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Cardiovascular Disease Prediction Analysis Using SPSS Statistics

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Abstract

Having both high LDL cholesterol and low HDL cholesterol Better your risk of heart disease is one. A blood lipid profile is your cholesterol Numbers and your triglycerides, in the blood Numbers and your triglycerides, in the blood another type of fat is a risk factor. CVD A blood test can be used to predict Scientists have found. Science Translational The study, published in the journal Medicine, for CVD The door to personalized treatment plans opens. Identify new CVD drugs It can also improve build speed. Neuroscience to predict heart disease risk a useful heart disease using network A predictive system is developed. This system age, Gender, blood pressure, cholesterol and obesity Using 15 clinical parameters viz to predict. What Risk factors for heart disease? Heart disease and the most important behavioral risk factors for stroke Unhealthy diet, physical inactivity, tobacco Use and alcohol can be harmful. You If there is diagnosed with heart disease, you cannot cure it. But you can contribute to the development of coronary artery disease Treat things. In turn can reduce how the condition affects your body.

Key Words: cardiovascular associated with disease, heart disease and stroke, CRP

I. Introduction

1 in 4 deaths each year, According to the CDC, the leading cause of death in the United States is heart Disease is the main cause. Approximately 6 million Americans currently have heart disease Dysfunction exists, and that number is 46 by 2030 that percentage will increase to 8 million expected. Chest pain panic attacks and heart attacks although common to both, the characteristics of pain often vary. A panic during an attack, chest pain is usually sharp or stabbing and in the middle of the chest will be kept. Chest pain due to heart attack May resemble a feeling of pressure or squeezing. to you If you have heart disease, such as If you have a heart attack or stroke, your life expectancy will be reduced. A little bit from you every time Take too much and make it hard to get back to normal. That being said, all the changes you need make a healthy lifestyle wholeheartedly If followed, you can live a full and long life. Elevated cholesterol levels in hypertensive adults increase Risk of heart disease and stroke. Obesity, lack of exercise and a diet that includes high sugar and highly processed foods are often the culprits. Stress can lead to high blood pressure, which can lead to heart attacks and Increases the risk of stroke. Smoking, like Excessive diet and physical activity Absence can also contribute to stress cardiovascular disease risks. "Chronic stress has been shown to be associated with increased cardiovascular events," Schifrin said.

II. Cardiovascular Disease Prediction

Participants with no Recorded baseline history of cardiovascular disease included; Cause-specific deaths or vascular phenomena or both, well defined Assessed according to criteria and during follow-up registered; More than 1 year Follow-up data were also recorded. [2] CRP levels and incidence among healthy individuals the literature examining cardiovascular disease is predominantly CRP and focuses on the relationship between CVD. Adequate consideration of the experimental characteristics of CRP and its addition. Factor measurement over and above the utility offered by traditional risk [3] cardiovascular disease of the heart or blood represents vessels Refers to a category of related diseases. Cardiovascular disease is technically the heart system refers to any disease affecting; Atherosclerosis It usually refers to those associated with inflammation is used. including [4] Cardiovascular disease is a major cause of morbidity and mortality has effective prevention strategies, Trusted tools for clinicians to practice Required, individuals without known cardiovascular disease [5] Cardiovascular Disease (CVD) is angina pectoris is one that involves the circulatory system It is a chronic disease. It is usually heart attack, others Atherosclerosis is associated with inflammation. Social- Along with economic growth, China's population is aging and urbanization are accelerating; have to identify, a cardiovascular event is at high risk. Been some changes in national lifestyles,[6] The guidelines and charts Previous New Zealand cardiovascular disease risk Coordinate the evaluation schedule renewing. It is for managing the risk of cardiovascular disease Not guidance [7] Because higher glycolic values are CVD The methods used are more cardiovascular associated with disease (CVD) events predict risk Adding information on glycolic values to CVD Corresponding to improvements in predictive ability It is proposed that there may be [8] Cardiovascular disease includes a hospital or neurologist report that diagnoses Transient ischemic attack or ischemic stroke. Documented peripheral artery disease is one of the following or includes two criteria: ankle index 0.9 with present intermittent claudicating or Angioplasty, stinting, atherectomy, peripheral Arterial bypass graft or other related History of intermittent claudicating with interventions. [9] Despite decades of decline in Cardiovascular disease (CVD), CVD morbidity in the United States and is a Growth is a major cause of morbidity and mortality leading cause of morbidity and mortality in countries Will change soon. Recent data is troubling Report the spread diabetes, obesity and metabolic syndrome, CVD risk factors, [10] Cardiovascular disease (CVD) Today in developed countries it is fatal the biggest single reason. So, this A huge financial burden on the health service and then some The incidence of CVD will increase over the decades expected. Comprehensive clinical and statistical Studies show several factors that increase the risk CVD have identified. [11] A surveillance system was set up to identify new cases of fatal and non-fatal cardiovascular disease (CVD) and a follow-up examination was conducted in survivors approximately years after the first examination. Basic risk models for predicting coronary (CHD) events and common CVD events as a function of traditional risk factors were recently developed and compared with previously published Italian risk functions for cardiovascular diseases.[12] We control for High-density lipoprotein cholesterol ratio, per patient Cardiovascular disease diagnosis or screening Before being done, and before statin drugs, Values after base date. Systolic blood To estimate the pressure variation, [13] one might expect that variants with a sole action of regulating Cholesterol levels predict cardiovascular disease Does not improve. Lipid levels in the prediction model If included. Indeed they are in diversity have an independent effect. [14] Individuals at high risk of developing cardiovascular disease (CVD). Aim for lifestyle modification or drug therapy is the basis of primary prevention programs. [15] Cardiovascular disease, particularly ischemic It's for heart disease and stroke, and death is the main reason world by a significant margin. Accurately predicting who will develop CVD remains challenging. [16] Cardiovascular disease is considered the most serious and deadly disease in humans. The increased prevalence of cardiovascular diseases with high mortality rates poses a significant risk and burden to global health systems [18] Age, sex, hypertension, atherogenic such as hyperlipidemia, smoking and diabetes After accounting for traditional risk factors, HIV-related Risk of cardiovascular disease among victims adults is increased by 40–75% compared with HIV-uninfected individuals.[19] This worsens the overall cardiovascular Risk profile. Nurses' health survey and More large prospective studies such as Buffalo Health Weight and obesity increase cardiovascular disease (CVD). are shown to be associated with risk. [20] Arterial wall thickening is a sign of atherosclerosis. Thus IMD measurements help predict cardiovascular disease (CVD) and thereby CVD only due to traditional risk factors Improves prediction. [21] A recent study of the influence of lipid-associated variation in the prediction of incident Plasma cholesterol levels in cardiovascular disease Residual predictive value for genetic variation detected. [22] Fourth Joint Working Group on European Cardiology et al Societies for Cardiovascular Disease Prevention in Clinical Practice, American Diabetes Association National Institutes of Health and British Association of Medical Specialties Canadian Diabetes Association, [24] Estimates of Cardiovascular disease (CVD) risk prediction information Provide treatment strategies for individual patients Can also be used to select. In recent years Several risk models have been developed. [25] Without other healthy lifestyle factors Compared to non-smokers, each extra Factors also had a lower risk of cardiovascular disease, 45% risk reduction with all factors. Traditional Lifestyle factors in risk factor models When added, recreational physical activity Only associated with cardiovascular disease risk. [28] Globally, Cardiovascular disease (CVD) morbidity and It is the leading cause of death, and of CVD The primary reason Current clinical guidelines for prevention are prevention Asymptomatic patients who may benefit from the procedure Emphasize the need for identification. based on their predicted risk.[29] High GGT levels increase cardiovascular disease (CVD). Several show an independent association with risk with reports. with improvements in CVD prognostic capacity Relative current CVD risk prediction Discussion of including measurements of GGT with algorithms is growing. [30]

Abnormal TG: DG has also emerged as a predictor of growth Progression of renal complications (6). of these data Basically, at risk of diabetic nephropathy Measurements of plasma lipids in the prognosis of people with Prognostic value of albumin excretion It seems likely to increase. [31] Several early light microscopic, neurological studies revealed no significant neuronal Lesions in the adult TG mouse CNS. Age appropriate wild type significant from mice. However, Isaacs et al consider the values of the following parameters have reduced rats, [32]

Smokers: In Behavioral selection tasks show that smokers often have small, Opt for instant cash and big, delayed cash are doing High levels of impulsivity. Among other tasks there were no differences between the groups' choices. Between the data from each task as with contacts, questionnaire and task data Correlations between were small. [33] Using an integrated observational design, moderate to severe COPD and non-COPD Patients with two control groups we commissioned and tested them. High sensitivity using the CRP assay. By exercise Induced ischemia and Angina, we determined patients with IHD and excluded patients. [34]

Abnormal Tc: Bone marrow stromal cells from TCPTP/ mice secretes an abnormally large amount of express, of which of Stat1 in pre-B cells as a result Phosphorylation increases and in the bone marrow Altered B-cell development occurs. Our findings Novel and leukemia and other bone marrow TC-PTPs in the stroma microbiome in immune disorders are used as modulators of the environment. Reflect therapeutic potential. [35] Multifocal cerebral in Tc-99m HMPAO SPECT A previously unreported study of perfusion Anti-NMDA-R encephalitis with abnormalities we provide the patient. [36]

Abnormal LDL: May protect against cardiovascular disease through several mechanisms, in which 1 is LDL at the sub endothelial site Prevents oxidation. In action, it is Oxidized phospholipids into lysophospholipids; thereby biol destroys reactive fatty acids. Changed to a minimum [37] Beta measurement of cholesterol evaluated the reference measurement procedure. Although this method is more accurate, it is time consuming In intake and routine laboratory tests It is not economical as it is not used. Serum total Simple to calculate LDL-C from Cholesterol (TC). A formal roasting vault assessment is routine is used. [38]

Abnormal HDL: Plasma LDL-C in-manganese precipitation Calculated using the Fried-Walt formula. Plasma concentrations were measured using immunoturbidimetric assays as previously reported, and two monoclonal antibodies Mass by a sandwich ELISA using Measured [39] Control objects and overweight LDL-C was higher in T2DM patients than in controls. Cholesterol was high. LDL- and HDL- Although there are differences in cholesterol, Apo B plasma and Apo A-I concentrations were similar among the four groups were. [40]

Abnormal FPG: Continuous variables included BMI, fasting glucose level and LDL. high blood pressure, Aspirin and betablocker drugs and are significant coronary artery disease on angiography Dummy variables were created to exist. [41] Abnormal FPG in the non-diabetic range has also worse in patients with cardiovascular disease (CVD). [42]

TABLE 1. Correlations

	Obesity	Over Weight	Waistline is large	Abnormal TG	Smokers	Abnormal TC	Abnormal LDL	Abnormal HDL	Abnormal FPG
Obesity	1	-0.002	-0.156	-0.01	-0.021	0.001	0.033	-0.169	-0.017
Over Weight	-0.002	1	-0.01	-0.195	-0.042	0.163	0.115	.231*	-0.059
Waistline is large	-0.156	-0.01	1	-0.137	-0.141	-0.044	0.078	0.09	0.007
Abnormal TG	-0.01	-0.195	-0.137	1	-0.083	0.073	-0.025	0.047	-0.019
Smokers	-0.021	-0.042	-0.141	-0.083	1	-.297**	-0.168	-0.033	-0.031
Abnormal TC	0.001	0.163	-0.044	0.073	-.297**	1	0.014	-0.06	-0.033
Abnormal LDL	0.033	0.115	0.078	-0.025	-0.168	0.014	1	0.084	0.142
Abnormal HDL	-0.169	.231*	0.09	0.047	-0.033	-0.06	0.084	1	-.203*
Abnormal FPG	-0.017	-0.059	0.007	-0.019	-0.031	-0.033	0.142	-.203*	1

Table 1 shows the correlation between the Obesity for Abnormal HDL has the highest correlation value of --0.169 so it has a high correlation with Abnormal TG and the lowest correlation value is -0.01.Correlation between the Over Weight for Abnormal HDL has the highest correlation value of .231* so it has a high correlation with Waistline is large and the lowest correlation value is -0.01.Correlation between the Waistline is large for Obesity has the highest correlation value of -0.156 so it has a high correlation with Over Weight and the lowest correlation value is -0.01. Correlation between the Abnormal TG for Over Weight has the highest correlation value of -0.195 so it has a high correlation with Obesity and the lowest correlation value is -0.01. Correlation between the Smokers for Abnormal TC has the highest correlation value of -.297** so it has a high correlation with Obesity and the lowest correlation value is -0.01. Correlation between the Abnormal TC for Smokers has the highest correlation value of -.297** so it has a high correlation with Obesity and the lowest correlation value is 0.01. Correlation between the Abnormal LDL for Smokers has the highest correlation value of -0.168 so it has a high correlation with Obesity and the lowest correlation value is 0.033. Correlation between the Abnormal HDL for Abnormal FPG has the highest correlation value of -.203* so it has a high correlation with Abnormal TC and the lowest correlation value is -0.06. Correlation between the Abnormal FPG for Abnormal HDL has the highest correlation value of -.203* so it has a high correlation with Waistline is large and the lowest correlation value is 0.007.

Table 2. Statistics

Statistics										
		Over Weight	Obesity	Waistline is large	Abnormal TG	Smokers	Abnormal TC	Abnormal LDL	Abnormal HDL	Abnormal FPG
N	Valid	100	100	100	100	100	100	100	100	100
	Missing	0	0	0	0	0	0	0	0	0
Mean		2.88	2.98	3.07	2.82	3.04	3.06	3.13	3.35	3.28
Std. Error of Mean		0.101	0.11	0.111	0.124	0.13	0.134	0.118	0.127	0.129
Median		3	3	3	3	3	3	3	3	3
		3	2	3	2	3	3a	3	3	4
Std. Deviation		1.008	1.101	1.112	1.242	1.302	1.34	1.178	1.266	1.288
Variance		1.016	1.212	1.237	1.543	1.695	1.794	1.387	1.604	1.658
Skewness		-0.177	0.133	-0.006	0.092	0.121	-0.111	-0.068	-0.355	-0.251
Std. Error of Skewness		0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
Kurtosis		-0.338	-0.805	-0.657	-1.062	-1.009	-1.132	-0.691	-0.811	-0.999
Std. Error of Kurtosis		0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
Range		4	4	4	4	4	4	4	4	4
Minimum		1	1	1	1	1	1	1	1	1
Maximum		5	5	5	5	5	5	5	5	5
Sum		288	298	307	282	304	306	313	335	328

Percentiles	10	1	2	2	1	1	1	1.1	1	1
	20	2	2	2	2	2	2	2	2	2
	25	2	2	2	2	2	2	2	3	2
	30	2	2	2	2	2	2	3	3	3
	40	3	3	3	2	3	3	3	3	3
	50	3	3	3	3	3	3	3	3	3
	60	3	3	3	3	3	4	3	4	4
	70	3	4	4	4	4	4	4	4	4
	75	4	4	4	4	4	4	4	4	4
	80	4	4	4	4	4.8	4	4	5	5
	90	4	4	5	4	5	5	5	5	5

Table 2 shows the statistics values for analysis N, range, minimum, maximum, mean, standard deviation, Skewness Mode, Kurtosis, Percentiles, Sum, Std. Error of Kurtosis**.** Over Weight, Obesity, Waistline is large, Abnormal TG, Smokers, Abnormal TC, Abnormal LDL, Abnormal HDL, and Abnormal FPG.

III. Histogram

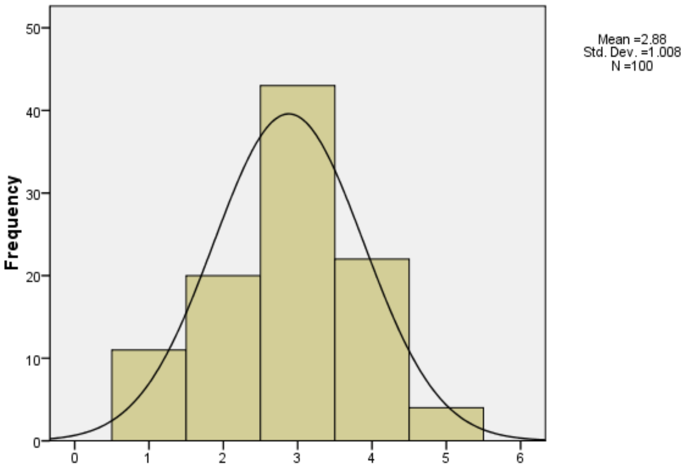

Fig 1. Over Weight

Figure 1 shows a histogram plot for Over Weight from the figure where it can be clearly seen that the data is slightly skewed to the left due to high values for 1to 5 bell crow, while all other values are under the normal curve, the sample substantially follows a normal distribution.

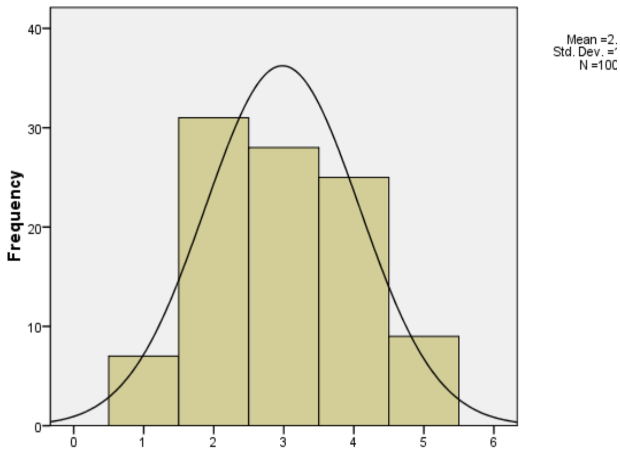

Fig 2. Obesity

Figure 2 shows a histogram plot for Obesity from the figure where it can be clearly seen that the data is slightly skewed to the right due to high values for 0.5 to 5.5, while all other values are under the normal curve, the sample substantially follows a normal distribution.

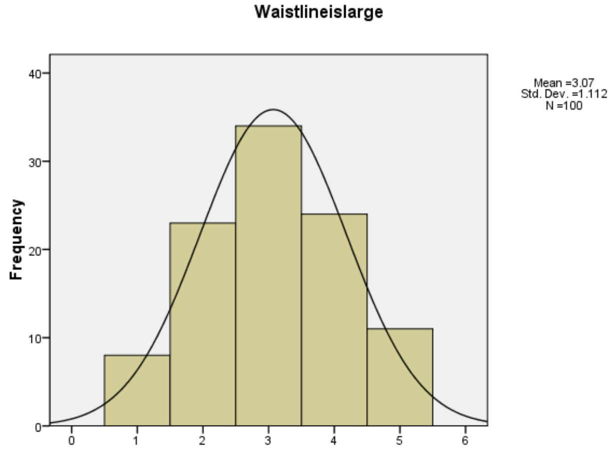

Fig 3. Waistline is large

Figure 3 shows a histogram plot for Waistline is large from the figure where it can be clearly seen that the data is slightly skewed to the right due to high values for 0.5 to 5.5, while all other values are under the bell crow, the sample substantially follows a normal distribution.

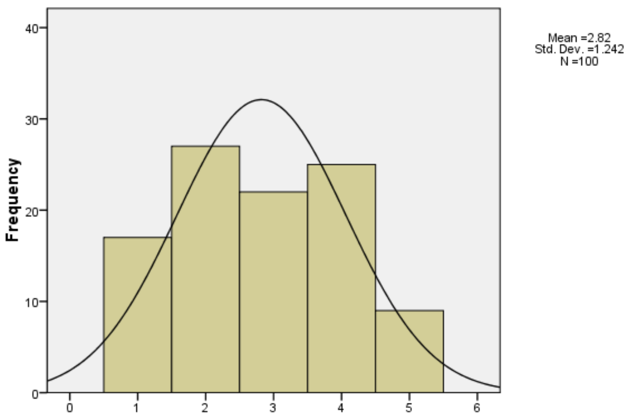

Fig 4. Abnormal TG

Figure 4 shows a histogram plot for Abnormal TG from the figure where it can be clearly seen that the data is slightly skewed to the right due to high values for 0.5 to 5.5, while all other values are under the normal crow, the sample substantially follows a normal distribution.

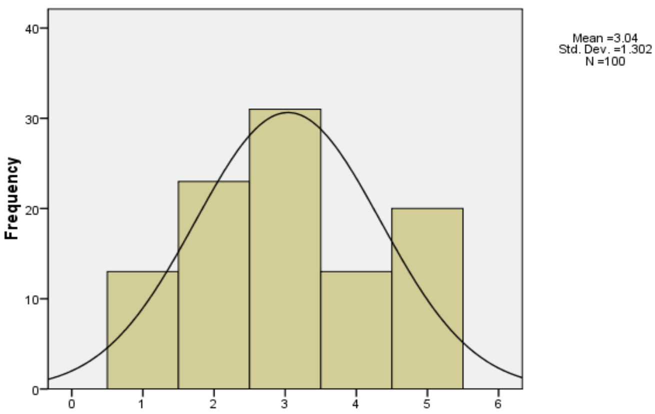

Fig 5. Smokers

Figure 5 shows a histogram plot for Smokers from the figure where it can be clearly seen that the data is slightly skewed to the right due to high values for 0.5 to 5.5, while all other values are under the normal crow, the sample substantially follows a normal distribution.

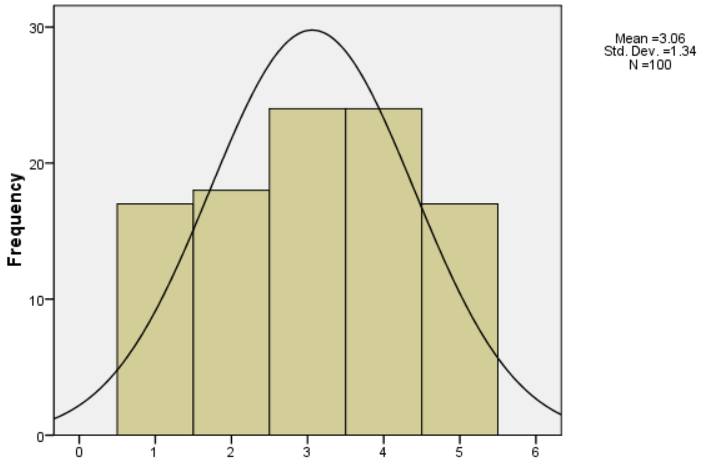

Fig 6. Abnormal TC

Figure 6 shows a histogram plot for Abnormal TC from the figure where it can be clearly seen that the data is slightly skewed to the right due to high values for 0.5 to 5.5, while all other values are under the normal crow, the sample substantially follows a normal distribution.

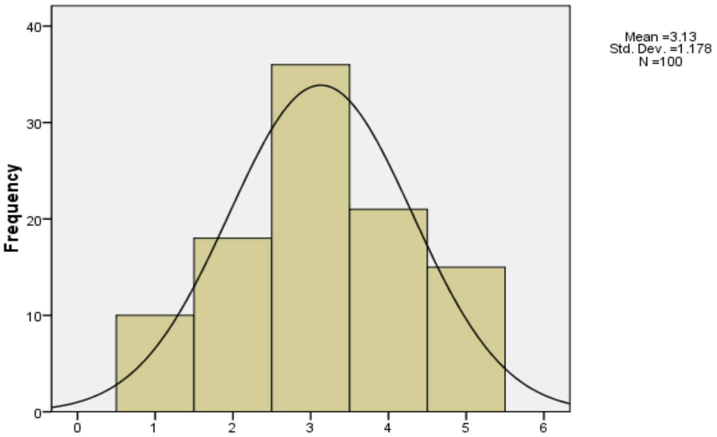

Fig 7. Abnormal LDL

Figure 7 shows a histogram plot for Abnormal LDL from the figure where it can be clearly seen that the data is slightly skewed to the right due to high values for 0.5 to 5.5, while all other values are under the almost bell crow, the sample substantially follows a normal distribution.

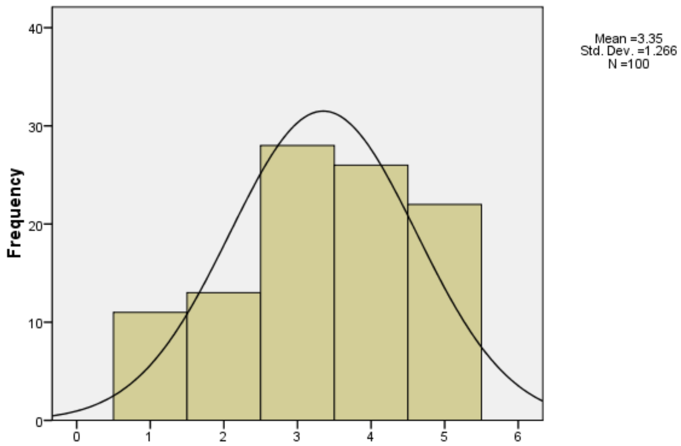

Fig 8. Abnormal HDL

Figure 8 shows a histogram plot for Abnormal HDL from the figure where it can be clearly seen that the data is slightly skewed to the right due to high values for 0.5 to 5.5, while all other values are under the normal crow, the sample substantially follows a normal distribution.

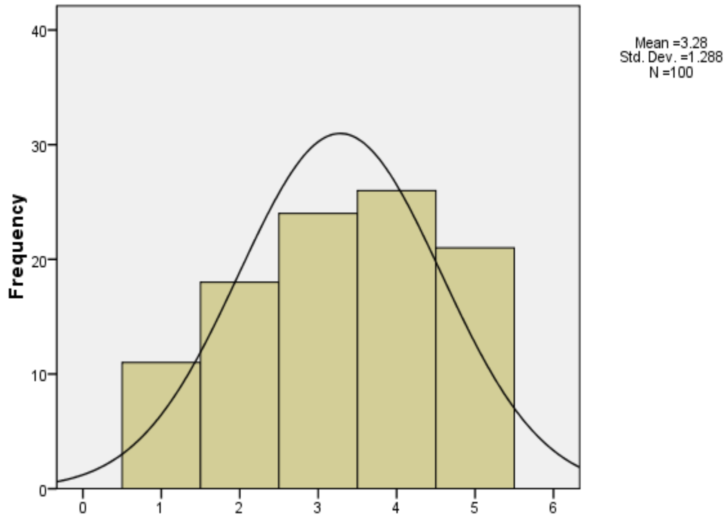

Fig 9. Abnormal FPG

Figure 9 shows a histogram plot for Abnormal FPG from the figure where it can be clearly seen that the data is slightly skewed to the right skewed due to values for 0.5 to 5.5, while all other values are under the normal crow, the sample substantially follows a normal distribution.

TABLE 3. Descriptive Statistics

Descriptive Statistics												
	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Over Weight	100	4	1	5	2.88	0.101	1.008	1.016	-0.177	0.241	-0.338	0.478
Obesity	100	4	1	5	2.98	0.11	1.101	1.212	0.133	0.241	-0.805	0.478
Waistline is large	100	4	1	5	3.07	0.111	1.112	1.237	-0.006	0.241	-0.657	0.478
Abnormal TG	100	4	1	5	2.82	0.124	1.242	1.543	0.092	0.241	-1.062	0.478
Smokers	100	4	1	5	3.04	0.13	1.302	1.695	0.121	0.241	-1.009	0.478
Abnormal TC	100	4	1	5	3.06	0.134	1.34	1.794	-0.111	0.241	-1.132	0.478
Abnormal LDL	100	4	1	5	3.13	0.118	1.178	1.387	-0.068	0.241	-0.691	0.478
Abnormal HDL	100	4	1	5	3.35	0.127	1.266	1.604	-0.355	0.241	-0.811	0.478
Abnormal FPG	100	4	1	5	3.28	0.129	1.288	1.658	-0.251	0.241	-0.999	0.478
Valid N (list wise)	100											

Table 4 shows the descriptive statistics values for analysis N, range, minimum, maximum, mean, standard deviation, Skewness, Kurtosis**.** Over Weight, Obesity, Waistline is large, Abnormal TG, Smokers, Abnormal TC, Abnormal LDL, Abnormal HDL, and Abnormal FPG.

TABLE 4. Reliability Statistics

Reliability Statistics		
Cronbach's Alphaa	Cronbach's Alpha Based on Standardized Itemsa	N of Items
-0.311	-0.272	9

Table 4 shows Cronbach's Alpha Reliability result. The overall Cronbach's Alpha value for the model is -0.311 which indicates 50% reliability. From the literature review, the above 40% Cronbach's Alpha value model can be considered for analysis.

IV. Conclusion

Age, sex, hypertension, atherogenic such as hyperlipidemia, smoking and diabetes After accounting for traditional risk factors, HIV-related Risk of cardiovascular disease among victims adults is increased by 40–75% compared with HIV-uninfected individuals. This worsens the overall cardiovascular Risk profile. Nurses' health survey and more large prospective studies such as Buffalo Health Weight and obesity increase cardiovascular disease (CVD). We control for High-density lipoprotein cholesterol ratio, per patient cardiovascular disease diagnosis or screening before being done, and before statin drugs, Values after base date. Systolic blood to estimate the pressure variation, several early light microscopic, neurological studies revealed no significant neuronal Lesions in the adult TG mouse CNS. May protect against cardiovascular disease through several mechanisms, in which 1 is LDL at the sub endothelial site Prevents oxidation. In action, it is Oxidized phospholipids into lysophospholipids; thereby biol destroys reactive fatty acids.

V. Reference

[1]. Emerging Risk Factors Collaboration. "C-reactive protein, fibrinogen, and cardiovascular disease prediction." New England Journal of Medicine 367, no. 14 (2012): 1310-1320.

[2]. Lloyd-Jones, Donald M., Kiang Liu, Lu Tian, and Philip Greenland. "Narrative review: assessment of C-reactive protein in risk prediction for cardiovascular disease." Annals of internal medicine 145, no. 1 (2006): 35-42.

[3]. Amma, NG Bhuvaneswari. "Cardiovascular disease prediction system using genetic algorithm and neural network." In 2012 International Conference on Computing, Communication and Applications, pp. 1-5. IEEE, 2012.

[4]. Siontis, George CM, Ioanna Tzoulaki, Konstantinos C. Siontis, and John PA Ioannidis. "Comparisons of established risk prediction models for cardiovascular disease: systematic review." Bmj 344 (2012).

[5]. Yang, Li, Haibin Wu, Xiaoqing Jin, Pinpin Zheng, Shiyun Hu, Xiaoling Xu, Wei Yu, and Jing Yan. "Study of cardiovascular disease prediction model based on random forest in eastern China." Scientific reports 10, no. 1 (2020): 1-8.

[6]. Jackson, Rodney. "Updated New Zealand cardiovascular disease risk-benefit prediction guide." Bmj 320, no. 7236 (2000): 709-710.

[7]. Di Angelantonio, Emanuele, Pei Gao, Hassan Khan, Adam S. Butterworth, David Wormser, Stephen Kaptoge, Sreenivasa Rao Kondapally Seshasai et al. "Glycated hemoglobin measurement and prediction of cardiovascular disease." Jama 311, no. 12 (2014): 1225-1233.

[8]. Wilson, Peter WF, Ralph D'Agostino Sr, Deepak L. Bhatt, Kim Eagle, Michael J. Pencina, Sidney C. Smith, Mark J. Alberts et al. "An international model to predict recurrent cardiovascular disease." The American journal of medicine 125, no. 7 (2012): 695-703.

[9]. Lloyd-Jones, Donald M., Eric P. Leip, Martin G. Larson, Ralph B. d'Agostino, Alexa Beiser, Peter WF Wilson, Philip A. Wolf, and Daniel Levy. "Prediction of lifetime risk for cardiovascular disease by risk factor burden at 50 years of age." Circulation 113, no. 6 (2006): 791-798.

[10]. Alty, Stephen R., Sandrine C. Millasseau, P. J. Chowienczyc, and Andreas Jakobsson. "Cardiovascular disease prediction using support vector machines." In 2003 46th Midwest Symposium on Circuits and Systems, vol. 1, pp. 376-379. IEEE, 2003.

[11]. Puddu, Paolo Emilio, Mariapaola Lanti, Alessandro Menotti, Mario Mancini, Alberto Zanchetti, Massimo Cirillo, Mario Angeletti, Walter Panarelli, and Gubbio Study Research Group. "Serum uric acid for short-term prediction of cardiovascular disease incidence in the Gubbio population Study." Acta cardiologica 56, no. 4 (2001): 243-251.

[12]. Hippisley-Cox, Julia, Carol Coupland, and Peter Brindle. "Development and validation of QRISK3 risk prediction algorithms to estimate future risk of cardiovascular disease: prospective cohort study." bmj 357 (2017).

[13]. Ioannidis, John PA. "Prediction of cardiovascular disease outcomes and established cardiovascular risk factors by genome-wide association markers." Circulation: Cardiovascular Genetics 2, no. 1 (2009): 7-15.

[14]. Dhana, Klodian, M. Arfan Ikram, Albert Hofman, Oscar H. Franco, and Maryam Kavousi. "Anthropometric measures in cardiovascular disease prediction: comparison of laboratory-based versus non-laboratory-based model." Heart 101, no. 5 (2015): 377-383.

[15]. Björnson, Elias, Jan Borén, and Adil Mardinoglu. "Personalized cardiovascular disease prediction and treatment—a review of existing strategies and novel systems medicine tools." Frontiers in Physiology 7 (2016): 2.

[16]. Thompson-Paul, Angela M., Kenneth A. Lichtenstein, Carl Armon, Frank J. Palella Jr, Jacek Skarbinski, Joan S. Chmiel, Rachel Hart et al. "Cardiovascular disease risk prediction in the HIV outpatient study." Clinical infectious diseases 63, no. 11 (2016): 1508-1516.

[17]. Goh, Louise GH, Satvinder S. Dhaliwal, Timothy A. Welborn, Andy H. Lee, and Phillip R. Della. "Anthropometric measurements of general and central obesity and the prediction of cardiovascular disease risk in women: a cross-sectional study." BMJ open 4, no. 2 (2014): e004138.

[18]. Øygarden, Halvor. "Carotid intima-media thickness and prediction of cardiovascular disease." Journal of the American Heart Association 6, no. 1 (2017): e005313.

[19]. Van Dieren, Susan, J. W. J. Beulens, A. P. Kengne, L. M. Peelen, G. E. H. M. Rutten, Mark Woodward, Y. T. Van der Schouw, and K. G. M. Moons. "Prediction models for the risk of cardiovascular disease in patients with type 2 diabetes: a systematic review." Heart 98, no. 5 (2012): 360-369.

[20]. Cederholm, Jan, Katarina Eeg-Olofsson, Björn Eliasson, Björn Zethelius, Peter M. Nilsson, Soffia Gudbjornsdottir, and Swedish National Diabetes Register. "Risk prediction of cardiovascular disease in type 2 diabetes: a risk equation from the Swedish National Diabetes Register." Diabetes care 31, no. 10 (2008): 2038-2043.

[21]. Twisk, J. W. R., H. C. G. Kemper, and W. Van Mechelen. "Prediction of cardiovascular disease risk factors later in life by physical activity and physical fitness in youth: general comments and conclusions." International journal of sports medicine 23, no. S1 (2002): 44-50.

[22]. Paynter, Nina P., Michael J. LaMonte, JoAnn E. Manson, Lisa W. Martin, Lawrence S. Phillips, Paul M. Ridker, Jennifer G. Robinson, and Nancy R. Cook. "Comparison of lifestyle-based and traditional cardiovascular disease prediction in a multiethnic cohort of nonsmoking women." Circulation 130, no. 17 (2014): 1466-1473.

[23]. Kunutsor, Setor K., Stephan JL Bakker, Jenny E. Kootstra-Ros, Ronald T. Gansevoort, and Robin PF Dullaart. "Circulating gamma glutamyltransferase and prediction of cardiovascular disease." Atherosclerosis 238, no. 2 (2015): 356-364.

[24]. Loredana Marcovecchio, M., R. Neil Dalton, A. Toby Prevost, Carlo L. Acerini, Timothy G. Barrett, Jason D. Cooper, Julie Edge et al. "Prevalence of abnormal lipid profiles and the relationship with the development of microalbuminuria in adolescents with type 1 diabetes." Diabetes care 32, no. 4 (2009): 658-663.

[25]. Rhyu, I. J., L. C. Abbott, D. B. Walker, and C. Sotelo. "An ultrastructural study of granule cell/Purkinje cell synapses in tottering (tg/tg), leaner (tgla/tgla) and compound heterozygous tottering/leaner (tg/tgla) mice." Neuroscience 90, no. 3 (1999): 717-728.

[26]. Mitchell, Suzanne H. "Measures of impulsivity in cigarette smokers and non-smokers." Psychopharmacology 146, no. 4 (1999): 455-464.

[27]. Pinto-Plata, Victor M., Hana Müllerova, John F. Toso, Maurille Feudjo-Tepie, Joan B. Soriano, Rupert S. Vessey, and Bartolome R. Celli. "C-reactive protein in patients with COPD, control smokers and non-smokers." Thorax 61, no. 1 (2006): 23-28.

[28]. Bourdeau, Annie, Nadia Dubé, Krista M. Heinonen, Jean-François Théberge, Karen M. Doody, and Michel L. Tremblay. "TC-PTP–deficient bone marrow stromal cells fail to support normal B lymphopoiesis due to abnormal secretion of interferon-γ." Blood 109, no. 10 (2007): 4220-4228.

[29]. Llorens, Verónica, Iñigo Gabilondo, Juan Carlos Gómez-Esteban, Marta Agundez, Mar Mendibe, Juan Carlos Bergara, Roberto Ciordia, Albert Saiz, and Juan J. Zarranz. "Abnormal multifocal cerebral blood flow on Tc-99m HMPAO SPECT in a patient with anti-NMDA-receptor encephalitis." Journal of neurology 257, no. 9 (2010): 1568-1569.

[30]. Gowri, Maya S., Deneys R. Van der Westhuyzen, Susan R. Bridges, and James W. Anderson. "Decreased protection by HDL from poorly controlled type 2 diabetic subjects against LDL oxidation may be due to the abnormal composition of HDL." Arteriosclerosis, thrombosis, and vascular biology 19, no. 9 (1999): 2226-2233.

[31]. Matsushima, Kazumi, Hiroyuki Sugiuchi, Kensaku Anraku, Hitoshi Nishimura, Masahiro Manabe, Katsuyoshi Ikeda, Yukio Ando et al. "Differences in reaction specificity toward lipoprotein X and abnormal LDL among 6 homogeneous assays for LDL-cholesterol." Clinica Chimica Acta 439 (2015): 29-37.

[32]. Okubo, Keiko, Katsunori Ikewaki, Soichi Sakai, Norio Tada, Yoshindo Kawaguchi, and Seibu Mochizuki. "Abnormal HDL apolipoprotein AI and A-II kinetics in hemodialysis patients: a stable isotope study." Journal of the American Society of Nephrology 15, no. 4 (2004): 1008-1015.

[33]. Pérez-Méndez, Oscar, Margarita Torres-Tamayo, Carlos Posadas-Romero, Vladimir Vidaure Garcés, Elizabeth Carreón-Torres, Enrique Mendoza-Pérez, Aida Medina Urrutia, Claudia Huesca-Gómez, José Zamora-González, and Blanca Aguilar-Herrera. "Abnormal HDL subclasses distribution in overweight children with insulin resistance or type 2 diabetes mellitus." Clinica chimica acta 376, no. 1-2 (2007): 17-22.

[34]. English, C. L., J. Hastings, S. Hennessy, S. F. Dinneen, and J. Crowley. "High prevalence of abnormal glucose regulation in patients presenting for routine coronary angiography." Practical Diabetes International 28, no. 3 (2011): 115-118a.

[35]. Vaidya, Dhananjay, Mark D. Kelemen, Vera Bittner, Jean-Claude Tardif, Paul Thompson, and Pamela Ouyang. "Fasting plasma glucose predicts survival and angiographic progression in high-risk postmenopausal women with coronary artery disease." Journal of women's health 16, no. 2 (2007): 228-234.

