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Retraction

Retracted: Prediction of Risk Takers in Arterial Hypertension Patients with Data Mining Application

Wireless Communications and Mobile Computing

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Alhazmi and F. Alassery, "Prediction of Risk Takers in Arterial Hypertension Patients with Data Mining Application," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5093049, 8 pages, 2022.

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Research Article

Prediction of Risk Takers in Arterial Hypertension Patients with Data Mining Application

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Hyper arterial pressure (HAP) is a disease that kills silently because it does not produce symptoms in the early stages, making it difficult to diagnose. When it is detected, its treatment is not accessible to everyone, which affects the disease's long-term development. Hypertension affects a large portion of the Iraqi population. In the current research paper, we have discussed how data mining can be applied to identify the status of the risk factors that affect arterial hypertension due to I10-I15 causes, evaluating the context variables disability, overwork, high-risk pregnancy, stress, high diets, and poor nutrition in the population between 50 and 64 years in the city of Baghdad. It is possible to see how data mining in large volumes of health data can generate new knowledge and thus uncover hidden patterns in the data through the development of this research. Attributes directly linked to disease prevalence can be found in data from Baghdad, Iraq, even if they are not directly linked to a specific cause. This shows that some variables are transversal to the development of the disease regardless of its categorization. Cluster analysis revealed that, even though these diseases are categorized as having different causes, they have a degree of incorrect classification of 40.71% because they present attributes with a similar behavior transversal to the disease and not the disease-specific cause for which it is categorized.

1. Introduction

According to the World Health Organization (WHO), chronic noncommunicable diseases represent 60% of deaths globally [1]. Currently, 77% of these diseases occur in developing countries. Its development seriously affects adults who are in the prime of their lives and at the time of greatest productivity. Specifically in Arabic countries, it is more frequently associated with elevated triglycerides, increased blood pressure, and glycemic abnormalities in women. At the same time, in men, it is more closely related to abdominal obesity, elevated blood pressure, and glycemic abnormalities, where the prevalence of this syndrome increased with age, being more accentuated in women. Dyslipidemia is prevalent, although with variations [2]. Between 13.4% and 44.2% of people have elevated blood pressure, which is a risk factor for arterial hypertension. With age, blood pressure increased with men, and pulse pressure increased more in women.

On the other hand, smoking accounts for between 38.6% and 45.4% of all risk factors. Younger men are more likely to be diagnosed with the disease (25-34 and 35-44 years) [3]. Men begin their careers at an average age of 13.7 years old, whereas women begin their careers at an average age of 14.2 years old, with a range of 13.7 to 20.0 years. Data mining is currently being used in a wide range of industries, including healthcare [4]. Applications in this area include the recognition of mental images, hospital patient management systems, and methods for analyzing symptoms, diseases, and treatment outcomes to predict and treat specialized diseases. For diseases like heart disease and high-risk pregnancies, being able to identify the factors that

Prediction of risk takers in arterial hypertension patients with data mining
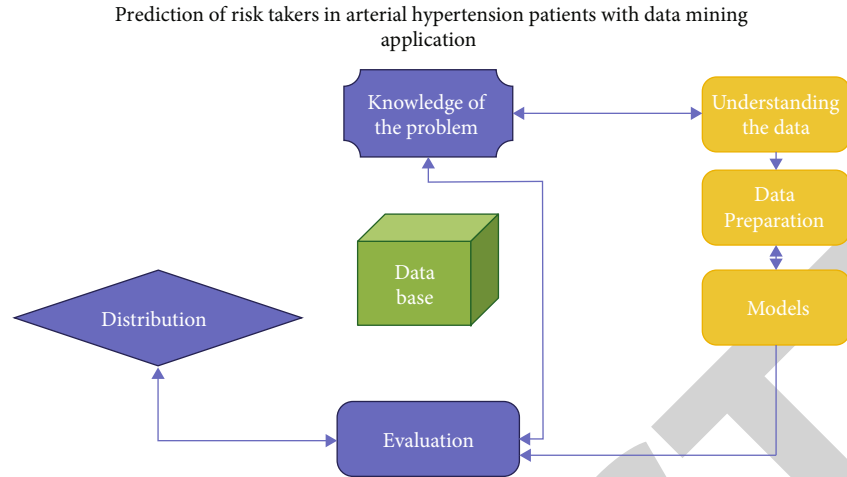application

Figure 1: A CRISP-DM process model.

influence a patient's risk of developing a disease is critical to their early treatment [4].

Based on good practices and the evolution of information analysis, new technologies have been established that seek to make the most of data to make important contributions to the different sciences reflected in our lives daily. That is why the present investigation presents data mining application in favor of health sciences. Through data mining, the different variables that affect patients can be evaluated and classified by different algorithms that facilitate this activity, such as KStar, FarthestFirst, and CART [5], which are found in more detail throughout the document. The research began with the premise of how data mining can be applied to be able to evaluate the causes in which arterial hypertension is classified so that the state of the risk factors can be identified, taking into account the variables whose change can affect the status of patients who are between 50 and 64 years old who are inhabitants of the city of Baghdad [6]. Taking into account the high mortality rate that occurs due to cardiovascular diseases, this document is intended to provide a clearer vision of the different causes and variables, that through data mining, a pattern or correlation between the different causes and that in this way it is possible to give a more assertive diagnosis of. Data mining has an important role as a support tool that allows the exploration, analysis, understanding, and application of the knowledge acquired in handling large volumes of information. The data mining algorithms make it possible to understand trends and behaviors in the data, thus allowing knowledge-based decision making [7].

Therefore, in this study, it is proposed to expose, through the use of the WEKA computational software and the application of some clustering models, how it can be contributed through the use of data mining techniques [8], both in the diagnosis of diseases and in the prevention of the causes that could derive in arterial hypertension, where the risk factors of the cause of death in the I10-I15 interval are detected, relating through a process of correlation context variables such as disability, overwork, pregnancy of high risk, stress,

high diets, and poor nutrition. Therefore, the research unites a set of studies and intends to respond through data mining to identify the status of the I10-I15 factors [9] with the search for the context variables associated with arterial hypertension, applying for this clustering models and association of attributes in the databases of the health sector in the city of Baghdad [10–13]. It is expected that by relating the methodology and algorithms for recognizing these patterns in HTN disease through the WEKA tool, the correlation curve of the state of said condition to factors correlated with the context variables is shown, illustrating the situation of patients between 50 and 64 years of age in the city of Baghdad, and establish good practices to stabilize these causes of death.

2. Material Methods

2.1. Research Approach. A quantitative approach is carried out to analyze the information available on the population with arterial hypertension in Baghdad [14–16], taking into account the causes I10-I15. This methodology is called quantitative because it allows the grouping of the variables associated with the phenomenon being investigated to present its measurement and behavior and allows certain decisions to be determined that may be relevant for both the detection and treatment of the disease.

2.2. Type of Research. This study is descriptive; for this purpose, we worked with WEKA as a software suite that supports several data mining (DM) tasks; it has the advantage that it provides interfaces for communication with the user. To account for the stated objective, the CRISP-DM methodology was considered, which identifies six steps to carry out the DM process. Figure 1 shows the steps identified by the CRISP-DM methodology process, highlighting the knowledge of the problem, data compression, data preparation, models, evaluation, and performance measurement:

The WEKA tool will allow various operations to be carried out before applying the data mining algorithms, in addition to various preprocessing tasks, among which attribute

TABLE 1: Attributes selected to perform the data mining process.

Attributes	Description
Marital status	est_civ
Age	Age
History of diseases in the family	ant_fam
If the person has a disability	Disc
How much work per day	hor_lab
Pregnancy	Question
In case of being pregnant	preg_time
Type of sex	Gender
If the person consumes alcohol	Alch
How often do you drink alcohol?	alch_cnto
Amount of alcohol consumed	alch_cntd
Voluntary drug use	Sad
Sedentary lifestyle	Will give
Cholesterol	Cabbages
Attributes	Description
Diabetes	Diabe
Triglycerides	Trigi
Do physical activity	Act_fis
Practice intensity	Act_fis_int
Strain	Tension
Blood pressure	pres_art
Weight	Weight
Height	Height
Take nicotine	Tobacco
How many do you consume per day?	tabac_cnts
How long have you been smoking	tabac_time
Have had heart surgery	oper_cora
Travel constantly	Trip
How often do you travel in a given period of time?	How much_travel
Employment status	est_lab
Belongs to any ethnic group	group_ethni
Rate the level of both work and daily stress	Stress
Level of schooling	Study
How long do you sleep	drm_time
Stratum	Stratum

filters stand out, with which all kinds of data transformations can be carried out. In this case, the first thing that will be done is the application of the remove filter, which consists of eliminating a range of attributes and thus finding different behaviors among the attributes obtained and thus filtering those attributes that are not relevant or were redundant for the study to classify the different variables later. Finally, only 34 attributes were taken into account, all considered within the dimensions of hypertension, Baghdad population, ages 50-64, and context, which are of interest for this study, as can be seen in Table 1.

2.2.1. Population. The public object of the present analysis is the population in the locality of Iraq in the city of Baghdad aged between 50 and 64 years with a diagnosis of AHT, approximately 7.5 million inhabitants, and approximately 5% of these are over 65 years of age.

2.3. Research Design

2.3.1. Phase I: Sample and Data Collection. The current status of the main factors that affect the diagnosis of hypertension and the target population was obtained. It is important

```
=== Summary ===

Correctly classified instances          9086          99.6709%
Incorrectly classified instances        30            0.3291%
Kappa statistic                         0.9822
Mean absolute error                     0.0016
Root mean squared error                 0.0339
Relative absolute error                 2.1078%
Root relative squared error             17.6233%
Total number of instances               9116

=== Detailed accuracy by class          =
```

	TP rate	FP rate	Precision	Recall	F-measure	MCC	ROC area	PRC area	PRC area
	0.955	0.000	0.977	0.955	0.966	0.965	0.975	0.964	I13
	0.939	0.001	0.92	0.939	0.929	0.929	0.988	0.945	I12
	0.978	0.000	0.986	0.978	0.982	0.982	0.996	0.979	I11
	0.994	0.001	0.988	0.994	0.991	0.99	0.997	0.994	I15
	0.999	0.012	0.999	0.999	0.999	0.986	0.997	0.999	I10
Weighted avg.	0.997	0.011	0.997	0.997	0.997	0.985	0.996	0.998	

```
=== Confusion matrix ===
a     b     c     d     e <-- classified as

84    1     0     0     3I      a = 113
0     92    0     0     6I      b = 112
0     0     219   4     1I      c = I11
0     0     2     494   1I      d = 115
2     7     1     2     8197I   e = I10
```

Figure 2: KStar ranking algorithm result.

to identify, based on each factor, which data are relevant and can be useful to process and obtain information that is decisive for the treatment of is. These will be known as the input data to be able to carry out a diagnosis in the prototype of the model [17].

(1) Description of the Repository. The database under analysis contains a population of 35,741 deaths from arterial hypertension that occurred in Iraq in 2021. The information was obtained in PDF files from the Arterial Hypertension databases in Iraq's National Health Information System. The data was first transformed into Excel to purge the database and work only with those necessary attributes for the research.

Once the cleaning was done, it was transformed into a CSV file to work the data with the WEKA software. The initial file contained 49 attributes, which correspond to descriptive data such as general patient data, product data, the cause of death, and information on the medical history of the product patient, to characterize the 35,741 cases of death from hypertension [18, 19].

2.3.2. Phase II: Proposal Design

(1) Business Understanding. As defined in the CRISP-DM model, the understanding of the business is the first phase, which is where the objects and requirements must be defined to meet the business perspective, which in this research is the identification of the risk factors mentioned above in arterial hypertension; for this, it is necessary to previously define what the clinical objectives of the investigation

are and what is the expected result of the investigation and take into account different situations that may hinder the fulfillment of these objectives, such as available resources, databases available, integrity in the same, and the privacy of the patient on the data [20].

(2) Understanding the Data. In this phase, you must begin to understand the data in order to become familiar with them; in this way, find problems in the stored data and finally be able to define a vision that allows you to understand the data you have, for which some tasks are needed to be carried out, mainly the initial collection of data, describing the data obtained, exploring the data (this refers to getting involved with the data and understanding what data is available and what information is relevant to the topic to be investigated) and as the last task to verify that the data obtained have the pertinent importance for the research.

(3) Data Preparation. In this phase, a selection, transformation, and purification will be carried out with the aim of creating a final database where a data standard is handled; for this, it is necessary to perform tasks such as defining reasons to preserve or eliminate data that serve the objective. For the investigation, purge missing data and determine its relevance; given the case that the highest percentage of data is lost, it should be omitted due to the uncertainty that it can generate in the final result and define common structures of the attributes that are possessed.

(4) Modeling. In this phase, the selected model is used to process the previously refined data; in this, it is subdivided into tasks to generate a test plan with which the effectiveness

TABLE 2: Final attributes used in data mining.

Attributes	Description	Variable
est_civ	Marital status	
Age	Age	
ant_fam	History of diseases in the family	
Disc	If the person has a disability	
hor_lab	How much work per day	
Question	Pregnancy	
preg_time	In case of being pregnant	
Gender	Type of sex	
Alch	If the person consumes alcohol	
alch_cnto	How often do you drink alcohol?	
alch_cntd	Amount of alcohol consumed	
Stupid	Voluntary drug use	
Will give	Sedentary lifestyle	
Cabbage	Cholesterol	
Diabe	Diabetes	
Trigi	Triglycerides	
Act_fis	Do physical activity	
Act_fis_int	Practice intensity	Nominal
Tension	Strain	
pres_art	Blood pressure	
Weight	Weight	
Height	Height	
Tobacco	Take nicotine	
tabac_cnts	How many do you consume per day?	
tabac_time	How long have you been smoking	
oper_cora	Have had heart surgery	
Trip	Travel constantly	
How much_travel	How often do you travel in a given period of time?	
est_lab	Employment status	
group_ethni	Belongs to any ethnic group	
Stress	Rate the level of both work and daily stress	
Study	Level of schooling	
drm_time	How long do you sleep	
Stratum	Stratum	

of the model and results can be validated. In this phase, it must be taken into account that it is possible to return to the data preparation phase due to what is found with the application of the model.

Data are classified according to the International Classification of Diseases scheme (ICD-10) [21, 22]. Once the data is organized in WEKA, a statistical analysis is performed, and in the application of the KStar algorithm, the causes of death due to hypertension (I10-I15) with the highest number of classified cases are reflected.

(5) Application of Data Mining Techniques. Once the data preparation process was carried out, which resulted in the

sintering of the dimension of the original database, given that the modeling stage requires selecting and filtering the process, the grouping of the data proceeded.

For the purposes of this study and considering the characteristics of the data, the KStar classification algorithm was implemented; this algorithm is based on the variables; that is, the classification of a variable is based on similar training variables, and it uses a distance function based on entropy [23]. The classification method generates the learning of the characteristics that identify a group to be classified within a certain class, which allows the understanding of the system that generates the data and predicts at a given moment the class to which a

new instance will belong. In order to evaluate the feasibility of the classifier, the evaluation is based on the percentage of correctly classified instances and is given by the confusion matrix that the classifier algorithm generates as a final result.

In Figure 2, it is observed that the columns of the matrix indicate the categories classified by the classifier and the rows the real categories of the data, while the elements in the main diagonal mean the classifications without failure. Those that are not on the main diagonal signify the errors that the algorithm made. Under this premise, the KStar algorithm produces a confusion matrix with 99.6709% of correctly classified instances; 9086 instances were correctly classified.

Continuing with the modeling stage, as a complement to defining the pattern of arterial hypertension death cases due to causes I10-I15, a clustering algorithm was applied. Clustering is defined in the DM as a process that divides the data into groups of similar objects, representing the data by cluster series achieves the simplification of these. Put it like this: clustering is an unsupervised machine learning technique.

In order to explain the dependent variable and establish the correlation of variables, the CorrelationAttributeEval algorithm was used. This evaluator attribute evaluates the value of an attribute by measuring the (Pearson's) correlation between it and the class. Nominal attributes are considered in a value base value by treating each value as an indicator. An overall correlation for a nominal attribute is carried through a weighted average.

The algorithm was applied with the ranker method; this method evaluates and orders attributes individually and eliminates the least valued ones. The result obtained can be seen in the results section.

(6) Evaluation. This phase has certain importance because it is the one that determines the effectiveness of the process and defines if the deliverable obtained includes the objectives to satisfaction; here, the effectiveness must be evaluated at the business level and based on the theories already prescribed on arterial hypertension. An expert on the subject must be included in this analysis due to the knowledge they possess to be able to evaluate correctly without any personal criteria; in addition, once validated, the steps to be followed must be reviewed to apply the research later [24, 25].

2.3.3. Phase III: Information Analysis. As a first step in the CRISP-DM methodology, a definition of what was expected as a result of the investigation will be made; as a second step, starting from the database of patients with arterial hypertension, the available data is understood, explored, and categorized manually in the first iteration; later, the already known database is taken, and a new one is created only with the main data that serve the research objective; After this, based on this new database. The *k*-means algorithm is applied through the WEKA tool, which through graphs shows us the clusters that it separates and determines the behavior of the data; with these clusters, it is evaluated if the results agree with what is expected.

```
Clustered instances
0        5154        57%
1        312         3%
2        197         2%
3        2785        31%
4        668         7%

Class attributes: cause_def
Classes to clusters:
0        1        2        3        4 <--- Assigned to clusters
3        242      191      1        62   II15
85       14       3        87       38   II11
27       14       1        35       19   II12
5038     4        0        2657     513  II10
4        38       2        5        36   II13

Cluster    0 <--- I10
Cluster    1 <--- I15
Cluster    2 <--- I12
Cluster    3 <--- I11
Cluster    4 <--- I13
Incorrectly clustered instances :   3712.0      40.7196%
```

FIGURE 3: Result of the execution of the FarthestFirst algorithm.

3. Results and Discussion

This section presents the results obtained through the use of data mining, applied to determine the pattern of characteristics of deaths from arterial hypertension that occur due to causes I10-I15 and the evaluation of the variables smoking, sedentary lifestyle, obesity, diabetes, stress, and cholesterol in the population between 50 and 64 years of age in the city of Baghdad (the variables are delimited in Table 2), and their intersection with the dependent variable causes I10-I15.

Considering the results of the exploratory statistical analysis of the repository and given that the causes of death of AH with the highest record in 2017 were the causes of I10-I15, therefore, the decision was made to work on this cause as an object of study with DM techniques.

Having applied the CorrelationAttributeEval algorithm correctly, the following attributes were selected. It was observed that the variable with the highest correlation was cabbage and trigi, which represents the information contained in the variables of cholesterol and triglycerides as a factor that triggers death. It was found that there is a weak positive correlation between variables given the correlation indices, which yielded 0.065953 as a result.

It can be seen that the attributes that refer to the lack of physical activity and stress generate a prevalence in most of the evaluated cases, and it can be understood in the context that not having a specific behavior will be the trigger of the disease if not that it can be the accumulation of different that is necessary for the development of the disease.

Once the evaluation of the applied model and the results obtained based on the applied algorithms have been carried out, it is possible to see how the disease behaves based on the variables selected in this way, answering the initial question. Due to this, it can be determined that the different causes described in sections I10-I15 are affected in a certain way in their behavior, prevalence, and evolution by variables not directly related to the disease, such as stress, overwork, and poor diet.
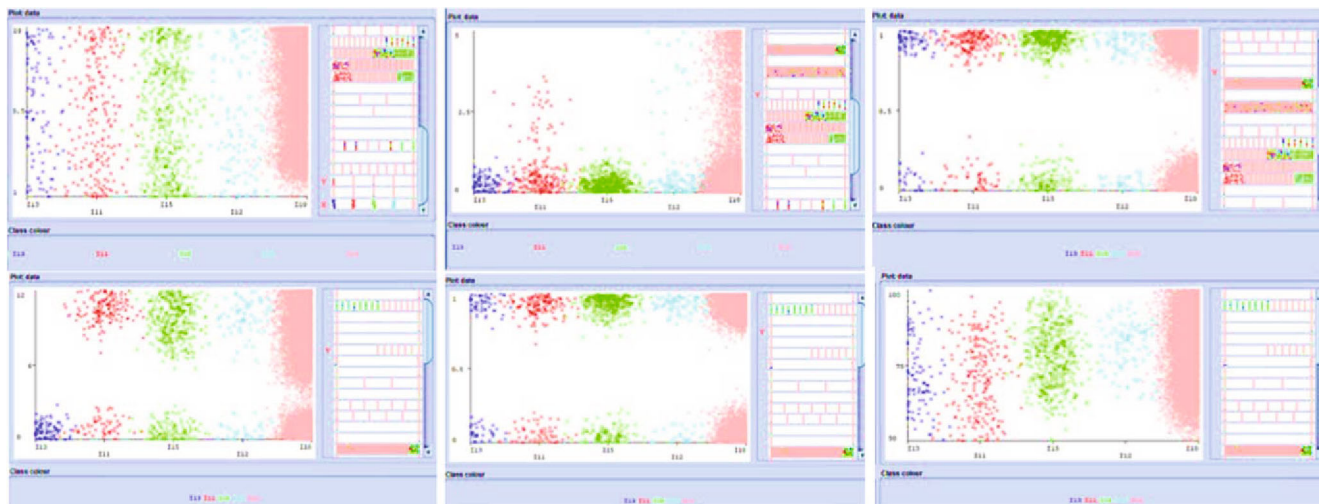
Figure 4: Clustering results using the FarthestFirst algorithm.

For this study, several clustering algorithms were tested. However, it was decided to use the farthest first because it is the one that allowed obtaining a higher percentage of duly grouped instances. This algorithm is a variant of the k-means algorithm. The farthest first starts by randomly selecting an instance that becomes the cluster centroid computes the distance between each of the instances and the center, and the distance that is furthest from the closest center is selected as the new cluster center [26]. The following clusters were obtained once the classification and clustering algorithms were applied (Figure 3).

Once the FarthestFirst algorithm was applied, it allows us to visualize graphically how the clusters are distributed according to each of the attributes present in the entered data; starting from this point, the causes I10-I15 are taken as the x-axis to be able to verify their behavior is based on the most important variables, which were found to generate a higher prevalence of the different causes. The result and behavior can be visualized in Figure 4.

4. Conclusions and Recommendations

4.1. Conclusions. The development of this research allows visualizing how the use of data mining in large volumes of data in the health area allows generating new knowledge about it and, consequently, determining hidden patterns in the data. In this specific case of data from the city of Baghdad, it was possible to determine the correlation of some of the 34 attributes directly with the prevalence of the disease regardless of the causes for which they were cataloged; with this, it is shown that some variables will be transversal to the development of the disease regardless of the categorization in which it is found.

Through the clusters, it was possible to determine that despite being categorized as different causes, they present a degree of 40.71% of instances incorrectly classified because they present attributes with a similar behavior that are transversal to the disease and not to the disease, a specific cause for which it is being categorized. Even so, it can be seen that

the I10 cause is the dominant hypertensive disease, which according to previous studies affects 90% of patients with some kind of hypertensive disease.

It is important to take into consideration that this research was only carried out based on the database of deaths from arterial hypertension in the city of Baghdad, which only allows the advantages of using data mining to be analyzed because the information processing is limited, and it is not possible to have feedback from patients to be able to feedback and improve the process, this being a limitation for the evolution of ideas after the research.

It was possible to show that through data mining techniques, it is possible to obtain very assertive results more comfortably; however, it is necessary to have equipment powerful enough to reduce analysis times, which are high if you do not count with the right equipment, and in the future, it can be a problem when generating results for health entities.

4.2. Recommendations

(i) Broaden the work base given that with a greater amount of information and more diversity in the population, and more factors that lead to deaths reported by AHT could be detected depending on the area and its qualities

(ii) Based on the development of the research, it could be verified if the behavior KStar, FarthestFirst, and CARTs of the causes of hypertension are equally affected in other cities of the country, in this way, to corroborate if the development of the diseases presents with the same evolution as the one demonstrated here

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

Acknowledgments

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