Available Online: 20 June 2026 DOI: 10.54254/3049-7248/2026.34688

Research progress on energy expenditure measurement methods for adolescent physical activities

Yibo Zhao, Yongfeng Lin*

College of Physical Education, Hebei Normal University, Shijiazhuang, China

*Corresponding Author. Email: zhaoyibo@hebtu.edu.cn

Abstract. Accurate measurement of energy expenditure during adolescent physical activities is fundamental for evaluating exercise intensity, scientifically developing exercise prescriptions, and monitoring physical health status. With increasing national attention to adolescent physical fitness, the demand for scientific monitoring of students' energy expenditure in physical activities has become increasingly urgent. This paper systematically reviews current mainstream energy expenditure measurement methods, including the doubly labeled water method, indirect calorimetry, heart rate monitoring, motion sensor methods, and physical activity questionnaires, analyzing the principles, characteristics, and limitations of each method when applied to adolescent physical activities. On this basis, the paper focuses on emerging technological directions for energy expenditure measurement, particularly non-contact measurement methods based on computer vision and deep learning-based energy expenditure prediction models. The review reveals that traditional measurement methods generally face challenges in adolescent physical education settings, including high cost, cumbersome operation, and interference from wearable devices with normal physical movement, whereas non-contact measurement methods show promise in overcoming these limitations. Finally, this paper provides an outlook on future research directions for energy expenditure measurement methods in adolescent physical activities.

Keywords: energy expenditure, adolescents, measurement methods, physical education, non-contact measurement

1. Introduction

Physical Activity Energy Expenditure (PAEE) refers to the increase in the body's energy consumption caused by physical activities [1]. The measurement of PAEE is fundamental for evaluating the intensity of physical activities, scientifically formulating exercise prescriptions, and monitoring physical health status [2]. The Centers for Disease Control and Prevention (CDC) in the United States has conducted continuous surveillance of adolescent physical health over multiple years, finding that nearly 30% of adolescents are overweight or obese, a figure that has nearly doubled over the past two decades. A common characteristic among overweight and obese adolescents is insufficient daily physical activity, leading to lower energy expenditure [3]. This phenomenon indicates that monitoring adolescent PAEE and arranging physical activities accordingly are of great significance to the healthy development of young people.

Copyright: © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

Middle school students are in a critical period of physical development [4]. Appropriate physical activities not only effectively promote students' healthy growth but also play an important role in enhancing their physical fitness. Monitoring the energy expenditure of middle school students during physical activities enables quantitative guidance for physical exercise, thereby scientifically promoting students' physical development and fitness improvement. The Healthy People 2020 initiative [5] in the United States specified that adolescents should spend no less than 50% of total physical education class time in moderate-to-vigorous physical activity. Determining whether students' physical activity intensity meets this standard requires scientifically sound measurement methods to ensure the quality and effectiveness of physical activities. Chinese researchers have used accelerometers to measure physical load in secondary school physical education classes and concluded that the overall exercise load of middle school physical education classes falls within the low-intensity range, failing to meet health standards [6].

Accurate measurement of energy expenditure during physical activities has become essential for assessing exercise intensity, guiding the formulation of exercise training prescriptions, and monitoring physical health levels [7]. However, when applied to school physical education settings, current mainstream energy expenditure measurement methods face challenges including high costs, cumbersome operation, and interference from wearable devices with students' normal movement. This paper aims to systematically review current major methods for energy expenditure measurement, analyze their characteristics and limitations in adolescent populations, and explore the development prospects of emerging non-contact measurement technologies, providing references for advancing technological innovation in adolescent physical activity energy expenditure measurement.

2. Basic concepts and influencing factors of energy expenditure

2.1. Definition and classification of energy expenditure

Energy Consumption (EC) refers to the energy required to maintain basal metabolism, the energy expended in physical activities, daily living, and work, as well as the energy consumed through the specific dynamic action of food [8]. PAEE refers to the increase in the body's energy expenditure resulting from physical activities, encompassing all physical activities undertaken during production or daily living processes. PAEE typically accounts for approximately 20% to 30% of total energy expenditure, and its magnitude is influenced by factors such as the intensity and duration of physical activities, the postures adopted, and the proficiency level of the performer. PAEE is one of the most important factors affecting the body's total energy expenditure, and its level directly determines the body's overall energy consumption. During physical exercise, the increase in energy expenditure consists of four components: work done by the horizontal displacement of the body's center of mass, work done by the vertical displacement of the center of mass, work done by the movement of the limbs and trunk, and work done to overcome external resistance [9]. Physical exercise and health are closely interrelated, and measuring energy expenditure during exercise is of great significance for subsequent sports nutrition supplementation and the development of exercise programs.

2.2. Factors influencing adolescent energy expenditure

Adolescent energy expenditure is influenced by multiple factors. From the perspective of individual characteristics, physiological variables such as sex, age, height, and body weight are fundamental factors affecting energy expenditure. Studies have shown that adolescents of different sexes exhibit significant differences in energy expenditure when performing exercises of equal intensity [10]. From the perspective of exercise characteristics, exercise intensity is the core determinant of energy expenditure magnitude. As exercise intensity increases progressively, the body's energy expenditure displays a nonlinear growth trend [11]. Furthermore, the energy expenditure characteristics of different sports events vary significantly; for example, the instantaneous energy expenditure intensity of sprinting events is far greater than that of long-distance running, although the latter may involve greater total energy expenditure per unit time [12]. With respect to body type, individual differences in height and weight also affect energy expenditure [13]; students with larger body sizes typically expend more energy when completing the same running distance. From the teaching environment perspective, energy expenditure also varies across different phases of physical education classes, with the warm-up phase generally exhibiting higher average energy expenditure [14]. Additionally, external factors such as ambient temperature and humidity may also have certain effects on adolescent energy expenditure.

3. Mainstream energy expenditure measurement methods

3.1. Doubly labeled water method

The Doubly Labeled Water (DLW) method is currently recognized as the gold standard for energy expenditure measurement [15]. This method requires participants to ingest water labeled with two stable isotopes, 2H and 18O, after which urine, blood, or saliva samples are periodically collected to detect the residual concentrations of the two isotopes. A formula is then used to calculate the participant's total energy expenditure over the specified time period. The primary advantage of the DLW method is its extremely high accuracy, as it can objectively reflect total energy expenditure under free-living conditions with virtually no interference with the participant's daily activities. However, the limitations of this method are also notable: the isotopic reagents are expensive, the sample collection and analysis cycle is lengthy (typically requiring 7 to 14 days), and specialized mass spectrometry equipment is needed. These factors make it difficult to implement the DLW method on a large scale in adolescent physical education research [16].

3.2. Indirect calorimetry

Indirect Calorimetry (IC) calculates energy expenditure during activity by measuring the body's oxygen consumption and carbon dioxide production, and then computing energy expenditure indirectly using the respiratory quotient. This method requires participants to wear a breathing mask during activity, and a specialized device collects the O_2 and CO_2 content in the exhaled air [17]. With the advancement of modern technology, IC measurement equipment has evolved from stationary gas analyzers to portable gas analyzers. The portable metabolic analyzers developed by COSMED Medical are among the most commonly used devices for energy expenditure measurement; these have been optimized to the fifth-generation product (Cosmed K5), which is lightweight and compact, incorporating an updated gas collection system capable of real-time collection and analysis of respiratory gas components during exercise [18]. Although IC provides high accuracy in laboratory settings, its application in physical education contexts still requires students to wear breathing masks, which may affect breathing patterns and normal athletic performance. Additionally, portable IC devices remain costly, typically priced at hundreds of thousands of RMB per unit.

3.3. Heart rate monitoring

Heart rate monitoring is based on the assumption of a linear relationship between heart rate and energy expenditure, estimating energy expenditure through heart rate changes measured during exercise [19]. This method is relatively simple to implement, and heart rate monitoring devices (such as heart rate straps and sports watches) are relatively low in cost, leading to their widespread use in measuring energy expenditure during adolescent physical activities. In physical education research, investigators often use heart rate telemetry or radial artery pulse measurement to assess students' exercise intensity during physical education classes. However, heart rate monitoring also has notable shortcomings: heart rate is influenced by multiple factors (such as emotion, temperature, and hydration status), and the linear relationship between heart rate and energy expenditure may break down during low-intensity or high-intensity exercise. Substantial inter-individual variation in heart rate necessitates individual calibration for each person. Among adolescents, greater heart rate variability may further compromise the accuracy of heart rate monitoring methods [20].

3.4. Motion sensor methods

Motion sensor methods estimate energy expenditure by using accelerometers, pedometers, and other sensor devices worn on the body to monitor acceleration changes during human movement, and then applying mathematical models [21]. Common motion sensors include the Actigraph series of accelerometers and Actiheart devices. The advantages of this method include ease of operation, convenient data collection and storage, and the ability to monitor continuously over extended periods. Chinese researchers have used Actigraph GT3X+ accelerometers to measure the physical load of 817 physical education classes in secondary schools and concluded that the overall exercise load of middle school physical education classes falls within the low-intensity range and fails to meet health standards [6]. International researchers have equipped adolescents with heart rate and accelerometer monitors during school commuting, physical activities, and daily leisure time, applying branch equation models to calculate the contribution of each activity type to total energy expenditure [22]. The main limitations of motion sensor methods include that measurement results vary depending on the body location where the sensor is worn [23], that sensors can only capture acceleration information and cannot fully represent the body's actual movement state, and that measurement accuracy drops markedly for exercises involving minimal acceleration changes, such as isometric contractions.

3.5. Physical activity questionnaires

Physical activity questionnaires estimate total energy expenditure by asking participants to recall and report the types, frequency, duration, and other characteristics of physical activities undertaken during a specified period, and then applying existing energy expenditure reference values such as Metabolic Equivalent (MET) values [24]. The advantages of this method are low cost and ease of implementation, making it particularly suitable for large-scale population surveys. The International Physical Activity Questionnaire (IPAQ) is one of the most widely used standardized questionnaires and has been translated into multiple languages for use worldwide [25]. However, the application of physical activity questionnaires in adolescent populations has significant limitations: adolescents' recall ability and self-assessment capacity are relatively limited, making them prone to recall and reporting biases; adolescent physical activities are typically intermittent and variable, making precise quantification through questionnaires difficult; and adolescents of different ages, sexes, and cultural backgrounds differ in their subjective perceptions of physical activity intensity, further reducing the accuracy of questionnaire-based methods.

4. Comparative analysis and application in physical education

A comprehensive comparison of the five mainstream energy expenditure measurement methods described above reveals that each method has its unique advantages and application scenarios but also exhibits distinct limitations. In terms of accuracy, the DLW method and IC rank at the highest level but are accompanied by high costs and complex operational procedures; heart rate monitoring and motion sensor methods offer moderate accuracy and are relatively simple to operate, but are substantially affected by individual differences and environmental factors; physical activity questionnaires provide the lowest accuracy but also the lowest cost, making them suitable for large-scale screening studies. Regarding applicability, when applied to adolescent physical education settings, all of these methods generally face challenges including high cost, cumbersome operation, and interference from wearable devices with students' normal movement. Although the DLW method and IC offer high precision, the procurement and maintenance costs of equipment are prohibitively high; a single portable metabolic analyzer typically costs several hundred thousand RMB, representing a significant financial burden for ordinary schools. Heart rate monitoring and motion sensor methods require students to wear chest straps, watches, or other sensors, which may interfere with normal movement and increase the risk of injury. Physical activity questionnaires do not affect students' normal movement, but the accuracy and objectivity of results are difficult to guarantee.

Current research on energy expenditure measurement in physical education primarily focuses on using instruments and devices to measure students' energy expenditure during physical activities in order to determine whether exercise intensity meets standards, or on investigating energy expenditure characteristics among student groups at different stages. For example, Chinese researchers have used heart rate telemetry and radial artery pulse measurement to survey physical education classes in junior and senior high schools in Shanghai, finding that different teaching contents produce significantly different physiological loads and energy expenditure values among students, and that different teaching contents have varying effects on students' fitness outcomes [26]. Furthermore, other researchers have conducted large-scale group studies on the energy expenditure characteristics of middle school students participating in physical education classes in specific regions, discovering differences in energy expenditure across different class phases and among individual students, with the warm-up phase exhibiting the highest average energy expenditure [14].

The above analysis indicates that existing energy expenditure measurement methods generally lack plug-and-play convenience in adolescent physical education settings, making it difficult to simultaneously achieve high measurement accuracy, low cost, and non-interference with movement. This current situation highlights the urgent need to develop new energy expenditure measurement technologies, particularly those that can achieve relatively accurate measurements at lower cost without interfering with students' normal movement.

5. Emerging technological directions for energy expenditure measurement

5.1. Non-contact measurement methods based on computer vision

With the rapid development of computer vision technology, video-image-based non-contact energy expenditure measurement methods have gradually become a research hotspot in this field. The fundamental approach of these methods is to indirectly estimate energy expenditure values by analyzing human posture changes and kinematic parameters during movement, thereby completely eliminating dependence on wearable devices [27]. Wen et al. [28] proposed a non-contact measurement method for energy expenditure during calisthenics based on the OpenPose computer vision algorithm, capturing key point movement information of the human body during exercise and establishing a mapping relationship between kinematic parameters and energy expenditure. This work provided empirical support for the feasibility of non-contact measurement of exercise energy expenditure. Koporec et al. [29] proposed a quantitative non-contact estimation method for energy expenditure based on video and 3D imagery, analyzing three-dimensional posture changes during human movement and establishing regression models between posture features and energy expenditure.

In physical education settings, non-contact measurement methods based on computer vision offer distinct advantages: first, they require no wearable devices on students and therefore cause no interference with normal movement; second, they can simultaneously monitor multiple students, making them suitable for group teaching scenarios; and third, equipment costs are relatively low, requiring only ordinary cameras and computing devices for deployment. However, these methods still face several technical challenges, including posture detection accuracy in complex environments, consistency of measurement results across different viewing angles, and individual identification and tracking in large groups. Additionally, the accuracy of human posture estimation from lateral-view videos is typically lower than that from frontal or rear-view perspectives, necessitating careful planning in system deployment.

5.2. Deep learning-based energy expenditure prediction models

In recent years, deep learning techniques have been introduced into the field of energy expenditure prediction, offering new technical pathways for improving measurement accuracy. Zhang [30] constructed an energy expenditure prediction model for male badminton players based on artificial neural networks, using athletes' kinematic and physiological parameters as input features and training the neural network to directly output energy expenditure predictions, achieving good predictive performance in specific sports scenarios. The core advantage of such methods is that deep learning models can automatically learn nonlinear mapping relationships between movement features and energy expenditure, without relying on the theoretically assumed linear formulas used in traditional methods, thereby exhibiting stronger expressive power when dealing with complex movement patterns.

In terms of specific model selection, Convolutional Neural Networks (CNNs) are suitable for learning energy expenditure patterns from spatial features (such as human posture keypoint coordinates); Long Short-Term Memory Networks (LSTMs) are well-suited for modeling temporal dependencies in movement sequences; and Multilayer Perceptrons (MLPs), with their simple network structure and fast processing speed, offer advantages in scenarios with high real-time requirements. The choice among different deep learning model architectures requires trade-offs based on the specific application scenario and data characteristics: deeper network structures generally yield higher prediction accuracy but also increase computational overhead and inference latency. Model parameter count and Floating-Point Operations (FLOPs) are also important indicators for assessing the feasibility of deploying energy expenditure prediction models in practice.

5.3. Multi-sensor fusion technology

Multi-sensor fusion technology represents an important research direction for improving the accuracy of energy expenditure measurement. This technology integrates data from multiple sensors (such as accelerometers, gyroscopes, heart rate monitors, and barometers) to capture human movement states from multiple dimensions and establish a more comprehensive description of movement characteristics, thereby enhancing the accuracy of energy expenditure estimation [31]. In adolescent physical activity settings, acceleration data from motion sensors can be fused with kinematic parameters extracted from video analysis, leveraging the complementarity of multi-modal information to overcome the limitations of single sensing modalities. For example, accelerometers excel at capturing highly dynamic movements, whereas video analysis is more proficient at identifying movement types and patterns; the fusion of these two approaches can effectively improve overall measurement performance. Multi-sensor fusion approaches are particularly suitable for adolescent populations, as adolescents' movement patterns are more diverse and irregular than those of adults, making it difficult for a single sensor to comprehensively capture their movement states.

6. Conclusion and outlook

Accurate measurement of energy expenditure during adolescent physical activities is of great significance for promoting students' healthy development and scientifically optimizing physical education. This paper has systematically reviewed the principles, characteristics, and limitations of five mainstream energy expenditure measurement methods, including the doubly labeled water method, indirect calorimetry, heart rate monitoring, motion sensor methods, and physical activity questionnaires. Overall, these traditional methods generally face a contradiction between accuracy and both cost and convenience when applied in adolescent physical education settings: high-accuracy methods are expensive and operationally complex, while low-cost methods offer limited accuracy and are susceptible to interference. This contradiction is particularly prominent in school physical education settings that require large-scale deployment, where traditional methods struggle to achieve a satisfactory balance among practicality, accuracy, and cost-effectiveness.

Future research directions for adolescent physical activity energy expenditure measurement methods include the following aspects. First, non-contact measurement methods based on computer vision will continue to advance in terms of reducing hardware costs, optimizing posture estimation algorithms, and improving adaptability to multiple scenarios, and are expected to become the mainstream energy expenditure measurement approach in adolescent physical education settings. Second, deep learning techniques will play an increasingly important role in energy expenditure prediction models; by constructing model architectures with stronger generalization capabilities and utilizing larger-scale training data, the transferability of models across different sports and different adolescent populations can be enhanced. Third, multi-sensor fusion solutions will develop toward lightweight and low-cost directions, integrating multiple sensors on wearable devices and implementing edge computing to reduce data transmission and processing latency. Fourth, the construction of large-scale databases of adolescent physical activity energy expenditure will become foundational work for advancing research in this field, providing standardized reference data for exercise prescription development for adolescents of different ages and sexes. Fifth, the deep integration of energy expenditure measurement technology with physical education will provide teachers with real-time teaching feedback, offering key technological support for the scientific and personalized development of physical education.

Funding project

Hebei Provincial Sports Science and Technology Research Project (Grant No. 2025QS02).

References

[1] Caspersen, C. J., Powell, K. E., & Christenson, G. M. (1985). Physical activity, exercise, and physical fitness: Definitions and distinctions for health-related research. *Public Health Reports, 100*(2), 126.

[2] Sirard, J. R., & Pate, R. R. (2001). Physical activity assessment in children and adolescents. *Sports Medicine, 31*, 439-454.

[3] Kann, L., McManus, T., Harris, W. A., Shanklin, S. L., Flint, K. H., Queen, B., Lowry, R., Chyen, D., Whittle, L., Thornton, J., Lim, C., Bradford, D., Yamakawa, Y., Leon, M., Brener, N., & Ethier, K. A. (2018). Youth Risk Behavior Surveillance — United States, 2017. *MMWR Surveillance Summaries, 67*(8), 1–114.

[4] Li, S. C. (2010). *Sports Anatomy*. Beijing: Higher Education Press.

[5] Healthy People 2020. (2020). Social determinants of cigarette smoking and electronic cigarette smoking among youth in the United States 2010-2018.

International Journal of Environmental Research and Public Health, 17(20).

[6] Li, H.-W., Liu, N., & Wang, Y.-B. (2019). Research on the exercise load characteristics of middle school physical education classes in Yaodu District, Linfen City based on accelerometer measurement. In *China Sport Science Society (Ed.), Compilation of abstracts of the 11th National Sports Science Conference*(p. 2). China Sport Science Society.

[7] Butte, N. F., Ekelund, U., & Westerterp, K. R. (2012). Assessing physical activity using wearable monitors: Measures of physical activity. *Medicine & Science in Sports & Exercise, 44*(1S), S5-S12.

[8] Liu, H.-C. (2018). *Research on the relationship between acceleration changes in different body parts and energy expenditure in college athletes during exercise* [Master's thesis, Capital University of Physical Education and Sports].

[9] Gray, A., Andrews, M., Waldron, M., North, J., & Exell, T. (2023). A model for calculating the mechanical demands of overground running. *Sports Biomechanics, 22*(10), 1256–1277.

[10] Zhang, Y. (2009). Sex differences in energy expenditure and substrate metabolism during cycling in ordinary college students. *Chinese Journal of Sports Medicine, 28*(5), 491-494.

[11] Van Loon, L. J. C., Greenhaff, P. L., Constantin-Teodosiu, D., Saris, W. H. M., & Wagenmakers, A. J. M. (2001). The effects of increasing exercise intensity on muscle fuel utilisation in humans. *Journal of Physiology, 536*(1), 295–304.

[12] Liu, X. X. (2002). Simulation analysis of internal energy consumption process in world elite 100 m sprinters. In *Compilation of Papers from the 10th National Sports Biomechanics Academic Conference* (p. 4).

[13] Lafortuna, C. L., Proietti, M., Agosti, F., Sartorio, A., & Galli, R. (2006). The energy cost of cycling in young obese women. *European Journal of Applied Physiology, 97*(1), 16–25.

[14] Shen, Z.-H. (2021). *Investigation and research on energy expenditure in physical education classes at Fengxian High School, Fengxian District, Shanghai* [Master's thesis, Shanghai University of Sport].

[15] Liu, J. M., Piao, J. H., & Yang, X. G. (2008). Research and application status of the doubly labeled water method in energy metabolism measurement. *Science Technology and Engineering*, (5), 1252-1258.

[16] Dai, J. S., & Sun, B. (2005). Review of physical activity measurement methods. *China Sport Science*, (9), 69-75.

[17] Sun, Q., & Sun, B. (2014). Energy consumption analysis of mountain climbing at different speeds: A case study of Zijin Mountain, Nanjing. *Journal of Nanjing Sport Institute (Natural Science)*, (3), 25-29.

[18] Wang, Y. F., & Wen, X. (2023). From direct calorimetry to computer vision technology: The history and future of physical activity energy expenditure measurement. *Journal of Shanghai University of Sport, 47*(4), 92-104.

[19] Freedson, P. S., & Miller, K. (2000). Objective monitoring of physical activity using motion sensors and heart rate. *Research Quarterly for Exercise and Sport, 71*(S2), 21-29.

[20] Vanhees, L., Lefevre, J., Philippaerts, R., Delvaux, K., Thomis, M., & Beunen, G. (2005). How to assess physical activity? How to assess physical fitness? *European Journal of Cardiovascular Prevention & Rehabilitation, 12*(2), 102–114.

[21] Xiang, J. F., & Li, Z. J. (2013). Research on the application of Actigraph triaxial accelerometer vector magnitude counts for monitoring daily physical activity. *China Sport Science, 33*(11), 75-83, 88.

[22] Slingerland, M., Borghouts, L. B., & Hesselink, M. K. C. (2012). Physical activity energy expenditure in Dutch adolescents: Contribution of active transport to school, physical education, and leisure time activities. *Journal of School Health, 82*(5).

[23] Ouyang, W.-B. (2021). *Research on the optimal wearing position of triaxial accelerometers for monitoring energy expenditure during badminton* [Master's thesis, Guangzhou Sport University].

[24] Dai, J. S., Li, J., Gu, Z. K., & Sun, B. (2006). Estimation of energy expenditure during walking and daily physical activities. *China Sport Science*, (11), 91-95.

[25] Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., Pratt, M., Ekelund, U., Yngve, A., Sallis, J. F., & Oja, P. (2003). International physical activity questionnaire: 12-country reliability

and validity. *Medicine & Science in Sports & Exercise, 35*(8), 1381–1395.

[26] Xia, J.-F. (2006). *Research on the relationship between physiological load and teaching content in 161 physical education classes in secondary schools* [Master's thesis, Shanghai Normal University].

[27] Lin, B. S., Wang, L. Y., Hwang, Y. T., Lee, I. J., & Young, C. P. (2016). Depth-camera-based system for estimating energy expenditure of physical activities. *IEEE Journal of Biomedical and Health Informatics, 20*(6), 1513–1521.

[28] Wen, X., Yang, Y. X., Gao, Y. L., & Chen, K. (2022). Non-contact measurement method for energy expenditure during calisthenics based on the OpenPose computer vision algorithm. *Journal of Shanghai University of Sport, 46*(8), 23–32, 55.

[29] Koporec, G., Vučković, G., Milić, R., & Stojmenović, M. (2018). Quantitative contact-less estimation of energy expenditure from video and 3D imagery. *Sensors, 18*(8), 2435.

[30] Zhang, L.-P. (2023). *Research on energy expenditure and prediction model of male badminton players based on artificial neural networks* [Master's thesis, Shandong Sport University].

[31] Harrell, J. S., McMurray, R. G., Baggett, C. D., Pennell, M. L., Pearce, P. F., & Bangdiwala, S. I. (2005). Energy costs of physical activities in children and adolescents. *Medicine & Science in Sports & Exercise, 37*(2), 329–336.