Gordon Institute of Business Science
University of Pretoria

Fitness wearable device adoption intention: A cross-sectional quantitative analysis

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A research project submitted to the Gordon Institute of Business Science. University of Pretoria, in partial fulfilment of the requirements for the degree of Masters of Business Administration

04 March 2025

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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04 March 2025

Abstract

Wearable fitness technology promises to offer health benefits to its users by monitoring and tracking activity and health metrics. Despite their promise to improve livelihoods and wellness, wearable fitness devices' adoption and usage rates have been muted, particularly in emerging economies. Many academic scholars have shown interest in the wearable device adoption domain in response to the low adoption and usage business challenge. However, the influence of general health and vitality perception on adoption intention has not been tested.

The study aimed to uncover health-related constructs that drive the inclination to adopt and use wearable devices. This study was a cross-sectional quantitative analysis with 120 participants who reported owning a wearable fitness device. This study employed weighted least squares regression analysis to reach the funding.

The four hypotheses were well supported: Intention to adopt wearable fitness devices was strongly recited by general health, vitality, and social influence. This study further revealed that the intention to adopt significantly explained variation in Actual use. Increasing the adoption rate of wearable devices may lead to better health outcomes for users and societies. Practitioners are encouraged to tailor their marketing strategies to appeal to the user by targeting wellness and health-conscious users. Future research should study more health-related constructs.

Keywords: General health, vitality, social influence, adoption intention

Table of Contents

Declaration .... **i**

Abstract .... **ii**

Table of Contents .... **iii**

List of Figures .... **ix**

List of Tables .... **x**

List of Acronyms .... **xii**

Chapter 1: Introduction to the Research Problem **1**

1.1 Introduction 1

1.2 Research Business Need 1

1.2.1 Wearable Fitness Tracker Market 2

1.3 Research Theoretical Need 2

1.4 Objectives of the Study and Context 4

1.5 Conclusion 5

Chapter 2: Literature Review **6**

2.1 Introduction 6

2.2 Wearable Fitness Technology 6

2.3 Theory Underpinning 6

2.3.1 Technology Adoption Model 6

2.3.2 Unified Theory of Adoption and The Use of Technology 7

2.4 Predictors Influencing the Intent to Adopt a Fitness Wearable Device 8

2.4.1 Health Consciousness 8

2.4.2 Health Motivation 9

2.4.3 Healthology 10

2.4.4 Health Belief 10

2.4.5 Health Interest 11

2.4.6 Health Improvement Expectancy 12

2.4.7 Quality of Life ... 12

2.4.8 Observed Gaps in Literature Relating to Health Constructs ... 13

2.4.9 Mental Health, Anxiety, and Vitality ... 13

2.4.9.1 Depression and Anxiety ... 13

2.4.9.2 Health Anxiety ... 14

2.4.9.3 Psychological Distress and Factors ... 14

2.4.9.4 Observed Gap in Literature Related to Mental State ... 16

2.4.10 Social Influence ... 16

2.4.10.1 Social Influence and Intention to Adopt Wearable Devices ... 17

2.4.10.2 Gaps in the Literature Related to Social Influence ... 20

2.4.11 Relevant Studies ... 20

2.5 Actual Use of Wearable Devices ... 21

2.6 Definition of Key Constructs ... 22

2.6.1 General Health (GH) ... 22

2.6.2 Vitality (VT) ... 22

2.6.3 Social Influence (SI) ... 22

2.6.4 Intention to Adopt (IA) ... 22

2.6.5 Actual Use (AU) ... 23

2.7 Chapter Summary ... 23

Chapter 3: Hypotheses ... 24

3.1 Introduction ... 24

3.2 Theory Model ... 24

3.3 Hypothesis Formulation ... 25

3.3.1 General health (GH) and Intention to Adopt (IA) (H1) ... 25

3.3.2 Vitality (VT) and Intention to Adopt (IA) (H2) ... 25

3.3.3 Social Influence (SI) and Intention to Adopt (IA) (H3) ... 25

3.3.4 Intention to Adopt and Actual Use (H4) ... 26

3.4 Chapter Summary ... 26

Chapter 4: Research Methodology and Design 27

4.1 Introduction 27

4.2 Purpose of Research Design 27

4.2.1 Research Philosophy 27

4.2.2 Strategy 28

4.2.3 Methodological Choices 28

4.2.4 Time Horizon 28

4.3 Population 29

4.4 Unit of Analysis 29

4.5 Sampling Technique Method and Size 30

4.6 Measurement Instrument 30

4.6.1 Studies that Employed Health Survey to Measure Health 30

4.6.2 General Health Definition 31

4.6.3 Vitality Definition 31

4.6.4 Questionnaires 31

4.7 Pilot Study 32

4.8 Data Collection Process 33

4.9 Data Analysis and Quality 33

4.9.1 Data Gathering 33

4.9.2 Missing Data 34

4.9.3 Normality 34

4.9.4 Outliers 34

4.9.5 Validity 35

4.9.5.1 Bivariate Pearson Correlation 35

4.9.5.2 Standardised Loadings and Average Variance Extracted 35

4.9.6 Reliability 36

4.9.7 Dimension Reduction 36

4.9.8 Descriptive Statistics 37

4.9.9 Hypotheses Testing 37
4.9.10 Weighted Least Square Regression 38
4.10 Limitations 38
4.11 Ethical Considerations 39
4.12 Chapter Summary 39
Chapter 5: Results 40
5.1 Introduction 40
5.2 Data Collection 40
5.3 Data Preparation 41
5.4 Missing Data 41
5.5 Descriptive Statistics 42
5.5.1 Age Demographics 42
5.5.2 General Health 42
5.5.3 Vitality Score 43
5.5.4 Social Influence 44
5.5.5 Intention to Adopt 44
5.5.6 Actual Use 45
5.6 Statistical Analysis 46
5.6.1 Normality 46
5.6.2 Outliers 47
5.6.3 Validity 48
5.6.3.1 Convergent Validity 48
5.6.3.2 Convergent Validity – Standardised Loadings 51
5.6.4 Reliability 52
5.6.5 Dimension Reduction 54
5.7 Hypotheses Testing 55
5.7.1 Assumptions of Regression Analysis 55
5.7.2 Outliers 56

5.7.3 Homoscedastic and Heteroskedastic Test 56

5.7.4 Multicollinearity 57

5.7.5 H1: General Health (GH) Positively Influences Intention to Adopt (IA) Fitness Wearable Device 57

5.7.6 H2: Vitality (VT) Positively Influences Intention to Adopt (IA) Fitness Wearable Device 59

5.7.7 H3: Social Influence Has a Positive Influence on Intention to Adopt Fitness Wearable Devices 60

5.7.8 H4: Intention to Adopt Positively Influences Actual Use of Fitness Wearable Devices 62

5.8 Chapter Summary 64

Chapter 6: Discussion of Results 65

6.1 Introduction 65

6.2 Summary of Results 65

6.3 Data Collection 66

6.4 Descriptive Statistics 67

6.4.1 Age Demography 67

6.5 Statistical Analysis 67

6.6 Hypothesis Testing 67

6.6.1 H1: General Health (GH) is a Significant Predictor of Intention to Adopt (IA) Wearable Fitness Device 67

6.6.2 H2: Vitality (VT) Positively Influences Intention to Adopt (IA) Fitness Wearable Device 70

6.6.3 H3: Social influence (SI) has a Positive Influence on Intention to Adopt (IA) Fitness Wearable Devices 72

6.6.4 H4: Intention to Adopt (IA) Positively Influences Actual Use (AU) of Fitness Wearable Devices 74

6.7 Empirical Model 76

6.8 Chapter Summary 78

Chapter 7: Conclusion and Recommendations 79

7.1 Introduction 79

7.2 Significance of the study 80

7.3 Reflections on Research Context 80

7.4 Methodology Overview 81

7.5 Main Results 82

7.6 Academic Contribution 83

7.7 Recommendations 83

7.8 Limitations and Areas for Future Studies 84

7.9 Study Conclusion 84

References 85

List of Appendices 97

Appendix A: Invitation to Participate and Consent Statement 98

Appendix B: Instrument – Questionnaire 99

Appendix C: Ethical Approval 102

Appendix D: Except of Raw Data 103

Appendix E: Code Book 104

Appendix F: Factor Analysis 106

Appendix G: Regression Test Results – Social Influence and Intention to Adopt 111

Appendix H: Regression Test Results – Vitality and Intention to Adopt 115

Appendix I: Regression Test Results: – Actual Use and Intention to Adopt 116

Appendix J: Regression Test Results – Actual Use and Intention to Adopt 118

Appendix K: Regression Test Results – Actual Use and General Health 120

Appendix L: Weighted Least Squares Regression Test Results – Actual Use and General Health 122

Appendix M: Weighted Least Squares Regression Test Results – Actual Use and Vitality 123

List of Figures

Figure 2.1: Merged Models..8

Figure 3.1: Conceptual Model 24

Figure 5.1: Age Demographic...42

Figure 5.2: General Health Levels...43

Figure 5.3: Vitality Scores..43

Figure 5.4: Social Influence Scores...44

Figure 5.5: Intention to Adopt Levels...45

Figure 5.6: Actual Use Levels..45

Figure 5.7: Heteroskedastic Test Results..56

Figure 6.1:Empirical Model..77

List of Tables

Table 2.1: Model Adaptation 7

Table 4.1: Measuring Instruments 31

Table 5.1: Missing Data Record 41

Table 5.2: Skewness and Kurtosis Test Results 46

Table 5.3: Kolmogorov-Smirnova and Shapiro-Wilk 47

Table 5.4: Percentage Outliers 48

Table 5.5: Bivariate Pearson Correlation 49

Table 5.6: Standardised Loading 52

Table 5.7: Cronbach's Alpha 53

Table 5.8: Reliability Test 53

Table 5.9: KMO and Bartlett's Test 54

Table 5.10: Outlier Percentage 56

Table 5.11: Collinearity Test Results 57

Table 5.12: Weighted Least Square Regression Summary for GH and IA 57

Table 5.13: Weighted Least Square Regression Anova GH and IA 58

Table 5.14: Weighted Least Square Regression Coefficients for GH and IA 58

Table 5.15: Weighted Least Square Regression Summary VT and IA 59

Table 5.16: Weighted Least Square Regression Anova VT and IA 59

Table 5.17: Weighted Least Square Regression Coefficients 60

Table 5.18: Regression Summary SI and IA 60

Table 5.19: Anova SI and IA, Weighted Least Square 61

Table 5.20: Regression Coefficients for SI and IA 61

Table 5.21: Regression Summary IA and AU 62

Table 5.22: ANOVA IA and AU 63

Table 5.23: Regression Coefficient IA and AU 63

Table 6.1: Summary of Results..65

Table 6.2: Empirical Model Rationale 77

List of Acronyms

AU	Actual Use
AVE	Average Variance Extracted
CR	Composite Reliability
GH	General Health
IA's	Intention to Adopt
KMO	Kaiser-Meyer Olkin
ME	Measurement Error
PLS-SEM	Partial Least Square Structural Equation Model
QoL	Quality of Life
SF	Short Form (Health Survey)
SI	Social Influence
SPSS	Statistical Package for Social Science
Stats SA	Statistics South Africa
SW	Shapiro-Wilk
TAM	Technology Adoption Model
TRI	Technology Readiness Index
USD	United States Dollar
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
VBN	Value Belief Norm
VIF	Variance Inflation Factors
VT	Vitality
WHO	World Health Organisation
WLS	Weighted Least Square

Chapter 1: Introduction to the Research Problem

1.1 Introduction

Chapter 1 introduces the background of wearable fitness devices and the academic and business challenges that gave rise to this research. This chapter further outlines academic findings related to the topics, consequently exposing the gap in the literature. Lastly, the research problem statement and objectives were also addressed.

1.2 Research Business Need

Self-monitoring devices have become known for reducing potential health risks, but adoption rates in emerging countries have been noticeably low (Yang et al., 2022b). Health issues such as obesity affect the worldwide community (1). According to the World Health Organisation (WHO), non-communicable disease mortality is led by physical inactivity, further citing that an inactive lifestyle surges mortality risk by 20% to 30% compared to physically active people (WHO, 2024b). Research by the World Health Organisation reported that 31% of people globally lack physical activity as they do not meet the 2.5 hours of bodily activity per seven days (Strain et al., 2024). Non-communicable illness health risks can be reduced by reducing alcohol consumption, unhealthy food choices, and increasing physical activity (Kristoffersson & Lindén, 2020). Studies have proved that utilising wearable fitness devices aids in providing health-related data that aid people in managing their health status (Yang et al., 2022b). A tracking technology that can be fixed on a person is called a fitness device (Swan, 2012). Fitness trackers are smart bands and smartwatches that can monitor heart rate and physical activities and can be connected to smartphones.

Wearable fitness devices are health-related technology that tracks the physiological activity of the user (Farivar et al., 2020). Wearable devices can also be interlinked with medical doctors' data to accurately diagnose and manage the user's or patients' health (Farivar et al., 2020). Bayoumy et al. (2021) demonstrated that wearable devices can predict users' health and prevent potential illnesses. Users of wearable devices can harness the health benefits that come with the data and information to make better health choices for improved Quality of Life (QoL).

1.2.1 Wearable Fitness Tracker Market

The worldwide fitness tracker market revenue is expected to surpass USD 45.66 billion in 2025, with a predicted 5.61% yearly growth rate (Statista, 2025b). The user penetration will be 11.03% in 2025 (Statista, 2025b). Despite a global increase in penetration rate, the average revenue per user has shown a considerable decline of 60% from 2017 to 2025, accounting for a 10% decline annually (Statista, 2025b). In South Africa, the industry revenue for fitness devices is forecasted to be USD 228.97 million in 2025, with a 5.03% yearly growth rate and a penetration rate of 10% for the next five years. The total decline rate in average revenue per user in South Africa was calculated to be 84%, indicating an annual decline rate of 20.47% (Statista, 2025a). Low adoption rate in emerging countries has been cited by (Yang et al., 2022a). Talukder et al. (2020a) recently posited that the adoption rate for wearable fitness devices remains low even in a country like China. South Africa's adoption rate for wearable devices is less pronounced, and the reasons behind the low level of acceptance by consumers are not fully known (Muller, 2022). Although wearable health devices hold significant promise for enhancing health outcomes and livelihood, their adoption rate among users remains low. This research intends to examine factors that may influence the adoption and actual use of wearable devices, particularly those related to health.

To increase wearable fitness adoption rates, it is imperative that a solution be devised to enable technology suppliers, manufacturers and marketers to innovatively appeal to potential and current audiences. By so doing, increased adoption and usage rate may result in better, healthier lives and wellness (Bao & Lee, 2024). Moreover, increased adoption and usage rate of wearable fitness devices may aid in minimising hospitalisation costs associated with patient admissions (Sergueeva et al., 2020).

1.3 Research Theoretical Need

Yang et al. (2024) employed Value Belief Norm (VBN) to test how health-related constructs influence the adoption intention of wearable fitness technology and actual usage in a Chinese sample aged 18-30. Findings by Yang et al. (2024) posited that social norms, health value, consciousness, and knowledge-seeking are significant predictors of adoption intention for wearable fitness technology. Moreover, the intention to adopt significantly influenced the actual usage of wearable tracking devices (Yang et al., 2024). Because this research was completed in China, scholars like Yang et al. (2024)

canvassed for more similar studies with additional health constructs to be carried out in countries demographically different from China. China has a population of 1.4 billion (Trading Economics, 2025), with 61% and 22% falling in the 16–69 years, 60 years, and older age groups, respectively (Textor, 2025). The researcher has proposed to test General Health, Social Influence, and Vitality in relation to the intention to adopt and actual usage of personal fitness devices in South Africa.

According to Statistics South Africa (Stats SA) (2025), the population in South Africa is 64 million, with 67% of the people aged 15–64 years and 7% above the age of 65. According to Hofstede's (2025) country culture tool, China is less individualistic compared to South Africa from a cultural perspective. South Africa has a high proportion of people aged 15–64 and a small number of older adults (Stats SA, 2025). Significant cultural differences warrant testing other health variables, including General Health and Vitality, on the intention to adopt tracking devices.

Many researchers, like Sergueeva et al. (2020), tested antecedents that affect the wearable tracker's intention to adopt. However, such scholars asserted that health status or concern should be tested based on adoption intention. Therefore, this study tests the influence of General Health and Vitality perception on adoption intention and actual usage. This study is unique in that General Health and Vitality perceptions have not been tested according to the literature reviewed for the last five years.

QoL significantly influenced the adoption and actual usage of personal fitness devices in Ghana (Larnyo et al., 2022). QoL is measured using Health Short Survey 36, which comprises eight subscales with General Health and vitality as one of the subscales (Ware et al., 1993). Larnyo et al.'s (2022) study is unique because, within the last five years, no record has shown that the Short Survey 36 measuring instrument has been used to measure a health construct such as QoL. However, a gap in the literature exists to measure General Health and Vitality using each subscale of the Short Survey 36 against the adoption intention of wearable devices. This will enrich the current state of understating of antecedents responsible for the intent to adopt wearable personal devices.

Fitness wearable technology dates back to 2009 in the market with the promise to transform adopter's livelihoods by giving them physical activity and health information (Muller, 2022). Fitness devices are likely to boost users' welfare if frequently used to track and engage in physical activities (Farivar et al., 2020). Larnyo et al. (2022) results posited that QoL was important in describing the intention to adopt wearable fitness devices. Despite the benefits that come with the adoption and usage of wearable fitness devices, the adoption rate for such devices remains low, more so in South Africa (Muller, 2022). According to Statista (2025b), the global acceptance rate is calculated to be 11% in 2025, with a yearly 5% growth rate for the South African market. The second problem is the low usage rate, which can be attributed to a dire 10% annual global decline in average revenue per user. The low adoption rate and low sustained use of such fitness devices can be perceived as obstacles that require to be solved for the user's health benefit and improved financial gain for device companies.

Non-communicable illness contributes significantly to mortality rates of the present day (Natalucci et al., 2023) as it accounts for over 73% of all motilities worldwide (WHO, 2024a). The risk factors include inadequate physical activity. The consequences of inactivity increase the risk of cardiovascular disease, diabetes, obesity and mental health and increase mortality rate (Białkowski et al., 2024). Thereby increasing the cost of the healthcare system for society (Białkowski et al., 2024). The risk and consequences of not fully understanding the drivers for the intention to adopt will result in unfruitful business decisions and strategies.

A number of scholars have explored various health-related constructs to determine their role in intention to adopt and actual usage. However, many of them still canvasse for additional studies to be undertaken to gain a comprehensive understanding of wearable fitness technology devices. For instance, health consciousness is a significant predictor of adoption intention for wearable medical devices (Yang et al., 2022a). Social influence was found to play a major influence on the intention to adopt wearable fitness technology, to name a few. An extensive literature review has proved that health status, more specifically General Health and Vitality, has not been explored to determine their role in the intention to adopt wearable fitness devices.

1.4 Objectives of the Study and Context

This investigation assesses the influence of General Health and Vitality on the adoption of wearable fitness devices. This research also studies the role of Social Influence on adoption intention and actual usage. A comprehensive analysis of how such health-related constructs affect fitness device adoption intention empowers wearable fitness device company owners and marketers to design and offer technology that appeals to their customers, which could increase adoption and usage rates.

This study is focused on surveying adults between the ages of 18 and above 60 as they are not part of the vulnerable population, are more likely to understand the question, and are likely to adopt wearable technology. Their primary geographic focus is on people living in South Africa because the country is developing and was cited as a low adopter of wearable fitness devices. Most respondents would generally be located in metropolitan areas such as Johannesburg and Cape Town to make the data-gathering process practical. The study was a survey-based cross-sectional study where respondents answered structured questionnaires using peer-reviewed measuring instruments. This study only focuses on wearable fitness trackers such as smartwatches and fitness wristbands.

1.5 Conclusion

In conclusion, wearable devices have a significant role in encouraging healthy lifestyles. However, adoption intent and usage rate have not been satisfactory, thereby impacting business. The conducted literature search and review suggest that fitness tracker devices are underexplored, and there's a need for further investigation into the antecedents of wearable fitness devices. The following chapter goes into detail to discuss links between General Health, Vitality perception, and Social Influence on intention to adopt.

Chapter 2: Literature Review

2.1 Introduction

Chapter 2 discusses academic findings on adoption intent and actual usage of wearable fitness devices from a health perspective. Health consciousness, QoL and health belief are some of the constructs that are presented. Chapter 2 presents the foundation theoretical framework that underpins this research and further exposes gaps in the literature. Lastly, the definition of key constructs is outlined. The key constructs that are defined in the chapter are General Health, Vitality, Intention to adopt and social influence.

2.2 Wearable Fitness Technology

Recently, scholars have had a high interest in appreciating the acceptance and use of wearable technology more from a wellbeing viewpoint (Mishra et al., 2023). Users of wearable personal devices are able to control their wellbeing while conducting regular work or home functions (Hayat et al., 2022a). Such wearable devices can be coupled with cellular devices through connectivity technology (Lee & Lee, 2020). Tracking of health conditions and instantaneous monitoring are some of the benefits that many brands like Fitbit use to market to their users (Wang et al., 2020). User health data like blood pressure, body temperature, cardio metrics and sugar levels in the blood can be measured and managed by wearable technologies (Talukder et al., 2020b). There are six groupings of wearable technologies. The most common are smart watches, followed by electrocardiogram chest straps and fitness trackers, which were number three most known to consumers (Huhn et al., 2022). This study focussed on wearable fitness devices, as well as medical wearable devices.

2.3 Theory Underpinning

2.3.1 Technology Adoption Model

This study is based on the Technology Adoption Model (TAM) by Davis et al. (1989). TAM was proposed to comprehend fully the reason behind the lack of adoption of computer technology in the work environment, while the perception was that companies could improve performance (Davis et al., 1989). TAM is useful to evaluate users' likelihood to adopt technology, given user intention analysis. Subjective norms, user usefulness perception attitude and ease of use perception can explain the intent to adopt (Davis et al., 1989). Singh et al. (2022) explored factors that drive wearable devices to influence their adoption intention employing TAM. Therefore, this study adopts the TAM to assess the proposed predictors of behavioural intent (intention to adopt).

2.3.2 Unified Theory of Adoption and The Use of Technology

TAM proved effective in organisational contexts; however, its applicability at the individual level was questioned due to its lack of consideration for voluntariness and social influence construct (Venkatesh & Davis, 2000). TAM was subsequently revised to incorporate elements of social influence and perceptive extents (Pancar & Ozkan Yildirim, 2023). This revision led to the development of the Unified Theory of Acceptance and Use of Technology (UTAUT) (Pancar & Ozkan Yildirim, 2023). The UTAUT model is recommended for this research on wearable fitness technology, with the proposed constructs aligned with the foundational theoretical model presented in Table 2.1.

Table 2.1: Model Adaptation

<table>
<tr><th>Proposed model</th><th>UTAUT model</th><th>Definition</th></tr>
<tr><td>General Health (GH)</td><td>Performance Expectancy</td><td rowspan="5">User perception about personal gains due to the use of a device (Venkatesh et al., 2003)</td></tr>
<tr><td>Vitality (VT)</td><td>Performance Expectancy</td></tr>
<tr><td>Social Influence (SI)</td><td>Social Influence</td></tr>
<tr><td>Intention to Adopt (IA)</td><td>Behavioural Intention</td></tr>
<tr><td>Actual Use (AU)</td><td>Use Behaviour</td></tr>
</table>

Source: Author's own.

Many scholars have employed quantitative methods to determine factors that drive technology adoption, with UTAUT being the most common. The UTAUT included several variables, including hedonic motivation, perceived usefulness and effort expectancy; however, in this study, health-related variables were explored to focus on the objectives of the research. Literature on health consciousness, health anxiety, and social influence impact on wearable devices has been extensively explored, and as a result, gaps in literature have been identified. Such gaps include General Health and Vitality being underexplored and actual usage of wearable devices not being well understood. UTAUT model was used as a baseline to respond to this study's objectives, specifically those related to health constructs (Figure 2.1).

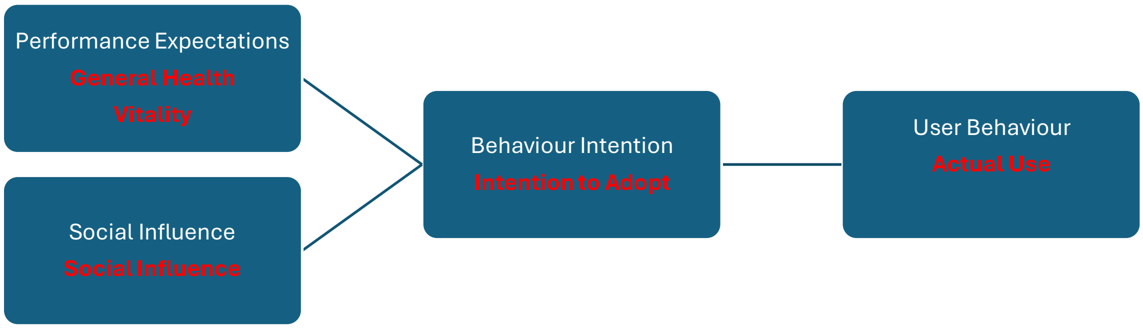

Figure 2.1: Merged Models

Source: Author's own.

2.4 Predictors Influencing the Intent to Adopt a Fitness Wearable Device

The following section outlines the current literature on health-related factors that influence or do not influence wearable fitness devices. These health factors include health motivation, health status, and QoL, among others. This section also discusses identified gaps in academic literature that require researchers' attention. Additionally, definitions of key terms have been presented.

2.4.1 Health Consciousness

Health consciousness has no significant impact on the intent to adopt fitness technology (Sergueeva et al., 2020). Similarly, Jo et al. (2019) reported that using wearable tracking devices did not significantly affect health indicators like weight reduction, lipid level, blood pressure or diabetes. The authors recommended further studies to validate or challenge these findings and to explore the effects of fitness device adoption on health results. However, the findings by Yang et al. (2022a) found contradicting results were health consciousness, perceived cost, accuracy of the technology, usefulness, and perceived compatibility revealed to be important in influencing the intent to adopt fitness technology. These results on health consciousness were inconsistent with Hayat et al. (2022b).

The inconsistency of results relating to health consciousness indicates a need for further study on how health-related measures influence the intention to adopt wearable technology. Secondly, as much as Jo et al. (2019) found intent to adopt fitness wearable technology not significant in predicting health status indicators, an opportunity exists to test whether health status indicators can predict intention to adopt.

2.4.2 Health Motivation

Hayat et al. (2022a) further investigated the effects of perceived product value on health motivation and adoption intent for clinical wearable devices. For context, taking part in preventative health actions with a strong desire is defined as health motivation (Dehghani et al., 2018). Dehghani et al. (2018) posited that health motivation moderates the intent to use and adopt wearable medical technology (Hayat et al., 2022a). The structural Equation Model was employed by Hayat et al. (2022a), which was similar to the research analysis methods performed by Yang et al. (2022a). Furthermore, health motivation was an insignificant predictor of adopting wearable medical devices (Hayat et al., 2022a).

Though this study included a health motivation construct to test its effects on perceived product value and intent to adopt wearable medical devices, the findings were constrained by the number of health variables (Hayat et al., 2022a). As a result of the limitation mentioned above, additional health-related construct antecedents should be investigated on how they influence the intent to adopt, and the actual usage of wearable devices is warranted. Bianchi et al. (2023) results suggested that health motivation could explain perceived usefulness, which in turn leads to intent to adopt health wearable devices in Chile. Given the potential benefit of wearable devices, academic studies in developing countries remain mute; as such, future research can explore this gap (Bianchi et al., 2023)

2.4.3 Healthology

Dehghani et al. (2018) proposed the term healthology, which explains the integration of health matters, technology, and information to provide noble healthcare requirements. Dehghani et al. (2018) found that aesthetic appeal positively influenced continuous intention and actual use, whereas complementary goods and healthology were insignificant predictors of continuous intention. However, healthology was significant in explaining the actual use of wearable health technology (Dehghani et al., 2018). The research by Dehghani et al. (2018) contributed positively to the current literature by introducing a novel model for constructs that predict continuous intent and actual usage of wearable health technology. On the contrary, the results of Seman et al. (2022) proved that healthology had no effect on the intention to adopt smartwatches. The reason for the mixed results could be due to the fact that smartwatches are different from a utility perspective compared to wearable fitness or health devices despite the fact that smartwatches might have fitness tracking devices. The difference in the findings also necessitates future research opportunities.

2.4.4 Health Belief

Zhang et al. (2017) further advanced insights on variables that affect intent to adopt wearable devices in healthcare by investigating health, technical, and consumer attributes. Health attributes (health beliefs) positively influenced the adoption intention of wearable wellness technologies. Technical factors (user convenience perception, usefulness perception, irreplaceability perception) and user attributes significantly influence intent to adopt health technology (Zhang et al., 2017). Studies on the intention to adopt health wearable devices are relatively new and scarce (Zhang & Mao, 2023). Therefore, further studies are needed to uncover deeper insights (Zhang et al., 2017). Additional investigations are needed to fully comprehend the factors influencing intention to adopt and actual use, more so within the health domain framework. Cheung et al. (2019) claimed that the intent to adopt wearable technology could be attributed to how the user perceives its use and how the customer views its novelty. The study by Cheung et al. (2019) was conducted in Hong Kong, meaning that its findings cannot be applied universally. This could prompt more studies to be conducted elsewhere in terms of different economic or cultural aspects.

Zhang et al. (2017) results on the effects of health belief on intent to adopt health devices were consistent with those of Chau et al. (2019). Firstly, they asserted that the antecedents of drivers for the adoption intention of health devices are limited. Moreover, Rehman et al. (2021) found health beliefs to be significant in predicting the intent to adopt wearable technology. Although Rehman et al. (2021) introduced replicated health belief construct in Saudi Arabia to increase generalisability and further introduced health information accuracy in the wearable device adoption intention, little is known regarding further health constructs, such as how General Health and Vitality using the Short Form Health Survey (SF) 36 influences adoption of wearable fitness technology. Lastly, Rehman et al. (2021) did not include actual use of the device as an additional natural step after adoption is established, which could add to the current literature.

2.4.5 Health Interest

Constructs that affect the intent to adopt a fitness tracker were further enhanced by Lee and Lee (2018), who tested constructs such as health interest, self-efficacy, personal innovation, interpersonal influence, and perceived expensiveness on intention to adopt. Two groups were tested: those who already knew about fitness trackers and those unaware of such a device (Lee & Lee, 2018). The results show that health interest, consumer attitude, and personal innovativeness positively and significantly influenced intent to adopt wearable fitness technology. The research contributed positively to the body of knowledge by incorporating health interests within its model (Lee & Lee, 2018). Future research should test the intent to adopt various health-monitoring fitness technology.

One of the limitations of Lee and Lee's (2018) study is that it was conducted in Hong Kong, rendering the results not generalisable across the world. As such, replication of this study in other parts of the world, like South Africa, with various cultures and income levels, would increase generalisability. More possible factors that drive the intention to adopt should be further tested, including health (Lee & Lee, 2018). Such possible factors could be the study of General Health measured by SF-36 on fitness adoption intention. Although Kang (2022) did not study health interests and the intention to continue using wearable health technology, they made an assertion that users' health interests should be explored to generate new insight. This could suggest that General Health and Vitality could be explored to add to the current discussion on health-related constructs.

2.4.6 Health Improvement Expectancy

Hayat et al. (2022b) further introduced two health-related constructs (health improvement expectancy and health consciousness) in the domain of technology adoption intention. The research posited that health consciousness notably influenced the adoption of wearable health devices (Hayat et al., 2022b). Although this is one of the recent studies that introduced two health-related constructs with the intention to adopt academic literature, it focused on senior adults in Pakistan, limiting its generalisability. Collecting data from other geographic locations from a mixed pool of age groups is warranted to increase predictive power (Hayat et al., 2022b). Lastly, this study did not include continuous intention or actual use of the device after the intention was established.

Yin et al. (2022) incorporated health expectations as a further construct to explain the intention to adopt. Health expectations and social influence were significant predictors of behavioural intent to accept medical wearable technology (Yin et al., 2022). Although Yin et al. (2022) studied health conditions' relationship with the perceived cost of wearable intelligent medical devices, little is known regarding how health condition or status is closely linked to the adoption and actual use of the device. Health conditions could be perceived as closely related to General Health and Vitality perception, as a result giving direction to explore these constructs further on their interaction with intention to adopt and actual usage.

2.4.7 Quality of Life

Larnyo et al. (2022) are among the first scholars to introduce another health construct measured as QoL derived from the SF-36 measuring instrument to the wearable device adoption and actual usage literature in an African continent context. Actual usage and QoL showed a significant link between the constructs (Larnyo et al., 2022). This study demonstrated that actual use leads to high QoL, which relates to overall good health. There is a need to test each dimension, such as General Health or Vitality, against the intention to adopt or use wearable fitness devices to gain in-depth insight.

Chandrasekaran et al. (2021) found results that contradict common stereotypes about older peoples' disinterest in the latest technology. This study revealed that the perceived health status of people, which encapsulates subcategories like General Health and Vitality, are essential factors in estimating intent to adopt wearable technology

(Chandrasekaran et al., 2021). This study used self-administered general health status questions without underlying items. A more robust general status measure, such as SF-36, measures General Health and Vitality using underlying validated items, which can increase the strength of findings when measuring wearable fitness devices.

2.4.8 Observed Gaps in Literature Relating to Health Constructs

Several health constructs (health consciousness, health motivation, and health belief) have been assessed to determine their effect on the intent to adopt wearable fitness trackers. One study by (Larnyo et al., 2022) measured QoL using standardised SF-36 on adoption intention and wearable device actual usage. However, QoL measures the entire spectrum under the measuring instrument SF-36, and a need to test each construct under the eight dimensions of the survey. Testing constructs separately under the SF-36, such as General Health and Vitality against the adoption intention and actual usage, extend the literature.

Many of the studies have remitted geographic location and age group as a limitation and canvassed their studies to be validated elsewhere, and only one study was conducted within the African context. This validates the need for a study to test different health constructs previously not tested, like General Health in a different geographic location like South Africa, covering all age groups above 18 years on intent to adopt and subsequent actual usage. This further advances the understanding of the various health constructs influencing adoption intention.

2.4.9 Mental Health, Anxiety, and Vitality

2.4.9.1 Depression and Anxiety

Singh et al. (2022) studied components influencing the intent to adopt health wearable health technology among older people above 60 for wellness using the protection motivation theory. The findings show that protective and utilitarian frameworks significantly impacted wearable health devices. The study grouped three constructs into the Utilitarian framework, and the second group of constructs included user vulnerability perception, user severity perception, and user confidence and all such variables were important in forecasting user intent to utilise health wearable technology (Singh et al., 2022). As part of the limitation, Singh et al. (2022) indicated that their findings were only focused on the intent to adopt wearable devices in the health domain. However, they did not test the continuous use of the wearable technology. Other population characteristics, such as age groupings and sex, need to be tested because their investigation was entirely on the elderly population.

Most importantly, forthcoming research can assess the relationship between consumers' depression/anxiety levels and the adoption intent of health wearable technology. More future studies can explore a sample of people with co-morbidity, lifestyle changes, and intentions to adopt wearable health devices. Depression/ anxiety levels are a measure of mental health that can be measured by SF-36 subscale Vitality to some extent.

2.4.9.2 Health Anxiety

Health anxiety is defined as individuals who are constantly worried and preoccupied by fear over bodily symptoms that may have been diagnosed or not (Meng et al., 2020). The results indicated that health consciousness and the value of the product significantly influenced the intent to adopt wearable medical technologies (Yang et al., 2022b). This result regarding health consciousness was consistent with Larnyo et al. (2022). Health anxiety was found to have been an insignificant predictor of user intention of medical wearable technology. Yang et al. (2022b) further canvased an investigation that incorporates personal health behaviour with the intent to adopt fitness devices that can be worn. Deep exploration regarding health variables which predict user intent to adopt should be investigated. Since health anxiety could be closely linked to mental health, a mental health metric such as Vitality measured by SF-36 could advance the body of knowledge

2.4.9.3 Psychological Distress and Factors

Choudhury and Asan (2021) explored how wearable devices impact mental health and the consequences of their designs. This study used an exploratory method instead of many previous scholars who utilised explanatory methods. The results suggest the 'Use of wearable devices' had a statistically notable indirect effect on 'psychological distress' (Choudhury & Asan, 2021). Another key finding was that improved 'health perception,' 'longer duration,' and 'self-care' were closely related to wearable devices' actual usage, which decreased 'psychological distress' (Choudhury & Asan, 2021). Psychological distress was measured using a scale that included depression and anxiety screens. This study was not specific as to which wearable devices were tested. However, Choudhury and Asan (2021) canvassed for further tests on specific wearable devices. As such, there is a need to examine the relationship between mental state, for example, Vitality, and the intent to adopt specific wearable health technology, e.g., fitness technology like smartwatches.

Bao and Lee (2024) examined the predictors and outcomes of wearable health technology use and subsequent health outcomes in Singapore. Among other constructs, physical and mental health was positively influenced by the utilisation of health applications and devices that can be worn. Bao and Lee's (2024) results were consistent with Choudhury and Asan (2021) regarding mental health and wearable fitness technology usage. Adoption intention and actual use were insignificantly associated with health valuation. Bao and Lee (2024) introduced the actual usage construct to the intent to adopt health wearable technology. As such, incorporating actual usage in forthcoming studies could provide robust results in understanding the effect of health predictors on the actual utilisation of the device.

Chen et al. (2022) explored various functions that affect the intent to adopt wearable trackers among the elderly age group. They sought to find out if psychological and physical factors drive the actual usage frequency of healthy wearable fitness devices within the elderly group of people in China. Chen et al. (2022) results show that the intent to use wearable devices cannot be statistically explained by the health anxiety of elderly people, which was found in line with the results found by Hayat et al. (2022a). Furthermore, a strong association between intention to use and actual usage was found (Chen et al., 2022). Although this study explored health anxiety, further studies under the mental health framework may provide deeper insight to determine the effect such constructs have on intent to adopt and real usage.

Health consciousness has been proven to influence the ease of use of mobile applications for physical activity (Acikgoz et al., 2023). However, ease of use was insignificant in predicting behavioural intention (Acikgoz et al., 2023). Health consciousness was insignificant in behavioural adoption intention of physical activity mobile applications (Acikgoz et al., 2023). These results are inconsistent with (Yang et al., 2024), where health consciousness could explain variation in the adoption intention of wearable health devices; perhaps the difference stems from the different types of technology studied. This study was one of the first to conduct fitness applications in Europe; therefore, future studies may be undertaken on other continents to increase generalisability. Acikgoz et al. (2023) encourage further studies to include physical health conditions and psychological constructs to deepen understanding of fitness application adoption. As a result, this study further underscores the need to investigate General Health, which is a measure of physical health condition and Vitality (mental state) to be tested against fitness wearable device adoption intention in different contexts like Africa.

2.4.9.4 Observed Gap in Literature Related to Mental State

In summary, the reviewed literature reveals psychological components which explain the intent to adopt a device that can be worn. Although these studies measured mental health factors, most explicitly testing depression and anxiety, they failed to address the role of Vitality on intention to adopt. Choudhury and Asan (2021) studied psychological distress but failed to test Vitality in isolation. Similarly, Chen et al. (2022) and Bao and Lee (2024) assessed overall mental health on wearable device adoption. However, Vitality was not examined.

Because Vitality measures energy level, pep, tiredness, and worn-out levels, it is vital for capturing mental health status. Given the current state of literature, it is evident that Vitality's effect on the intent to adopt fitness wearable devices remains largely unexplored. Studying Vitality could reveal a necessary deep understanding of the state of energy levels for respondents' intent to adopt wearable technology, filling the gap in the literature.

2.4.10 Social Influence

Social influence is extensively studied in the adoption intention of technology. Social influence describes how other people's goals balance one's desires (Gani et al., 2024). This definition stems from the fact that not all behaviours are self-motivated, as other people's opinions and views about what to do and don't do matter in one's decision-making process (Izuagbe & Popoola, 2017).

2.4.10.1 Social Influence and Intention to Adopt Wearable Devices

The phenomenon whereby individuals are influenced by those they perceive as superior is referred to as social influence (Venkatesh et al., 2012). According to Sergueeva et al. (2020), social influence played a major part defining consumers' intentions to adopt body worn tracking technology. The above mention study was confined to the US, which affects its generalisability. Additionally, the study did not specify the type of device used (Venkatesh et al., 2012). Vooris et al. (2019) identified social pressure as a significant factor influencing buyers' decisions to purchase and use health trackers. Future examinations ought to validate or challenge these findings by conducting surveys with a wider audience.

Sergueeva et al. (2020) demonstrated that consistency, drive for pleasure, enabling circumstances, social influence and performance anticipation shown to be linked with use of wearable fitness technology. The factors of cost assessment, concealment fears, and health consciousness insignificantly influenced the inclination to accept the technology (Sergueeva et al., 2020). A limitation of this research is its focus on the United States, which may affect its generalisability. According to Sergueeva et al. (2020), forthcoming investigations must consider including well-being status, age, and types of wearable devices as intermediating parameters.

Many studies have measured and tested antecedents of wearable tracking devices using quantitative methods. However, Abouzahra and Ghasemaghaei (2020) sought to employ qualitative analysis to comprehend in depth the antecedent responsible for the adoption intention of fitness technology for senior citizens. Abouzahra and Ghasemaghaei (2020) posited that the adoption of wearable fitness devices among senior adults was driven by social influence, but it was not enough to encourage continuous usage. This study was conducted in Canada, adding to its limitations. The authors canvassed for similar studies to be performed in developing countries because there are differences in physical activity between developed and developing nations.

Mishra et al. (2023) researched constructs that explain variations of the fitness technology's actual use using UTAUT, and the research revealed that social influence, privacy concerns, and data accuracy were significant in expiating actual use. Social influence was indirectly related to actual usage through performance expectations (Mishra et al., 2023). One of the confines of this analysis was that it was completedduring COVID-19 when respondents were isolated. As such, a similar survey is warranted after the global pandemic era, as actual usage of such devices may have changed.

Gani et al. (2024) explored the effects of social influence on behavioural intention toward smart health devices on female respondents using the TAM model. Social influence was moderated by the influence of user-perceived usage of innovative health technology (Gani et al., 2024). One of the limitations is that the study was conducted in one nation (Bangladesh), and such findings may be different in nations with other cultures. Furthermore, studies from similar countries could strengthen the accuracy and further validate this study. This study did not test how social influence directly iaffects the adoption desire of personal activity devices, presenting a literature gap to be explored.

Pancar and Ozkan Yildirim (2023) used UTAUT 2 to test how social influence impacts behavioural adoption. The actual use of wearable devices cannot be significantly predicted by constructing social influence (Pancar & Ozkan Yildirim, 2023). Whereas social influence was found to be a key construct in Venkatesh et al. (2003), it is controlled by age, sex, and user experience in predicting behavioural intention in Pancar and Ozkan Yildirim's (2023) study, which contradicts one of the highly cited peer-reviewed studies. This study focused on general wearable health devices. However, a need to determine the social contribution to the inclination to adopt wearable devices, such as a fitness device sample of respondents, can be explored.

Bianchi et al. (2023) studied parameters that drive acceptance intention for non-consumers of personal activity technology in Chile using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. Social influence, hedonic motivation, and perceived usefulness strongly influenced fitness tracker adoption intention (Bianchi et al., 2023). This study only examines the social influence on adoption intention. Still, it does not extend the scope toward the actual use of the device, creating a gap in the literature as no guarantee can be made regarding intention leading to actual use. This study is a novel one of its kind because most such studies that test social influence on adoption are carried out in industrialised countries whereases (Bianchi et al., 2023) and were conducted in an emerging economy (South America) as there are cultural differences between industrial countries and non-industrial. This study is also unique as it studies the direct relationship of social influence and adoption rate as opposed to (Gani et al., 2024). However, these results are inconsistent with those found by Pancar and Ozkan Yildirim (2023). Part of the study's limitation is owed to the sample frame, which consisted of a younger population with high-income privileges and excluded the older segment. As such, incorporating a wider age bracket can provide insightful results.

Social influence was found to be responsible for explaining variance in behavioural intention from a sample tested in China (Yin et al., 2022). Bianchi et al.'s (2023) results were consistent with that of Yin et al. (2022). Although this study tested a few antecedents of behavioural intention, it failed to test the relationship between wearable device actual usage and social influence.

Results found by Rahman et al. (2022) were also consistent with those found by Bianchi et al. (2023) and Zhang and Mao (2023), where social influence statistically explained movement in the acceptance of wearable device among teenagers in Bangladesh. The results are limited to one location, Bangladesh; as a result, further examination may be undertaken elsewhere to increase generalisability. Well-explored constructs by peer-reviewed scholars, such as hedonic motivation, price value, and effort expectancy, could not statistically explain adoption intention by teenagers in Bangladesh (Rehman et al., 2021). This emphasises the need and importance of testing social influence variables in other countries that may be geographically different or have cultural differences to understand better the drivers creating inconsistent results.

Social influence could not predict inclination to use wearable activity technology in a study done in Ethiopia on device users with diabetes (Walle et al., 2023). These results were inconsistent with Bianchi et al. (2023) and Zhang and Mao (2023) findings. (Walle et al., 2023) proposed additional research should be conducted to understand better how users' social circle influences user intention to adopt in various settings.

A recent study conducted by Wu and Lim (2024) among elderly adults in China found social influence to be a predictor of technology use. This study contradicts the work of Walle et al. (2023), Wu and Lim (2024) employed two theoretical frameworks, namely UTAUT2 and Technology Readiness Index (TRI). Incorporating such two frameworks in the study was rarely practised in most literature of this type. Although technology acceptance among elderly people is similar, this study does not address social-economic and cultural disparities likely to exist in developing nations like South Africa. As such, Wu and Lim (2024) canvased future research to be conducted in diverse countries with different cultural landscapes to increase its generalisability.

Results from two countries (the Philippines and India) showed that social influence was found to be insignificant in explaining variation in adoption intention (Pandey et al., 2022). Pandey et al. (2022) further canvassed for this study to be repeated in other countries with different cultural backgrounds to increase its validity.

2.4.10.2 Gaps in the Literature Related to Social Influence

In summary, the current literature on wearable fitness device adoption and social influence provides insightful results but also reveals significant literature gaps, especially in cross-cultural settings. Scholars such as Venkatesh et al. (2012) and Sergueeva et al. (2020) highlight that social influence is important in predicting behavioural intent due to normative pressures from external forces. In contrast, scholars such as Pancar and Ozkan Yildirim (2023) and Walle et al. (2023) suggest that mediating variables such as performance expectancy and respondents' demographics impact social influences in predicting intention to use wearable devices. Moreover, most research emanates from advanced economies with unique cultural settings, like Chile, Bangladesh, and the US, limiting generalisability. South Africa is an emerging economy with distinct cultural characteristics compared to many Western and Eastern countries, which presents a distinct prospect to assess the effect of the user's social circle on intent to adopt the technology.

2.4.11 Relevant Studies

Several scholars have examined the antecedent of the desire to adopt body-worn or medical devices with health predictors that include health anxiety, health expectations, and health consciousness, to name a few. Many of them canvassed for more health-related constructs to be explored further, and Larnyo et al. (2022) introduced QoL assessed by the SF-36 health survey as a health variable to determine if the actual usage of body-worn technology has a considerable impact on QoL. According to the investigator's knowledge, this is the only most recent study that utilised SF-36. The study showed a significant link between wearable device usage and QoL

In a study by Zhu et al. (2021) on the health-promoting lifestyle of older adults in China, the SF-36 was employed to determine their health status by studying physical health, mental health, and social support. The study found poor health levels and high levels of chronic illness in the Shanghai community of China. In summary, SF-36 was employed to evaluate health status.

A study in Slovenia that investigated patients with chronic disease intention to adopt mobile health technology used SF-36 to measure respondents' health-related QoL (Dolničar et al., 2024). The SF-36 scores, which included General Health, Body Pain, and Vitality, were utilised to establish baseline health status before and during exposure to mobile health solutions (Dolničar et al., 2024). The main aim was to understand the influence of existing health conditions on the adoption intention of mobile health technology (Dolničar et al., 2024). SF-36 scores were used as predictors of inclination to adopt mobile health devices. The study found the health-related QoL measured by SF-36 significant to the intention to use the mobile health device (Dolničar et al., 2024). In summary, the SF-36 instrument was used as a proxy to measure health status against adoption intention.

2.5 Actual Use of Wearable Devices

There has been contracting evidence regarding adoption intention and actual usage of fitness wearable devices; however, industry records suggest that users do not use the device briefly after adoption (Windasari et al., 2021). Dehghani et al. (2018) went beyond traditional testing methods by examining actual model usage to understand the factors driving it. Previous scholars studied samples from wearable device users and non-users. However, Dehghani et al. (2018) only used a sample of wearable device users to understand user behaviour better. Dehghani et al. (2018) suggested that the social influence construct on continuous usage and actual use may provide further areas of research for wearable devices.

A theoretical model that links intention to continuous use of wearable devices such as smartwatches and actual use was developed by (Dehghani et al., 2018). The developed model by Dehghani et al. (2018) confirmed that continuous intention significantly influences the actual use of wearable devices. Moreover, Pancar and Ozkan Yildirim's (2023) findings suggest that behavioural intention was an important factor in explaining actual usage. Dehghani et al. (2018) further recommended that social influence should be tested to determine its role in continuous intention. Other scholars like Wei et al. (2021) results confirmed that usage behaviour was influenced significantly by user intention to use fitness application technologies.

Yang et al. (2024), one of the most recent articles that expanded the VBN to include health constructs like health knowledge-seeking, health value, health consciousness, and social norms to predict the adoption intention of wearable activity devices in the Chinese population across age 18–30 years. Results show that social and personal norms strongly predict the intention to adopt fitness devices. Furthermore, intention to adopt fitness devices significantly affected actual usage (Yang et al., 2024). As the study was conducted in China, Yang et al. (2024) suggested that the survey be validated in other regions with diverse demographic characteristics, and the study focused on a few health constructs. Additional health variables need to be tested. They are elaborated on below.

2.6 Definition of Key Constructs

2.6.1 General Health (GH)

This refers to the overall health perception of the individual current state and future measured by the SF-36 instrument (Ware et al., 1993). Individuals who perceive themselves as healthy may be propelled to advance their health by accepting new devices to enhance their health.

2.6.2 Vitality (VT)

This construct is part of the mental health fraternity, which seeks to explain an individual's energy levels, tiredness and vigour measured by SF-36 instruments (Ware et al., 1993). Individuals with high energy level perception generally have high motivation levels, which might encourage the adoption of new solutions if they expect the solution to improve their energy levels

2.6.3 Social Influence (SI)

The extent to which an individual's decisions are impacted by those they think are important to them, e.g., colleagues, friends, or social norms (Gani et al., 2024). It can be expected that if important people in one's life recommend a health device, the person is likely to adopt it.

2.6.4 Intention to Adopt (IA)

Intention to adopt is described as the willingness and determination of an individual to engage in a particular activity (Davis et al., 1989). For this study, the intention was to adopt wearable health devices. According to TAM, actual behaviour is predicted intention (Davis et al., 1989)

2.6.5 Actual Use (AU)

Actual use denotes the frequency with which a device is utilised, quantified by days or weeks. This actual usage is forecasted by the intention to adopt the device.

2.7 Chapter Summary

After a careful examination of academic articles dating back five years ago on intention to adopt wearable devices, a few health-related constructs have been extensively explored, some results showing inconsistencies and a few being validated. A gap in the academic research exists to examine the General Health and Vitality (measured by SF-36) effects on inclination to accept fitness technology in a developing country like South Africa. Furthermore, social influence on the inclination to accept personal activity devices has also been extensively investigated. However, inconsistent results are still prevalent owing to cultural and socioeconomic differences in geographic location. Therefore, the function of social influence on adoption intention requires further testing. Lastly, wearable device adoption is widely researched; however, the actual usage of the device is still underexplored. Exploring General Health, Vitality, Social Influence, and actual usage construct on intention to adopt one model closes the current gaps in the literature.

Chapter 3: Hypotheses

3.1 Introduction

Chapter 3 presents hypotheses for the primary constructs under investigation, namely General Health (GH), Vitality (VT), and Social Influence (SI). The suggested model is derived from the UTAUT and is also graphically represented to show the relationship between the constructs (Figure 3.1). Lastly, hypotheses are listed and presented as H1 to H4.

3.2 Theory Model

This study is founded on the Unified Theory of Adoption and the use of technology developed by Venkatesh and Davis (2000), as many researchers widely employed it to provide deep insight into factors that influence technology adoption. UTAUT model suggests that behavioural intention to adopt technology is influenced by user performance expectancy, effort expectancy, user social influence, and facilitating conditions. The predictors are moderated by sex, age, user experience, and voluntariness of Use. Larnyo et al. (2022) employed the UTAUT model for wearable medical devices among dementia patients.

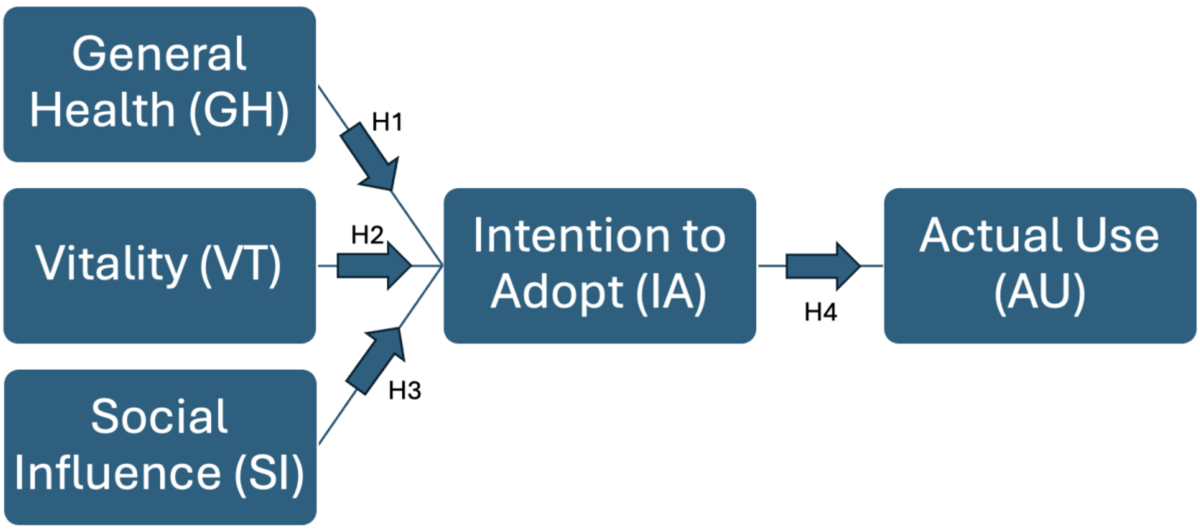

Figure 3.1: Conceptual Model

Source: Author's own.

3.3 Hypothesis Formulation

3.3.1 General health (GH) and Intention to Adopt (IA) (H1)

Health value and health consciousness are significant predictors of intention to adopt (Yang et al., 2024). In addition, Rahman et al. (2022) found that health beliefs influence the intention to adopt wearable devices to be significant. Larnyo et al. (2022) employed an SF-36 measuring instrument to measure the QoL influence on technology adoption intention and found positive significant results. Drawing on these mentioned health constructs by Rahman et al. (2022), Yang et al. (2024), and Larnyo et al. (2022), it is hypothesised:

H1: *General Health (GH) is a significant predictor of Intention to Adopt (IA) wearable fitness device.*

3.3.2 Vitality (VT) and Intention to Adopt (IA) (H2)

Improved mental health was significantly linked to the adoption of digital health technology in a study conducted in Singapore (Bao & Lee, 2024). Larnyo et al. (2022) utilised SF-36 measuring items to measure QoL, which encompasses mental health and found positive significant results in the adoption of wearable health devices. The QoL measure under SF-36 encompasses mental health, which includes Vitality. If a wearable tracking device is perceived to improve an individual Vitality, people with high Vitality scores may adopt it. Therefore, it can be hypothesised that:

H2: *Vitality (VT) significantly influences Intention to Adopt (IA) wearable fitness devices.*

3.3.3 Social Influence (SI) and Intention to Adopt (IA) (H3)

Sergueeva et al. (2020) results revealed that social influence had a statistically substantial effect on wearable devices adoption inclination, such as smartwatches and fitness devices. In a more recent study by Bianchi et al. (2023), who employed the UTAUT model, the intention to adopt a fitness tracker was significantly influenced by social influence. Individuals are prone to embrace a fitness device if people in their environment recommend, encourage or endorse the technology. Hence:

H3: *Social Influence (SI) has a significant influence on Intention to Adopt (IA) wearable fitness devices.*

3.3.4 Intention to Adopt and Actual Use (H4)

Larnyo et al. (2022) showed that the Actual Use of fitness devices had a positive significance on QoL, and intention to adopt fitness devices was statistically significant for QoL. It is warranted that once a person intends to adopt a fitness device, a high likelihood of actual usage can be expected. Therefore:

H4: *Intention to Adopt (IA) significantly affects the Actual Use (AU) of the wearable fitness device.*

3.4 Chapter Summary

The proposed theoretical underpinning for this research is the UTAUT adapted to suit the objectives of this research. The primary constructs hypothesised were General Health, Vitality, and Social Influence as predecessors to the inclination to adopt wearable fitness devices. The preceding chapter details the research methodology and design for the research.

Chapter 4: Research Methodology and Design

4.1 Introduction

Chapter 4 outlines the research purpose, philosophy and strategy. This chapter further details how certain statistical assessments were done and how their results impact this study. Data collection and preparation are also discussed at length, and lastly, tests such as dimension reduction and regression model are also detailed.

4.2 Purpose of Research Design

Pancar and Ozkan Yildirim (2023) studied antecedents that affect the adoption intention of wearable technology using the UTAUT model. An explanatory design was employed to test such an antecedent on the adoption intention of wearable devices. A similar study by Gao et al. (2015) studies the effects of trust and privacy concerns on intention to adopt wearable fitness devices using explanatory design. Both studies by Gao et al. (2015) and Pancar and Ozkan Yildirim (2023) are related to this study; as such, this study also follows an exploratory design.

This study tested whether General Health, Vitality, and Social Influence affect the intention to accept wearable activity devices. An explanatory research plan was proposed for its ability to describe general phenomena rather than individual occurrences (Baskerville & Pries-Heje, 2010).

4.2.1 Research Philosophy

A positivist approach was used for this study as it aligns with the research design and objectives for the study. The positivist approach ensures generalisability and is suitable for reaching research objectives (Crossan, 2003). The benefit of this philosophy can be attributed to unbiased reporting prediction (Saunders & Lewis, 2017). The positivist approach further allows for concepts to be measured quantitatively by operationalising them (Crossan, 2003). This study aims to measure the antecedent (General Health, Vitality and Social Influence) of intention to adopt fitness devices. Similar studies, such as Larnyo et al. (2022), who studied the antecedent of wearable technology, also employed a positivist research approach. An interpretivism approach, which studies subjectivities and experience (Elliott & Timulak, 2005), would not yield research objectives for the study as the alternative focuses more on exploratory rather than explanatory analysis.

4.2.2 Strategy

An online survey with structured questionnaires was created and sent to potential respondents. The reasons for this selected strategy are that online surveys provide shorter and more enjoyable to responders, fewer mistakes and blank items. Other added benefits include the increased geographical spread of respondents, and responses can commence immediately (Nayak & Narayan, 2019). Web based surveys offer superior efficiency (Dillman & Bowker, 2001). Bianchi et al. (2023) also made use of an online survey to study drivers that influence health wearable devices. Therefore, an online survey was proposed.

4.2.3 Methodological Choices

The majority of scholar, such as Pancar and Ozkan Yildirim (2023), who studied the antecedent of adoption intention of fitness wearable devices, utilised mono method strategy to reach their conclusion. Sergueeva et al. (2020) studied barriers and factors associated with wearable technology adoption and used mono-method choice. Mono-methods would also be sufficient to study the statistical relationship between General Health, Vitality, Social Influence and intention to adopt. Therefore, the methodological choice selected was monomethod using an online survey. Furthermore, the mono-method approach ensures consistency as data can be collected uniformly, thereby reducing any variation that is likely to occur when a mixed method is used.

4.2.4 Time Horizon

This research was a cross-sectional study that surveyed respondents from 27th October 2024 to 23rd December 2024. This was in line with previous scholars such as Rahman et al. (2022), who utilised a cross-sectional approach to study health belief influence on the adoption of wearable technology. Dolničar et al. (2024) also employed a cross-sectional approach to understand the role of user's health conditions on the intention to adopt health wearable devices. Based on the literature stated above, this study also utilised a cross-sectional study.

4.3 Population

This study's population is South African adults from the age of 18 and over. This target population was selected to analyse how the independent health and social constructs influence fitness adoption intention and usage. The target population is also individuals who are current and potential users of wearable fitness devices. The group was chosen because they were more likely to aid the reach achieve its objectives. The population included people over the age of 18 to observe with the ethical criteria of the University. Furthermore, a respondent above 18 years of age is considered an adult who could sign legal documents such as a consent form. The population for this study also included people who frequently engaged with digital technology and online communication channels, thereby increasing the reach of the survey.

4.4 Unit of Analysis

The unit of analysis for this study was users of fitness wearable technologies. Although the individual-level units of analysis are the most common, they are appropriate for capturing the perceptions and or behaviours of respondents (Kumar, 2018). Each data point represented the user's personal perception of General Health and Vitality and the intention to adopt wearable fitness devices. The research's objective was to establish how individual variables affect General Health, Vitality' and Social Influence impacts the intention to adopt and actual usage of wearable fitness devices. Individual units of analysis also align with the study's online structured survey (Kumar, 2018).

Furthermore, individuals' viewpoints are not diluted due to aggregation, which supports data reliability for each data point. An individual unit of analysis was used to support research objectives as regression analysis could be used to study the association between adoption and actual usage intention and health attribute perceptions. The literature analysis also exposed that most studies which investigated the intention to adopt wearable fitness devices employed individual-level units of analysis. For instance, Pancar and Ozkan Yildirim (2023) showed that price value, hedonic motivation and habit were significant in explaining adoption intention. Therefore, it was deemed appropriate to select the individual level as a unit of analysis for this study.

4.5 Sampling Technique Method and Size

The selection of sampling techniques (probability or non-probability) is dependent on financial factors, research objectives and the size of the population (Sharma, 2017). This study selected nonprobability due to the research objectives and the nature of the investigation. The survey was shared on various online communication channels to reach a wider audience; however, this approach is likely to present selection bias limitations (Acharya et al., 2013). A sample of 100 respondents was advised for a population size of 10,000 and above, with a 30% safety margin added to compensate for people who might not respond (Israel, 1992). Research by Dolničar et al. (2024) explored antecedent wearable health devices on chronic disease patients and sampled 103 responses to run Partial Least Square Structural Equation Model (PLS-SEM). Therefore, 120 respondents were sampled due to the reasons outlined above

4.6 Measurement Instrument

4.6.1 Studies that Employed Health Survey to Measure Health

This study aims to explore the relationship between health status or health-related constructs and the intention to adopt wearable devices. A health measuring instrument named SF-36 has been used widely in the medical and health fraternity to determine the QoL or even used as a perceived self-diagnosis of health status. SF-36 comprises 36 items and eight scales: General Health, Vitality, Mental Health, Body Pain, Physical Function, and Role Function (physical or emotional) (Luscombe, 2000). The scales are scored on a Linkert scale. For this study, extensive literature research suggests that none of these scales have been employed to test for their influences on intention to adopt wearable fitness devices.

4.6.2 General Health Definition

General Health is part of the eight domains assessed under the SF-36 (Ware et al., 1993). General health evaluates the overall perception of a person's health, incorporating current and future health (Ware et al., 1993). General Health is measured from five rating items ranging from excellent to poor. Responses are then scored; a higher score indicates better perceived health and a low score indicates poor health perception (Ware et al., 1993).

4.6.3 Vitality Definition

Vitality is also a part of the eight domains assessed under SF-36, which measure the respondent's energy levels, feelings of tiredness, and fatigue (Ware et al., 1993). The four items measure how a person feels full of life, the frequency at which a person feels worn out, and the weather of whether the person feels energetic (Ware et al., 1993). These items are measured on the Linkert scale, and responses scored from 0–100. Vitality is closely linked to mental well-being and psychological status.

4.6.4 Questionnaires

A number of scholars prefer to use questionnaires for quantitative research because they have the ability to articulate claims about the sampled group (Roopa & Rani, 2012). Because this research is also quantitative, a questionnaire was selected as a measuring instrument. Table 4.1 indicates the measuring instruments employed alongside their Cronbach's Alpha's. These instruments were deemed valuable given that their Cronbach's Alphas were above 0.65, which is considered an acceptable range by Bonett and Wright (2015).

Table 4.1: Measuring Instruments

Type	Description	Item abbreviated	Cronbach's Alpha
Intention to adopt (Guo et al., 2016)	Measure intention and willingness to adopt wearable fitness technology	Predict Predict Plan	0.891

Type	Description	Item abbreviated	Cronbach's Alpha
Social instrument (Venkatesh et al., 2003)	Assess how individuals decision is impacted by peers and social circle	People important People influence	0.866
General Health (Ware et al., 1993)	Measure self-reported current and future health status perception.	Excellent health Healthy Get sick Get worse (removed)	0.723
Vitality (Ware et al., 1993)	Measures self-reported perception of current and future mental health status	Pep Energy Word out Tired	0.90
Actual Use (Godoe & Johansen, 2012)	Captures user utilisation frequency of the device	Actual use, one item	N/A

Source: Author's own.

4.7 Pilot Study

After ethical clearance was approved by the GIBS committee (see Appendix C), a pilot study was initiated. A Google Form link addressed to the measuring instrument was shared with 10 respondents, who were likely to critically analyse and review the form and questions before sending it out to the population. The aim of the pilot exercise is to invite an independent review of the questionnaire for the purpose of feedback. The feedback highlighted a few spelling mistakes and comments on the flow and structure of some questions. Most questions were structured in a multiple-choice question format, and a few were drop-down menus. The feed suggested that the form be uniform with only a multiple-choice format style. Although the pilot study was conducted, the researcher mistakenly excluded the demographic questionnaire when the survey was distributed. Secondly, the pilot study feedback failed to notice the exclusion of demographic questionnaires. The only demographic question that was included was age.

4.8 Data Collection Process

The data were gathered through web survey platform, Google Forms. The url address to the survey form was shared on social media to reach more people. The choice of the online distribution channel was to remove geographical constraints (Nayak & Narayan, 2019) as this method has the potential to reach respondents who are remotely relocated. Respondents were required to complete and approve included in the survey by signing a consent form. The form detailed the need for the study and how the data would be processed. Personal identities were not stored to protect the subjects and comply with Ethical Committee Guidelines. The data will be stored in an online storage platform called Google Drive for a minimum of 10 years.

The date of distribution through WhatsApp was 27 October 2024. The Google Form link was shared with everyone on the researcher's WhatsApp contact list and WhatsApp groups. The link was sent to 160 recipients on the researcher's WhatsApp. Respondents were asked to share the link with as many people over 18 as possible to increase responses. Within two weeks, a total of 100 respondents had responded. The 100 respondents were a combination of users and non-users of wearable devices. The number of responses began to decline after the two-week period. To increase participation, the researcher had to follow up on people who did not acknowledge the WhatsApp text, and the number increased to 120 responses. The research's third attempt to increase response was to send messages to LinkedIn contacts and Facebook. As such, the number increased to 209, made up of respondents with and without wearable fitness devices was reached on the 24th December 2024.

4.9 Data Analysis and Quality

4.9.1 Data Gathering

The data was gathered using the Google Form platform, which is an online channel that allows for data to be captured by the responder, who chooses the appropriate answer to the question asked. The Google Form listed all the survey questions, and under each question, a list of options was listed for the respondent to choose from. After the survey conduction period was completed, the file was then downloaded for further analysis. The file was opened using Microsoft Excel file format depicting both numeric values and string texts. The data was then coded using Linkert scales, where responses were assigned numerical values. For instance, the strongly disagree option was assigned the numerical value one, and the strongly agree option was assigned the numerical value 5 or 7, depending on the number of options available. The respondents who selected confirmed that owned wearable devices were assigned one, and those who did not were assigned a value of 2. The data was then separated into responders with wearable devices and those without. One 120 respondents were eligible for further statistical analysis.

4.9.2 Missing Data

A prerequisite to performing rigorous statistical data analysis is a complete data set (Blunch, 2012). The prepared data indicated that there were no missing values from visual inspection. This is because the Google Online Survey restricted the respondents from submitting the survey if some questions were not completed. The prepared dataset had 1903 data points, and there were no gaps in the Excel spreadsheet. This means that no imputation or data cleaning took place, and as such, the integrity of the dataset was maintained. The file was imported to Statistical Package for Social Science (SPSS) for statistical tests to be conducted.

4.9.3 Normality

Many statistical analyses require the data to be distributed normally; this means that the majority of the spread should be centred around the mean (Cramer & Howitt, 2004). The normality of a data set is tested using three methods (Razali & Wah, 2011), specifically through the analysis of skewness and kurtosis indices. For a dataset to be classified as normal, the Z value must range between -1.96 and 1.96. Additionally, normality tests were conducted to address hypersensitivity due to small sample sizes (Field, 2013). Shapiro-Wilk (SW) results were presented to enhance statistical rigour. A p-value of 0.05 or less is considered significant.

4.9.4 Outliers

Outliers in a dataset are shown by vertical box plots (Hoagline & Iglewicz, 1993). In large samples, outliers can be trimmed, but winsorising was preferred due to the small sample size. The data is considered normally distributed if outliers are less than 5% (Davidov et al., 2018). This study found an outlier percentage of 1.27%, indicating normal distribution.

4.9.5 Validity

Validity is the degree to which a measurement or deduction is formulated to relate to a real-world phenomenon or occurrence (Rich et al., 2018). In other words, real-world accuracy can be related to validity, and the types of validity include construct, convergent and content (Hajjar, 2018). Construct validity can be defined as the level at which the measurement tool can accurately describe the theoretical construct it aims to measure (Rich et al., 2018).

4.9.5.1 Bivariate Pearson Correlation

This study employed bivariate Pearson correlation as the first test to measure construct validity by examining two theoretical variables to determine whether they are actually related. The Pearson coefficient ranges from -1 to 1 with associated relevant p values to indicate significance (Schober et al., 2018). According to Cohen (2013), a correlation coefficient of around 0.1 is considered weak, while a correlation coefficient of 0.3 is said to be moderate and around 0.5 and higher is considered strong (Cohen, 2013). This study ran Bivariate correlations between a pair of related variables within the same construct to validate whether the two variables correlate or not. If the correlation is strong and significant, the test is deemed convergent. By conducting Pearson correlation, the study was able to determine potential variables that could weaken the model.

4.9.5.2 Standardised Loadings and Average Variance Extracted

The study assed Average Variance Extracted (AVE) and standardised loadings further confirm convergent validity. Standardised loadings are used to determine whether the observed items strongly resemble the intended construct, where items with higher loading (usually greater than 0.70) mean a strong relationship between the items and construct (Cohen, 2013). Convergent validity can be established if items below 0.7 are removed (Hair et al., 2012). The second step was to calculate AVE by using the formula:

$$Average\ Variance\ Exctracted\ (AVE) = \frac{\Sigma(standardised\ loading^2)}{Number\ of\ indicators}$$

Where AVE values above 0.5 or higher are acceptable (Hair et al., 2012), research closely related to this study by Dehghani et al. (2018), which tested underlying factors influencing the intention to continue using wearable devices, also utilised an AVE threshold of 0.5 and higher to determine convergent validity for the construct. With the robust validate constructs in place, items that loaded adequately were carried forth for further statistical computation.

4.9.6 Reliability

Reliability was assessed using two methods for consistency and instrument stability. The two methods employed were Cronbach's Alpha and Composite Reliability (CR). Employing both methods ensures robust evidence is provided to prove constructs consistent for this study. Internal consistency and reliability of a scale are usually estimated by Cronbach's Alpha (Pancar & Ozkan Yildirim, 2023). Nunnally (1975) confirmed that values above 0.7 are generally acceptable. Furthermore, CR offers additional detail, unlike Cronbach's alpha, because it incorporates individual loads of each construct, rendering the test more rigorous (Hair et al., 2014). The formula for CR can be expressed as:

$$Composite\ Reliability\ (CR) = \frac{(\sum Standardised\ Loadings)^2}{(\sum Standardised\ Loading)^2 + \sum(ME)}$$

Where ME is the Measurement Error = 1-(standardised Loadings)^2

The acceptable range for CR is recommended to be between 0.6 and 0.8 for exploratory factor analysis (Chin, 1998) and 0.7 and higher for confirmatory factor analysis (Henseler et al., 2012).

4.9.7 Dimension Reduction

The method of reducing complicated data into a number of variables that retain original information is referred to as dimension reduction (Jolliffe, 2002). This research used Exploratory Factor Analysis to achieve dimension reduction. To validate suitability for Exploratory Factor Analysis, Kaiser-Meyer Olkin (KMO) test was employed. A KMO value close to 1 indicates that the items have a strong correlation and are compact (Abdi & Williams, 2010). A KMO of 0.5 and above is acceptable (Blunch, 2012), and this threshold was used for the purpose of this study. Bartlet Test of Sphericity test was also reported to establish whether the identify matrix deviates significantly from the correlation matrix. Factor analysis can only be justified when the sigma value is less than 0.005 (Hair et al., 1995).

4.9.8 Descriptive Statistics

An initial overview of the data was explored using a basic analysis of the variables by performing descriptive analysis. This analysis was conducted on age demographics, General Health perception, Vitality perception, intention to adopt and actual utilisation rate. These variables were explored, given that the study mistakenly excluded other general demographic parameters like sex and personal income. Furthermore, mean, range and min skewness were also presented. The reason for performing descriptive analysis is to provide a holistic overview of central tendencies and deviations, normality detection, and a comprehensive profile of the construct (Field, 2024).

4.9.9 Hypotheses Testing

Prior to selecting the type of regression analysis to use, certain assumptions must be met (Hayes, 2017). The relationship between the independent and department variables is assumed to be linear (Field, 2024). There should be no correlations between error terms of observation, thereby maintaining observation independence, especially for time series analysis (Tabachnick & Fidell, 2013). The residuals should present a homoscedasticity profile to avoid inefficiencies in the estimates (Field, 2024). Normal distribution of the residuals should be maintained, especially for hypothesis tests (Tabachnick & Fidell, 2013). There should be no high multicollinearity when dealing with multiple predictors (Field, 2024).

This study tested for normality and detected outliers to maintain the linearity assumption. The data for the analysis was gathered using web based survey method where participants were independent of each other, and the independence assumption was not violated. A residual and fitted value plot was conducted to determine the homoscedasticity assumption. Even though the plot suggests heteroscedasticity, an appropriate model (weighted least square regression) was selected to address homoscedasticity assumption violation. Kurtosis, skewness and SW tests were conducted to ensure normality of residuals. Variance Inflation Factors (VIF) were presented to ensure multicollinearity was not a concern. In summary, all key assumptions for regression modelling were observed and addressed accordingly.

4.9.10 Weighted Least Square Regression

To address heteroscedasticity, this study employed a weighted least square (WLS) regression model. WLS aligns the weight to all observations, meaning observations with high variance receive less weight than those with lower variance. The WLS weight estimator formula is:

$$\beta \ \_WLS = (X^{1}WX)^{-1}XWy$$

Where:

X: Predictor parameter matrix

Y: Explained parameter vector

W: Weighted factors oblique matrix

WLS regression:

$$Y = \beta_0 + \beta_1 X_1 + \cdots \ldots + \beta_k X_k + \in$$

Y: Explained factor, β0: Baseline value, βk :Model estimate, X: Predictor parameter, and Residual term

4.10 Limitations

This study sampled 120 respondents who have an interest in wearable fitness devices. Even though the 120 sample size was acceptable, a larger sample size could improve the results. Yang et al. (2024) tested the antecedent of the Internet of Things for wearable devices using a sample size of 866 and further stated the limitation of the study was the sample size. This study's research philosophy was positivist, so the results cannot be generalised because interpretivism could further enrich the results. Respondents' experiences could be captured by interpretivism philosophy (Elliott & Timulak, 2005). This research was a cross-sectional analysis, taking into account observations at a point in time and suggesting a correlation between the constructs as opposed to causality. This study also measured the health perception of respondents. As a result, the response may not have been a true reflection of their health status, experiences and actual usage of wearable devices. The sampled respondents are likely to make use of smartphones and the internet, mainly from urban areas, which renders the results biased.

4.11 Ethical Considerations

The online forms circulated to participants outlined the reason of the study and information about the rights to stop at any point during the survey without any implications. The participants were also informed that they gave consent by continuing to submit the survey. Confidentiality and privacy were maintained by not collecting personal identifiers. However, the records will be saved in a password protected online storage facility for the next ten years. Ethical approval was also granted before the survey commenced.

4.12 Chapter Summary

The study used a positivist approach to study the correlation between health-linked constructs and technology adoption. This study sampled 120 participants across South Africa through web based online survey from 27th October to 23rd December 2024. The study utilised peer-reviewed measuring instruments to measure the constructs. Weighted least square regression analysis was employed to address normality concerns. The methodology design selected aligned with the research objectives

Chapter 5: Results

5.1 Introduction

Chapter five outlines how the data was collected, analysed and tested. The data was tested for normality using various statistical techniques. A presentation of construct validity and reliability results is also elaborated in the sections below. The results from regression analysis, which highlights ANOVA and coefficient factors, are also presented under each hypothesis.

5.2 Data Collection

The data collection involved surveys to collect primary data from respondents. Survey questionnaires from related measuring instruments were used. Data collection was conducted 5 days after the Ethical Committee granted ethical clearance. The survey was distributed through social communication channels. Google Forms was used to collect the data, and as part of the form, a privacy disclosure and consent use statement was outlined before the respondents could complete the survey. The respondent was asked to distribute to their contacts over 18. The data collection period was from 27th October 2024 to 23rd December 2024.

A pilot survey was distributed to 10 responders who highlighted a few spelling mistakes and commented on the flow and structure of a few questions. The researcher addressed the pilot survey comments accordingly. Although the Ethical Committee submission survey submission had a demographic survey, the research mistakenly excluded some demographic questions when the survey was sent out. The pilot survey was unable to detect that demographic questions were missing. The total number of responses from the survey reached 209 on the 24th of December 2024. The raw data was then analysed to separate the respondents into groups: users with wearable devices and users without. Only users with wearable fitness devices were studied.

5.3 Data Preparation

The data was collected using the Google Forms tool. The raw data from Google Forms was downloaded for further processing. Only 120 respondents confirmed having a wearable device were analysed. Appendix D presents a sample of the raw data. All questions on the Goggle Form were made mandatory to ensure that respondents answered all questions and that no data was missed. The respondents gave informed consent by ticking the consent box before completing the survey. Furthermore, respondents were notified that anonymity would be observed and no personal identity information was recorded to maintain privacy.

The data was then transformed through the coding process, where the data was coded on an Excel spreadsheet (Appendix E). The following variables under the General Health construct were reversed after Cronbach Alpha revealed negative statistics:

- Tired
- Worn
- Sick
- Get worse

5.4 Missing Data

A visual scan of the data was conducted, and no missing data was observed. The number of data records is indicated in Table 5.1. As no data was missing, no imputation or case deletion was performed.

Table 5.1: Missing Record

Missing Data Summary	
Total	1936
Missing Data	0
Percentage of Missing data	0%

Source: Author's own.

5.5 Descriptive Statistics

5.5.1 Age Demographics

The age profile for the respondents ranges from 20–24 and above 50 (Figure 5.1). On average, most respondents were between 35 and 44 and reported that they had wearable fitness devices. Such an average age group suggests that most respondents are middle-aged. Furthermore, the standard deviation of 1.596 indicates that age groups in the sample measured vary considerably.

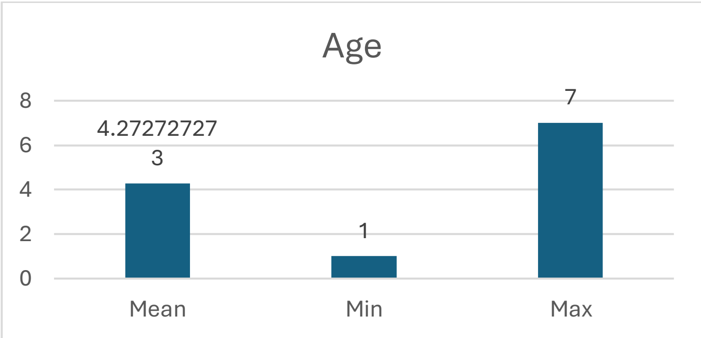

Figure 5.1: Age Demographic

Source: Author's own.

5.5.2 General Health

Respondents generally reported that they do not expect to get sick soon; secondly, their health will not worsen (Figure 5.2). The response also suggests that respondents perceived themselves in good health condition. In summary, respondents' General Health can be considered to have a positive self-perception of health.

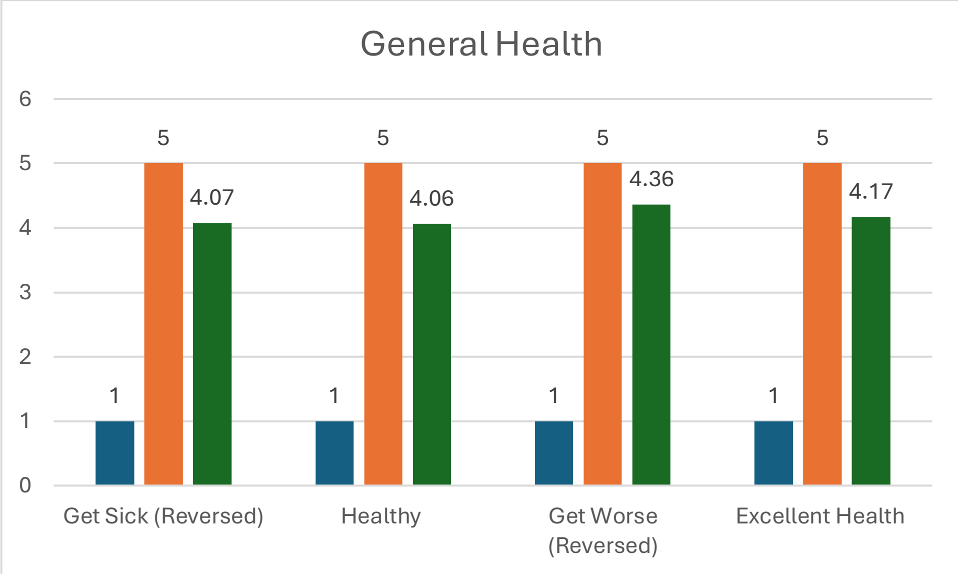

Figure 5.2: General Health Levels

Source: Author's own.

5.5.3 Vitality Score

Respondents' responses on the Vitality items have an average of 4.14 out of a scale of 6, indicating a 69% score on the Vitality scale (Figure 5.3). The results suggest that respondents are generally energetic or full of pep. However, they also felt less worn and tired most of the time. The tired and Worn measure has been reversed. Respondents generally have high Vitality scores, indicating high energy levels.

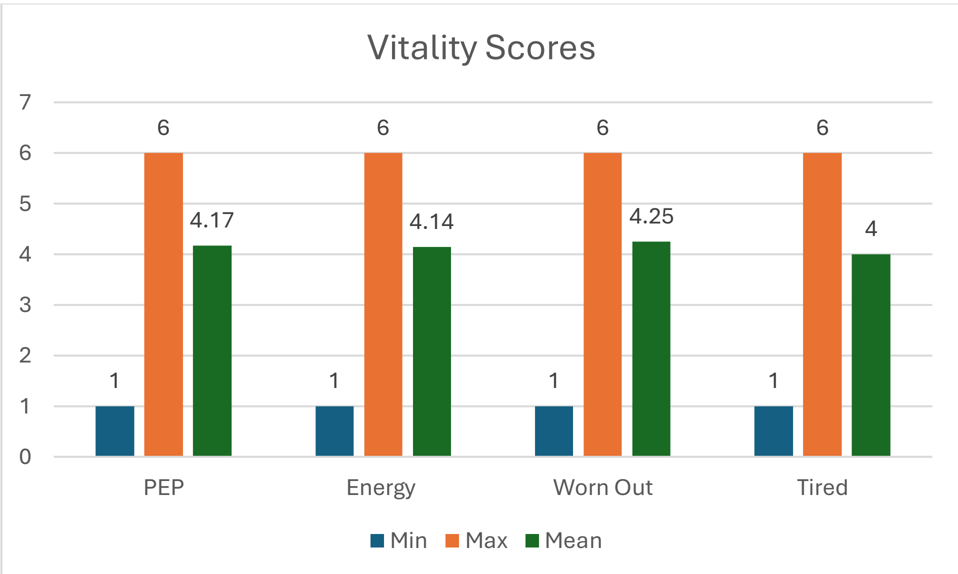

Figure 5.3: Vitality Scores

Source: Author's own.

5.5.4 Social Influence

These results on the social influence construct suggest that respondents are slightly above the midpoint at 3.45 and 3.37 for people influence and people important, suggesting that people around them influence their decisions (Figure 5.4). Some respondents reported they strongly disagree that people around them influence their choices. However, some reported directly opposite of that nation, reflecting a spread and variability of opinions.

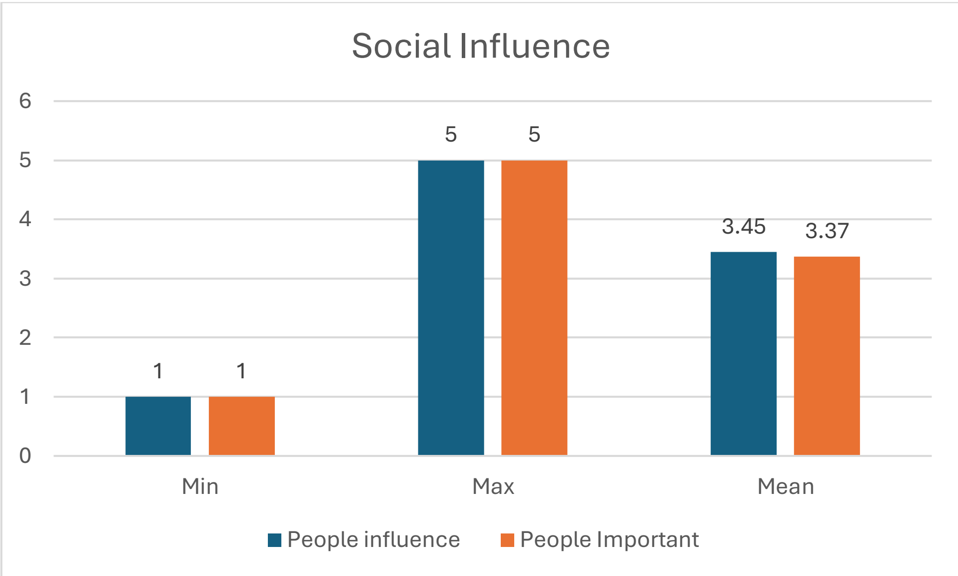

Figure 5.4: Social Influence Scores

Source: Author's own.

5.5.5 Intention to Adopt

The respondents reported overall high intention to adopt wearable devices, with a mean score of 4.4, 4.37, and 4.47 for Intend, Predict, and Plan, respectively (Figure 5.5). A standard deviation of 1 further suggested that the response varied somewhat because some respondents reported neutral or no intention to adopt the device. In summary, the sampled group is more inclined to adopt the wearable fitness device.

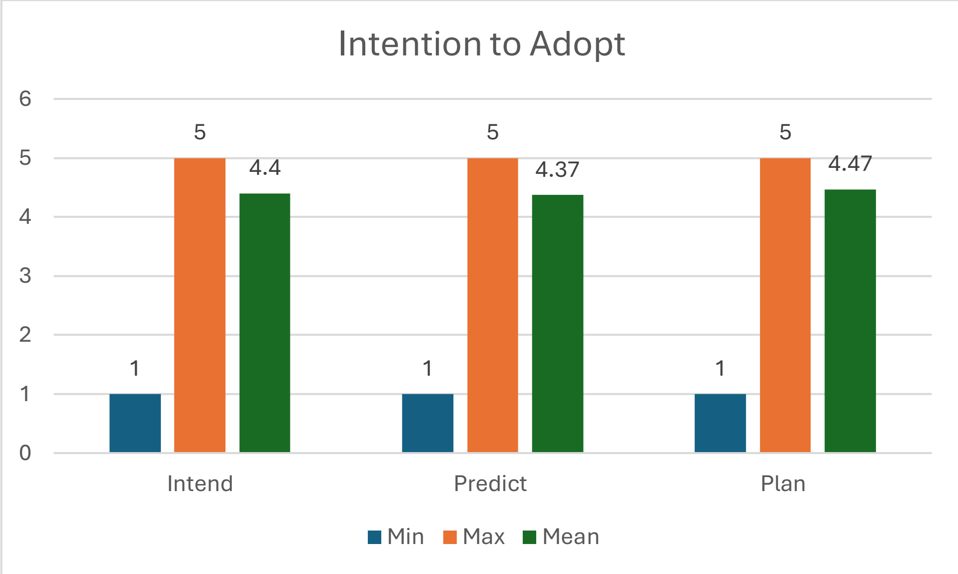

Figure 5.5: Intention to Adopt Levels

Source: Author's own.

5.5.6 Actual Use

On average, the respondents used their wearable fitness device between once and a few times a week, suggesting moderate usage. The mean score is 4.64 (Figure 5.6). The range from 1 to 7 indicates that some used the device several times a day, while some did not use it all. A standard deviation of 2.195 indicated that the usage patterns differ substantially. In summary, the respondents' actual usage of the device is moderate.

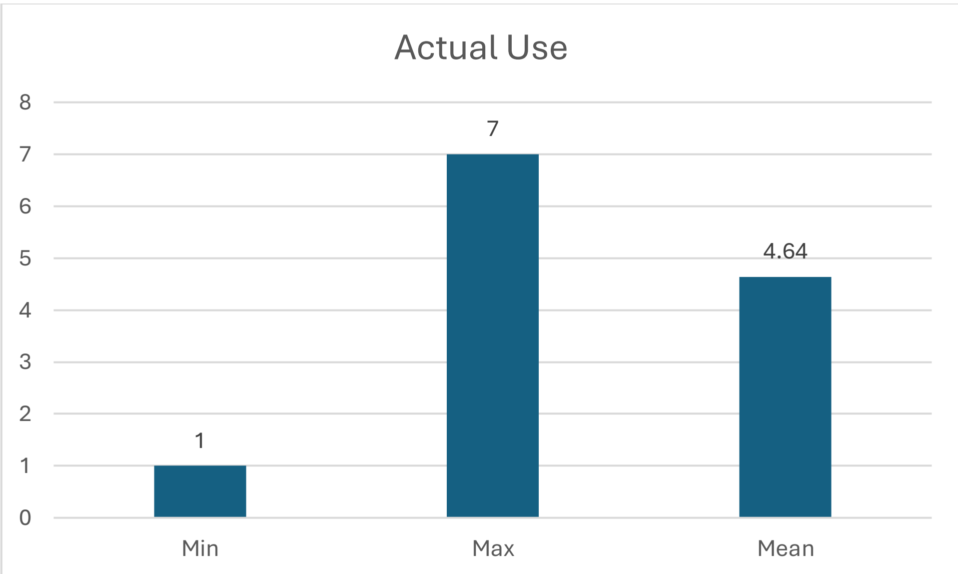

Figure 5.6: Actual Use Levels

Source: Author's own.

5.6 Statistical Analysis

5.6.1 Normality

The data was tested for normality by analysing Z scores for Skewness and Kurtosis. The Z values for skewness text showed the data is negatively skewed (Table 5.2). The skewness z values for variables people influence and people important were found to fall within the acceptable rand of -1.96 and 1.96. Similarly, eight out of 14 variables were found to be outside the range of -1.96 and 1.96, and such variables were: intend, predict, people influence, people important, actual use, healthy and excellent health. The results for Skewness and Kurtosis suggest that the data is not distributed normally; however, further tests are conducted below to make a conclusive assertion.

Table 5.2: Skewness and Kurtosis Test Results

		Skewness			Kurtosis		
Variable	**Mean Statistics**	**Std. Error**	**Statistics**	**Z Skewness**	**Std. Error**	**Statistics**	**Z Kurtosis**
Intend	4.4	-2.09	0.22	-9.5	3.894	0.437	8.91075515
Predict	4.37	-2.012	0.22	-9.145455	3.588	0.437	8.21052632
People influence	3.45	-0.329	0.22	-1.495455	-0.984	0.437	-2.2517162
Plan	4.47	-2.298	0.22	-10.44545	5.555	0.437	12.7116705
People important	3.37	-0.28	0.22	-1.272727	-1.187	0.437	-2.7162471
Actual Use	4.64	-0.506	0.22	-2.3	-1.153	0.437	-2.6384439
Get sick	4.07	-1.036	0.22	-4.709091	0.171	0.437	0.39130435
Healthy	4.06	-1.043	0.22	-4.740909	1.164	0.437	2.66361556
Get worse	4.36	-1.068	0.22	-4.854545	-0.028	0.437	-0.0640732
Excellent Health	4.17	-1.114	0.22	-5.063636	1.761	0.437	4.02974828
PEP	4.17	-0.581	0.22	-2.640909	-0.258	0.437	-0.590389
Energy	4.14	-0.57	0.22	-2.590909	-0.329	0.437	-0.7528604
Worn Out	4.25	-0.848	0.22	-3.854545	0.078	0.437	0.1784897
Tired	4	-0.78	0.22	-3.545455	-0.061	0.437	-0.1395881

Source: Author's own.

Kolmogorov Smirnova and Shapiro-Wilk are widely used to test for normal distribution in a data set, where higher statistics mean high deviation from the mean (Steinskog et al., 2007). The test statistics and P value of less than 0.001 seem to suggest that the data is not normally distributed (Table 5.3).

Table 5.3: Kolmogorov-Smirnova and Shapiro-Wilk

	Kolmogorov-Smirnova		Shapiro-Wilk	
Variable	**Statistic**	**Sig**	**Statistic**	**sig**
Intend	0.368	<.001	0.614	<.001
Predict	0.359	<.001	0.631	<.001
Plan	0.374	<.001	0.604	<.001
People influence	0.169	<.001	0.887	<.001
People important	0.182	<.001	0.88	<.001
Use	0.202	<.001	0.851	<.001
Get sick	0.272	<.001	0.794	<.001
Healthy	0.3	<.001	0.802	<.001
Get worse	0.356	<.001	0.726	<.001
Excellent Health	0.311	<.001	0.743	<.001
PEP	0.222	<.001	0.907	<.001
Energy	0.228	<.001	0.903	<.001
Worn Out	0.243	<.001	0.869	<.001
Tired	0.244	<.001	0.877	<.001

Source: Author's own.

5.6.2 Outliers

Table 5.4 presents several outliers found in the clean data. A total of 23 outliers out of 1815 observations were found, representing 1.27%, which is less than the recommended 5% outlier percentage (Davidov et al., 2018). Thus, no winsorising of values was conducted.

Table 5.4: Percentage Outliers

Variable	Clean data
Intend	4
Predict	5
Plan	3
People Influence	0
People Important	0
Actual Use	0
Get Sick	0
Healthy	4
Get Worse	3
Excellent health	4
PEP	0
Energy	0
Worn out	8
Tired	0
Total	23
Number of data point	1815
Percentage outliers	1.27%

5.6.3 Validity

5.6.3.1 Convergent Validity

A bivariate Pearson correlation analysis was performed to evaluate the strength of the relationship between two variables and assess convergent validity. In this context, a correlation coefficient of +1 denotes a perfect positive correlation, -1 signifies a perfect negative correlation, and 0 indicates the absence of any correlation. The result for bivariate correlation is presented in Table 5.5. Pearson correlation with P values less than 0.001 was considered to be significant.

Intend and predict had a correlation of 0.86 with a p-value less than 0.001, intend and plan had a correlation value of 0.697, and predict and plan Pearson correlation was

0.838. The results indicated that the three items were significantly highly correlated; therefore, the convergent validity was confirmed among the three items.

People influence and people important items had a Pearson correlation of 0.765 with a p-value of 0.001. The Pearson and p-value for people influence and people important confirms that the two items are related and convergent accordingly. Construct Actual Use was not tested for convergent as it had only one item.

Get Sick and Healthy had a Pearson correlation of 0.415 and a p-value of less than 0.001, indicating a strong, significant correlation. This demonstrates that the convergence between the two items was validated. On the contrary, Get Sick and Get Worse had a Pearson correlation of 0.224 and a p-value of 0.013, which indicates a weak correlation, and as such, the convergent was not validated. Get Sick and Excellent Health Pearson correlation was recorded to be 0.44 with a p-value of less than 0.001, suggesting a moderate correlation between the two items. As a result, convergence between the two items was validated. The Pearson correlation between Healthy and Get Sick was 0.247, with a P value of 0.006. These results indicated a weak, insignificant correlation; therefore, the convergent between Healthy and Get Sick was not validated. Healthy and Excellent Health scored a Pearson correlation of 0.628 with a p-value of less than 0.001, indicating a strong positive and significant correlation between the two items. Convergent was validated for Healthy and Excellent Health. Get Worse and Excellent Health Pearson correlation was 0.270 and a p-value of 0.003, confirming weak positive and significant correlation. Therefore, the convergent between items Get Worse and Excellent Health was validated.

Table 5.5: Bivariate Pearson Correlation

		Pearson correlation	**Significant (p)**	**Conclusion**	**Convergent validity**
Intent	Intend and Predict	0.680	P<0.001	Strong correlation	Yes
	Intend and Plan	0.697	P<0.001		
	Predict and plan	0.838	P<0.001		

		Pearson correlation	Significant (p)	Conclusion	Convergent validity
Social Influence	People influence and people important	0.765	P<0.001	Strong correlation	Yes
Actual Use	Actual use	Only one variable			Yes
General Health	Get Sick and Healthy	0.415	P<0.001	Positive correlation	Yes
	Get Sick and Get Worse	0.224	P=0.013	Weak correlation	No
	Get Sick and Excellent Health	0.444	P<0.001	Moderate correlation	Yes
	Healthy and Get Worse	0.247	P<0.006	Weak correlation	No
	Healthy and Excellent Health	0.628	P<0.001	Strong correlation	Yes
	Get Worse and Excellent Health	0.270	P=0.003	Weak correlation	
Vitality	PEP and Energy	0.857	P<0.001	Strong positive correlation	Yes
	PEP and Worn Out	0.649			
	PEP and Tired	0.651			

		Pearson correlation	Significant (p)	Conclusion	Convergent validity
	Energy and Worn out	0.635			
	Energy and Tired	0.288			
	Worn out and Tired	0.816			

Source: Author's own.

PEP and Energy Pearson correlation was found to be 0.857 with a p-value of less than 0.001, indicating a strong positive correlation. The PEP and Worn Out and Tired Pearson correlations were 0.649 and 0.651, which suggests a strong correlation. Energy and Worn Out had a Pearson correlation of 0.635, indicating a strong positive correlation. The energy and Tired correlation was found to be 0.288, suggesting a weak correlation between the two items. Worn out and Tired had a Pearson correlation of 0.816, which reflected a strong positive correlation. All constructs under the Vitality construct were found to be significant and positively correlated due to a p-value of less than 0.001. This suggests that all items under the Vitality construct measuring the same construct and their convergent have been validated.

5.6.3.2 Convergent Validity – Standardised Loadings

The standardised loadings for all the items are outlined in Table 5.6 to validate their convergent further. Items under the intent construct were found to be loading above 0.75, and the AVE was recorded to be 0.75, thereby validating convergent for all the items. All two items under the social influence construct had standardised loadings of 0.79 and above with AVE of 0.77, confirming convergent validity. Actual Use validity was not calculated due to its single item under the construct. General Health items loaded well above 0.50 except for Get Worse, with standardised loadings of 0.35. As a result, the AVE was found to be 0.41, suggesting poor convergence of items under the construct. The Get Worse item was then removed to improve the AVE score. After removing the Get Worse item, the AVE score was 0.52, which rendered the convergent validity acceptable as the AVE was above 0.5. The get Worse item was removed from the analysis for the remainder of the thesis.

Items PEP, Energy, Worn Out, and Tired had standardised loadings above 0.7 and AVE 0.69 above the 0.5 threshold discussed in the methodology section. Therefore, all items under the Vitality construct were found to be acceptable from a convergent validity perspective.

Table 5.6: Standardised Loading

Construct	Variables	Standardised loading	AVE	Comment
Intent	Intend	0.75	0.75	Acceptable convergent validity
	Predict	0.90		
	Plan	0.94		
Social influence	People important	0.79	0.77	Acceptable convergent validity
	People influence	0.96		
Actual Use	AU			
General Health	Get sick	0.55	0.52	Acceptable convergent validity
	Healthy	0.77		
	Excellent health	0.81		
Vitality	PEP	0.91	0.69	Acceptable convergent validity
	Energy	0.91		
	Worn out	0.74		
	Tired	0.74		

Source: Author's own.

5.6.4 Reliability

Cronbach test to determine internal consistency within the variables is reported in Table 5.7. Most construct's Cronbach Alpha was above 0.7, indicating that internal consistency was established and all variables can be accepted. The Get Worse variable under General Health was removed due to its negative effect on Cronbach's Alpha score. Actual Use Cronbach's Alpha could not be tested because the construct had one item.

Table 5.7: Cronbach's Alpha

Construct	Variable	Cronbach's Alpha	Comments
Intend	Intent Predict Plan	0.891	Internal consistency established. Accept
Social Influence	People influence People important	0.866	Internal consistency established. Accept
General Health	Get sick Healthy Excellent health	0.723	Internal consistency established. Accept
Vitality	Pep Energy Worn out Tired	0.90	Internal consistency established. Accept
Actual Use	Actual use	N/A	N/A

Source: Author's own.

Composite reliability confirms whether the items are reliably measuring what is intended (Fornell & Larcker, 1981). Table 5.8 shows the composite reliability for all the constructs or dimensions. Four dimensions have composite reliability from 0.7 to 0.9, which is considered desirable because a high internal consistency was established and reliability was achieved. This high reliability affirms that although the scales were designed in different settings, they are still valid within this study. Composite reliability for Actual Use could not be calculated because the dimension has one item. However, factor loadings were used to test its reliability.

Table 5.8: Reliability Test

Construct	Composite Reliability	Comment
Intent	0.9	High internal consistency, high reliability
Social influence	0.87	High internal consistency, high reliability
Actual Use	Not calculated	

Construct	Composite Reliability	Comment
General Health	0.72	High internal consistency, high reliability
Vitality perception	0.89	High internal consistency, high reliability

Source: Author's own.

5.6.5 Dimension Reduction

KMO is used to determine whether or not the given data is viable for factor analysis (Kaiser, 1974), while Bartlett's Test of Sphericity compares correlation and identity matrix to see if there are any statistical differences (Bartlett, 1950). KMO results for this study are found in Table 5.9. For all the constructs, accept Actual Use. Construct Intent had a KMO value of 0.72, indicating acceptable sampling adequacy and significant Bartlett's Test of Sphericity, confirming that the data is suitable for factor analysis. KMO value of 0.50 for the Social construct was poor despite significant Bartlet's Test of Sphericity, and caution ought to be exercised when reporting the results. KMO value was not calculated for Actual Use since the construct had one item. General Health's KMO value was 0.66, indicating that the data is borderline suitable for analysis despite being supported by the Bartlett Test of Sphericity. Get Worse was omitted because it failed to converge in validity testing, meaning it does not relate well with the construct. The Vitality KMO value was 0.745, which indicates acceptable sampling adequacy and is well supported by Bartlet's Test of Sphericity, demonstrating that factor analysis is appropriate.

Table 5.9: KMO and Bartlett's Test

Construct	Items	KMO	Bartlett's Test of Sphericity	Comment
Intention to adopt	Intend	0.720	Chi-square 229.027 P<0.001	Acceptable sampling, Statistically significant: factor analysis suitable
	Predict			
	Plan			
Social Influence	People Influence	0.500	Chi-square:104.41	Poor sampling, statistically

Construct	Items	KMO	Bartlett's Test of Sphericity	Comment
	People Important		P<0.001	significant: factor analysis suitable
Actual Use	Actual Use	Only one factor cannot do factor analysis		
General Health	Get Sick	0.660	Chi-square:89.847 P<0.001	Mediocre sampling, Statistically significant: factor analysis suitable
	Healthy			
	Excellent health			
Vitality	PEP	0.745	Chi-square:0.745 P<0.001	Acceptable sampling, statistically significant: factor analysis suitable
	Energy			
	Worn Out			
	Tired			

Source: Author's own.

5.7 Hypotheses Testing

5.7.1 Assumptions of Regression Analysis

A sample size of 120 was used to ensure compliance with the recommended sample size for regression analysis, as discussed in Chapter 5. The data used was tested for normality through outlier, skewness, kurtosis, and SW, represented in Tables 5.2 and 5.3. It was established that the data was not normal, so a suitable regression method was selected. The WLS regression model is proposed, and results have been tabled under each hypothesis.

5.7.2 Outliers

The data had 23 outliers representing 1.27% of outliers, alleviating the need to winsorizing because the percentage outlier is less than the threshold.

Table 5.10: Outlier Percentage

Total	23
Number of data point	1815
Percentage outliers	1.27%

Source: Author's own.

5.7.3 Homoscedastic and Heteroskedastic Test

Heteroskedasticity refers to unstable variance in error terms of all predictor variables, which also means that the assumption for ordinary least square regression is violated (White, 1980). This means that a different regression model should be considered when estimating the model. As such, the weighted least square was selected, and the results were shown under each hypothesis. Figure 5.7 below clearly shows that the scatter plot of the predicted values and residuals is not randomly located. A negatively sloping trend can be noticed, proving that heteroscedasticity is at play.

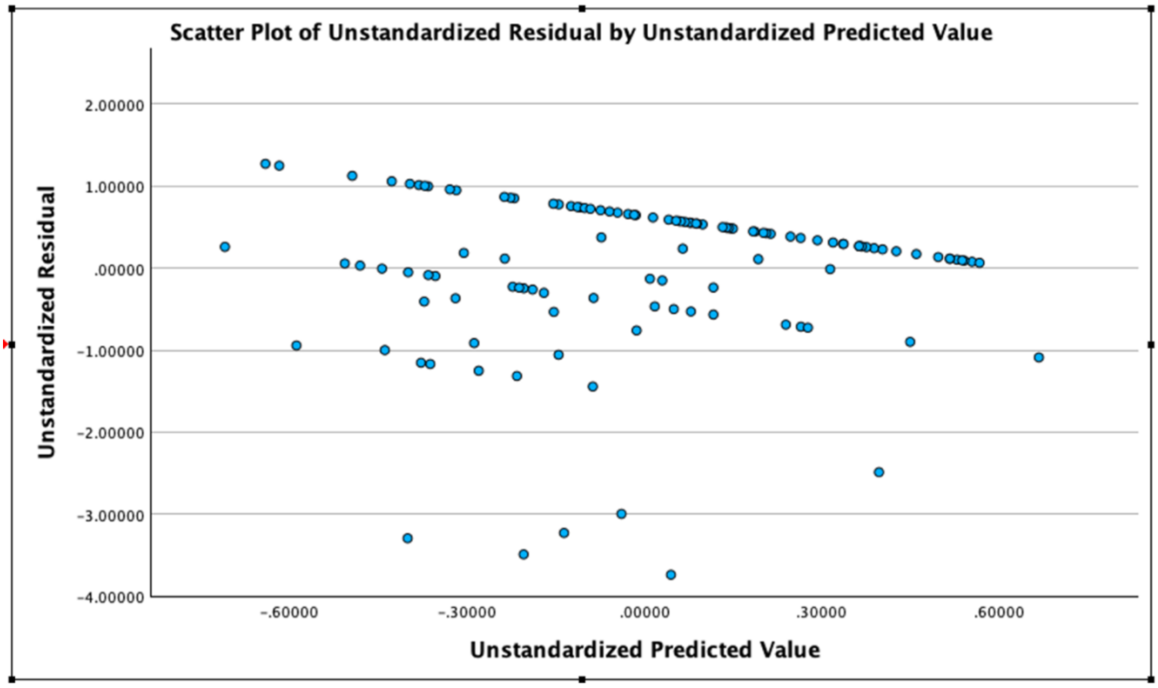

Figure 5.7: Heteroskedastic Test Results

Source: Author's own.

5.7.4 Multicollinearity

The data was tested for multicollinearity, shown in Table 5.11, and the results show that multicollinearity is not a concern because the VIF is between 1 and 2, which is below the threshold of 10. The tolerance, which is an inverse of VIF, measures the variance in a predictor and is all above 0.1, suggesting that no severe collinearity exists. This test confirms that the multicollinearity assumption for regression is not violated.

Table 5.11: Collinearity Test Results

Construct	Tolerance	VIF
Social Influence (SI)	0.981	1.019
General Health (GH)	0.769	1.301
Vitality (VT)	0.763	1.310

Source: Author's own.

5.7.5 H1: General Health (GH) Positively Influences Intention to Adopt (IA) Fitness Wearable Device

Table 5.12 indicates the summary factors for the regression model between predictor GH and dependent variable IA. The coefficient correlation R of 0.860 reflects a strong positive correlation between GH and IA. R Square of 0.740 suggests that GH explains 74% of the variation in IA. The adjusted R square 0.738 is more accurate than the R square as it also indicates the high explanatory power that GH has on IA.

Table 5.12: Weighted Least Square Regression Summary for GH and IA

Regression summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimation**
1	0.860a	0.740	0.738	1.41854725
a. Predictor: (Constant), General health (GH) b. Dependant Variable: Intention to Adopt (IA) c. Weighted Least Square Regression Weighted by Weight				

Source: Author's own.

The Anova Table 5.13 for the GH and IA relationship below presents the Regression sum of squares value (682.44), which indicates the variation in IA explained by GH. The Residual sum of squares is 239.461, which means the unexplained variation. Furthermore, the regression sum of squares is more significant than that for residual, which indicates that GH explains most of the variation in IA. The F-value 339.140 with a P-value (<0.01) suggests the model is highly significant.

Table 5.13: Weighted Least Square Regression Anova GH and IA

ANOVA.a.b						
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
	Regression	682.444	1	682.44	339.140	<0.01c
	Residual	239.461	119	2.012		
	Total	921.905	120			
a. Dependent Variable: Intention to adopt (IA) b. Weighted Least Square Regression Weighted by Weight						
c. Predictors: (Constant), General health (GH)						

Source: Author's own.

The unstandardised coefficient B (0.236) indicates that one unit increase in GH, 0.236 units of IA will also increase (Table 5.14). The standardised Coefficient Beta is 0.860, which is closer to 1, which suggests that GH has a strong effect on IA. A value of 18.416 and a p-value of (<0.001) further confirm that the impact of GH on IA is statistically significant.

Table 5.14: Weighted Least Square Regression Coefficients for GH and IA

Coefficients.a.b					
Model	**Unstandardised Coefficients**		**Standardised Coefficients Beta**	**t**	**Sig**
	B	**Std. Error**			
(Constant)	0.005	0.015		0.330	0.742
General Health (GH)	0.236	0.013	0.860	18.416	<0.001
a. Dependent Variable: Intention to Adopt (IA) b. Weighted Least Square Regression Weighted by Weight					

Source: Author's own.

5.7.6 H2: Vitality (VT) Positively Influences Intention to Adopt (IA) Fitness Wearable Device

The regression summary for the VT and IA is presented in Table 5.15 with a coefficient correlation of R 0.791, which indicates a positive, strong relation between the two constructs. The R square suggests that VT explains 62.5% variation in IA. The adjusted R square recorded at 0.622 is more accurate than the R square, indicating a high exoplanetary power VT has on IA.

Table 5.15: Weighted Least Square Regression Summary VT and IA

Regression summary.b.c				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimation**
1	0.791a	0.625	0.622	1.70468130
a. Predictor: (Constant), Vitality (VT)				
b. Dependent variable: Intention to Adopt (IA)				
c. Weighted Least Squares Regression-Weighted by Weight				

Source: Author's own.

The Anova Table 5.16 presents results for VT and IA with regression sum of squares value 576.098 notably larger than the residual sum of square value 345.807, suggesting that the model explains a large proportion of variance in IA. One predictor, VT, was used in the model; hence, the degree of freedom is 1. The value of 198.249 with a p-value of (<0.001) further suggests that VT is a strong significant predictor of IA.

Table 5.16: Weighted Least Square Regression Anova VT and IA

ANOVA.a.b						
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
	Regression	576.098	1	576.098	198.249	<0.001c
	Residual	345.807	119	2.906		
	Total	921.903	120			
a. Dependent Variable: Intention to adopt (IA)						
b. Weighted Least Square Regression-Weighted by Weight						
c. Predictors: (Constant), Vitality (VT)						

Source: Author's own.

The coefficient table for the VT and IA relationship is shown below in Table 5.17. The coefficient (0.175) suggests that, for every unit increase in Vt, IA will increase by 0.175, holding other variables constant. The standardised coefficient Beta 0.791, close to 1, shows that VT has a strong effect on IA. t of 14.080 with a p-value (<0.001) further validates that there is a significant statistical effect of VT on IA, which means the results were not a random occurrence.

Table 5.17: Weighted Least Square Regression Coefficients

Coefficients a.b					
Model	**Unstandardised Coefficients**		**Standardised Coefficients Beta**	**t**	**sig**
	B	**Std. Error**			
(Constant)	0.198	0.010		19.553	<0.01
Vitality (VT)	0.175	0.012	0.791	14.080	<0.001

Source: Author's own.

5.7.7 H3: Social Influence Has a Positive Influence on Intention to Adopt Fitness Wearable Devices

Table Regression summary for Bivariate Liner Regression Test for Social Influence (SI) and Intention to Adopt (IA). A linear regression summary of SI and IA is shown in Table 5.18 below, with coefficient correlation, R measuring 0.923, which indicates a positive, strong relation between the two constructs.

Table 5.18: Regression Summary SI and IA

Regression summary b.c				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimation**
1	0.923a	0.852	0.851	1.07002872
a.Predictor: (Constant), Social influence (SI)				
b.Dependent variable: IA				
c. weighted Least Square Regression -Weighted by Weight				

Source: Author's own.

The coefficient of determination R square value is 0.852, suggesting that SI explains 85.2% of the variation in IA, which is considered a high explanatory power. The adjusted R square improved the R measure to 0.851, a more accurate measure of variability.

Table 5.19 below presents Anova's results for SI and IA. The high F values (686.184) and p-value of (<0.001) indicate that SI significantly predicts IA. As a result, construct SI has a strong statistical effect on construct IA. The regression model's sum of squares (785.655), proportionally larger than the Residual's sum of squares (138.250), suggests the model explains a large amount of variance in IA. Lastly, the one predictor (SI) was employed in the model as seen by the degree of freedom of (1).

Table 5.19: Anova SI and IA, Weighted Least Square

ANOVA a.b						
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
	Regression	785.655	1	785.655	686.184	<0.001c
	Residual	136.250	119	1.145		
	Total	921.905	120			
a. Dependent Variable: Intention to adopt (IA)						
b. Weighted Least Square Regression- Weighted by Weight						
c. Predictors: (Constant), Social influence (SI)						

Source: Author's own.

Regression coefficients for SI and IA are indicated below in Table 5.20.

Table 5.20: Regression Coefficients for SI and IA

Model	**Unstandardised Coefficients**		**Standardised Coefficients Beta**	**t**	**sig**
	B	**Std. Error**			
(Constant)	-0.009	0.012		-0.788	0.432
Social Influence	0.352	0.13	0.923	26.195	<0.001
a. Dependent Variable: Intention to adopt (IA)					
b. Weighted Least Squares Regression-Weighted by Weight					

Source: Author's own.

Holding other variables constant, the unstandardised coefficient (0.352) suggests that a unit increase in SI increases IA by 0.352. SI has a standardised coefficient Beta of 0.923, which is close to 1, indicating that SI strongly affects IA. A t equal to 26.195 with a p-value of <0.001 further confirms the strong statistical effect SI has on AI.

5.7.8 H4: Intention to Adopt Positively Influences Actual Use of Fitness Wearable Devices

The regression Table 5.21 below indicates a statistical summary of intention to adopt (IA) and actual use (AU). A strong relationship between IA and Au is suggested by observing the R (0.738). R square (0.544) further indicates that 54.4 % variation in actual use is due to intention to adopt. Moreover, 54.2% of the variance is still attributed to the intention to adopt after adjusting for possible overfitting, as observed with adjusted R square (0.541). The standard error measured (0.924) indicates a good model fi. The string explanatory power and correlation supports hypothesis H4: Intention to adopt positively influences actual use of fitness wearable devices

Table 5.21: Regression Summary IA and AU

Regression summary.b				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimation**
1	0.738a	0.544	0.541	0.924
a. Predictor: (Constant), Intention to adopt (IA) b. Dependent Variable: Actual Use (AU) c. Weighted Least Square Regression Weighted by Weight				

Source: Author's own.

The ANOVA Table 5.22 presented below indicates a high value of F statistics (142.185), suggesting that the influence of intention to adopt on actual use is significant because the sig. (p-value <0.01). The regression sum of squares (121.436) shows that variance in actual use is due to the intention to adopt. In conclusion, a high F -statistic that is significant suggests that the relation between intention to adopt and actual use is statistically significant. Therefore, hypothesis H4, intention to adopt positively influences the actual use of fitness wearable devices, is supported.

Table 5.22: ANOVA IA and AU

ANOVA.a.b						
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
	Regression	121.436	1	121.436	142.185	<0.01c
	Residual	101.634	119	0.854		
	Total	223.070	120			
a. Dependent Variable: Actual use (AU)						
b. Weighted Least Square Regression Weighted by WeightAU						
c. Predictors: (Constant), Intention to adopt (IA)						

Source: Author's own.

Table 5.23 below presents the regression coefficients for intention to adopt and actual use.

Table 5.23: Regression Coefficient IA and AU

Model	**Unstandardised Coefficients**		**Standardised Coefficients Beta**	**t**	**Sig**
	B	**Std. Error**			
(Constant)	4.671	0.030		155.172	<0.001
Intention to adopt (IA)	0.532	0.045	0.738	11.924	<0.001
a. Dependent Variable: Intention to adopt (IA)					
b. Weighted Least Squares Regression-Weighted by Weight					

Source: Author's own.

The unstandardised coefficient Beta (0.532) suggests that a unit increase in intention to adopt increases actual use by 0.532. Moreover, the standardised Beta (0.738) indicates the strength of the relations, suggesting a strong link between the IA and AU. Lastly, a significant influence of intention to adopt on actual use is observed by a t-value of 11.924 with a p-value of less than 0.001. To conclude, the results support hypothesis H4: Intention to adopt positively influences actual use of fitness wearable devices is supported.

5.8 Chapter Summary

The results chapter extensively presents the data collection and statistical analysis to conclude hypothesis testing. The data presented some elements of abnormality. WLS Regression was employed to address heteroscedasticity and abnormality. The results show that all four hypotheses are supported. The following chapter presents the discussion of the results in detail.

Chapter 6: Discussion of Results

6.1 Introduction

This chapter summarises the results, data collection methodology, and statistical test employed to arrive at the results. Chapter 6 further presents all four hypotheses and discusses them in detail by comparing and contrasting them with recent literature. Lastly, a theoretical model is presented to summarise this study's results.

6.2 Summary of Results

Table 6.1 below outlines a summary of the results fully described in Chapter 5.

Table 6.1: Summary of Results

Section	Outcome
Data Analysis	The raw data comprised 209 entries. After removing entries without wearable devices, 120 remained. The data had no missing data.
Normality	Skewness and Kurtosis indicate the data is not distributed normally. WLS Regression was employed to address abnormality.
Outliers	Percentage outliers less than 5% of the recommended percentage.
Validity	Bivariate Pearson correlation results confirmed convergent validity for Intention to Adopt, Vitality, and Social influence. Get Worse item caused a weak correlation. Standardise loadings above 0.7. The Get Worse item was removed due to low loading.
Reliability	Cronbach's Alpha is above 0.7, suggesting internal consistency. The Get Worse item was removed because it negatively affected Cronbach's Alpha. All constructs had acceptable composite reliability.

Section	Outcome
Dimension reduction	The intention to adopt construct KMO 0.72 suggests that factor analysis is acceptable. Social Influence KMO 0.500, poor sampling but suitable for factor analysis. General Health and Vitality, suitable factor analysis.
Multicollinearity	VIF between 1-2, multicollinearity is not a concern.
Hypothesis H1: (GH>IA)	General Health (GH) positively influences intention to adopt (IA) wearable fitness devices. Statistically confirmed.
Hypothesis H2: (VT>IA)	Vitality (VT) positively influences intention to adopt (IA) fitness wearable devices.
Hypothesis H3: (SI>IA)	Social influence has a positive influence on the intention to adopt fitness wearable devices.
Hypothesis H4: (AU>IA)	Adoption intention significantly influences the actual use of fitness wearable devices.

Source: Author's own.

6.3 Data Collection

The number of respondents that responded to the survey was 209; however, only 120 respondents had wearable fitness devices. Dolničar et al. (2024) conducted a similar study with a sample size of 103, investigating factors that drive intention to adopt mobile health devices among patients with chronic disease. The data was collected through Google forms, which were sent to various online social media channels such as WhatsApp, LinkedIn, and Facebook. to reach respondents. Respondents were required to consent to participate in the survey before completing a questionnaire with multiple questions linked to a Likert scale. The questionaries were adapted from established and validated scales such as the SF-36 for General Health and Vitality questions. The challenge experienced during the survey was a lack of quick response because the survey was sent out toward the end of the year, and respondents were slightly reluctant to respond.

6.4 Descriptive Statistics

6.4.1 Age Demography

The survey respondents' minimum age was between 20 and 24, and the highest was above 50. The sample had an average age of 35–44, suggesting that the sample is primarily made of young adults who own a wearable fitness device. This aligns with the finding of Venkatesh et al. (2003), who posits that young adults are more likely to adopt new technology. The age data had a standard deviation of 1.596, indicating significant variance of age groups within the sample. The considerable standard deviation suggests that fitness wearable devices appeal to both young adults and older respondents.

6.5 Statistical Analysis

The data was observed for normality by analysing skewness and kurtosis results, and such results suggest that the data is not normally distributed. Bai (2005) affirmed that negatively skewed data can present biased results. However, the data had an outlier percentage of 1.24%, which is less than the recommended 5%. A bivariate person correlation was conducted to ensure convergent validity for all constructs. All constructs' convergent validity was confirmed with an expectation of construct General Health affected by item Get Worse, causing weak correlation with most items. Standardised loadings were established for each construct with loading above 0.7. Item Get Worse was dragging the loadings below 0.7, so the item was excluded from the analysis. Furthermore, reliability was established by calculating Cronbach's Alpha on all constructs in isolation to determine internal consistency.

6.6 Hypothesis Testing

6.6.1 H1: General Health (GH) is a Significant Predictor of Intention to Adopt (IA) Wearable Fitness Device

The results show that General Health had a standardised coefficient of 0.860 and a p-value less than 0.001 when tested against IA through regression modelling. Furthermore, the Adjusted R square of 0.738 suggested that the predictor of General Health had high explanatory power on Intention to Adopt. Therefore, H1 was supported because General

Health (GH) is a significant predictor of the intention to adopt wearable fitness devices (IA). These results can be expected because people who perceive themselves as healthy may be motivated to use technology that will encourage them to stay healthy by monitoring their health indicators and possibly prompt them to lead an active lifestyle. Moreover, people who perceive themselves as healthy may intend to adopt wearable fitness devices because they expect the technology to enhance or maintain their health.

Furthermore, General Health's significant positive relationship with the Intention to adopt wearable fitness devices squarely aligns well with the theoretical model UTAUT by Venkatesh and Davis (2000), where performance expectancy was found to be an antecedent of behavioural intentions. Therefore, people who perceive themselves as healthy expect the fitness device to improve their performance expectancy perspective; hence, they are more prone to adopt the technology. The significant association between General Health and intention to adopt further reinforces that performance expectations play a vital role in behavioural intention on the UTAUT model. This result further confirms the theoretical findings of Davis et al. (1989) on the TAM from a user usefulness perspective because people are likely to adopt technology due to their perceived use. In this case, people who perceive themselves as healthy adopt the wearable fitness device because they perceive the device as something that would be useful in maintaining or improving their health.

The observed results are consistent with the findings of Yang et al. (2024), which reported that health consciousness and health value significantly impact wearable medical devices. The similarity in results could be attributed to the data-gathering process, as both utilised online surveys to reach out to respondents. As a result, respondents who may be reached through online surveys could have a high propensity to adopt new technology, making them more prone to adopt wearable fitness devices. While this research employed UTAUT as a theoretical framework to assess adoption intention, Yang et al. (2024) employed Value-Belief-Norm (VBN) (Stern et al., 1999). The VBN theory suggests that people are likely to adopt technology when they perceive its value aligns with personal beliefs (Stern et al., 1999). The two theoretical models focus on behavioural intention to adopt technology and perceived benefits that drive the adoption of technology. To conclude, the similarity in results could be attributed to similar data collection and sampling techniques and theoretical foundation.

The results of this study were further consistent with the results of Cheung et al. (2019), which found a significant relationship between health belief and adoption intention through perceived usefulness. The similarity in results may be attributed to the similar fundamental theoretical TAM. However, Cheung et al. (2019) incorporated the Health Belief Model (HBM) to determine its relation with adoption intention. Cheung et al. (2019) also employed an online survey research methodology with respondents aged between 18 and 65. The population found through online channels is potentially more prone to technology, increasing their chances of adopting wearable fitness devices. The two study by Cheung et al. (2019) strengthen the idea that health perceptions are essential in the adoption intention decision for wearable fitness devices. In addition, the results support the findings of Rahman et al. (2022), who found that health belief was a significant predictor of wearable health devices among teenagers in Bangladesh. Despite similarities in foundational theories for this study and Rehman et al. (2021), respondents' ages ranged from 13 to 19 years, extending the age compared to the age group sampled for this results. This further asserts that health-related constructs such as General Health and Health Belief significantly affect adoption intention irrespective of sampled age.

General Health's significant relationship with adoption intention for wearable devices was inconsistent with the findings of Sergueeva et al. (2020), which found no statistical evidence between health consciousness and intention to adopt wearable devices. This is an interesting finding, although both studies employed the UTAUT theoretical framework as the foundation. The difference in results could stem from the difference in the sample, as Sergueeva et al. (2020) were conducted in the United States, which has stark differences in economic and social fundamentals. Firstly, South Africa is an economy with low and high-income groups with challenges to decent healthcare access, compelling and motivating people to adopt wearable fitness devices. In contrast, US consumers may not see the need to adopt fitness devices to improve or maintain a healthy lifestyle because healthcare is accessible and wearable fitness devices are not a priority. Another possible reason why the two studies found contradictory results is that this study used regression analysis, which studies direct relationships between independent and dependent variables and fails to capture indirect effects unless modelled as such. At the same time, Sergueeva et al. (2020) employed PLS-SEM modelling, which is more exploratory and allows for an indirect relationship to emerge. Therefore, using different statistical methods may have contributed to the other findings.

This study found General Health to be significant in explaining the intention to adopt wearable fitness devices. This study's result was contrary to the findings by Hayat et al. (2022a) and Jo et al. (2019), which found that health motivation did not influence intention to adopt wearable medical devices. This could be attributed to the fact that this study measures overall health perception, whereas Hayat et al. (2022a) measurement is focused on motivational aspects, which does not capture the same behavioural influence.

In conclusion, Hypothesis H1: General Health (GH) is a significant predictor of Intention to Adopt (IA) wearable fitness devices, which is strongly supported by statistical evidence and other academic literature. The regression analysis indicated a standardised coefficient of 0.860 ($p<0.001$), indicating a strong significant relationship between the GH and IA. These results are consistent with the UTAUT model's performance expectancy and align with recent literature. Overall, statistical evidence suggests that individuals who perceive themselves as healthy are likely to adopt wearable fitness devices.

6.6.2 H2: Vitality (VT) Positively Influences Intention to Adopt (IA) Fitness Wearable Device

This study found that Vitality positively influences the intention to adopt wearable fitness devices. This is evident as reported in Table 5.15, which indicates a p-value (<0.001) for the Vitality coefficient. The relationship between Vitality and intention to adopt was strong, as demonstrated by the adjusted R square of 0.622 in Table 5.13, indicating that 62.5% of the variance in IA is due to variance in VT. The results of this study have confirmed hypothesis H2: Vitality positively influences intention to adopt fitness wearable devices. These results suggest that people who perceive themselves to have high energy levels are likelier to adopt wearable fitness devices because they perceive that they will increase and maintain their energy levels. The literature review suggests that the relationship between Vitality and intention to adopt has not yet been established. Therefore, this study has added Vitality to the body of knowledge as an antecedent of intention to adopt wearable fitness technology. Vitality is a health metric that is very related to mental health (Ware et al., 1993). As such, mental health-related literature is analysed against the results of this study.

This study further confirms the findings of Venkatesh and Davis (2000), who assert that behavioural intention is driven by performance expectations, social influence, and hedonic motivation, among other constructs. Vitality is not explicitly included in the UTAUT model. However, some model constructs correspond with Vitality's significant relationship with technology adoption. Performance expectancy is a strong predictor of technology adoption under the UTAUT model, which means people are prone to adopt the technology if they perceive personal performance gains attached to the device. Similarly, in this study, people who perceive themselves as having high vitality levels may adopt the technology if they expect the fitness device to enhance or maintain their energy levels. This study adds and aligns with the notion that if technology users believe personal gain can be derived from the technology, they are more likely to adopt it.

This study has deepened the understanding of the role of Vitality in the intention to adopt wearable fitness devices. Larnyo et al. (2022) found QoL a significant predictor of intention to adopt wearable devices among a young age group with Dementia in Ghana. QoL is a construct measured using a set of questionnaires derived from SF-36. This study deepens the literature by evaluating a sub-construct (Vitality) of QoL to determine its relationship with intention to adopt. These results highlight that people are inclined to adopt wearable devices if they perceive themselves as having high energy and motivation. This study adds to the literature discourse by separating Vitality as a distinct construct that drives the intention to adopt.

The study results suggest that Vitality plays a significant role in explaining the intention to adopt wearable fitness devices. This result is contradicted by Yang et al. (2022b), who found health anxiety insignificant when explaining technology adoption. People who perceive themselves as having high Vitality are motivated to adopt wearable fitness devices to maintain their energy levels or improve. However, people who possess health anxiety have a constant worry about their health situation, whether clinically diagnosed or not. Health anxiety refers to individuals who are fearful due to body symptoms and are likely to engage in activities that improve their health (Meng et al., 2020). It was unexpected to discover that health anxiety was not a significant predictor of adoption intention. One of the reasons for this might be that people with health anxiety are preoccupied with the possible illness to the point that they fail to see the health benefits associated with adopting wearable medical devices. On the other hand, people who exhibit a high level of Vitality perceive the benefits of adopting wearable fitness technology.

This study found Vitality to be significant in the intention to adopt wearable devices. This means that people who perceive themselves as having better mental health will likely adopt fitness wearable devices. Converse, Choudhury, and Asan's (2021) findings suggest that wearable device adoption had a negative indirect influence on psychological distress as a result of better mental health. Choudhury and Asan (2021) suggest that people who adopt wearable devices may be compelled to lead an active lifestyle, for instance, running, walking, and healthy eating habits that aid mental health. This study has added to the literature by testing Vitality, a measure of mental health as a predictor of intention to adopt a fitness wearable device. Therefore, the two studies complement and reinforce each other, deepening the understanding of the influence of mental health on technology adoption.

This study was further complemented by Bao and Lee's (2024) findings, which suggested that the use of wearable devices significantly influences mental and physical health, suggesting that people who use wearable devices experience better health outcomes. Better mental health outcomes are related to high levels of Vitality, creating a reinforcing loop between intention to adopt, use of the device, and better mental Vitality.

To conclude, hypothesis H1: Vitality (VT) measured by SF-36 positively influences intention to adopt (IA) fitness wearable device is well supported by statistical results that show a standardised co-efficient of 0.791 and a p-value of <0.001. This means that people who perceive themselves as having high Vitality levels are more likely to adopt wearable fitness devices. This study further confirms the UTAUT theoretical model as Vitality corresponds closely with performance expectations. Moreover, this study deepened the findings of Larnyo et al. (2022) by distinctively measuring Vitality in isolation with the intention of adopting. However, this study was contradicted by the findings of Yang et al. (2022b), who found that health anxiety is an insignificant contributor to adoption intention. To the best of the researcher's knowledge, this is the first time Vitality was tested as a predictor of adoption intention, thereby deepening the body of knowledge in understanding adoption drivers.

6.6.3 H3: Social influence (SI) has a Positive Influence on Intention to Adopt (IA) Fitness Wearable Devices

The third hypothesis sought to evaluate whether social influence significantly influences the intention to adopt fitness wearable devices. As shown in Table 16, the regression results reveal that Social Influence (SI) accounts for an 85.1% variation in Intention to Adopt, suggesting a high explanatory power. Secondly, the ANOVA Table 17 indicates that the sum of squares of the regression is 785.655, materially higher than the residual, suggesting that the model explains a large amount of variance in IA. Lastly, the standardised coefficient beta for SI 0.923 is close to 1 with a p-value of less than 0.002, confirming that SI has a strong statistical significance on IA. Therefore, hypothesis H3, Social Influence (SI), has a positive influence on the intention to adopt fitness wearable devices, which is supported by the results.

The results of this study are consistent with the foundational theory by Venkatesh et al. (2003), which found social influence to be a significant predictor of behavioural intention to adopt the technology. The UTAUT model by Venkatesh et al. (2003) posited that gender, experience, and voluntaries of use moderated the effect of social influence on behavioural intention. This means that an individual's decision to adopt technology, in this case, a fitness wearable device, depends on the opinions and persuasion of others that are important to the individual. The UTAUT model was developed in work environments, and this study was conducted amongst health-conscious consumers who perceive themselves as healthy. The similarity with the results could be attributed to similar research design and methodology. In conclusion, this study further reaffirms the UTAUT, suggesting that social influence significantly contributes to adopting wearable devices.

The results of this study are consistent with the findings of Sergueeva et al. (2020), who suggested that Social Influence was significant in explaining the intention to adopt wearable tracking devices in the US. Because this study was conducted in South Africa, with different economic and cultural norms compared to the US, the generalisability of social influence effects in intention to adopt has been increased, thereby adding to the body of knowledge. This study was similar to Sergueeva et al. (2020) in many respects; for instance, the sample was collected through social internet platforms, research design, and age group distribution.

The results of this research further support the results of Abouzahra and Ghasemaghaei (2020), who found social influence to be a significant driver of wearable device adoption among senior citizens residing in Canada. Abouzahra and Ghasemaghaei's (2020) findings proved to be consistent with this study despite the difference in methodologies and age groups employed for both studies. This study employed quantitative methods with a sample of 121 age groups from 20 to 50, while Abouzahra and Ghasemaghaei (2020) sampled from age 65 to 75 years using qualitative analysis. These results suggest that the social influence on technology adoption is paramount despite age group, socioeconomic levels, and methodology design. This research has added to the literature further supporting the notion that social influence is a key driver for technology adoption.

Similar results were found in a study by Gani et al. (2024), which found that social influence plays a significant role in women's intention to adopt smart healthcare devices in developing countries such as Bangladesh. Despite the differences in geographical location, culture, socioeconomic level, type of wearable device, and gender, both studies concluded that people's decisions are influenced by those perceived to be vital to them. This study further reinforces the critical role that social influence plays in wearable fitness adoption.

This study contradicts the findings of Pancar and Ozkan Yildirim (2023), who studied factors that drive the adoption of wearable health devices using mixed methods research design. Pancar and Ozkan Yildirim's (2023) findings suggest that social influence is not a significant explainer for the use of wearable health devices. This could be because the study focused on wearable health devices, which are fundamentally different from general fitness devices. People might perceive the wearable device as part of their health treatment regimen prescribed by their healthcare practitioner. As a result, social influence may not play a crucial role in the adoption of such wearable health devices; the individual might adopt the device based on the recommendation provided by the health practitioner. Walle et al. (2023) also suggested that social influence is insignificant in predicting the health wearable device adoption intention from a sample conducted in Ethiopia. Comparing the results of all three studies aids in strengthening the literature on device adoption and concludes that social influence on intention to adopt wearable devices may be significant depending on which type of wearable device is in question.

In conclusion, mixed results seem to have emerged from the literature regarding the role of social influence on wearable device adoption intention. The results of this study support H3: Social influence has a positive influence on intention to adopt fitness wearable devices. This study was consistent with several scholars across different countries with different cultural and socioeconomic backgrounds, suggesting that an individual's decision to adopt a wearable fitness device is affected by people who are important to the individual.

6.6.4 H4: Intention to Adopt (IA) Positively Influences Actual Use (AU) of Fitness Wearable Devices

The results in Table 5.17 show that the adjusted R Square between the Actual Use and Intention to Adopt is 0.541, indicating that the independent variable is responsible for

54.1$ variation in Actual Use. This was further demonstrated by the Anova table, which showed that the regression model sum of squares is significantly more considerable than the residual, suggesting that the model is statistically strong. Lastly, the standardised coefficient Beta is 0.738 with a sigma value of less than 0.001, implying that the model is statistically significant. This supports the conclusion that Intention to adopt is a significant predictor of AU. Hypothesis H4: The intention to adopt positively influences the actual use (AU) of wearable fitness devices, and this is fully supported.

The results of this study are supported by the survey conducted by Dehghani et al. (2018), which suggests that continuous intention is a significant predictor of actual use. Continuous intention is the constant use of services currently in use or products, and it is closely linked to behavioural intentions (Dehghani et al., 2018). This study suggests that people who intend to adopt fitness devices are likelier to use the device in actual reality. Both studies found similar results because of similar underlying theoretical models and research design, even though (Dehghani et al., 2018) employed the Theory of Planned Behaviour. The result of this study employed weighted least square regression to eliminate the effects of heteroscedasticity and reinforce the validation of the relationship between the variables. Such statistical methodological rigour strengthens the statistical analysis to safely conclude that the results complement the findings presented by Dehghani et al. (2018).

Yang et al.'s (2024) findings suggested that the intention to adopt wearable fitness devices significantly influenced actual use based on the VBN Model conducted in China. The VBN model indicates that the behavioural intentions of individuals are shaped by their values, beliefs, and norms. The VBN model suggests that the intention to adopt wearable devices is an antecedent of actual adoption, similar to what this study found. This phenomenon means consumers' intention to adopt the technology will eventually translate into actual usage. The results of this study are consistent with Yang et al. (2024) due to similar underpinning theoretical models that link adoption intention with actual use. Yang et al. (2024) utilised PLS-SEM, while this study employed weighted least square regression to come to the same conclusion, highlighting the similarities and differences in methodological rigour. This study adds to the literature by broadening the understanding of adoption intention to actual usage.

Bao and Lee's (2024) findings may be inconsistent with the results of this study, as Bao and Lee (2024) found that the intention to use wearable devices was not a material predictor of actual use in certain areas. The results of this report align with the TAM and UTAUT, which suggest that actual use is determined by behavioural intention. However, Bao and Lee (2024) suggest that factors such as social norms and perceived usefulness predict actual usage. The difference may be due to geographical context, where, for this study, consumers perceive a direct link between the intention to adopt a wearable device and actual use. In contrast, Bao and Lee's (2024) context is driven primarily by social influence, isolating the intention of the wearable device altogether. Another contrast could be attributed to the fact that the sample of this study might be more incentivised to reach specific health goals as a function of individualistic goals. In contrast, Bao and Lee's (2024) study sample in Singapore may exhibit high social influence (descriptive norms). This study contributes to the literature by validating the TAM from a wearable fitness device perspective.

In conclusion, the results of this study show the standardised coefficient Beta has a p-value of less than 0.001, suggesting that there is a strong significant relationship between intention to adopt (IA) and actual use (AU), therefore hypothesis H4: Intention to adopt positively influences actual use (AU) of fitness wearable devices has been supported. The results of the study were consistent with various scholars' results despite differences in methodologic design and theoretical foundation, which highlights the vital role adoption intention plays in actual use. One study was found to be inconsistent with the results of this study, which may be a result of social differences between the two samples. This study has reinforced the results of foundational theories and added new insight into the adoption intention and actual use of literature discourse.

6.7 Empirical Model

The model in Figure 6.1 indicates how the different constructs relate based on the problem statement, academic literature, methodology, results, and discussion. The model posits that General Health, Vitality, and social influence significantly predict the intention to adopt wearable fitness devices (Table 6.1). The second layer posits that the intention to adopt significantly predicts the actual use of the device. The arrow represents the causal passage between the constructs.

Table 6.2: Empirical Model Rationale

Construct	Rationale
General Health	Individuals who perceive their health to be good are likely to believe adopting the wearable fitness device will improve and or maintain their health, intending to adopt the device as a result
Vitality	Individuals with a high perception of Vitality lead active lifestyles and are prone to adopt fitness devices
Social Influence	Opinions and recommendations of the individual social circle strongly affect an individual's intention to adopt wearable fitness devices.
Intention to Adopt	Individuals who intend to use the device have a high chance of using the device frequently
Actual Use	Intention to adopt is a significant predictor of using a wearable fitness device.

Source: Author's own.

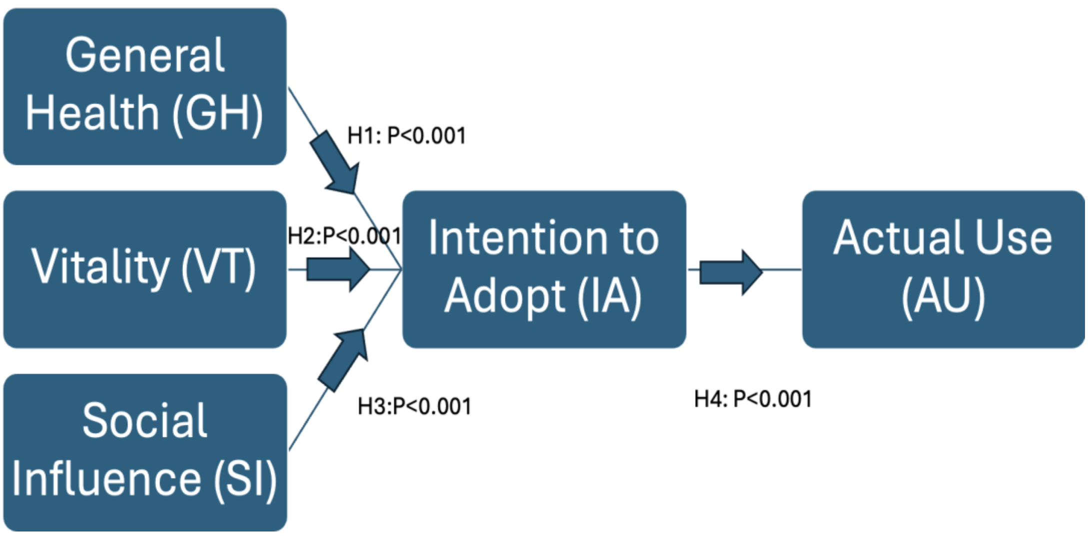

Figure 6.1:Empirical Model

Source: Author's own.

6.8 Chapter Summary

This chapter synthesizes the hypothesis, results, and reviewed literature. The outcome from the synthesis led to all hypotheses being supported by both statistical results and academic literature. The empirical model suggests that General Health, Vitality, and Social Influence statistically explain the inclination to adopt a device. Lastly, device usage is explained by adoption intention.

Chapter 7: Conclusion and Recommendations

7.1 Introduction

This study aimed to determine user-health perceptions' role in the desire to adopt and use wearable fitness technology. The reason for this study was the low adoption rate of wearable devices and the advancement of academic literature that included the proposed health perception constructs in the TAM. The user-health perceptions studied are General Health and Vitality perceptions evaluated using the Health Survey instrument. This study further tested the effects of social influence on wearable fitness technology adoption and usage. The objective was to assess whether there is any statistical relationship between health perception and user adoption and usage.

Self-monitoring technology has gained popularity mainly due to the potential to improve health among its users. However, user adoption and user rates have been low globally, especially in emerging countries (Yang et al., 2022a). The market for fitness devices is forecasted to increase by 5.61% in 2025. However, the user rate has declined by 60% since 2017 (Statista, 2025a). Slow growth and declining usage rates are serious concerns for users and fitness device companies. This study aimed to investigate the factors influencing adoption and usage rates to provide insights that could help improve these metrics.

Literature reviews that date five years prior reveal that most scholars employ the UTAUT model to study technology adoption and usage frequency. An example of such studies is by Larnyo et al. (2022), who found QoL strongly linked with adoption intent for wearable technology. The UTAUT model shows that social influence and user performance expectancy have an explanatory relationship with technology adoption (Venkatesh & Davis, 2000). This study has incorporated the General Health and Vitality perception construct into the proposed empirical model to match these two constructs with the performance expectancy found in the UTAUT model. The rationale is that users with high General Health and Vitality scores are likely to adopt wearable technology due to the expectation that the device will improve their wellness.

7.2 Significance of the study

Many academic scholars have researched health antecedents that affect wearable technology adoption to respond to the low adoption rate of such devices. For instance, Sergueeva et al. (2020) studied health consciousness, Hayat et al. (2022a) investigated health motivation, and Rehman et al. (2021) analysed the health belief relationship on adoption intention. This study extended the literature by testing General Health and Vitality perceptions on wearable technology user adoption and usage, being a first as per the literature reviewed. Adding General Health and Vitality perception to the adoption model highlights this research's academic contribution.

There is also a practical reason this study matters from a business perspective. The results could be used by device manufacturers to better understand performance elements expected by users. For instance, users who perceive themselves as healthy adopt the device to improve or maintain their health, and health-tracking functionalities in these devices are essential to the consumer. Manufacturers of such devices can continuously add features that help improve health outcomes for the user. Marketers can also devise marketing strategies that appeal to health-conscious consumers to increase adoption and sales.

This study matters due to its social impact on the community as it highlights the health benefits of wearable fitness adoption to encourage physical activity globally. A recent study by Larnyo et al. (2022) has shown that a high QoL drives adoption and user rate, improving health outcomes. Adopting and using wearable devices have a self-positive enforcement cycle, encouraging healthy lifestyles and decreasing the risk of illness and mortality.

7.3 Reflections on Research Context

The theoretical model that underpins this study is the UTAUT which has been a widely acetated framework to asses components that are necessary for a technology to be adopted (Venkatesh & Davis, 2000). The UTAUT model for technology intention has antecedents, such as user performance expectation and social influence (Venkatesh & Davis, 2000), which are essential for this study. For users to adopt a technology, they should be able to evaluate how its adoption will benefit them. As such, this study has taken the view that General Health and Vitality perception could be closely related to performance expectations. Behavioural intention is closely related to the intention to adopt.

One of the reviewed studies that is closely linked to this study is the research completed by Larnyo et al. (2022), who posited that QoL (health status perception) statistically explains the variation in the adoption of Intent for fitness devices. This study researched the QoL construct on a granular level by testing General Health and Vitality, which are components of QoL. Health belief (self-opinion about one's health) strongly predicted wearable fitness technology adoption and usage (Rahman et al., 2022). These two studies highlighted the importance of perception in adopting wearable trackers.

The researcher has further noticed inconsistent results relating to social influence and adoption of the technology. For example, Gani et al. (2024) and Pancar and Ozkan Yildirim (2023) contracted each other on social influence and user intention to adopt. To address this inconsistency, the study examined social influence in a different cultural and economic context and with a new age group to enhance generalisability.

It is important to stress that, after a careful literature review, General Health and Vitality have not been explored from a technology adoption and usage domain. Studying General Health and Vitality perception constructs will deepen the understanding on a granular level of how these variables affect adoption intention. Providing insights and recommendations that practitioners can implement to drive adoption

7.4 Methodology Overview

This study followed a research design and strategy that involved collecting data from online means at a point in time. This strategy was chosen to reach a larger audience with minimal effort, and the cross-sectional survey strategy was able to address research questions. This study employed widely known measuring instruments such as the SF-36 by Ware et al. (1993), social instruments from Venkatesh et al. (2003) and actual use by Godoe and Johansen (2012). Non-probability sampling, which generated 209 respondents, was selected because it was the most efficient method and did not compromise the research quality and results. The data collection period was from 27th October 2024 to 23rd December 2024.

As the data was found to be not normally distributed through normality tests, a suitable regression model called weighted least squares was selected to test the variables to address heteroscedasticity. Cronbach's Alpha test, composite reliability, KMO, and Bartlett's sphericity test were conducted to ensure reliability and validity were observed.

7.5 Main Results

This study had four hypotheses to evaluate. General Health (GH) is a significant predictor of intention to Adopt (IA) wearable fitness devices, which was the first hypothesis. This hypothesis was formulated from several academic literature, one of which is the study by Larnyo et al. (2022), which posited that QoL drives the Intent to adopt fitness technology. Moreover, Yang et al. (2024) findings asserted that technology adoption is predicted by health consciousness and value. The second hypothesis was that Vitality (VT) significantly influences the intention to adopt wearable fitness devices (IA). Acquisition of digital wearable health devices was strongly linked to improved psychological distress (Bao & Lee, 2024). QoL construct has a construct called mental health. As such, an assumption can be made that improved mental health predicts QoL (Larnyo et al., 2022).

The third hypothesis was that social influence (SI) has a significant influence on the intention to adopt wearable fitness devices (IA). This hypothesis was built on the assertion that fitness device adoption intention could be statistically explained by variance in social influence (Sergueeva et al., 2020). The last hypothesis: Intention to Adopt (IA) significantly affects the Actual Use (AU) of the wearable fitness device. The foundation study that this hypothesis was formulated by Larnyo et al. (2022) suggested that device usage affects overall wellness

Results for the first hypothesis suggest that GH is a strong predictor of IA, which is consistent with Larnyo et al. (2022) results and the UTAUT model. These results indicate that users who perceived themselves as healthy have a higher chance of adopting, accepting, and using the device. Secondly, the Vitality (VT) hypothesis was supported by the fact that VT positively influences the intention to adopt fitness wearable devices. the results reveal that people who perceive themselves as having high Vitality or energy are inclined to accept fitness devices. Vitality results were also found to be consistent with the findings of Larnyo et al. (2022), which found QoL significant in predicting the inclination to accept fitness devices.

The third hypothesis on social influence on the acceptance of wearable devices was supported by the results and by scholars such as Abouzahra and Ghasemaghaei (2020).

The study results on Social Influence suggested that external forces persuade users to accept wearable fitness devices from people in close relationships with the user. The last, hypothesis 4, Intention to adopt (IA) positively influences actual use (AU) of fitness wearable devices, was supported by statistical results (Yang et al., 2024). Hypothesis 4 results suggest that if users are inclined to accept the device, there is a strong chance that they will use the device.

7.6 Academic Contribution

The results of this study have expanded the foundational theoretical understanding of technology adoption by incorporating General Health and Vitality into the model. The study filled a gap that suggests that health perception is an important factor to consider for the inclination to accept wearable devices. Statistical evidence has shown that the technology acceptance procedure considers consumers' health and energy perception. This study is unique because it was conducted in a country that is culturally and economically different from previous studies.

7.7 Recommendations

The application for this study is broad, mainly leaning towards marketing and design domains. These results prove that people who consider themselves healthy will likely accept fitness devices. Therefore, marketing strategies should target such people. The marketing strategies should be tailor-made to appeal to this type of consumer. These could be sportspeople, people who attend farmers' markets or visit health food stores. Manufacturers may need to continuously improve health metrics elements on the fitness devices to enhance user experience and appeal to their expectations for the technology.

Social influence's role in user decision-making highlights the need for practitioners to identify influential and prominent public figures who endorse the technology, for instance, sports figures and social media influencers across different market segments. Practitioners could formalise strong partnerships with health workers and hospital companies to drive adoption using the power of social influence. Practitioners can increase adoption and actual use by strategically positioning the device as a health improvement product.

7.8 Limitations and Areas for Future Studies

This study focused on people who confirmed to own a wearable fitness device, and the group that did not have the device was not evaluated. Therefore, an opportunity arises to analyse the groups that do not have devices on the same constructs, such as General Health and Vitality. The study would be able to determine antecedents that drove adoption for individuals who do not have the device.

Furthermore, another opportunity for future research is to compare two groups, those who own the fitness device and those who do not own it, to test whether statistical differences can be observed between the two groups.

One of this study's limitations is excluding demographical factors such as age and income from the analysis, and future research should incorporate such variables to determine how they influence the inclination to accept and use fitness devices. The literature review revealed that most researchers employ quantitative analysis to study technology adoption, at least from a health perception perspective, thereby exposing the need for qualitative analysis to in-depth insight. Lastly, this study measured two health constructs out of eight under the SF-36 measuring instrument; future research could measure the rest of the constructs to determine their effect on the adoption and use of wearable devices.

7.9 Study Conclusion

This study sought to investigate factors that statistically affect the inclination to accept wearable fitness devices. The study sampled 120 individuals from South Africa through an online survey. The results show that General Health, Vitality, and Social Influence have a bearing on Adoption inclination. Practitioners are encouraged to devise marketing strategies that appeal to people who perceive themselves as healthy to drive up the adoption rate. This study achieved its objectives

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List of Appendices

Appendix A	Invitation to Participate and Consent Statement
Appendix B	Instrument – Questionnaire
Appendix C	Ethical Approval
Appendix D	Excerpt of Raw Data
Appendix E	Code Book
Appendix F	Factor Analysis
Appendix G	Regression Test Results – Social Influence and Intention to Adopt
Appendix H	Regression Test Results – Vitality and Intention to Adopt
Appendix I	Regression Test Results: – Actual Use and Intention to Adopt
Appendix J	Regression Test Results – Actual Use and Intention to Adopt
Appendix K	Regression Test Results – Actual Use and General Health
Appendix L	Weighted Least Squares Regression Test Results – Actual Use and General Health
Appendix M	Weighted Least Squares Regression Test Results – Actual Use and Vitality

Appendix A: Invitation to Participate and Consent Statement

Informed consent letter for Questionnaire

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfilment of an MBA.

I am conducting research on how social influence, vitality, health perception affects the adoption and actual use of fitness wearable devices. To that end, you are asked to compete the survey. This will help us better understand how social influence and health perception influence the adoption and actual use of fitness wearable device. The survey should not take more than 15 minutes of your time. Your participation is voluntary, and you can withdraw at any times without penalty. Your participation is anonymous and only aggerated date will be report. By completing the survey, you indicate that voluntarily participate in this research. If you have any concerns, please contact my supervisor or me. Our details ate provided below.

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Appendix B: Instrument – Questionnaire

Demographic

- Age (Venkatesh et al., 2003)
  - 20-24,
  - 25-29,
  - 30-34,
  - 35-39,
  - 40-44,
  - 45-49,
  - above 50
- Gender
  - Male,
  - Female
- Residence
  - Urban,
  - Rural
- Income level
  - Under R 400 000.00
  - R 600 000-R 799 999
  - R 800 000- R 999 999
  - R1 000 000 and above

	Strongly disagree (1)	Disagree (2)	Neutra (3)l	Agree (4)	Strongly agree(5)
	1	2	3	4	5
Intention to adopt (IA)					
• I intend to use wearable fitness tracker in the next three months					
• I predict I will use wearable fitness tracker in the next three months					

• I plan to use wearable fitness tracker in the next three month					
Social Influence (SI)					
• People who influence my behaviour think I should use the wearable fitness trackers					
• People who are important to me think I should use the wearable fitness trackers					

General Health (GH)	Definitely false	Mostly false	Don't know	Mostly true	Definitely true
• I seem to get sick a little easier than other people					
• I am as healthy as anybody I know					
• I expect my health to get worse					
• My health is excellent					

Actual Use (AU)	Not at all (1)	Once a month (2)	A few times a month(3)	Once a week (4)	A few times a week (5)	Once a day (6)	Several times a day (7)
• Do you actually use wearable fitness device to monitor your health indicators (e.g sleep, heart rate, blood pressure)							

Vitality (VT): These questions are about how you feel and how things have been with you during the past 4 weeks. For each question, please give the one answer that comes closest to the way you have been feeling.	None of the time (1)	A little of the time (2)	Some of the time (3)	A good bit of the time (4)	Most if the time (5)	All the time (6)
• Did you feel full of pep?						
• Did you have a lot of energy?						
• Did you feel worn out?						
• Did you feel tired?						

Appendix C: Ethical Approval

Ethical Clearance Approved External Inbox ×

GIBS

Masters Research <MastersResearch@gibs.co.za>

to me, Masters

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Mpho Khorombi,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.

Appendix D: Except of Raw Data

Timestamp	Username	Do you have a wearable fitness device such as fitbit or smartwatch?	What is your age?	I intend to use wearable fitness tracker in the next three months	I predict I will use wearable fitness tracker in the next three months	I plan to use wearable fitness tracker in th
2024/10/27 3:45:13 pm EEST		Yes	30-34	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 3:58:31 pm EEST		No	30-34	Agree (4)	Agree	Agree
2024/10/27 4:01:39 pm EEST		Yes	40-44	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 4:30:17 pm EEST		Yes	35-39	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 6:02:02 pm EEST		Yes	40-44	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 6:20:08 pm EEST		Yes	Above 50	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 6:32:39 pm EEST		Yes	40-44	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 6:34:53 pm EEST		Yes	45-49	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 6:48:41 pm EEST		Yes	25-29	Agree (4)	Agree	Agree
2024/10/27 6:50:47 pm EEST		Yes	20-24	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 6:52:43 pm EEST		Yes	35-39	Strongly agree(5)	Agree	Agree
2024/10/27 6:53:07 pm EEST		Yes	35-39	Strongly disagree (1)	Strongly disagree	Strongly disagree
2024/10/27 7:05:21 pm EEST		Yes	40-44	Strongly agree(5)	Agree	Agree
2024/10/27 7:27:01 pm EEST		Yes	35-39	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 7:27:17 pm EEST		No	Above 50	Disagree (2)	Disagree	Disagree
2024/10/27 7:27:43 pm EEST		Yes	30-34	Strongly disagree (1)	Strongly Agree	Strongly agree
2024/10/27 7:41:38 pm EEST		No	Above 50	Strongly disagree (1)	Strongly disagree	Strongly disagree
2024/10/27 7:42:50 pm EEST		No	45-49	Agree (4)	Agree	Agree
2024/10/27 7:43:30 pm EEST		No	40-44	Strongly disagree (1)	Strongly disagree	Strongly disagree
2024/10/27 7:43:47 pm EEST		Yes	35-39	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 7:44:53 pm EEST		No	25-29	Agree (4)	Strongly Agree	Strongly agree
2024/10/27 7:45:35 pm EEST		No	45-49	Neutral (3)	Neutral	Neutral
2024/10/27 7:46:27 pm EEST		Yes	35-39	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 7:49:13 pm EEST		Yes	40-44	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 7:54:53 pm EEST		Yes	30-34	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:08:39 pm EEST		Yes	35-39	Strongly disagree (1)	Agree	Agree
2024/10/27 8:22:51 pm EEST		Yes	45-49	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:23:21 pm EEST		Yes	45-49	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:25:51 pm EEST		Yes	30-34	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:28:00 pm EEST		Yes	40-44	Agree (4)	Strongly Agree	Strongly agree
2024/10/27 8:29:04 pm EEST		Yes	45-49	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:32:47 pm EEST		Yes	40-44	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:38:20 pm EEST		Yes	30-34	Agree (4)	Agree	Agree
2024/10/27 8:39:54 pm EEST		Yes	35-39	Agree (4)	Neutral	Neutral
2024/10/27 8:40:15 pm EEST		Yes	25-29	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:40:17 pm EEST		Yes	25-29	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:43:05 pm EEST		Yes	40-44	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:43:20 pm EEST		Yes	Above 50	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:43:52 pm EEST		Yes	40-44	Strongly agree(5)	Agree	Agree
2024/10/27 8:44:42 pm EEST		Yes	30-34	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:45:19 pm EEST		Yes	30-34	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:45:45 pm EEST		Yes	Above 50	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:52:02 pm EEST		Yes	35-39	Disagree (2)	Strongly disagree	Strongly disagree
2024/10/27 8:53:41 pm EEST		No	45-49	Strongly disagree (1)	Strongly disagree	Strongly disagree
2024/10/27 8:53:48 pm EEST		Yes	35-39	Strongly agree(5)	Strongly Agree	Strongly agree
2024/10/27 8:55:59 pm EEST		Yes	Above 50	Strongly disagree (1)	Strongly Agree	Strongly agree
2024/10/27 8:57:28 pm EEST		Yes	45-49	Strongly agree(5)	Strongly Agree	Strongly agree

M 0 | AVERAGE | MIN 0 | MAX 0 | COUNTA 209

Appendix E: Code Book

Questions	Label
1. Email	Email
2. Do you have a wearable fitness device such as fitbit or smart watch?	Fitness device
3. What is your age	Age
4. I intend to use wearable fitness tracker in the next three months	Intend
5. I predict I will use wearable fitness tracker in the next three months	Predict
6. I plan to use wearable fitness tracker in the next three months	Plan
7. People who influence my behavior think I should use the wearable fitness trackers	People influence
8. People who are important to me think I should use the wearable fitness trackers	People important
9. Do you actually use wearable fitness device to monitor your health indicators (e.g. sleep, heart rate, blood pressure)	Actual Use
10. I seem to get sick a little easier than other people	Get Sick
11. I am as healthy as anybody I know	Healthy
12. I expect my health to get worse	Get worse
13. My health is excellent	Excellent Health
14. During the past 4 weeks, did you feel full of pep(lively, energetic, motivated)?	Pep
15. During the past 4 weeks, did you have a lot of energy?	Energy
16. During the past 4 weeks, did you feel worn out?	Worn out
17. During the past 4 weeks, did you feel tired?	Tired

Code book- Fitness device Coded to Numeric Data

Fitness device	Code
Yes	1
No	2

Code book- Age Coded to Numeric Data

Age	Code
20-24	1
25-29	2
30-34	3
35-39	4
40-44	5
45-49	6
Above 50	7

Code book- Intend Coded to Numeric Data

Intend	Code
Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Code book- Predict Coded to Numeric Data

Predict	Code
Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Code book- Plan Coded to Numeric Data

Plan	Code
Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Code book- People Influence Coded to Numeric Data

People Influence	Code
Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Code book- People important Coded to Numeric Data

People Important	Code
Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Appendix F: Factor Analysis

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.720
Bartlett's Test of Sphericity	Approx. Chi-Square	229.027
	df	3
	Sig.	<.001

Communalities

	Initial	Extraction
Intend	1.000	.749
Predict	1.000	.859
Plan	1.000	.871

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.479	82.621	82.621	2.479	82.621	82.621
2	.360	12.002	94.623			
3	.161	5.377	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
Intend	.866
Predict	.927
Plan	.933

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Rotated Component Matrix[a]

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	104.412
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
People influence	1.000	.883
People important	1.000	.883

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.765	88.265	88.265	1.765	88.265	88.265
2	.235	11.735	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
People influence	.939
People important	.939

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Rotated Component Matrix[a]

a. Only one component was extracted.

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.656
Bartlett's Test of Sphericity	Approx. Chi-Square	89.847
	df	3
	Sig.	<.001

Communalities

	Initial	Extraction
Get sick	1.000	.541
Healthy	1.000	.718
Excellent Health	1.000	.740

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.998	66.604	66.604	1.998	66.604	66.604
2	.631	21.040	87.644			
3	.371	12.356	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
Get sick	.735
Healthy	.847
Excellent Health	.860

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Rotated Component Matrix[a]

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.745
Bartlett's Test of Sphericity	Approx. Chi-Square	364.584
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction
PEP	1.000	.801
Energy	1.000	.783
Worn Out	1.000	.769
Tired	1.000	.766

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.118	77.957	77.957	3.118	77.957	77.957
2	.555	13.886	91.843			
3	.184	4.610	96.453			
4	.142	3.547	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
PEP	.895
Energy	.885
Worn Out	.877
Tired	.875

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.795	3	2.265	2.341	.077[b]
	Residual	113.205	117	.968		
	Total	120.000	120			

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Predictors: (Constant), REGR factor score 1 for analysis 3, REGR factor score 1 for analysis 2, REGR factor score 1 for analysis 4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	9.687E-17	.089		.000	1.000		
	REGR factor score 1 for analysis 4	.008	.103	.008	.076	.939	.763	1.310
	REGR factor score 1 for analysis 2	.212	.091	.212	2.341	.021	.981	1.019
	REGR factor score 1 for analysis 3	.083	.102	.083	.815	.417	.769	1.301

a. Dependent Variable: REGR factor score 1 for analysis 1

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	REGR factor score 1 for analysis 4	REGR factor score 1 for analysis 2	REGR factor score 1 for analysis 3
1	1	1.529	1.000	.00	.23	.06	.23
	2	1.000	1.237	1.00	.00	.00	.00
	3	.951	1.268	.00	.02	.94	.05
	4	.520	1.715	.00	.74	.00	.73

a. Dependent Variable: REGR factor score 1 for analysis 1

Appendix G: Regression Test Results – Social Influence and Intention to Adopt

Variables Entered/Removed[a,b]

Model	Variables Entered	Variables Removed	Method
1	REGR factor score 1 for analysis 2[c]	.	Enter

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. All requested variables entered.

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.923[a]	.852	.851	1.07002872

a. Predictors: (Constant), REGR factor score 1 for analysis 2

b. Dependent Variable: REGR factor score 1 for analysis 1

c. Weighted Least Squares Regression - Weighted by Weight

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	785.655	1	785.655	686.184	<.001[c]
	Residual	136.250	119	1.145		
	Total	921.905	120			

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. Predictors: (Constant), REGR factor score 1 for analysis 2

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.009	.012		-.788	.432
	REGR factor score 1 for analysis 2	.352	.013	.923	26.195	<.001

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.6936338	.4404385	-.0091029	.35203560	121
Residual	-3.47276735	1.32437658	.00910292	.98385981	121
Std. Predicted Value[c]	.	.	.	.	0
Std. Residual[c]	.	.	.	.	0

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. Not computed for Weighted Least Squares regression.

Variables Entered/Removed[a,b]

Model	Variables Entered	Variables Removed	Method
1	REGR factor score 1 for analysis 3[c]	.	Enter

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. All requested variables entered.

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.860[a]	.740	.738	1.41854725

a. Predictors: (Constant), REGR factor score 1 for analysis 3

b. Dependent Variable: REGR factor score 1 for analysis 1

c. Weighted Least Squares Regression - Weighted by Weight

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	682.444	1	682.444	339.140	<.001[c]
	Residual	239.461	119	2.012		
	Total	921.905	120			

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. Predictors: (Constant), REGR factor score 1 for analysis 3

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t
1	(Constant)	.005	.015		.330
	REGR factor score 1 for analysis 3	.236	.013	.860	18.416

Coefficients[a,b]

Model		Sig.
1	(Constant)	.742
	REGR factor score 1 for analysis 3	<.001

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.6859089	.2970449	.0051037	.23576609	121
Residual	-3.98793483	1.31665170	-.00510371	1.00226616	121
Std. Predicted Value[c]	.	.	.	.	0
Std. Residual[c]	.	.	.	.	0

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. Not computed for Weighted Least Squares regression.

Appendix H: Regression Test Results – Vitality and Intention to Adopt

Variables Entered/Removed[a,b]

Model	Variables Entered	Variables Removed	Method
1	REGR factor score 1 for analysis 4[c]	.	Enter

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. All requested variables entered.

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.791[a]	.625	.622	1.70468130

a. Predictors: (Constant), REGR factor score 1 for analysis 4

b. Dependent Variable: REGR factor score 1 for analysis 1

c. Weighted Least Squares Regression - Weighted by Weight

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	576.098	1	576.098	198.249	<.001[c]
	Residual	345.807	119	2.906		
	Total	921.905	120			

a. Dependent Variable: REGR factor score 1 for analysis 1

b. Weighted Least Squares Regression - Weighted by Weight

c. Predictors: (Constant), REGR factor score 1 for analysis 4

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	.198	.010		19.553
	REGR factor score 1 for analysis 4	.175	.012	.791	14.080

Coefficients[a,b]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 4	<.001

Appendix I: Regression Test Results: – Actual Use and Intention to Adopt

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	REGR factor score 1 for analysis 1[b]	.	Enter

a. Dependent Variable: Actually use

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.217[a]	.047	.039	2.152

a. Predictors: (Constant), REGR factor score 1 for analysis 1

b. Dependent Variable: Actually use

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.135	1	27.135	5.862	.017[b]
	Residual	550.865	119	4.629		
	Total	578.000	120			

a. Dependent Variable: Actually use

b. Predictors: (Constant), REGR factor score 1 for analysis 1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	
		B	Std. Error	Beta	t
1	(Constant)	4.636	.196		23.704
	REGR factor score 1 for analysis 1	.476	.196	.217	2.421

Coefficients[a]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 1	.017

a. Dependent Variable: Actually use

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.88	4.94	4.64	.476	121
Residual	-3.936	4.119	.000	2.143	121
Std. Predicted Value	-3.691	.631	.000	1.000	121
Std. Residual	-1.830	1.914	.000	.996	121

a. Dependent Variable: Actually use

Appendix J: Regression Test Results – Actual Use and Intention to Adopt

Variables Entered/Removed[a,b]

Model	Variables Entered	Variables Removed	Method
1	REGR factor score 1 for analysis 1[c]	.	Enter

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. All requested variables entered.

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.738[a]	.544	.541	.924

a. Predictors: (Constant), REGR factor score 1 for analysis 1

b. Dependent Variable: Actually use

c. Weighted Least Squares Regression - Weighted by WeightAU

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	121.436	1	121.436	142.185	<.001[c]
	Residual	101.634	119	.854		
	Total	223.070	120			

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Predictors: (Constant), REGR factor score 1 for analysis 1

Coefficients[a,b]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t
1	(Constant)	4.671	.030		155.172
	REGR factor score 1 for analysis 1	.532	.045	.738	11.924

Coefficients[a,b]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 1	<.001

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.71	5.01	4.67	.532	121
Residual	-4.007	4.294	-.035	2.143	121
Std. Predicted Value[c]	.	.	.	.	0
Std. Residual[c]	.	.	.	.	0

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Not computed for Weighted Least Squares regression.

Appendix K: Regression Test Results – Actual Use and General Health

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.480	1	13.480	7.653	.007[c]
	Residual	209.591	119	1.761		
	Total	223.070	120			

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Predictors: (Constant), REGR factor score 1 for analysis 3

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t
1	(Constant)	4.974	.022		229.449
	REGR factor score 1 for analysis 3	.079	.029	.246	2.766

Coefficients[a,b]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 3	.007

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.74	5.07	4.97	.079	121
Residual	-4.072	2.259	-.337	2.194	121
Std. Predicted Value[c]	.	.	.	.	0
Std. Residual[c]	.	.	.	.	0

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Not computed for Weighted Least Squares regression.

Coefficients[a,b]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 2	.614

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.97	5.01	4.99	.011	121
Residual	-4.008	2.028	-.350	2.196	121
Std. Predicted Value[c]	.	.	.	.	0
Std. Residual[c]	.	.	.	.	0

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Not computed for Weighted Least Squares regression.

Appendix L: Weighted Least Squares Regression Test Results – Actual Use and General Health

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.246[a]	.060	.053	1.327

a. Predictors: (Constant), REGR factor score 1 for analysis 3

b. Dependent Variable: Actually use

c. Weighted Least Squares Regression - Weighted by WeightAU

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.480	1	13.480	7.653	.007[c]
	Residual	209.591	119	1.761		
	Total	223.070	120			

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Predictors: (Constant), REGR factor score 1 for analysis 3

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	
		B	Std. Error	Beta	t
1	(Constant)	4.974	.022		229.449
	REGR factor score 1 for analysis 3	.079	.029	.246	2.766

Coefficients[a,b]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 3	.007

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.74	5.07	4.97	.079	121
Residual	-4.072	2.259	-.337	2.194	121
Std. Predicted Value[c]	.	.	.	.	0
Std. Residual[c]	.	.	.	.	0

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Not computed for Weighted Least Squares regression.

Appendix M: Weighted Least Squares Regression Test Results – Actual Use and Vitality

Variables Entered/Removed[a,b]

Model	Variables Entered	Variables Removed	Method
1	REGR factor score 1 for analysis 4[c]	.	Enter

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. All requested variables entered.

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.208[a]	.043	.035	1.339

a. Predictors: (Constant), REGR factor score 1 for analysis 4

b. Dependent Variable: Actually use

c. Weighted Least Squares Regression - Weighted by WeightAU

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.651	1	9.651	5.381	.022[c]
	Residual	213.419	119	1.793		
	Total	223.070	120			

a. Dependent Variable: Actually use

b. Weighted Least Squares Regression - Weighted by WeightAU

c. Predictors: (Constant), REGR factor score 1 for analysis 4

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t
1	(Constant)	4.977	.022		228.672
	REGR factor score 1 for analysis 4	.058	.025	.208	2.320

Coefficients[a,b]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 4	.022

Variables Entered/Removed[a,b]

Model	Variables Entered	Variables Removed	Method
1	REGR factor score 1 for analysis 4[c]	.	Enter

a. Dependent Variable: Actually use
b. Weighted Least Squares Regression - Weighted by WeightAU
c. All requested variables entered.

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.208[a]	.043	.035	1.339

a. Predictors: (Constant), REGR factor score 1 for analysis 4
b. Dependent Variable: Actually use
c. Weighted Least Squares Regression - Weighted by WeightAU

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.651	1	9.651	5.381	.022[c]
	Residual	213.419	119	1.793		
	Total	223.070	120			

a. Dependent Variable: Actually use
b. Weighted Least Squares Regression - Weighted by WeightAU
c. Predictors: (Constant), REGR factor score 1 for analysis 4

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	4.977	.022		228.672
	REGR factor score 1 for analysis 4	.058	.025	.208	2.320

Coefficients[a,b]

Model		Sig.
1	(Constant)	<.001
	REGR factor score 1 for analysis 4	.022