Integration of Real-Time Data from Wearable devices in cardiovascular risks Prediction

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Thank you for the guidance of Dr. Martine Mathieu-Campbell from North Carolina State University in the development of this research paper.

Abstract - **According to the most recent WHO statistics, Egypt ranks 15th in the world for coronary heart disease mortality, with coronary heart disease accounting for 32.40% of all deaths (Ramadan et al., 2024). so A trustworthy tool for early cardiovascular risk identification must be found. These days, the most widely used methods rely on the technology sector, including wearable technology. In real-time health monitoring, wearable technology is essential, especially for identifying the risks of cardiovascular disease (CVD). The accuracy and dependability of the Fitbit Charge HR2 and Apple Watch Series 2 in monitoring heart rate and estimating cardiovascular risk are compared in this study. A total of 46 individuals, aged 18 to 56, (20 men and 26 women), finished a 65-minute regimen that included both sedentary and treadmill activity. Decision trees, support vector machines, random forests, and rotation forest models were used to record and evaluate heart rate, steps, distance, and calories. Rotation forests had the best classification accuracy, according to the results, with Fitbit and Apple Watch both scoring 89.3% and 82.6%, respectively. Nonetheless, the Apple Watch demonstrated more dependability in cardiovascular risk prediction, as evidenced by a larger correlation with the reference method 0.85 than the Fitbit 0.0567. Fitbit exhibited more errors (MAE: 74.5, RMSE: 79.73) than the Apple Watch (MAE: 66.42, RMSE: 67.55). According to these results, the Apple Watch offers more precise heart rate readings for determining cardiovascular risk, even if Fitbit is better at classifying activities.**

Index Terms - Apple Watch, Fitbit, Cardiovascular risk, Machine learning.

I. Introduction

By tracking vital signs, wearable technology has become a fundamental component of daily life and is essential in the early diagnosis of a number of illnesses, including cardiovascular diseases (CVDs). CVDs were responsible for over 17.9 million deaths globally in 2019, or 32% of all fatalities. Heart attacks and strokes were responsible for 85% of these (World Health Organization, 2021). Increased or reduced blood flow, frequently brought on by disorders like clogged arteries, hypertension, or irregular heartbeats, can cause heart attacks to happen unexpectedly.

In light of these dangers, ongoing vital sign monitoring via wireless wearable technology can help identify early warning indicators, including irregular heartbeats or dips in oxygen levels, enabling prompt medical attention and lowering the chance of serious consequences. The purpose of this study is to examine the precision and dependability of data from the Fitbit and Apple Watch in identifying hazards to cardiovascular health. Heart rate, calories, and activity levels are among the important metrics that these smartwatches track.

In order to evaluate how well these devices monitor heart rate variability and identify early signs of CVDs, it will specifically examine datasets that are already available. The potential of these wearables in cardiovascular monitoring has been emphasized by earlier studies. According to Hernando et al. (2018), the Apple Watch is a useful tool for evaluating cardiovascular risk factors since it can monitor heart rate with high accuracy. Their research looked at its application in tracking heart rate variability, a crucial sign of cardiovascular health, and discovered encouraging findings for the early diagnosis of CVD. In a similar vein, Fitbit is useful for monitoring heart rate and physical activity, according to a study by Jo et al. (2019). This might help at-risk people manage their cardiovascular problems better.

According to Vaduganathan et al. (2022), CVDs continue to be the world's top cause of mortality and significantly contribute to health loss and excessive health system expenses. Since 1990, the Global Burden of Diseases, Injuries, and Risk Factors (GBD) project has monitored changes in mortality and disability and has offered a current assessment of the state of cardiovascular health on a national, regional, and worldwide scale. The GBD research also calculates the burden of illness caused by 88 disease risk variables. According to Reda et al. (2021), males are more likely than females to develop cardiovascular diseases in Egypt. The most prevalent risk factor is abdominal obesity, which is followed by high blood pressure. Nonetheless, women were more likely than males to have the majority of traditional risk factors (except from smoking). It might be difficult to regularly assess heart rate, particularly at home, because these measures usually depend on hospital-grade equipment for continuous monitoring.

By continually monitoring heart rate, a wristwatch might assist overcome this difficulty and enable early diagnosis and intervention to prevent the beginning of cardiac illnesses. Compared to healthy people, patients with diabetes, hypertension, and dyslipidemia have vascular abnormalities that make it more difficult to continuously monitor their heart rates. In the latter phases of many chronic illnesses, these disturbances may lead to vascular dysfunction. Based on this research, the purpose of this study is to compare the two devices—the Fitbit and the Apple Watch—in order to assess how well they work for practical health monitoring applications.

II. METHODOLOGY

Description of the dataset

The used dataset was gathered as part of the Harvard dataset: Replication Data for: Using Fitbit and Apple Watch data for indirect calorimetry as the criterion, machine learning techniques were applied to predict the types of physical activity. The dataset used was part of a study conducted by Harvard Dataverse [https://doi.org/10.7910/DVN/ZS2Z2J]. There were forty-six participants, twenty of whom were males and twenty of whom were women, ranging in age from eighteen to fifty-six. The participants were required to wear a Fitbit Charge HR2 and an Apple Watch Series 2. Each participant finished a 65-minute regimen that included 25 minutes of sitting or lying down and 40 minutes of total treadmill time. Energy expenditure was measured using indirect calorimetry. The activity class—lying, sitting, walking at one's own pace, three METS, five METS, and seven METS—was the study's outcome variable.
This dataset, which consists of 20 columns and 6264 rows, contains several variables that are used to track biological activity. The dataset had the following variables: distance (miles), calories (Cal), steps (1071), and heart rate per minute.

Data analysis

This study applied four different machine learning models: decision trees, support vector machines, random forests, and rotation forest models**,** to predict cardiovascular risks by detecting the relation between heart rate and other factors and calculating the accuracy of each device in predicting cardiovascular risks.

III. Figures, Tables and Equations

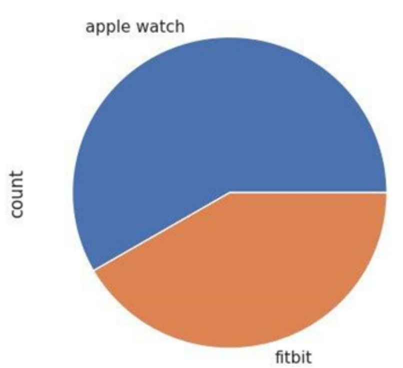

Figure 1: Percentage of Apple Watch and Fitbit observations used in the study

	count	mean	std	min	25%	50%	75%	max
Unnamed: 0	6264.0	3132.500000	1808.405375	1.000000	1566.750000	3132.500000	4698.250000	6264.000000
X1	6264.0	1771.144317	1097.988748	1.000000	789.750000	1720.000000	2759.250000	3670.000000
age	6264.0	29.158525	8.908978	18.000000	23.000000	28.000000	33.000000	56.000000
gender	6264.0	0.476533	0.499489	0.000000	0.000000	0.000000	1.000000	1.000000
height	6264.0	169.709052	10.324698	143.000000	160.000000	168.000000	180.000000	191.000000
weight	6264.0	69.614464	13.451878	43.000000	60.000000	68.000000	77.300000	115.000000
steps	6264.0	109.562268	222.797908	1.000000	5.159534	10.092029	105.847222	1714.000000
hear_rate	6264.0	86.142331	28.648385	2.222222	75.598079	77.267680	95.669118	194.333333
calories	6264.0	19.471823	27.309765	0.056269	0.735875	4.000000	20.500000	97.500000
distance	6264.0	13.832555	45.941437	0.000440	0.019135	0.181719	15.697188	335.000000
entropy_heart	6264.0	6.030314	0.765574	0.000000	6.108524	6.189825	6.247928	6.475733
entropy_setps	6264.0	5.739984	1.256348	0.000000	5.909440	6.157197	6.247928	6.475733
resting_heart	6264.0	65.869938	21.203017	3.000000	58.134333	75.000000	76.138701	155.000000

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Table I
Description of Dataset variables and the most important statistical parameters

IV. RESULTS & DISCUSSION

The analysis dataset included 3656 and 2608 minutes of Apple Watch and Fitbit data, respectively. The test included decision trees, support vector machines, random forest, and rotation forest models. Rotation forest models had the highest classification accuracies at 82.6% for Apple Watch and 89.3% for Fitbit. Classification accuracies for Apple Watch data ranged from 72.5% for sitting to 89.0% for 7 METS. For Fitbit, accuracies varied between 86.2% for sitting to 92.6%
for 7 METS. In cardiovascular risk there is a strong positive correlation between heart rate and Karvonen Heart rate intensity which is a method used to calculate intensity of activities as r = +0.78 approximately near to 1. There is also a weak negative relation between heart rate and amount of calories, r=- 0.14. Comparing the accuracy for prediction of cardiovascular risks between Apple Watch and Fitbit, the Apple watch has correlation 0.85 to the reference calculation while the Fitbit 0.0567 to the reference correlation. Fitbit MAE: 74.5 and RMSE: 79.73. For Apple Watch- MAE: 66.42 and RMSE: 67.55.
Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, making early detection and risk assessment crucial for prevention and intervention (Vaduganathan et al.,2022). With the growing adoption of wearable health devices like Apple Watch and Fitbit, real-time monitoring of physiological parameters such as heart rate, step count, sleep duration, and activity levels has become increasingly accessible. These devices generate vast amounts of data that can be leveraged for early detection of cardiovascular risks.

This study focuses on heart rate to predict the risk of cardiovascular diseases and compare between Apple Watch and Fitbit. Heat rate is affected by multiple factors such as Karvonen Heart rate intensity which is a method to detect the intensity of different activities from sitting to MET7. By calculating the correlation between two variables, it was 0.78 which expresses a strong positive correlation, as Karvonen Heart rate intensity (independent) increases heart rate increases(dependent). In addition to a causation relationship between the two variables. This relation clearly appears through the scatter plot graph. The relationship between heart rate and calories is inversely proportional as the amount increases, heart rate decreases.

However it is a weak inverse relation when r=-0.14. There is a huge difference between the mean of the heart rate value and other values in reference calculations as mean= 86 and standard deviation equals 28.66. The minimum heart rate was recorded 2.22 and the maximum was 194.33. For fitbit, mean = 78, standard deviation=29, minimum= 2.22 and the maximum= 164. And for Apple Watch, mean equal 91, standard deviation= 26.78, minimum value=33 and maximum value= 194.

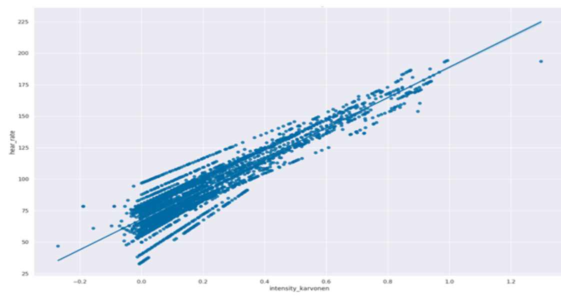

Figure 2: The relationship between Karvonen Heart rate intensity(independent) and heart rate(dependent)

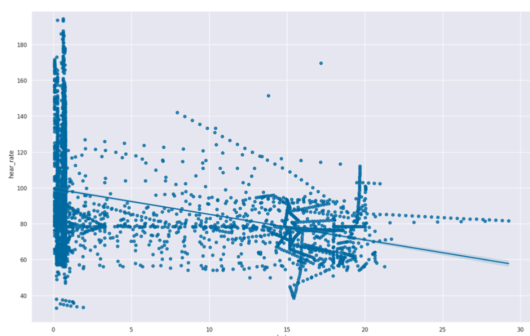

Figure 3: The relationship between calories (independent) and heart rate (dependent)

Each device's error in predicted heart rate can be determined by calculated MAE and RMSE. They used to indicate the error between the heart rate measurements from the Fitbit and Apple Watch compared to the reference device where MAE measures the average absolute difference between the predicted (device Heart rate) and actual (reference heart rate) values. Lower is better (closer to zero means more accurate). Fitbit MAE = 74.49, On average, Fitbit's heart rate measurement deviates by 74.49 bpm from the reference. Apple Watch MAE = 6.43, Apple Watch's HR deviates by 66.43 bpm on average. RMSE is similar to MAE, however it penalizes larger errors more heavily. It gives more weight to big errors (high deviations). Lower is better (smaller RMSE means fewer large errors). Fitbit RMSE = 79.73 means Fitbit has larger fluctuations in error. Apple Watch RMSE = 67.55 means Apple Watch has fewer extreme errors. Since the Apple Watch has lower RMSE, it suggests that the Fitbit has more large errors (outliers). The accuracy of recording the change of heart rate from each device varies. By analysing the data it is observed that the Apple Watch is more reliable than the Fitbit with correlation equal to 0.85 closer to reference calculation and Apple Watch was 0.0567 closer to reference calculation. Similarly, Apple Watch shows higher sensitivity in recording different activities than the Fitbit from sitting to intense activities (MET7). MET (Metabolic Equivalent of Task) is a unit that measures the amount of energy (calories) burned during an activity relative to resting metabolism, as MET increases the intensity of activity increases.

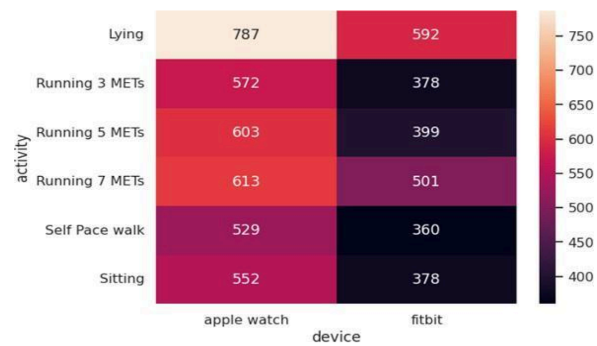

Figure 4: Comparison between Apple Watch and Fitbit in recording activity.

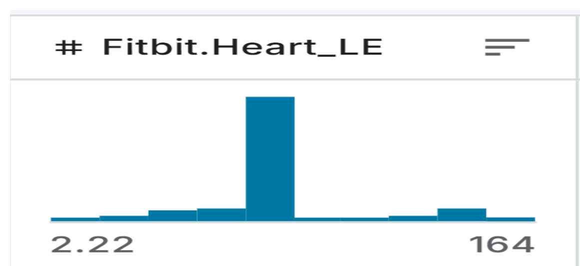

figure5:Histogram comparison of Fitbit Heart rate data

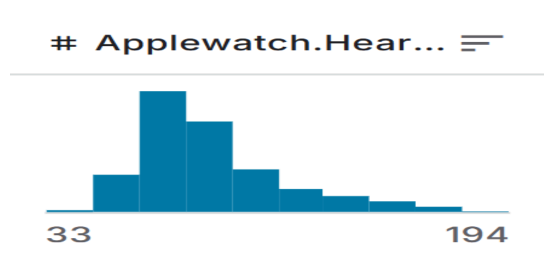

figure6: Histogram comparison of Apple Watch Heart rate data

Figure 7: Activity distribution by age (left) and gender (right), showing counts for different activity types.

The disparity in activity levels among age groups suggests that younger individuals typically engage in more strenuous exercise, which is frequently associated with higher heart rates. Older people, on the other hand, engage in a wider range of activities, including less strenuous ones like sitting and lying down, which are associated with lower heart rates. From a gender perspective, the data shows that heart rate responses vary by activity type, with some activities such as running at 5 METs and 7 METs showing more equal participation between the sexes. Despite possible individual variations in heart rate control, this may indicate similar cardiovascular responses to exercise in both sex. Furthermore, it is evident that wearable technology, such as the Fitbit and Apple Watch, is crucial for monitoring cardiovascular stress and spotting abnormal heart rate patterns given the established correlation between heart rate and activity level. The results of this study highlight the value of continuous heart rate monitoring for the early detection of cardiovascular problems and customized medical care. While the positive outcomes are impressive, it is important to consider a number of restrictions. First, the study relied on a small sample size (46 participants), which may not be representative of the general population. Furthermore, factors such as skin tone, wrist location, and individual physiological differences may have impacted the accuracy of heart rate measurements.

Previous research has suggested that wearable sensors may operate differently across various groups; this is an issue that needs more investigation. The reliance on two specific gadget models (Fitbit Charge HR2 and Apple Watch Series 2) is another limitation. With the advancement of technology, new models may yield different results. To increase the relevance of findings, future research should incorporate a wider range of demographics, updated device models, and larger sample sizes. According to the study's findings, wearable technology particularly the Apple Watch may be useful for identifying cardiovascular concerns early on. For people who already have heart problems or are at risk of developing cardiovascular diseases, their ability to monitor heart rate variability and spot abnormal patterns is advantageous.

Nevertheless, due to the differences in accuracy among various devices, healthcare providers ought to carefully assess wearable data and contemplate clinical validation techniques before depending on them for medical decision-making.

Overall, this study highlights the potential of wearable technology to track cardiovascular health while also highlighting its limitations. Compared to Fitbit, the Apple Watch demonstrated higher accuracy in heart rate detection and cardiovascular risk prediction. Both devices provide valuable information, but future developments in machine learning algorithms and sensor technologies may increase their reliability. It is projected that wearable technology will become more significant in remote patient monitoring and preventative healthcare as it develops, opening up new avenues for early disease detection and individualized health care.

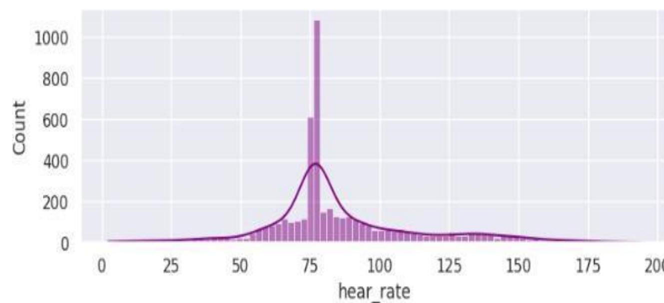

Figure 8: The distribution reflects insights into the variation and occurrence of recorded values of heart rate.

V. CONCLUSION

This study assessed the accuracy and reliability of the Fitbit Charge HR2 and Apple Watch Series 2 in measuring heart rate and predicting cardiovascular risk. The findings indicate that while Fitbit classified activities with a higher accuracy (89.3%) than the Apple Watch (82.6%), the Apple Watch provided more accurate heart rate measurements and had a higher correlation with the reference method (0.85 vs. 0.0567 for Fitbit). Furthermore, compared to Fitbit (MAE: 74.5, RMSE: 79.73), the Apple Watch showed lower error rates (MAE: 66.42, RMSE: 67.55), suggesting that it could be a more reliable tool for assessing cardiovascular risk. These results highlight the benefits and limitations of each gadget, with Fitbit excelling in classifying activities and the Apple Watch offering more precise heart rate monitoring—a crucial component in assessing cardiovascular risk. It is suggested that adding additional physiological metrics, such as blood pressure, oxygen saturation (SpO_2), and sleep quality, could increase the wearable devices' ability to predict cardiovascular risks in a more comprehensive way, increasing their accuracy and applicability for monitoring cardiovascular health. According to the research, wearable technology, such as the Fitbit and Apple Watch, has special advantages and provides important insights into cardiovascular health. As wearable technology continues to advance, further research and development is essential to enhancing the accuracy, reliability, and medical integration of these devices for effective cardiovascular disease treatment and prevention.

References

[1] Bai, Y., Tompkins, C., Gell, N., Dione, D., Zhang, T., & Byun, W. (2021). Comprehensive comparison of Apple Watch and Fitbit monitors in a free-living setting. PloS one, 16(5), e0251975. https://doi.org/10.1371/journal.pone.0251975

[2] Fuller, Daniel, 2020, "Replication Data for: Using machine learning methods to predict physical activity types with Apple Watch and Fitbit data using indirect calorimetry as the criterion.", https://doi.org/10.7910/DVN/ZS2Z2J, Harvard Dataverse, V1

[3] Gupta, S., Srivastava, D., Choudhary, R., & Verma, A. (2024). Smart wearable for continuous health monitoring. *International Journal of Engineering Research & Technology (IJERT), 13*(10). https://www.ijert.org

[4] Hernando, D., Roca, S., Sancho, J., Alesanco, Á., & Bailón, R. (2018). Validation of the Apple Watch for Heart Rate Variability Measurements during Relax and Mental Stress in Healthy Subjects. Sensors (Basel, Switzerland), 18(8), 2619. https://doi.org/10.3390/s18082619

[5] Habehh, H., & Gohel, S. (2021). Machine Learning in Healthcare. Current genomics, 22(4), 291–300. https://doi.org/10.2174/1389202922666210705124359

[6] Huhn, S., Axt, M., Gunga, H.-C., Maggioni, M., Munga, S., Obor, D., Sie, A., Boudo, V., Bunker, A., Sauerborn, R., Bärnighausen, T., & Barteit, S. (2022). The impact of wearable technologies in health research: Scoping review. *JMIR mHealth and uHealth, 10*, e34384. https://doi.org/10.2196/34384

[7] Husom, E. J., Dautov, R., Nedisan, A.-A., Gonidis, F., Papatzelos, S., & Malamas, N. (2022). Machine learning for fatigue detection using Fitbit fitness trackers. *Proceedings of the International Conference on Machine Learning and Applications*, 41–52. https://doi.org/10.5220/0011527500003321

[8] Hariharan, U., Kotteswaran, R., Akilan, T., & Janardhanan, J. (2021). Smart wearable devices for remote patient monitoring in Healthcare 4.0. In *Proceedings of the International Conference on Intelligent Computing and Applications*. Springer. https://doi.org/10.1007/978-3-030-63937-2_7

[9] Jo, A., Coronel, B. D., Coakes, C. E., & Mainous, A. G., 3rd (2019). Is There a Benefit to Patients Using Wearable Devices Such as Fitbit or Health Apps on Mobiles? A Systematic Review. The American journal of medicine, 132(12), 1394–1400.e1. https://doi.org/10.1016/j.amjmed.2019.06.018

[10] Jang, S., & Kim, M. (2025). Digital fitness revolution: User perspectives on Fitbit's role in health management. *Behavioral Sciences, 15*(2), 231. https://doi.org/10.3390/bs15020231

[11] Khushhal, A. A., Mohamed, A. A., & Elsayed, M. E. (2024). Accuracy of Apple Watch to Measure Cardiovascular Indices in Patients with Chronic Diseases: A Cross Sectional Study. Journal of multidisciplinary healthcare, 17, 1053–1063. https://doi.org/10.2147/JMDH.S449071

[12] Maher, S., Hannan, S. A., Tharewal, S., & Kale, K. V. (2019). HRV-based human heart disease prediction and classification using machine learning. International Journal of Computer Applications, 177(27), 29-34

[13] Moshawrab, M., Adda, M., Bouzouane, A., Ibrahim, H., & Raad, A. (2022). Cardiovascular events prediction using artificial intelligence models and heart rate variability. *Procedia Computer Science, 203*, 231–238. https://doi.org/10.1016/j.procs.2022.07.030

[14] Oyeleye, M., Chen, T., Titarenko, S., & Antoniou, G. (2022). A Predictive Analysis of Heart Rates Using Machine Learning Techniques. International journal of environmental research and public health, 19(4), 2417. https://doi.org/10.3390/ijerph19042417

[15] Rodgers, J. L., Jones, J., Bolleddu, S. I., Vanthenapalli, S., Rodgers, L. E., Shah, K., Karia, K., & Panguluri, S. K. (2019). Cardiovascular Risks Associated with Gender and Aging. Journal of cardiovascular development and disease, 6(2), 19. https://doi.org/10.3390/jcdd6020019

[16] Ramadan, A., Soliman, M. A., Hamad, A. A., El-Samahy, M., Roshdy, M. R., Diab, R. A., Abdalla, Y. E., Emara, M., Azooz, A. K., Abo El-Lail, D. S., Elbanna, E. H., Almalki, M. E., Abdelazeem, B., Ali, A. S., & Negida, A. (2024). Cardiovascular Disease and Stroke Risk Among Egyptian Resident Physicians: A Cross-Sectional Multicenter Study. Cureus, 16(4), e58024. https://doi.org/10.7759/cureus.58024

[17] Reda, A., Bendary, A., Elbahry, A., Farag, E., Mostafa, T., Khamis, H., Wadie, M., Bendary, M., Abdoul Azeem, B., & Salah, R. (2021). Prevalence of atherosclerosis risk factors in Egyptian patients with acute coronary syndrome: final data of the nationwide cross-sectional 'CardioRisk' project. *Journal of public health in Africa*, *11*(2), 1368. https://doi.org/10.4081/jphia.2020.1368

[18] Ringeval, M., Wagner, G., Denford, J., Paré, G., & Kitsiou, S. (2020). Fitbit-Based Interventions for Healthy Lifestyle Outcomes: Systematic Review and Meta-Analysis. *Journal of medical Internet research*, *22*(10), e23954. https://doi.org/10.2196/23954

[19] Sugiyama, M. (2016). Introduction to statistical machine learning. Morgan Kaufmann

[20] Staffini, A., Svensson, T., Chung, U.-i., & Svensson, A. K. (2022). Heart Rate Modeling and Prediction Using Autoregressive Models and Deep Learning. Sensors, 22(1), 34. https://doi.org/10.3390/s22010034

[21] Shin, G., Jarrahi, M. H., Fei, Y., Karami, A., Gafinowitz, N., Byun, A., & Lu, X. (2019). Wearable activity trackers, accuracy, adoption, acceptance, and health impact: A systematic literature review. *Journal of Biomedical Informatics, 93*, 103153. https://doi.org/10.1016/j.jbi.2019.103153

[22] Vaduganathan, M., Mensah, G., Turco, J., et al. (2022). The global burden of cardiovascular diseases and risk: A compass for future health. *Journal of the American College of Cardiology, 80*(25), 2361–2371. https://doi.org/10.1016/j.jacc.2022.11.005

[23] Vijayan, V., Connolly, J., Condell, J., McKelvey, N., & Gardiner, P. (2021). Review of wearable devices and data collection considerations for connected health. *Sensors, 21*(16), 5589. https://doi.org/10.3390/s21165589

[24] Vijayan, V., Connolly, J. P., Condell, J., McKelvey, N., & Gardiner, P. (2021). Review of Wearable Devices and Data Collection Considerations for Connected Health. *Sensors (Basel, Switzerland)*, *21*(16), 5589. https://doi.org/10.3390/s21165589

[25] **Wairimu, G. M. (2025).** Wearable imaging devices: Future of continuous monitoring. *Research Invention Journal of Biological and Applied Sciences,* *5*(2), 1–6. https://doi.org/10.59298/RIJBAS/2025/521600