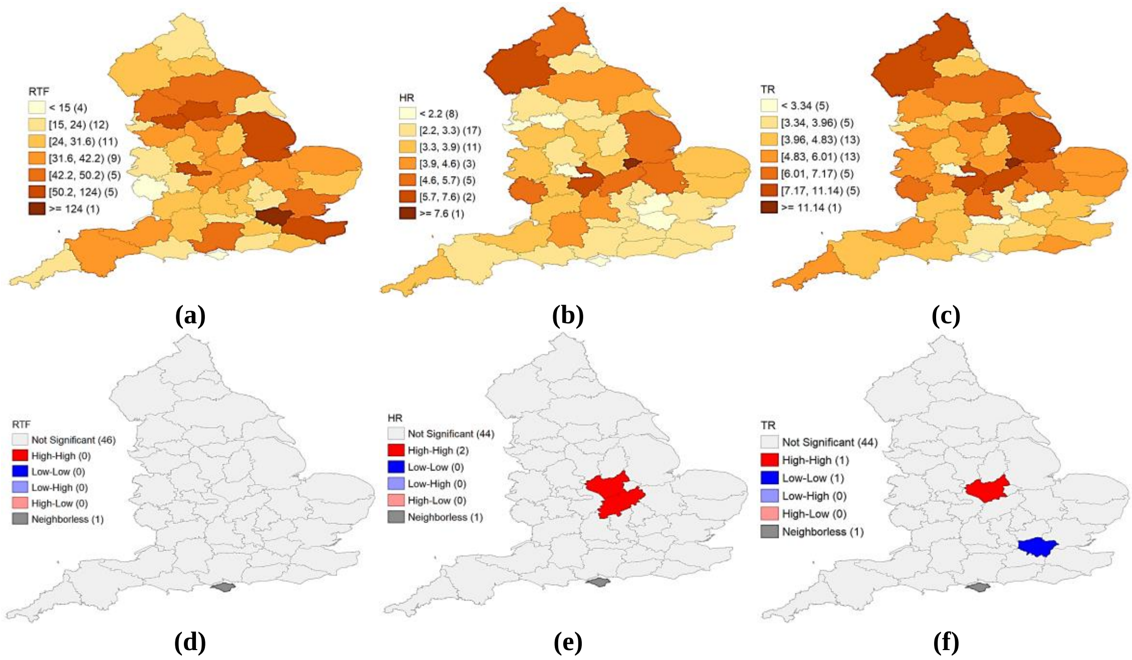


Figure 6.8. Cluster maps of RTF (a), HR (b), and TR (c) indices and spatial cluster maps based on the regional RTF (d), HR (e), and TR (f) indices of England.

According to Figure 6.8a, Greater London County had the highest subdivision-level RTF in England (124). Regions with higher RTF levels were in the southeast and center of this country. Areas with high HR values were in the center and north of this country (Figure 6.8b). Rutland County, located in the country's center, had the highest TR index (Figure

6.8c). Regarding the HR index, two significant HH cluster cores (Leicestershire County and Northampton Shire County) were detected (Figure 6.8e). In terms of the TR index, two significant cluster cores, including one HH (Leicestershire County) and one LL (Greater London), were identified (Figure 6.8f).

Cluster maps of the USA are represented in Figure 6.9.

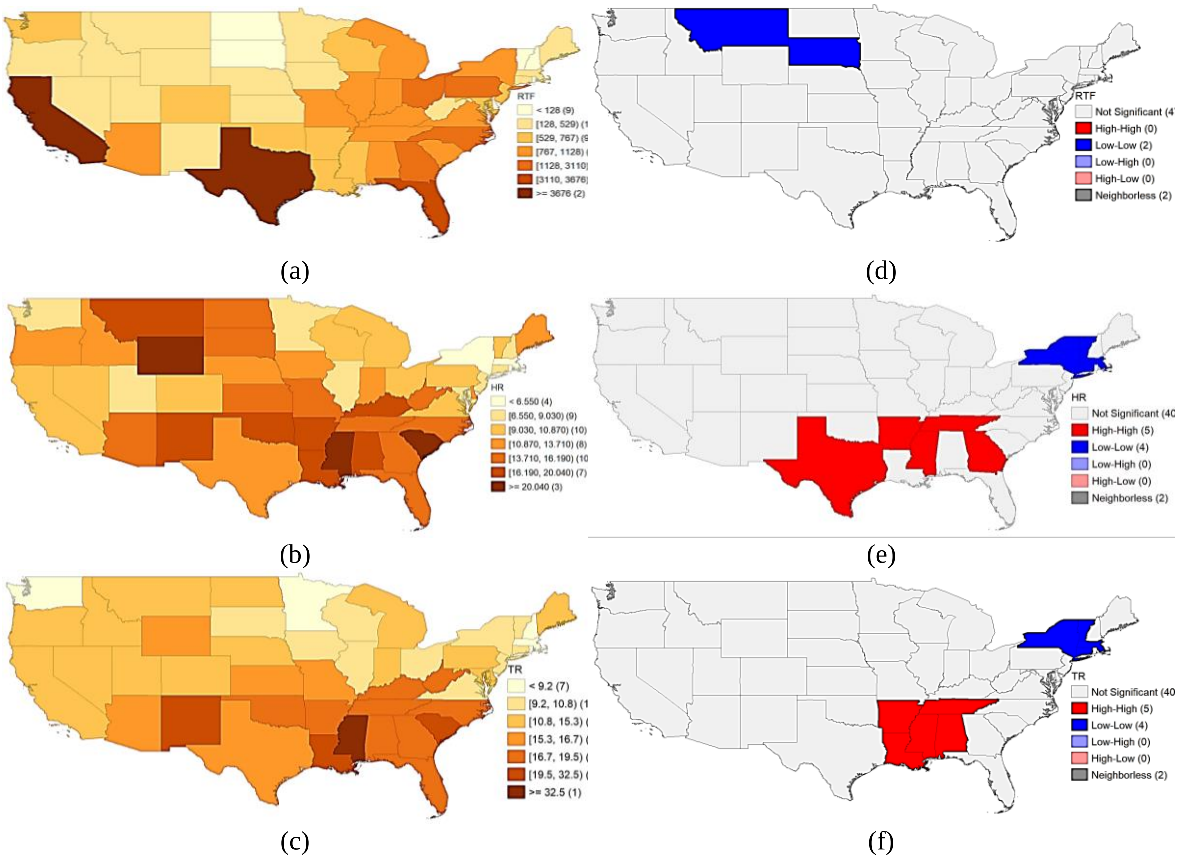


Figure 6.9. Cluster maps of RTF (a), HR (b), and TR (c) indices and spatial cluster maps based on the regional RTF (d), HR (e), and TR (f) indices of the USA. Significant hot (in red) and cold (in blue) spots are defined in the cluster maps.

California, Texas, and Florida have the highest RTF indices, and most regions with low RTF rates are in the north and northeast (Figure 6.9a). Areas with high HR indices are located in the southeast, center, and north. Most states in the south and southeast had high TR values (Figure 6.9b). Regarding the RTF index, two significant LL regions (Montana and South Dakota) exist in the country's north (Figure 6.9d). Regarding the HR index, four

HH cluster cores (Texas, Arkansas, Mississippi, Tennessee, and Georgia) in the south and four LL regions (New York, Connecticut, Massachusetts, and Vermont) in the northeast were detected (Figure 6.9e). Figure 6.9f exhibits the identified cluster cores regarding the TR index, including five significant HH regions (Arkansas, Louisiana, Mississippi, Alabama, and Tennessee) in the south and four LL regions in the northeast (New York, Connecticut, Massachusetts, and Vermont).

6.4. Discussion

In this section, country-level and regional road safety indicators of four countries with different backgrounds were evaluated using statistical and spatial analysis methods. Accordingly, similarities and differences between these countries regarding these indices were identified. Problematic regions regarding RSIs were detected, and significant associations between studied variables were revealed.

6.4.1 Country-level Variables

The steady increase in motorization rates and significant drops in road fatalities in developing countries led to significant decreases in HR and TR rates in these countries. On the other hand, the road fatality indices were stable in the developed ones. Despite the considerable reduction of RSIs in developing countries, the fatality levels in these countries are still excessive. These findings are in accordance with the annual report of the World Health Organization (2018a). A previous study suggests that countries with higher motorization rates tend to have lower TR values (Elvik et al., 2009). However, the results of our research demonstrated that England, with a lower MR level than the USA, has a lower TR index. Developing countries have experienced a rapid increase in motorization rates, indicating more vehicles on the road. Improvements in infrastructure, such as the expansion of road networks and increased vehicle access, often accompany this increase. Simultaneously, there have been significant drops in road fatalities in these countries. This can be attributed to several factors, including improved road safety measures, infrastructure development, and enhanced emergency response. Developed countries generally have well-established road safety systems. These countries have invested in advanced road safety measures over many years, leading to a stable trend in road safety performance indices.

6.4.2 Subdivision-level Variables

Significant associations were observed between the countries' population, RTF, and RMV indices. The graphs in Figure 6.1 suggest that these significant relationships could be linear or nonlinear in various countries. Thus, models for the developed and developing countries had to be constructed separately due to different socioeconomic characteristics, as was suggested in previous studies (Wachnicka et al., 2021). Additionally, it was observed that in all countries, a limited number of regions (1 to 3) had extreme RTF, RMV, or population indices, and the remaining areas formed a cluster with lower and similar measures. From a statistical point of view, removing these extreme data could be practical. However, since these regions with high populations are not independent data points and are connected to the rest of the country, the authors believe that removing these regions from datasets is not logical. Further investigation regarding removing the extreme values in the suggested models is needed. Additionally, the data indicate that these relationships between variables remain significant even after eliminating regions with excessive rates. These findings suggest that higher exposure values (such as population) in all countries mean higher road fatalities. A higher population or number of vehicles means increased traffic volume and higher exposure to crash risk. With more vehicles on the road, the probability of accidents occurring also increases. A larger population means more individuals are exposed to the risks associated with road travel. More people using the roads increases the likelihood of encountering hazardous situations, such as reckless driving, poor road conditions, or inadequate infrastructure.

Results suggest a similarity between the countries regarding the correlations between pop-RTF, pop-RMV, pop-TR, RMV-RTF, RMV-HR, and RTF-MR variable pairs. On the other hand, differences between countries regarding the associations between HR-TR, HR-MR, and TR-MR variable pairs were observed. These findings suggest that the associations between some road safety-related variables could also be similar in countries. The significant and linear associations between HR and TR indices in developed countries indicate that subdivisions in these countries have similar motorization rates, and there is no considerable difference between most regions regarding the MR index. At the same time, the same association is not significant in developing countries, indicating great diversity in TR, HR, and MR indices. The lack of a significant association between fatality per population and fatality per registered motor vehicle indices in developing countries reflects the diversity in motorization rates and road safety conditions across different regions. It highlights the need for targeted and specific interventions, such as region-specific road safety measures, infrastructure improvements, and road safety-related educational campaigns, to address the varying challenges and reduce the disparities in fatality rates within developing countries.

The represented HR-MR and TR-MR scatter plots indicate the considerable differences between subdivisions of developed and developing countries regarding road safety performance. These findings suggest a nonlinear association between regional MR and TR indices. When the regional MR index is below 300 (vehicle per 1000 individuals), regions tend to have excessive TR rates, and regions with MR greater than 300 tend to have low TR indices. In regions with lower motorization rate, the risk of traffic crashes and fatalities are higher. This association between administrative division-level MR and TR is in accordance with previous studies, which indicate a similar relationship between country-level MR and TR indices (Elvik et al., 2009). This similarity between the subdivision- and country-level MR-TR graphs is fascinating, and further investigation regarding this finding is needed.

Comparing the HR-MR and TR-MR scatter plots revealed that comparing regions based on their TR indices is more appropriate. Additionally, it was observed that when areas with similar MR levels were compared, areas of developed countries had lower TR and HR indices. The difference between the regional HR and TR indices of the developing countries is significant (Figure 6.4), and several regions of these countries have similar RSIs to areas of developed countries, but several subdivisions have extreme TR and HR indices. These observations indicate the importance of the MR index in comparing regions in terms of road safety indicators. For example, when the subdivisions of all countries are compared based only on the HR index (without considering the number of RMVs and the MR index), it can be concluded that the road safety performance of regions in developing and developed countries is similar. However, after including the MR index in the comparison process, the gap between developing and developed countries is revealed, and it is possible to conclude that roads are safer in developed countries. A considerable difference between both types of countries regarding the subdivision level TR index was observed. Additionally, the majority of regions in developed countries had higher MR indices. A higher motorization rate could mean more interaction between humans and vehicles and, simultaneously, more congestion and lower speeds. Our findings suggest that the regional HR index is independent of the motorization rate, and on the other hand, there is a significant association between the regional TR and the motorization rate. These findings suggest that the HR index may not be a proper index for comparing geographic regions' road traffic safety performance when the TR index is available.

Reviewing the road safety reports by various road safety-related institutes revealed that no attention has been given to the road safety performance of subdivisions of countries in these reports. Each country comprises geographic regions that could have different values regarding an RSI. This dissertation revealed the considerable differences between subdivisions in developed and developing countries regarding 3 RSIs. Providing statistics indicating a country's divergence in regional RSI could be insightful and beneficial. For example, Egypt's country-level HR index in the study period was 6.8, but the HR index of 5 subdivisions of this country was above 15, and the highest regional HR index was 36.15. The results presented in this section indicate that the standard deviation or range statistic of subdivision-level RSIs of countries could be a proper statistic for representing the road safety conditions in subdivisions of countries. It could be beneficial to include the suggested statistics of countries in road safety studies and reports to provide more expressive information about the road safety condition in a country.

6.4.3 Spatial Analysis Results

Spatial analysis results indicate that the most populated subdivisions or their neighboring regions are significant LL cluster cores regarding the TR index in the countries. This phenomenon could result from congestion, lower speed, or higher road safety infrastructures in these regions. Further studies are needed to evaluate the reason for this phenomenon. The local HH clusters in terms of the TR and HR indices were in the same area in both developed countries. The observed significant linear relationship between HR and TR indices supports this finding. Thus, it is highly probable that the locations of hotspots in terms of TR and HR indices in most developed countries are the same. The distribution of subdivisions regarding the TR index was cluster-like, and significant LL or HH spatial clusters were detected in the countries. These findings proved that countries are not homogenous regarding subdivision-level RSIs, and regional variations in RSIs could exist in most countries, despite their socioeconomic background. The identified significant and massive spatial clusters of subdivisions in Türkiye and the USA indicate the considerable divergence inside these countries regarding RSIs. Additionally, these findings suggest that road safety is a public health problem in these countries, and further studies are needed to examine the reasons for the existence of these vast spatial clusters.

The spatial analysis results in Türkiye, such as the identified significant clusters, are in accordance with previous studies (Ahmadpur and Gokasar, 2021; Erdogan, 2009). The result of spatial analysis in England indicated that despite low RTF levels in this country, significant LL and HH cluster cores exist in this country. There are safe regions in unsafe countries and unsafe regions in safe countries, and these findings should be considered by researchers, decision-makers, and authorities when comparing regions based on their RSIs. These results are in line with the findings of Lassarre and Thomas (2005). Thus, spatial analysis is needed to identify road safety-deficient regions regarding RSIs, even in countries with low road fatalities, such as England. The findings of this dissertation regarding low HR indices in southern parts of England are in accordance with the findings of Wachnicka et al. (2021). The conducted statistical and spatial analyses significantly contributed to identifying road safety-deficient regions in the countries. In all studied countries, it was observed that the TR index is higher in underdeveloped regions, and the same index is low in undeveloped subdivisions. This finding is in accordance with previous studies (Ahmadpur and Gokasar, 2021; Erdogan, 2009; Tortum and Atalay, 2015; Wachnicka et al., 2021).

7. CONCLUSIONS AND RECOMMENDATIONS

Because of the complexity of road safety issues, regional road safety studies should be conducted in countries with various backgrounds, and their result combines to reach a major conclusion. Although numerous road safety studies have been conducted in various countries, little attention has been paid to severity indices, the association between RSIs, and spatial distribution of sub-divisions regarding road safety performance. Also, the difference and similarities between developed and developing countries regarding road safety performance have been neglected in the literature. This dissertation tried to fill that gap by studying regional road safety conditions in five countries. In this respect, this dissertation does not just provide an overview of the relevant literature, but it also provides a critical review of regional road safety indicators. Although researchers in road safety fields are targeted first in this dissertation, the ideas and insights offered throughout the dissertation can be utilized by authorities and policymakers focusing on implementing road fatality preventive programs, policy upgrades, or systematic improvement initiatives.

7.1. Conclusions Regarding Spatial Analysis

- Comparing the result of Türkiye and Iran with the literature indicate that RTCs are more severe in the remote and underdeveloped regions in developing countries. Spatial distribution and diversity within Türkiye and Iran regarding RSIs and the existence of a vast cluster of regions with low road safety performance prove that road safety is a public health problem in developing countries. The HR and TR risk rates provide opposite and different maps. Thus it is suggested that further consideration should be given in the process of selecting an RSI for comparing administrative divisions of a country. This issue is important, especially in the process of budget allocation and road safety policy implementation.
- Regional variability of socioeconomic variables and RSIs in studied regions demonstrated that governments and road authorities should implement region-based specific road safety policies to reduce RTF and RTC rates more efficiently.
- Positive Moran's I index did not guarantee the observation of significant cluster cores regarding an index. On the other hand, when Moran's I is negative, the

nonexistence of hot or cold spots is highly potential.

- Observation of local clusters regarding RSIs in England shows that even in a country with low RTF levels, hotspots exist, and consequently, regional road safety studies must be conducted in all countries to identify road safety deficient regions and conduct regional crash preventive programs. The location of hot and cold spots regarding the TR and HR indices are the same in the USA and England. Thus, the same pattern could also be observed in other developed countries.

7.2. Conclusions Regarding Influencing Factors on Road Safety Indices

- In developing countries such as Iran and Türkiye, the general road safety conditions are better in regions with higher income and education levels. By increasing income and education levels, it is possible to reduce the adverse effects of road crashes in developing countries. The presence of heavy vehicles and rural population significantly influences road fatality rates on intercity roads in developing countries.
- The studied road crash severity, including the FPC (fatality per crash), FPNF (fatal crash per non-fatal crash), and FPI (fatality per injury) indices, have similar attributes, and each one could be used in road safety studies as a crash severity indicator based on data availability.
- Modeling crude RSIs, such as RTF, using socioeconomic indices is easier than ratio-one RSIs, such as HR. Also, modeling severity indices are more challenging than other RSIs. This finding should be considered in future road safety studies. In administrative divisions of countries, higher exposure values, such as population or RMVs, mean higher road fatalities.
- There is a nonlinear association between MR and TR indices of sub-divisions, and regions with higher motorization rates tend to have a lower TR index. The association between developed countries' regional HR and TR indices is significant and linear. Comparing regions based on their TR index is more appropriate.

7.3. Overall Conclusions

- The absence of a standard system for naming or organizing the RSIs was observed, and each study refers to the RSIs differently. A standard system is needed to organize and categorize the RSIs in road safety studies.
- Reviewed literature regarding road traffic safety issues in various provinces of Iran showed that a significant fraction of RTCs were preventable. Accordingly, decision-makers and experts are recommended to deliberate on the literature that explains the causes and locations of road traffic safety problems. This consideration could aid them in precise and efficient planning toward reducing RTCs.

7.4. Future Work

- Given the existence of substantial spatial clusters in terms of RSIs in countries such as the USA, and the increasing number of road fatalities in recent years, we highly advise that future studies identify the root cause of these spatial clusters in order to effectively enable future research on reducing road traffic crashes and related fatalities.
- Further studies in other countries regarding the associations between RSIs and socioeconomic variables are suggested. Also, observed spatial patterns suggest that spatial analysis regarding road safety indices in other countries is needed.
- In this dissertation, the influence of various socioeconomic indices on RSIs was evaluated. In the future, the impact of railway systems and land transport modes on the road safety performance of regions could be evaluated.
- Our review indicates that a limited number of road safety studies have compared developing and developed countries in terms of road safety performance, and an insufficient number of studies have been conducted regarding road safety conditions in developing countries. Thus, further road safety studies are needed to fill this gap in the literature.

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