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The Functional Role of Blood Elements on Cardiac Factors

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Abbreviation: HGC: Hemoglobin Concentration; RCI: Red Cell Index Hematocrit; SBP: Systolic Blood Pressure; DBP: Diastolic BP, CI: Cardiac Index; HR: Heart Rate; MAP: Mean Arterial Pressure; MCVP: Mean Central Venous Pressure; HCT: Hematocrit; PVI: Plasma Volume Index; AT: Appearance Time; UO: Urinary Output; MCT: Mean Circulation Time; BSI: Body Surface Index; CRS: Card Record Sequence

Introduction

The functional role of blood elements in human body is very complex which can only be predicted through proper probabilistic modeling. The report focuses how a probabilistic model can interpret the internal complex functional mechanism of a blood element on cardiac factors (or parameters). The report considers four blood elements such as hemoglobin concentration (HGC), red cell index (RCI), hematocrit (HCT) and plasma volume index (PVI), and seven cardiac factors such as systolic blood pressure (SBP), diastolic BP (DBP), cardiac index (CI), heart rate (HR), mean arterial pressure (MAP), mean central venous pressure (MCVP), shock type (Shock). The functional role of these four blood elements on seven cardiac factors are focused in the report through probabilistic modeling based on a real data set of 113 shock patients including 20 characters [1], the report seeks the following queries.

a. How do we identify the relationship between a blood element and any cardiac factor?
b. Does any blood element affect on any cardiac factor?
c. What is the association of a blood element with any cardiac factor?
d. What will happen on the cardiac factor if the blood element level is high or low?
e. What are the explanatory variables of the blood element?
f. How do we decrease or increase the blood element level?

The data description and patient population is given in [1]. These are not restated herein. The considered study characters of the data set are:

a. Height,
b. Age,
c. Sex (male=0, female = 1),
d. Systolic blood pressure (SBP),
e. Diastolic BP (DBP),
f. Shock type (Shock) (non-shock=1, hypovolemic=2, cardiogenic, or bacterial, or neurogenic or other=3),
g. Survival status (Survive) (survived=1, death=2),
h. Hematocrit (HCT),
i. Heart rate (HR),
j. Hemoglobin concentration (HGC),
k. Cardiac index (CI),
l. Plasma volume index (PVI),
m. Appearance time (AT),
n. Mean arterial pressure (MAP),
o. Urinary output (UO),

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p. Mean central venous pressure (MCVP),
q. Mean circulation time (MCT),
r. Body surface index (BSI),
s. Red cell index (RCI),
t. Card record sequence (initial=1, final =2) (CRS).

The given data set is a multivariate data, and the above study can be conducted in two ways. One way is the modeling of any blood element with the remaining other factors & variables. The other way is the modeling of any cardiac factor with the remaining other factors & variables. For any random study variable (here any blood element or cardiac factor) its mean and variance (if non-constant) may be explained by many explanatory variables. Note that all the four considered blood elements are heteroscedastic. Generally, physiological variables (or characters) are always heteroscedastic. Naturally, for heteroscedastic variable, mean and variance are to be modeled by joint generalized linear models (JGLMs) with Log-normal and Gamma distributions [2-5]. The report considers only the modeling of four blood elements with the remaining other cardiac factors & variables. Based on the probabilistic models of the four blood elements, the associations of these blood elements with the cardiac factors are focused in the report.

Detailed JGLMs analyses of plasma volume index (PVI) and red cell index (RCI) are given in [6]. From table 2 in Das, et al. [6], the probabilistic model of PVI can be written as follow.
Gamma fitted PVI mean ($\hat{\mu}$) model [7] is $\hat{\mu}$ = exp. (4.4400+0.0066 Height–0.1944 Sex–0.1122 Survive -0.0785 Shock2-0.0033 Shock3 -0.0033 DBP+0.0117 MCVP–0.7273 BSI +0.0452 CI–0.0083 HCT+0.0520 CRS), and the Gamma fitted PVI variance ($\hat{\sigma}^2$ model is $\hat{\sigma}^2$ = exp. (5.0798-0.0194 Age -0.0340 Height -0.6254 Sex -0.2895 CI-0.0019 UO-0.0209 HCT).

From the above mean & variance models of PVI, the following associations of PVI with the cardiac factors can be concluded.
a. Mean PVI is inversely associated with DBP (P<0.0001), interpreting that PVI rises as DBP decreases.
b. Mean PVI is directly associated with MCVP (P<0.0001), implying that PVI rises as MCVP increases.
c. Mean PVI is directly associated with CI (P<0.0001), indicating that PVI rises as CI rises.
d. Mean PVI is inversely associated with Shock at level 2 (P=0.0103), interpreting that as PVI increases, the incidence of shock will be decreased at level 1 (i.e., for non-shock patients) than at level 2.
e. Variance of PVI is inversely associated with CI (P=0.0003), concluding that PVI variance rises as CI decreases.

These above associations of PVI with the cardiac factors are summarized in Table 1.

From the Table 3 in Das, et al. [6], the probabilistic model of (Z=Log RCI) can be written as follow.
Log-normal fitted RCI mean ($\hat{Z}$) model Table 2 in Das & Lee [7] is $\hat{Z}$ = 2.0914+0.0011 Age – 0.0689 Shock2-0.0156 Shock3 -0.1877 BSI+0.0066 PVI+0.0325 HGC+0.0148 HCT, and the Log-normal fitted RCI variance ($\hat{\sigma}^2$) model is $\hat{\sigma}^2$ = exp. (3.7240–0.0282 Height - 0.1284 Shock2 + 0.5488 Shock3 + 0.0051 SBP - 0.1796 CI - 0.0014 UO - 0.0140 PVI – 0.0398 HCT).

From the above mean & variance models of (Z=Log RCI), the following associations of RCI with the cardiac factors can be concluded.
a. Mean RCI is inversely associated with Shock at level 2 (P=0.0522), implying that that as RCI increases, the incidence of shock will be decreased at level 1 (i.e., for non-shock patients) than at level 2.
b. Variance of RCI is inversely associated with CI (P=0.0397), concluding that RCI variance rises as CI decreases.
c. Variance of RCI is partially directly associated with Shock at level 3 (P=0.0783), implying that RCI variance increases at higher Shock level 3 than at levels 1 & 2.
d. Variance of RCI is partially directly associated with SBP (P=0.1758), interpreting that RCI variance rises as SBP increases.

These above associations of RCI with the cardiac factors are summarized in Table 1.

Detailed JGLMs analysis of Hemoglobin concentration (HGC) is given in Das & Lee [7]. From Table 2 in Das & Lee [7] the probabilistic model of (Z=LogHGC) can be written as follow.
Log-normal fitted HGC mean ($\hat{Z}$) model (Table 2) is
$\hat{Z}$ = 1.5961-0.0178 Survive–0.0019 MCVP +0.0015 AT+0.0240 HCT,
and the Log-normal fitted HGC variance ($\hat{\sigma}^2$) model is
$\hat{\sigma}^2$ = exp. (-0.8350–0.5595 Sex+0.3716 Shock2-0.3894 Shock3-0.0123 SBP+0.0074 HR +0.0420 MCVP–0.1374 CI +0.0018 UO–0.0934 HCT).

From the above mean & variance models of (Z=Log HGC), the following associations of HGC with the cardiac factors can be concluded.

i. Mean HGC is partially inversely associated with MCVP (P=0.0924), indicating that HGC increases, as MCVP decreases.
ii. Variance of HGC is inversely associated with SBP (P=0.0001), concluding that HGC variance increases, as SBP decreases.
iii. Variance of HGC is partially directly associated with HR (P=0.0768), implying that HGC variance increases, as HR rises.
iv. Variance of HGC is partially inversely associated with CI (P=0.0678), interpreting that HGC variance increases, as CI decreases.
v. Variance of HGC is partially directly associated with MCVP (P=0.0679), indicating that HGC variance increases, as MCVP rises.

These above associations of HGC with the cardiac factors are summarized in Table 1.

Detailed JGLMs analysis of Hematocrit (HCT) is given in Das & Lee [8]. From Table 1 in Das & Lee [8], the probabilistic model of HCT can be written as follow.

Gamma fitted HCT mean ($\hat{\mu}$) model (Table 2) is

$\hat{\mu}$ = exp. (2.6877 - 0.0554 Shock2 - 0.0348 Shock3 - 0.0001 UO - 0.0014 PVI + 0.0811 HGC), and the Gamma fitted HCT variance ($\hat{\sigma}^2$) model is

$\hat{\sigma}^2$ = exp. (- 5.525 + 0.922 Survive - 0.005 SBP - 0.006 HR + 0.119CI + 0.141 HGC).

From the above mean & variance models of HCT, the following associations of HCT with the cardiac factors can be concluded.

i. Mean HCT is inversely associated with Shock at level 2 (P=0.0014), implying that as HCT rises, incidence of shock decreases at level 1 (i.e., for non-shock patients) than level 2.
ii. Mean HCT is inversely associated with Shock at level 3 (P=0.0281), concluding that as HCT rises, incidence of shock decreases at levels (1 & 2) than level 3.
iii. Variance of HCT is partially inversely associated with SBP (P=0.0947), interpreting that as SBP rises, HCT variance decreases.
iv. Variance of HCT is partially directly associated with CI (P=0.1049), implying that as CI increases, HCT variance increases.
v. Variance of HCT is partially inversely associated with HR (P=0.0718), concluding that as HR rises, HCT variance decreases.

These above associations of HCT with the cardiac factors are summarized in Table 1.

Model	Variable	Associated with	Associated Type	P-value
Mean	HGC	MCVP	-ve	0.0924
Variance	HGC	HR	+ve	0.0768
	HGC	SBP	-ve	0.0001
	HGC	MCVP	+ve	0.0679
	HGC	CI	-ve	0.0678
Mean	PVI	Shock2	-ve	0.0103
	PVI	DBP	-ve	<0.0001
	PVI	MCVP	+ve	<0.0001
	PVI	CI	+ve	<0.0001
Variance	PVI	CI	-ve	0.0003
Mean	RCI	Shock2	-ve	0.0522
Variance	RCI	Shock3	+ve	0.0783
	RCI	CI	-ve	0.0397
	RCI	SBP	+ve	0.1758
Mean	HCT	Shock2	-ve	0.0014
	HCT	Shock3	-ve	0.0281
Variance	HCT	SBP	-ve	0.0947
	HCT	HR	-ve	0.0718
	HCT	CI	+ve	0.1049

Table 1: Association of cardiac factors with blood elements HGC, PVI, RCI & HCT level.

The report has shown the effects of four blood elements (HGC, PVI, RCI & HCT) on seven cardiac factors (DBP, SBP, CI, MCVP, HR, MAP & Shock type). From Table 1, it is observed that mean PVI, RCI & HCT levels are associated with the incidence of shock. If their levels are high, the incidence of shock decreases for non-shock patients than shock patients. Overall from the report, it is implied that all the four blood elements level should be little high, but very low level may invite many cardiac problems. Medical practitioners & every cardiac patient should care on all the four blood elements level.

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