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| RESEARCH ARTICLE

Modeling on the Perfusion Index for the Students of the Statistics Department in Mawlana Bhashani Science and Technology University

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| ABSTRACT

This study aimed to explore the key determinants of the perfusion index (PI)—a physiological marker reflecting the ratio of pulsatile to non-pulsatile blood flow in peripheral tissue, measured using a pulse oximeter. The research sought not only to identify factors influencing the increase or decrease in PI but also to develop a predictive model based on associated variables. Data were collected from Statistics students at MBSTU through stratified random sampling, using a structured questionnaire comprising 37 items. Relevant physiological measurements, including weight, height, pulse rate, systolic and diastolic blood pressure, and PI, were obtained using appropriate instruments. Univariate and bivariate analyses were conducted to assess significant relationships. PI was found to be positively correlated with diastolic pressure, body weight and exercise duration. A predictive model incorporating smoking status, exercise time, and body weight yielded an R^2 of 0.774, suggesting strong explanatory power. Further research could enhance model accuracy by increasing the sample size, incorporating more variables, and including a broader age range. As PI reflects cardiovascular health and heart strength, promoting physical activity and a healthy diet is essential for improving perfusion.

| KEYWORDS

Perfusion Index (PI), Correlation Coefficient and Stepwise forward Multiple regression

| ARTICLE INFORMATION

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1. Introduction

In peripheral tissues, such as the fingertips, toes, and earlobes, the perfusion index (PI) is a non-invasive metric that shows the proportion of pulsatile to non-pulsatile blood flow (Manap et al., 2024). Pulsatile blood flow, also known as the rhythmic flow of blood throughout the circulatory system, is made possible by the contraction and relaxation of the heart. Unlike steady flow, this flow varies with each heartbeat and represents the cyclical nature of the cardiac cycle. Variations in pressure and velocity define this flow type, which can impact energy dissipation, blood vessel wall shear stress, and other physiological aspects (Painter et al., 2006). The pulse oximeter provides vital information about hemodynamic status and autonomic nervous system function by measuring the peripheral index (PI), which evaluates the strength of the peripheral pulse (Hung et al., 2024). During exercise, pulse oximeters are commonly used in clinical and research settings to continuously and noninvasively estimate the oxyhemoglobin saturation (%SpO2) of arterial blood (Mengelkoch et al., 1994). Because arterial oxyhemoglobin saturation indicates the degree of arterial blood oxygenation, specifically arterial oxygen partial pressure, it can be used to diagnose hypoxemia, a condition characterized by decreased arterial oxygenation. At sea level, the average arterial oxygen partial pressure values fall between approximately 100 mmHg at age 20 and 80 mmHg at age 80 (Marini, 1987). Thus, it's especially crucial in circumstances when blood flow could alter due to various physiological stressors, such as following surgery or in populations that are under a lot of stress (A. Lima & J. Bakker, 2018).

The perfusion index (PI), a non-invasive measure derived from pulse oximetry, provides crucial information about peripheral blood circulation. Its interpretation requires a basic understanding of its physiological foundations. The elementary of PI measurement and its clinical relevance are by described (Jubran, 2015). However, (Allen, 2007) emphasizes the impact of the autonomic nervous system on peripheral blood flow, which is a crucial factor to take into account when analyzing PI data from students who are under varying degrees of stress and cognitive load. Statistical modeling is necessary to accurately interpret PI data, especially when individual variance is taken into account. Regression and analysis of variance (ANOVA), two statistical methods relevant to physiological data, are thoroughly reviewed in (Andy Field, 2018). Furthermore, (Fitzmaurice et al., 2012b) also emphasize the importance of using mixed-effects models to account for people's inherent diversity, which is a crucial consideration when evaluating PI data from a diverse student body.

Recent studies have expanded the use of PI beyond clinical settings to cover broader groups, such as university students, because it offers crucial insights into stress-related physiological changes and cardiovascular health (Gamal et al., 2022). Circulatory dynamics and autonomic function may be impacted by increased cognitive demands, emotional stress, and lifestyle decisions associated with the academic environment (Raghavan Srinivasan et al., 2021). Academic stress has been shown to stimulate the hypothalamic-pituitary-adrenal (HPA) axis, causing autonomic dysregulation that may manifest as altered vascular responses and perfusion patterns (Leistner & Menke, 2020). Furthermore, prolonged screen time and mental strain have been linked to vasoconstrictive effects, which may further influence PI changes (Kumar et al., 2023). PI, like other physiological measures, can show how the autonomic nervous system regulates blood flow and reacts to stimuli both inside and outside the body. (Coutrot et al., 2021). Students whose scholastic load and stress levels vary will be able to identify those at risk of circulatory dysfunction if they understand how PI fluctuates. Despite the fact that PI has been extensively studied in therapeutic settings, little is known about how it is used in educational institutions, particularly for students who have high cognitive burdens (Sharma et al., 2021).

This research focuses on modeling the Perfusion Index for students in the Statistics Department at Mawlana Bhashani Science and Technology University. This study aims to better understand how PI-related factors affect vascular health by examining several key components, including lifestyle choices, cognitive load, and academic stress. The findings of this study might also provide a non-invasive means of tracking students' health, enabling universities to implement stress-reduction health initiatives. The Perfusion Index could be used to identify students who are at risk and encourage healthier academic practices if it is effective (Potter & Bolls, 2012).

By examining the variables influencing PI in Mawlana Bhashani Science and Technology University students, this article aims to bridge the gap. It focuses on lifestyle decisions, environmental factors, academic stress, and cognitive load. In order to understand how these factors interact and impact perfusion dynamics in the student body, our work aims to identify the primary determinants influencing PI and simulate their interactions using advanced statistical modeling approaches. Furthermore, this study aims to provide a predictive framework that will assist educators and medical experts in more accurately assessing students' wellbeing and developing solutions that meet their specific needs.

Thus, the research topics for this study are as follows:

RQ1: What variables go into determining the Perfusion Index?
RQ2: How can we model the Perfusion Index using the variables related to it?

These study questions seek to identify the different interactions with PI and the mechanisms via which they operate, paying special emphasis to the academic setting and lifestyle choices. Using statistical methods, the study will examine how these variables interact and create a model that faithfully captures the underlying physiological processes.

The study's remaining portion is structured as follows: The materials and methodology, which include a description of the dataset, various statistical tests, and an outline of the assessment criteria for those tests, are contained in Section 2. The findings of the analysis of the sample dataset are shown in Section 3. The last thoughts are summed up in Section 4, which also suggests future study areas.

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 of statistics department in Mawlana Bhashani Science and Technology University 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 Mawlana Bhashani Science and Technology University. The population was divided into five strata based on year of study: first year (55 students), second year (50 students), third year (55 students), fourth year (61 students), and masters (55 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.

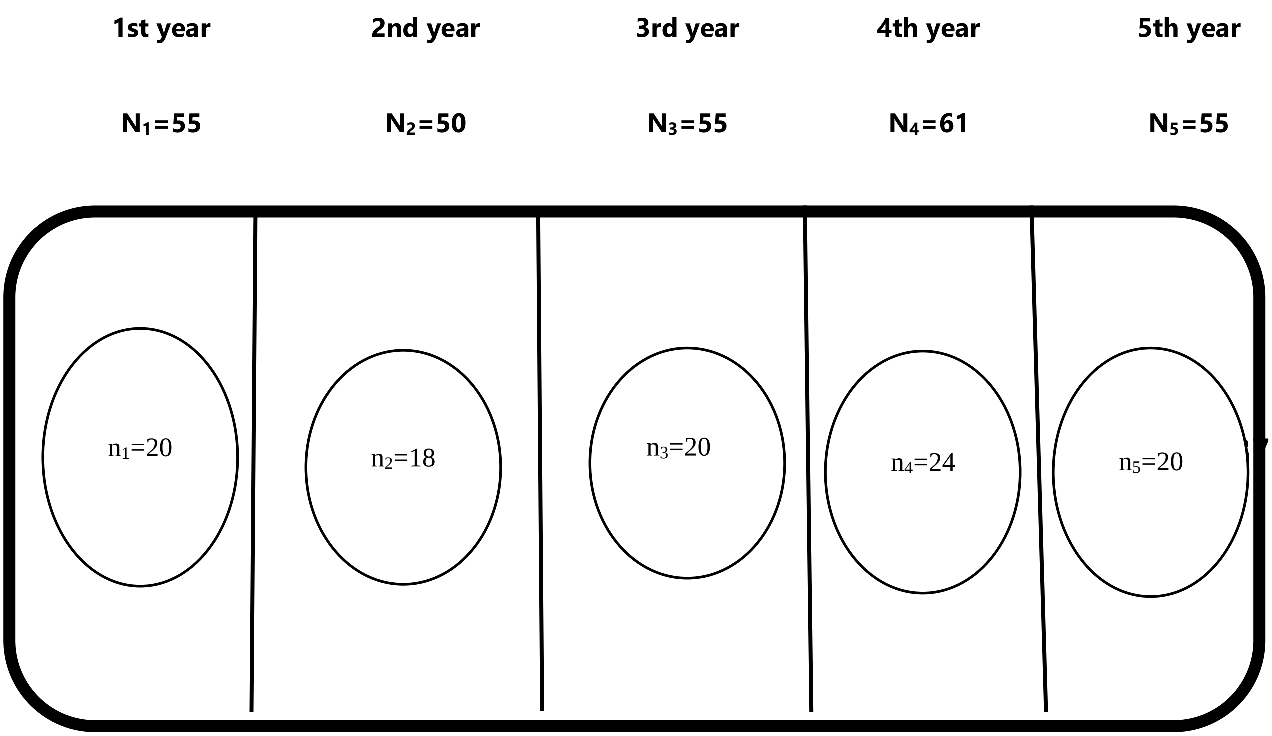

Figure 1: Stratified random sampling framework

Proportion allocation was used to determine the sample size from each stratum, resulting in 20 students from the first year, 18 from the second year, 20 from the third year, 24 from the fourth year, and 20 from the masters. The total sample size was 102 students out of 275, calculated as $n = 20 + 18 + 20 + 24 + 20 = 102$. 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 (*CardiacDirect*, n.d.).

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(*CardiacDirect*, n.d.).

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 Statistical Analysis

All data for this study were collected through a structured questionnaire(Containing 37 questions) and entered into SPSS (IBM, version 25) for detailed analysis. An approximate mathematical formula was used in this study for calculating sample size. We considered approximately 80% CI that means approximately 20% level of significance in the formula(Welch, 1951a)). We initially used the given formulae for determining sample size:

$n = \frac{N}{1+Nd^2}$ where, n = Sample size, N = Population size and

d = marginal error

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 weight, exercise time, and smoking habits. 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.

2.4.1 Stepwise Regression Analysis

Stepwise regression is one method for determining which variables are most crucial to include in a regression model. Because it combines forward selection and backward exclusion techniques, it is a very powerful tool for identifying significant variables in a model (Ruengvirayudh & Brooks, 2016). This study employed stepwise regression to identify significant factors influencing the Perfusion Index. First, every potential predictor variable is taken into account. Variables are added or removed repeatedly in accordance with specific criteria, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). This increases the model's interpretability and explanatory power by ensuring that the final model only contains the most relevant predictors (Silhavy et al., 2018).This is an illustration of the forward selection and backward exclusion stages in the Stepwise Regression technique (Silhavy et al., 2018). The steps involved are as follows:

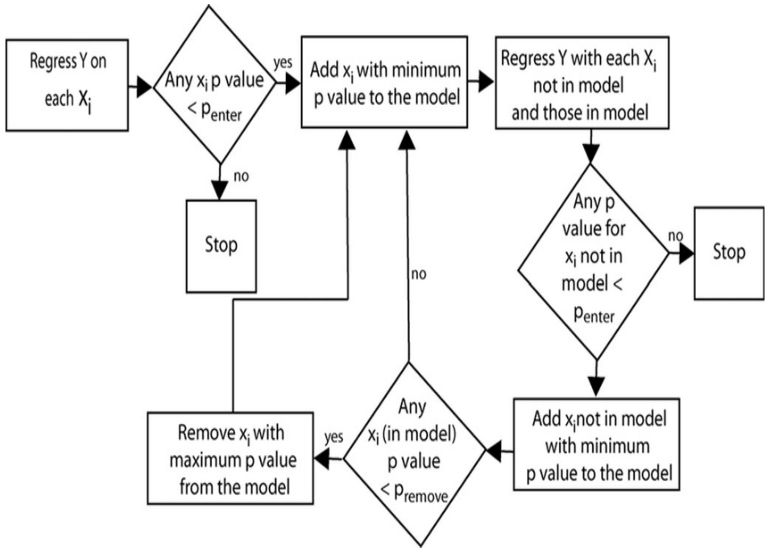

Figure 2: Flow-Chat of Stepwise Regression

- **Forward Selection**: At the beginning, the model has no predictors. Predictors are added one at a time based on their significance.
- **Backward Elimination**: Beginning with every predictor, backward elimination eliminates those that are not statistically significant.

The p-value of each variable determines whether predictors are included or excluded in Stepwise Regression; normally, the threshold is $p < 0.05$ for inclusion and $p > 0.10$ for exclusion (Andy Field, 2018). This technique helps identify the most important predictors and avoid overfitting (Kleinbaum et al., 1988).

3. Results

The study collected data from 102 participants, encompassing categorical and continuous health-related variables. Of the participants, 60.78% were male and 39.22 were female. A total of 71.2% were late risers, while 90.20% were non-smokers. Most participants exhibited normal blood pressure (86%), whereas only 2% indicated elevated pressure. The respondents' parents exhibited a propensity for normal blood pressure, with 40.45% of the mothers and 52.27% of the fathers within the normal range. Health conditions, such as asthma (86.36%), allergies (60.91%), chest pain (80%), and mental stress (51.82%) were significantly prevalent.

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

Variable	Range	Min	Max	Mean	SE	Sk
Age	9.4933	17.7723	27.5157	23.3294	0.1278	-0.165
Exercise time	23.0527	0.00	20.7509	4.3623	0.2933	1.5635
Sleeping time	7.0301	5.0409	12.7072	7.8898	0.0741	0.4115
Daily Eaten Rice	1616.344	48.4542	1561.015	375.6735	14.232	1.5088
Daily Eaten Bread	6266.781	0.00	5687.308	71.0802	29.8146	13.6809
Daily Drinking water	9330.368	1.917	8419.924	2613.892	108.5657	1.3203
Daily Eaten Fish	4829.918	0.00	4874.838	365.3143	31.0437	6.0073
Daily Eaten Meat	2546.648	0.00	2313.443	339.3738	25.5754	2.9256

Amount of Cold Drinks Taken in a Week	2083.092	0.00	2077.075	409.7389	32.4647	1.7291
Eaten Vegetable Daily	1152.148	0.00	1166.923	215.7369	13.454	1.9099
Eaten Cinnamon Daily	241.0922	0.00	255.0877	13.9007	2.7971	4.1162
Height in Cm	134.8492	58.0756	193.1804	169.1368	0.9147	-4.7034
Weight in Kg	54.0701	38.1345	94.4487	61.959	0.7679	0.4545
Oxygen Saturation Level%	37.2807	54.5958	99.4436	97.1548	0.2524	-6.8403
Pulse Rate in BPM	111.8279	8.2835	115.0601	85.7101	0.8166	-0.6187
Systolic mmHg	57.3594	76.5672	132.8298	114.4517	0.8098	-0.5932
Diastolic mmHg	54.0508	55.056	99.9851	71.8439	0.6472	-0.4931

Table 1 presents the summary statistics for various lifestyle and health-related variables of students. The average age of respondents was approximately 23.3 years, ranging from about 17.8 to 27.5 years. The negative skewness (−0.165) indicates a higher concentration of younger respondents. On average, students exercised for 4.36 hours per week, with a positively skewed distribution, indicating that most students exercised less than the mean. The average sleeping time was about 7.89 hours, ranging from roughly 5 to 12.7 hours. The positive skewness indicates that more students reported longer sleep durations. Students consumed on average 375g of rice and 71g of bread daily, while the maximum bread intake reached nearly 5700g, showing high variation and skewness. Water intake averaged 2613 ml per day. Fish and meat consumption were 365g and 339g on average, respectively. All food intake variables showed positive skewness, indicating fewer high consumers. Vegetable intake averaged 215g per day, while cinnamon consumption was low at about 14g. Both variables were positively skewed. The average height and weight of the students were 169.1 cm and 61.96 kg, respectively. Height was negatively skewed, suggesting more students were shorter than the mean. Oxygen saturation levels averaged 97.15%, within healthy limits. The average pulse rate was 85.71 BPM, systolic pressure was 114.45 mmHg, and diastolic pressure was 71.84 mmHg—all within typical ranges, though slight negative skewness was observed for each.

Table 2: Descriptive Statistics of Perfusion Index

Statistic	Perfusion Index
N (Valid)	102
N (Missing)	0.00
Mean	4.9259
Std. Error of Mean	0.22927
Median	4.2000
Mode	1.10
Variance	10.566
Skewness	0.748
Std. Error of Skewness	0.172
Kurtosis	0.060

Std. Error of Kurtosis	0.341
Range	15.00
Minimum	0.00
Maximum	15.00

Table 2 shows that the mean of the perfusion index of the respondents was 4.92 and the median was 4.2 and the mood was 1.10. It is an alarming news that the average and mode of perfusion index for study students are less than 5. So, the condition of blood flow was very poor and the hearth blood circulation of statistics students was quite ominous. The maximum value of the perfusion index was found 15 which was good news. It is a good condition of blood circulation. The variance of perfusion index was 10.5. The distribution is negatively skewed and platokurtic. That means the distribution was very much dispersed.

Table 3: Correlation coefficients for different variables

Variables	Perfusion Index	Diastolic Blood Pressure (mmHg)	Body Mass Index (BMI)	Weight (Kg)	Exercise Time or Playing Time
Perfusion Index	1	0.219**	0.025	0.211**	0.275**
Sig. (2-tailed)	—	0.002	0.728	0.003	0.000
Diastolic Blood Pressure (mmHg)	0.219**	1	0.037	0.310**	0.043
Sig. (2-tailed)	0.002	—	0.604	0.000	0.548
Body Mass Index (BMI)	0.025	0.037	1	0.221**	0.071
Sig. (2-tailed)	0.728	0.604	—	0.002	0.314
Weight (Kg)	0.211**	0.310**	0.221**	1	0.083
Sig. (2-tailed)	0.003	0.000	0.002	—	0.240
Exercise Time or Playing Time	0.275**	0.043	0.071	0.083	1
Sig. (2-tailed)	0.000	0.548	0.314	0.240	—

Table 3 depicted the correlation analysis that revealed several significant relationships among the studied variables. Perfusion Index showed a significant weak positive correlation with diastolic blood pressure ($r = 0.219$, $p = .002$), body weight ($r = 0.211$, $p = 0.003$), and exercise or playing time ($r = 0.275$, $p < 0.001$), indicating that higher values of these factors are associated with increased perfusion levels. However, the correlation between Perfusion Index and BMI was very weak and non-significant ($r = 0.025$, $p = 0.728$), suggesting that BMI may not be a key determinant of perfusion. Diastolic pressure was more correlated with weight ($r = 0.310$, $p < 0.001$) than any other, while BMI also showed a modest association with weight ($r = 0.221$, $p = 0.002$). No significant relationships were observed between exercise time and BMI ($r = 0.071$, $p = 0.314$) or diastolic pressure ($r = 0.043$, $p = 0.548$). These findings emphasize the influence of weight, blood pressure, and activity on perfusion.

3.1 Pretest of OLS Assumption

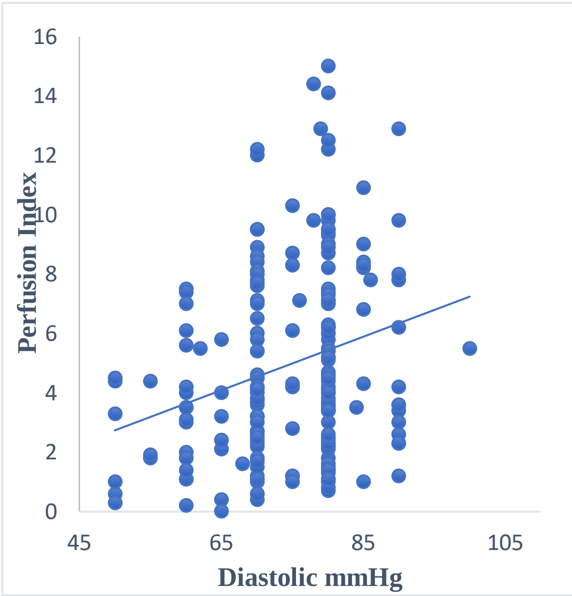

Figure 3: Relationship between PI and diastolic

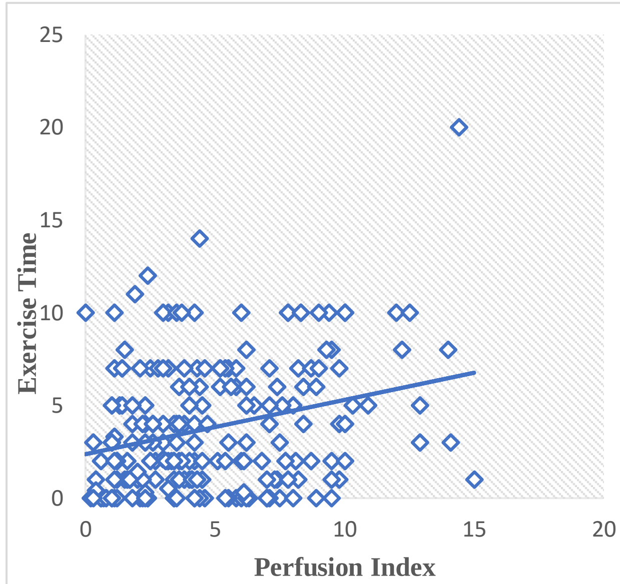

Figure 4: Relationship between PI and Exercise Time

The scatter plots (Figure 3 and Figure 4) show linear relationship between perfusion index and diastolic and perfusion index and exercise time.

3.2 Normality check

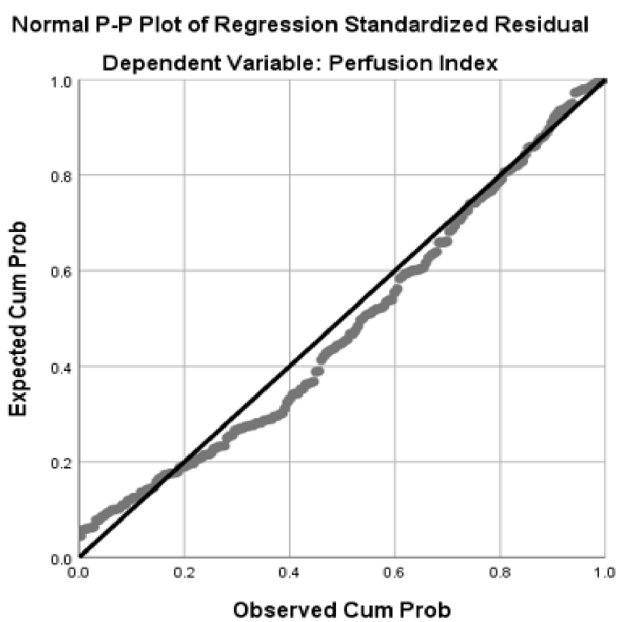

Figure 5 Normal Probability Plot of Perfusion Index

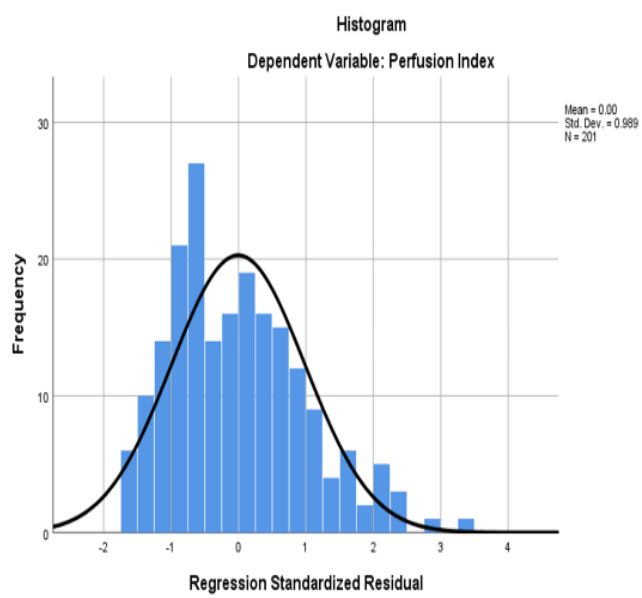

Figure 6 Histogram of Purfusion Index

The histogram and normal probability plot show that the dependent variable "perfusion index" follow a normal distribution except for some values.

Now, Step-wise forward regression is used to identify the most significant predictors of the Perfusion Index (PI) from a set of independent variables. 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 4: Step-wise multiple linear Regression

Dependent Variable: Perfusion Index
Method: Step-wise forward Multiple Regression through the Origin

Model	Predictor Variable	Unstandardized B	Std. Error	Standardized Beta	t-value	Sig. (p)
1	Weight in Kg	0.082	0.005	0.829	15.503	0.000
2	Weight in Kg	0.058	0.006	0.591	9.230	0.000
	Exercise time or playing time	0.385	0.070	0.354	5.533	0.000
3	Weight in Kg	0.064	0.006	0.646	9.923	0.000
	Exercise time or playing time	0.373	0.068	0.343	5.516	0.000
	Smoking habit	-2.643	0.941	-0.138	-2.808	0.006

Table 4 shows that three linear regression models of Perfusion Index prediction. All were fit by the origin. Weight in Kg in Model 1 is strongly and positively associated (B = 0.082, β = 0.829, $p < 0.001$), as greater body weight is associated with more perfusion. Model 2 also includes Exercise time or playing time, which is also positively correlated to Perfusion Index (B = 0.385, β = 0.354, $p < 0.001$). The coefficient of Weight decreases slightly but remains intact (B = 0.058, β = 0.591), showing partial mediation by exercise. Model 3 includes Smoking habit, which is strongly negatively related with Perfusion Index (B = –2.643, β = –0.138, p = 0.006). Weight (B = 0.064, $p < 0.001$) and Exercise time (B = 0.373, $p < 0.001$) remain significant. These findings demonstrate that greater body weight and greater activity are associated with improved perfusion, while smoking adversely affects it. Stepwise inclusion of variables enhances explanatory power and highlights the importance of lifestyle factors for vascular well-being.

Table 5: Model Summary

Model	Predictors	R	R^2	Adjusted R^2	Std. Error of Estimate	ΔR^2	F Change	df1	df2	p-value
1	Weight (kg)	0.829	0.688	0.685	3.40	0.688	240.33	1	109	<0.001
2	Weight (kg), Exercise/Playing Time	0.870	0.757	0.752	3.01	0.069	30.62	1	108	<0.001
3	Weight (kg), Exercise/Playing Time, Smoking habit	0.880	0.774	0.767	2.92	0.017	7.89	1	107	0.006

The fitted model was,
Perfusion Index=0.064×Weight+0.373×Exercise Time−2.643×Smoking Habit
The above fitted model indicates that Weight, exercise time and smoking habit are the determinants of perfusion index.

Here, the coefficient 0.064 means if all other variables are constant, one unit increases in weight will increase 0.064 unit in perfusion index. The coefficient 0.373 means if all other variables are constant, one unit increases in exercise time will increase 0.373 unit in perfusion index. If all other variables are constant, then the coefficient (-2.643) of smoking status means the perfusion index is 2.643 times less for smoker than a non-smoker respondent.

The R^2 of this model is 0.774 that means about 77.4% variations are explained by the explanatory variables (determinants). Perhaps, there have any other determinants that they can also influence greatly for increase and decrease of perfusion index which were not mentioned or not identified through our model.

4. Discussion

The results of our research on the perfusion index (PI) of students from the Statistics Department at the MBSTU offer substantial insights into the physiological dynamics of these individuals, shaped by variables including weight, physical activity and smoking habits. 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, weight and smoking behaviorssignificantly predict the perfusion index. These findings correspond with prior research indicating the significance of physical activity and blood pressure in cardiovascular health(Fitzmaurice et al., 2012a)(Coutrot et al., 2021). Our discovery that exercise duration positively correlates with PI ($r = 0.275$, $p < 0.01$) aligns with research (Gamal et al., 2022), which illustrated the advantages of regular exercise in enhancing circulatory dynamics. The identified negative correlation between smoking habits and PI (-2.643), indicating that smokers exhibited diminished perfusion levels, supports previous research demonstrating that smoking adversely affects vascular function and decreases blood flow(Painter et al., 2006), (Allen, 2007).

Our regression model, which explained 77.4% of the variance in PI, represents a substantial improvement over prior studies. While previous research has generally relied on univariate or simple multivariate models(Jubran, 2015), 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 weight (0.064),exercise time(0.373), and smoking habit (-2.643) contribute to PI, with significant implications for health interventions targeting students (A. Lima & J. Bakker, 2018). 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 MBSTUwas 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 0.774, it demands the further extension of the present research. The fitted model is helpful smokers and non-smokers students, as they were included as the dummy variables in the model. After applying stepwise linear regression to the dataset, it was found that only the variables “Weight” 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 exercise time.Post-test of OLS was not been done in our study. The same research can be extended by increasing the sample size by including different departments from the MBSTU. This research can include people of different age groups from the tangail district. It can be expanded by increasing the number of features. 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.

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