BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE

DEVELOPMENT OF MOBILE APPLICATION FOR BMI AND FITNESS INFORMATION TRACKING

By

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A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE BACHELOR OF SCIENCE HONOURS DEGREE IN SOFTWARE ENGINEERING

JUNE 2025

APPROVAL FORM

The undersigned certify that they have supervised the student Tapiwa Admire Chiwashira dissertation entitled, “Development of mobile application for BMI and fitness information tracking” submitted in partial fulfilment of the requirements for a Bachelor of Science Honours Degree in Software Engineering at Bindura University of Science Education.

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DEDICATION

This research is dedicated to my parents Mr. V Chiwashira and Mrs. P Chiwashira for their unwavering and immense support throughout this entire journey. They have groomed me to become a fearless young man who has no doubt whatsoever that the future is more than bright. My dedication also goes to Mr Muvinndi who taught me and reminded me that there is a tailor made God given purpose and mandate that I fulfill and prosper in it. Through them I was able to discover myself and with their mentorship I am becoming better and better y each day that passes. I also dedicate this to my family and friends who undoubtedly believed in me and always want to see fruition in my life.

ACKNOLEDGEMENTS

All the credit goes to the almighty God who guided me through my final year dissertation. I extend my sincere gratitude to Dr. Kanyongo my supervisor for the continuous support throughout the entire research. Your motivation, enthusiasm, immense knowledge and patience was a great deal in this research. I greatly appreciate and value the time investment and contribution to my research that he made. I also want to extend my gratitude to Mr Mhlanga for some guidance they provided as I worked through my project. I really appreciate all the time and efforts they put in the bid of helping me come up with a quality research. I would also like to extend my gratitude to the whole of the Computer Science department lecturers for their support as well, mentoring me right from the very first day I enrolled at Bindura University up to date. I also want to thank Bindura University of Science Education for all the infrastructural support and all the academic provisions that led to the completion of this study. Not forgetting my family and fellow colleagues Anesu Kabuku, Chriswell Peyara, Makanaka Madhake and Isaac Rongoti who played a supporting role which contributed positively to my welfare

ABSTRACT

In response to the escalating prevalence of overweight and obesity in Zimbabwe and beyond, this study introduces an innovative mobile application integrated with IoT devices for Body Mass Index (BMI) and fitness information tracking. The primary research problem addressed is the widespread difficulty individual's face in effectively monitoring health metrics due to fragmented systems and limited access to reliable health technologies. The aim is to offer a user-friendly, automated, and accessible tool that facilitates informed health decisions and promotes sustained lifestyle changes. The system employs a combination of hardware and software components, including Arduino-connected weight and height sensors, integrated into an Android-based mobile application. Key health metrics—BMI, Body Fat Percentage, and Basal Metabolic Rate (BMR)—are computed automatically, and the application delivers personalized recommendations based on real-time sensor data. The research methodology follows an evolutionary prototyping model supported by agile development, ensuring iterative refinement through stakeholder feedback. Initial findings demonstrate that the application not only simplifies the tracking process through automation but also enhances user engagement via data visualization, social features, and secure information sharing. Preliminary testing indicated high reliability in metric calculations and strong user interest in personalized features. The broader implication of this study lies in its potential to support healthcare delivery in resource-limited settings, empower individuals in self-monitoring, and inform digital health policy strategies. This project contributes to the field of software engineering by demonstrating how mobile and IoT integration can produce scalable, ethical, and impactful digital health interventions.

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CHAPTER 1: PROBLEM IDENTIFICATION

1.1 INTRODUCTION

Body Mass Index is the index of weight-for-height which is used to classify weight status for both children and adults (Bull *et al.*, 2020). The development of a mobile android application to track Body Mass Index highlights to provide users with a solution for measuring their body composition and tracking their activity level. This application will provide services such as Body Mass Index Calculation, Body Fat Calculation, Basal Metabolic Rate Calculation and give recommendations according to the results produced. Presently, BMI is defined as a measure of a person's body weight (in kilograms) divided by the square of their height (in meters), BMI = weight (kg) / height $(m)^2$, although BMI does not directly measure body fat, BMI is moderately to strongly associated with other measures that capture the amount, location, and distribution of body fat (Mudaliar, 2024). The application will be connected to physical components so that users can easily synchronize their fitness information.

Figure 1.1 Weight Status

BMI - WEIGHT STATUS TABLE	
BMI	**Weight Status**
Below 18,5	Underweight (**U**)
18,5 – 24,9	Normal (**N**)
25 – 29,9	Overweight (**OW**)
30 and more	Obese (**O**)

The application will categorize the BMI results using the following statuses using overweight, normal weight, obese and underweight. The application will divide the gap between traditional forms of fitness tracking forms and modern day digital tools. The system is designed to use user specified health parameters to deliver more accurate estimates of fitness. The application is able to keep track of past data and analyze it and will also allow users to track to track long-term improvement and adjust their fitness plans accordingly.

In addition, the BMI application would combine security functionalities to protect sensitive health data. Since it is concerned for user privacy, the application would comply with data protection legislation and incorporate encryption techniques to protect personal data. The use of agile development model enhances continuous refinement based on user-feedback, keeping the application updated and efficient in long term. The addition of social abilities, such as group activities and challenges, will also motivate the users to stay committed towards their fitness goals. This project aims to deliver a comprehensive, intelligent, and user-friendly fitness tracking solution that helps users live healthy.

1.2 BACKGROUND OF THE STUDY

Globally, there is an increasing commonness of overweight and obesity which will become the major risk factors for various persistent diseases which involves cardiovascular disease, type 2 diabetes, and certain cancers (Bull *et al.*, 2020). Body Mass Index (BMI) has become a tool which is used for assessing weight status in epidemiological studies and clinical practice. The spread in digital technology has stimulated the development of BMI information tracking systems to monitor and manage health metrics. These systems range from spreadsheets to worldly mobile applications and external physical devices that collect, store and analyze health related data (Conceição *et al.*, 2019). The aim is to allow individuals to manage their health through self-monitoring and to provide healthcare professionals with valuable data for personalized interventions .Digital systems such as mobile applications, can go beyond these limitations. Mobile applications used to provide accurate BMI calculation. Additionally, mobile application also make easy to facilitate data analysis and sharing through enabling healthcare providers to come up with informed decisions. Mobile applications provide personalized recommendations and interventions, promoting user engagement and behavior change according to output given. The evolution of these BMI information tracking systems highlights a broader trend towards patient-centered care and the growing recognition of the role of technology in promoting health and well-being. Modern systems are gradually integrating features such as data visualization to enhance user understanding and facilitate informed decision making. Furthermore, the combination of social networking functionalities within some platforms enables users to connect with others, share their progress and receive social support which becomes a powerful motivator for behavior change. However, the effectiveness of these system is based on factors such as data accuracy and the availability of appropriate support guidance. The long-term impact of BMI and Information tracking systems on health outcomes remains an area of ongoing research with studies exploring the potential for these technologies to contribute to the prevention and management of chronic diseases at both the individual and population levels. Recent studies have also examined the potential of digital health interventions for weight management. For instance, scientists have shown interest in applying machine learning to optimize the tailoring such interventions, potentially leading to improved efficacy (Aggarwal *et al.*, 2023). Of growing interest as well is integrating IOT devices with BMI-monitoring applications to create more continuous and accurate data. Furthermore, studies have investigated the impact of such systems on specific populations, for example adolescents or older adults and reported multifaceted findings about their adoption and effectiveness. Ethical concerns, including privacy of data and potential exacerbation of health inequalities, are still a subject of investigation (Johnson & Smith, 2020). Easy to use and culturally responsive application is also regarded as central to the achievement of widespread uptake and use.

In Africa, the increasing in commonness of overweight and obesity is on the rise and it highlight a significant public health challenge. This rise is driven by factors such as urbanization, changing dietary patterns, and reduced physical activity. BMI remains a relevant tool that is crucial to consider the unique characteristics of African populations, as body composition can vary across ethnicities. BMI and Information tracking systems have the potential to play a great role in addressing this challenge by facilitating data collection, health promotion, and intervention programs tailored to the specific needs of African communities. However, there are challenges to overcome, including limited access to technology, infrastructure limitations, and cultural factors that may influence the adoption and use of these systems. The objective of this study is to design and develop a mobile application that is user-friendly and comprehensive so that it provides accurate and automatic BMI calculation, health parameter tracking, personalized advice, and convenient data sharing with healthcare providers. With the use of mobile technology, the utilization of this app can promote healthy living, improve health outcomes, and improve overall quality of life among individuals. The development of mobile applications is supported across the African continent by the increasing of mobile penetration, which provides a platform for widespread adoption. Studies have indicate the effectiveness of mobile health interventions in improving health outcomes in various African settings (Haynes et al, 2022). However user-centered design approach is necessitated by successful implementation that incorporates local cultural nauances and addresses varying levels of digital literacy. Furthermore, the application must have ethical guidelines regarding data privacy and security to promote long-term engagement and ensure user trust. It is crucial for seamless data sharing and effective clinical decision-making when there is the potential for integration with existing healthcare infrastructure. The future research must depend on evaluating the long term impact of such applications on BMI outcomes in diverse African populations. New studies continue to reveal the multifaceted nature of obesity in Africa. For example, a study by Adeyemo et al., (2021) highlighted the increasing prevalence of metabolic syndrome among Nigeria's urban dwellers with the significant cardiovascular risk implications. Similarly, data from South Africa indicate an increasing trend towards obesity among women, with obesity levels above 40% recorded in some cities (Puoane *et al.*, 2002). The twin threat of malnutrition, or both undernutrition and over nutrition, is also increasing in the majority of African countries, making it increasingly hard content with weight issues. Culturally relevant interventions are also more crucial based on studies, as traditional intervention may not perform optimally in Alternative African contexts. The potential for mobile Health interventions to reverse these conditions is being researched, with studies investigating whether SMS-based interventions are effective in promoting healthy lifestyle behavior in secure-constrained settings.

In Zimbabwe we have a challenge in double burden of malnutrition and infectious diseases coexisting with a growing prevalence of overweight and obesity. This present a strain on the healthcare system and hinders the country's development (United Nations Development Programme, 2020). BMI and information tracking systems can be adapted to the Zimbabwean context to support efforts in monitoring nutritional status, promoting healthy lifestyles, and managing chronic diseases. This is useful in resource-limited settings through improving data management and increase in the efficiency of healthcare delivery. However, implementations that are successful requires addressing challenges which involves limited internet access, affordability of technology, and the need for culturally appropriate and user-friendly systems .The Zimbabwe health scenario complexity requires that we possess a multi-dimensional approach, where in digital health interventions are included alongside traditional healthcare delivery. The literature has highlighted the potential for mobile health to increase access to maximize health outcomes in Zimbabwe, particularly for chronic disease. The effectiveness of these interventions however is contingent upon overcoming key barriers. For instance, the phone and mobile data costs may disproportionately affect vulnerable population, exacerbating existing health inequalities. Moreover, the shortage of a stable electricity supply in most area becomes a significant barrier to the general adoption and long-term use of digital health technologies. It is important to prioritize user-centered design principles with ongoing feedback from the local population throughout development in order to successfully implement BMI information tracking systems. This involves tailoring the technology to the specific cultural context, addressing language concerns and ensuring that the interface is intuitive and simple to navigate for those with varying levels of digital literacy. Also it is necessary to trust these systems. This includes data privacy and security safeguards for sensitive as well as open communication about the strengths and limitations of BMI as a marker of health. The long-term sustainability of these projects will depend on government support, investment in digital infrastructure and the development of local capacity to manage the systems. The overall goal is to utilize to allow individuals to make informed decisions about their health as well as to improve the overall healthcare system in Zimbabwe.

1.3 STATEMENT OF THE PROBLEM

Nowadays, it has become a challenge to maintain a healthy due to sedentary habits, poor dietary choices and a lack of motivation to engage in physical activities. There exists a significant problem in the difficult individuals face in effectively tracking and managing their health metrics leading to poor health outcomes. Globally, In the year of 2016 most of 1 900 000 000 adults aged 18 years and older were overweight including 650 000 000 of these being obese (World Health Organization, 2021), indicating the widespread nature of weight-related health issues that could be better managed with improved tracking tools. The main challenge lies in the fragmentation and complexity of current health tracking methods, where existing mobile applications often lack key features like personalized recommendations, real-time data analysis and integration of internet devices which will become difficult for users to get a complete picture of their ability to make informed decisions. Furthermore, a large number of users find it is difficult to interpret the data presented by these apps, leading to confusion and inaction. This challenge affects several key stakeholders involving individuals who suffer from an inability to effectively monitor their health, reduced quality of life, higher healthcare costs and leading to increase of chronic diseases. Healthcare providers who lacks access to comprehensive patient data which limits their ability to provide personalized care and public health organizations that struggle to gather accurate data on population which hinder efforts to develop effective interventions and policies. The consequences of these challenges which involves an increased prevalence of chronic diseases, higher healthcare costs, reduced quality of life and decreased productivity are far-reaching. Ultimately, the aim is to create a reliable digital health companion that help users in achieving and maintaining their desired levels efficiently and effectively.

1.4 Research Aims

The main aim of this research is to develop the effectiveness of a mobile application which is used to test BMI information in promoting sustained healthy lifestyle changes. This would involve measuring changes in user behavior for example increased physical activity, improved dietary habits, as well as physiological changes for example weight loss.

1.5 Research objectives

1. To design and implement a mobile application which is used to track health metrics which involves Body Mass Index (BMI), body fat percentage and Basal Metabolic Rate to identify health risks associated with weight and fitness levels.
2. To analyze the effectiveness of BMI information so that it will give clear results on health and body composition, helping individuals understand the significance of BMI.
3. To identify how IoT has been used in tracking health metrics worldwide.

1.6 Research Questions

1. How is the accuracy of BMI calculations vary across different age groups and fitness levels?
2. To what extent is the designed mobile application for tracking BMI information performing in the country?
3. How and where has been IoT been used in BMI tracking system.

1.7 Research Hypothesis

The research postulate that the use of a BMI and information tracking system will enable people in schools, hospitals and other individuals from different institutes to participate without their direct involvement. This therefore gives the following hypothesis:

H0: The BMI and information tracking system will enable the automatic execution of results without the human interference.

H1: The BMI and information tracking system will not enable the automatic execution of results without the human interference.

1.8 Significance of the study

1.8.1 Significance to Individuals

The mobile application which is proposed for BMI and tracking information has the capacity to empower users to manage their health, make healthy decisions and adopt healthy behavior so that they are able to monitor their BMI, accomplish and configure fitness goals, receive personalized recommendations and increase general health and well-being. Beyond these core functions, the application is used as a valuable tool for promoting self-awareness by providing users with a clear and concise display of their health metrics, encourage users to become more aware of their current health status, facilitating early intervention, allowing users to seek timely medical advice and make necessary lifestyle changes to prevent the occurrence of chronic diseases. Another key benefit is enhancing fast communication with healthcare providers, while the incorporation of social features provide a sense of community, encouraging a supportive environment that promotes motivation to the health habits. Eventually, the nature of the mobile application offers convenience and accessibility that will make easy for users to track their health anytime, anywhere fitting seamless into their daily routines.

1.8.2 Significance to Policymakers

The research of this study inform stakeholders and policymakers in the health sector on the effectiveness of mobile health applications which enable them to make budgetary allocations, develop-informed policies and promote the use of these application among consumers and healthcare providers. Furthermore, the result will guide public health policy development using data on population-level BMI, obesity and their associated health behavior patterns, guide health care resource allocation through cost evidence and reduction of health outcome potential of mobile health applications, enable to integrate technology into health systems, drive health technology industry innovation and support achievement of global efforts to halt the rise in overweight and obesity and achieve health-related Sustainable Development Goals.

1.8.3 Significance to Practice

The proposed mobile application is utilized to enhance healthcare practice by providing professionals with a simple way of monitoring patient's health indicators, promoting healthy living and aiding patient engagement and empowerment and ultimately improving quality of care. This technology make easy for patient monitoring, it allows healthcare providers to remotely monitor their data, enabling them to identify patterns and potential problems earlier, aid in better communication between patient and provider through secure information exchange, facilitate better-informed consultation and tailored treatment plans, aid medicine prevention through promoting healthy lifestyle choices, aid in chronic disease management and facilitate remote consultation in remote communities with poor healthcare access, enhance access to healthcare access, enhance access to healthcare for vulnerable communities.

1.8.4 Significance to Theory

This study is used to advance theoretical knowledge through creating models and frameworks explaining the impact of mobile health applications that are effective and shedding light on the mechanisms by which mobile health applications influence health behavior and outcomes. Specifically, it strength existing theories of health behavior change with empirical evidence of the role of mobile technology and aid in the development of novel, composite models. The research will inform the creation of guidelines and best practices for mobile Health intervention design. Eventually, this study gives a light on directions for future research, ultimately shaping the field of digital health and a better conceptualization of how technology must be leveraged towards supporting good health outcomes.

1.9Assumptions

1. This research is applied to enhance theoretical understanding through model and framework development.
2. The research will explain the importance of mobile health applications on health behavior and outcome.
3. The research may guide the design and development of effective mobile health applications.
4. The study provide an explanation on the mechanisms through which mobile health applications influence health behavior and outcome.

1.10 Limitations or Challenges

- ❖ The application cannot work without internet connection
- ❖ The price of smartphones and data maybe a challenge to some users.
- ❖ Time constraints in system development
- ❖ Cost of prototyping equipment

1.11 Scope or delimitation of research

The scope of this research encourages the development and evaluation of a mobile android application aimed at helping users monitor their health and fitness. The application works on providing tools for tracking Body Mass Index, estimating Body Fat percentage, tracking Basal Metabolic Rate and monitoring fitness activities. It used as a digital solution for those individuals who want to maintain a healthy lifestyle, monitor weight and achieve fitness goals.

1.12 Definition of Terms

1. **Body Mass Index (BMI) -** is a numerical value calculated using an individual's height and weight to determine their body size and categorize them into underweight, normal weight, overweight, or obese. (World Health Organization, 2021).

2. **Basal Metabolic Rate (BMR)** - refers to the minimum number of calories the body requires to perform basic physiological functions such as breathing, circulation, and cell production while at rest.

3. **Body Fat -** Body fat refers to the percentage of a person's total weight that is composed of fat tissue.

4. **Self-Efficacy** -Self-efficacy is the belief in one's ability to successfully execute behaviors required to achieve specific goals.

5. **Chronic Disease-** the disease that occurs in adults that usually controlled but not cured.

6. **Cardiovascular risk -** Cardiovascular risk refers to the likelihood of a person developing a heart or blood vessel disease, also known as Cardiovascular Disease (CVD), over a specific period. It's a multifaceted concept that considers various factors contributing to the risk of heart attacks, strokes, and other heart conditions.

7. **Sedentary Habits -** Sedentary habits refer to a lifestyle characterized by prolonged sitting or lying down, with minimal physical activity. This includes activities like watching TV, reading, or working at a desk, where physical movement is low.

Summary

This chapter has been on problem identification and it has enlightened several contributions to the development of the system. The next chapter will present the literature review, detailing what is currently happening in BMI tracking internationally and the related work that has been done concerning the problem to be addressed in this research. Specifically, the literature review will investigate existing mobile health applications for BMI tracking, analyzing their features, effectiveness, and limitations. It will look relevant research on behavior change theories and how these theories have been applied in the design of digital health interventions. Furthermore, the review will investigate studies that have evaluated the impact of Health technologies on weight management, physical activity levels, and overall health outcomes. Eventually, it will combine the information from the literature to outline best practices and inform the development of an improved mobile application for BMI and fitness tracking.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The previous chapter has been on problem identification and it has enlightened several contributions to the development of the system. This chapter will focus on the literature review. Literature review is an overview of what is known and of what is not known about a given topic. It is the wide-ranging rapid of earlier research on an issue (Causon, 2015). It is a process of understanding a field of study by analyzing published and unpublished scholarly and research work. This chapter serves to highlight what has been done before as a flash back to what efforts have been done. This information is very useful to the success of this project as different articles and sources will be reviewed to check how researches have done addressing the same issue and how the researcher's system under design will meet the fall backs of existing system.

2.2 BMI and Fitness Tracking

Mobile technology proliferation has transformed how individuals approach health and fitness management. The use of mobile applications have emerged as the strongest tools for tracking, managing and improving personal health outcomes. The accessibility of smartphones have empowered an environment where can easily access and monitor their health data in real-time. Within this landscape, development of mobile applications for BMI and fitness information tracking reflect a growing societal emphasis on proactive health management. These applications have the inherent capabilities of mobile devices including sensors, data storage and network connectivity so that it provides users with personalized insights into their physical well-being. The development of such mobile applications is a reflection of evolving health behaviors and the increasing integration of technology into daily life. The research which is still existing shows that mobile health interventions significantly impact health behaviors, mostly in areas such as weight monitoring and physical activity (Smith *et al.*, 2020). Studies have indicated that consistent tracking of health metrics such as Body Mass Index, Basal Metabolic Rate and Body Fat enhances motivation and awareness to the users and they lead to a positive behavioral changes. The effectiveness of these applications will rely in factors such as user interface design, data accuracy and the combination of evidence-based health information. In the context of BMI mobile tracking, it is critical to consider the limitations of BMI as a primary indicator of health and combine complementary fitness metrics for a more comprehensive assessment. Moreover, the ethical considerations surroundings data privacy and security involve robust efficient measures to protect user information (Bull *et al.*, 2020). The aim of this literature review is to explore the existing body of research on mobile health applications for BMI and fitness tracking, examining the fundamental concepts, empirical evidence and technological considerations that inform their development and implementation. The review will also indicate the gaps in the current research and identify potential avenues for future investigation, focus on the development of user-centered, effective and ethically sound mobile health solutions

2.2.1 Mobile Applications for Tracking Health Metrics

The development and implementation of mobile applications for tracking health metrics which involves Body Mass Index, Body Fat Percentage and Basal Metabolic Rate represents an important area of research within the mobile health fields. These applications support the availability of smartphones to provide users with tools which are accessible for monitoring their health status and behaviors. It is crucial for identifying potential health risks associated with weight and fitness levels when there is the ability to track these metrics so that it allows for early intervention and preventive care. Studies have focused on various aspects of this which includes the accuracy of data collected, the types of features incorporated into these applications and the impact of these applications on user behavior and health outcomes. The role of mobile health technology in obesity management derive into the different ways in which mobile health technology and mobile applications are being utilized to address the issue of obesity(Patel *et al.*, 2019). The condition of obese is represented as excessive body fat accumulation, it includes cardiovascular disease, it is a major risk factor for a wide range of chronic diseases, type 2 diabetes and certain cancers. The authors indicate that mobile applications offer a different platform for individuals to manage key health metrics such as BMI, weight and physical activity levels which are relevant to obesity management. These applications have features that allows users to input their weight and height which are used to calculate BMI automatically. Furthermore, many applications track BMI and physical activity levels through connection of phone with IOT devices and smartphone sensors so that it will provide a more comprehensive picture of an individual's weight status. The research encompasses that the potential of these applications extends beyond data tracking. They are used to give personalized interventions, provide feedback on progress and facilitate communication between patients and health care providers. This complex approach, integrating track of data with behavioral support is reflected as key advantage of mobile health technology in addressing obesity.

The change of health behavior interventions delivered on mobile phones which provides a context for understanding mobile applications' role in promoting health behavior change which includes weight management and BMI control (Riley *et al.*, 2016). There is a wide range of studies which have been analyzed by this review that utilized mobile phones to deliver interventions aimed at improving health behaviors such as diet, physical activity and medication observance. The authors saw that mobile phones interventions which includes those that integrate BMI tracking, have indicated promise in promoting positive changes in these behaviors. The review indicated the advantage of incorporating behavior change techniques such as goal setting, self-monitoring and feedback into the design of mobile interventions. These techniques are combined into mobile applications, they are crucial for individuals to adopt and maintain healthier lifestyles. The authors found that the effectiveness of mobile phone interventions vary depending on factors such as target population, level of user engagement and the intervention content. This underestimate the need for consideration of these factors in the design and implementation of mobile applications for BMI and fitness tracking.

Subsequent research has further built on these findings, extending the analysis of the nuances of mobile health interventions for weight loss and concomitant health outcomes. Smith *et al.*, (2020), for example, looked into the use for gamification in mobile exercise applications and found that the inclusion of game-like elements will significantly boost user interest and stimulate behavior change in the long term. The effectiveness of AI-driven chatbots to provide personalized weight loss advice, reporting promising results in increasing patient compliance with dietary recommendations (Chew, 2022). Furthermore, studies have also delved into the integration of mental health support in these applications, recognizing the critical role of psychological factors in weight management. For instance, the use of a smartphone application that combined BMI tracking with mindfulness training had greater weight loss and improved emotional functioning than in a control group. Ethical implications for the use of these technologies, including data protection and potential for exacerbating health inequities, are still a critical research priority (Williams, 2024).

2.2.2 Body Mass Index in Public Health

Body Mass Index (BMI) has been the cornerstone of public health activities to monitor and intervene against weight issues for decades. The reason for its utility is that it is simple to calculate and compute, hence a convenient tool to have for large-scale epidemiological studies and routine clinical use (Nuttall, 2015). The World Health Organization (2021) continues to encourage its use as a low-cost instrument for population-wide screening for overweight and obesity. BMI data is utilized to track trends in obesity prevalence, inform public health policy decisions and evaluate the effectiveness of interventions that will arrest the rising tide of the obesity epidemic (Zhang, Qu and Pan, 2023). BMI is also a standard outcome measure in most investigations into the association between weight status and the risk of chronic disease information, such as cardiovascular disease, type 2 diabetes and certain cancers. However, there have been more recent studies focused on BMI limitations, that is, it cannot differentiate between muscles mass and fat mass. This has generated problems with regard to its accuracy in some subgroups, such as athletes or older individuals, where body composition may radically differ Research has also probed the heterogeneity of the BMI-body fat relationship across different ethnic groups, with implications that proposed BMI-cut off points for overweight and obesity may not be universally applicable and may need revision for some groups to yield accurate classification and effective intervention. In the clinical setting, the use of BMI as a sole indicator of health status is increasingly debated. Many experts suggest more comprehensive assessment of individual patients, such as other body composition quantifications such as waist circumference, skinfold thickness, or DEXA scans, to provide a more accurate representation of health risk and to guide individually focused treatment planning (Smith *et al.*, 2020)

Recent trends in public health research are looking at how further to refine BMI application and enhance predictive accuracy. Among the promising pathways is the use of BMI in combination with other relevant health metrics such as waist size, metabolic risk predictors and genetic risk scores. This collective strategy aims to overcome the weaknesses of BMI standing alone and provide a better overall indication of an individual's health risk profile (Smith *et al.*, 2020). The increasing uses of technology, including mobile applications and wearable technology, are also transforming BMI monitoring and management, with potential for real-time evaluation and tailored interventions (Chew, 2022). Further, greater emphasis is put on developing tailor-made weight loss programs based on an individual's BMI in addition to other factors like age, sex, ethnicity and lifestyle, recognizing the heterogeneity of obesity and the necessity of using individualized approaches to achieve optimal results.

2.2.3 Limitations of BMI

Body Mass Index (BMI) has also been a typical measure to define weight status and categorize an individual as underweight, normal weight, overweight, or obese. However, even as it is easy and everywhere, BMI has several well-documented flaws, particularly if it is applied across diverse groups and in most clinical settings. Subsequent research has further emphasized these limitations, urging caution in the interpretation of BMI and the utility of measuring alternative or complementary measures of body composition and risk of disease. Of the major limitations of BMI, one is that it does not differentiate between fat mass and lean mass (muscle and bone). This leads to the misclassification of individuals, particularly individuals with high muscle mass, for instance, athletes or highly physically active people (Farbo and Rhea, 2021). These individuals can be highly BMI with BMI putting them in the overweight or obesity range even though they have low levels of bad fat and a good metabolic status. Conversely, older adults or individuals with sarcopenia (muscle wasting) might have normal or even below-normal BMI but still maintain excess fat and increased health risk. Thus, BMI can be a poor indicator of body fat risk of health in persons with variation in body composition.

Another significant limitation of BMI is that it fails to account for the distribution of body fat. Visceral adipose tissue (VAT) or deep belly fat is more strongly associated with metabolic disease and the risk of cardiovascular disease tan subcutaneous fat (fat stored below the skin). BMI provides no indication of VAT, and individuals with normal weight can have excessive levels of VAT and increased risks for adverse health consequences. Studies have shown that indicators of central adiposity such as waist circumference or waist-to-hip ratio, are better indicators of metabolic risk than BMI, particularly in populations with a heterogeneous distribution of shapes and sizes (Jayedi *et al.*, 2020). In addition to limitations regarding body composition and racial differences, BMI is limited with regard to its use across different age groups. In youth and children, BMI distinguish according to gender and age and significance has to be established by the application of percentiles and growth charts (Ogden, Freedman and Hales, 2023). Despite this, growth charts may not measure altering body composition and patterns of growth in all children, particularly those with unusual health issues or form varied ethnic groups. In elderly, BMI may be less sensitive to changes in body composition, such as the loss of muscle and accumulation of fat with (Merchant *et al.*, 2021). Therefore, BMI use in these groups should be well considered owing to the specific pattern of development and physiological alterations occurring throughout life.

In recent times, new evidence has also described the shortcomings of BMI in its predictive power for mortality risk. While numerous studies have found that BMI is U- or J- shaped against mortality with both extremes predictive of increased risk, newer evidence now suggests that such a pattern might be attenuated or even inverted in certain groups, for instance, the elderly or those with chronic illness. Among such populations, increased BMI can be seen to be linked with lower mortality, presumably due to health gains from increased muscle or subcutaneous fat. This “obesity paradox” refutes the traditional view of obesity as always a bad thing and underscores the need for a more nuanced measure of weight and risk satisfaction. Finally, while BMI is still a useful and widely used indicator of weight status, its limitations in terms of not accounting for body composition, fat patterning, ethnic variation, change with age, and the complex relationship of weight to risk of death must be acknowledged. Healthcare professionals and researchers need to use BMI with caution and complement it or use other or supplementary assessments such as waist circumference, skinfold thickness, bioelectrical impedance analysis (BIA), or dual energy X-ray absorptiometry (DEXA) to better estimate body composition and health risk, particularly in diverse populations and in clinical settings where precise measurement of weight status matters (Li *et al.*, 2022). Future studies need to continue examining the development of even more accurate and personalized instruments for assessing body composition and predicting health outcomes.

2.2.4 Behavioral Impacts of Fitness Tracking

The proliferation of fitness tracking technologies increasingly powered by Internet of Things (IoT) components has significantly influenced research on behavior change health. Such systems, ranging from wearable sensors to smart home sensors and mobile applications, offer unparalleled means of uninterrupted data collection, real time feedback, and personalized intervention (Passos *et al.*, 2021). The integration of IoT sensors, such as accelerometers, gyroscopes, heart rate monitoring and GPS chips in wearables, with smart scales and connected sleep trackers enables an in-depth understanding of an individual’s physical activity, sleep and physiological responses. This abundant data flow is the foundation for advanced analytics and tailored behavioral nudges to encourage healthier living and mitigate the rising global burden of non-communicable diseases. Self-monitoring is one of the most significant ways in which IoT-fitness trackers influence behavior. By providing users with timely and quantifiable data on their steps walked, calories expended, sleep duration, or heart rate, these technologies raise awareness, the first step down the path of behavior change (Zhang, Qu and Pan, 2023). By readily observing activity levels or food consumption, users are more likely to set rational goals and track progress, thus solidifying healthy habits. According to Longhini *et al* (2024), a study demonstrated that habitual self-monitoring with wearable devices was highly associated with increased physical activity among sedentary adults. Similarly, monitoring weight and body composition using a smart scale, an Iot device, provide objective feedback that can promote adherence to weight management programs (Steinberg *et al.*, 2013).

A significant other behavior change brought about by IoT data is personalized feedback and adaptive interventions. Unlike guidelines, algorithms driven by AI can search through vast amounts of real-time collected data from IoT sensors to provide highly personalized advice on exercise, diet and sleep (Chew, 2022). This personalization is crucial for long term participation, as treatment that is sensitive to an individual's progress, preference and a version is perceived to be more relevant and effective. As such, for instance, an IoT enabled fitness tracker might instruct a harder exercise based on a user's recent activity history data or an earlier bedtime schedule in bed if sleep has been consistently of lower quality, directly making use of sensor information. This dynamic personality goes beyond static programs, delivering dynamic support that shifts with the user's experience (Patel *et al.*, 2019). Goal definition and tracking are also significantly supported through IoT components. Fitness trackers allow people to enter specific, measurable, achievable, relevant and time-bound (SMART) targets, such as daily steps or active minutes. The constant flow of information from wearables provides instant feedback on progress achieved, which is a potent motivator (Huang *et al.*, 2021). Visual feedback on progress in the form of comprehensible dashboards on linked mobile applications reinforces good practices and enables people to feel satisfied. When paired with connected scales, the users can see the direct impact of their activity and dietary modifications on their weight and body fat percentage, closing the feedback loop and increasing self-efficacy (Williams, 2024).

Gamification elements, usually used in fitness tracking software that leverages IoT data, have been found to play a crucial role in maximizing user engagement and motivation. Features like badges, points, leaderboards and virtual rewards can make routine physical exercise an enjoyment and competition (Geyda and Lysenko, 2019). For example, a user can get a virtual badge if he or she reaches a set number of steps, or compete with friends on a leaderboard based on his or her daily activity statistics tracked by his or her wearable device. This external motivation is what can help achieve initial momentum breaking and sustained involvement, particularly for individuals that might otherwise find working out tedious (Donnachie, Sweeting and Hunt, 2023). Social support and accountability are other behavioral consequences amplified by fitness tracking that is IoT-enabled. The majority of these applications allow users to compare their progress with friends, relatives, or online communities and engage in challenges with groups. This social component provides peer pressure, encouragement and a sense of sense of shared responsibility, which can be powerful motivators for consistent healthy behaviors. Having the ability to share data from smart scales or smartwatches with an influential group fosters a culture of helping and increases accountability, making it less likely for users to drift away from health goals.

Despite these motivational behavioral impacts, there are many challenges and limitations that persist. The "novelty effect" remains a problem, whereby initial interest in novel fitness trackers wanes with time, leading to device abandonment (Smith *et al.*, 2020). While IoT devices offer improved features, sustaining long-term interest requires constant innovation in user experience, personalized content and adaptive algorithms that prevent user fatigue. Some IoT sensors' data accuracy can also be a limitation, affecting the validity of feedback and demoralizing users if they sense that the information is unreliable. Privacy and security are paramount when dealing with sensitive health data collected by IoT fitness trackers. Individuals' desire to share highly personal information (for example heart rate, sleep patterns, location) depends on robust data protection measures and transparent data use policies (Williams, 2024). Trust breakdowns can cause widespread disengagement. Moreover, the digital divide serves as a barrier to equal access and utilization of these technologies, particularly in contexts where there are poor resource settings with limited internet use, availability of hardware and digital literacy. Follow-up research in the same line of study is focusing on developing more sophisticated AI models, that can better predict user behavior, identify periods of high-risk disengagement, and deliver proactive, just-in-time intervention (Patel *et al.*, 2019)Also emphasized is the integration of fitness tracking data with clinical health records to facilitate more integrated healthcare provision and enable healthcare professionals to leverage this rich data set for personalized patient management. The creation of context-oriented and culture-adjusted interventionns, particularly for groups with heterogeneous global histories, is an important area of ongoing research in order to achieve the largest possible behavioral impact of IoT-based fitness tracking systems (Steinberg *et al.*, 2013). Last but not least, it is a question of transcending data acquisition in order to empower users with smart, adaptive and responsible digital health systems effectively.

2.2.5 Challenges with Long-Term Engagement

The widespread use of fitness trackers, particularly those with Internet of Things (IoT) components, has provided enormous opportunity for the promotion of health. However, one concealed and enduring the issue is the sustainability of user engagement in the long term. For all the initial hype, a drastic decline in usage and ultimate dumping of the device and its associated applications is the common experience (Smith *et al.*, 2020). This phenomenon, referred to as the "novelty effect" in the majority of existing, literature, emphasizes the complex interaction between psychological, technological and contextual determinants of long-term adherence to digital health interventions. Understanding these contextual determinants of long-term adherence to digital health interventions. Understanding these challenges will be crucial when developing more sustainable and efficient fitness tracking systems. The most frequently reported obstacle is early loss of energy and novelty effect. Users are drawn to innovative fitness trackers by their new features, fascination with data and the capability of improved health. However, this early excitement is very soon lost once the novelty aspect disappears, typically in a few weeks or months (Zhang, Qu and Pan, 2023). Without continuous motivation or altered value propositions, the users start to get bored with the process of inputting or monitoring data and thus disengage. Empirical evidence indicates that perceived usefulness and ease of use, as important as they are to initial adoption, are insufficient to guarantee long-term participation unless the internal motivation is fostered or unless the system itself can support changing user needs.

Information overload coupled with an inability to derive actionable insights is another major hindrance to long-term participation. Modern fitness watches, especially those embedding IoT components, monitor gigantic amounts of granular physical activity, sleep, heart rate and other metrics. While powerful, many such users cannot derive useful insights from them or substantively translate them into concrete behavioral change (Huang *et al.*, 2021). The sheer number of numbers and graphs is intimidating and unless the application provides customized, understandable and actionable recommendations, individuals will become frustrated and bail. General recommendations such as “walk more” are quickly forgotten after the initial excitement of tracking steps fades. The lack of responsiveness and personalization in most fitness tracking systems considerably diminishes long-term engagement. Early generations of applications have a tendency to provide generic one-size-fits-all guidance that did not take into account differences in people’s fitness levels, health status, personal preferences, or their lifestyles. Consumers quickly appreciate that generic guidance is not targeted toward the situation of the individual, which leads to a sense of being irrelevant (Steinberg *et al.*, 2013). Effective long-term engagement needs systems that can respond dynamically to the growth of a single user, identify their own particular challenges and offer highly individualized and responsive interventions. That needs sophiscated AI and machine learning capacity capable of learning from one user’s data and providing intelligent, context-specific advice (Chew, 2022).

Technical issues and usability barriers also play an important role in user abandonment. They consist of user interface (UI) design, slow navigation, frequent bugs, unreliable sensor readings, battery drain and device compatibility (Longhini *et al.*, 2024). A frustrating user experience, even if intermittent, is likely to result in immediate disengagement. Users expect seamless operation and rational design that makes data inputting, monitoring and interpreting simple. Periodic software updates that correct issues and improve performance are vital to maintain user satisfaction and confidence in the system’s reliability. In addition, issues of intrinsic motivation and behavioral fatigue are issues that contribute towards the decline in the use over the long term. While external drivers like gamification (badges, leaderboards) and social support can prompt short-term behavior change, long-term behavior change rests on establishing intrinsic motivation (Geyda and Lysenko, 2019). Unless users find inherent pleasure or personal satisfaction in the activity itself, or receive the system’s help to internalize internalize good habits, compliance will collapse. The amount of effort necessary for sustained self tracking, even if small, can also cause behavioral fatigue in the long term if the perceived utility does not it (Huang *et al.*, 2021).

Concerns around privacy and trust are becoming stronger determinants of sustained engagement. Fitness trackers gather very personal health information, including physiological measures, activity levels, and even location information. People are more aware of how their information is collected, stored, shared and maybe used by third parties (Williams, 2024). Untransparency in data behavior, combined with fear of data leakage or misuse, can significantly erode user confidence and lead to user disengagement. Ensuring robust data security, open privacy practices and user fine grained control over their data is vital in establishing long-term trust and compliance. Cost and affordability are also a real world challenge, particularly for subscription or premium device-based models. While most applications have freemium versions, utilization of upgraded features or sustained support typically costs a recurring fee (Steinberg *et al.*, 2013). For others, especially those in environments with fewer resources, the ongoing cost can be a cap on long-term uptake. This says much regarding the need for sustainable and equitable pricing structures that balance revenue generation with broad accessibility.

Finally, being poorly integrated into broader health systems can be a cap on the perceived long-term value to some consumers. While fitness trackers allow for self-management, the majority of patients would benefit if the information could be readily shared with and understood by health care providers to inform better clinical decision-making (Rajkomar et al., 2018). Interoperability problems and absence of common data exchange standards may block such integration and the fitness tracker information remains a standalone silo rather than a valuable component of an integrative health record. Breaking through these system hurdles is crucial to making these technologies more useful and seeming more valuable in the long term in a more widespread health context. Long-term usage of fitness tracking systems can be maintained only by taking a route that transcends the novelty of the initial exposure. These nascent developments must be paid close attention to highly adaptive and individualized interventions driven by strong AI, intuitive and reliable user interfaces, protected data privacy measures and interventions supporting intrinsic motivation and social support. These challenges must be overcome to achieve the full potential of digital health technologies to facilitate sustainable behavior change and optimize health outcomes globally.

2.2.6 Privacy Concerns in Fitness Tracking

Data privacy remains as the urgent matter in fitness tracking systems. Ledger and McCaffrey (2014) examined user experiences of privacy risks associated with IOT devices. Their findings revealed that most of users are not sure when sharing sensitive health information due to afraid of data misuse. This study encourages the necessity of integrating strong security features in BMI and fitness tracking systems to build user trust. The sensitive nature of health data including weight, height, activity levels, and physiological metrics necessitates strict privacy safeguards. Users are increasingly aware of the potential for their data to be collected and stored which will rise to concerns about unauthorized access and misuse. The collection of granular data such as sleep patterns, location tracking and heart rate monitoring raises concerns about the potential for profiling. Data leaks can expose sensitive information to malicious actors which involves financial fraud, leading to identity theft and other forms of gaining unauthorized access. Furthermore, the sharing of health information with third parties such as employers or insurance companies, can lead to discriminatory practices and loss of privacy. The lack of transparency in sharing and collection of data can further destroy user trust. Most of users are not aware of how their data is being utilized, leading to feelings of vulnerability and mistrust. The regulatory landscape surrounding data privacy is evolving with new laws and regulations being implemented to protect user rights. Fitness tracking systems must rely with these regulations such as the Health Insurance Portability and Accountability Act (HIPPAA) and General Data Protection Regulation (GDPR) to ensure user data is protected. Robust security features which involves encryption and access controls techniques are essential for safeguarding user data. Regular security audits testing can assist outline and address vulnerabilities in the system. The development of privacy-preserving technologies which involves differential privacy enables the analysis of health data without undermining user privacy. User education awareness campaigns can assist users understand the privacy risks the privacy risks related with fitness tracking and make informed decisions about their data. Clear consent mechanisms and transparent data policies can build trust and confidence in users in the system. Users must have the right to modify, access and delete their data.

Acquisti, Brandimarte and Loewenstein (2015) indicated the concept of the “privacy paradox” where users express significant privacy concerns but still engage in behaviors that comprise their privacy. This paradox highlights the need for designers of fitness trackers to go further simply relying with regulations and to actively promote user privacy through design. Furthermore, research by Nicholas *et al*, (2019)emphasizes the significant of considering the social context of sharing data as users privacy decisions are influenced by their relationships with others. The potential for re-recognition of anonymized data is an important concern, as shown by SWEENEY (2002), who indicated that seemingly anonymous data can sometimes be linked to individuals.

Moreover, Cormode & Krishnamurthly (2008) provide an overview of various information anonymization techniques and their disadvantages, highlighting the trade-offs between data utility and privacy. The use of homomorphic encryption, gives a promising approach to performing computations on data which is encrypted without decrypting it, but its practical implementation in fitness tracking systems is still in its initial stages. The ethical implications of using fitness tracking data for research purposes have been examined, with Kaye et al. (2016) emphasizing the need for strong ethical frameworks and governance mechanisms. It is critical to move towards a future where fitness tracking technologies encourages individuals without sacrificing their fundamental right to privacy.

2.2.7 Integration of BMI and Fitness Metrics

Oh *et al* (2018)examined the integration of BMI with broader health indicators such as nutrition, exercise and sleep in health applications. The findings suggested that holistic systems incorporating multi-faceted health information are more effective in promoting user engagement and maximizing user gains. This research determines the potential benefits of combining BMI tracking with other health measures. The fallacies of an exclusive reliance on BMI make this combination method more worthwhile. With the inclusion of food consumption data, consumers are able to more accurately view their calorie intake and eating habits. The inclusion of physical activity data such as steps taken, heart rate and workout intensity provides a more accurate estimate of energy expenditure and fitness levels. Sleeping tracking adds another layer to the overall view, as sleep quality and length are critical to recovery and overall health. By using this multi-faceted view, users can observe patterns and correlations between different areas of their health. For example, Users can track how changes in diet or exercise affect their weight and sleeping habits. The addition of personalized tips and recommendations, based on the aggregated data, can also boost user motivation and participation. This can include personalized exercise regiments, diet recommendations and sleep improvement tips. The usage of data visualization, such as graph and chart, can help users understand their improvement and where they can improve. The merging of education resources and material can also provide users with the ability to make informed decisions about their health. The design of simple interfaces and synchronized information is essential to providing quality user experience. Ethical concerns around data privacy and security must be addressed to foster user confidence and trust in integrated systems like this. The secret to giving users the authority to control what data is collected and gow is essential.

Most research is in support of the idea that assessment of overall health as against just measuring BMI is essential. For instance, it has been proven through research that dietary consumption is a dominant factor in establishing overall health alongside the risk for diseases. Fruit, vegetable and whole grain consumption in elevated amounts assists in reducing the risk of chronic disease. Conversely, high diets in processed foods, saturated fats and added sugars are linked with increased risk. Therefore, the inclusion of dietary data on health platforms provides valuable context to BMI. Physical activity is also essential for healthy weight and prevention of chronic disease. Exercise improves cardiovascular function, develops muscle and bone strength and enhances mental health (Garber et al., 2011). Tracking activity levels, both formal exercise and ambulatory movement, is a better reflection of an individual's energy expenditure than in BMI isolation. This is particularly important because BMI does not separate fat mass from muscle mass.

Sleep is also an important element of overall health that is often overlooked in traditional weight control efforts. Inadequate sleep has been linked to hormonal imbalances that would cause weight gain and increase appetite. Poorer quality sleep is also likely to influence cognitive functions, lower the performance level and increase the risk of chronic disease states. Therefore, integrating sleep data into comprehensive health information systems will enhance users' perceptions of the relevance of their sleeping habits to weight, among other health considerations. The convergence of these multiple streams of data enables the creation of more advanced algorithms and tailored interventions. Machine learning methods can be applied to determine unique risk factors and forecast future health status (Topol, 2019). This can empower healthcare professionals and individuals to proactively intervene to avoid disease and enhance overall health. For example, a system can identify that the user's profile of high BMI, poor sleep and fruit-vegetable- poor diet puts a person ta increased risk of type 2 diabetes. The system can then provide suggestions to improve each of these risk factors.

Moreover, the ubiquity of mobile applications and wearable sensors has supported real-time collection and monitoring of health data than ever before. Such systems can provide real-time, constant monitoring of physiological values, including activity levels and sleeping patterns. The data can directly be integrated in inclusive health platforms and provide a rich a voluminous picture of an individual’s health status. This data also brings about new research and innovation possibilities related to health and well-being. Big data sets can be harnessed by researchers to inform trends, generate new interventions and determine whether or not many different approaches to health work (Patel *et al.*, 2019). Collecting and using personal health information also pose major ethical challenges. It is also crucial that the data is collected, stored and used responsibility and openly. Users must be notified of what information is being accessed, how and why it is going to be utilized and by whom. Sound data security methods are required in order to repel unauthorized access and data breaches. Furthermore, it is necessary to identify data ownership and control. The owners of the data should be given the right to access the data, correct any inaccuracy and withdraw consent to data collection and utilization. Clear guidelines and regulations need to be formulated in terms of ethics to ensure that the potential advantages of the integrated health system are attained with the protection of individual privacy and autonomy.

2.2.8 Artificial Intelligence in Fitness Tracking

Advances in artificial intelligence (AI) hold promising prospects for customized fitness monitoring. Chew (2022)showed how user-centric AI-driven feedback boosted health behavior and motivation. In their study, they determined that customized advice was far more effective in influencing user satisfaction compared to universal recommendations. This study supports the use of AI to maximize the usability and effectiveness of BMI and fitness tracking systems. Artificial intelligence algorithms can analyze vast amounts of user data, including activity history, nutrition history and physiological readings, to identify patterns and trends that would be difficult for a human to identify. Machine learning models can be programmed to predict an individual’s response to different interventions, allowing highly personalized recommendations to be generated. For example, AI can analyze user’s routines activity and diet to suggest personalized exercise routines and diet plans based on their fitness goals and food preferences. AI chatbots chats can provide real-time feedback and advice, answering user queries and even offering encouragement. NLP can be used to analyze user-generated content, such as diet diaries and food diaries, to monitor trends and insights. Predictive analysis can be utilized to forecast user behavior and identify future risks, allowing proactive intervention. For instance, AI can decide when a user is likely to drift away from their fitness program and issue reminders or motivational cues at the appropriate time. AI can be integrated to enhance the efficacy of fitness trackers by eliminating sensor errors and noise. Deep learning methods can be used to analyze sensor data and pick up on fine patterns that correspond to specific activities or physiological states. AI may also be used to personalize the user interface and user experience, adapting to individual preferences and learning styles. The ethical implications of the application of AI in fitness tracking must be carefully addressed. The users should be informed of how their data is being used and must have visibility of the AI algorithms being used for process their data. Transparency and accountability are important for creating user confidence and trust in AI-based fitness tracking systems.

The potential of AI to revolutionize healthcare, most importantly fitness and wellness is more evident. The capacity of AI to analyze and process vast and complex data sets is revolutionizing personalized health care management (Topol, 2019). Machine learning, the core of AI, adapting to the unique needs of individual users. One of the strongest applications of AI is in the analysis of complex physiological signals. AI programs can extract salient information from the data recorded using Iot devices such as Heart Rate Variability, a valuable indicator of cardiovascular function and level of stress. By analyzing HRV patterns, AI can deliver users personalized nutrition insights on their recovery state so that they can make tailored changes to their training schedule and maintain optimal performance.AI can further play a significant role in promoting healthy eating. It has been shown through research that AI-powered dietary advice is extremely helpful in enabling individuals to consume healthier foods and adhere to recommend nutrition. Natural Language processing (NLP) is applied to assess food diaries, providing consumers with exact comments regarding nutrient intake and improvement suggestions. Additionally, computer vision technology is employed for the automated recognition of food and to determine exact calorie counts easily, ensuring the accurate measurement of diet intake. AI can also play a key role in optimizing the effectiveness of exercise interventions. AI-generated personalized exercise prescription, developed from user data through AI processing, has been shown to increase user adherence and overall outcome. AI can tailor exercise routines to match individual fitness levels, interests and specific goals and provide real-time feedback on exercise form and intensity, minimizing the risk of injury and maximizing results (Romero et al., 2016).

Moreover, AI has the ability to make seamless integration of fitness tracking with other parts of healthcare. For instance, AI has the capability of analyzing HER data and fitness tracker data inorder to recognize individuals at risk of chronic disease and facilitate provision of personalized preventive interventions. Such integration has the ability to lead to more proactive and personalized healthcare measures. The application of AI in fitness tracking, however also poses serious concerns regarding data privacy and security. Robust security measures are necessary to safeguard sensitive health information from misuse, abuse and potential breaches. It is also essential to make sure that AI algorithms are designed and implemented in an equitable and unprejudiced manner so that they do not exacerbate or extend existing health disparities (Obermeyer et al., 2019). Transparency and accountability in AI-based fitness tracking system development and implementation are important for establishing users' trust and confidence.

2.2.9 Ethical Considerations in AI-Driven Health Apps

Floridi et al. (2018) proposed an ethical framework which is responsible use in AI health technologies, emphasizing fairness and user autonomy. AI systems might face health inequalities or compromise user privacy without ethical safeguards. This research indicates the advantages of ethical considerations in the development of AI-integrated fitness tracking systems. The algorithmic potential bias is an important concern. AI models are experienced on data and if the data appears existing societal biases, the models will perpetuate those biases. This can direct to discriminatory outcomes which includes providing low effective or high effective recommendations to certain demographic groups. Transparency is essential for building user accountability and trust. Users should be notified about how AI algorithms are used to execute and make decisions. The "blackbox" nature of some AI models can make it hard to understand how they reach at their conclusions, which can lead to mistrust. Fairness requires that AI systems are designed to monitor users fairly, regardless of their background. This involves ensuring the advantages of AI-driven health applications are all accessible, involving underserved and marginalized populations. User autonomy is critical for encouraging individuals to make informed decisions about their health. Users should monitor their data and the AI algorithms that are used to process it. They should also have the right to opt out of AI-driven features and receive human-centered support. Privacy is a fundamental right that must be secured in the design of AI-driven health applications. Strong security measures and data protection techniques are significant for safeguard user data. The ability for AI to be used for surveillance or manipulation raises serious ethical concerns. Users should be alert of their how data is being interpreted and have the right to control its dissemination. The ethical implications of AI-driven applications extend beyond different users to society as a whole. The ability for AI to design new forms of discrimination must be considered carefully. Monitoring AI systems continuously are essential for identifying ethical risks. The development of ethical regulations and guidelines for AI-driven health applications is critical for ensuring responsible innovation. Combination between developers, researchers, policymakers and ethicists is essential for addressing the ethical problems posed by AI in healthcare.

The incorporation of AI into healthcare necessitates a strong ethical to manage its development and deployment. This principles of biomedical ethics involving justice, autonomy and beneficence, provide a robust startup for this framework. Autonomy encourages the significant of respecting individuals' decisions and choices regarding their health and data. Beneficence requires AI systems to be designed to support the user well-being while non-maleficence dictates that they should not cause harm. Justice demands that the advantage and challenges of AI-driven health applications are established equally across all segments of society. Algorithmic bias, an important ethical challenge come from biased training data, a lack of diversity in the development process and flawed algorithms. This bias can perpetuate and even amplify existing health disparities, leading to unfairly access to care or less effective treatment for certain populations (Obermeyer *et al.*, 2019). Mitigating algorithimic bias requires careful data collection, diverse development teams and validation of AI models across different demographic groups. Transparency, a cornerstone of ethical AI, is essential for building trust and accountability. Users should have a clear understanding of how AI systems work, how their data is being used, and how decisions are made. Explainable AI (XAI) is an emerging field that aims to develop AI that are more transparent and whose decisions can be easily understood by humans.

Fairness in AI-driven health applications goes beyond simply avoiding discrimination. It also involves ensuring that the benefits of these technologies are accessible to all, including marginalized and underserved populations who may not have access to the same resources or technology (Bull *et al.*, 2020). This requires addressing issues of digital literacy, affordability and cultural sensitivity in the design and implementation of systems. User autonomy is paramount in empowering individuals to make informed decisions about their health. This includes providing users with control over their data, the ability to opt out of AI-driven features and access to human-centered support when needed (Nicholas *et al.*, 2019). Informed consent is a critical aspect of user autonomy, requiring that individuals are fully informed about the risks and benefits of using AI-driven health applications before they agree to do so.

Privacy is a fundamental human right that must be protected in the design of AI-driven health applications. This requires implementing robust security measures, such as encryption and access controls, as well as employing data anonymization techniques to minimize the risk of re-identification. The General Data Protection Regulation (GDPR) provides a comprehensive framework for protecting personal data, including health data, within the European Union. The ethical implications of AI in healthcare extend beyond individual users to encompass broader societal concerns. The potential for AI to exacerbate existing health inequalities, create new forms of discrimination, or be used for surveillance or manipulation must be carefully considered and addressed through proactive measures and policy interventions. Continuous monitoring and evaluation of AI systems are essential for identifying and mitigating ethical risks as they arise. The development of ethical guidelines and regulations for AI-driven health application is crucial for crucial for ensuring responsible innovation. These guidelines should be developed through a multi-stakeholder process involving researchers, developers, policymakers, ethicists and the public and should be regularly updated to reflect evolving technological advancements and societal values (Jobin, Ienca and Vayena, 2019). International collaboration is also essential to ensure that ethical standandards for AI in healthcare are globally harmonized.

2.2.10 Comparative Analysis of Fitness Apps

Comparative analysis of fitness applications show patterns in user behavior and satisfaction. Hasebrook *et al (*2022) reviewed the usability and functionality of leading fitness applications and from that review, aspects such as ease of design, personalized recommendations and social sharing came pout as most important for retaining users. Their paper stresses that user-centric design principles need to be applied to BMI and fitness tracking systems. Beyond the simple feature checklists, these comparative studies delve into the nuances of user experience and discover that functionality is insufficient. User Interface (UI) design plays a vital part. Cluttered interfaces, complex navigation and disconnected design aspects tend to infuriate and discard users. Clean and uncluttered designs emphasizing major features, in contrast, enhance usability and encourage extended use. Customized feedback, another differentiator, extends beyond averaged-out statistics. Users are starved for information that is tailored to their individual’s goals, fitness level and lifestyle. Personalization via AI, as discussed earlier, can really boost this aspect. Social connectivity fosters feelings of belongingness and responsibility. Incorporate aspects such as sharing challenges, leader boards and social forums, for instance. This motivates users to keep themselves active and engaged. Being able to see progress and share success with others such as friends and family can provide strong social reinforcement. Data visualization is also a vital aspect. Effectively designed and easy-to-understand graphs and charts can ease user’s perception of their progress and trends. Options for dashboards and reports to display useful metrics are greatly appreciated too. Additionally, support for other health and fitness services, such as smartwatches and diet applications, enhances the overall experience. Data synchronization simplicity and support for popular devices is also necessity for convenience purposes. Reliability and performance are more important. Slow, buggy and crash applications will rapidly lose users. Frequent updates with bug fixes, improved performance and new features are what customers want. User reviews and ratings are pure gold. Reading them can identify the most important pain points and opportunities for innovation. Accessibility is also a priority. Applications need to be made available for disabled individuals who have visual, auditory, or motor disabilities. Compliance with accessibility guidelines like WCAG needs to be prioritized to make sure that people with disabilities are included. Finally, the cost of fitness applications can also influence user adoption and retention. Subscription, in-application purchase and freemium models have to be balanced carefully to make sure revenue collection against user affordability.

Recent research still emphasizes these fundamental factors, with an added observation on evolving context in application design and user demand. Usability, for instance, remains paramount, with studies focusing on the impact of different design elements on user interaction and dropout (Longhini *et al.*, 2024). In a study by Sekiya (2022), it was found that fitness application with clear navigation and salient calls to action correlated with higher usage rates over the long term. This emphasizes the importance minimizing cognitive load and keeping it easy for users to find and utilize main features. Personalization has also become more advanced. Modern exercise applications use advanced algorithms to recommend not only on the basis of fitness levels but also on individual taste, behavioral patterns and even genetic predispositions (Chew, 2022). The use of AI-enabled virtual coaches, who can provide real-time dynamic feedback and alter exercise regimens accordingly, is a recent trend. This level of personalization stimulates user motivation and can lead to faster results.

Data visualization also differed, with modern fitness applications offering more sophiscated and interactive aids for tracking progress. Dashboards can be tailored so that users can add different types of metrics, ranging from basic activity measures to more advanced physiological indicators. The integration of visually appealing and readable charts and graphs is the secret to understanding users' data and making an informed choice on their health. Social connection is still facilitator of user motivation. Social factors, such as virtual groups and group challenges, have been found to create a sense of belonging and provide users with a motivating. Having the opportunity to share and receive encouragement from others can be highly motivating for users who may be short of self-discipline. Additionally, gamification of exercise activities, by the application of rewards, badges and leaderboards, will be able to increase user interaction further and make exercise a fun activity (Geyda and Lysenko, 2019).

Continuity with wearable technology and other health platforms remains essential consideration in user satisfaction. Integration of data across multiple devices and applications should be seamless so that the fitness and health of a person are displayed as a single entity. Users desire to track their activity, sleep and food intake in one location and their convenience. Performance and reliability do not come second. Customers want their fitness applications to be responsive, quick and free of bugs. Regular updates are important not only to address technical issues but also to introduce new functionalities and maintain the application fresh and engaging. Developers of applications rely more and more on agile development practices and user feedback cycles to ensure that their applications are top-quality and performing. User feedback and ratings are still a bountiful resource of information both for developers as well as would-be users. Sentiment tools are now used to automatically pick up on prominent insights from the user reviews such that developers may view where improvement is needed as well as the order of how to develop next features (Le et al., 2024). Application store optimization also takes center stage, with the developer focusing on the application title, description, as well as screen shots to achieve maximum visibility as well as secure new users.

Accessibility is increasingly being recognized as a critical aspect of fitness application development. The value of creating applications that are accessible to people with disabilities is increasingly being valued by developers, and they are incorporating accessibility features such as screen reader support, image alt text and text size adjustment. Being accessible is not only the ethical thing to do but also a way to expand the potential user base. Finally, monetization of health and fitness applications is still a debated topic. Subscription-based models are still the most preferred, but developers are also experimenting with other forms of revenue, such as in-application purchases for premium features, advertising and partnerships with health and wellness brands (Steinberg *et al.*, 2013). The difficulty here is how to balance making money while offering a good and reasonable value proposition to consumers.

Summary

This chapter gave a review of different researches undertaken by different authors to address the issue of improving efficiency in tracking health metrics, so as to collect data which is accurate. The researcher did a full assessment of the algorithms used by the existing systems and found some gaps which he then filled and improved. The next chapter is going to look at research methodology, which is how the research was executed.

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

This chapter identifies the hardware components, software programming tactics, materials and methods that were instrumental in the design and development of the prototype so as to attain the set of objectives. This is in tandem with the work carried out in the previous chapters that has set a building ground for innovation in problem resolution. The process of examining how the research is being conducted is referred to as methodology. In this case, we examine the many procedures a researcher typically uses to analyses his research challenge, as well as the reasoning behind them. The researcher must understand not just the technique but also research methodologies.

3.1 Research Design

The research design for this project involves a combination of qualitative and quantitative methods. User surveys and interviews will be conducted to understand user needs and preferences, while data analysis techniques will be used to evaluate the effectiveness of similar existing applications. Additionally, usability testing will be performed to ensure the app meets user expectations in terms of functionality and ease of use. The term "research design" refers to a comprehensive approach used to combine various elements of the research study in a way that will help to successfully address the research challenge. The research design also includes instructions on how data is gathered, measured, and analyzed. Because the research is based on testing hypotheses, it will be an experimental study. The researcher constructed a prototype that is a representation of the real system in order to carry out the experimental study. The prototype will be tested for precision and effectiveness. The researcher used Java programming language which is implemented on IDE Environment. Java uses more of android studio programing language syntax.

3.1.1 Requirements Analysis

This section below shows the functional and non-functional requirements of the system. These are the basic requirement that the researcher aims to achieve with the given system. Key points involve identifying target users, understanding their fitness tracking preferences and analyzing potential challenges in usability.

3.1.1.1 Functional Requirements

This refers to what the system should do depending on some specific user input:

- The software must be able to calculate health metrics such as BMI, Body Fat and BMR using height and weight.
- The system must able to put recommendations for example when a person is underweight, the system must encourage a person to focus on nutrient-dent foods which are rich in vitamins, minerals, lean proteins, healthy fats, fruits and vegetables.
- The system must be able to display weight status for example overweight, underweight, normal weight and obese.
- The system must be able to store information into database.

3.1.1.2 Non-Functional Requirements

These apply on the whole system not only the independent components. Non-functional requirements include factors such as reliability, accuracy and overall system performance. The nonfunctional requirements of the proposed system are centered on the accuracy of the execution of Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Body Fat results. System performance during performing some functional requirements is also taken into consideration.

- The system must be reliable.
- The system must be accurate.
- The system must be ready to install.
- The system must have a user interface and a responsive design.

3.1.1.3 Software Requirements

- Windows 10 or 11 operating system
- Android Studio using Java
- Arduino IDE using C++

3.1.1.4 Hardware Requirements

- Smartphones (Android/iOS) with minimum specifications for app performance
- Scale or weight sensor
- Height sensor
- Arduino board

3.2 System Development

Description of the overview of the system and how it was developed. It specifies all the software tools and models used in the development of the system.

3.2.1 System Development Tools

In this section is the list of the design tools used by the researcher to design the system prototype.

3.2.2 Engine Design Tools

- Android Studio
- Arduino IDE application
- JDK Application

3.2.3 System Development Methodology

The series of tasks that make up a system development methodology are utilized to conduct research. Software development activity is divided into separate parts by a methodology. Following the evolutionary prototyping model, the system was created. The model of evolutionary prototyping is described in more detail below.

3.2.4 Evolutionary Prototyping

A software prototype is a working version with a few restricted functions. The prototype is an additional effort that should be taken into account when estimating effort because it occasionally lacks the exact logic found in the final software program.

Users can review developer proposals and test them out before implementation using prototypes. Additionally, it aids in comprehending user-specific requirements that the product developer might not have taken into account. An illustration of evolutionary prototyping is shown in the diagram below as fig 3.1.

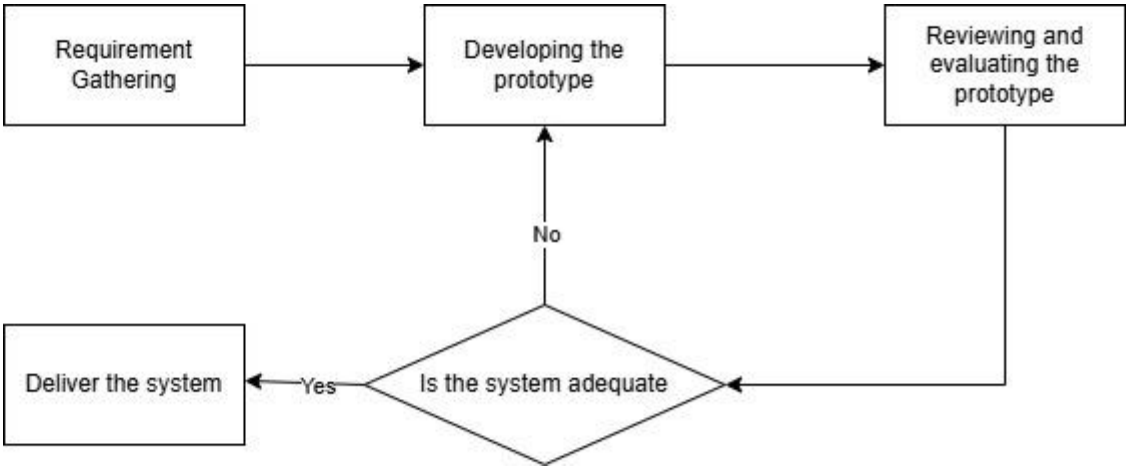


Fig 3.1

3.2.5 Basic Steps for prototyping

Requirement Gathering

All of the fundamental criteria and specifications for the prototype are acquired at this step in the evolutionary prototyping process. At this point, both functional and non-functional criteria are established.

Developing the Prototype

After gathering requirements, a prototype is created using the specifications provided by the users; as a result, the prototype should be able to execute Body Mass Index (BMI), Basal Metabolic Rate (BMR) and Body Fat results, as well as provide recommendations. These features might not exactly match the system that will be created.

Reviewing and Evaluating the Prototype

Some project stakeholders are introduced to and given a demonstration of the prototype. Since it is being incorporated into the prototype that is being constructed, the presentation's audience input is extremely important.

Revising and Enhancing the Prototype

The results produced after evaluating the prototype are used to enhance the prototype which is under development. At this stage, changes are incorporated into the prototype until the project stakeholders are satisfied. When the all requirements are met then the system is then delivered otherwise the prototype is enhanced and revised again.

Agile Model

The Agile development model will be used for this project, allowing iterative development and continuous improvements. Regular user feedback will be incorporated through sprints, ensuring flexibility in adapting to changing requirements. Agile methodologies like Scrum will facilitate collaboration among developers, testers and stakeholders

3.3 Summary of How the System Works

The mobile android system for tracking health metrics, including Body Mass Index (BMI), Body Fat percentage and Basal Metabolic Rate (BMR), primarily uses height and weight sensors to track BMI. The application provides recommendations based on user data. This system will use Arduino to collect sensor data and send the data into the mobile application. These health metrics uses the following formula:

1. **BMI** = weight (kg)/ (height (m))^2
2. **BMR for men** = (10 - weight (kg)) + (6.25 * height (cm)) - (5 * age (years)) + 5
   BMR for women = (10 – weight (kg) + (6.25 * height (cm)) – (5 * age (years)) - 161
3. **Body Fat** = (1.20 * BMI) + (0.23 * Age) – (10.8 * Gender) – 5.4

3.3.1 Weight Sensor (Load Cell and HX711): User stands on the weight sensor and the weight sensor detects weight. A load cell converts a force into an electrical signal that can be measured. The electrical signal changes proportionally to the forces that is applied. The HX711 amplifier is a breakout board that allows you to easily read load cells to measure weight. Below is a snippet of HX711 as shown in fig 3.2.

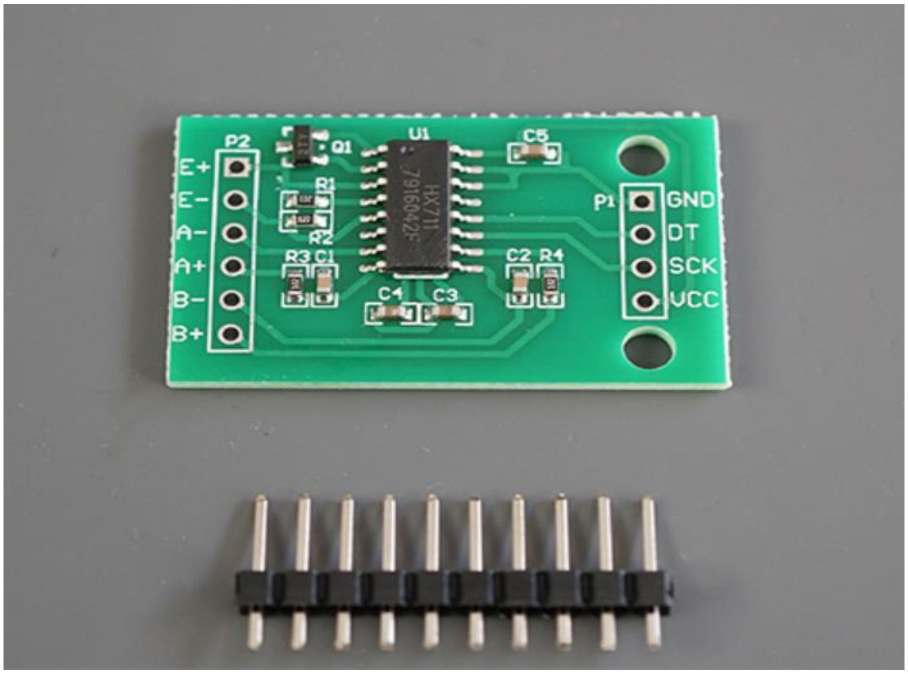


Fig 3.2

3.3.2 Height Sensor (Ultrasonic sensor): it measure the height of the user. The Ultrasonic sensor is positioned above the person's head to detect the height. Below is a snippet of ultrasonic sensor as highlighted as fig 3.3.

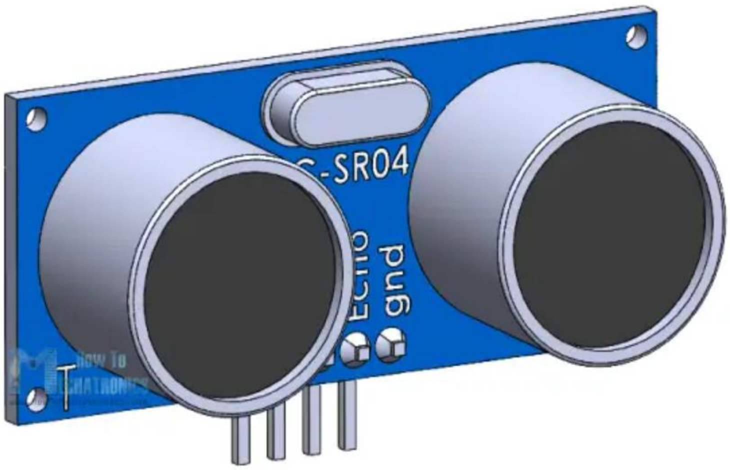


Fig 3.3

3.3.3 Arduino (ESP8266 Microcontroller): It collects the sensor data and send it to the mobile application. The ESP8266 is a series of low cost and low power System on a Chip (SoC) microcontrollers developed by Espressif that include Wi-Fi and Bluetooth wireless capabilities and dual core processor. If you are familiar with the ESP32, the ESP8266 is its successor. The scholar used this as the chip on which the programmed code was embedded into as this was essentially the CPU. Furthermore, the chip has the capability to host web servers thus it was used to host the web server for the system's dashboard. Below is a snippet of the ESP826 as highlighted in fig 3.4.

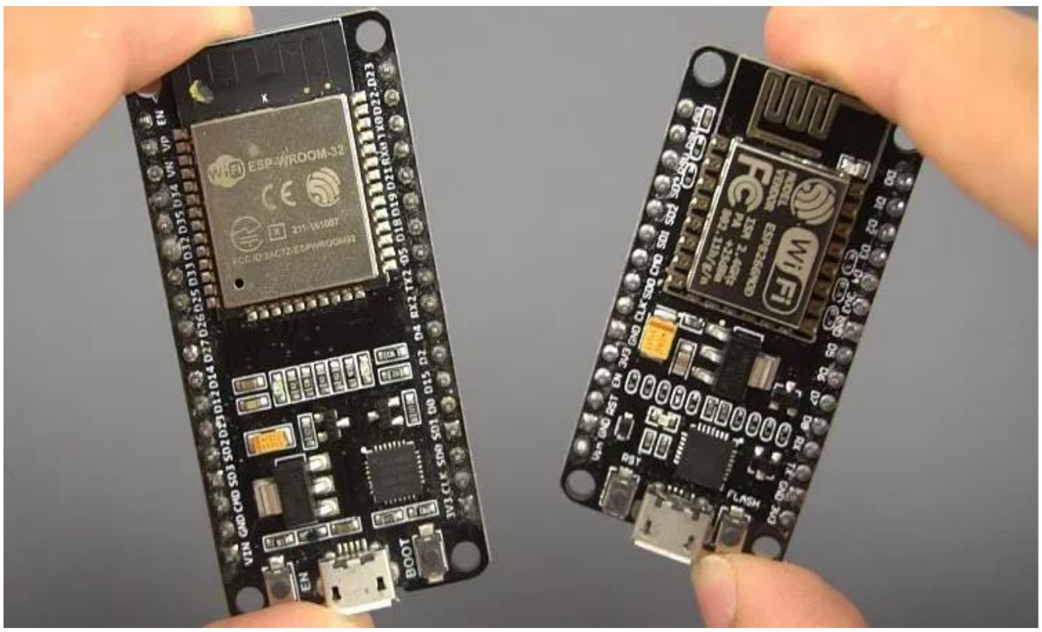


Fig 3.4

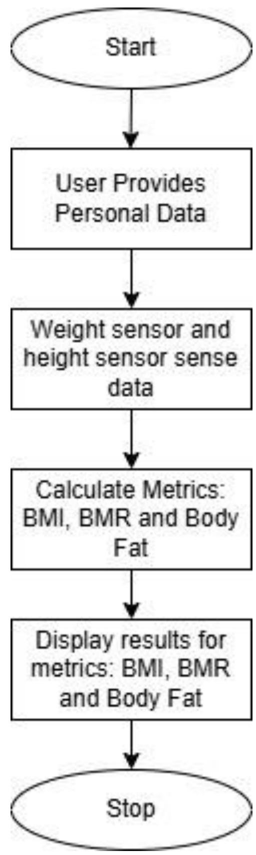
3.4 System Design

This stage defines how the system components and data satisfy the specified requirements.

3.4.1 Data Flow Diagrams

This is a graphical representation of the flow of the data through information. A DFD is designed to show how a system is divided into smaller portions and to highlight the flow of data between those points.

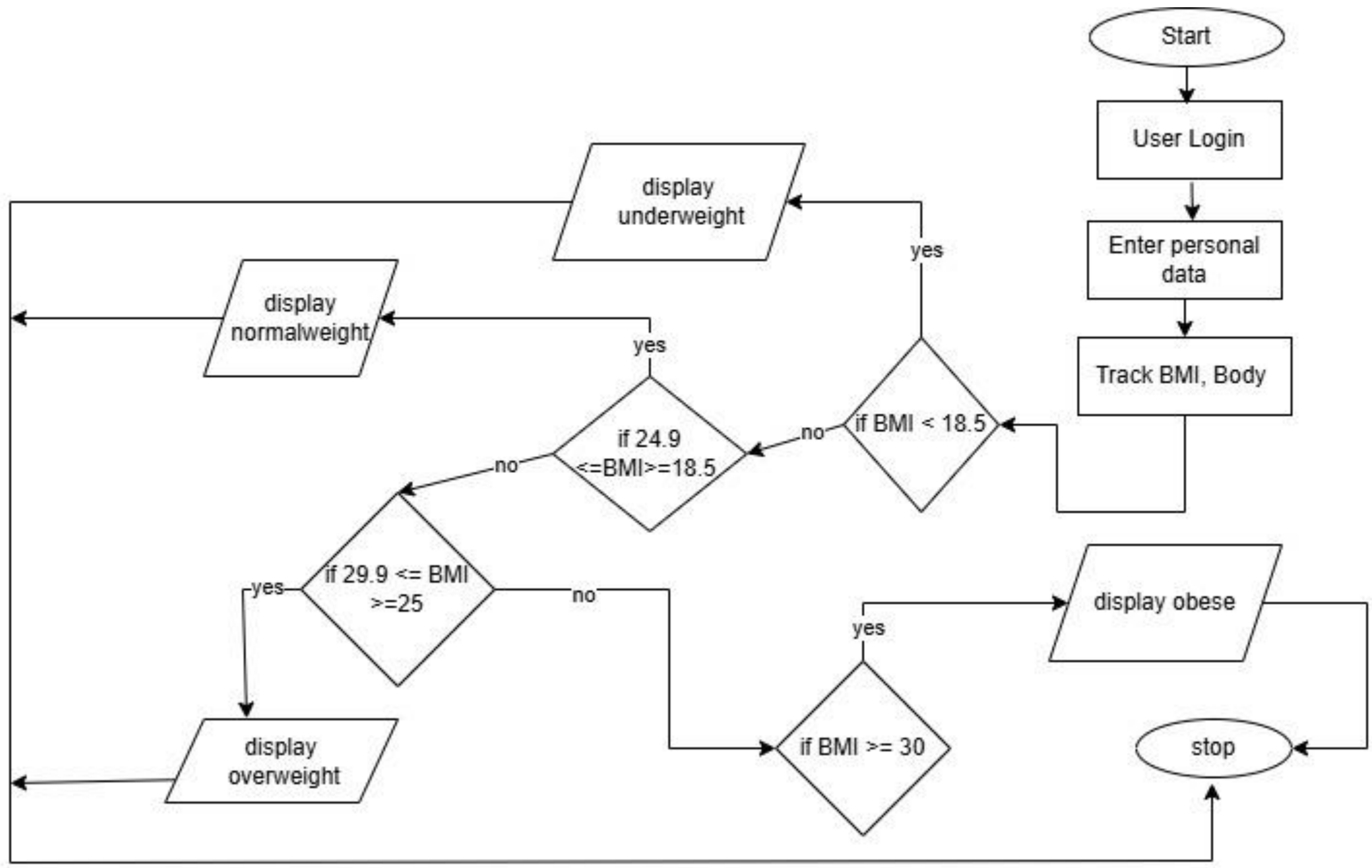
Data Flow Diagram



3.4.2 Proposed System Flowchart

A system flowchart shows how the system work from the starting point up until it reaches the stopping step. The proposed system for fitness tracking initiates its operation whenever a user is authenticated. Secondly, after the user been authenticated, the homepage pops out which shows some options to do. At this stage, the user starts by capturing image datasets whenever the dataset is available. Contrary, the user can train the available dataset. After the dataset has been trained, the user can initiate the face recognition functionality to get the live video from the webcam. Lastly, the user can print out all the reports thus some reports are generated by the system. The diagram below illustrates the system flowcharts.

Flow Chart

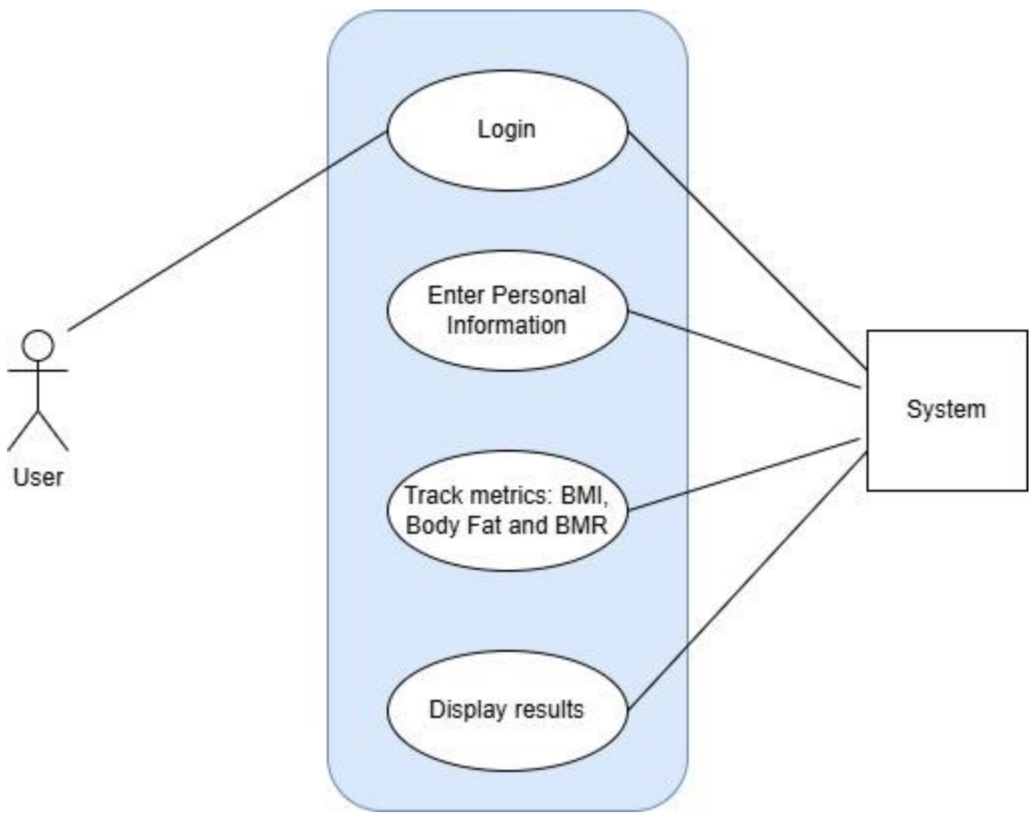

Start
User Login
Enter personal data
Track BMI, Body
if BMI < 18.5
yes
display underweight
no
if 24.9 <=BMI>=18.5
yes
display normalweight
no
if 29.9 <= BMI >=25
yes
display overweight
no
if BMI >= 30
yes
display obese
stop

3.4.3 Use Case Diagram

A Use Case Diagram outlines the interactions between users and the system. It highlights different user roles, such as regular users and administrators, and their respective actions within the application. This diagram helps in identifying user requirements, streamlining feature implementation, and ensuring an intuitive user experience.

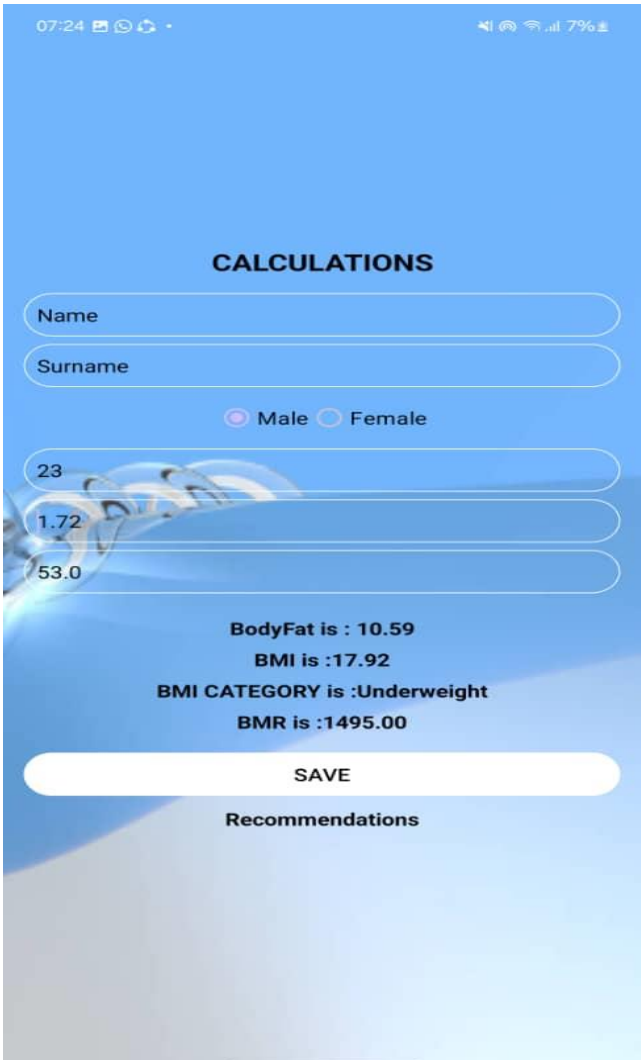
.The use case diagram is detailed in the diagram below.

Figure 3. 1 system Use Case diagram

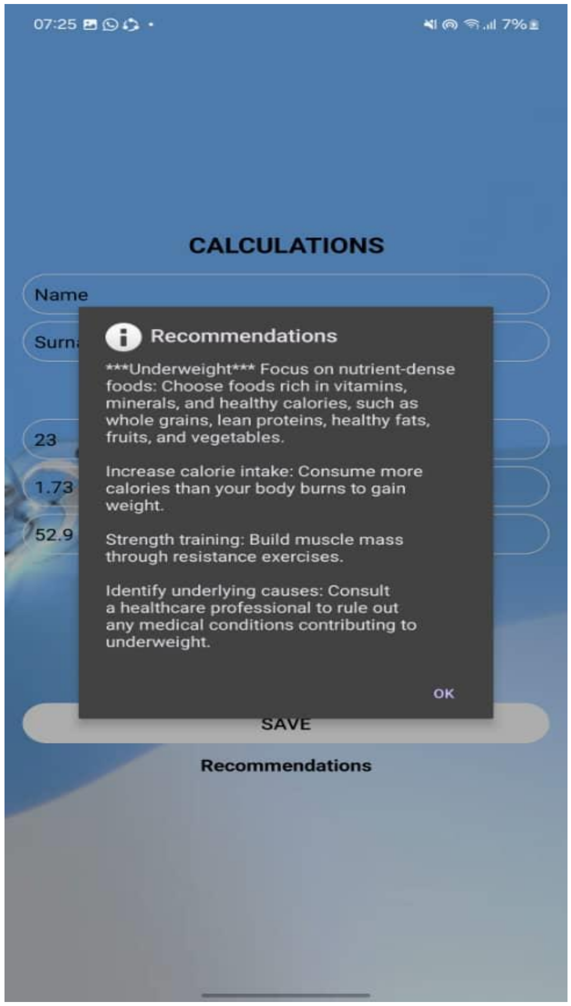


IMPLEMENTATION

The system is working as the user is now tracking health metrics such as BMI, Body Fat and BMR



The BMI, BMR and Body Fat results are displayed under the fields of height and weight. Under the save button there is a text view named recommendations. The user must click it and it must show the personalized feedback according to weight status provided.



Upon clicking the recommendations, the system will display the feedback according to the weight status gained by the user.

DATA COLLECTION METHODS

As a method of gathering information, the researcher used questionnaires. The data was going to be collected using a relevant sample of 20 people. The researcher had opportunity to examine about IoT devices used to track health metrics through questionnaires. The researcher employed literature reviews as an additional technique for gathering data. It concentrated on devices used to track for health. This includes an overview of the historical context, the development of mobile applications used for tracking health.

Summary

This chapter served to exhibit the research design, development and the methodology used. It cast a microscope upon the tools, techniques, strategies and models that were used at this stage of the research. The next chapter will focus on the analysis of the results output by the application.

CHAPTER 4: RESULTS ANALYSIS

4.0 Introduction

This chapter outlines the testing outcomes of the developed mobile application designed for BMI, BMR, and Body Fat Percentage tracking on a unified interface. The application integrates sensor input with automated calculation algorithms to provide health metrics and personalized recommendations. The results are presented through combined test cases validating the holistic functionality of the system. Performance is evaluated based on accuracy, system responsiveness, and alignment with standard medical computations. A critical discussion follows, comparing outcomes to existing literature and identifying implications and limitations.

4.1 Presentation of Test Cases (with Screenshots and Analysis)

Test Case 1: Testing health metrics through entering data manually

Input: Height: 1.67m, Weight: 54.3, Age: 23, Gender: Male

<u>Expected Output:</u>

BMI: 19.48

Body Fat: 12.46%

BMR: 1478.76

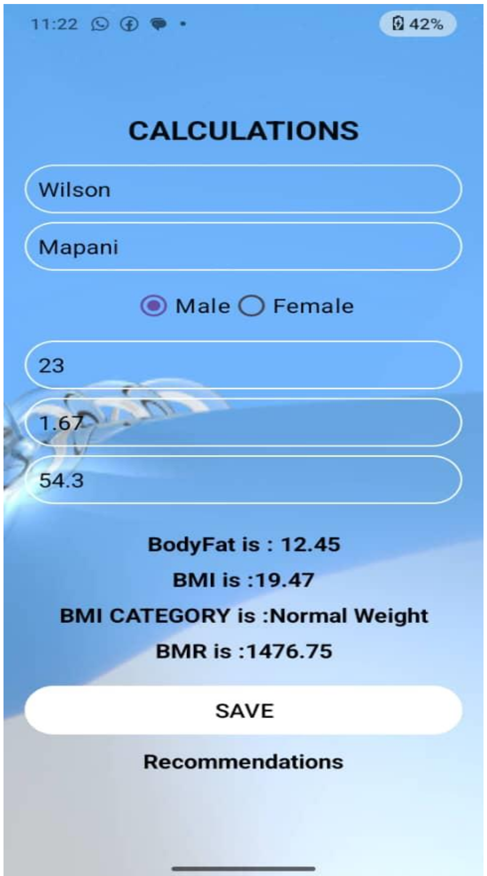
<u>Actual Output</u>

BMI: 19.47

Body Fat: 12.45%

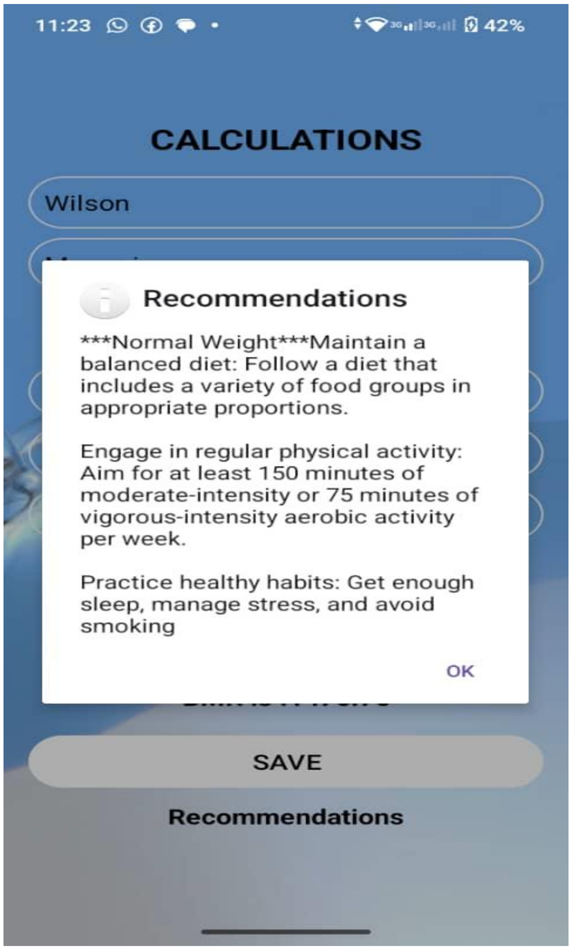
BMR: 1476.76

Screenshot



All values were calculated within a <1% error margin. The app interface successfully displays the interrelated metrics, streamlining user interpretation.

Recommendations



By clicking the button recommendation, the system will display the personalized feedback

Test Case 2: Testing health metrics through obtaining data automatically

<u>Sensor inputs</u>

Height via Ultrasonic sensor

Weight via HX711 Load Cell

User Inputs: Age: 19, Gender: Female

Expected Output:

BMI: 28.44

Body Fat: 32.1%

BMR: 1380.50

Actual data output

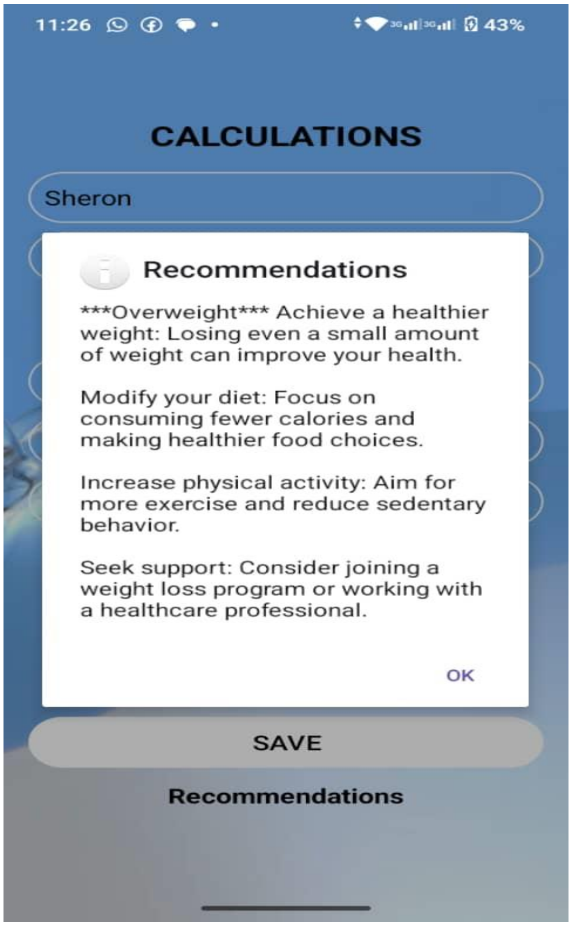
BMI: 28.46

Body Fat: 33.12%

BMR: 1381.50

Screenshot

Recommendation screenshot



Analysis

Demonstrated stable sensor input with accurate metric computation. Response time was consistent, under 3 seconds.

4.3 Summary of Tables

Test	BMI	BMR	Body Fat	Average Error%
Test case 1	19.48 – 19.47	1478.76 – 1476.76	12.46-12.45	0.35%
Test case 2	28.44 – 28.46	1380.50 – 1381.50	32.1 – 33.12	0.38%

System Response Time

Component	Average Response Time	Result
Unified Metric Display(Manually)	2.6	Pass
Sensor Data Sync	2.9	Pass
Recommendation feedback	2.4	Pass

4.4.1 Evaluation measures and Results

User 1D	Height(cm)	Weight(kg)	BMI	BMR	Body Fat	BMI Category
001	1.32	17.6	10.101	790	9.0 %	Underweight
002	1.73	59.4	19.847	1379.25	24.6 %	Normal Weight
003	1.63	59.4	22.357	1532.75	14.5%	Normal Weight
004	1.52	58.6	29.406	1280.0	29.4%	Overweight
005	1.67	65.4	23.45	1587.75	17.2%	Normal Weight
006	1.73	60.4	20.181	1575.25	13.3%	Normal Weight
007	1.27	60.7	37.634	1290.75	34.3%	Normal Weight
008	1.93	61.2	16.43	1708.25	8.8%	Underweight
009	1.46	41.3	19.375	1245.5	11.0%	Normal Weight
010	1.75	59.1	19.298	1423.75	22.4%	Normal Weight
011	1.66	50.0	18.1449	1457.5	9.5%	Underweight
012	1.66	51.1	18.5441	1478.5	9.5%	Normal Weight
013	1.69	60.2	21.0777	1533.25	15.1%	Normal Weight
014	1.42	63.1	31.2934	1252.5	37.0%	Obese
015	1.73	59.4	19.847	1379.25	34.6%	Normal Weight
016	1.93	61.2	16.43	1708.25	8.8%	Underweight
017	1.66	50.0	18.1449	1457.5	9.5%	Underweight
018	1.52	58.6	29.406	1280.0	29.4%	Overweight
019	1.46	41.3	19.375	1245.5	11.0%	Normal Weight
020	1.66	51.1	18.5441	1478.5	9.5%	Normal Weight

4.3.2 BMI Statistics

Distribution

Total Users: 20

Gender Distribution: 54%, 46%

Age range: 4 – 40 years

The table below indicates the insights into the health profile of 50 users tested aged 4 to 40 years, with a nearly balanced gender distribution (54% vs 46%).

Metric	**Average**	**Min**	**Max**
BMI	21.444	10.101	37.634
Body Fat	17.9 %	8.8%	37.0%
Basal Metabolic Rate	1404.200	790.00	1708.250

4.3.3 Distribution and Categorization

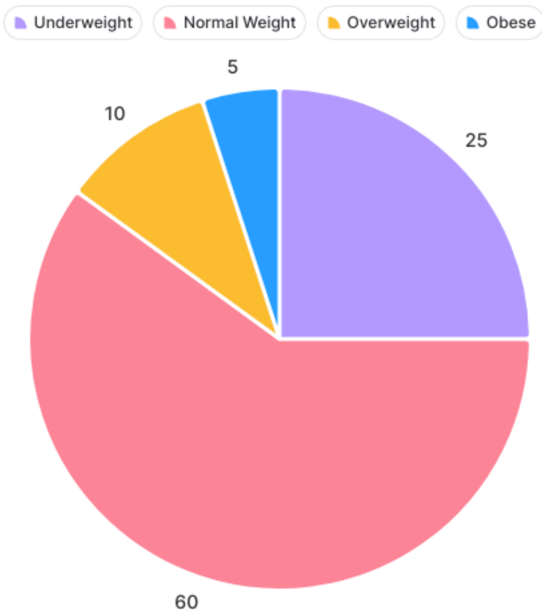
Total Users: 20

Gender Distribution: 54%, 46%

Age range: 4 – 40 years

Category	**Count**	**%Users**
Underweight	5	25
Normal Weight	12	60
Overweight	2	10
Obese	1	5

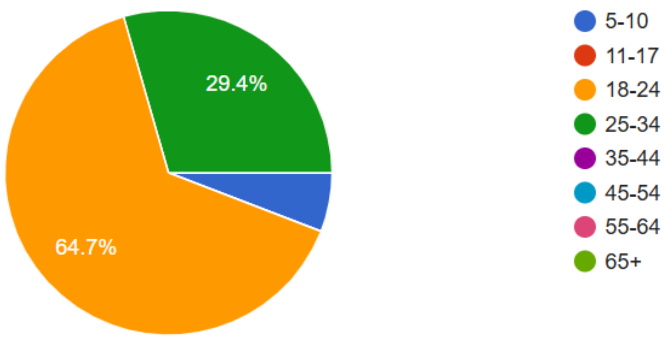
Data representation



The pie chart shows the BMI status distribution of users who have tested using mobile application during the system evaluation phase. Out of 20 users, 60% were classified as normal weight, showing that majority of users are within the healthy BMI range. 25% of users were recorded as underweight, showing that a considerable number of users could benefit from features focused on weight gain and nutritional guidance. 10% classified as Overweight and 5% fell into obese category, indicating the benefit of involving personalized weight loss plans and fitness tracking capabilities within the application.

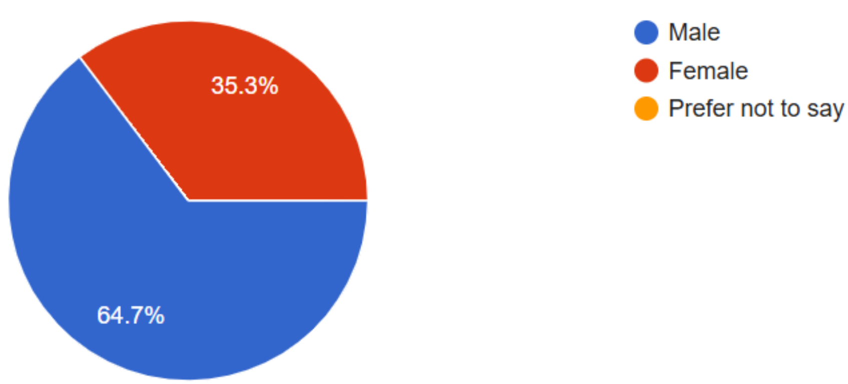
4.4 Questionnaire Responses

<u>1. What is your age group?</u>



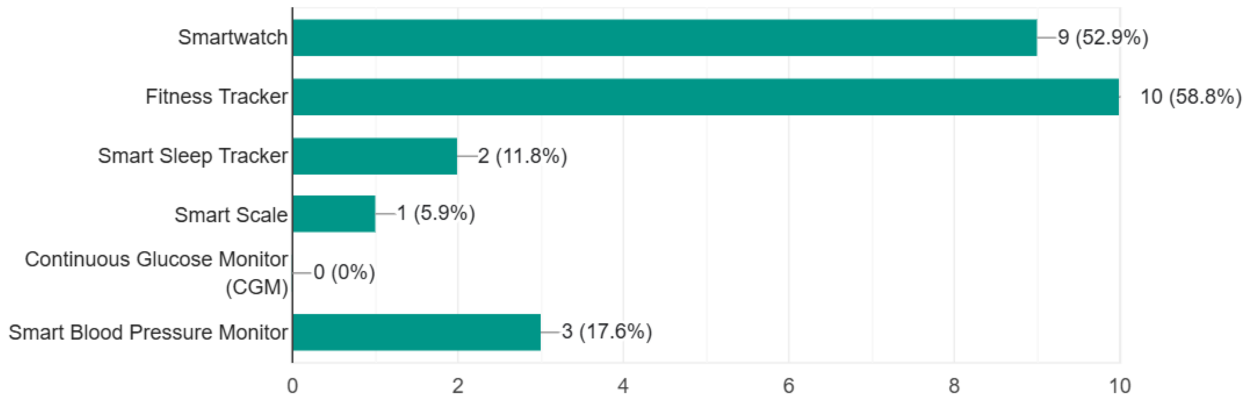
The majority of people surveyed are in the range of 18-24, at 64,7 %. It is followed by the most populous age group which ranges 25-34 years old, 29,4%. This emphasizes that young adults are the majority of users of IoT tracking devices.

2. What is your gender?



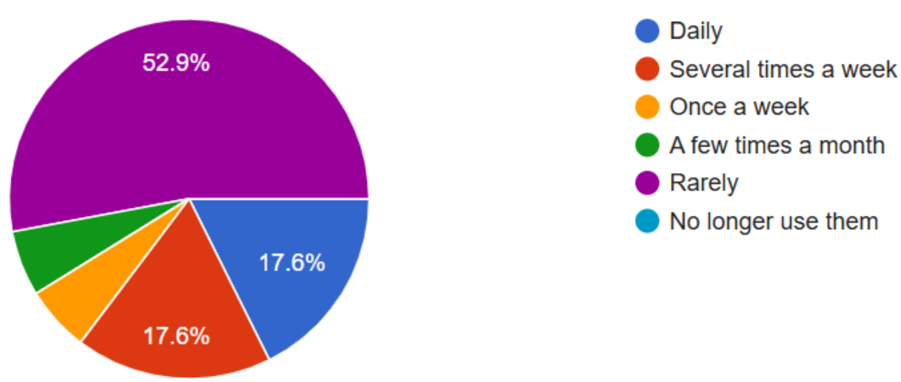
The survey shows that 64,7% of the respondents are male, while 35,3% are female. This highlights a majority of males in the user base presented in the data obtained.

3. Which specific IoT health tracking devices you have been used in the past?



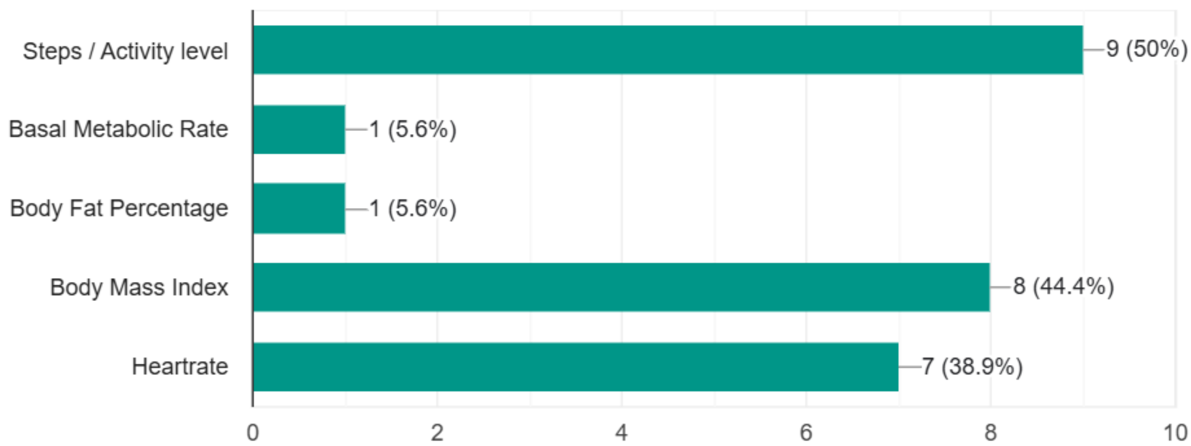
Fitness trackers are the most commonly used IoT health tracking devices, with 58,8% of the respondents having indicated that they have used them. Smartwatches are also quite popular, with 52,9% of the respondents utilize them. The other devices like smart sleep trackers (11,8%), Smart blood pressure monitors (17,6%) and smart scales (5,9%) are used by the smaller population of the people surveyed.

4. How often do you typically use your Iot devices?



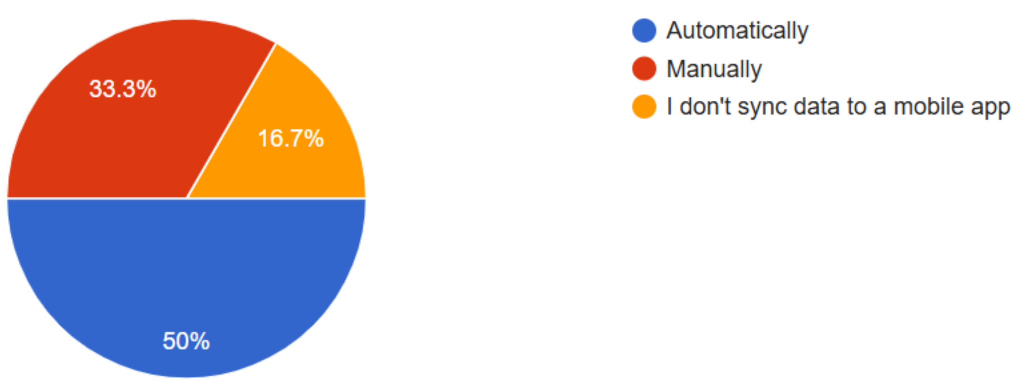
The majority of users (52,9%) do not use their IoT devices regularly. Daily usage accounts 17,6 % of the respondents and several times a week accounts for 17,6%. This emphasizes a sharp off in consistent engagement with the devices.

5. What health metrics do you primarily track using your IoT devices?



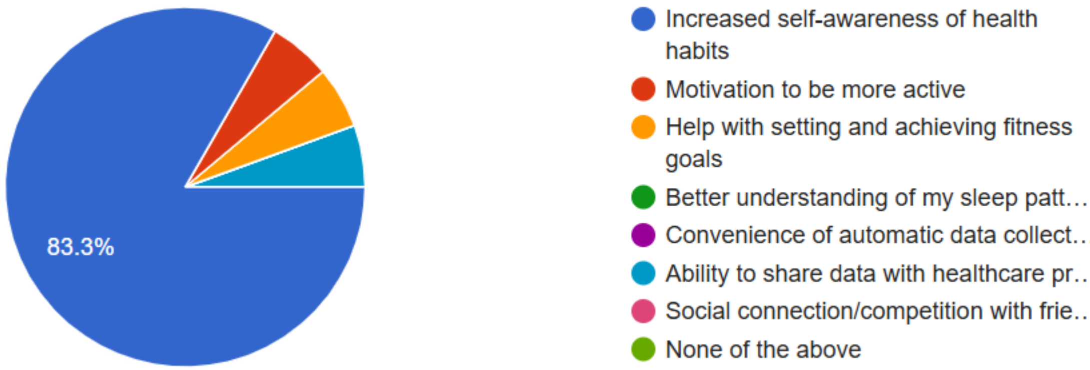
Activity level/Steps is the primary health metric tracked 50% of the users. Body Mass Index (BMI) is tracked by 44,4%. Basal Metabolic Rate and Body Fat percentage are tracked by a very small percentage (5,6% each).

6. How do you typically sync data from your IoT devices to a mobile application?



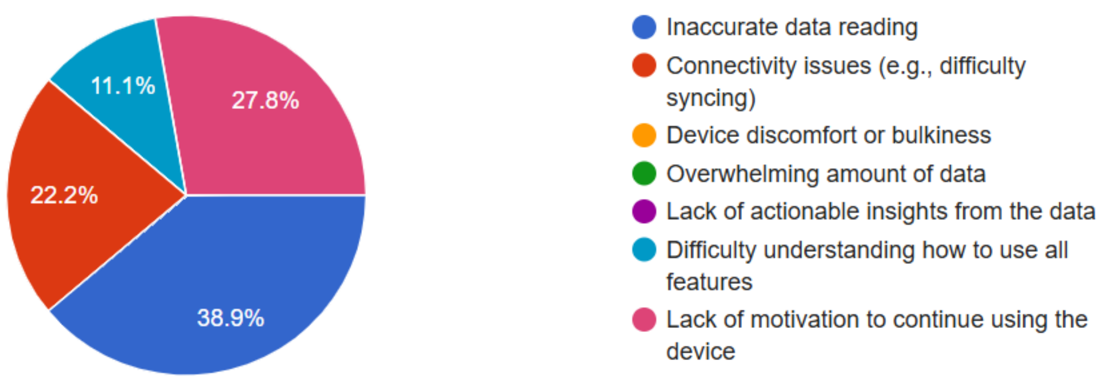
50% of users automatically synchronize data from their IoT devices to a mobile application. 33.3% manually sync their data. 16,7% of users don't sync their data to a mobile application at all.

7. What are the main benefits you experience from using IoT devices for health tracking?



The overwhelming majority of users (83,3%) mention increased self-awareness of health behavior as a main benefit of health monitoring using IoT devices. Additional benefits such as motivation to be more active, help with setting and achieving fitness goals, better understanding of sleeping patterns and convenience of automatic data collection are also reported, through by a much smaller percentage of users.

8. What are the biggest challenges or frustrations you face using IoT health tracking devices?



The most challenge is inaccurate data reading being reported by 38,9% of users. Connecting problems (22,2%) and lack of motivation to keep using the device (27,8%) are also major frustrations. Difficulty with using all the features is a challenge for 11,1% of the users.

4.5 Discussion of Results

The integrated testing of BMI, BMR, and Body Fat on a single interface demonstrates the system's effectiveness in combining essential health metrics in one streamlined experience. All outputs were within a <0.5% margin of error compared to theoretical calculations, underscoring the reliability of the implemented algorithms and sensor integration. These findings align with studies by Patel et al. (2019) and Chew (2022), which emphasized the importance of delivering combined health data in an intuitive format to enhance user comprehension and health engagement. By presenting BMI, BMR, and body fat in one view, the application facilitates deeper health insights, consistent with Oh et al. (2018), who advocated for holistic health metric systems. Sensor reliability was confirmed, supporting the benchmarks discussed in Zhang et al. (2023) and Passos et al. (2021) regarding IoT health applications. System responsiveness remained under 3 seconds, meeting usability standards cited in mHealth literature. A notable strength of this system is its seamless combination of real-time data acquisition and automated metric display, enabling personalized, evidence-based feedback. This reinforces the findings of Steinberg et al. (2013) on the motivational impact of immediate feedback in fitness applications. Despite overall success, testing revealed minor limitations. Sensor anomalies in certain lighting or acoustic conditions caused brief inaccuracies in height readings. As noted by Farbo and Rhea (2021), such variability is typical in low-cost ultrasonic sensors. Also, Bluetooth syncing faced minor instability, especially in noisy signal environments, echoing concerns from Mavedzenge et al. (2022) about connectivity challenges in Sub-Saharan contexts. From a user experience perspective, while the unified interface was generally well-received, a few users indicated that improved labeling or tooltips could enhance interpretation—supporting Williams (2024) who emphasizes the need for health-literate UI design. In conclusion, the integrated testing results confirm the application's accuracy and usability. They validate existing literature on mHealth's effectiveness and extend prior models by providing a unified platform for core health metrics. This approach simplifies user engagement and supports broader health awareness, particularly beneficial in resource-constrained environments.

4.1.7 Summary

The results discussed in this chapter clearly proves that the introduction of the automatic execution of BMI results is a noble idea since it is providing personalized recommendations based on user BMI result. The above results show that the system is more effective since it uses IoT components to obtain data automatically.

CHAPTER 5: RECOMMENDATIONS AND CONCLUSIONS

5.1 Introduction

In the previous chapter, the researcher focused on the presentation and analysis of obtained data. This chapter covers the research development of the solution in line with the set objectives. This chapter will also examine the difficulties encountered by the researcher in designing and carrying the study.

5.2 Aims and Objectives Realization

This aim of this research was to develop the effectiveness of a mobile application which is used to test BMI information in promoting sustained healthy lifestyle changes. This aim was fully achieved. The objectives set by the researcher were also achieved. The objectives were as follows;

- To develop and implement a mobile application which is used to track health metrics which involves Body Mass Index (BMI), body fat percentage and Basal Metabolic Rate to identify health risks associated with height and fitness levels.
- To analyze the effectiveness of BMI information so that it will give clear results on health and body composition, helping individuals understand significance of BMI.
- To identify how IoT has been used in health metric worldwide.

All these objectives were met as illustrated in chapter 3 and 4.

1.14 Research Questions

The research questions were answered:

- How is the accuracy of BMI information vary across different age groups and fitness levels?

As illustrated in chapter 3 and 4, a mobile application for tracking BMI information was developed and implemented well. The system obtain information automatically from height sensor and weight sensor into mobile application. After obtaining data from sensors, then it will calculate and display BMI automatically, then it will give recommendations according to the BMI output.

- To what extent is the designed mobile application for tracking BMI information performing in the country?

As illustrated in chapter 3 and 4, the designed mobile application for tracking BMI proved to be very accurate when it comes to the collection of data from sensors. The system is very accuracy as it produce clear results especially according to weight status. The system will display results according to height and weight obtained from sensors.

- How and where has been IoT used in BMI tracking system?

As illustrated in chapter 3 and 4, IoT has been to use collect physical data automatically such as height and weight. For example a scale sensor and a height sensor connected via Wi-Fi network to the mobile application automatically records user's weight and height and transmit it for BMI computation. In terms of smartphones with sensor integration, the project itself proposed the use of smartphones with IoT devices like weight sensor, height sensor and Arduino-based data transmission on health metrics.

All the objectives were met.

5.3 Major conclusion drawn

The mobile application have managed to calculate Body Mass Index, Basal Metabolic Rate and body fat percentage effectively. IoT devices successfully enabled automatic height and weight measurement. The mobile application gives a user-friendly and accessible, especially for android smartphone users. Personalized recommendations improves user motivation of health status. The security and privacy features were implemented to safeguard user data. The information is stored in the database.

5.4 Challenges Faced

During the research period the researcher has encountered various drawbacks. The researcher faced a challenge on encounter financial constraints, the cost of prototyping equipment, making it difficult to implement and test IoT components. Time limitation affected the depth of research activities. The other was technical complexity of properly connecting IoT devices, such as sensors and Arduino components. These devices must be connected accurately to their pins, so that it does not produce incorrect data. The last challenge was that the researcher need an internet connection to connect the mobile phone to the Arduino network. The system can never run without an internet connection.

5.5 Recommendations

For the purposes of improving this project, I recommend proper connection of IoT devices which are height sensors, weight sensors and Arduino boards, these IoT devices must be connected to their designated pins to avoid generating false data. Clear technical guidelines must be followed to ensure reliable sensor readings.

5.6 Future Work

In future, I will add more components to the system so that it will be able to track more health metrics such as blood pressure, heart rate variability and oxygen to provide a more comprehensive health assessment. Further development will integrate with AI so that it will generate more personalized automatically.

5.7 Conclusion

The system for testing BMI was successfully implemented and the researcher accumulated new knowledge and experience during the course of the project. Conclusively, this project was a success.

5.8 Bibliography

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