World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Modeling on the Perfusion Index for the Students of the Statistics Department at the University of Rajshahi

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World Journal of Advanced Research and Reviews, 2025, 27(02), 085-102

Publication history: Received on 25 June 2025; revised on 30 July 2025; accepted on 02 August 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.27.2.2842

Abstract

Our research was to investigate the determinants of perfusion index (PI), which can get into the increase and decrease of PI and also build the model on PI as well as the relationship between PI and different study variables. PI, calculated using a pulse oximeter, shows the ratio of the pulsatile blood flow to the non-pulsatile blood flow or static blood in peripheral tissue. The information of PI, together with their preditors, was collected/measured from the students of Statistics at Rajshahi University, adapting the stratified random sampling through a questionnaire containing 52 questions. Weights, heights, pulse rate, diastolic blood pressure, systolic blood pressure, and perfusion index are recorded by respective measurement tools. Univariate analysis was used to determine significant determinants, and bivariate association and correlation can also be implied. It was found that there was a positive correlation between PI and diastolic blood pressure, PI and weight, PI and exercise time, and PI and eating mangoes. A statistically significant difference was detected between the PI of males and females and smokers and non-smokers ($p<0.05$). Also, a significant association ($p<0.05$) was found between blood pressure levels and classes of different PI. Finally, a model was created involving the most significant determinants: sex, smoking status, exercise time, and diastolic blood pressure. As the value of R^2 is 0.759, there is a scope for further extension of this research, including the increase of sample size, study variables, and involvement of different age groups of people. PI is the indication of sound health, strength of heart, and way of detecting heart disease, so we should take necessary steps to facilitate exercise time and maintain a healthy life. We also have to eat a healthy diet to raise the perfusion index.

Keywords: Perfusion Index (PI); Independent Two Sample T-test; Stepwise forward regression; Pulse Oximeter; pulsatile blood flow

1. Introduction

The perfusion index (PI) in peripheral tissues, including the fingertips, toes, and earlobes, is a non- invasive measure indicating the ratio of pulsatile to non-pulsatile blood flow [1]. The heart's contraction and relaxation facilitate pulsatile blood flow, which refers to the rhythmic movement of blood throughout the circulatory system. This flow, in contrast to constant flow, embodies the cyclical nature of the cardiac cycle and fluctuates with each heartbeat. This flow type is characterized by variations in pressure and velocity, which can affect various physiological factors, energy dissipation, and shear stress on blood vessel walls [2]. The pulse oximeter measures the peripheral index (PI), which assesses the strength of the peripheral pulse, thereby providing crucial insights into hemodynamic status and autonomic nervous system function [3]. In clinical and research settings, pulse oximeters are commonly used during exercise to provide a noninvasive continuous estimate of the oxyhemoglobin saturation of arterial blood (%SpO_2) [4]. Arterial

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oxyhemoglobin saturation indicates the degree of arterial blood oxygenation, specifically arterial oxygen partial pressure, and can thus be used to diagnose hypoxemia, a condition characterized by decreased arterial. The arterial oxygen partial pressure is age-dependent, with typical values ranging from approximately 100 mmHg at age 20 to approximately 80 mmHg at age 80 at sea level [5], [31]. So, it is especially relevant for conditions where blood flow may fluctuate due to various physiological stressors, such as during surgery or in populations experiencing stress [6].

The perfusion index (PI), a non-invasive measure derived from pulse oximetry, provides valuable information regarding peripheral blood circulation. Its interpretation requires a fundamental understanding of its physiological foundations. [7] elucidates the core principles of PI measurement and its clinical significance. While [8] emphasizes the impact of the autonomic nervous system on peripheral blood flow, a crucial factor in assessing PI data among students subjected to varying stress levels and cognitive load. Statistical modeling is crucial for accurately interpreting PI data, especially when accounting for individual variation. [9] provides a comprehensive overview of statistical methodologies relevant to physiological data, including regression and analysis of variance (ANOVA). Furthermore, [10] emphasize the necessity of employing mixed-effects models to account for the inherent diversity among individuals, a crucial consideration when analyzing PI data from a heterogeneous student population. Recent research has expanded the application of PI beyond clinical settings to encompass broader populations, including university students, as it offers valuable insights into stress-related physiological changes and cardiovascular health [11], [12]. The academic environment is associated with increased cognitive demands, emotional stress, and lifestyle habits that may impact autonomic function and circulatory dynamics [13], [32]. Academic stress has been shown to activate the hypothalamic-pituitary-adrenal (HPA) axis, leading to autonomic dysregulation that can manifest in altered perfusion patterns and vascular responses [14]. Furthermore, prolonged exposure to mental workload and screen time has been linked to vasoconstrictive effects, which may further influence PI fluctuations [15]. Like other physiological parameters, PI can indicate the autonomic nervous system's control of blood flow and its response to internal and external stressors [16], [17]. Knowing how PI fluctuates will enable students whose academic load and stress levels vary to spot those at risk of circulatory dysfunction. Although many studies have examined PI in clinical settings, its application in academic institutions, especially for students with high cognitive loads, remains under-researched [18].

Modeling the Perfusion Index for students in the Statistics Department at the University of Rajshahi is the main emphasis of this paper. This study aims to contribute to a deeper understanding of how PI-related factors impact circulatory health by examining several key factors, including academic stress, cognitive load, and lifestyle choices. The findings of this study could also provide a non-invasive method for tracking student well-being, enabling universities to implement health plans that reduce stress-related health hazards. The Perfusion Index could be a valuable tool for identifying at-risk students and encouraging healthier academic practices if effective [19].

Focusing on academic stress, cognitive load, lifestyle choices, and environmental conditions, this paper aims to bridge the gap by examining the factors influencing PI in students at the University of Rajshahi. This study aims to identify the primary variables influencing PI by employing advanced statistical modeling methods and to model their interactions, thereby understanding how they interact and impact perfusion dynamics in the student population. This study also aims to provide a predictive framework that enables health professionals and academics to more accurately assess student well-being and develop interventions tailored to their specific needs. Hence, in this study, the research questions are:

- RQ1: What variables does the Perfusion Index rely on?
- RQ2: How do we model the Perfusion Index using the variables connected to it?

These research questions, with particular attention to the academic environment and lifestyle choices, aim to uncover the various interactions with PI and the mechanisms by which they function. The study will investigate the interactions between these variables and develop a model that accurately reflects the underlying physiological processes using statistical tools.

The remaining part of the study is organized as follows: Section 2 contains the materials and methodology, including a description of the dataset, different statistical tests, and an overview of the evaluation criteria for those statistical tests. Section 3 presents the results of analyzing the example dataset. Section 4 summarizes the concluding remarks and outlines directions for future research.

2. Materials and Methodology

2.1. Description of Data Set

The dataset related to the perfusion index focuses on students' various health and socio-economic parameters, including height, weight, food habits, and demographic factors such as age, monthly income, expenditure, parents' occupation, education level, and oxygen saturation level, pulse rate, and blood pressure measured using pulse oximeter tools. The study sample was collected from students in the University of Rajshahi statistics department through a scheduled questionnaire, which was collected directly from the students. This cross-sectional study used a stratified random sampling technique to select a sample of students from the Department of Statistics at the University of Rajshahi. The population was divided into five strata based on year of study: first year (98 students), second year (97 students), third year (95 students), fourth year (98 students), and masters (85 students), ensuring homogeneity within each stratum and heterogeneity between strata using factors like perfusion index, age, food habits, income, expenditure, height, and weight. Simple random sampling was applied within each stratum using the remainder approach of a random number generator, and sub-samples were combined to form the study sample.

1st year	2nd year	3rd year	4th year	5th year
N_1=91	N_2=97	N_3=95	N_4=98	N_5=85

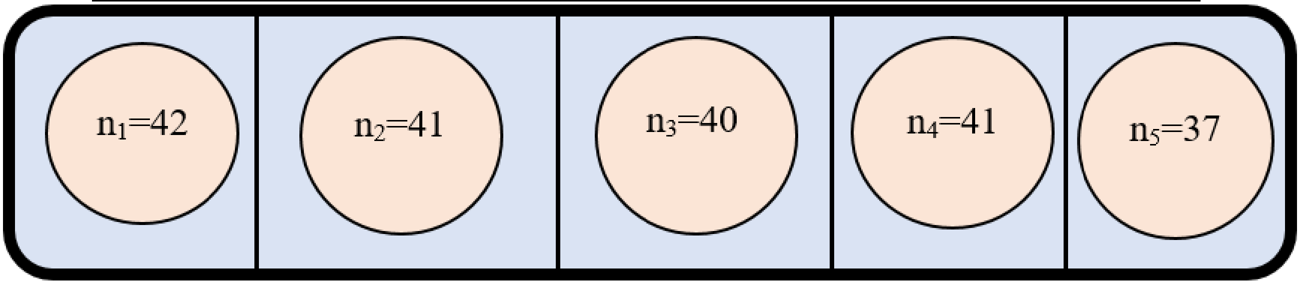

Figure 1 Stratified random sampling

Proportion allocation was used to determine the sample size from each stratum, resulting in 42 students from the first year, 41 from the second year, 40 from the third year, 41 from the fourth year, and 37 from the masters. The total sample size was 201 students out of 473, calculated as $n = 42 + 41 + 40 + 41 + 37 = 201$. In the study, the perfusion index, measured by pulse oximeter tools, was considered the output variable. In contrast, explanatory variables included height, weight, oxygen saturation level, pulse rate, blood pressure level, food habits, and socioeconomic and demographic factors such as age, monthly income and expenditure, parents' occupation, education level, and additional variables.

2.2. Material properties

In this cross-sectional study, we use a questionnaire divided into four sections: personal information, socioeconomic information, food habits, and anthropometric measurement. The respondents' answers cover the whole questionnaire except for some questions in the anthropometric section, which are measured by the plus oximeter.

The normal range of the perfusion index (PI) varies from 0.02% to 20%. There is no universally agreed-upon "normal," so it's a good idea to keep track of your baseline reading and monitor how it changes over time. Things like artery disease, diabetes, obesity, blood clots, and other health problems can affect your perfusion [20].

A higher PI, closer to 20%, means your arteries are dilated and blood flow is strong. On the other hand, a lower PI, closer to 0.02%, could signal that your arteries are constricted and blood flow is weak [20].

2.3. Data pre-processing

Data preprocessing is an essential step in the classification framework that guarantees the high accuracy of the findings. It consists of three parts: editing, coding, and tabulation.

2.4. Ethics statement

Prior to collecting data, we obtained ethical clearance from the Ethical Committee, Institute of Biological Sciences (IBSc), Rajshahi University, Bangladesh, to conduct research on the Perfusion Index for the students of the Statistics Department.

2.5. Statistical Analysis

All data for this study were collected through a structured questionnaire and entered into SPSS (IBM, version 25) for detailed analysis. Initially, Descriptive Statistics were calculated to summarize the health, lifestyle, and dietary variables gathered from the participants. The Shapiro- Wilk Test for Normality was applied to test the data distribution, with results showing that the data followed an approximately normal distribution, as confirmed by histograms and P-P plots. Stepwise Regression Analysis was employed to identify the key predictors of the Perfusion Index, focusing on variables like diastolic blood pressure, exercise time, and smoking habits. The Two- Sample t-test was used to compare the means of the Perfusion Index across different groups, including sex, mental stress, and smoking habits, to detect significant differences. The model's reliability and generalizability were assessed through Cross-validation, ensuring the robustness of the findings. Finally, Pearson Correlation Analysis was conducted to explore the relationships between Perfusion Index and other health-related variables. Statistical significance was accepted at $p < 0.05$, providing a clear threshold for interpreting the results.

2.6. Stepwise Regression Analysis

Stepwise Regression is a method to select the most significant variables for inclusion in a regression model. It combines forward selection and backward elimination techniques, making it a highly efficient approach for identifying key predictors in a model [21]. In this study, Stepwise Regression was employed to identify significant predictors of the Perfusion Index. The process begins with all potential predictor variables. Iteratively adds or removes variables based on specific criteria, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). This ensures that only the most relevant predictors remain in the final model, thereby improving the model's explanatory power and interpretability [22]. Below is an illustration [22] of the Stepwise Regression process, showing the forward selection and backward elimination steps. The process proceeds as follows:

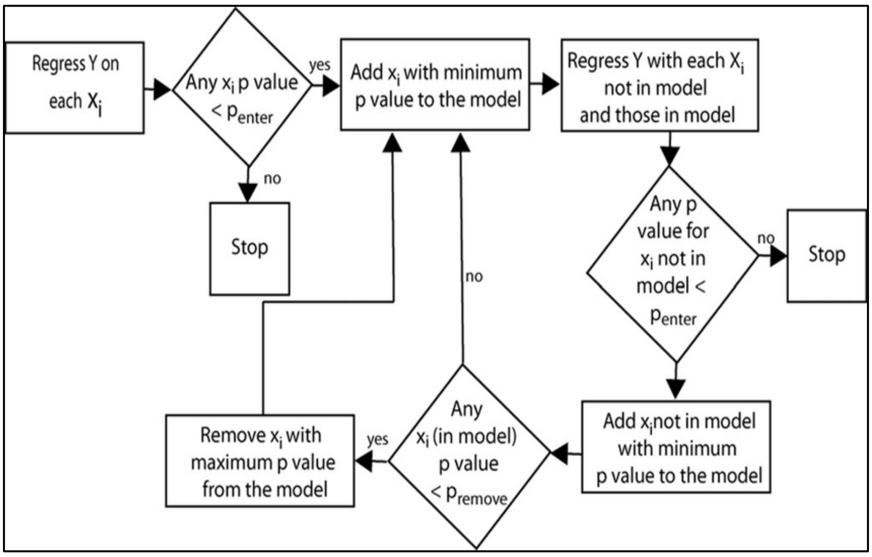

Figure 2 Stepwise Regression

- **Forward Selection**: The model starts with no predictors. Predictors are added one by one based on their significance.
- **Backward Elimination**: Starts with all predictors and removes those not statistically significant.

In Stepwise Regression, the inclusion or exclusion of predictors is determined based on the p- value of each variable, typically with a threshold of $p < 0.05$ for inclusion and $p > 0.10$ for exclusion [9]. This method helps identify the most important predictors while avoiding overfitting [23].

2.7. Two-Sample t-test

The Two-Sample t-test (also known as the independent samples t-test) is a statistical test used to compare the means of two independent groups and determine whether there is a statistically significant difference between them [24]. In this study, the Two-Sample t-test was used to compare the Perfusion Index across various groups, including sex, mental stress levels, and smoking habits.

The null hypothesis (H_0) for the t-test assumes no significant difference between the two group means. The alternative hypothesis (H_1) suggests that there is a significant difference. The t-test statistic is calculated using the following formula:

$$t = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where, $\bar{X}_1$ and $\bar{X}_2$ are the sample means of the two groups, s_1^2 and s_2^2 are variance of both groups, and n_1 and $n_2$are the sample size of two groups. The t-statistic is then compared to the critical value from the t-distribution table based on the chosen significance level (usually α=0.05) and the degrees of freedom. If the calculated t-value exceeds the critical value, the null hypothesis is rejected, indicating a significant difference between the two groups [25].

3. Results

The study gathered data from 201 participants, encompassing categorical and continuous health- related variables. Of the participants, 67.2% were male and 32.8% were female. A total of 61.2% were late risers, while 90.5% were non-smokers. Most participants exhibited normal blood pressure (86.6%), whereas only 2.5% indicated elevated pressure. The distribution of the blood groups indicated that B+ (31.8%) and O+ (30.3%) were the predominant types. The respondents' parents exhibited a propensity for normal blood pressure, with 45.7% of the mothers and 59.2% of the fathers within the normal range. Health conditions, such as asthma (87.6%), allergies (64.2%), chest pain (77.6%), and mental stress (56.7%), were significantly prevalent.

Table 1 Descriptive Statistics of Health, Lifestyle, and Dietary Variables Among Respondents

Variable	**Range**	**Min**	**Max**	**Mean**	**SE**	**Sk**
Age	9.00	18.00	27.00	22.53	0.12	-0.17
Expenditure	45000	0.0	45000	5677	288	5.9
Exercise time	21.00	0.0	21.00	4.2378	0.31	1.6
Sleeping time	7.00	5.00	12.00	7.74	0.082	0.41
Daily Eaten Rice	1450.00	50.00	1500.00	402.4129	13.80772	1.559
Daily Eaten Bread	6000.00	0.00	6000.00	69.9104	30.17924	13.464
Daily Drinking water	8998.00	2.00	9000.00	2684.6119	107.10513	1.290
Daily Eaten Fish	5000.00	0.00	5000.00	350.5473	31.66359	6.377
Daily Eaten Meat	2500.00	0.00	2500.00	328.0398	26.62824	3.010
Amount of Cold Drinks Taken in a Week	2000.00	0.00	2000.00	419.4428	35.53642	1.811
Eaten Vegetable Daily	1200.00	0.00	1200.00	205.9950	13.93865	2.106
Eaten Cinnamon Daily	250.00	0.00	250.00	14.5100	2.68912	3.945
Height in Cm	129.00	60.00	189.00	164.7410	0.89607	-4.841
Weight in Kg	57.00	37.00	94.00	60.7851	0.77093	0.470
Oxygen Saturation Level%	40.00	60.00	100.00	97.8259	0.25611	-6.850

Pulse Rate in BPM	113.70	8.30	122.00	78.6433	0.85221	-0.607
Systolic mmHg	60.00	80.00	140.00	113.1940	0.76300	-0.607
Diastolic mmHg	50.00	50.00	100.00	74.5550	0.66528	-0.519

Table 1 shows the following-

The mean of the respondents was about 22 years. The minimum age was 18 years, and the maximum was 27 years. The distribution of the age is negatively skewed. So, there were more respondents between 18 and 22.5 years old.

From the descriptive statistics, we can say that the monthly expenditure of our statistics students in RU was 5591 taka.

On average, each student does approximately 4.2 hours of exercise or playing.

The average sleeping time in a day for respondents was 7.73 hours. Besides, the minimum value of sleeping time in a day for our study respondents was 5 hours, and the maximum value of sleeping time in a day for our respondents was 12 hours. The value of skewness was positive. So, the number of students is between 7 and 12 hours interval than those between 0 and less than 7 hours interval.

On average, each respondent ate approximately 402 gm of rice and approximately 70 gm of bread.

Some calculations for descriptive statistics are given in a table for specific food quantities, such as daily consumed fish, daily consumed meat, daily consumed vegetable, and so on.

The mean height was 164.747 cm. The minimum height was 129 cm, and the maximum was 189 cm. The value of skewness is -4.481, which means the population's frequency is more between the minimum and mean values.

The mean weight was 60.785 kg. The minimum weight was 37kg, and the maximum was 189 kg. The skewness value is .470, which means the population's frequency is greater between the maximum and mean values.

Our respondents' average pulse rate was 78.643. This is within the normal range and indicates a good health condition.

Among the students, systolic blood pressure varies from 80 to 140 with a mean value of 113 mmHg. This distribution shows a negatively skewed and platykurtic curve pattern. So, the distribution of this variable was very much scattered

The maximum diastolic mmHg value was 100mmHG among the respondents, and the minimum was 50mmHG among the students. The average diastolic mmHg value of study students/respondents was 74.55 mmHg.

Table 2 Descriptive Statistic for Perfusion Index

Perfusion Index		
N	**Valid**	**201**
	Missing	**0**
Mean		4.9259
Std. Error of mean		0.22927
Median		4.2
Mode		1.10
Variance		10.566
Skewness		0.748
Std. Error of Skewness		0.172
Kurtosis		0.06

Std. Error of Kurtosis	0.341
Range	15
Minimum	0
Maximum	15

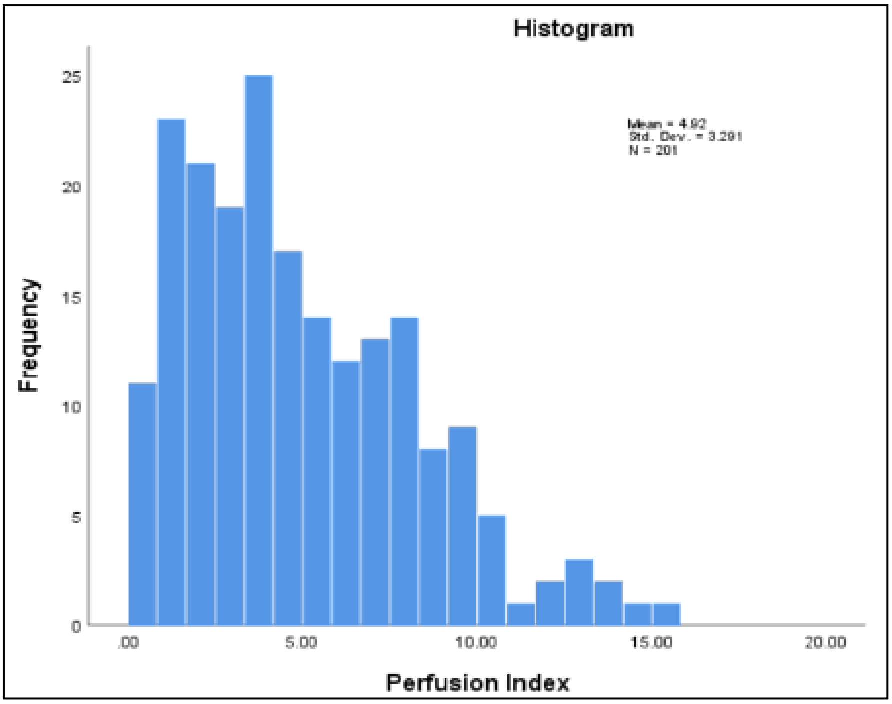

Figure 3 Histogram of Perfusion Index

Table 2 shows that the mean of the perfusion index of the respondents was 4.92, the median was 4.2, and the mood was 1.1. It is alarming news that the average and mode of perfusion index for study students are less than 5. So, the blood flow condition was very poor, and the heart-blood circulation of statistics students was quite ominous. The maximum perfusion index value was 15, which was good news. It is a good condition for blood circulation. The variance of the perfusion index was 10.5. The distribution is negatively skewed and platykurtic. That means the distribution was very much dispersed.

Table 3 Correlation coefficients for different variables

		Perfusion Index	Diastolic mmHg	Body Mass Index	Weight in Kg	Eaten Mango Weekly	Eaten Cinnamon Daily	Eaten Vegetable Daily	Exercise time or playing time
Perfusion Index	Pearson Correlation	1	0.219**	0.025	0.211**	0.155*	-0.008	0.091	0.275**
	Sig. (2-tailed)		0.002	0.728	0.003	0.028	0.911	0.197	0.000
	N	201	200	201	201	201	201	201	201
Diastolic mmHg	Pearson Correlation	0.219**	1	0.037	0.310**	0.086	-0.102	-0.013	0.043

	Sig. (2-tailed)	0.002		0.604	0.000	0.227	0.149	0.852	0.548
	N	200	200	200	200	200	200	200	200
Body Mass Index	Pearson Correlation	0.025	0.037	1	0.221**	-0.013	0.119	-0.041	0.071
	Sig. (2-tailed)	0.728	0.604		0.002	0.860	0.092	0.566	0.314
	N	201	200	201	201	201	201	201	201
Weight in Kg	Pearson Correlation	0.211**	0.310**	0.221**	1	0.117	0.012	-0.012	0.083
	Sig. (2-tailed)	0.003	0.000	0.002		0.099	0.861	0.864	0.240
	N	201	200	201	201	201	201	201	201
Eaten Mango Weekly	Pearson Correlation	0.155*	0.086	-0.013	0.117	1	0.055	-0.008	0.040
	Sig. (2-tailed)	0.028	0.227	0.860	0.099		0.434	0.909	0.576
	N	201	200	201	201	201	201	201	201
Eaten Cinnamon Daily	Pearson Correlation	-0.008	-0.102	0.119	0.012	0.055	1	0.047	-0.012
	Sig. (2-tailed)	0.911	0.149	0.092	0.861	0.434		0.510	0.864
	N	201	200	201	201	201	201	201	201
Eaten Vegetable Daily	Pearson Correlation	0.091	-0.013	-0.041	-0.012	-0.008	0.047	1	0.042
	Sig. (2-tailed)	0.197	0.852	0.566	0.864	0.909	0.510		0.554
	N	201	200	201	201	201	201	201	201
Exercise time or playing time	Pearson Correlation	0.275**	0.043	0.071	0.083	0.040	-0.012	0.042	1
	Sig. (2-tailed)	0.000	0.548	0.314	0.240	0.576	0.864	0.554	
	N	201	200	201	201	201	201	201	201

** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed).

The Pearson coefficient between perfusion index-related variables is shown in Table 4. The correlation analysis reveals several significant relationships among the studied variables. The Perfusion Index shows a moderate positive correlation with Diastolic Blood Pressure ($r = 0.219$, $p < 0.01$), Body Weight ($r = 0.211$, $p < 0.01$), and Exercise Time ($r = 0.275$, $p < 0.01$), indicating that individuals with higher perfusion levels tend to have higher blood pressure, greater body weight, and engage more in physical activity. Additionally, a weak but significant positive correlation is observed between the Perfusion Index and Mango Consumption ($r = 0.155$, $p < 0.05$), suggesting a possible dietary influence on vascular performance.

Diastolic Blood Pressure is strongly associated with Weight (r = 0.310, p < 0.01), implying that as body weight increases, so does diastolic pressure. Body Mass Index (BMI), while significantly related to Weight (r = 0.221, p < 0.01), does not show notable associations with other variables in the study.

Dietary variables such as cinnamon and vegetable intake do not significantly correlate with the Perfusion Index or other health markers. Exercise Time is only significantly correlated with the Perfusion Index, with no meaningful associations found with blood pressure, BMI, or dietary factors. The findings highlight that physiological factors like blood pressure and weight and lifestyle behaviors like physical activity influence the Perfusion Index. At the same time, dietary variables (except mango intake) appear to have limited direct associations.

Table 4 Group Statistics for Perfusion Index across Different Groups

Group Statistics					
Variables	Perfusion Index	N	Mean	Std. Deviation	Std. Error Mean
Sex	Female	66	3.6015	2.801	0.3448
	Male	135	5.5734	3.2676	0.2812
Mental Stress	Yes	87	4.7149	2.9515	0.3164
	No	114	5.0869	3.4656	0.3246
Smoking habit	Yes	19	3.5584	2.2083	0.5066
	No	182	5.0687	3.3125	0.2455
Early and Late Riser	Early riser	78	5.1449	3.1134	0.3525
	Late Riser	123	4.7871	3.3395	0.3011

The table shows that the mean Perfusion Index values are not similar across the different groups. For Sex, the mean for males (5.57) is significantly higher than for females (3.60), indicating a clear difference between the two groups. When considering mental stress, individuals reporting no mental stress have a slightly higher mean (5.09) compared to those with mental stress (4.71), showing a slight difference. In terms of smoking habits, there is a noticeable difference, with non- smokers having a significantly higher mean (5.07) compared to smokers (3.56). Finally, early risers have a higher mean (5.14) than late risers (4.79), though the difference is relatively small.

In this case, we used a two-sample t-test to compare the means of Perfusion Index between two independent groups (e.g., males vs. females, smokers vs. non-smokers) to see if there was a statistically significant difference between them. The two-sample t-test is appropriate here because we are examining the difference in means between separate groups that are unrelated or paired, which is precisely the scenario with gender, smoking status, and other independent categories. In this case, the null hypothesis is that the perfusion index for the independent groups was the same, whereas the alternative hypothesis is the opposite.

Table 5 Two-Sample T-test

Two Sample t-test										
Variables	**Perfusion Index**	**Levene's Test for Equality of Variances**		**t-test for Equality of Means**					**95% Confidence Interval of the Difference**	
		F	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Mean Difference**	**Std. Error Difference**	**Lower**	**Upper**
Sex	Equal variances assumed	5.085	0.025	4.486	199	0.000	2.11856	0.47222	1.18737	3.04975

	Equal variances are not assumed.			4.794	153.744	0.000	2.11856	0.44195	1.24549	2.99163
Mental Stress	Equal variances assumed	1.216	0.272	-0.355	199	0.723	-0.16669	0.46952	-1.09256	0.75918
	Equal variances are not assumed.			-0.360	193.083	0.719	-0.16669	0.46341	-1.08068	0.74730
Smoking habit	Equal variances assumed	8.226	0.005	-1.914	199	0.057	-1.50861	0.78819	-3.06288	0.04566
	Equal variances are not assumed.			-2.673	27.569	0.012	-1.50861	0.56442	-2.66559	-0.35164
Early and Late Riser	Equal variances assumed	0.164	0.686	0.76	199	0.448	0.3578	0.47098	-0.571	1.28655
	Equal variances are not assumed.			0.772	172.42.	0.441	0.3578	0.46362	-0.5573	1.2729

Based on the two-sample t-test results, we can assess whether the Perfusion Index differs across the independent groups. For Sex, the p-value (0.000) is less than 0.05, so we reject the null hypothesis, indicating a significant difference in the Perfusion Index means between males and females. For Mental Stress, the p-value (0.723) is more significant than 0.05, so we fail to reject the null hypothesis, suggesting no significant difference in the Perfusion Index means between individuals with and without mental stress. In the case of Smoking Habit, the p-value (0.012) is less than 0.05, leading us to reject the null hypothesis, meaning that there is a significant difference in the Perfusion Index means between smokers and non-smokers. Finally, the p-value (0.441) is more significant than 0.05 for Early and Late Risers, so we fail to reject the null hypothesis, indicating no significant difference in Perfusion Index between early risers and late risers.

Overall, the Perfusion Index showed significant differences between sexes and smoking habits, while mental stress and sleeping patterns (early vs. late risers) showed no significant differences.

Table 6 Descriptive statistics for different blood pressure levels

Perfusion Index								
	N	**Mean**	**Std. Deviation**	**Std. Error**	**95% Confidence Interval for Mean**		**Minimum**	**Maximum**
					Lower Bound	**Upper Bound**		
Low	22	3.65	2.792	0.595	2.4123	4.888	0	12
Normal	174	5.027	3.252	0.247	4.5405	5.514	0.2	15
High	5	7.02	3.903	1.745	2.174	11.87	2.2	12.9
Total	201	4.926	3.25	0.229	4.4738	5.378	0	15

Table 7 ANOVA table for different blood pressure levels

ANOVA					
Perfusion Index	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	59.52	2	29.761	2.869	0.059
Within Groups	2054	198	10.372		
Total	2113	200			

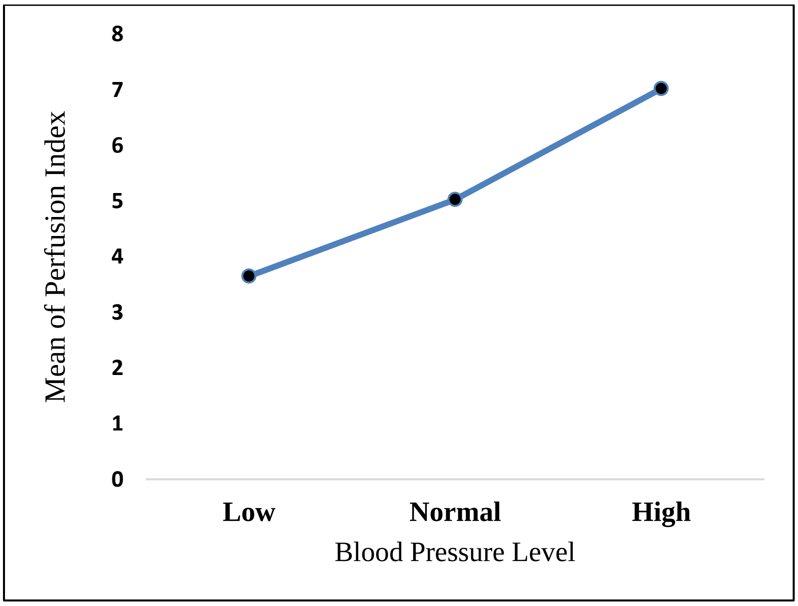

Figure 4 Mean plot of PI for blood pressure levels

Among the 201 respondents, the Perfusion Index means for low, normal, and high blood pressure groups were 3.65, 5.027, and 7.02, respectively (Table 7), suggesting a potential difference. An F- test (Table 8) was conducted to compare the means of the Perfusion Index across these three blood pressure levels. The null hypothesis (Ho) stated that all means were equal, while the alternative hypothesis (H1) stated that at least one mean was different. The p-value obtained from the F-test was 0.059. When using a significance level of p = 0.05, we fail to reject the null hypothesis, meaning there is no statistically significant difference between the Perfusion Index means for the three blood pressure groups. However, if we adjust the significance level to p = 0.06, we would reject the null hypothesis, suggesting significant differences in the Perfusion Index across the different blood pressure groups. Thus, depending on the significance threshold chosen, we either fail to find a significant difference (p = 0.05) or conclude that there is a difference (p = 0.06) among the means of the three blood pressure groups.

3.1. Pretest of OLS Assumption

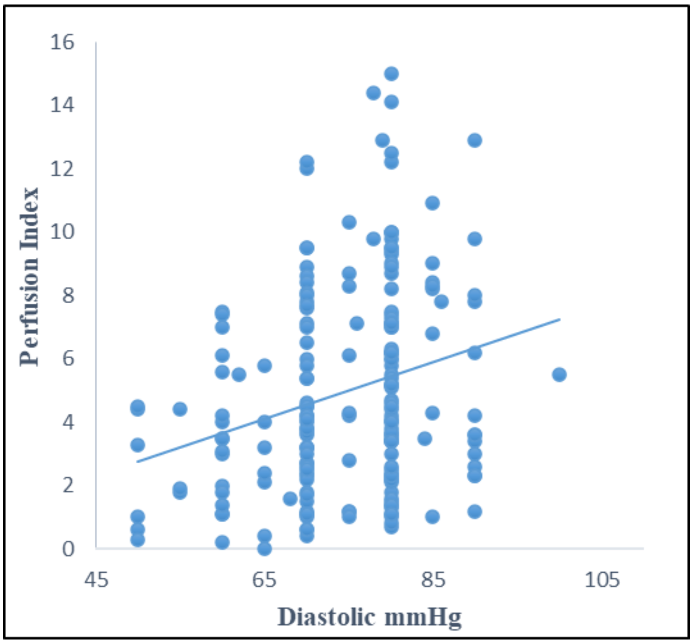

Figure 5 Relationship between PI and diastolic

Figure 6 Relationship between PI and Exercise Time

The scatter plots (Figure 5 and Figure 6) show a linear relationship between perfusion index and diastolic and perfusion index and exercise time.

3.2. Normality check

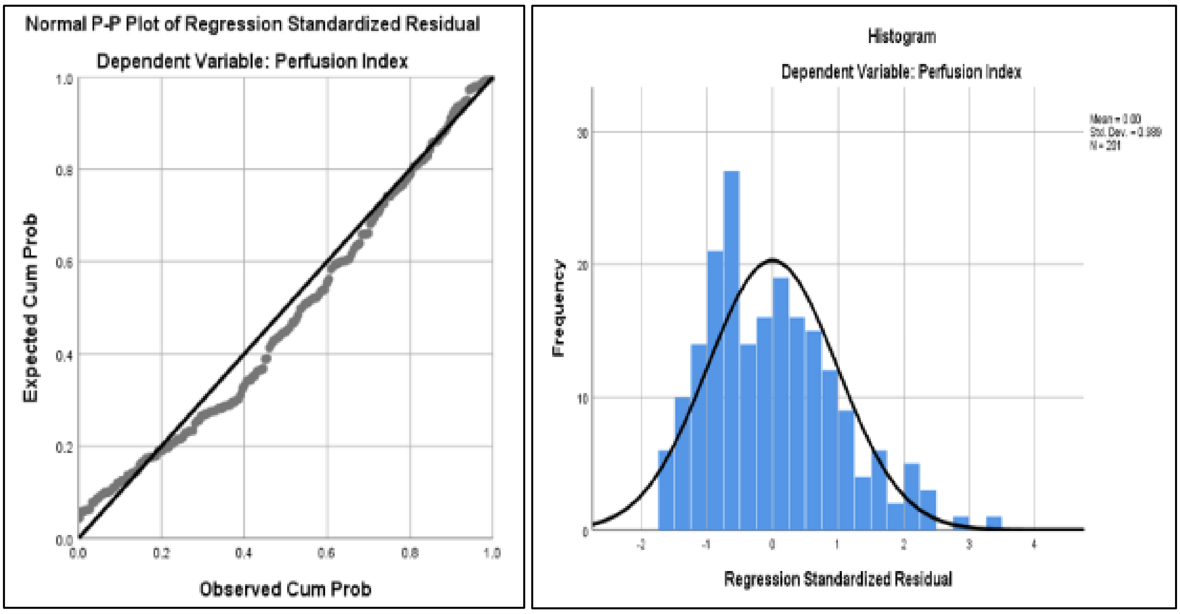

Figure 7 P-P Plot and Histogram of Perfusion Index

The histogram and normal probability plot show that the plots follow a normal distribution except for some values.

Now, Stepwise regression is used to identify the most significant predictors of the Perfusion Index (PI) from a set of independent variables, such as diastolic blood pressure. Stepwise regression is a statistical method that automatically selects the best subset of predictors by adding or removing variables based on specific criteria, typically the Akaike Information Criterion (AIC) or p-values. This approach helps create a more parsimonious model, avoiding overfitting and ensuring that only the most relevant variables are included in the regression model, improving the interpretability and accuracy of the results.

Table 8 Step-wise multiple linear Regression

Step-wise Multiple Linear Regression									
Model	**Unstandardized Coefficients**		**Standardize d Coefficients**	**95.0% Confidence Interval for B**		**Collinearity Statistics**		**t**	**Sig.**
variable	**B**	**Std. Error**	**Beta**	**Lower Bound**	**Upper Bound**	**Tolerance**	**VIF**		
Diastolic mmHg	0.045	0.005	0.579	0.035	0.056	0.272	3.676	8.633	0.000
Exercise time or playing time	0.162	0.049	0.166	0.065	0.258	0.489	2.045	3.314	0.001
Sex of the respondents	1.616	0.478	0.225	0.673	2.558	0.278	3.6	3.381	0.001
Smoking habit	-2.182	0.725	-0.114	-3.612	-0.751	0.857	1.167	-3.008	0.003

Dependent Variable: Perfusion Index

3.3. Linear Regression through the Origin

Table 9 Model Summary

Model	R	R Square[b]	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
4	0.871[e]	0.759	0.754	2.92679	0.011	9.048	1	197	0.003	1.872

The fitted model was,

Perfusion index = (0.045*diastolic mmHg) + (0.162*exercise time) + (1.616*sex of respondents) + (-2.182*smoking habit)

The above-fitted model indicates that diastolic mmHg, exercise time, respondents' sex, and smoking habits are the determinants of the perfusion index.

Here, the coefficient 0.045 means that if all other variables are constant, one unit increase in diastolic mmHg will increase by 0.045 units in the perfusion index. The coefficient 0.162 means that if all other variables are constant, one unit increase in exercise time will increase by 0.162 units in the perfusion index. Again, the coefficient (1.616) of sex of respondence means if we take male instead of female respondents, then 1.616 unit increases in perfusion index. If all other variables are constant, then the coefficient (-2.182) of smoking status means the perfusion index is 2.182 times less for a smoker than a non-smoker respondent.

If we take several samples, we get about the exact estimates of the coefficients, as the standard error of the estimates is tiny. The discriminants (std. error) of the coefficients of diastolic mmHg, exercise time, sex, and smoking status are .005, .049, .478, and .725, respectively. Here, all the obtaining coefficients are significant.

The $R^2$of this model is 0.759, which means that about 75.9% of variations are explained by the explanatory variables (determinants). Perhaps other determinants can also greatly influence the increase and decrease of the perfusion index, which were not mentioned or identified in our model.

3.4. Post-test of OLS Assumption

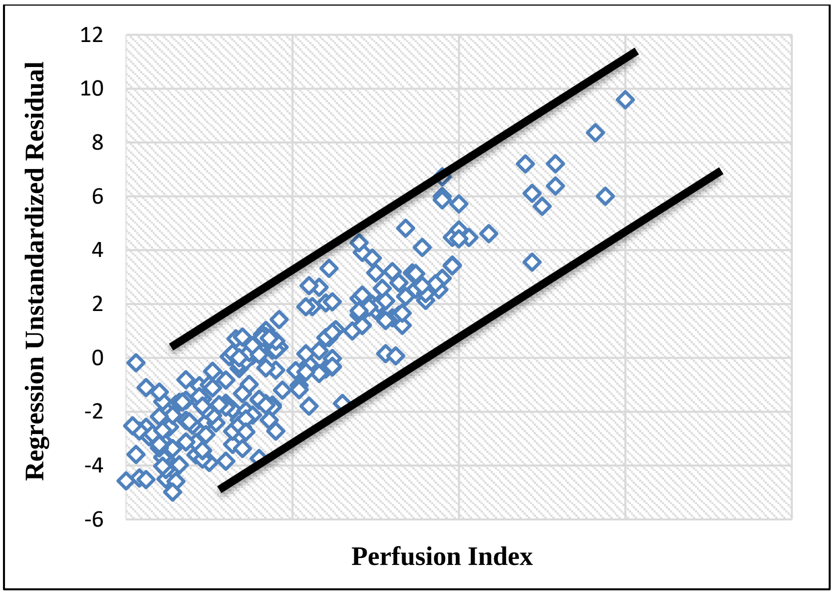

Figure 8 Plot of PI and Unstandardized Residual

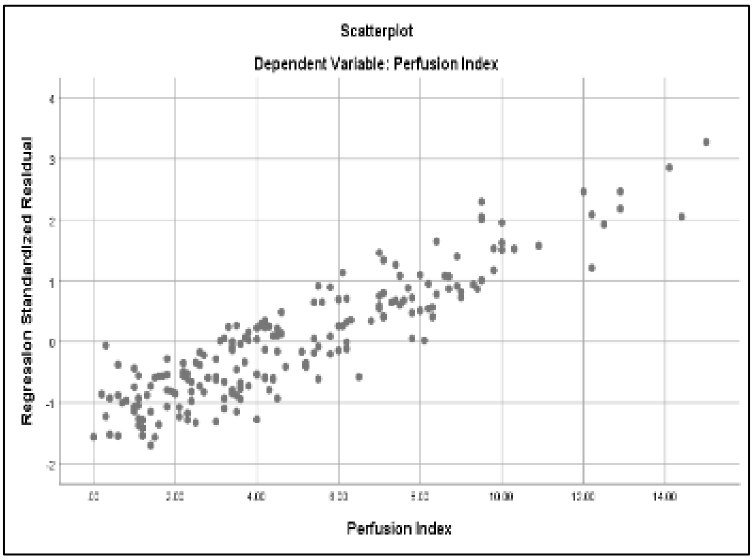

Figure 9 Plot of PI and Standardized Residual

There is no heteroscedastic problem in our dataset. Here, we plotted the residual and dependent variables and standardized the residual and dependent variables. From the plots, we observed that the error variance was approximately constant. The Durbin-Watson statistic was 1.9, which was nearly 2. Therefore, there is no autocorrelation problem in our dataset. The variance inflation factor values indicate that our fitted regression is free from the problem of multicollinearity, as the VIF was less than 5 for all explanatory variables.

4. Discussion

The results of our research on the perfusion index (PI) of students from the Statistics Department at the University of Rajshahi offer substantial insights into the physiological dynamics of these individuals, shaped by variables including blood pressure, physical activity, smoking habits, and gender. The research employed a stratified random sampling technique and utilized statistical methods such as stepwise regression and Pearson correlation analysis to investigate the primary factors influencing the perfusion index. Our findings contribute innovatively to the literature by utilizing PI to evaluate student health, specifically regarding academic stress and lifestyle decisions.

The research indicates that exercise duration, diastolic blood pressure, gender, and smoking behaviors significantly predict the perfusion index. These findings correspond with prior research indicating the significance of physical activity and blood pressure in cardiovascular health[26] [16]. Our discovery that exercise duration positively correlates with PI ($r = 0.275$, $p < 0.01$) aligns with research [11], which illustrated the advantages of regular exercise in enhancing circulatory dynamics. The identified negative correlation between smoking habits and PI (-2.182), indicating that smokers exhibited diminished perfusion levels, supports previous research demonstrating that smoking adversely affects vascular function and decreases blood flow [2], [8].

The significant difference in PI between males and females ($t = 4.486$, $p < 0.05$) highlights acknowledged gender disparities in cardiovascular health. This corresponds with previous studies suggesting that males generally exhibit enhanced vascular performance compared to females owing to physiological differences [3]. The study further illustrates the impacts of psychological stress. However, it showed no significant difference in PI ($p = 0.723$), contradicting other studies that propose stress exacerbates autonomic dysregulation [14], [15]. This discrepancy may be attributed to the unique academic environment of the University of Rajshahi, which may not elicit as significant physiological changes as those observed in more stressful contexts, such as clinical settings.

Our regression model, which explained 75.9% of the variance in PI, represents a substantial improvement over prior studies. While previous research has generally relied on univariate or simple multivariate models [7], [32], our use of stepwise regression allows for a more refined understanding of how multiple variables interact to influence PI. The model's coefficients provide precise insights into how individual factors such as diastolic blood pressure (0.045), exercise time (0.162), and sex (1.616) contribute to PI, with significant implications for health interventions targeting students [6]. Our approach, including statistical significance tests and correlation analysis, offers a robust and comprehensive view of the complex physiological relationships at play, surpassing earlier work in its scope and analytical depth.

Our work stands out in several ways compared to other studies, such as those by 16 and 14. Most studies on PI have been conducted in clinical settings, often focusing on older adults or patients with known health conditions. In contrast, our study provides insights into a younger, academically-stressed population, showing the potential of PI as a non-invasive, real-time indicator of student well-being. Additionally, while studies on lifestyle factors and PI are emerging, few have utilized a comprehensive dataset that includes physiological measurements (e.g., PI, blood pressure) and lifestyle variables (e.g., exercise, smoking, diet) to explore their interactions. This holistic approach adds novelty to our findings and strengthens the generalizability of the results to other academic populations.

In conclusion, this study illustrates the efficacy of the perfusion index as a significant instrument for monitoring student health, equipping universities with actionable data to develop wellness programs targeting stress and circulatory health. The findings underscore critical domains for forthcoming research, especially investigating the interplay between environmental factors, screen time, and cognitive load with physiological health indicators. Our findings provide a more refined and contextually relevant comprehension of PI, establishing a foundation for subsequent research in academic environments.

5. Conclusion

The project overview is thoroughly explained in the Results and Discussion section. The descriptive statistics imply that the perfusion index of Rajshahi University students was comparably lower than those of strengthened values. This implies that necessary programs or initiatives should be taken so that the perfusion index of the students can be geared up. A model was built to sketch out the determinants of the perfusion index. As the value of R^2 was 0.759, it demands the further extension of the present research. The fitted model is equally helpful for male and female students and smokers and non-smokers, as they were included as the dummy variables in the model. After applying cross-validity predictive power to the fitted model, it was found that only the variables diastolic blood pressure and exercise time were the two determinants of the perfusion index. This research demanded an increase in facilities so that the students could increase their perfusion index by increasing their diastolic blood pressure and exercise time. The same research can be extended by increasing the sample size by including different departments from the University of Rajshahi. This research can include people of different age groups from the Rajshahi district. It can be expanded by increasing the number of determinants. Several regression models, such as nonlinear regression, will be disposed of for better modeling. Reliability checking can be applied to the model in further research. Advanced statistical analysis, such as machine learning algorithms, can be deployed for more accurate modeling.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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