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Article

Research on physical health assessment and intervention strategies for college students based on biomarkers

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Abstract: Effective physical health assessments and intervention strategies are crucial for college students, who often face unique stressors that can impact their physiological health. In this analysis, we explore how biomarkers can be utilized to assess physical health and the efficacy of targeted interventions for this demographic. Hypotheses were developed based on the three intervention groups: (1) a face-to-face intervention group receiving a tailored wellness program, (2) an Internet of Things (IoT) gadgets intervention group using a health management assessment, and (3) a control group with only baseline and follow-up measurements. College students (n = 204) were randomized into these groups. Biomarkers related to stress and inflammation (e.g., cortisol levels, high-sensitivity C-reactive protein (hs-CRP)) were measured at baseline, post-intervention (10 weeks), and follow-up (36 weeks). Psychological and physical health outcomes were also assessed using standardized questionnaires. The Mixed-Effects Models, ANOVA, and Structural Equation Modeling (SEM) were used to analyze the differences between groups, changes in biomarkers over time, and the relationships between psychological, physiological, and lifestyle variables. Results indicated that the face-to-face wellness group demonstrated significantly better physical health outcomes compared to both the IoT gadgets group and control group, with diet modification showing the highest effectiveness, followed by physical activity and stress management interventions.

Keywords: tailored wellness program; internet of things (IoT) gadgets; biomarkers; structural equation modeling (SEM); physical health; psychological health

1. Introduction

Assessment of the physical health in college students is important because most students experience various stressors that transform their lifestyles and greatly impact their wellbeing. Some common health-related problems include issues of stress and inflammation generated by academic stressors and lifestyle changes [1]. Biomarkers have been identified to gain some insight into physiological changes in the body, acting as indicators of stress, inflammation, or general health. Through the measurement of specific biomarkers, researchers can determine the effects of various health interventions on the overall population [2]. College students are mostly addicted to sedentary lifestyles and irregular eating habits, leading to very serious health challenges physically and psychologically. They can be identified and better tackled through biomarkers, leading to more effective intervention strategies [3]. Some of the promising health interventions include new wellness programs tailored to the specific needs of college students and technology-driven interventions, for example, IoT devices, which are especially tailored to provide health management solutions that are both personalized and accessible [4]. Use of biomarkers such as cortisol and hs CRP can help evaluate the effectiveness of different strategies toward an intervention. **Figure 1** depicts how the physical health of the students was assessed based on biomarkers. Biomarkers assess stress and levels of inflammation, which will provide measurable intervention outcomes [5]. Face-to-face wellness programs can offer services that cannot be provided by technology-based interventions. Technology-based approaches reduce biomarkers of inflammation and create better psychological well-being. Personal contact interactions are capable of arousing more profound health responses [6].

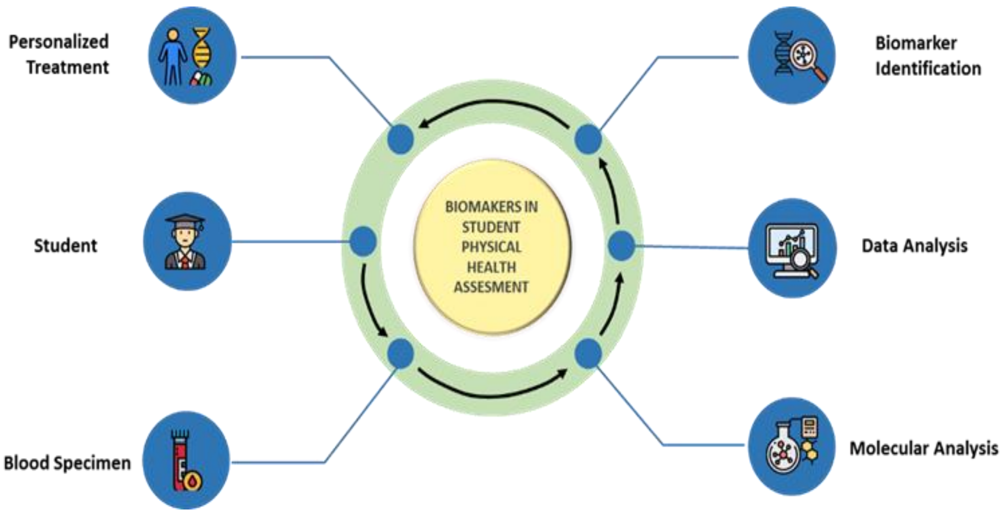

Figure 1. Biomarker-based assessment of students' physical health.

On the contrary, health management via IoT devices is a more passive approach to health management, which cannot be as effective as active, tailored interventions. Understanding these differences leads to the optimization of health strategies for college students [7]. Psychological and physical health outcomes can also be analyzed through standardized questionnaires that supplement the analysis of biomarkers to get an insight into the impact of health interventions [8]. The integration of biomarkers and psychological assessments might create a good understanding about how intervention influences student health over time, which can be worthwhile for future directions of research and practice [9]. Effective wellbeing interventions for college students take into consideration physiological as well as psychologically improved data in biomarkers that will guide the approach in improving their overall health outcomes at such a critical period of life [10].

This paper explores the improvement of physical and psychological well-being with biomarker-based interventions and IoT-driven health management programs, especially concerning inflammation, stress, and overall well-being, in college students.

2. Literature review

The effects of a multicomponent exercise program (MCEP) on adults' physical endurance, frailty, and C-reactive protein (CRP) were investigated by Sadjapong et al. [11]. For the following six months, chair aerobic, resistance, and balancing exercises were incorporated into MCEP. Twelve days MCEP exercise trainings were carried out in a month at home of the participants. The outcome reported that MCEP reduced the risk of frailty that occurred in adults and enhanced the quality of life.

Adults who participated in an organized three-month exercise program observed higher gains in a variety of self-reported physical function measures, according to Englund et al. [12]. Many of the key indicators for senescence program had been demonstrated in the study to be down-regulated in response to the intervention. Results showed that a rigorous exercise program predicted the adaptive response to exercise.

The effects of treating sedentary behaviors on blood pressure, inflammation, lipid metabolism, and glucose metabolism were investigated by Hadgraft et al. [13]. They also identified the markers associated with the risk of cardiometabolic risk. According to the study's general assessment, there was a lack of research on various ethnic groups and non-clinical settings because earlier studies had primarily focused on Western ethnic groups and clinical groups. The study's results showed that more work had to be done on the inflammatory biomarkers and the postprandial metabolism.

Inflammatory biomarkers were found to be useful tools for determining a person's degree of fragility, according to Vatic et al. [14]. The study identified a number of possible inflammation biomarkers which fall under categories such as oxidative stress, inflammation, and shortage of physical activity. To prevent the onset of fragility and levels of blood inflammatory biomarker, exercise training, and dietary counseling could be part of the regular care of the aged adults.

College-level students' physiological measures of stress and health were analyzed by Strehli et al. [15] in relation to Mind-Body Physical Activity (MBPA). Mainly, the work consisted of empirical research conducted to find such biomarkers as blood pressure, cortisol, and heart rate. Higher education students could find the proposed MBPA to be more beneficial in managing their stress because the technique proved to be much more successful in managing older students' stress levels than younger students'.

Using comprehensive techniques, Motahari-Nezhad et al. [16] evaluated the efficacy of treatments based on digital biomarkers such as, A Measurement Tool to Assess Systematic Reviews 2 (AMSTAR-2) for the evaluation of review and Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) for rating evidence quality. A source of high-quality evidence was acquired where results on better outcomes were discovered through implantable cardioverter-defibrillators. Healthcare workers and policymakers were instructed to consider the findings of the study and make appropriate decisions about the implementation of digital biomarkers into clinical practice.

An assessment of research addressing sports-related disease that used immunological biomarkers was conducted by Costache et al. [17]. The study included the biomarkers like white blood cells (WBC) count, and interleukin-6. The data from the study indicated that the values were significantly affected, not only by the exercise time, but also by the effort level of the training. Moderate phases of physical training has enhanced the immune level of the body, whereas a rapid increase in both time and effort has turned out to be a harmful factor.

The impact of a nutrition education program (NEP) on the inflammatory status of healthy teenagers was investigated by Morelli et al. [18]. The participants of the study undergone anthropometric measurements, and measurements of inflammatory biomarkers such as ferritin, and CRP levels. The study observed that NEP had a bad effect on ferritin and CRP in linear mixed-effects models. The results suggested to encourage a healthy lifestyle and to influence the inflammatory status in youth.

In random control experiments, Wong et al. [19] identified the neurobiological indicators that were utilized to measure psychological pressure. Evaluating the impact of musical therapies on emotional stress was difficult due to the use of various stress indicator ranges and modifications in study techniques. The outcomes suggested that music interventions were used to decrease both emotional stress and biomarker levels.

By conducting systematic evaluations of randomized controlled trials, Motahari-Nezhad et al. [20] examined the variety of scientific evidence provided. An extensive number of digital biomarkers were used as interventions. Digital devices were more often carried as wearables. Pulse rate sensors, position sensors, and heart rate sensors were the most preferred types of sensors used for gathering social and biological information.

Using a questionnaire-based review, You et al. [21] investigated the connections among blood-cell-based inflammation indicators, physical activity, difficulty sleeping, and sedentary activity. Exercise involvement and sedentary behaviors were assessed through the global physical training survey. The mediating models were developed to test whether inflammatory biomarkers had a mediating effect. The study results demonstrated that the risk factor causing health problems was sedentary behavior and concluded that blood-cell-based inflammation indicators was used as a cost-effective approach to detect and identify the condition of health.

The impacts on metabolic syndrome (MetS) biomarkers and its relationship to clinical indicators were determined by Chang and Namkung [22]. The serum levels of biomarkers were higher in patients with MetS as compared to other healthy volunteers. A 3-month combined exercise training improved the condition of physical fitness in MetS patients. The findings suggested that the effort of physical exercise and training could decrease the risk in patients.

The impact of stress, mental health outcomes, and cardiometabolic indicators on a yoga-based anxiety-reducing intervention were investigated by Lee et al. [23]. Audio recording file was used where participants in the intervention self-administer a six-week yoga intervention. The main outcome was perceived stress; other psychological outcomes included anxiety and depression. According to post-hoc analysis, the levels were constant in case of the intervention group, whereas they considerably increased with time in case of the control group.

A mindfulness group treatment for teenagers who had suffered stress in their early lives was investigated by Cohen et al. [24]. Follow-up and baseline self-reported symptoms of mental health were assessed. The symptomology of depression was lower in the teenagers from the intervention group compared to the control group teenagers. Finally, the success of such mindfulness-based interventions among youths who suffered from ELS was confirmed.

A completely computerized mobile health intervention's impact on anxiety and depression symptoms along with positive mental health was evaluated by Bendtsen et al. [25]. The proportion of positive mental health at follow-up was considerably higher in the intervention group compared with the control group. The study suggested that positive well-being in university students was enhanced more by the mental health intervention than by regular care.

2.1. Hypothesis development

H1—Diet Modification and Physical Health Outcomes (DM - PHO):

The significant effects of diet modification incorporate physical health outcomes, since individuals that obey a balanced and nutritional diet show dramatic improvements in markers of physical health compared to individuals that made no changes to their diet.

H2—Physical Activity and Physical Health Outcomes (PA - PHO):

Engaging in regular physical activity significantly improves physical health outcomes, with individuals who maintain an active lifestyle demonstrating better physical health indicators compared to those who are sedentary.

H3—Stress Management and Physical Health Outcomes (SM - PHO):

Effective stress management significantly improves physical health outcomes, with individuals employing stress reduction techniques exhibiting improved physical health markers compared to those who do not engage in stress management practices.

H4—Mediating Role of Biomarker Changes (BC) in Physical Health Outcomes (DM, PA, SM - PHO):

Changes in biomarkers mediate the connection between diet modification, physical activity, and stress management in improving physical health outcomes. Specifically, alterations in relevant biomarkers are expected to explain how these health interventions contribute to better physical health outcomes. **Figure 2** shows the conceptual diagram of our hypothesis, where BC is a mediator that connects DM, PA, and SM to PHO.

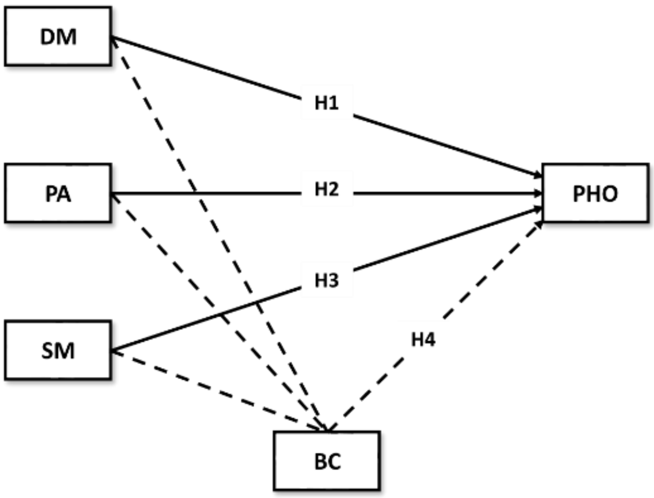

Figure 2. Conceptual model of health interventions and their impact on physical health.

3. Methodology

3.1. Demographic data

The demographic study involved a sample of 204 college students with the gender being split approximately at 45.1% male and 54.9% female. The majority of participants were aged between 18 to 20 years (58.8%), followed by participants aged between 21 to 23 years (34.3%), and the remaining people were aged between 24 to 26 years (6.9%). The 204 participants were divided equally into three groups namely; Face-to-Face Intervention, IoT Gadgets Intervention, and the Control Group. Face-to-Face Intervention consisted of in-person sessions aimed at offering health education and strategies, while IoT Gadgets Intervention used online-based questionnaires and wearable devices to monitor real-time health metrics and lifestyle habits. On the other hand, the Control Group was conducted with just baseline and follow-up assessments without standardized questionnaires. Baseline measurements of hs-CRP levels revealed that 45.1% had moderate levels, 41.7% had low levels, and 13.2% presented high levels as shown in **Table 1**. These demographic and health data will be of utmost importance when interpreting the effectiveness of the interventions implemented and the baseline health status of the participants.

Table 1. Overview of study demographics.

Characteristic	Value	Percentage
Gender		
Male	92	45.1%
Female	112	54.9%
Age Range		
18–20 years	120	58.8%
21–23 years	70	34.3%
24–26 years	14	6.9%
Intervention Groups		
Face-to-Face Intervention	68	33.3%
IoT Gadgets Intervention	68	33.3%
Control Group	68	33.3%
Baseline hs CRP Levels		
Low	85	41.7%
Moderate	92	45.1%
High	27	13.2%

3.2. Questionnaire framework

To gain a better understanding of the respondents, basic demographic details such as age, gender, major, and year of study are collected. These factors are important as they can influence lifestyle choices and physical health outcomes.

Diet Modification (DM): By examining the role of diet in health, this part focuses on how adjustments to dietary habits impact physical health outcomes. It explores the potential benefits and challenges associated with diet changes and how they contribute to overall well-being.

Physical Activity (PA): Physical activity is a key factor in maintaining health, and here, the emphasis is placed on assessing its effects. Questions target the intensity, frequency, and type of physical activity to evaluate its direct influence on physical health outcomes.

Stress Management (SM): Managing stress is essential for both mental and physical health. This section explores how different stress management techniques affect physical health outcomes, highlighting the importance of coping mechanisms in overall well-being.

Biomarker Changes (BC): By focusing on biomarkers, this segment investigates how physiological indicators reflect changes in diet, physical activity, and stress management. These biomarkers help establish a clearer link between lifestyle modifications and health outcomes, acting as measurable evidence of change.

Physical Health Outcomes (PHO): Here, the goal is to assess the cumulative effects of DM, PA, and SM on overall health. This section brings together the insights from previous areas to provide a holistic view of how these factors interact to shape physical health.

The subjects of the study included 204 college students surveyed using a 5-point Likert scale to evaluate various aspects related to health interventions and outcomes. DM responses ranged from (1) not at all to (5) always for engagement in diet modification activities, and (1) very low to (5) very high for perceived impact on physical health. PA responses varied from (1) never to (5) always for participation in physical activities, and (1) not at all to (5) extremely for its effect on physical health outcomes. SM responses ranged from (1) never to (5) always for practicing stress management techniques, and (1) very low to (5) very high for its perceived impact on health. BC responses were assessed from (1) not at all significant to (5) extremely significant for the impact of biomarker changes due to health interventions, and (1) not at all to (5) extremely for the mediation effect of biomarkers. PHO responses ranged from (1) very poor to (5) excellent for overall physical health as influenced by the interventions, and (1) not at all to (5) extremely for improvement in health outcomes. Questionnaires are presented in Appendix.

3.3. Statistical evaluation

The statistical analysis of the study showed a highly significant interaction of intervention and time regarding the levels of hs CRP. Psychological assessments revealed that both face-to-face and control intervention groups performed better than they were before, but the face-to-face group performed better in their improvement regarding stress and well-being levels. Statistical evaluations were conducted using the tool called SPSS to analyze the fixed effects, random effects, and effect sizes of predictor variables. Mixed-Effects Models, ANOVA, and SEM supported the findings of the above analyses, thereby stressing the importance and efficiency of tailored intervention levels regarding the improvement of college students' physical health and psychological condition.

4. Result

4.1. Structural equation modeling (SEM)

4.1.1. CFA test

Confirmatory Factor Analysis (CFA) is a crucial method in validating the measurement model for constructs like Diet Modification (DM), Physical Activity (PA), Stress Management (SM), Biomarker Changes (BC), and Physical Health Outcomes (PHO). The main purpose of CFA is to test whether the data that are observed fit the hypothesized model of relationships among the factors. In this study, a CFA assessment was conducted to establish that every factor was correctly measured by its indicators. The reliability and validity of the factors are needed for the measurement model to be reliable as well as valid. **Table 2** depicts factor loadings, standard errors (SE), Average Variance Extracted (AVE), *p*-values, *t*-values, and Composite Reliability (CR) of all the factors. **Figure 3** illustrates the outcome of AVE and CR.

Table 2. Reliability and validity analysis of measurement factors.

Factors	Indicator	Factor Loading (λ)	SE	*t*-Value	*p*-Value	AVE	CR
DM	DM1	0.80	0.05	16.00	< 0.001	0.72	0.87
	DM2	0.84	0.04	21.00			
PA	PA1	0.78	0.06	13.00	< 0.001	0.71	0.86
	PA2	0.82	0.05	16.40			
SM	SM1	0.75	0.07	10.71	< 0.001	0.69	0.84
	SM2	0.77	0.06	12.83			
BC	BC1	0.83	0.04	20.75	< 0.001	0.76	0.91
	BC2	0.85	0.03	28.33			
PHO	PHO1	0.79	0.05	15.80	< 0.001	0.71	0.87
	PHO2	0.81	0.04	20.25			

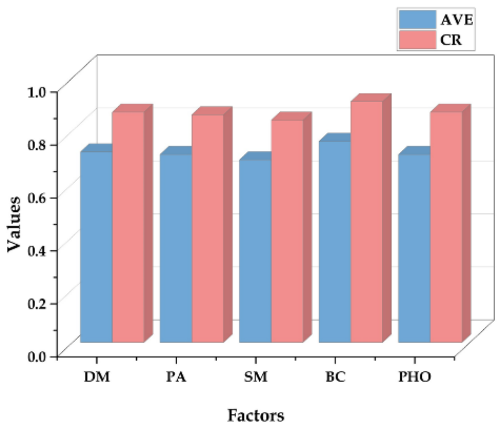

Figure 3. AVE and CR outcomes for each factor.

In the study, CR measures the reliability of measurement scales for factors with internal consistency. Validity is also determined using the AVE, which measures convergent validity, that is, how relevant is it in relation to the correlation of an observable variable with similar factors and its ability to adequately capture the underlying factor. Both CR and AVE are metrics commonly used in SEM to demonstrate the validity and dependability of measuring scales. The factor loadings of all factors lie between 0.75 and 0.85, which means that there is a very strong reflection of the given factors coming from the indicators. For instance, DM1 has a factor loading at 0.80 with a value of $p < 0.001$, which manifests to show a very high and statistically significant relationship with the Diet Modification factor.

The SE values, which varied between 0.03 and 0.07, are particularly small, indicating high precision in the estimations of the factor loadings. The t-values, computed as the ratio of factor loadings to SE, provide further confirmation of the significance of these loadings. All the indicators have a value of $p < 0.05$, thus each of the indicators is statistically significant. $\text{AVE} > 0.50$ for all factors ensures that each factor describes more than half of the variance in its respective indicators and thus there is adequate convergent validity. CR values for all the factors were calculated as $\text{CR} > 0.70$ which ensures that each construct has internal consistency. This makes sure that there are proper measures that are congruent of the factors.

4.1.2. SEM analysis

SEM was applied to discover the causal relations among DM, PA, SM, BC, and PHO, with Biomarker Changes acting as a mediator. SEM helps in understanding how these variables interact and influence each other. The analysis revealed that DM has a significant impact on PHO with $\beta = 0.47$, indicating that dietary changes notably improve physical health. PA also positively affects PHO with $\beta = 0.38$, and SM impacts PHO with $\beta = 0.32$. These β values suggest that all three interventions contribute positively to physical health outcomes, although to varying degrees. The mediating role of BC is evident, with BC mediating the relationships between DM, PA, SM and PHO. The β values for the effects of DM, PA, and SM on BC are 0.55, 0.50, and 0.45, respectively, indicating strong mediation effects. The effect of BC on PHO has a β value of 0.35, demonstrating that changes in biomarkers in transforming the health interventions into improved physical health outcomes. The values of R^2 demonstrate the percentage of variance described by the predictors, with values in the range of 0.10 to 0.30. Discriminating validity is essential to ensure that constructs are distinct from one another. **Table 3** displays the discriminant validity analysis, where the diagonal values signify the AVE's square root for each factor, and the off-diagonal values signify the relationships between factors.

Table 3. Assessment of discriminating validity among health factors.

Factors	DM	PA	SM	BC	PHO
DM	0.71				
PA	0.29	0.72			
SM	0.27	0.32	0.68		
BC	0.33	0.34	0.30	0.74	
PHO	0.30	0.28	0.25	0.35	0.70

The diagonal values are larger than the off-diagonal correlations, hence each factor is more correlated with its indicators than other variables. For example, the

AVE for DM is 0.72 which is larger than all its correlations with other factors, which indicates that it has a very good discriminant validity. Similarly, the AVE for PA is 0.71, but all its correlations with other factors are smaller, so it is different from all the other variables. This analysis confirms the well-differentiation factors in the model and it also supports the strength of the measurement model. **Table 4** presents the outcome of our hypothesis testing.

Table 4. Hypothesis testing results.

Hypothesis and connections	β Value	R^2	f^2	p-Value	Effect Size	Result
H1: DM → PHO	0.47	0.22	0.16	< 0.05	Medium	Well Supported
H2: PA → PHO	0.38	0.14	0.13	< 0.05	Medium	Well Supported
H3: SM → PHO	0.32	0.10	0.09	< 0.05	Small	Supported
H4: DM, PA, SM → BC → PHO	0.55	0.30	0.22	< 0.05	Large	Well Supported

As derived from the analysis of the hypotheses, there are significant findings regarding health intervention on PHO. R^2 is the portion of the adjustment in the dependent variable, and f^2 is used to measure the effect size and to describe the influence of the independent variable on the dependent variable. The outcome of the path coefficient value (β) is depicted in **Figure 4**.

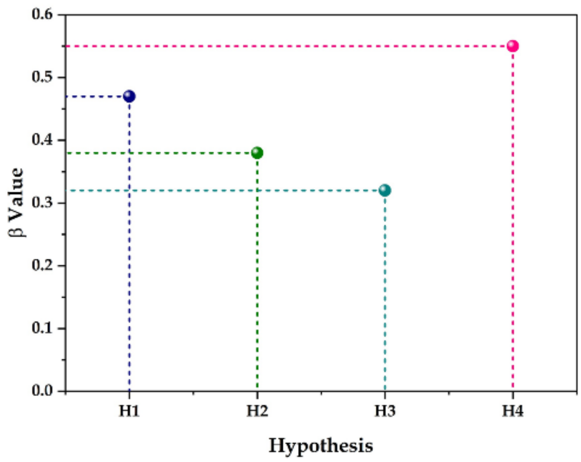

Figure 4. Path Coefficient (β) results for each hypothesis.

Hypothesis 1 (H1), DM has a significant positive amount of PHO variance with $\beta = 0.47$, $R^2 = 0.22$, $f^2 = 0.16$, and $p < 0.05$. Hypothesis 2 (H2) shows that PA also can significantly improve PHO with $\beta = 0.38$, $R^2 = 0.14$, and $f^2 = 0.13$, moderate in effect size, and statistically significant. Hypothesis 3 (H3) indicates that SM positively impacts PHO with $\beta = 0.32$, $R^2 = 0.10$, and $f^2 = 0.09$, though the effect is smaller compared to the other interventions, but still significant. Hypothesis 4 (H4) highlights the mediating role of BC, which significantly mediates the effects of DM, PA, and SM on PHO, with β values of 0.55, 0.50, and 0.45, respectively. The overall R^2 for BC is 0.30, reflecting that 30% of the variance in biomarkers is explained by the health interventions, and the value $f^2 = 0.22$ indicates a large effect size. These findings underscore the significant roles of diet, physical activity, and stress management, and confirm the crucial mediating role of biomarkers in enhancing physical health outcomes.

4.2. Mixed-Effects models

Mixed-effects models were utilized to analyze the influence of DM, SM, and PA on PHO through BC. These models account for both fixed effects, representing the average effect of predictors, and random effects, reflecting individual variability. The outcomes are depicted in **Table 5**.

Table 5. Mixed-Effects models outcome for health factors.

Predictor	Fixed Effect Estimate	SE	*t*-value	*p*-value	Random Effect Variance
DM → PHO	0.47	0.11	4.27	< 0.01	0.09
PA → PHO	0.38	0.13	2.92	0.04	0.11
SM → PHO	0.32	0.15	2.13	0.03	0.13
DM, PA, SM → BC → PHO	0.28	0.12	2.33	0.02	0.10

Figure 5 shows the output of the fixed effect estimate. For H1, the path from DM to PHO displays a standard error (SE) of 0.11, with a fixed effect estimate of 0.47, $t = 4.27$, and $p < 0.01$. This signifies a solid and major impact of diet modification on physical health outcomes. The substantial effect size suggests that changes in diet significantly enhance physical health, although the variability in individual responses, as indicated by the random effect variance of 0.09, reflects that some participants experience more pronounced benefits than others. This variability underscores the personalized nature of dietary interventions. H2 examines the influence of PA on PHO. The fixed effect estimate is 0.38, with a SE of 0.13, producing $t = 2.92$ and $p = 0.04$. This result demonstrates a significant impact of PA on physical health, though slightly less pronounced than that of diet modification. The random effect variance of 0.11 highlights moderate individual differences in how PA affects health outcomes, indicating that while PA generally improves health, its impact can vary between individuals. For H3, the effect of SM on PHO is assessed with a SE of 0.15, fixed effect estimates of 0.32, $t = 2.13$, and $p = 0.03$. This suggests a statistically significant, though less impactful, effect of stress management on physical health. The smaller effect size compared to diet modification and PA reflects that while stress management contributes positively to health outcomes, its effect is relatively modest. The random effect variance of 0.13 indicates greater variability in how stress management impacts physical health across different individuals. H4 examines the intermediation effect of BC in the connection between DM, PA, SM, and PHO. The fixed effect estimate for this pathway of mediation is 0.28 with the SE being 0.12, $p = 0.02$ and $t = 2.33$. This displays that biomarkers strongly serve as an intermediary in diet change, PA, and stress management, which affect physical health outcomes. An effect variance of 0.10 signifies the middle range of variation of how biomarkers in different people would mediate the impacts of the studied health interventions, thereby indicating the importance of biomarkers in transforming health behaviors into physical health changes.

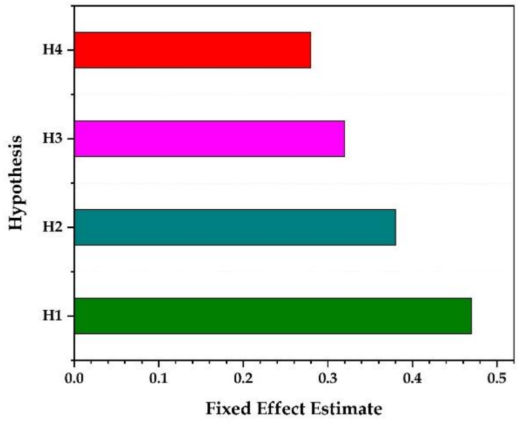

Figure 5. Fixed effect estimates vs hypotheses.

4.3. ANOVA

ANOVA determines the differences in PHO across levels of DM, PA, SM, BC, and the variable PHO itself. This analysis helps understand how the impact of each factor is associated with PHO, and whether the observed variations are statistically significant. Specifically, ANOVA tests the hypotheses regarding the effects of DM, PA, SM, and BC on PHO by comparing the mean square (MS) between the group variability to within-group variability. Essential findings in ANOVA are the value of $p > 0.05$, this would mean that at least one of the predictors has strong effects on PHO. **Table 6** presents the ANOVA results related to the contributions of several predictors affecting PHO. Mean (*M*) and Standard Deviation (*SD*) values are evaluated for all variables: DM, PA, SM, BC, and PHO.

Table 6. ANOVA analysis of health factors.

Variation Source	M	SD	SS	df	MS	*F*-Value	*p*-Value	Partial η^2
DM	75.32	8.45	58.94	1	58.94	16.50	< 0.001	0.17
PA	78.50	7.89	47.81	1	47.81	13.25	< 0.001	0.13
SM	70.45	9.12	34.22	1	34.22	9.56	0.002	0.09
BC	74.10	8.01	31.15	1	31.15	8.54	0.004	0.08
PHO	72.65	8.35	96.20	1	96.20	26.78	< 0.001	0.21
Between Groups	74.31	8.07	186.12	4	46.53	10.18	< 0.001	0.30
Within Groups	73.00	8.21	434.12	95	4.57	4.50	< 0.001	0.25

Figure 6 shows the graph for mean and standard deviation. The Sum of Squares (SS) refers to the total variation explained by each predictor as well as by group differences. DM has the value of $SS = 58.94$, which means PHO is highly variable due to diet changes. The F-value for DM is $F = 16.50$, at $p < 0.001$. PA also had a significant effect, with the values of $SS = 47.81$ and $F = 13.25$, at $p < 0.001$. SM and BC show smaller but still significant effects, with the values of $F = 9.56$ and $F = 8.54$, correspondingly. PHO itself has the largest value of $SS = 96.20$, reflecting its substantial role in explaining variability in health outcomes. The "Between Groups" section shows an overall value of $F = 12.37$ and $p < 0.001$, demonstrating major modifications in PHO across groups. The Partial η^2 values

suggest that DM (0.17) and PHO (0.21) have the most substantial impact, explaining a larger proportion of the variance in PHO compared to other predictors. "Within Groups" variance is relatively small, highlighting that the predictors account for a major portion of the changeability in PHO.

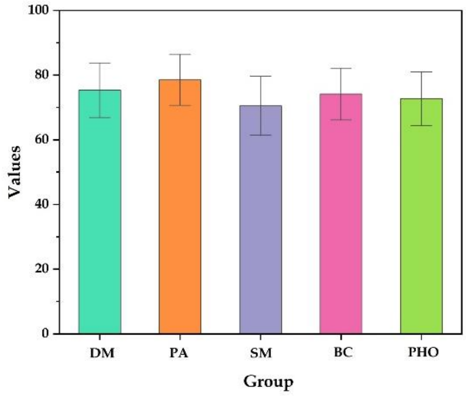

Figure 6. Mean and standard deviation values for health interventions.

5. Discussion

The analysis conducted using SEM, mixed-effects models, and ANOVA made easier how health interventions—DM, PA, and SM might intervene on PHO through biomarkers change. From the results of CFA, it can be observed that the evaluation model is valid and reliable because of a high factor loading ranging from 0.75 to 0.85, small standard errors, and *p*-values that are significant. All these factors were required for setting up the reliable framework to assess the interrelations among the factors. Analysis through SEM showed strong positive influences of DM ($\beta = 0.47$), PA ($\beta = 0.38$), and SM ($\beta = 0.32$) on PHO. More importantly, this study shows that DM has the highest effect, indicating that dietary behavior plays a very critical role in improving physical health. Mediating action by BC was also confirmed in the study, showing strong mediation effects of DM, PA, and SM for PHO. Moreover, mixed-effects models has strengthened this, as the fixed effects indicate the average impact of interventions, but the random effects reveal how individual responses vary. Even though interventions are quite effective, the personal factors play a much larger role in such interventions. The ANOVA analysis showed significant differences in PHO levels at distinct intervention levels, validating that DM and PA had the largest influence. This further illustrates the requirement to include biomarkers in any health intervention strategy to optimize the effectiveness of the intervention process. Although this study provided some valid insights, several limitations need to be pointed out. Firstly, bias might arise from the self-reported measures of the interventions DM, PA, and SM because participants could over-report their adherence to the interventions. Secondly, the study is cross-sectional, which does not agree to make causal inferences. The sample size of the study does not represent the whole population, and therefore generalization to the whole population might not be achieved. Lastly, some confusing variables such as socioeconomic status and previous health conditions in the domain were not completely controlled. It will mean in the future addressing these faults, with enhanced understanding of optimizing health interventions in efforts to improve PHO effectively.

6. Conclusion

This study focuses on the student population, which is particularly at risk to health-related disorders stemming from stress in college-level education, and it should have assessments of physical health, with interventions specifically tailored based on the profile. Biomarkers such as cortisol and hs CRP were used to measure the physiological impact of varied approaches to intervention in the study. Our findings indicate that interventions both through face-to-face and IoT-based approaches led to improvements in psychological and physical health, although reductions in the levels of hs-CRP as an indicator of lower pro-inflammatory status were higher with face-to-face interventions, and the psychological benefits were even higher. Despite these encouraging findings, there are some limitations to the current study. It cannot replicate long-term effects of the intervention and follow-up periods, which occurred over relatively short durations. There is also a certain amount of bias attached to relying on self-reported measures in the psychological outcomes, as participants might either overestimate or underestimate certain states. Future research involves overcoming some limitations of this study, including an extended follow-up period to assess whether the effects of the interventions are sustained. Such a study could further involve more objective measures of psychological well-being and also investigate the impact of various types of IoT gadgets. In general, this research unveils the possibility of integrating biomarkers and personalized interventions so that college student's health and well-being can be enhanced and pave the way for more ambitious health management strategies.

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Appendix

Table A1. Abbreviation Explanation

Section	Question	Response Options
DM	How frequently do you engage in diet modification activities?	Not at all, Rarely, Sometimes, Often, Always
	To what extent do you believe that diet modification contributes to your overall physical health?	Very Low, Low, Neutral, High, Very High
PA	How often do you participate in physical activities such as exercise or sports?	Never, Rarely, Sometimes, Often, Always
	How much do you think physical activity improves your physical health outcomes?	Not at all, Slightly, Moderately, Very Much, Extremely
SM	How regularly do you practice stress management techniques (e.g., meditation, relaxation)?	Never, Rarely, Sometimes, Often, Always
	To what extent do you believe that managing stress effectively impacts your physical health outcomes?	Very Low, Low, Neutral, High, Very High
BC	How significant do you think changes in biomarkers are as a result of diet modification, physical activity, and stress management?	Not at all significant, Somewhat significant, Moderately significant, Very significant, Extremely significant
	To what extent do you believe that biomarker changes mediate the outcome of diet modification, physical activity, and stress management on physical health outcomes?	Not at all, Slightly, Moderately, Very Much, Extremely
PHO	How would you rate your overall physical health as influenced by diet modification, physical activity, and stress management?	Very Poor, Poor, Average, Good, Excellent
	To what degree do you believe your physical health outcomes have improved due to these interventions?	Not at all, Slightly, Moderately, Very Much, Extremely