

Role of Body Mass Index on Brain Stroke Patients

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Abstract

The article identifies the correlation (or associations) between body mass index (BMI) and brain stroke patients using 750 real study subjects including both normal and brain stroke individuals. The present outcomes have been obtained herein using joint statistical modeling. It is derived herein that mean BMI is negatively associated with the joint interaction effect (JIE) of age and hypertension (HYP) i.e., AGE*HYP ($P=0.0040$), age and heart disease (HRT) status i.e., AGE*HRT ($P<0.0001$), age and stroke (STR) i.e., AGE*STR ($P=0.0013$), HYP and smoking (SMO) status i.e., HYP*SMO ($P=0.0102$), while it is positively associated with the JIEs of residence type (RES) and STR i.e., RES*STR ($P=0.0438$), HYP and HRT i.e., HYP*HRT ($P=0.0119$) and HRT*STR ($P=0.0493$). In addition, mean BMI is positively associated with the JIE of glucose (GLU) levels and ever married (MAR) i.e., GLU*MAR ($P=0.0232$), GLU and work type (WOR) i.e., GLU*WOR ($P=0.0312$) and GLU*SMO ($P=0.0383$). Moreover, the variance of BMI is positively associated with the JIEs of RES*HYP ($P=0.0449$), HRT*STR ($P=0.0003$), GLU*HYP ($P=0.0504$), SMO*HYP ($P=0.1975$), while it is negatively associated with the JIE of HRT*RES ($P=0.0176$). Also the variance of BMI is positively associated with GLU*HYP ($P=0.0504$), and it is negatively associated with GLU*GEN ($P=0.2046$). There are some more associations of BMI levels with some other factors for brain stroke patients in the both mean and variance models. These derived associations of BMI with heart and diabetes diseases factors, and also physical and lifestyle parameters may be helpful for the brain stroke patients, medical practitioners and researchers. In addition, care should be taken on BMI, glucose levels and smoking at older ages.

Keywords: body mass index (bmi); brain stroke (str); blood glucose (glu) level; heart disease (hrt) status; hypertension (hyp); joint generalized linear models (jglms)

1.Introduction

Overweight (or obesity) and body mass index (BMI) are major global health issues that are associated with increased brain stroke and mortality rates. In the past two decades, overweight and obesity have reached a very high level over the world, and these invite major public health issues [1]. The total obesity and overweight trends have increased since 2000, even although the high-income population showed a slow-down between 2000 and 2010 [2]. Some studies pointed out that being overweight is one of the causal risk factors for chronic diseases such as heart and diabetes, and it leads to metabolic dysfunctions that lead to cardiovascular disease and death [3,4]. Brain stroke and simply stroke are considered as the second leading cause of death globally and they reveal a substantial contributor to impairment [5,6]. Overweight or high BIM level, being a risk factor for brain stroke [7], and it requires a thorough investigation of its causal factors and effects on stroke

outcomes for enhanced treatment strategies and prevention [8]. BMI is the most used obesity index that is associated with more comorbidities [9], less quality of life, poorer social functioning and impaired physical function [10]. Several current studies show that the association between BMI and health risk factors is more intricate than previously realized [11]. Paradoxically, higher BMI level was also associated with better survival in various cardiovascular conditions such as acute myocardial infarction [12], heart failure [13], coronary artery bypass surgery [14], coronary artery disease [15], and valvular surgery [16]. This “obesity paradox” has led many to wonder if the same shielding properties of high BMI level could apply to those with a stroke. This current study sought to examine the associations between BMI and all-cause mortality of brain stroke patients. Note that BMI is a body fat measure, which is calculated based on height (in meter) and weight (in kg), and it is generally ranging from 18 to 35, and it is defined as $BMI = \text{Weight (kg)} / \text{Height (m)}^2$. Here it is observed that BMI is a composite

function of obesity, which is a widely used screening tool in medical science, and it provides a simple obesity's numeric measure of a subject's weight in relation to its height as stated above. BMI is commonly applied to categorize individuals as underweight, normal weight, overweight, or obese. It is considered as an important risk factor for many diseases such as diabetes, cardiovascular disease, and hormonal disorders such as polycystic ovary syndrome (PCOS) etc. [1,9,17,18]. People are categorized as underweight class if BMI values < 18.5. When the BMI value lies between 18.5 to 24.9, the people are categorized as normal weight. When the BMI value lies between 25.0 to 29.9, the people are categorized as overweight. When the BMI value lies between 30.0 to 34.9, the people are categorized as obese (class I). When the BMI value lies between 35.0 to 39.9, the people are categorized as obese (class II). People are categorized as extremely obese (class III) if BMI values > 39.8. In the above, it is observed that many earlier research articles have studied the effects of BMI on the brain stroke patients applying simple bivariate correlation, simple or multiple regression, statistical modelling, machine learning and meta-analysis approaches [1, 6, 8, 11, 19]. The considered brain stroke data set is a physiological heteroscedastic data set, which is not considered in the previous articles. Therefore, the previous studies regarding the association of BMI with the several parameters of the brain stroke patients are misleading. In addition, there are very few previous articles regarding the relationship of BMI with the other risk factors of the brain stroke patients. Moreover, the earlier articles do not adopt any appropriate model fitting diagnostic tools on their final accepted BMI models, which may be doubtful. The effects of body mass index on the brain stroke subjects are very few examined based on probabilistic modeling. The present report examines the following research hypotheses regarding BMI of the brain stroke subjects.

- Is there any association of BMI values with cardiac risk factors, lifestyle and physical factors for brain stroke patients?
- If it is valid, how can we obtain the most probable BMI values association model?
- What is the most probable BMI values probabilistic model?
- What are the effects of BMI values on the brain stroke subjects?

The current report explores the above research queries considering the following paragraphs such as materials & methods, statistical analysis & results, discussions, limitations and conclusions. The report has obtained a BMI values probabilistic model revealed in Table 1 adopting the brain stroke data set, which is displayed in the materials section. The probabilistic BMI values mean-variance models are derived by joint generalized linear models (JGLMs) that is shortly stated in the methods section. The present obtained BMI findings are reported in the results section, while the current BMI outcomes are illustrated in the discussion section. Based on the derived BMI values mean & variance joint models, the current article has obtained some necessary information that are illustrated in the conclusions section.

2. Materials and Methods

2.1 Materials

The present BMI values statistical joint models have been derived herein from a subset of 750 random sample units out of 4981 normal and brain stroke sample subjects. The currently used brain-stroke data set. The data set includes both normal and brain strokes subjects, which are basically two types. One type is stroke ischemic, which is the lack of blood flow, and the other type is hemorrhagic that is due to bleeding. These two brain stroke types affect some parts of the brain to stop functioning properly.

The present used brain stroke data set includes 11 study characters/factors such as sex or gender (GEN) (male=0; female=1), hypertension (HYP) (no hypertension=0, hypertension=1), age, heart disease (HRT) (no heart disease= 0, heart disease =1), work type (WOK) (Govt job=1; private=2; self-employed=3; children=0), ever-married (MAR) (no married=0; married=1), residence-type (RES) (rural=0; urban=1), body mass index (BMI), average glucose level in blood (GLU), stroke (STR) (no stroke=0; stroke=1), smoking-status (SMO) (never smoke or former=1; smoker=2).

2.2 Statistical Methods

The report considers body mass index (BMI) as the aimed random response variable that is to be modeled with the remaining lifestyle, cardiac and physical characteristics/factors. It is examined that the response BMI is heteroscedastic and non-normally distributed random variable. The variance of BMI can't be stabilized by any suitable transformation, so BMI is modeled in the present report using joint generalized linear models (JGLMs) under both the log-normal and gamma distribution, which is clearly illustrated in the books by Lee, Nelder and Pawitan [20], Das [21]. JGLMs for both the gamma and log-normal distribution are shortly presented herein.

JGLMs for log-normal distribution: For the positive response Y_i (=BMI) with $E(Y_i=BMI) = \mu_i$ (mean) and $Var(Y_i=BMI) = \mu_i^2$ say, where μ_i 's are dispersion parameters and $V(\cdot)$ reveals the variance function. Generally, log transformation $Z_i = \log(Y_i=BMI)$ is adopted to stabilize the variance $Var(Z_i) \approx 1$, but the variance may not always be stabilized [22]. For developing a BMI improved model, JGLMs for the mean and dispersion are adopted herein. For the response BMI, assuming log-normal distribution, JGL mean and dispersion models (with $Z_i = \log(Y_i=BMI)$) are as follows:

$$E(Z_i) = \mu_{zi} \text{ and } Var(Z_i) = \sigma_{zi}^2,$$

$$\mu_{zi} = x_{it} \beta \text{ and } \log(\sigma_{zi}^2) = g_{it} \gamma,$$

where x_{it} and g_{it} are the explanatory factors/variables vectors of BMI associated with the mean regression coefficients β and dispersion regression coefficients γ , respectively.

JGLMs for gamma distribution: In the above stated Y_i 's (=BMI), the variance has two portions such as μ_i (based on the mean parameters μ_i 's) and (free of μ_i 's). The variance function $V(\cdot)$ displays the GLM family distributions. For instance, if $V(\cdot) = 1$, it is normal, Poisson if $V(\cdot) = \mu$, and gamma if $V(\cdot) = \mu^2$ etc. Gamma JGLMs mean and dispersion models of BMI are as follows: and, where μ_i and σ_{zi}^2 are the GLM link functions attached with the mean and dispersion linear predictors respectively, and, x_{it} and g_{it} are the explanatory factors/variables vectors of BMI attached with the mean and dispersion parameters respectively. Maximum likelihood (ML) method is used for estimating the mean parameters of BMI, while the restricted ML (REML) method is applied for estimating the dispersion parameters of BMI, which are explicitly stated in the book by Lee, Nelder and Pawitan [16]. For JGLMs, interested readers may go through the articles [23,24].

3. Statistical analysis & Results

3.1 Statistical Analysis

The current article aims to identify the effects of BMI on the brain stroke patients. Statistical model of BMI has been developed on the remaining 10 explanatory variables such as physical parameters (AGE and SEX or GEN), heart disease related parameters (subject's heart disease status (HRT), hypertension (HYP) and subject's stroke status (STR)), biochemical, social & lifestyle parameters (glucose (GLU) levels, residence type (RES), ever

married (MAR), work type (WRK), smoking status (SMO)). Final BMI values model has been taken based on the lowest Akaike information criterion (AIC) value (within each class) that reduces both the squared error loss and predicted additive errors [25, p. 203--204]. According to the AIC rule, JGLMs Log-normal fit (AIC= 3890.222) is better than gamma fit (AIC=3897.474). Table 1 reveals the summarized JGLMs results of the BMI values analysis of both the joint mean-variance models under both the log-normal and gamma distribution. Final selected log-normal model (Table 1) contains some partially significant effects such as AGE*WOR (or

age.workty2) ($P=0.1070$) (mean model), GLU*GEN (or glucose.gen2) ($P=0.2046$) (variance model), SMO*HYP (or smoking.hypert2) ($P=0.1975$) (variance model) and RES*MAR (or resi2.emarried2) ($P=0.1101$). These partially significant effects may have a great role in the model and they are known as confounders or interaction effects in the subject Epidemiology. All other insignificant effects are included in both the models using the marginality rule of Nelder [26], which states that if any higher order interaction effect is significant, then all its lower order interaction effects and marginal effects should be included in the model.

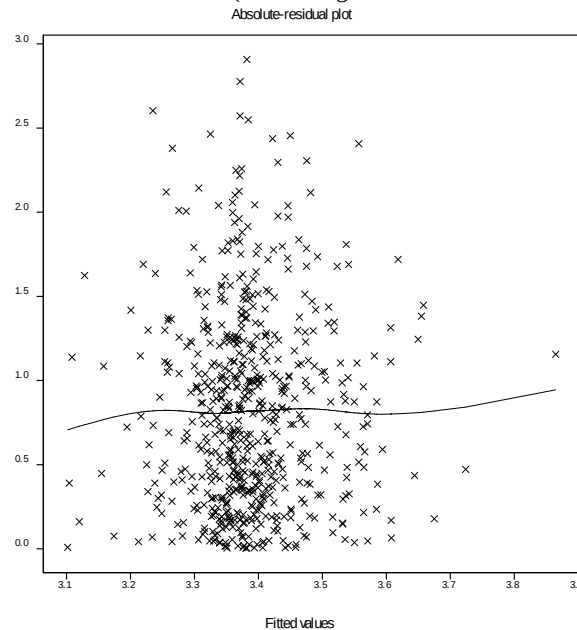


Figure 1 (a)

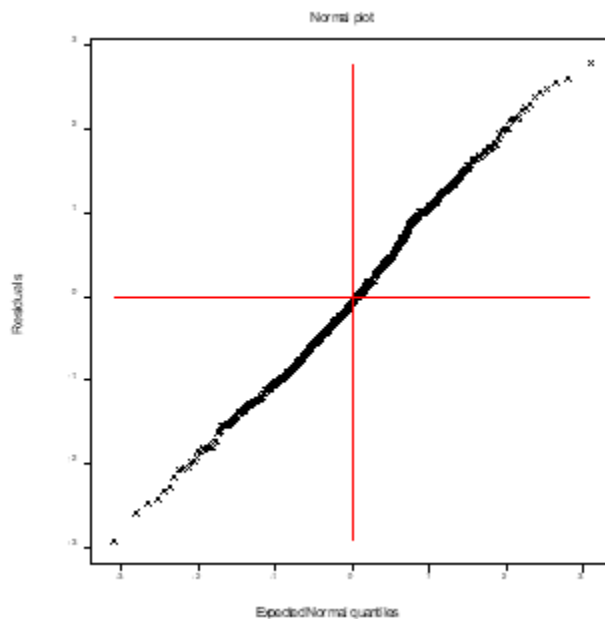


Figure 1 (b)

Figure 1: For the joint Log-normal fitted models of body mass index (BMI) (Table 1), the (a) absolute residuals plot with the fitted values, and (b) the normal probability plot for mean model

The developed BMI values Log-normal fitted JGLM (Table 1) is a data obtained model that is to be tested by model checking tools. The current valid conclusions about BMI levels are extracted from the data derived Log-

normal fitted BMI levels probabilistic joint models (Table 1) that should be taken using suitable graphical diagnostic tools that is shown in Figure 1. Figure 1(a) reveals the absolute residuals plot for the Log-normal fitted BMI

vales model (Table 1) with respect to the fitted values, which is almost linear flat line, showing that variance is constant with the running means. Figure 1(b) presents the normal probability plot for the Log-normal fitted BMI values mean model (Table 1) that does not reveal any lack of fit. Therefore, both the figures 1(a) and 1(b) do not show any discrepancy in the Log-normal fitted BMI values model (Table 1). The above Figure 1(a) and Figure 1(b) confirm that the Log-normal fitted BMI values model is an approximate form of the unknown true BMI values model.

3.2 Results

Table 1 displays the BMI values fitting summarized results. On the basis of AIC rule, Log-normal fitted BMI values JGLM gives better results than Gamma fitted model. Therefore, the final accepted BMI values model is Log-normal fitted JGLM. These fitted two models have some discrepancies, which are clear in Table 1. But both the models have similar interpretations. The common discrepancies between the fitted Log-normal and Gamma models are pointed out in the articles by Das [27], Das and Park [28]. In the current article, Log-normal fitted (Table 1) findings are reported, as its AIC value is lower than the Gamma fit. The associations between the mean BMI values and heart disease related parameters (subject's heart disease status (HRT), hypertension (HYP) and subject's stroke status (STR)) are illustrated in the following lines. It is derived herein that mean BMI values is negatively associated with the joint interaction effect (JIE) of age and hypertension (HYP) i.e., AGE*HYP ($P=0.0040$), while both the marginal effects AGE ($P<0.0001$) and HYP ($P=0.0003$) are positively associated with mean BMI. Mean BMI is negatively associated with the JIE of age and heart disease (HRT) status i.e., AGE*HRT ($P<0.0001$), while both the marginal effects AGE ($P<0.0001$) and HRT ($P<0.0001$) are positively associated with mean BMI. Mean BMI is negatively associated with the JIE of age and stroke (STR) i.e., AGE*STR ($P=0.0013$), while both the marginal effects AGE ($P<0.0001$) and STR ($P=0.0099$) are positively associated with mean BMI. Mean BMI is negatively associated with the JIE of HYP and smoking (SMO) status i.e., HYP*SMO ($P=0.0102$), while HYP ($P=0.0003$) is positively and SMO ($P=0.0150$) is negatively associated with mean BMI. Also, mean BMI is positively associated with the JIEs of residence type (RES) and STR i.e., RES*STR ($P=0.0438$), while both the RES ($P=0.0206$) and STR ($P=0.0099$) are positively associated with BMI. Mean BMI is positively associated with the JIEs of HYP and HRT i.e., HYP*HRT ($P=0.0119$), while both the HYP ($P=0.0003$) and HRT ($P<0.0001$) are positively associated with BMI. Mean BMI is positively associated with the JIEs of HRT and STR i.e., HRT*STR ($P=0.0493$), while both the HRT ($P<0.0001$) and STR ($P=0.0099$) are positively associated with BMI. In addition, mean BMI is positively associated with the JIE of glucose (GLU) levels and ever married (MAR) i.e., GLU*MAR ($P=0.0232$), while MAR ($P=0.0152$) is positively associated with BMI and GLU ($P=0.2556$) is indifferent to BMI. Mean BMI is positively associated with the JIE of GLU levels and work type (WOR) i.e., GLU*WOR ($P=0.0312$), while WOR is partially positively associated with BMI, but GLU level ($P=0.2556$) is indifferent to BMI. Mean BMI is positively associated with the JIE of GLU levels and SMO i.e., GLU*SMO

($P=0.0383$), while SMO ($P=0.0150$) is negatively associated with mean BMI, but GLU level ($P=0.2556$) is indifferent to BMI. Moreover, the variance of BMI is positively associated with the JIEs of RES*HYP ($P=0.0449$), while RES ($P=0.0408$) is positively associated with the BMI's variance and HYP ($P=0.0019$) is negatively associated with it. BMI's variance is positively associated with the JIEs of HRT*STR ($P=0.0003$), while HRT ($P=0.0001$) is negatively associated with BMI's variance, but STR ($P=0.7643$) is insignificant to it. BMI's variance is partially positively associated with the JIEs of SMO*HYP ($P=0.1975$), while HYP ($P=0.0019$) is negatively associated with BMI's variance, but SMO ($P=0.9761$) is indifferent to it. Also, BMI's variance is negatively associated with the JIE of HRT*RES ($P=0.0176$), while HRT ($P=0.0001$) is negatively associated with BMI's variance, and RES ($P=0.0408$) is positively associated with it. Also the variance of BMI is positively associated with GLU*HYP ($P=0.0504$), while HYP ($P=0.0019$) is negatively associated with BMI's variance, but GLU ($P=0.7264$) is insignificant to it. In addition, BMI's variance is partially negatively associated with GLU*GEN ($P=0.2046$), while GEN ($P=0.0034$) is positively associated with BMI's variance, but GLU ($P=0.7264$) is insignificant to it. There are some more mean BMI levels associations with some other factors such as GEN*SMO ($P=0.0017$), AGE*MAR ($P=0.0020$), AGE*RES ($P=0.0066$), MAR*WOR ($P=0.0378$), while BMI's variance is additionally associated with AGE*SMO ($P=0.0994$), RES*MAR ($P=0.1101$) and SMO*WOR ($P=0.0859$) for brain stroke patients in the both mean and variance models (Table 1). From Table 1, Log-normal fitted GLU levels mean (z) model is $z = 3.1062 - 0.0005 \text{ glucose} + 0.3444 \text{ hypert2} + 0.1617 \text{ emarried2} + 0.1315 \text{ workty2} + 0.1084 \text{ res2} + 0.0047 \text{ age} - 0.0446 \text{ gen2} - 0.0784 \text{ smoking2} + 0.0801 \text{ gen2*smoking2} - 0.0041 \text{ age*hypert2} + 0.5537 \text{ heartd2} - 0.0087 \text{ age* heartd2} - 0.0028 \text{ age*emarried2} - 0.0022 \text{ age*res2} + 0.2053 \text{ stroke2} - 0.0038 \text{ age*stroke2} + 0.0009 \text{ glucose*emarried2} + 0.0621 \text{ res2*stroke2} - 0.1024 \text{ emarried2*workty2} + 0.0959 \text{ hypert2* heartd2} - 0.0839 \text{ hypert2* smoking2} + 0.0617 \text{ heartd2* stroke2} + 0.0005 \text{ glucose* workty2} + 0.0005 \text{ glucose* smoking2} - 0.0016 \text{ age*workty2}$, and from Table 1, the Log-normal fitted BMI levels variance (z) model is $z = \exp(-3.647 - 0.0028 \text{ age} + 0.839 \text{ gen2} - 1.854 \text{ heartd2} + 0.547 \text{ resi2} + 0.0006 \text{ glucose} - 0.0028 \text{ glucose*gen2} - 0.014 \text{ smoking2} - 0.0115 \text{ age*smoking2} - 1.443 \text{ heartd2} + 0.663 \text{ res2*hypert2} + 0.445 \text{ smoking2* hypert2} - 1.022 \text{ heartd2*resi2} - 0.047 \text{ stroke2} + 1.804 \text{ heartd2* stroke2} + 0.285 \text{ emarried2} - 0.472 \text{ resi2*emarried2} - 0.156 \text{ workty2} + 0.524 \text{ smoking2*workty2} + 0.0052 \text{ glucose* hypert2})$. From the above BMI values mean (z) and variance (z) models, it is noted that mean BMI values is explained by many factors and their interaction effects such as gen2*smoking2 , age*hypert2 , age* heartd2 , age*emarried2 , age*res2 , age*stroke2 , glucose*emarried2 , res2*stroke2 , emarried2*workty2 , hypert2* heartd2 , hypert2*smoking2 , heartd2*stroke2 , glucose*workty2 , glucose*smoking2 , age*workty2 , while the BMI values variance is expressed by glucose*gen2 , age*smoking2 , res2*hypert2 , smoking2*hypert2 , heartd2*resi2 , heartd2*stroke2 , resi2*emarried2 , smoking2*workty2 and glucose* hypert2 .

Model	Covariates	LOG-NORMAL FIT				GAMMA FIT			
		estimate	s.e.	t(611)	P-value	Estimate	s.e.	t(611)	P-value
Mean	constant	3.1062	0.0806	38.514	<0.0001	3.1238	0.0811	38.536	<0.0001
	Glucose (GLU)	-0.0005	0.0004	-1.138	0.2556	-0.0005	0.0004	-1.188	0.2353
	hypert 2 (HYP)	0.3444	0.0948	3.632	0.0003	0.3331	0.0948	3.513	0.0005
	emarried 2(MAR)	0.1617	0.0664	2.435	0.0152	0.1648	0.0664	2.481	0.0134
	workty 2 (WOR)	0.1315	0.0704	1.866	0.0625	0.1288	0.0709	1.818	0.0695
	resi 2 (RES)	0.1084	0.0467	2.321	0.0206	0.1197	0.0469	2.550	0.0110
	Age (AGE)	0.0047	0.0011	4.251	<0.0001	0.0047	0.0011	4.222	<0.0001
	gen 2 (GEN)	-0.0446	0.0179	-2.484	0.0132	-0.0364	0.0180	-2.025	0.0433
	smoking 2 (SMO)	-0.0787	0.0322	-2.440	0.0150	-0.0785	0.0321	-2.447	0.0147
	gen 2 .smoking 2	0.0801	0.0254	3.157	0.0017	0.0767	0.0253	3.032	0.0025
	age.hypert 2	-0.0041	0.0014	-2.891	0.0040	-0.0040	0.0014	-2.821	0.0049
	heartd 2 (HRT)	0.5537	0.0936	5.914	<0.0001	0.5436	0.0929	5.852	<0.0001
	age.heartd 2	-0.0087	0.0014	-6.340	<0.0001	-0.0087	0.0014	-6.412	<0.0001
	age.emarried 2	-0.0028	0.0009	-3.108	0.0020	-0.0029	0.0009	-3.263	0.0012
	age.resi 2	-0.0022	0.0008	-2.725	0.0066	-0.0023	0.0008	-2.916	0.0037
	stroke 2 (STR)	0.2053	0.0793	2.588	0.0099	0.1933	0.0796	2.429	0.0154
	age.stroke 2	-0.0038	0.0012	-3.233	0.0013	-0.0037	0.0012	-3.088	0.0021
	glucose.emarried 2	0.0009	0.0004	2.276	0.0232	0.0009	0.0004	2.323	0.0205
	resi2 .stroke 2	0.0621	0.0307	2.020	0.0438	0.0636	0.0307	2.071	0.0388
	emarried2 .workty 2	-0.1024	0.0492	-2.081	0.0378	-0.0977	0.0494	-1.977	0.0485
	hypert2 .heartd 2	0.0905	0.0359	2.523	0.0119	0.0937	0.0357	2.623	0.0089
	hypert2 .smoking 2	-0.0839	0.0326	-2.575	0.0102	-0.0821	0.0326	-2.519	0.0120
	heartd2 .stroke 2	0.0617	0.0313	1.970	0.0493	0.0666	0.0311	2.140	0.0327
	glucose.workty 2	0.0005	0.0002	2.160	0.0312	0.0005	0.0002	2.171	0.0303
	glucose.smoking 2	0.0005	0.0002	2.076	0.0383	0.0005	0.0002	2.076	0.0383
	age.workty 2	-0.0016	0.0010	-1.614	0.1070	-0.0016	0.0010	-1.618	0.1062
Dispersion	Constant	-3.647	0.375	-9.71	<0.0001	-3.621	0.374	-9.67	<0.0001
	Age (AGE)	-0.0028	0.0046	-0.62	0.5355	-0.0030	0.0045	-0.66	0.5095
	gen 2 (GEN)	0.839	0.286	2.94	0.0034	0.862	0.285	3.03	0.0025
	heartd 2 (HRT)	-1.854	0.481	-3.86	0.0001	-1.868	0.481	-3.88	0.0001
	resi 2 (RES)	0.547	0.266	2.05	0.0408	0.506	0.265	1.91	0.0566
	Glucose (GLU)	0.0006	0.0018	0.35	0.7264	0.0007	0.0018	0.37	0.7115
	glucose.gen 2	-0.0028	0.0022	-1.27	0.2046	-0.0030	0.0022	-1.35	0.1775
	smoking 2 (SMO)	-0.014	0.499	-0.03	0.9761	0.031	0.498	0.06	0.9522
	age.smoking 2	-0.0115	0.0070	-1.65	0.0994	-0.0121	0.0069	-1.74	0.0824
	hypert 2 (HYP)	-1.443	0.464	-3.11	0.0019	-1.456	0.463	-3.15	0.0017
	resi2 .hypert 2	0.663	0.330	2.01	0.0449	0.670	0.329	2.04	0.0418
	smoking 2 .hypert 2	0.445	0.346	1.29	0.1975	0.472	0.345	1.37	0.1712
	heartd2 .resi 2	-1.022	0.429	-2.38	0.0176	-1.042	0.429	-2.43	0.0154
	stroke 2 (STR)	-0.047	0.154	-0.30	0.7643	-0.032	0.153	-0.21	0.8337
	heartd2 .stroke 2	1.804	0.497	3.63	0.0003	1.811	0.497	3.64	0.0003
	emarried 2 (MAR)	0.285	0.228	1.25	0.2118	0.266	0.228	1.17	0.2424
	resi2 .emarried 2	-0.472	0.295	-1.60	0.1101	-0.450	0.294	-1.53	0.1265
	workty 2 (WOR)	-0.156	0.182	-0.85	0.3956	-0.144	0.182	-0.79	0.4298
	smoking 2 .workty 2	0.524	0.304	1.72	0.0859	0.487	0.304	1.60	0.1101
	glucose.hypert 2	0.0052	0.0027	1.96	0.0504	0.0052	0.0027	1.96	0.0504
	AIC	3890.222				3897.474			

Table 1: Results for mean and dispersion models for BMI from Log-normal & Gamma fit

4. Discussions

The summarized BMI values analysis findings are presented in Table 1, and it shows that the most suitable BMI values model is Log-normal fitted mean and variance models that are presented in the above results paragraph. These BMI's mean and variance models reveal many complex associations of BMI values with cardiac, diabetes disease parameters, and along with many other lifestyle, social and physical parameters. The derived associations of BMI values with the above parameters are presented in the following paragraphs. From the Log-normal fitted mean model (Table 1), it is derived herein that

mean BMI values is negatively associated with the joint interaction effect (JIE) of age and hypertension (HYP) i.e., AGE*HYP (P=0.0040), while both the marginal effects AGE (P<0.0001) and HYP (P=0.0003) are positively associated with mean BMI. It interprets that mean BMI increases as the joint effect AGE*HYP decreases. In other words, it implies that the individuals at lower ages with higher BMI may have hypertension, which are generally observed in practice. Note that when the joint effect is statistically significant, the marginal effects are not important. Then the marginal effects are less important. Here it is observed that BMI is positively associated with both the AGE and HYP, this implies that as age (hypertension) increases,

BMI increases, which is really observed in some cases. Mean BMI is negatively associated with the JIE of age and heart disease (HRT) status i.e., AGE*HRT ($P<0.0001$), while both the marginal effects AGE ($P<0.0001$) and HRT ($P<0.0001$) are positively associated with mean BMI. It implies that BMI increases as the joint effect AGE*HRT decreases. It means that individuals at younger ages with heart disease may have higher BMI values. These are observed in practice. Here also, BMI is positively associated with both the AGE and HRT. This shows that individuals with higher BMI values may have heart disease at older ages, which are really observed in many cases. Mean BMI is negatively associated with the JIE of age and stroke (STR) i.e., AGE*STR ($P=0.0013$), while both the marginal effects AGE ($P<0.0001$) and STR ($P=0.0099$) are positively associated with mean BMI. It implies that BMI increases as the joint effect AGE*STR decreases. It indicates that individuals at younger ages with higher BMI values may have strokes. These are observed in practice. Here also, BMI is positively associated with both the AGE and STR. This implies that individuals with higher BMI values may have strokes at older ages, which are generally observed in many cases. Mean BMI is negatively associated with the JIE of HYP and smoking (SMO) status i.e., HYP*SMO ($P=0.0102$), while HYP ($P=0.0003$) is positively and SMO ($P=0.0150$) is negatively associated with mean BMI values. This reveals that mean BMI value increases as the joint effect HYP*SMO decreases. In other words, BMI value increases for the non-smoker and no-hypertension individuals. Also, mean BMI value is positively associated with HYP, while it is negatively associated with SMO. These show that BMI is higher for hypertension individuals, while it is lower for smokers. These are really observed in practice. Also, mean BMI is positively associated with the JIEs of residence type (RES) and STR i.e., RES*STR ($P=0.0438$), while both the RES ($P=0.0206$) and STR ($P=0.0099$) are positively associated with BMI. This shows that mean BMI value increases as the joint effect RES*STR increases. It expresses that mean BMI value increases for the urban individuals with stroke. In addition, mean BMI value is positively associated with both the marginal effects RES (rural=0; urban=1) and STR, which implies that BMI value is generally higher for urban individuals and stroke. Mean BMI is positively associated with the JIEs of HYP and HRT i.e., HYP*HRT ($P=0.0119$), while both the HYP ($P=0.0003$) and HRT ($P<0.0001$) are positively associated with BMI. This indicates that mean BMI value increases as the joint effect HYP*HRT increases. It implies that mean BMI value increases for hypertension and heart disease individuals. Moreover, mean BMI value is positively associated with both the marginal effects HYP and HRT, these indicate that BMI value is higher for hypertension and heart disease individuals. Mean BMI is positively associated with the JIEs of HRT and STR i.e., HRT*STR ($P=0.0493$), while both the HRT ($P<0.0001$) and STR ($P=0.0099$) are positively associated with BMI. This implies that mean BMI value increases as the joint effect HRT*STR increases. It shows that mean BMI value increases for stroke and heart disease patients. Moreover, mean BMI value is positively associated with both the marginal effects HRT and STR, these show that BMI value is higher for stroke and heart disease patients. From these above mean BMI value associations with cardiac disease related parameters such as hypertension, stroke and heart disease status, it is observed that mean BMI value is higher (or positively) linked with these cardiac parameters along with their many joint interaction effects. In addition, mean BMI value is positively associated with the JIE of glucose (GLU) levels and ever married (MAR) i.e., GLU*MAR ($P=0.0232$), while MAR ($P=0.0152$) is positively associated with BMI and GLU ($P=0.2556$) is indifferent to BMI. This implies that mean BMI value increases as the joint effect GLU*MAR increases. It means that married individuals with higher glucose levels may have higher BMI values, which are commonly observed

in practice. Also, mean BMI value is positively associated with MAR, while it is indifferent to GLU levels. These indicate that mean BMI value is higher for ever married individuals. Mean BMI is positively associated with the JIE of GLU levels and work type (WOR) i.e., GLU*WOR ($P=0.0312$), while WOR ($P=0.0625$) is partially positively associated with BMI, but GLU level ($P=0.2556$) is indifferent to BMI value. This indicates that mean BMI value increases as the joint effect GLU*WOR increases. It means that private & self employed workers with higher glucose levels may have higher BMI values, which are commonly observed in practice. In addition, mean BMI value is partially positively associated with WOR (Govt job=1; private=2; self-employed=3; children=0), while it is indifferent to GLU levels. These indicate that mean BMI value is higher for private & self employed individuals. Mean BMI is positively associated with the JIE of GLU levels and SMO i.e., GLU*SMO ($P=0.0383$), while SMO ($P=0.0150$) is negatively associated with mean BMI, but GLU level ($P=0.2556$) is indifferent to BMI. This shows that mean BMI value increases as the joint effect GLU*SMO increases. It indicates that smokers with higher glucose levels may have higher BMI values, which are commonly observed in practice. Note that mean BMI value is negatively associated with SMO (never smoke or former=1; smoker=2), while it is indifferent to GLU levels. It interprets that mean BMI value is higher for non-smoker individuals. In the above, the associations of mean BMI values are illustrated with cardiac and diabetes disease risk factors. Moreover, there are many more associations of mean BMI values (Table 1) with some lifestyle, physical and social parameters. It is shown that mean BMI value is positively associated with GEN*SMO ($P=0.0017$), while both the marginal factors GEN ($P=0.0132$) and SMO ($P=0.0150$) are negatively associated with it. This indicates that mean BMI value increases as the joint effect GEN*SMO increases. Mean BMI value is negatively associated with AGE*MAR ($P=0.0020$), while both the marginal factors AGE ($P<0.0001$) and MAR ($P=0.0152$) are positively associated with it. This implies that mean BMI value increases as the joint effect AGE*MAR decreases. Also, mean BMI value is negatively associated with AGE*RES ($P=0.0066$), while both the marginal factors AGE ($P<0.0001$) and RES ($P=0.0206$) are positively associated with it. This shows that mean BMI value increases as the joint effect AGE*RES decreases. Mean BMI value is negatively associated with MAR*WOR ($P=0.0378$), while both the marginal factors MAR ($P=0.0152$) and WOR ($P=0.0625$) are positively associated with it. This indicates that mean BMI value increases as the joint effect MAR*WOR decreases. Moreover, mean BMI value is partially negatively associated with AGE*WOR ($P=0.1070$), while both the marginal factors AGE ($P<0.0001$) and WOR ($P=0.0625$) are positively associated with it. This indicates that mean BMI value increases as the joint effect AGE*WOR decreases. In the above, the associations of mean BMI value with cardiac, diabetes disease risk factors along with some lifestyle, physical and social factors are illustrated based on the derived Log-normal fitted mean model (Table 1). Similarly, there are many associations of BMI value with these parameters in the dispersion model (Table 1). Note that the interpretations of BMI value in the dispersion model are mainly related with the scatteredness of the variable, so it is less important in Medical science, while it is very important in quality engineering. A few interpretations of BMI value in the dispersion model (Table) are illustrated in the following lines. The variance of BMI values is positively associated with the JIEs of RES*HYP ($P=0.0449$), while RES ($P=0.0408$) is positively associated with the BMI's variance and HYP ($P=0.0019$) is negatively associated with it. It implies that BMI values of the subjects are highly scattered when the subjects have higher joint effect of RES*HYP. Similarly, BMI's variance is positively associated with the JIEs of HRT*STR ($P=0.0003$), while HRT ($P=0.0001$) is negatively associated with BMI's variance, but STR ($P=0.7643$) is insignificant to it.

This indicates that BMI values of the subjects are highly scattered when the subjects have higher joint effect of HRT*STR. These two above interpretations of BMI's variance simply indicate the scatteredness of BMI values in the study subjects. There are many more associations of BMI's variance model (Table 1). A few are noted as follows. BMI's variance is partially positively associated with the JIEs of SMO*HYP ($P=0.1975$), while HYP ($P=0.0019$) is negatively associated with BMI's variance, but SMO ($P=0.9761$) is indifferent to it. Also, BMI's variance is negatively associated with the JIE of HRT*RES ($P=0.0176$), while HRT ($P=0.0001$) is negatively associated with BMI's variance, and RES ($P=0.0408$) is positively associated with it. Also the variance of BMI is positively associated with GLU*HYP ($P=0.0504$), while HYP ($P=0.0019$) is negatively associated with BMI's variance, but GLU ($P=0.7264$) is insignificant to it. In addition, BMI's variance is partially negatively associated with GLU*GEN ($P=0.2046$), while GEN ($P=0.0034$) is positively associated with BMI's variance, but GLU ($P=0.7264$) is insignificant to it. Several important findings regarding BMI associations of brain stroke patients have been derived and illustrated in the above. It is noted that for the brain stroke subjects, mean BMI is associated with AGE*HYP ($P=0.0040$), AGE*HRT ($P<0.0001$), AGE*STR, HYP*SMO ($P=0.0102$), RES*STR ($P=0.0438$), HYP*HRT ($P=0.0119$), HRT*STR ($P=0.0493$), which are all cardiac disease related joint interaction effects. Similarly, for the brain stroke subjects, mean BMI is associated with GLU*MAR ($P=0.0232$), GLU*WOR ($P=0.0312$), GLU*SMO ($P=0.0383$), which are all diabetes disease related joint interaction effects. Besides these, mean BMI is associated with many physical, lifestyle, social joint interaction effects such as GEN*SMO ($P=0.0017$), AGE*MAR ($P=0.0020$), AGE*RES ($P=0.0066$), MAR*WOR ($P=0.0378$), AGE*WOR ($P=0.1070$). In addition to these above, BMI has many associations in the dispersion model (Table 1).

5. Limitations

The fundamental strength of the present article is an advanced statistical modelling research methodology, consequently the obtained outcomes have been accepted based on model diagnosis tests. In addition, the outcomes focus on the real facts that are observed in practice. The present study had some limitations that should be addressed in the future work. The study has only eleven explanatory variables of brain stroke. The data set has excluded many important factors such as daily physical activity, alcohol drinking status, diet quality, daily calorie consumed, lifestyle, etc.

6. Conclusions

The report has derived the associations of BMI values for the brain stroke patients along with the cardiac, diabetes disease related risk factors, and along with the other physical, lifestyle and social factors. The fitted BMI values probabilistic model has been accepted herein based on the smallest AIC criterion, on comparison of the estimate's standard errors, joint Gamma and Log-normal models, and along with the graphical diagnostic checking plots (Figure 1). It is observed that both the Gamma and Log-normal models have similar interpretations (Table 1). Most of the mean BMI associations for the brain stroke patients derived herein focus on the real facts that are frequently observed in our society. The obtained BMI associations for the brain stroke patients herein though not completely eventual but are expressive. The advanced scientific research approaches should have complete faith on the above extracted outcomes for BMI's associations of the brain stroke patients as the derived fitted models have been accepted based on graphical diagnostic plots checking and comparison of Log-normal and Gamma fitted models. The fitted BMI values mean & variance models

(Table 1) are obtained from the data set as noted in the material section. One can easily verify the reported BMI's findings from the data set. In addition, the parallel outcomes will be obtained from any similar brain stroke data set, which is not verified herein. The reported BMI's brain stroke related findings present many real facts that are rarely pointed out in any previous articles. BMI's variance model findings are completely new in the brain stroke literature, while most of the BMI's mean model findings are also completely new in this literature. Moreover, the current BMI brain stroke study can help all the common people, medical practitioners, researchers and brain stroke subjects. It is concluded that BMI values have very critical functional roles (derived in Table 1) on the brain stroke subjects that should be known to the common people and medical practitioners for suitable treatment processes. The current brain stroke BMI study advises all people to control BMI values, glucose levels and smoking habits.

Abbreviations

AIC Akaike information criterion

BMI Body mass index

GLU Average blood glucose

HYP Hypertension

HRT Heart disease

JIE Joint interaction effect

JGLMs Joint generalized linear models

ML Maximum likelihood

MAR Ever married

PCOS Polycystic ovary syndrome

RES Residence type

RML Restricted maximum likelihood

SMO Smoking

STR Brain stroke

Declarations: The article is an original interesting research report that has been prepared based on advance statistical data analysis using, which has not been submitted in any journal for publication.

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Conflict of interest: The authors confirm that this article content has no conflict of interest.

Ethical approval: Note that the current study has been performed based on a secondary data set, which is available in the site-
<https://www.kaggle.com/datasets/jillanisoftech/brain-stroke-dataset/data>
 The ethics approval and the subject consents are not required for a secondary published data set.

Data availability statement:

The data is available in the site-

<https://www.kaggle.com/datasets/jillanisoftech/brain-stroke-dataset/data>

Informed consent statement: Not applicable

Sample availability: The authors declare no physical samples were used in the study

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