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An Empirical Study to Detect Mental Wellness Through Artificial Intelligence: A Promising Approach for Timely Intervention

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Abstract

The field of mental health has witnessed growing recognition of the importance of early detection and intervention in promoting overall well-being and preventing the progression of mental disorders. In recent years, artificial intelligence (AI) has emerged as a powerful tool with the potential to revolutionize mental healthcare by enabling timely identification of individuals at risk and facilitating early intervention. This research paper explores the role of AI in the early detection of mental wellness, examining its applications, benefits, challenges, and future implications.

The paper begins by highlighting the significance of early detection in mental health through biomarker feedback captured through contactless AI computer vision-based vital monitoring systems. The paper highlights the critical finding of mental wellness through clinical trials conducted in the presence of a competent practitioner. After a thorough analysis of the data set, researchers have concluded that the heart rate and BP-Systolic are the major variables that affect the mental stress index.

Keywords: Artificial Intelligence, mental health, biomarker, heart rate variability, Regression.

Introduction

In the modern era, where technological advancements are shaping the world in unprecedented ways, the realm of healthcare is undergoing a profound transformation, thanks to the integration of Artificial Intelligence (AI) into various aspects of medical practice.

One area where AI is demonstrating remarkable potential is in the early detection of mental wellness issues, presenting a promising approach for timely intervention and improved patient outcomes. Mental health, long shrouded in stigma and misunderstanding, is gaining the attention it deserves as societies recognize its significance in overall well-being. With AI-driven tools and techniques, healthcare providers are now better equipped than ever to identify potential mental health concerns at an early stage, enabling timely and targeted interventions that can make a significant difference in the lives of individuals and communities.

The Role of AI in healthcare has been expanding rapidly over the past few years, encompassing tasks ranging from diagnostics to treatment planning and patient monitoring. However, its application to mental health is particularly intriguing due to the complex and often elusive nature of psychological well-being. Mental health disorders, which include conditions like depression, anxiety, bipolar disorder, and schizophrenia, can have a profound impact on an individual's life, affecting their thoughts, emotions, and behaviours. Early detection is critical because it allows for timely intervention, preventing the escalation of symptoms, and enhancing the efficacy of treatment strategies.

Traditional methods of mental health assessment often rely on self-reporting, clinician observations, and standardized questionnaires. While these methods have proven valuable, they can be subject to biases, limited by the availability of skilled professionals, and reliant on individuals' willingness to disclose their experiences truthfully. Here is where AI steps in as a game-changer, offering objective and data-driven approaches that complement traditional methods.

Machine Learning (ML), a subset of AI, plays a pivotal role in this paradigm shift. By analyzing large datasets of various patient characteristics, behaviours, and even linguistic patterns, ML algorithms can identify subtle patterns and correlations that might be overlooked by human clinicians.

Furthermore, AI can leverage other forms of data such as biometric information which can track physiological signals like heart rate variability, sleep patterns, and physical activity levels.

ML algorithms can then analyse these data streams to spot deviations from baseline patterns, indicating potential mental health changes.

The implementation of AI in early mental health detection also addresses the issue of accessibility. In many parts of the world, access to mental health professionals is limited, leading to underdiagnoses and under treatment of mental health conditions. AI-powered tools can bridge this gap by providing preliminary assessments and recommendations remotely, allowing individuals to seek help without the barriers of distance or stigma. This approach is particularly relevant in rural and underserved areas, where access to mental health services is scarce.

However, it's important to note that while AI shows great promise, its integration into mental health diagnostics is not without challenges. Ethical concerns related to data privacy, informed consent, and potential biases in algorithms must be carefully considered. The sensitive nature of mental health data requires stringent safeguards to ensure patient confidentiality and prevent unauthorized access.

Additionally, biases inherent in training data can result in algorithmic biases that disproportionately affect marginalized populations, reinforcing existing disparities in healthcare.

Collaboration between AI experts, mental health professionals, and ethicists is paramount to ensure the responsible and effective implementation of AI-driven mental health solutions. Transparency in algorithm development, regular audits for bias, and a strong regulatory framework are essential to mitigate these challenges.

In conclusion, the role of Artificial Intelligence in the early detection of mental wellness represents a transformative approach to mental healthcare. Through the amalgamation of machine learning, natural language processing, and biometric data analysis, AI offers a powerful means of identifying potential mental health concerns at an early stage. By leveraging data-driven insights, AI-enabled tools can provide timely interventions, leading to improved patient outcomes and a reduction in the overall burden of mental health disorders on individuals and societies. However, it is crucial to tread carefully, addressing ethical concerns and biases, and fostering collaboration between experts from diverse fields. With responsible development and implementation, AI holds the potential to revolutionize the way we approach mental health, making timely intervention and support more accessible and effective than ever before.

Literature Review

Mental health disorders pose a significant global burden, affecting individuals' well-being and socioeconomic systems. Early detection and intervention play a pivotal role in mitigating the severity of these conditions. Recent advancements in artificial intelligence (AI) and biomarker research have opened up new avenues for identifying potential mental health issues at an early stage. This literature review aims to explore the evolving role of AI in conjunction with biomarker feedback for the early detection of mental wellness, highlighting its potential benefits and challenges.

Biomarkers and Mental Health: Biomarkers are measurable biological indicators that provide insights into various physiological and pathological processes within the body. In the context of mental health, biomarkers hold promise as objective measures that can help identify early signs of disorders. Neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET), have shown the ability to identify structural and functional abnormalities associated with mental health conditions (Savitz et al., 2019). Additionally, molecular biomarkers like cytokines and neurotransmitter levels have been linked to mood disorders and stress responses (Zieba et al., 2019).

Role of Artificial Intelligence: AI algorithms, particularly machine learning and deep learning, are revolutionizing various fields by processing and analyzing vast amounts of data to extract patterns and insights. In the context of mental health, AI has shown promise in identifying subtle patterns within biomarker data that may not be easily discernible by human clinicians alone. Machine learning models have been trained to recognize biomarker patterns indicative of different mental health conditions, aiding in the early detection and prediction of disorders (Chekroud et al., 2016).

Applications of AI in Mental Wellness

The growth in the usage of artificial intelligence in medical field exponential. It is used in diagnosing, predicting and curing the multiple diseases is well proven.

a. Predictive Models: AI-powered predictive models utilize historical data, including biomarker feedback, to forecast the likelihood of an individual developing a mental health disorder. These models consider a combination of factors such as genetic predisposition, environmental influences, and biomarker profiles (Gan et al., 2020).

b. Diagnostic Support: AI-based diagnostic tools leverage biomarker data and combine it with other clinical information to assist healthcare professionals in accurately diagnosing mental health conditions. These tools can offer more objective and personalized assessments, improving diagnostic accuracy (Shatte et al., 2019).

c. Early Intervention: AI algorithms can detect subtle changes in biomarker trends over time, enabling early intervention before symptoms become severe. This approach could potentially prevent the progression of disorders and improve treatment outcomes (Dwyer et al., 2021). Though the applications of AI are many folds but it is wrapped with challenges as enumerated here.

a. Data Privacy and Ethics: The integration of AI and biomarkers raises concerns about data privacy and patient consent. Safeguarding sensitive biomarker data and ensuring ethical use of AI algorithms are critical considerations (Fradkin et al., 2019).

b. Generalization and Bias: AI models trained on specific populations may exhibit bias and have limitations when applied to diverse groups. Ensuring generalizability and fairness is crucial to avoid exacerbating health disparities (Norgeot et al., 2019).

c. Clinical Validation: The translation of AI-based biomarker predictions into clinical practice requires rigorous validation to ensure reliability and efficacy. Clinical trials and longitudinal studies are necessary to establish the clinical utility of these approaches (Kessler et al., 2022).
[Insert Figure 1]

Materials And Method

The detection of mental stress is a critical aspect of maintaining overall well-being. Heart rate variability (HRV) has emerged as a valuable physiological marker to assess the autonomic nervous system's response to stress. This section outlines the materials and methods used for detecting mental stress levels through HRV analysis, providing insights into the experimental setup, data collection, and analysis techniques.

Respondent’s Profile
The researchers collaborated with Bwell Healthtech, which has an innovative product called Wellness Selfie which is a computer vision and AI-based Physical & Mental Health monitoring of Heart rate, Respiration Rate, Oxygen Saturation, cuff less Blood Pressure, and Stress levels within a few seconds through a contactless Video Selfie.

They have extended supports to researchers to conduct a sample test of a diverse group of adult participants (n = 78) was selected for the study.

[Insert Table 1]
Table 1 indicates the respondent’s profile ranged in age from 21 to 63 years and had no history of cardiovascular diseases, autonomic dysfunction, or any other medical conditions that could affect HRV.

Informed consent was obtained from all participants before their involvement in this study.

Experimental Setup
The study was conducted in a controlled environment, ensuring minimal external disturbances.

a. Participants were seated comfortably in a quiet, well-lit room.
b. Heart Rate Monitoring: HRV data were collected using a non-invasive contactless selfie-based application which has been certified with 95%+ accuracy by various established health facilities and regulators.

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Results

This statistical analysis report investigates the relationships between physiological indicators (Blood Pressure - BP, Heart Rate - HR, and Interbeat Interval - IBI) and the Mental Stress Index (MSI) as the dependent variable. The study employs correlation analysis to examine the strength and direction of linear relationships between variables, assessing potential associations among the physiological indicators and mental stress. Multicollinearity diagnostics are applied to identify and mitigate issues arising from high intercorrelations among independent variables.

Variable importance analysis is conducted to assess the individual contribution of BP, HR, and IBI to the variation in the Mental Stress Index. This analysis aids in understanding the relative significance of each physiological indicator in predicting mental stress levels.

Furthermore, the report delves into causal relationships through advanced statistical techniques to unravel the dynamics between the physiological parameters and mental stress. This involves assessing causality, directionality, and potential feedback loops in the relationship.

The findings of this study contribute to a comprehensive understanding of the intricate connections between physiological measures and mental stress, providing insights that may inform healthcare practices, stress management strategies, and further research endeavors.

The dataset utilized in this statistical analysis comprises physiological measurements and mental stress indices collected from a sample population. Blood Pressure (BP), Heart Rate (HR), and Interbeat Interval (IBI) serve as the independent variables, while the Mental Stress Index (MSI) is the designated dependent variable. Physiological data were acquired through non-invasive selfie and AI based monitoring system, and mental stress indices were obtained through established psychological assessments developed by the provider.

The Data Preprocessing, prior to analysis, the dataset undergoes meticulous preprocessing to ensure accuracy and reliability. This includes handling missing data, checking for outliers, and standardizing or normalizing variables as needed. Preprocessing aims to enhance the quality of the dataset for robust statistical analysis.

Correlation analysis is conducted using Excel to examine the linear relationships between BP, HR, and IBI, and the Mental Stress Index. Correlation coefficients are calculated to quantify the strength and direction of these relationships, providing insights into the potential connections between physiological parameters and mental stress.

To address potential multicollinearity among the independent variables, variance inflation factors (VIF) are calculated to check the Multicollinearity. VIF values exceeding a predefined threshold indicate high multicollinearity, prompting consideration for variable exclusion or other mitigation strategies.

Variable importance analysis is carried out to evaluate the relative contribution of BP, HR, and IBI to the variation in the Mental Stress Index. This involves techniques such as regression analysis and feature importance calculations to discern the individual impact of each physiological parameter.

Further authors have conducted correlation analysis through Heat Map developed through python code. It clearly indicates that there is a strong relationship between weight versus BMI ($r=0.78$) and heart rate versus stress index ($r = 0.72$). Through this one can conclude that higher weight leads to high value of BMI, which significantly leads to increased level of stress index.

So, if a person is overweight then he will get higher level of BMI, which will lead to increased level of mental stress index.

[Insert Figure 1]
[Insert Figure 2]

This study adheres to ethical guidelines governing human research. Informed consent is obtained from participants, and measures are taken to ensure confidentiality and privacy. The study protocol is reviewed and approved by the relevant ethical review board.

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The combination of robust data collection, preprocessing, and the application of statistical tools provides a comprehensive approach to exploring the relationships between physiological indicators and mental stress. The results of this analysis aim to contribute valuable insights to the fields of mental health and physiological monitoring.

Discussions

Following data set (refer table 2) have been collected through camps basis voluntary participation and acceptance to participate in the research analysis.

[Insert Table 2]
[Insert Table 3]

The observations of the correlation analysis (refer table 3) clearly indicate the relationship of stress index with heart rate, BP systolic and IBI. Weight has no direct co-relation with mental stress as the co-relation co-efficient value is < 0.7 with stress Index so no multi-collinearity exists. Weight has direct co-relation with BMI as the co-relation co-efficient value is > 0.7 so multi-collinearity exists. BMI has no direct co-relation with mental stress as the co-relation co-efficient value is < 0.7 with stress Index so no multi-collinearity exists. BMI has no direct co-relation with any other independent variables as the co-relation co-efficient value is < 0.7 so no multi-collinearity exists among them. Heart rate has direct co-relation with mental stress as the co-relation co-efficient value is > 0.7 with stress Index so multi-collinearity exists. HR has no direct co-relation with any other independent variables as the co-relation co-efficient value is < 0.7 so no multi-collinearity exists among them. BP Systolic has no direct co-relation with mental stress as the co-relation co-efficient value is < 0.7 with stress Index so no multi-collinearity exists. BP Sys has no direct co-relation with any other independent variables as the co-relation co-efficient value is < 0.7 so no multi-collinearity exists among them. BP Diastolic has no direct co-relation with mental stress as the co-relation co-efficient value is < 0.7 with stress Index so no multi-collinearity exists. BP Diastolic has no direct co-relation with any other independent variables as the co-relation co-efficient value is < 0.7 so no multi-collinearity exists among them. IBI has no direct co-relation with mental stress as the co-relation co-efficient value is < 0.7 with stress Index so no multi-collinearity exists. IBI Dia has no direct co-relation with any other independent variables as the co-relation co-efficient value is < 0.7 so no multi-collinearity exists among them.

After checking the correlation and multi-collinearity, researchers have carried out regression analysis. The independent variables taken in this study are weight, BMI, heart rate, BP Systolic, BP Diastolic and IBI. The dependent variable is mental stress Index. Table 4 shows the multiple regression output.

[Insert Table 4]
The regression output in table 4 indicates that coefficient of determination is 58%, shows that 58% of the variance is explained through the independent variables considered here in this study. The less value of R^2 is also due to the other subjective factors which leads to mental stress to any human being. The authors have used python to find the regression analysis and split the dataset in 60 and 40 proportion. This indicates 60% training and 40% test data set. Upon applying linear regression model using python, researchers have concluded the developed regression model is showing the 59% of the variance in the dataset.

[Insert Table 6]
The above model shown in table 6 is taken at 10% significance level. Accordingly, the dependent variable, mental Stress Index is coming dependent on heart rate (having p-value less than 5%), BP-Systolic (p- value = 4%) and IBI (p-value = 6%). The regression model developed here is as follows:

Y (Mental Stress Index) = -2004.31 + 16.97 (Heart Rate) +1.94 (BP-Systolic)

Other independent variables like weight, BMI, BP-Diastolic are not significantly related to the final output i.e., Mental Stress Index. The above model developed for Mental Stress Index is showing the minimum errors and it can be relied for the prediction purpose of the respondents.

Conclusion

The materials and methods outlined in this study effectively demonstrated how AI based HRV analysis can serve as a reliable tool for detecting mental stress levels.

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The combination of HRV metrics provides valuable insights into the autonomic nervous system's response to stress induction. By understanding the physiological changes associated with mental stress, healthcare professionals can develop targeted interventions to mitigate stress-related health risks and enhance overall well-being. After the analysis of the data, researchers have found that stress index is having a high degree of correlation with heart rate. Later, researchers have applied the regression on the dataset and found that stress index is having relationship with heart rate, and BP-Systolic positively (checked at 10% of significance level). Other variables like BMI, BP-Diastolic and IBI have found insignificant with respect to dependent variable, i.e., Stress Index. Therefore, one concludes that people should consider and pay full attention towards their heart rate. Heart rate should be monitored regularly and must take an immediate action, as soon as there is any alarming sign.

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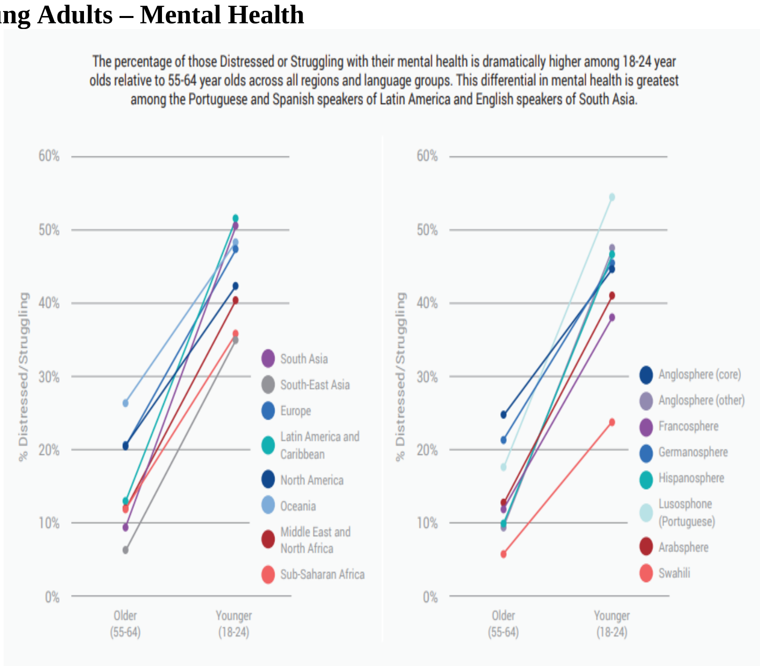
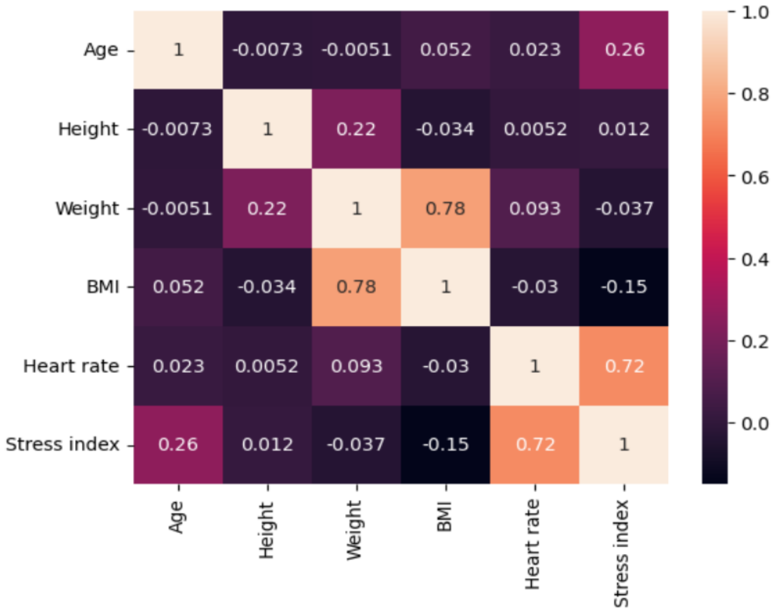
Figure 1: Globally Young Adults – Mental Health



Source: Author's compilation

Figure 2: Heat Map for the Correlation Analysis



Source: Author's computation

Table 1: Respondent's Profile

Description	Count	% of the total sample size (n=78)
Age Group	21-63 years	90%
Background	No history of Cardiovascular and any other medical ailment	80%
Environment	Controlled	90%

Source: Author's Compilation

Table 2: Dataset of 78 sample

Weight (kg)	BMI	Heart Rate	BP-Systolic	BP-Diastolic	IBI	Stress Index
90	28.1	77	146	93	772.58	51.85
72	23.5	65	133	85	912.9	96.85
70	22.1	61	114	78	967.9	34.77
70	22.6	83	134	91	727.92	254.15
64	19.8	87	165	96	688.82	246.99
87	26.6	91	140	93	665.67	168.27
65	21	88	134	86	680.75	263.2
78	24.6	76	130	88	783.8	82.08
90	28.4	74	138	80	798.1	101.84
73	23.6	88	126	75	671.32	123.33
64	22.7	80	136	72	743.47	164.97
108	33.3	84	128	90	710.71	193.32

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74	23.6	71	135	76	846.46	134.27
72	23.2	106	132	93	569.83	202.94
70	21.6	74	124	79	823.44	78.86
75	23.1	99	131	87	605.03	403.44
65	21.5	73	135	78	815.28	197.04
70	21.4	72	111	84	831.86	57.94
64	21.6	78	149	78	766.04	153.01
81	26.1	62	122	74	941.37	40.31
68	27.2	74	108	71	810.48	85.27
85	25.7	67	130	92	887.76	92.96
76	24	82	133	81	723.72	214.14
56	18.1	81	130	75	749.34	112.78
93	29	84	138	87	715.87	174.33
70	22.1	76	133	81	788.29	123.76
76	24.5	82	136	83	730.34	162.51
70	21.8	70	119	75	857.83	121.21
52	16.4	77	122	72	789.58	102.72
79	30.9	73	119	78	818.75	139.3
68	29	64	125	69	937.78	53.82
73	29.6	77	121	76	776.13	119.43
65	27.1	65	130	77	901.56	150.12
60	18.9	79	149	77	757.68	534.8
90	28.4	83	170	92	724.79	245.42
55	19	67	128	85	883.33	89.33
85	26.5	75	140	83	801.67	130.13
75	24.5	70	122	73	858.33	179.67
84	25.9	82	124	80	730.16	243.31
60	18.9	62	132	80	961.94	55.96
68	25	89	130	84	651.92	157.91
60	20.8	60	134	80	956.85	36.46
75	24.2	74	115	85	803.47	60.1
65	20.3	72	119	82	857.29	40.02
63	27.6	76	127	91	790.79	226.76
75	25.1	81	137	92	750.44	193.53
90	30.4	65	134	91	924.72	133.26
72	23.5	69	142	73	857.55	147.29
66	27.1	62	125	71	964.72	115.59
60	18.5	107	144	84	558.33	614.46
53	21.8	59	103	73	1017.24	65.57
60	19.6	74	147	79	815.2	53.28
63	25.9	65	127	74	908.33	71.21
58	17.9	79	135	80	759.68	154.23
82	32.8	74	131	70	801.39	87.56
84	32.8	90	141	90	665.89	235.74
80	24.4	74	139	100	809.05	151.68
60	26	69	117	70	847.58	48.24
80	24.4	94	137	92	641.3	393.69
67	23.2	64	128	80	925.26	69.96
85	26.5	103	136	98	579.5	394.89

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70	24.2	69	111	74	871.09	222.04
58	18.3	79	122	75	742.98	142.66
55	20.2	94	108	71	638.29	221
77	23.5	96	132	93	619.79	360.14
92	28.1	68	151	91	882.03	94.87
80	25	86	132	85	693.7	454.72
100	30.9	84	135	87	718.02	118.09
85	26.8	89	110	70	673.06	277.42
75	30.4	88	137	84	671.23	144.67
86	26.8	74	134	91	800.68	95.57
55	18.6	91	136	77	659.07	400
73	25.9	84	152	88	708.54	223.14
62	25.5	105	129	84	569.67	406.42
60	19.8	88	132	96	681.78	306.3
60	19.4	85	129	82	700	134.27
78	24.6	69	115	72	866.67	161.49
87	32	82	125	82	739.65	67.7

Source: Author's Data collection

Table 3: Correlation Analysis

	Weight (kg)	**BMI**	**Heart Rate**	**BP-Systolic**	**BP-Diastolic**	**IBI**	**Stress Index**
Weight (kg)	1						
BMI	0.77	1					
Heart Rate	0.093	-0.030	1				
BP-Systolic	0.213	0.031	0.265	1			
BP-Diastolic	0.417	0.148	0.408	0.526	1		
IBI	-0.124	0.007	-0.985	-0.295	-0.401	1	
Stress Index	-0.037	-0.149	0.722	0.296	0.278	-0.690	1

Source: Autor's Computation

Table 4: Regression Output

Regression Statistics	
Multiple R	0.76
R Square	0.58
Adjusted R Square	0.54
Standard Error	80.90
Observations	78.00

ANOVA

	df	SS	MS	F	Significance F

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Regression	6	630895	105149	16.068	1.4096E-11
Residual	71	464625	6544.02		
Total	77	1095520			

Table 6: Regression Analysis

	Coefficients	**Standard Error**	**t Stat**	**P-value**
Intercept	-2004.31	842.10	-2.38	0.02
Weight (kg)	0.09	1.44	0.06	0.95
BMI	-3.20	3.90	-0.82	0.41
Heart Rate	16.97	5.12	3.32	0.00
BP-Systolic	1.94	0.94	2.06	0.04
BP-Diastolic	-1.54	1.64	-0.94	0.35
IBI	1.02	0.54	1.88	0.06

Source: Author’s computation