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An Empirical Study on the Principles of Promoting Physical Health and Electronic Screen Use in Adolescents in the Context of Big Data

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ABSTRACT
Purpose: Though the quantity of time adolescents spend using digital devices has raised widespread concerns that this time could be detrimental to mental health, these possible harmful effects have not been well investigated. Intersectionality is a theoretical approach that has been used more often in empirical studies of health disparities to examine how social variables interact to produce health inequalities. Digital technologies have emerged as a primary means of delivering health-related services in recent times, a tendency that has been further strengthened by the ongoing COVID-19 pandemic. This paper investigates the connection between the general well-being of adolescents and suggests that, by using our country's "Adolescent Physical Health Statistics Analysis in 2020" as a benchmark for regression evaluation, the results of health training on interventions within the framework of the empirical research on the establishment of adolescent health data management and services systems can effectively reinforce the attachment the hypothesis of the physical in nature health of adolescents.
Method: The findings of the study demonstrate that by preventing students from engaging in physical activity, the notion of adolescence physical health management can enhance the physical health of teenagers. When processing data, GBDT works well with a sizable training collection. As sample size grows, the precision rate can approach 97.47%. The RF a position outperforms the GBDT method in terms of precise classification for male gender sitting forward bending development. With regard to the boys' 1000-meter managing promotional classifying operation, the RF approach yielded the greatest promotion identification rate, at 79.45%. When 70% of the training set is used in the male pulling ups to enhance the classification effect, the RF technique achieves the greatest precision rate, 97.07%.
Results: The classification success rate for females who stand for long jumping advancement ranges from 41% to 78%, according to the results of the effect of classification study. The RF method works best when the learning set is less than 50%; its maximum is 53.93%; the GBDT method performs best whenever the training set is lower than 50%; both the RF and GBDT indications have advantages in Macro-F1.
Conclusion: When practice rate arrives at 80%, the GBDT technique achieves an average reliability rate of 87.77%; on the Macro-F1 the index, the GBDT method is clearly the best. In the advertising of assessing the effect on the final health level of girls, the accuracy rates of the RF and GBDT methods vary between 80% to 97%, and the precision rates of the NN technique range from 70% to 97%. The article aims to educate the reader on the subtle distinctions between pertinent terms used at the interface of physical activity and digital wellness, as well as provide state-of-the-art descriptions for them. This is because unclear terminologies is a major source of difficulty in communicating science and can impede the advancement of empirical as well as theoretical studies.
Keywords: Digital Health, Scientific Communication, GBDT Methods, Macro-F1 Index, Promotion Accuracy, Classification Accuracy, Physical Activity, Digital Technologies, (COVID-19), Adolescent Physical Health, Regression Analysis, Big Data Management, Health Inequality, Empirical Study.

I. INTRODUCTION

The broad adoption of digital gadgets has drastically altered how people socialise, work, and play. The swift advancements in broadband connections, flat panel displays, and handheld computing capacity have resulted in gadgets that characterise and influence contemporary children [1]. Teenagers, for instance, now spend 16.0 hours a week online, more than doubling from a median of 8 hours a week in 2005. The substantial amount time that is spent using these technological devices, particularly in young adulthood, has raised concerns that their use may have a negative impact on social and mental health [2]. Although growth-oriented and clinical researchers have questioned the efficacy of this limitation-focused strategy, and their the American College of Paediatrics is recommending that restrictions be placed on young people's time spent on screens, [1], demonstrating that there are progressive costs of screen time for the children's wellness. The purpose of the current study was to assess several theories on the relationship between screen period of time and mental health, [2], as well as to define and measure moderate digital activity use empirically [2, 3]. The so-called displacement hypothesis, which holds that the negative impacts of technology are directly correlated with exposure, is the dominant perspective on screen time effects that has characterised the literature too far. Negative effects are attributed to the replacement of digital activities with alternatives like reading books, exercising, and interacting with family and friends [3].

This theory holds that while "overuse" of technology can do more harm than good, such as interference with extra or additional social events or school, it can also be beneficial in an interconnected culture when used in moderation. In the fairy tale, Goldie finds that moderation is just right in terms of beds and porridge. In a similar vein, [3], it's possible that excessive tech use can replace other worthwhile activities while "too little" use robs young people of vital social insights and peer activities. According to our Goldilocks hypothesis, there are moderate levels, or experimentally derived balancing points, that are "just right" for young people who are ideally connected [3].

Health disparities across social lines continue despite significant advancements in healthcare technology and preventive medicine over the previous few decades. Individuals who belong to marginalised groups that are characterised by social traits, such as race or ethnic origin, gender, sexual preference, or socioeconomic level, [3, 4], are nonetheless more likely to suffer from chronic illnesses and have a lack of physical and mental wellness both locally and internationally. Life-course perspectives emphasise how these marginalised populations are excessively exposed to a growing number of dangers that might harm their health and are unable to access services that can promote their health from an early age [4]. Consequently, this sets marginalised people up for a trajectory of declining health at a younger age than their non-marginalized peers, with some evidence—though conflicting—pointing to the possibility that these differences could expand with age [4, 5]. Such stark health disparities have highlighted the need for an expanded awareness of the social components of health anchored in these traits in pursuit of health equality [5].

Intersectionality, which with its emphasis on the co-production of many systems of oppression, has gained recognition among academics as being especially appropriate for the study of health inequalities. It is true that interconnectedness has gained acceptance and intellectual traction quickly, gaining the title of "most important conceptual advancement that feminist research, combined with related fields, have provided so far [6]." Shortly after Black feminism in the United States rose to prominence in the 1960s and 1980s and began criticising earlier feminist and anti-racist organisations that disregarded the needs of Black women, the concept of intersectionality entered the academic mainstream. In other words, while antiracist discourse mostly benefited Black males, feminist discourse tended to address the issues of White middle-class women. The concept of intersectionality to develop, [6], which emphasises how various oppressive institutions interact to create distinct challenges, appeared to be a suitable reaction to the insufficiency of earlier political movements in defining the social injustices faced by Black women [6, 7].

A number of articles that characterise interconnectedness as a useful tool to explore how intersecting statuses impact health demonstrate the practical importance of an intersectionality viewpoint to disparities in healthcare research. In this context, a PubMed search can be quite illuminating. Searching for articles before to 2010 utilising keywords related to intersectional and health inequalities produced a mere eight matches [7]. Just three of these eight papers included empirical studies; the other five were theoretical or concept works that provided insights into how intersectional and health studies can be integrated. However, 300 publications came up in the same PubMed search for research published in 2013 or later [8]. There is now a substantial body of published research on overlapping health, most of it empirical [8].

The intersection has, however, taken a while to evolve in scientific health disparities studies. There is currently agreement on how to experimentally model intersectionality, which is however there is disagreement on whether the complexity of intersectional can be quantified. Indeed, some academics have conjectured that because intersection is a theoretical structure that was not originally intended for measuring, predict, or explain health consequences, [8], it may not be a good fit for empirical studies on health. As academics have pointed out, this problem might originate from intersectionality's seeming conflict with positive thinking, the theory of knowledge that forms the basis of a large portion of empirical studies on health [9]. The intersection sheds light on the numerous socially constructed situations that people who occupy various points of intersection encounter, in contrast to positivism, which maintains that only one "true" and unbiased truth can be found by carefully planned and value-neutral study. Because of this, a number of academics have cautioned against the abuse or improper utilisation of interconnectedness in empirical investigation and have even proposed that these approaches might need to be rethought in order to properly investigate the factors creating disparity among numerous marginalised groups [10].

An increasing body of research indicates that, in addition to other personal habits like nutrition and sleeping, continuous vigorous physical activity plays a critical role in maintaining or regaining physical as well as mental wellness over the course of a person's lifetime. Almost one-third of older people along with more than two-thirds of teenagers globally do not meet the minimum standard of frequent physical activity, [10, 11], despite the fact that the research indicated above indicates that it is an essential requirement to ensure general health. The later results, which show that a sizable portion of the worldwide population must be categorised as not physically active, are concerning from the standpoint of public health. Within this framework, there is also research indicating that physical inactivity levels rise with age and that a significant portion of waking hours is spent sedentary for older persons, with the latter group even showing an increase in the past few years [11].

Public health measures associated to the Coronavirus disease 2019 (COVID-19) (e.g., home imprisonment) have greatly worsened the problem that a significant portion of the population worldwide does not meet the necessary level of physical activity. Unfortunately, this has resulted in a further rise in sedentary behaviours and a decline in the amount of vigorous physical activity among elderly people as well as the general public [12]. The evidence offered above indicates that, particularly in the ageing population, acceptable defensive measures, such as treatments to promote regularly and organised forms of active living, which are defined by bodily physical activity and/or cardiovascular exercise, ought to be implemented [11, 12]. This is since greater instances of lack of exercise and sedentary behaviour are demonstrated to have negative health consequences. The assumption that regular and scheduled physical activity is essential for healthy ageing is being supported by a growing body of the information. Awareness being physically fit requires an awareness of one's physical condition [12]. Teaching youth about sports in order to encourage physical activity is one of the main objectives of high-quality physical education. One of the primary causes of adolescents' inactivity is a lack of information about their physical condition. Understanding physical health is thought to be fundamental to the study of cognitive sports. It is regarded as one of the main three elements of physical literacy, in addition to understanding what constitutes a healthy lifestyle and the importance of being physically active [13]. It serves as the foundation and requirement for obtaining physical literacy. Still, there is a declining tendency in youth physical health. The majority of youth still only reach pass or fail levels, and only few of them advance to good or exceptional.

Reduced amounts of inactive spent in front of computer screens and oversees (Screens Time, ST) and more Physical Activity (PA), which is defined as “any bodily movement created by skeletal muscles leading to an increase in energy expenditure1,” have been scientifically linked to improved physical in nature, psychological development and mental health, particularly in young people and adolescents [14]. The World Health Organisation (WHO) and other writers recommend low amounts of for recreational use Screen Time (ST) and 60 minutes of moderate-to-vigorous PA per day for young people and adolescents in order to promote a healthy lifestyle. While guidelines for ST in children and adolescents are still up for debate, a number of specialists have developed guidelines suggesting that youngsters should only engage in recreation ST for no more than two hours [15].

Numerous nations have effectively pursued these objectives through the implementation of various structured, i.e., supervised and recurring opportunities for physical activity, like extracurricular activities athletic events in schools, and unstructured opportunities, like accessible sports facilities or running routes in young people's daily lives. Thus, the COVID-19 pandemic and the ensuing closure of public recreation centres and organised sports in the majority of countries led to significant adjustments in young people's daily schedules and possibilities for physical activity [16].

1.1 Physical activity as a potential mediator of the association between SES and physical fitness

A positive reciprocal connection between regular exercise and physical fitness has been demonstrated by an earlier longitudinal study, spanning from childhood through the adolescent years. Additionally, a favourable correlation between children and adolescents' cardiovascular health and vigorous-intensity physical exercise was shown by a comprehensive meta-analysis and review of 23 research [16]. The World Health Organisation recommends adolescents and kids to participate in moderate-to-intense physical activity for at least 60 minutes a day due to the health advantages of physical activity. On the other hand, it came to light that those with lower socioeconomic status were more likely to be physically inactive [16, 17]. Additionally, children from lower-SES families might not have as much access to green spaces and outdoor playthings like bicycles and jump ropes. In consequence, the absence of these chances for outside play may be detrimental to the establishment of physical abilities [17].

1.2 Recreational activities as a potential mediator of the association between SES and physical fitness

Much less has been learned about the possible impact of additional leisure pursuits on physical fitness, despite the obvious link between exercising and fitness. Interestingly, a young age sporting events are typically unplanned and carried out by participation in other leisure pursuits like reading and singing. A prior study revealed that young children' progress in jumping and maintaining dynamic balance was linked to their involvement in a developmentally suitable movement and musical programme [17]. However, prior research has shown that drawing abilities are linked to cognitive processes like inhibition and fine-motor coordination, even if drawing practices may not directly impact the growth of their gross motor abilities.

These mental functions may be linked to exercise incentive through self-regulation behaviours, such as the capacity to begin and maintain an exercise regimen in the face of distractions from the outside. These mental processes are also engaged in the practice of exercise. For instance, modern society is becoming more and more dependent on electronic gadgets, which are widely used for online learning and enjoyment [13]. As a result, even in the early grades, children may have less time for play and movement. Numerous studies have shown that there is a correlation between a high prevalence of electronic gadgets and less time spent interacting with parents and children. Evidence reveals that many Chinese children are unable to comply with the guideline made by health authorities for young people and adolescents to keep their electronic device screen time to two hours or less each day. The likelihood of children from low-income homes abusing electronic gadgets is higher. Youngsters from low-SES homes are likewise more likely to have mobile phones in their bedrooms. It is unknown if certain early-life practices would have comparable or distinct effects on these cardiovascular elements, given that physically fitness encompasses multiple elements [13, 14].

1.3 Theories and Methods for Encouraging Adolescent Physical Well-Being

1.3.1 Current Conditions and Strategies for Promoting Youth Physical Activity

While sports facilities and infrastructure vary greatly between nations, they have many characteristics. There are emblematic schools that the youth adore, much like every school throughout Japan has a sports pitch and everyone school in the US and Canada has a football pitch. Seasonal events offer their own advantages, such as snow and ice in the northern region and aquatic activities in the south. For local or school options, a few local courses are reserved. National educational requirements will be chosen by condition-affected provinces and cities. It is possible to apply local self-control in the absence of any conditions [14]. To help with evaluating and assessing, it is important to provide more details on the material and delivery method of health education. This will help physical education teachers understand the subject matter better. Experts, academics, and the vast majority of teachers in physical education will go their separate ways if the current national physical education programme standards are maintained at the current level and do not have the support and close collaboration of local and school education functional departments at all levels [15]. This will prevent the training objectives and content from being deeply integrated. This article proposes the Physical Health Promotion Theoretical (PHPT), which focuses on unit exercises, streamlined groupings, and diverse physical education curricular paradigms.

1.4 Adolescent Physical Data Assessment Framework

1.4.1 Juvenile physical health requirements decision matrix:

While the information of indicators C3–C11 is limited to expressing quantitatively through the field of semantics the knowledge of indications C1 and C2 is represented by exact numbers. The two types of teenagers' health standards' data for decision-making is expressed as visual blur numbers in order to create a standardised matrix using a specific way.

1.4.2 Weighted physical fitness requirements decision matrix for each stage:

$w(T) = K\big(y(T-1), \ldots, (t-n), u(T-d-1), \ldots, u(k-d-n)\big).$ ……1

1.4.3 The best solutions, both positive and negative, for the physical fitness requirements at every phase:

First, choose the positive and negative optimal options in accordance with the rules, taking into account the size of the specified comparison information [14]. Then, for cost-based metrics, the highest possible value of the stage candidate information will be chosen by the negative perfect solution, and the smallest amount of the stage applicants data will be chosen by the beneficial ideal solution; similarly, for the benefit index, the maximum value of the stage candidate data will be chosen by the positive ideal answer, and the power source minimum value of the prospective physique data at the stage will be chosen by the ideal solution that is not favourable [15].

$P(d_i, w_j) = p(d_i)p(w_j|d_i)$ ……2

$p(w_j|d_i) = \sum_{k=1}^{k} p(w_j|z_k)p(Z_k|d_i),$ ……..3

$\lambda(Ai, Aj) = \left[\log\left(\frac{|x_{Ai}-a_{Ai}|}{w_{Ai}}\right), log\left(\frac{|y_{Ai}-y_{Ai}}{h_{Ai}}\right), \log\left(\frac{w_{Ai}}{w_{Aj}}\right), \log\left(\frac{h_{Ai}}{h_{Aj}}\right)\right]$……..4

1.4.4 How closely each physical fitness data point aligns with the stage's optimum solution:

First, use the formula to get the separation between each healthy lifestyle data point and the beneficial and detrimental ideal solutions in the stage [15]. Next, use the formula to determine how close each physical data point is to the ideal solution in the stage. Each physical information point's proximity in stage 1 is,

$y = \beta X + \varepsilon,$
$\varepsilon = \lambda W + \xi.$ ……………5

$\phi = V \times \frac{n}{Q} + \frac{Q}{(^{D}/_{2})2\times\pi\times3800.'}$ …….6

$(In - \alpha W)y = (In - \alpha W)X\beta + \epsilon.$ ……7

$f_R^A = w_G^{Ai,Aj}.V,$
$w_G^{Ai,Aj} = \max\{0, w_G.\varepsilon(f_R^A, f_R^A)\}.$ …..8

1.5 Big Data Services for Physical Health Model

Three fundamental concepts guide the overall development of a big data service complex for data-driven physical health:

- Addresses seven fundamental components: intelligent data, user needs, smart technology, big data physical health, [15, 16], physical health personnel, big data service platforms, and physically health analytic techniques;
- Mirroring the four attributes of demand sensibility, technical information, multisource information and service paradigm;
- Understanding the three fundamental components of the user services intelligent push function, mental health services big data studies, and demand big data perceptions [17]. The formula for this is as follows:

$x_i = \sum_{j=1}^{n} w_{ij}y_j - \theta_{i,}$ …….9

$BMI(b) = 2n\, In\,(\sigma) + n\, In(2\pi) + n\left\{\frac{m+tr(s)}{n-2-tr(s)}\right\},$ ………10

$F = \sum_{i=1}^{k}\sum_{q\in D_i}|q - n_i|^2,$ ….11

$W(T) = K(T-1), u(T-d-1)),$ ………12

1.5.1 Technological Operational Model and Theory of Physical Health Promotion

Cross-professional optimisation is part of the psychological wellness big data service system optimisation process. The system is no longer basic. Establish the system's primary target performance first, then designate it as the "restructuring pole [17, 18]." These are typically the big data service system's primary features and capabilities [19, 20]. This is how it is represented mathematically:

$U = \sum_{i=1}^{g}\left\{p_i | \sum_{j=1}^{k} p_j^{(1)}\right\}.$ ………13

$U = \{P_1|D, L, f_2Q, d, l, P_2|f_1, u, P_3|N, M, I\}$. ….14
$IR = \sum_{s-1}^{U} \sum_{d-1}^{K} f_{s,} DS_{s,} d$, …….15
$y_i = \beta(u_i, v_i) + \sum_{j=1}^{p} \beta_j (u_i, v_i) x_{ij} + \varepsilon_j \beta_{j*}$ …….16
$\beta_j = (X^T W_j X)^{-1} X^T W_j Y$. ……17
$x_{ik}(s) \leftarrow x_{jL}(s)$, ……18
$\sigma_{ikjl} = \begin{cases} \sum_{\Delta_{ikjl}}^{n} \left(x_{ik}(\varepsilon) - x_{jl}(\varepsilon)^2\right) \Delta_{ikjl}(\varepsilon), & \Delta_{ikjl} > 0, \\ & \Delta_{ikjl} > 0, \end{cases}$ …..19
$\Delta_{ikjl} = \sum_{\delta=1}^{n} \Delta_{ikjl}(\varepsilon)$. ….20

1.6 Objectives of the study

- Determine the most important markers of physical health, such as levels of physical activity, food preferences, sleep patterns, and the frequency of prevalent health problems.
- Look at the socioeconomic, environmental, and demographic aspects that affect adolescent screen usage habits and physical well-being.
- Make practical suggestions based on evidence to improve physical health and control adolescent screen usage.
- Evaluate the programmes and policies in place to encourage physical activity and control adolescent screen time.

II. LITERATURE REVIEW

(Robinson, T. N., 2017) [21] One of the well-researched effects of screen media consumption is obesity. Numerous observational research discover links between exposure to screen media and higher obesity risks. Children's gain in weight has decreased in randomised controlled studies where screen time is limited in community settings, indicating a cause and effect connection. According to available data, children and adolescents who are exposed to screen media are more likely to become obese because of increased eating during viewing sessions, exposure to high-calorie, low-nutrient marketing for food and beverages that shapes children's preferences, requests for purchases, and consumption patterns, and shorter sleep durations.
(Granic, I., Morita, H., 2020) [22] Teenagers are today living in a hybrid world that connects online environments to offline contexts; we are in the midst of a global shift where digital "screens" are no longer only amusement devices and diversions. However, psychology researchers looking into how digital experiences affect mental health tend to concentrate on associations with "screen time," which results in theoretical and oversimplified findings. We suggest a different, practical method of researching adolescent mental health in the digital era, which looks at the reasons behind and mechanisms by which digital media impact teenage growth.
(Odgers, C. L., 2020) [23] Teenagers are using digital tools to engage with one another and spend a growing amount of time internet. The record levels of social media consumption and mobile device ownership have sparked worries that the continual connectedness of teenagers is negatively affecting their mental health. In order to compile the information currently available about the relationships between teenage digital technology use and psychological wellness, this overview synthesised data from three different sources: (a) narrative evaluations and meta-analyses performed between 2014 and 2019; (b) large-scale preregistered cohort studies; and (c) demanding longitudinal and environmentally friendly momentary assessment studies. The review specifically focused on anxiety and depression in adolescents.
(Filos, D., Lekka, I., 2021) [24] A serious issue for public health in Europe and around the world is obesity. Additionally, childhood obesity is becoming more common. The concentration of fast food restaurants is one factor that is contributed to this rise in childhood obesity. As a result, environmental factors must be the main focus of preventive health initiatives aimed at reducing childhood obesity. As of right now, there are no methods in place to quantify living environment characteristics' objective impact on overweight and obesogenic activities. The goal of the H2020 project "Big O: Big Data against Childhood Obesity" is to combat childhood obesity by developing new big data-based evidence sources.

2.1 Association Theory of the Adolescents Physical Prevention Theory's Effect on Adolescents

Big data on health can refer to any quantity of information about physical fitness and health. At this point, the types and volume of health data are growing enormously due to the ongoing acceleration of digitization in the physical fitness industry.

H1: *Adolescents' physical fitness can be effectively improved by targeted wellness training and the use of the training's outcomes as part of the experimental investigation phase of the development of an unhealthy teenage data management and service systems.*
H2: *Exercise can result in good behavioural improvements, transfer negative feelings, and increase a person's sense of empowerment and self-efficacy,*
H3: *The concept and practice of collaborative management provide a useful and relevant intervention in the area of juvenile physical exercise management.*

III. SETTLEMENT OF CONCEPTS AND SERVICES FOR ADOLESCENTS PHYSICAL HEALTH INTO AN EMPIRICAL LEARNING MODEL

3.1 Information Sources for Physical Fitness based on empirical research

The investigation item for this paper is the General College Adolescents Physical Test Data from 2016 to 2020. There are 4854 female data and 11,927 male data among them. The objective fundamental requirements must be taken into full consideration during the study process. It is necessary to look into and analyse the experiment's viability before starting any study [25]. And the research objects are established based on fully satisfying relevant theories. Sports training, associated techniques, including theories of physical development make up the majority of the research content for this course [25, 26].

3.2 Steps for Analysing Data in Empirical Research

(1) Analysing test data physically:

Use the Python matplotlib package as a tool to visualise the data distribution for each data item, encompassing discrete and numerical information, [26], when dealing with enormous quantities of data.

(2) Synthesis and extraction of physical features:

The data undergoes additional processing to offer trustworthy data for the subsequent machine learning an algorithm after a straightforward exploratory investigation into the dataset in the data comprehension step [26]. Tests have shown that the dataset contains no missing or duplicate data points.

(3) Processing body data using a representation:

Following the data preparing stage's manipulations, the dataset satisfies the necessary conditions and is immediately suitable for creating models and learning advancement. Based on the increasing technique, which is essentially an additive model, [26], the Random Forest Algorithmic (RF) model is used to accomplish the RF algorithm's circulation, and the Graduated Boosters Trees Algorithm (GBDT) model is employed to achieve the GBDT algorithm. The goal is to continually optimise to increase the value among the actual value mistake and the error value, [27], which can be expressed by the loss function, i.e., to minimise the loss function's value.

IV. EMPIRICAL EVALUATION OF BIG DATA PHYSICALLY HEALTH MARKETING THEORY AND ENGINEERING

4.1 Data on Male Physical Condition

Following the identification of the study object, the male physical activity measuring data is computed and processed in accordance with the teenage physical data evaluation modelling approach, and the female measuring data is also incorporated into the model [26].
When it comes to processing data, the GBDT technique performs best since it has the greatest level of precision (89.52%) as the fraction of training sets grows. It also performs best in the Macro-F1 index, outperforming the other two methods by a substantial margin. Table 1 displays the physique classification of data training study information [27].

Table 1 Impact of a male 50-meter running grade predictor.

Ratio of Training Sets (%)	The Algorithm of Random Forest	Gradient Boosting Tree Reliability (%)	Neural Network Techniques	The Algorithm of Random Forest	Macro-F1 Indexing Boosting Tree with Gradient	Neural Network Techniques
20	69.89	68.94	67.08	0.897	0.369	0.339
30	65.79	68.97	69.54	0.658	0.269	0.746

40	64.28	65.89	61.08	0.197	0.549	0.645
60	63.89	63.49	67.89	0.497	0.849	0.519
80	61.20	64.58	67.98	0.986	0.219	0.249
90	61.05	69.89	69.36	0.619	0.518	0.894

Table 2 illustrates that boys between the ages of 17 and 18 weigh 2.49 kg more on median than the average. In 18 years, there is a 5.84 kg distinction, whereas in 17 years, there is only a 0.10 kg change. Boys among the ages of 17 and 18 weigh 4.01 kg more on aggregate than the minimum, with a maximum differential of 4.89 kg between the ages of 17 and 18 [27]. Boys between the ages of 17 and 18 weigh 9.87 kg more on mean than what is required and more than 3 kg more on average than the minimal requirement. For individuals eighteen years of age, the largest discrepancy is 2.49 kg, and the bare minimum is 0.98 kg. With an average variation of 0.97 kg, teenage girls between the ages of 17 and 18 weigh about the same as the population as a whole.

Table 2 Physical mass ratio in young boys that are sports.

Ratio of Training Sets (%)	The Algorithm of Random Forest	Increasing the gradient Tree Precision (%)	Neural Network Techniques
20	89.89	78.98	79.14
30	79.58	72.54	75.96
40	89.86	76.98	78.49
50	48.96	78.48	73.65
60	96.69	71.59	79.45
70	74.89	74.59	78.96

Males' pull-ups encourage categorization findings, as indicated in Table 3, indicate that the precision of categorization for boys' pull-ups ranges from 98% and 89% [28]. The RF approach achieves its greatest accuracy when the initially batch proportion is 90%; the rate is 59.09%; the GBDT method is clearly superior on the Macro-F1 index.

Table 3 Relationships between BIA, ADP, and DXA and BAI/BMI.

Techniques for Measuring Body Fate Rate	r	R^2	See
Impedance of Biological Energy (BIA)	0.89/0.84	0.54/0.28	2.25/2.48
Air Distribution (ADP)	0.96/0.47	0.94/0.69	3.96/8.98
X-ray Absorption with Double Energy (DXA)	0.98/0.24	0.78/0.96	8.47/7.95

Table 4 illustrates the rejection of risky and rather uninteresting sports like running and throwing and gymnastic. Because of things like routines for exercise, instructors, and the implementation of strategies, the content regarding wellness education is unclear. Curriculum arrangements are seen in many schools. Put it on the shelf, unidentified [28, 29]. Since the curricular requirements were implemented twenty years ago, nothing has altered in this situation. It is dubious to delegate all duties to physical education instructors and local schools, as this indicates that issues with wellness education still need to be resolved.

Table 4 Macro-F1 index for tracking female performance.

Training Set Ratio (%)	Macro-F1 Index		
	Random Forest Algorithm	Gradient Boosting Tree	Neural Network Algorithm
20	0.989	0.746	0.748
30	0.349	0.865	0.865
40	0.649	0.846	0.548
50	0.548	0.868	0.585
60	0.218	0.856	0.542
70	0.648	0.874	0.648
80	0.891	0.964	0.648
90	0.967	0.986	0.976

This study revealed that there are nonlinear associations between digital screen time and mental wellness as well as that moderate use of digital devices is safe [29, 30]. Our Goldilocks hypothesis is supported by the constantly observed concave-down quadratic connections and experimentally derived points of convergence, which show that post hoc the amount of time spent groupings used in previous studies simplify the nature of the relationships between computer screen time and adolescents' well-being. We measured moderate screen participation and discovered that, while high levels of involvement may have a detectable, albeit little, detrimental impact, the digital categories of activities we looked at are unlikely to pose a material harm to mental health at these moderate levels [31, 32]. The fact that all of these outcomes are firsts may be due to the fact that earlier research employed omnibus measures, which did not distinguish among the various forms of usage of digital screens and calculated screen time dosages using arbitrary cut-offs. These methods have limitations because, when impacts are calculated, they pool no detrimental and possibly dangerous quantities of involvement since they ignore informative variance. The field benefits from this study in several ways. Here, we talk about two. First, this research emphasises how important it is to take into account the larger social and developmental situations that surround the usage of digital screens [32, 33].

The aforementioned examples highlight how difficult it can be to distinguish between terminology like "information technology well-being," "electronic health," "mobile one's health," "a telehealth," "online medical care," and "virtual rehabilitation," since their definitions somewhat overlap. Furthermore, it should be highlighted that while the methodology suggested in this article can be used as a reference to employ acceptable wording, a blanket recommendation cannot be made because the appropriate terminology heavily depends on the specific scenario.

V. CONCLUSION

Digital technologies have gained popularity in recent years as a means of promoting physical activity, both in scientific study and real-world applications (e.g., wearables, online classes, smartphone apps).

The technology for promoting physical health in kids serves three purposes: advancement, evaluation, and assessment. Countermeasures are developed to encourage particular groups to improve physical activity and give consideration to their physical health using the analysis of test results and the advertisement of development trends. This study looks at and evaluates the physical health information of teenagers in my nation. The premise of Physical Health Promotions is that teenagers' well-being can be effectively improved by the outcomes of health interventions training, which is part of the empirical investigation that is component of the development of a the health of adolescents data management service system.

When data is being processed, GBDT works well with a sizable training set. As sample size grows, the accuracy percentage can approach 97.78%. The RF approach outperforms the GBDT method in terms of classification accuracy for male sitting bending forward improvement. With regard to the boys' 1000-meter running promotional classification effect, the RF approach yielded the greatest promotion accuracy rate, at 57.77%. The RF approach achieves the greatest accuracy rate of 96.85% in the male pull-ups and encourages the identification effect, when the fraction of the training block is 75%. The classification success rate for girls with long jump progression is between 52% and 55%, according to the results of the categorical effect. The RF approach works best when the training set falls below than 75%; the maximum is 58.69%, and the remaining methods are GBDT.

The technique is the best; its maximum is 96.65%; RF and GBDT both have benefits in the Macro-F1 index. The GBDT method accomplishes the highest level of precision of 89.65% when the percentage of the training set is 80%; on the Macro-F1 index, the GBDT technique is clearly the best. The RF and GBDT methods' accuracy in promoting the classification impact on the final fitness level of girls ranges from 48% to 86%, while the NN method's accuracy ranges from 80% to 87%.

This article's small study population makes it difficult to fully capture the impact of improving every adolescent's physical health. Even though the GBDT algorithm's accuracy can reach 79% when the dataset's percentage is 70%, this component needs more research because there may be a few training variables for distinct sampling and outcomes.

VI. REFERENCES

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