Journal of ASEAN University Sport Vol. 1, No. 1, Tahun 2026, pp. xx-xx
ISSN: xxxx-xxxx (Print), xxxx-xxxx (Online)
https://journals.smartmotionedu.id/index.php/jaus

How Can We Use An Android App To Assess A Student's Physical Education Needs?

Syed Lamsah Syed Chear[1], Chaylasy Gnophanxay[2], Jihan Dwi Wulandari[3]*

[1]*Faculty of Education and Social Sciences, Universiti Selangor, Selangor, Malaysia*
[2]*Faculty of Sports Science and Physical Education, National University of Laos, Vientiane, Laos*
[3]*Faculty of Sport Science and Health, Universitas Negeri Surabaya, Surabaya, Indonesia*

Correspondence Email: *jihan.23373@mhs.unesa.ac.id*

Article Info:
Received: *20-04-2026*
Revised: *25-04-2026*
Accepted: *29-04-2026*
Online: *30-04-2026*

Keywords:
diagnostic assessment; physical education; strava app; physical fitness; students.

ABSTRACT

In the context of university-level physical education, this study assesses an Android-based monitoring program called Strava as a diagnostic assessment tool. This quantitative study used a one-time measurement cross-sectional design with 78 mechanical engineering students chosen through purposive sampling to address the critical absence of reference data on physical condition. Using the GPS-enabled Strava app, participants ran 1.6 kilometres while being tracked in real time. According to descriptive analysis, the group's reference level was "good," with an average physical fitness score of 3.97. The students' actual physiological performance, as measured by running duration, varied significantly (standard deviation = 2.24), yet their final results were remarkably uniform (standard deviation = 1.78). This fact suggests that genuine physiological capacity cannot be accurately represented by conventional assessment tools. In the end, compared to traditional assessment scales, the Strava app allows for a more methodical and objective diagnostic evaluation. In order to create differentiated and adaptable physical education programs that are suited to each student's unique physical demands, it is imperative that this digital technology be integrated. This will guarantee learning effectiveness and lower the risk of injury.

Journal of ASEAN University Sport Vol. 1, No. 1, Tahun 2026, pp. xx-xx
ISSN: xxxx-xxxx (Print), xxxx-xxxx (Online)
https://journals.smartmotionedu.id/index.php/jaus

INTRODUCTION

Physical education in higher education is vital for improving students' physical fitness and quality of life, particularly given the growing prevalence of sedentary lifestyles during their studies (Edelmann et al., 2022). However, in reality, the learning process is often not based on students' initial fitness levels (Wijaya et al., 2024). The lack of baseline data results in suboptimal exercise programmers, as they fail to account for individual variations in physical ability (van der Ven et al., 2024). This situation significantly increases the risk of injury for students with low fitness levels, whilst simultaneously hindering meaningful physical adaptation for those with higher fitness levels (Robinson et al., 2016).

Systematically, diagnostic assessment is a crucial step in identifying students' initial abilities before the learning process begins (Rahmadewi, 2025). Through this assessment, educators can gain a deep understanding of students' levels of physical fitness. However, in practice, traditional approaches based on manual recording are often ineffective as they are prone to data errors and slow processing (Paulsen et al., 2020). Furthermore, most previous research has focused on the application of conventional fitness tests without utilising digital technology capable of providing accurate, real-time results (Giurgiu et al., 2023). Consequently, there is a need for innovation in the implementation of more modern, technology-based diagnostic assessments (Foster & Piacentini, 2023).

With the rapid advancement of technology, Android-based apps have become a viable alternative for facilitating diagnostic assessments (Hamzah & Sosnovsky, 2023). Strava is an application that automatically record physical activity in real time, demonstrating consistent measurement reliability in previous validation studies. By using this application, physical fitness data can be collected, recorded, and analyzed in a more systematic and effective manner (Acar & Pedro, 2025). Furthermore, the real-time feedback function enables educators to monitor assessment results quickly, allowing them to use this information as a basis for designing more tailored and flexible learning programmers (Pedro et al., 2024; van der Eijk et al., 2024)

However, to date, research that specifically integrates GPS-based applications such as Strava as a diagnostic assessment tool within the context of physical education at university level remains limited (Jastrow et al., 2022). This study offers a novel approach by positioning the Strava application as a diagnostic assessment tool, rather than merely a physical activity tracker. Filling a research gap regarding the limited adoption of technology in measuring students' baseline fitness, this study aims to implement Android-based diagnostic assessment in physical education at university level. Specifically, this study aims to map and analyze students' physical fitness profiles at the outset of their studies. The findings of this study are expected to form the basis for designing physical education programmers that are safer, more efficient, and tailored to students' individual needs.

METHODS

Participants and Sampling

This study employs a quantitative observational approach utilizing a cross-sectional, single-trial measurement design to assess students' baseline physical fitness. The population for this study consists of Mechanical Engineering students from the 2024 intake who are enrolled in the Physical Education and Fitness course. The sampling technique used purposive sampling, with the criteria being active Mechanical Engineering students from the 2024 cohort who attended the entire series of Physical Education and Fitness lectures and possessed a smartphone as a medium for the application. The sample size in this study was 78 students, comprising 71 male students and 7 female students aged between 18 and 22 years.

Instruments

The primary instrument in this study was an Android-based application, namely Strava, which was used to record students' physical activity in real time via GPS integration. The Strava application was selected because it possesses a high level of validity and reliability in measuring outdoor physical activity parameters, as confirmed in previous studies (Giurgiu et al., 2023). In addition, supporting instruments were also used, namely: Android-based smartphones and Google Forms for data consolidation.

The physical fitness variable measured and recorded automatically via this application is Duration, which measures the total time taken to complete the activity in minutes, with a predetermined running distance of 1.6 km. Subsequently, these raw measurement results were converted into two derived variables, namely: Fitness Category (an ordinal scale of 1–5, ranging from very poor to excellent) and Score (a final score of 0–100.)

Procedures

Data collection was carried out in three main stages. Firstly, students were briefed on how to use the Strava app and how to link it to their student accounts. Secondly, physical activity tests were conducted, such as a 1.6 km run, during which students could record their activity in real time using the GPS on their smartphones. Thirdly, data was extracted (data mining) from the app's activity logs into a spreadsheet format for statistical analysis.

Data Analysis

The data obtained were analyzed using descriptive statistical techniques in SPSS 25. Descriptive statistical analysis was carried out to describe the physical fitness profiles of the students based on the measured parameters, such as the mean, standard deviation, minimum and maximum values. Furthermore, the data on the time taken to cover the specified distance (1.6 km) was classified into five fitness level categories based on the 1.6 km running test standards established by Kline et al. (1987). This analysis served to objectively interpret the mapping of the students' initial physical condition.

RESULTS

Physical fitness data from 78 students was collected using an Android-based app (Strava) and analyzed using descriptive statistics. A summary of the analysis results is presented in Table 1.

Table 1. Descriptive Statistics

	N	Minimum	Maximum	Mean	SD
Age	78	18.00	22.00	19.24	0.84
Duration	78	4.50	17.56	8.97	2.24
Category	78	1.00	5.00	3.97	1.16
Value	78	70.00	85.00	70.26	1.78

Table 1 shows that the participants' ages ranged from 18 to 22 years, with 71 male students (91%) and 7 female students (9%). Regarding physical performance, significant variation was found in the 1.6 km running time, ranging from 4.50 minutes to 17.56 minutes (SD = 2.24). This wide range of durations reflects a marked diversity in physical capacity amongst students at the start of their studies.

Furthermore, the results of converting running times into fitness categories showed an average score of 3.97. This finding indicates that, collectively, the students' level of physical fitness falls within the "Good" category. Meanwhile, the final mark variable showed an average of 70.26 with a fairly small standard deviation (SD = 1.78). This suggests that the distribution of students' marks tends to be homogeneous or even, despite significant differences in their physical running times**.**

DISCUSSION

The findings of this study indicate that the use of an Android application for diagnostic assessment provides a comprehensive overview of students' baseline physical fitness levels. The main results show that students' average fitness levels fall within the 'good' category; however, significant variation was found in activity duration parameters. This variation highlights the urgency of diagnostic assessment as a crucial step in designing data-driven learning. Identifying baseline conditions is vital in physical education, as imposing a one-size-fits-all exercise program on individuals with differing physical capacities has the potential to reduce the effectiveness of physiological adaptation and significantly increase the risk of injury (Räisänen et al., 2023; (Robinson et al., 2016).

The wide range of times taken to run 1.6 km (4.50 to 17.56 minutes) reflects a marked diversity in cardiovascular capacity amongst the students. This striking diversity is consistent with the findings of Edelmann et al. (2022), who stated that heterogeneity in students' physical fitness is strongly influenced by a tendency towards a sedentary lifestyle during their studies. This situation also highlights the lack of data-driven interventions regarding previous physical education history, meaning that students are accustomed to following general programs without consideration of each individual's physical readiness (Yao et al., 2025).

The contrast between the wide range of running speeds and the highly uniform distribution of students' final marks (SD = 1.78) is an interesting finding of this study. This phenomenon suggests that the grading rubric system (scoring 70–85) in physical education may not yet be fully sensitive to actual physiological output, but rather still accommodates aspects of student participation or effort (Tremoen et al., 2024). This discrepancy highlights the urgent need for digital diagnostic assessments in designing training programs. Educators require tools that provide accurate raw performance data (such as duration and distance), rather than merely "letter/numerical grades" (Kovoor et al., 2024; Sousa et al., 2023).

In practical terms, this research suggests that the integration of technology into diagnostic assessment significantly improves the accuracy and utilization of data. The use of technology fosters the development of data-driven teaching practices, enabling educators to rapidly adapt their teaching strategies (Foster & Piacentini, 2023). This transformation is fully aligned with the concept of adaptive learning, which utilizes objective data as the primary basis for differentiating the intensity of exercises according to the unique physical needs of each student (Wu, 2025; Rahmadewi, 2025).

It is important to note the presence of an extremely low minimum duration namely, 4.50 minutes for a 1.6 km run. Rather than discarding these outlier values, this study retained the raw data to highlight the key challenges associated with the use of GPS-based mobile applications for unsupervised diagnostic evaluation. Such physiologically implausible times for non-athletes indicate potential technological limitations (e.g., GPS signal interference) or issues with student compliance with instructions (e.g., use of vehicles). These specific results suggest that, although digital applications provide a highly systematic benchmark, their implementation in physical education programmes still requires a certain level of supervision by teachers or cross-validation protocols to ensure absolute data integrity. The demographic imbalance of the sample, comprising 91% male students and 9% female students, is one of the limitations of this diagnostic mapping. The overall physical fitness score of 3.97 largely reflects a male physiological profile, as the standards used are inherently dependent on gender-specific characteristics. To ensure that educational interventions align with the unique physiological realities of the female minority group, teachers should group data by gender when applying these diagnostic results to future pedagogical designs or adaptive learning modules.

CONCLUSION

The findings suggest that utilizing a GPS-based application facilitates a more objective and systematic diagnostic assessment of students' baseline physical fitness compared to traditional rubrics. Collectively, students' fitness levels fall into the 'good' category. However, there is a striking variation in physical capacity regarding completion times. This phenomenon arises when these variations in actual performance do not align with the distribution of final grades, which tends to be homogeneous. This discrepancy highlights the urgent need for a shift towards digital assessment. A key element in creating more flexible and varied physical education programs is the use of accurate performance data, such as time and distance covered. By applying this data-driven approach, educators can tailor training loads to maximize physiological adaptation and reduce the risk of injury among students.

ACKNOWLEDGMENTS

The authors would like to thank the following institutions for their assistance and for providing the necessary environment for this research: Faculty of Sport and Health Science, Universitas Negeri Surabaya.

FUNDING STATEMENT

This study is an independent research project and received no external funding.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest regarding the publication of this article.

REFERENCES

Acar, N., & Pedro, D. (2025). Functional data analysis for wearable sensor data: A systematic review. *AStA Advances in Statistical Analysis, 109*(3). https://doi.org/10.1007/s10182-025-00531-8

Edelmann, D., Pfirrmann, D., Heller, S., Dietz, P., Reichel, J. L., Werner, A. M., Schäfer, M., Tibubos, A. N., Deci, N., Letzel, S., Simon, P., Kalo, K., & Miller, J. (2022). *Physical Activity and Sedentary Behavior in University Students – The Role of Gender , Age , Field of Study , Targeted Degree , and Study Semester*. *10*(June), 1–12. https://doi.org/10.3389/fpubh.2022.821703

Foster, N., & Piacentini, M. (2023). *Innovating Assessments to Measure and Support Complex Skills*.

Giurgiu, M., Ketelhut, S., Kubica, C., Nissen, R., Doster, A., Thron, M., Timm, I., Giurgiu, V., Nigg, C. R., Woll, A., Ebner-priemer, U. W., & Bussmann, J. B. J. (2023). *Assessment of 24-hour physical behaviour in adults via wearables : a systematic review of validation studies under laboratory conditions*. *7*, 1–12.

Hamzah, A., & Sosnovsky, S. (2023). Providing Students With Mobile Access to an Assessment Platform: *International Journal of Mobile and Blended Learning*, *15*(2). https://doi.org/https://doi.org/10.4018/IJMBL.318224

Jastrow, F., Greve, S., & Süßenbach, J. (2022). Digital technology in physical education: A systematic review of research from 2009 to 2020. *German Journal of Exercise and Sport Research, 52*(4), 504–528. https://doi.org/10.1007/s12662-022-00848-5

Kline, G. M., Porcari, J. P., Hintermeister, R., Freedson, P. S., Ward, A., McCarron, R. F., Ross, J., & Rippe, J. M. (1987). Estimation of VO2max from a one-mile track walk, gender, age, and body weight. *Medicine & Science in Sports & Exercise*, *19*(3), 253–259.

Kovoor, M., Durairaj, M., Subhash, M., Hussain, Z., Ashraf, M., & Phaneendra, L. (2024). Measurement : Sensors Sensor-enhanced wearables and automated analytics for injury prevention in sports. *Measurement: Sensors*, *32*(December 2023), 101054. https://doi.org/10.1016/j.measen.2024.101054

Paulsen, A., Harboe, K., & Dalen, I. (2020). Data entry quality of double data entry vs automated form processing technologies: A cohort study validation of optical mark recognition and intelligent character recognition in a clinical setting. *Health Science Reports*, *3*(4), e210. https://doi.org/10.1002/hsr2.210

Pedro, B., Trujillo, S., & Velarde-camaqui, D. (2024). *The current landscape of formative assessment and feedback in graduate studies : a systematic literature review*.

Rahmadewi, S. (2025). *DIAGNOSTIC ASSESSMENT AS THE FOUNDATION FOR ADAPTIVE AND DIFFERENTIATED LEARNING TRANSITION TO THE*. *24*(2). https://doi.org/10.20414/tsaqafah.v24i2.14168

Räisänen, A. M., Galarneau, J., van den Berg, C., & Eliason, P. (2023). Who does not respond to injury prevention warm-up programs? A secondary analysis of trial data from neuromuscular training programs in youth basketball, soccer, and physical education. *Journal of Orthopaedic & Sports Physical Therapy, 53*(2), 94–102. https://doi.org/10.2519/jospt.2022.11526

Robinson, M., Siddall, A., Bilzon, J., Thompson, D., Greeves, J., Izard, R., & Stokes, K. (2016). Low fitness, low body mass and prior injury predict injury risk during military recruit training: a prospective cohort study in the British Army. *BMJ Open Sport & Exercise Medicine*, *2*(1), e000100. https://doi.org/10.1136/bmjsem-2015-000100

Sousa, A. C., Ferrinho, S. N., & Travassos, B. (2023). The Use of Wearable Technologies in the Assessment of Physical Activity in Preschool- and School-Age Youth: Systematic Review. *International Journal of Environmental Research and Public Health*, *20*(4). https://doi.org/10.3390/ijerph20043402

Tremoen, T., Sørensen, A., & Lagestad, P. (2024). *The past and current role of pupil 's effort and physical tests in Norwegian physical education teacher 's assessment*. *December*, 1–12. https://doi.org/10.3389/feduc.2024.1437937

van der Eijk, M., Jacobs, U., & Tempelman, C. (2024). Enhancing self-learning skills and quality through formative actions and feedback within chemistry classes in the laboratory – A useful model. *Education for Chemical Engineers*, *48*, 22–30. https://doi.org/https://doi.org/10.1016/j.ece.2024.05.001

van der Ven, E., Patra, S., Riemann-Lorenz, K., Kauschke, K., Freese-Schwarz, K., Welsch, G., Krause, N., Heesen, C., & Rosenkranz, S. C. (2024). Individualized activity recommendation based on a physical fitness assessment increases short- and long-term regular physical activity in people with multiple sclerosis in a retrospective cohort study. *Frontiers in Neurology*, *15*, 1428712. https://doi.org/10.3389/fneur.2024.1428712

Wijaya, M. B., Kurniawan, W. R., & Putra, R. B. A. (2024). *Indonesian Journal for Physical Education and Sport Identifikasi Pelaksanaan Assessment diagnostic Kurikulum Merdeka Pembelajaran Pendidikan Jasmani Sekolah Dasar*. *5*(2), 416–435.

Wu, Y. (2025). *Data driven pedagogy in physical education a new paradigm in teaching effectiveness*. 1–15.

Yao, G., Zhang, J., Soh, K. G., Bai, X., & Xiao, W. (2025). *Effective implementation of the Sport Education Model in physical education : A meta-analysis of participant and intervention characteristics*. https://doi.org/10.1371/journal.pone.0331228