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Data analysis methods for evaluating cardiovascular disease in patients

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ABSTRACT

Data analysis in the healthcare sector can be an important tool for identifying patterns in the data. When it comes to low-density lipoprotein (LDL) cholesterol test results, lower values are preferable. This paper details a factor analytical method whose main objective is to create a very effective risk prediction model for cardiovascular incidence. Both qualitative and quantitative methods were used to generate and test the hypothesis. To investigate the attributes' associations with and relevance to cardiovascular, a data understanding analysis is specifically carried out. This paper aims to evaluate the variables affecting LDL-C by using data analytics. Consistency, convergent, and discriminant have all been considered when evaluating the prediction model. The results showed that high-density lipoprotein (HDL) significantly reduces LDL with (P 0.001, = 0.04), whereas, total cholesterol (TC) has a considerable impact on LDL with (P 0.001, r = 0.92), whereas, Very-low-density lipoprotein (VLDL) significantly affects LDL with (P 0.001, = −0.16) and, triglycerides (TG) significantly affects LDL with (P 0.001, = −0.20). The outcome will be a prediction model based on a neural network and data analysis.

1. Introduction

The field of medicine is developing very quickly, and numerous studies have found a connection between elevated cholesterol levels and the development of cardiovascular diseases like vascular disease and stroke. LDL-C reduction is the main objective of lipid-lowering medications, which is used to classify people according to their risk of developing cardiovascular disease. Intense lipid-lowering therapy with statin drugs is advised following a stroke attack [1]. There hasn't been enough study on the ideal level related to the low-density lipoprotein in preventing heart problems after a stroke [2]. Aiming for ideal plasma lipoprotein levels and reducing the risk of heart disease traditionally required advice to restrict dietary fat. This leads to the conclusion that a person's lifetime cumulative exposure to LDL-C greatly influences their likelihood of developing the vascular disease [3]. Compared to the standard technique, straight homogenous assays are frequently used in hospitals to test LDL-C since they are sufficiently accurate and precise. Nonetheless, because many of these methods are expensive, they are not routinely performed in clinical laboratories. Instead, most clinical laboratories calculate LDL-C using the Friedewald formula. It is frequently used for normal LDL assessment and a range of biomedical studies since it is straightforward, affordable, and easy to use [4]. This formula has several restrictions. Medical LDL-C measurement is typically pricy and time-consuming [5], The Friedewald formula as well as other related formulas depend on computations utilizing the other lipid profile variables of TC, HDL, and TG, therefore research started exploring ways to anticipate its level in computational methods. The researchers have demonstrated that the formulas are inaccurate since they depend on a constant quantitative relation and variable lipid profile parameters that don't follow predictable patterns, even though study and experimentation have shown more effective methods for determining the LDL-C values even when the other parameters are erratic [5], innovative techniques that can correctly categorize and forecast depending on the patient's medical history, taking into account the most significant risk factors [6,7]. This study focuses on the analysis and significance of hypothesis testing of various variables affecting LDL-C, which is the primary indicator, predictor, and cause of cardiovascular, a type of harmful disease. This requires accurate analysis of each variable for such harmful diseases on human health.

2. Review of previous related studies

Cholesterol, particularly LDL-C, has piqued the interest of researchers due to its detrimental effect on human health and even life. A

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Table 1
Summary of previous related studies.

Previous studies	results
Liu et al. [8]	They proposed that having high levels of TC and LDL-C could be a health risk for intellectual disability.
Cainzos-Achirica et al. [9]	With prolonged treatment durations, the benefits of LDL-C lowering do not appear to be stable but rather steadily increase.
Alder et al. [10]	They show that the variability in LDL-C is increased by 16.2 points when a statin and a bile acid sequestrant are taken together.
Katzmann et al. [11]	Diabetes and hypertension constituted the most common heart disease risk variables among patients examined by medical doctors accordingly (81.7% and 74.7%).
Li et al. [12]	Using machine learning with gradient boosting (LDL-CX) and neural networks, better correlations with directly measured LDL-C were demonstrated.
Banda et al. [13]	Clinical significance at the local website is achieved by manually reviewing the charts of participants who were identified by the algorithm and verified in a different location.

summary of prior related investigations is included in Table 1.

Direct homogenate assays are often used in laboratories to detect LDL-C because they assess LDL-C with adequate precision and accuracy in contrast to the reference method. However, several of these techniques are not often employed in clinical laboratories due to their high cost [4]. Previous studies demonstrated that the equations are inaccurate because they rely on a constant ratio value and variable lipid profile variables that don't follow predictable patterns [14], new techniques that can accurately classify and predict based on the patient's medical record, including the most influencing risk factors, have been developed, even though experiments and research started to find more effective ways for detecting the LDL-C values [6]. Therefore, this study used a neural network to predict and identify the risk factors affecting LDL-C value in patients. The dataset is subjected to factor analysis to produce a useful prediction and evaluation of the parameters.

2.1. LDL-C benefits and issues

Longer treatment periods tend to continuously boost the effects of LDL-C lowering rather than being fixed. There is consistency between the results of simple randomized clinical trials and the highly substantial relationships between LDL-C and cardiovascular events discovered in random studies [15]. No symptoms exist for high cholesterol. Sadly, excessive cholesterol is typically only identified in the setting of a complication, such as a heart attack or stroke. It can be recognized with normal laboratory tests. Poor food, smoking, and a sedentary lifestyle are some factors that contribute to the reasons. Less frequently, genetics could also have a role in elevated cholesterol. Early issues and a considerable rise in cholesterol levels can be caused by a genetic abnormality. Statistics show that one in 250 persons is impacted. Because of this, the physician must be aware of both the patient's medical history and genetic factors [15]. LDL cholesterol can accumulate on blood vessel walls when there is an excess of it in the body. Plaque is the term for this accumulation, which can result in health issues like stroke and heart disease [16].

2.2. Lipid profile risk factors

A thorough empirical analysis of the lipid profile risk factors context has been conducted [17,18], An accumulation of lipids (cholesterol and triglycerides) in the blood can damage blood vessels and arteries and raise the risk of cardiovascular disease [19,20]. According to L. Samsell [21], they conclude that the gynoid fat ratio, which is closely connected with diabetes and lipoprotein in people of normal weight, may serve as a marker of the risk of metabolic and cardiovascular disorders. To examine the significance of lipids and LDL cholesterol in defining CVD risk in diabetes patients, it is necessary to analyze Cardiovascular risk in a big sample of diabetic people [22]. From the perspective of the present study, it is an essential matter to identify and predict LDL-C level earlier for patients Fig. 1 shows the conceptual model. Such perspectives have participated in motiving the present study to suggest the hypotheses as shown below.

H1. There is a significant effect between HDL factor and LDL-C level.

H2. There is a significant effect between the VLDL factor and LDL-C level.

H3. There is a significant effect between Triglyceride factor and LDL-C level.

H4. There is a significant effect between the Total cholesterol factor and LDL-C level.

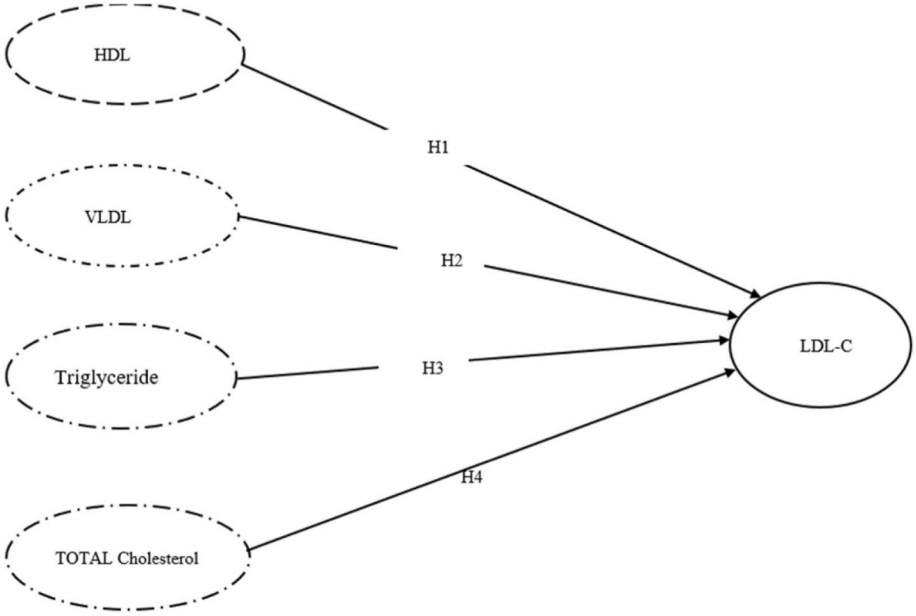

Fig. 1. Conceptual model of the study.

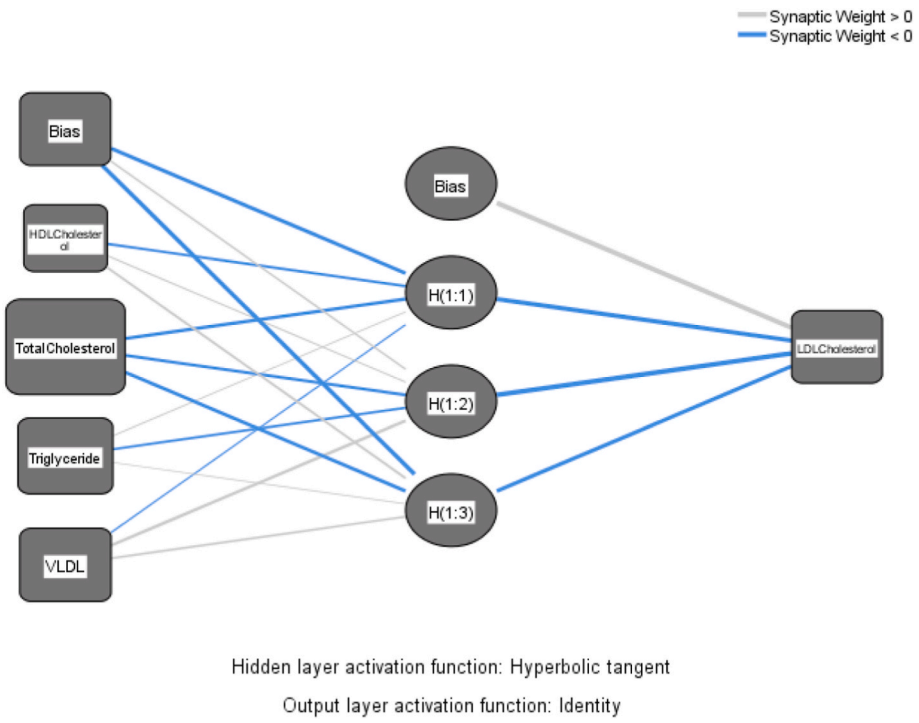

Fig. 2. Architecture of neural network.

3. Methodology

To clarify the research issue and goals, a thorough literature review was done. Research design is the method of arranging research activity in ways that are most likely to achieve the research objective, including data collection [23,24]. It presents credible information for research purposes and offers exploratory, descriptive, and hypothesis-testing studies as the three basic research design types [24]. For this study, both qualitative and quantitative methods utilizing hypothesis generating and testing were the most appropriate [25]. Data on lipid profiles were gathered from the Middle East Medical Lab at Basra city in Iraq, which included the patient's total cholesterol (TC), triglycerides (TG), High-density lipoprotein (HDL), and low-density lipoprotein (LDL). Values from lipid profiles that lacked total cholesterol, triglycerides, HDL, and LDL were removed. Only the first result from any lipid profile tests that the same patient obtained during the study period was included in the dataset. Following a review of the lab, a total of 7430 records of lipid profiles were selected for the inquiry. The 7430 profiles' data were then randomly divided into a training set (70% of the total data) and a test set (30% of the total data). To create the prediction models, 5195 lipid profile data were employed, and the remaining 2240 lipid profile data were used to test the models. The patient dataset is used to train the model through a neural network. Every lipid profile parameter was assessed using Cobas Integra 400 plus (Roche Diagnostics). Before running the neural network, data were prepared for analysis. Random number generation allows replicating the results of neural networks exactly irrespective of providing training again and again. The total dataset was divided into three parts namely training, testing, and holdout.

Moreover, the links between the independent variables affecting LDL-C are addressed by the hypotheses. A statistical hypothesis is a claim regarding one or even more sample size (s) [26] As part of this study's design, the interactions with an independent variable and the dependent variables were tested. The independent variables that affect LDL-C are HDL, TC, VLDL, and triglycerides, while LDL-C is the dependent variable. Statistical analysis was carried out using SPSS to test the correlation between numerical variables including LDL-C, VLDL, TC, Triglyceride, and HDL through the Pearson Correlation approach. Additionally, measurement model estimation was done to evaluate the reliability and determine how different variables affected the results. In addition, analysis was performed to evaluate consistency, convergent, discriminant, and testing the hypothesis. In addition, PLC-regression outer model analysis was used to compare and predict the model along with the neural network.

3.1. Research paradigm

A paradigm is a theoretical framework that guides the development of scientific (and other) hypotheses and the conduct of scientific knowledge. Paradigm shifts are significant alterations in thought and behavior [27]. Ontological studies focus on "what's out there to know," dealing with the hypothesis of the nature of reality [28]. On the other side, epistemological issues center on how to become conscious of the thing being studied. "What and how can we know about it?" [29]. The goal of this study is to predict LDL-C levels based on several parameters. Therefore, the suitability of epistemological for this research can be described in the following points.

1. The epistemological premise is that obtaining the patient's profile is the ideal route to get data [30] because it necessitates a study of their circumstances. The goal of this study is to investigate and forecast patients' LDL-C levels.
2. LDL-C and related metrics are modifiable following the patient's state. A social constructivist viewpoint embraces the dynamic, evolving character of information, that is not fixed but rather part of a continuous process, influenced by social activity. With patients, new risk factors may emerge.

This study focuses on the analysis and significance of hypothesis testing of various variables affecting LDL-C, which is the primary indicator, predictor, and cause of cardiovascular. Therefore, this work would be best approached in the sense of the social constructivism paradigm, since it shows the multiplicity of factors that have interacted to assess the distinctive and dynamic character of the patient's under

Table 2
Parameters estimate.

Predictor		Predicted -Hidden Layer 1			Output Layer LDL-C
		H(1:1)	H (1:2)	H(1:3)	
Input Layer	(Bias)	−9.816	.185	−16.389	
	HDL	−.504	.137	.365	
	TC	−2.852	−.811	−6.352	
	TG	.089	−.418	.027	
	VLDL	−.143	.661	.295	
Hidden Layer 1	(Bias)				69.176
	H (1:1)				−27.534
	H (1:2)				−71.878
	H (1:3)				−15.539

Table 3
Measurement model evaluation.

Construct	Loadings	AVE	CR
HDL	0.885	0.918	0.856
VLDL	0.742	0.719	0.843
Triglyceride	0.648	0.942	0.917
TC	0.690	0.671	0.781

Table 4
Correlation of the parameters.

LDL	VLDL	TC	TG	HDL
(1.000)	−0.366	0.079	−0.366	0.030
−0.366	(1.000)	0.443	0.998	0.238
0.079	0.443	(1.000)	0.443	0.839
−0.366	0.998	0.443	(1.000)	0.238
0.030	0.238	0.839	0.238	(1.000)

review [31].

4. Results and discussions

4.1. Neural network

In this study, the network is constructed with a single hidden layer. The input layer contains the predictors. For this study, the input layer will contain VHDL, TC, Triglyceride, and HDL parameters. contains invisible components or nodes. The number of each hidden unit depends on the variables, and the form of the function depends on the network type and user-controllable parameters. LDL-C will be presented in the output layer. Based on the functionality of the predictor parameters, a multilayer perceptron neural network is utilized to construct a prediction model for the dependent variable. Fig. 2 shows the architecture of the neural network.

By learning a mapping from data to parameter values, neural networks are used to "recognize" or estimate the parameter values of a specific structural econometric model. This study simulates the dataset generated under various ranges of parameters using the structural model to train the neural network. Table 2 shows parameter estimates.

4.2. Data analysis

To identify the significant effects of the parameters in LDL-C a measurement model estimation was performed to assess validity), the discriminant of the validity which includes the indicator and the outer loading, and also to evaluate the consistency reliability. The outcomes found for the reflective measurement model are shown in Table 3.

Table 5
Discriminant Validity using Fornell and Lacker Criterion.

	HDL	VLDL	Triglyceride	TC
HDL	0.832			
VLDL	0.356	0.782		
Triglyceride	0.364	0.399	0.922	
TC	0.355	0.478	0.433	0.766

Table 6
Cross-loadings.

	HDL	VLDL	Triglyceride	TC
HDL	0.733	−0.255	0.355	−0.001
VLDL	0.294	0.839	0.051	−0.211
Triglyceride	0.367	0.399	0.998	−0.211
TC	−0.041	−0.200	0.704	0.674
LDL	−0.175	−0.232	0.663	0.839

To determine the dependability of the parameter for each build, the composite reliability was determined. The dependability of the variable constructs has been confirmed by the composite correlations, which are all greater than 0.7 [32]. The Average Variance Extracted (AVE) is used to assess the converging accuracy of the measurement model [33,34]. According to Table 1, all of the test's hypotheses have AVE values higher than 0.5, indicating that they all fulfill the criteria for convergent validity [35]. The correlation presented in Table 4 provides evidence that all parameters converge on the same construct.

The Pearson correlation methodology, which offers a number ranging from 1 indicating a total positive correlation to 0 indicating a total negative correlation, is the most often used method for assessing numerical parameters. Moreover, using the Fornell and Larcker method is a popular method to evaluate a measurement model's discriminant validity [36]. The findings in Table 5 indicate that the values are significantly greater than 0.50 for each particular element in the main square root and higher than the correlations for the elements in the associated rows and columns, satisfying the criteria for a significant value. According to Valencia et al. [37] and due to the concepts' obvious differences compared to one another, this demonstrates that discriminant validity has been obtained.

In this study it is important to check the discriminant validity, it demonstrates how accurately a test measures the hypothesis it was intended to measure. Particularly, discriminant validity assesses the relationship between constructs that conceptually ought not to be correlated to one another. In addition, comparing the cross-loadings between constructs is one method for obtaining the discriminant validity evaluation shown in Table 6. According to Table 6, each indication has an increase on its specific construct but a lower loading on some other constructions. This suggests that the investigation model constructs are unique from one another and have a good level of discriminant validity.

4.3. Structural model evaluation

To perform a structural model evaluation there is a need to use six different tests according to Ghasemy et al. [38]. These tests involve assessing the structural model for correlation problems, the importance, and significance of the relationship between the conceptual framework,

Table 7
Full collinearity VIF.

Constructs	Full collinearity VIF
HDL	1.311
VLDL	1.428
TRIGLYCE	1.122
TC	1.199

Table 8
Results of hypotheses testing.

Hypothesis	Relationships	P-value	Path Coefficient(β)	Effect.Size (f2)	Comments	Decision
H1	HDL -LDL	<0.001	0.250	0.089	Significant	Supported
H2	VHDL-LDL	<0.001	0.344	0.129	Significant	Supported
H3	Triglyce-LDL	<0.001	0.257	0.199	Significant	Supported
H4	TC-LDL	<0.001	0.250	0.089	Significant	Supported

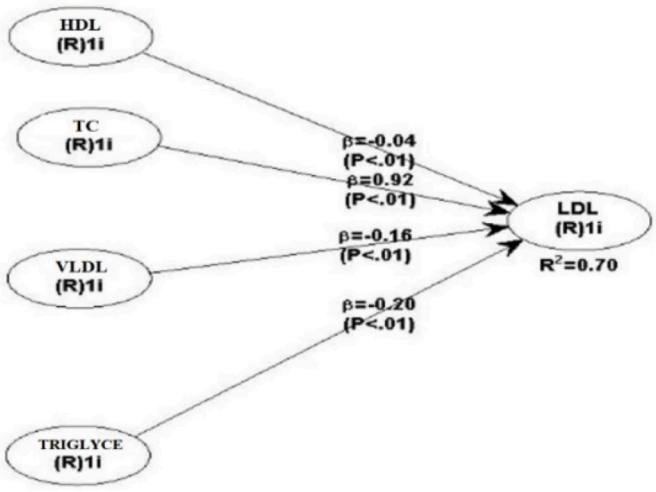

Fig. 3. Prediction model.

the level of the coefficient of determination R2, the significance level (f2), and the significance of the prediction. The variance inflation factor (VIF) is employed to assess the collinearity of the model. All of the fixtures in the model have VIF values lower than 3.3, which satisfies the cut-off value proposed by Diamantopoulos and Siguaw [39]. This suggests that the model is free of collinearity issues. This study's R2 value of 0.30 shows that the model has a considerable degree of predictive accuracy. The VIF values are shown in Table 7.

4.4. Hypothesis testing and predication model

The findings of the hypothesis testing are shown in Table 8. The findings show that HDL significantly reduces LDL (P 0.001, = 0.04), which is consistent with hypothesis 1. Concerning H2 the finding showed that TC has a considerable impact on LDL (P 0.001, r = 0.92). Additionally, VLDL significantly affects LDL (P 0.001, = −0.16), supporting H3, and finally, TG significantly affects LDL (P 0.001, = −0.20), supporting H4. Fig. 3 shows the structural model outcomes.

According to Cohen [40] who advise, the effect sizes (f2) of the connections are interpreted. Slight effects are defined as f2 values above 0.02 and up to 0.15, moderate effects as 0.15 and up to 0.35, and big impacts as 0.35 and above. Variables evaluating the hypothesis do indeed have an impact and connection to LDL-C.

The p-value is a measurement used in this study to determine statistical significance; if it is less than the significance level, the result is considered statistically significant. The importance of the data analysis has been shown by the cross-loading, correlation, and discriminant test, among other methods. To develop a prediction model, this study used SPSS Analysis and the PLC-regression outer model analysis approach. With an R2 of 70%, the variables studied have a significant impact on LDL-C.

5. Conclusion

To identify the possibility of developing cardiovascular disease. This study tested four parameters within the hypothesis to evaluate the prediction model produced by this study. LDL is the dependent variable, and the independent variables are the combined effects of HDL, TC, VLDL, and TG. The P-value was used in this study as statistically significant which has been proven to be significant in the data analysis stage. A prediction model has also been developed from this study based on a neural network and the analytics of data to identify the level of LDL-C. The results showed that all variables have a significant impact on LDL-C with an R2 of 70%. In addition, the R2 value of 0.30 shows that the model has a considerable degree of predictive accuracy.

CRediT authorship contribution statement

Waleed Noori Hussein: Conceptualization, Methodology, Study design, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Zainab Muzahim Mohammed:** Conceptualization, Methodology, Study design, Validation, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Zainab A. Almnaseer:** Conceptualization, Investigation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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