FACTORS INFLUENCING THE ADOPTION OF SMARTWATCHES: A PLS-SEM ANALYSIS USING SMARTPLS

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Computer Science and Engineering

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APPROVAL

This Thesis titled **"Factors Influencing the Adoption of Smartwatches: A PLS-SEM Analysis using SmartPLS"**, submitted by Fatema Faruque Fama, ID No: 0242310005103029 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 06-07-2024.

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ABSTRACT

This study explores how people incorporate smartwatches into their daily lives. I used Partial Least Squares Structural Equation Modeling (PLS-SEM) as the statistical approach, utilizing the SmartPLS tool to analyze the factors influencing people's decision to use and integrate these smart wearables into their routines. I looked at a bunch of different factors that might play a role in this, like how useful people find the smartwatch (perceived usefulness), how much they enjoy using it (perceived enjoyment), how much they think it's worth paying for (price value), whether it aligns with their preferences and interests, and even if they see it as a status symbol. I collected data from 265 people using a survey made with Google Forms. They shared their thoughts and experiences with smartwatches, giving us a good insight into what drives their decisions. The analysis reveals that perceived enjoyment, attitude, and perceived behavioral control have the most substantial impacts on the intention to adopt smartwatches. Additionally, factors like hedonic motivation and compatibility significantly contribute to shaping user attitudes toward smartwatches. This examination provides an in-depth understanding of the intricate relationship between these factors, addressing their combined impact on the adoption of smartwatches. Understanding all these factors gives tech companies, marketers, and policymakers valuable information to make better smartwatches and to market them effectively. Making smartwatches enjoyable and easy to use is key to getting more people to use them. I also pointed out areas for future research, suggesting that I should keep an eye on new trends and technologies in the wearable device market to stay relevant to users' changing preferences and advancements in technology.

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CHAPTER 1

Introduction

1.1 Introduction

Wearable technology is becoming more and more commonplace every day. Wearable technology is predicted to play a crucial role in our daily lives shortly [1]. The most common kind of wearable technology at the beginning of their spread is the smartwatch. More than just telling the time, smartwatches—small computers—are one of the newest developments in the information technology industry [2]. They can do many cool things, like telling you the time, sending messages, tracking your steps, and even monitoring your heart rate.

This research explores the complex dynamics surrounding the adoption of smartwatches, providing insight into people's perspectives, preferences, and activities about incorporating such devices into their daily lives. Smartwatch adoption is influenced by several important aspects, including perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol. These factors all have a significant effect on the adoption of new technologies. Gaining a complete understanding of the process of technological acceptability in the wearable technology area requires understanding how these elements interact and impact people's decisions to use smartwatches.

To understand this complex topic better, a complete dataset was compiled using a Google Form survey, which received responses from 265 people. The survey included 50 questions ranging from statistical data to more complex features of users' interactions with smartwatches. I will be using a method called Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data thoroughly and draw meaningful conclusions.

As technology keeps changing, it is crucial to understand the reasons behind people's adoption of smartwatches in their daily routines. This study aims to dig into people's opinions and feelings about smartwatches, including how much influence others have on their decisions. By using PLS-SEM, I am hoping to uncover some really helpful insights. These insights will not just be useful for discussions in academics but also help us figure out practical ways to make smartwatches better and more widely accepted in our lives where humans and technology meet.

1.2 Motivation

The motivation for this research originates from the rapid growth and development of wearable technology, particularly smartwatches, in the current digital era. Understanding the elements that impact wearable device adoption is becoming more and more important for customers and technology providers as these devices become more commonplace. This study looks into how smartwatches are adopted, with the goal of adding to the growing body of information on how technology is accepted and used in developing nations [3].

Specifically, the study draws upon the Partial Least Squares Structural Equation Model (PLS-SEM) method to examine the various factors influencing the adoption of smartwatches. By identifying these factors, the researchers seek to provide insights that can help technology service providers improve their products and services to better meet the needs and desires of consumers.

Overall, the motivation behind this research lies in advancing our understanding of technology adoption and providing practical insights that can inform industry stakeholders and policymakers in their efforts to promote the adoption of wearable technology.

1.3 Rational of the Study

I aim to investigate the reasons underlying people's decisions to include smartwatches in their daily lives. Even if smartwatches are becoming increasingly common, it's important to understand the underlying causes that are either promoting or impeding their adoption. To address this, I am carrying out a comprehensive inquiry using a Google Forms survey that is intended to collect a variety of viewpoints and insights from consumers about their experiences with smartwatches.

This research is important as it provides insight into the reasons behind people's perceptions of smartwatch functionality and usability, and how smartwatch's different functionality influence their daily life. Utilizing a technique known as Partial Least Squares Structural Equation Modeling (PLS-SEM), our goal is to determine how various elements, such as perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol influence a person's desire to wear a smartwatch on an everyday basis.

Technology service providers, policymakers, and other industry stakeholders can benefit greatly from the study's conclusions. Understanding the factors influencing smartwatch adoption can inform product development, marketing strategies, and policy initiatives.

1.4 Research Questions

The study addresses specific research questions related to the factors influencing consumers to purchase smartwatches. And they are:

I. How does the perceived usefulness of smartwatches influence individuals' intention to adopt them?
II. To what extent does perceived enjoyment impact users' attitudes toward smartwatch adoption?
III. What role does perceived behavioral control play in actual smartwatch usage and recommendation behavior?
IV. How do subjective norms affect attitudes and intentions toward smartwatch adoption?
V. How do perceptions of smartwatches as status symbols influence adoption intentions?

1.5 Expected Outcome

The intended result of this study project is to provide a thorough understanding of the variables influencing the adoption of smartwatches in daily life. The study attempts to clarify the complex relationships between perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, status symbol, and adoption intention in the context of smartwatch technology by utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM).

To provide an in-depth understanding of the fundamental dynamics, the main objective is to collect precise insights into how these factors affect user's ability to seamlessly integrate smartwatches into their daily routines. Furthermore, by identifying the critical factors influencing users' perceptions and actions regarding smartwatches, the research hopes to improve theoretical models concerning technology adoption.

For business stakeholders, including technology companies, the findings can provide valuable insights into consumer preferences and behavior, informing product development, marketing strategies, and policy initiatives aimed at promoting smartwatch adoption.

By raising awareness and understanding among consumers, the research can empower individuals to make informed decisions about smartwatch adoption. Ultimately, the study hopes to help both experts and everyday users understand smartwatches better and make them more user-friendly.

1.6 Project Management and Finance

A well-structured plan is required for the effective completion of this research project. Tasks involve reviewing the literature, designing a survey, collecting data, analyzing SmartPLS data, and interpreting the results. A timeline with goals ensures that work is done efficiently, and regular team meetings encourage collaboration and solve any difficulties. Clear communication and adaptability are essential for navigating the project's many stages.

Financial resources provided for this study cover survey distribution, SmartPLS software licensing, and prospective data storage and analysis fees. Efficient finance management is crucial to sustaining the research's quality and scope. Transparent budgeting ensures that the project continues on track and that any unforeseen expenses are addressed as soon as possible to ensure the study's successful completion.

Table 1.1: Project Management Table

Work	Time
Data Collection	1 Month
Literature Review	1.5 Month
Experiment Setup	1 Month
Implementation	1 Month
Report Writing	1.5 Month
Total	6 Months

1.7 Report Layout

There are six chapters in the paper. Every chapter includes numerous components that are fully described and discussed from a range of perspectives. The contents of this report are listed below:

- Introduction: Introduces the study on smartwatch adoption, outlining the motivation, rationale, research questions, expected outcomes, project management, and report structure.
- Background: Provides foundational context, reviews related works, conducts a comparative analysis, defines the scope of the problem, and discusses challenges.
- Research Methodology: Describes the research subjects, data collection procedures, statistical analysis methods, proposed PLS-SEM methodology, and implementation requirements.
- Experimental Result and Discussion: Details the experimental setup, presents and analyzes the results, and discusses the implications of the findings.
- Impact on Society, Environment, and Sustainability: Examines the societal, environmental, and ethical impacts of smartwatch adoption and outlines a sustainability plan.
- Summary, Conclusion, Recommendation, and Implication for Future Research: Summarizes the study's findings, provides concluding remarks, and suggests implications for further research.
- References

CHAPTER 2

Background

2.1 Preliminaries

This research document's initial sections lay the groundwork for a thorough investigation of smartwatch adoption in daily life from the partial least squares structural equation modeling (PLS-SEM) standpoint. The document opens with a title page that is clearly defined and has a brief abstract that summarizes the goals and methods of the research. The acknowledgments provide gratitude for the support received, and the lists of figures, tables, acronyms, abbreviations, and symbols, as well as the table of contents, act as a navigational aid for the remainder of the content. The clarification of specialist words improves communication clarity. Last but not least, the introduction establishes the context, significance, and goals of the study in addition to placing the following analysis and results in a broader context.

2.2 Related Works

In the article "Wearable Technologies and Its Future Applications," Mesut Çiçek [1] examined the state of wearable technologies and their possible uses in the future. Çiçek's study provides information about wearable technology's present situation as well as future developments. The article clarifies the wide range of uses for wearable technology by looking at several industries, including healthcare, fitness, entertainment, and communication. Additionally, Çiçek explores the technological components of wearables, focusing on connectivity possibilities, data processing, and sensors. The study also discusses prospects and problems related to wearable technology, such as user acceptability, battery life, and privacy issues. In summary, Mesut Çiçek provides a comprehensive overview of wearable technologies' present and future landscape, making it a valuable contribution to the field.

Chuah, S.H.-W. et al. [2] [2016c] investigated the factors influencing the adoption of smartwatches in their paper. The two main areas of the study are visibility and usefulness.

The authors provide insightful analysis of the factors influencing smartwatch adoption, providing an important context for understanding the decision-making process involved in accepting this technology. Their research, which is clearly and thoroughly reported, adds to our knowledge of the factors that influence people's decisions to wear smartwatches. This paper is a valuable resource for those curious about how technology and behavior interact.

Akter, S. et al. [3] [2018] conducted a study investigating the factors that influence the adoption of smartwatches. Using a partial least squares method, the authors examined several variables related to smartwatch adoption. The study offers important insights into the decision-making process underlying the adoption of this technology by looking at these variables. Offering a thorough examination of smartwatch adoption, the report makes a substantial contribution to the area that will benefit wearable technology practitioners and researchers alike.

Dutot, V., Bhatiasevi, V., and Bellallahom, N. [4] [2019] conducted a study on smartwatch adoption across three countries, applying the Technology Acceptance Model (TAM). The authors looked into the variables impacting people's adoption of smartwatches in various cultural contexts using the TAM framework. This study offers insightful information about how smartwatches are accepted and used, providing a thorough analysis that advances our knowledge of how people adopt new technologies. The study's conclusions are relevant to researchers and experts in the field who wish to adopt and diffuse wearable technology.

Kranthi, A.K. and Ahmed, K.A.A. [5] [2018] explore the factors influencing smartwatch adoption among IT professionals in their paper. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model is developed in this study to provide a more comprehensive understanding of smartwatch uptake in a work environment. Through a discussion of the specific needs and preferences of IT professionals, the authors provide an understanding of the particular elements stimulating adoption within this population. By offering a specific framework for analyzing smartwatch adoption in work environments, the research adds to the body of knowledge. This framework can be used to guide workplace wearable technology promotion initiatives.

Arpacı, İ. et al. [6] [2020] present a novel approach for predicting the adoption of smartwatches in their paper. The study investigates the application of machine learning methods to predict smartwatch adoption. The authors want to increase the precision of predictions and expand our understanding of the factors driving smartwatch uptake by utilizing modern computational methods. With its data-driven approach to predicting consumer behavior in the context of wearable technology adoption, the research makes a major contribution to the area. This study has impacts on academia and business, offering insightful information to policymakers and marketers who want to encourage the adoption of smartwatches.

Wu, Lianghong, Wu, Liang-Chuan, and Chang, S.-C. [7] [2016] delve into consumers' intentions to adopt smartwatches in their paper. The purpose of the study is to determine what factors affect the tendency of consumers to embrace smartwatches. Through an analysis of multiple factors including perceived utility, social impact, and usability, the writers offer insightful perspectives on the thought processes of prospective users of smartwatches. Their study advances our knowledge of consumer behavior about the adoption of wearable technology. Researchers and business people looking to comprehend and encourage consumer adoption of smartwatches will find this study to be a useful resource.

Beh, P.K. et al. [8] [2019] explore the use of smartwatches for health and fitness monitoring in their paper. Using a combination of threat assessment and the UTAUT2 paradigm, the authors investigate the factors that affect wristwatch adoption. For those working in the field of wearable technology, this study provides insightful information about how people see and use smartwatches for health-related reasons.

King, C. and Sarrafzadeh, M. [9] [2017] provide a survey titled "A Survey of Smartwatches in Remote Health Monitoring". The potential of smartwatches for remote health monitoring is examined in this research. The authors examine case studies and the literature to analyze the potential and constraints of smartwatches for remote health monitoring. For medical practitioners who want to use wearable technology to enhance patient care, this survey is helpful.

Elnagar, A. et al. [10] [2022] conducted a study titled "Prediction of the Intention to Use a Smartwatch: A Comparative Approach Using Machine Learning and Partial Least Squares Structural Equation Modeling". The study compares the effectiveness of machine learning and partial least squares structural equation modeling in predicting the intention to use a smartwatch. The authors analyzed data using these two methods to gain insights into the factors influencing individuals' intention to adopt smartwatches. This research contributes to our understanding of wearable technology adoption and provides valuable insights for researchers and practitioners in the field of health informatics.

Al-Emran, M. [11] [2021] explored why people might use smartwatches for learning in his study. He combined two models, the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF), to see how well smartwatches meet the needs of learners. Using detailed data analysis, the study found that if people think smartwatches are useful, easy to use, and suitable for their tasks, they're more likely to use them for learning. This research helps educators and tech developers understand how to better incorporate smartwatches into educational settings.

2.3 Comparative Analysis and Summary

Using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine how smartwatch adoption occurs reveals important information about the complex dynamics influencing user behavior. Examining factors like perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol, the study explores complex relationships that impact smartwatch adoption.

It is possible to investigate these relationships and evaluate how they affect the tendency of consumers to adopt smartwatches by utilizing PLS-SEM. A solid framework that clarifies the underlying mechanisms at work is revealed through the methodical analysis of reflective structures utilizing measurement and structural models.

In conclusion, the study outlines the complicated environment of smartwatch adoption and provides an analysis of the corresponding significance of different aspects. Theoretical frameworks and practical consequences are enhanced by these findings, enabling stakeholders to improve smartwatch design and execution for smooth everyday engagement. This comprehensive research contributes to our understanding of focused-on-user technology adoption, enabling more knowledgeable and flexible interactions between humans and technology in the digital age.

2.4 Scope of the problem

The scope of the subject addressed in this study includes the complex landscape of smartwatch adoption. Understanding the factors impacting the acceptability and integration of smartwatches is becoming increasingly important as technology continues to influence various facets of human lives. Specifically, the research delves into dimensions such as perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol, employing Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore their connections and influence on user behavior.

By studying how smartwatches are adopted, the study provides insightful information on what influences consumers' opinions and preferences regarding this technology. By providing an in-depth analysis of these variables and clarifying their significance and interactions within the framework of smartwatch adoption, it aims to further intellectual engagement. The research ultimately advances our knowledge of the opportunities and difficulties associated with the widespread use of smartwatches in the ever-changing context of modern daily life.

2.5 Challenges

There are several difficulties in using partial least squares structural equation modeling (PLS-SEM) to investigate the variables impacting the adoption of smartwatches. The complex interplay between human behavior and perception is a major obstacle. Due to the natural complexity of these processes, understanding user attitudes regarding smartwatches which are influenced by things like perceived usefulness and social influence poses a substantial challenge.

Furthermore, it's important but difficult to guarantee the accuracy and quality of the data. The reliability of the results could be jeopardized by preconceptions, mistakes, or misunderstandings in the data gathered through a Google Form survey. In addition, the rapid development of technology and the fluctuating demands of users require constant adjustment, which makes it challenging to fully capture all relevant aspects.

PLS-SEM methodology demands accurate model specification and a thorough examination of path coefficients. An additional degree of complexity is added to the study by striking a balance between the breadth and depth of analysis while staying focused on the research objectives.

Lastly, it is naturally difficult to ensure that the results can be applied to a population larger than the one that was sampled. The study's findings must be carefully interpreted and cautiously used to ensure that they may be applied to wider situations.

To guarantee the validity and reliability of the study's contributions to our understanding of smartwatch adoption patterns, it is essential to address these issues.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation

My research project is titled "Adoption of Smartwatches in Daily Life." This research aims to use Partial Least Squares Structural Equation Modeling (PLS-SEM) to identify and assess the major factors influencing consumers' adoption of smartwatches. The principal tool employed in this investigation is a structured questionnaire survey that is distributed to a subset of prospective smartwatch users. Perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol are just a few of the variables that the survey is intended to collect information on. To examine the connections between the factors that have been identified and the adoption of smartwatches, partial least squares (PLS) analysis is utilized. An in-depth review of a collection of research on technology adoption theories and related studies provides a theoretical framework for the research. The study model is developed with the help of this literature review, which also helps discover important factors impacting the adoption of smartwatches. Based on the literature review and theoretical framework, hypotheses are formulated to test the relationships between the identified factors and smartwatch adoption. These theories serve as a framework for the analysis and interpretation of the data that was gathered from the questionnaire survey. The findings are discussed in terms of their theoretical implications for technology adoption research and their practical significance for smartwatch manufacturers and marketers.

3.2 Data Collection

A structured survey presented using an internet platform, primarily Google Forms, is used to collect data regarding this research. The poll includes 50 carefully constructed questions meant to capture a wide range of characteristics related to smartwatch adoption. These characteristics include age, gender, marital status, academic qualification, profession, and smartwatch usage experience which provide an understanding of the participants' diverse origins. Furthermore, the poll goes into various aspects of smartwatch adoption, looking into perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol. Including these characteristics seeks to present a complete picture of participant's perceptions, attitudes, and behavioral tendencies toward smartwatches in their daily lives. The attributes-rich data acquired will be useful in conducting a complex and extensive analysis utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM).

Table 3.1: Survey Questionnaires

Variables	Code	Items
Perceived usefulness	PU1	The use of a smartwatch would improve my productivity/performance
	PU2	The use of a smartwatch would improve my effectiveness
	PU3	The use of a smartwatch would help me
	PU4	In general, the use of a smartwatch would be beneficial
Perceived enjoyment	PE1	The use of a smartwatch would be a pleasant experience
	PE2	I would have fun using of smartwatch
	PE3	The use of a smartwatch would be interesting
	PE4	The use of a smartwatch would be worth to enjoyable
Price Value	PV1	The smartwatch is reasonably priced
	PV2	Smartwatch is a good value for the money
	PV3	At the current price, the smartwatch provides a good value
Hedonic motivation	HM1	Using a smartwatch is fun
	HM2	Using a smartwatch is enjoyable
	HM3	Using a smartwatch is very entertaining
Compatibility	CM1	A smartwatch is compatible with my personal values
	CM2	A smartwatch is compatible with my personal culture
	CM3	The smartwatch is compatible with my preferred work practice
Attitude	ATT1	The use of a smartwatch would be a good idea.
	ATT2	The use of a smartwatch would be a wise idea.
	ATT3	I would like the idea of using a smartwatch
	ATT4	The use of a smartwatch would be a pleasant experience.
Subjective norm	SN1	People who are important to me would think that I should use smartwatch
	SN2	People whose opinions are valued by me would prefer that I should use a smartwatch
	SN3	People who influence me would think that I should use a smartwatch
Perceived behavioral control	FC1	I think that I would be able to use a smartwatch
	FC2	I think that using a smartwatch would be entirely within my control

	FC3	I think that I have the resources, knowledge, and ability to use a smartwatch
Adoption Behavior	AB1	I currently use a smartwatch.
	AB2	I will recommend using a smartwatch to my friends or others.
	AB3	Smartwatch is my first choice when I need to buy a watch
Personal innovativeness	PI1	If I heard about smartwatch, I would look for ways to experiment with it
	PI2	Amongst my peers, I am usually the first to try out a smartwatch
	PI3	In general, I am not hesitant to try a smartwatch
	PI4	I like to experiment with smartwatch
Perceived trust	PT1	I feel a smartwatch would be trustworthy
	PT2	I feel a smartwatch would be reliable.
	PT3	I feel a smartwatch would be controllable
	PT4	I feel a smartwatch would be efficient.
Status symbol	SS1	A smartwatch is a symbol of identity and status.
	SS2	People who use smartwatches are brave innovators.
	SS3	People who use smartwatches are practitioners of environmental protection

3.2.1 Demographic Statistics

As seen in Table 3.1, there are more males (189) than females (76) among the respondents, making the male-to-female ratio about 2.5 to 1. This means 71.32% of the respondents are male, and 28.68% are female. Most of the respondents are young adults, with 93.58% (248 out of 265) being between 18 and 25 years old. When it comes to education, a large majority, 86.79% (230 out of 265), have an Honors degree. Only a few have advanced degrees, with 5.28% (14 out of 265) holding a Master's and just 0.38% (1 out of 265) having a PhD. Looking at marital status, most of the respondents are single, with 83.40% (221 out of 265) identifying as single and 16.60% (44 out of 265) as married. In terms of smartwatch usage, the experience varies. The biggest groups have been using smartwatches for less than a year or between 1-2 years, with 27.17% (72 out of 265) in each category. There are also quite a few with 2-4 years of experience (25.66% or 68 out of 265), and a smaller group with more than 4 years (20.00% or 53 out of 265). When it comes to jobs, most of the respondents are students, making up 75.85% (201 out of 265). Some don't work (12.83% or 34 out of 265), and others are spread across the public sector (2.64% or 7 out of 265), private sector (3.02% or 8 out of 265), business (5.28% or 14 out of 265), and freelancing (0.38% or 1 out of 265).

In summary, most of the respondents are young (93.58% between 18-25 years), educated (86.79% with an Honors degree), single (83.40%), and students (75.85%) with varying levels of experience using smartwatches

Table 3.2: Demographic Data

Variables	Category	Frequency	Percentage
Gender	Male	189	26.68%
	Female	76	71.32%
Age	18-25 years	248	93.58%
	26-30 years	15	5.66%
	31-35 years	1	0.38%
	36-40 years	0	0.00%
	41-45 years	0	0.00%
	46-50 years	0	0.00%
	51-55 years	0	0.00%
	56-60 years	0	0.00%
	61-65 years	0	0.00%
	Above 65 years	1	0.38%
Highest Academic Qualification	No recognized academic degree	5	1.89%
	HSC or equivalent	8	3.02%
	Diploma or equivalent	7	2.64%
	Honors or equivalent	230	86.79%
	Masters or equivalent	14	5.28%
	PhD or equivalent	1	0.38%
	Post Doctorate or equivalent	0	0.00%
	Others	0	0.00%
Marital Status	Single	221	83.40%
	Married	44	16.60%
Smartwatch Usage Experience	No experience	0	0.00%
	Less than 1 year	72	27.17%
	1-2 years	72	27.17%
	2-4 years	68	25.66%
	More than 4 years	53	20.00%
Profession	Don’t work	34	12.83%
	Public sector	7	2.64%
	Private sector	8	3.02%
	Student	201	75.85%
	Business	14	5.28%
	Freelancing	1	0.38%
	Others	0	0.00%

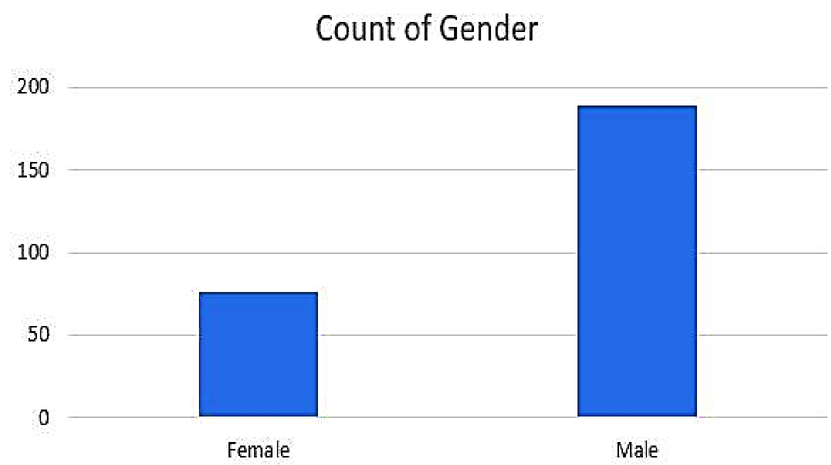

Figure 3.1: Gender Distribution Bar Chart

The above bar chart of Figure 3.1 represents the gender distribution in smartwatch adoption, with 189 males (shown by a higher, blue bar) greatly outnumbering 76 females (shown by a shorter, blue bar). Though lacking precise labels, the chart paints a clear picture of a gender imbalance in smartwatch adoption, with males exceeding females by 113 individuals. While the data speaks for itself, it's crucial to remember that statistics, like bars on a chart, can sometimes only tell part of the story.

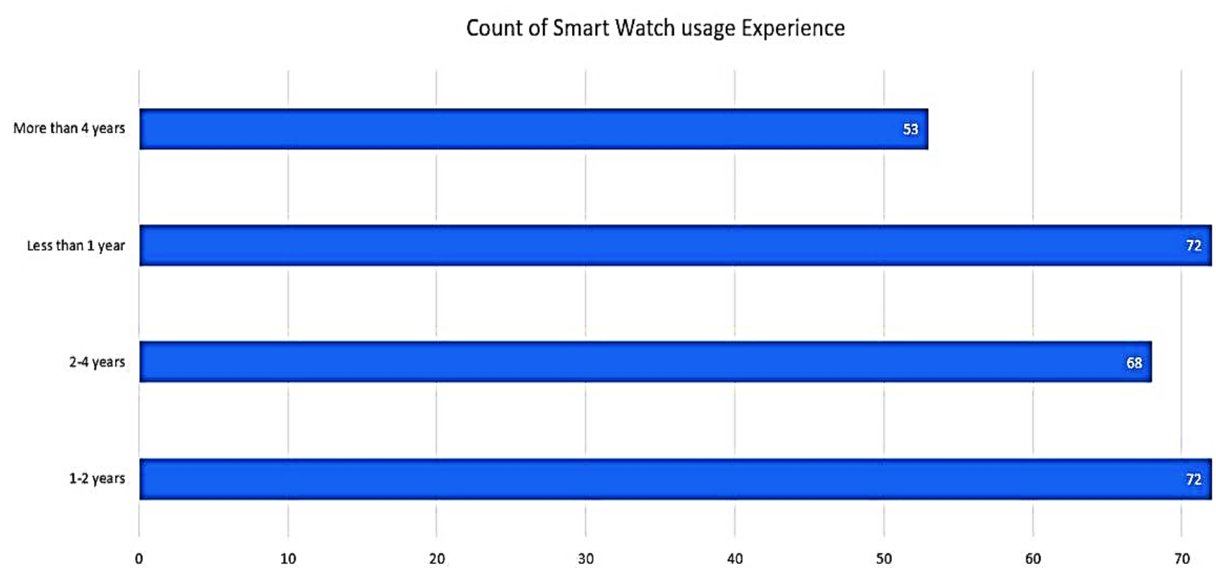

Figure 3.2: Distribution of Smart Watch Usage Experience Among Respondents

The above bar chart of Figure 3.2 titled "Count of Smart Watch Usage Experience" shows how many people have used smartwatches for different lengths of time. The largest groups are those who have used a smartwatch for "Less than 1 year" and "1-2 years," with 72 people each. Next, 68 people have used one for "2-4 years." The smallest group is those with "More than 4 years" of experience, with 53 people. This suggests that most smartwatch users are relatively new, with fewer long-term users.

3.3 Statistical Analysis

PLS-SEM is a statistical approach used for modeling complex relationships between observed and latent variables. In my research, I used Partial Least Squares Structural Equation Modeling (PLS-SEM) as the statistical approach, utilizing the SmartPLS tool to perform the analysis. PLS-SEM is a versatile method capable of managing the intricate relationships created by the use of smartwatches in everyday life. Since the paper likely used a PLS approach, the statistical analysis would involve several steps: Summarizing the data collected from respondents. Descriptive statistics might include measures like mean, median, standard deviation, and frequency distributions for variables such as demographics (age, gender, marital status, etc.) and constructs related to smartwatch adoption (perceived usefulness, perceived enjoyment, price value, trust, etc.). Next PLS path modeling is used to test hypotheses about the relationships between latent variables (e.g., perceived usefulness, enjoyment, price value, trust) and observed variables (e.g., intention to adopt a smartwatch). This analysis assesses the strength and significance of these relationships. Researchers often assess the reliability and validity of their measurement scales. Using indicators and measuring parameters such as composite reliability, and average variance extracted (AVE), the measurement model analysis ensures the reliability and validity of reflective constructs such as perceived usefulness and price value. The structural model analysis involves examining the stated relationships between constructs while evaluating overall model fit using metrics such as Standardized Root Mean Square Residual (SRMR). Lower SRMR values indicate better fit, suggesting that the model's implied correlations closely match the observed correlations. Using bootstrapping approaches, hypothesis testing determines the significance and directionality of path coefficients. Based on the results of the statistical analyses, researchers would then test their hypotheses to determine whether the relationships between variables are statistically significant. R2 values are used to assess predictive relevance, which provides insight into the model's explanatory capacity. The sensitivity analysis verifies that the results are strong under different model specifications. This exact statistical method, which includes both reflective and formative dimensions strives to uncover the complexities of smartwatch adoption by providing a thorough and data-driven analysis of user behaviors and attitudes.

3.4 Proposed methodology

The following flowchart, seen in Figure 3.3, provides an overview summary:

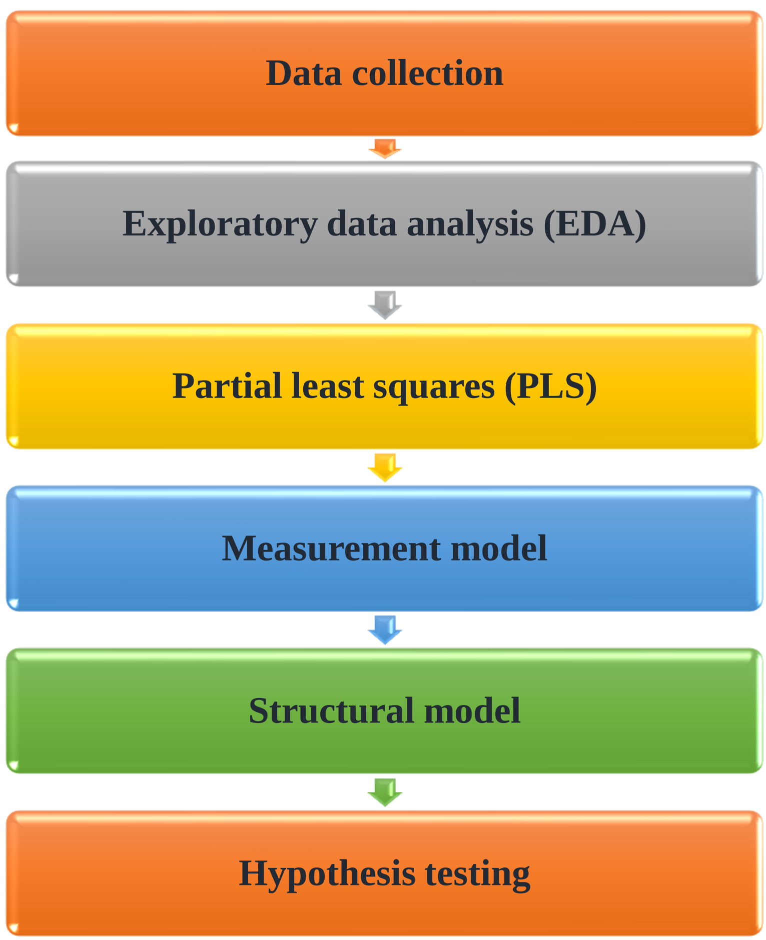

Figure 3.3: Flow diagram of methodology

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) knowing the unseen patterns inside the hole data. We can extract several kinds of information from the data set using EDA, which helps us choose the machine learning model and make other decisions [12]. Since EDA is the initial move in identifying the characteristics and patterns in the collected dataset, it is a crucial phase in this study. The dataset, which consists of 265 responses to 50 survey questions, will be examined using descriptive statistical methods. To gather information on response variety and variability, a single variate analysis will be utilized to look at the distribution and central trends of each variable. This kind of analysis will examine their relationships to determine whether there are any correlations or dependencies between the two variables. Data patterns and trends will be better understood with the use of visualizations like scatter plots, box plots, and histograms. Throughout the EDA process, it's essential to iteratively refine your model based on insights gained from the data exploration. Additionally, visualizations play a crucial role in EDA, as they help understand complex relationships and identify patterns that may not be apparent from numerical summaries alone.

Partial least squares (PLS)

SmartPLS is a user-friendly software tool designed for Partial Least Squares Structural Equation Modeling (PLS-SEM), providing researchers across disciplines such as enterprise, social studies, and engineering [13]. With its intuitive graphical interface, researchers can easily specify and estimate complex PLS-SEM models without requiring advanced programming skills. With SmartPLS, researchers can assess complicated connections between observable variables and latent constructs. Its user-friendly interface makes measurement and structural model analysis easier, making it appropriate for researchers with varied degrees of statistical competence. SmartPLS is especially useful in dealing with reflective and formative constructions at the same time, providing a dynamic platform for comprehensive analysis in studies. Overall, SmartPLS simplifies the process of conducting PLS-SEM by providing a user-friendly interface, robust analytical capabilities, and visualization tools to support researchers throughout the model-building and analysis process.

Model specification

The model specification in PLS-SEM involves articulating the theoretical framework and hypotheses guiding the studies as "Adoption of smartwatches in daily life". It is an important stage in the research approach because it involves the specific defining of links between constructs in the investigation. It is like drawing a map before going on a journey. It's about deciding where you want to go (your hypotheses), what landmarks you'll use to know you're on the right path (indicators), and how you think you'll get there (the connections between different points). You also need to make sure your map makes sense and is based on what you already know (theory or previous research). This step helps researchers organize their ideas and plan how they will test them using data.

Measurement model

The measurement model is a crucial part of the study, especially in the "Adoption of smartwatches in daily life." It specifies how observed indicators are related to their corresponding latent variables (constructs). The measurement model aims to establish the reliability and validity of the latent constructs by examining how well the indicators represent them. This phase analyzes the reliability and validity of the survey's reflective constructs, such as perceived usefulness (PU), perceived enjoyment (PE), perceived behavioral control (FC), subjective norm (SN), hedonic motivation (HM), attitude (ATT), and status symbol (SS). The measurement model ensures the robustness of the measurement instruments by evaluating indicator reliability (factor loading (FL)), indicator validity (variance inflation factor (VIF)), internal consistency reliability (composite reliability), and convergent and discriminant validity. It confirms the accuracy and consistency of the acquired data, providing a foundation for further studies in Structural Equation Modeling (SEM).

Structural model

The structural model represents how the latent variables in the model relate to one another. This involves specifying the paths or arrows representing the hypothesized causal relationships between constructs. This can involve examining the significance and strength of paths between constructs, as well as exploring moderating effects. The focus is on testing ideas about how things cause other things. In PLS-SEM, we evaluate the structural model using path coefficients, which tell us the strength and direction of the relationships between ideas like Perceived Utility (PU), Perceived Enjoyment (PE), Perceived Behavioral Control (FC), Subjective Norm (SN), Hedonic Motivation (HM), Attitude (ATT), and Status Symbol (SS). We also check if these relationships are statistically supported by looking at their significance. The Structural Model gives us a detailed analysis of how these things work together to shape user behavior and attitudes toward adopting smartwatches in everyday life.

Hypothesis Testing

Hypothesis testing is used in PLS-SEM to assess the significance of the correlations between different constructs in a model. To do this, we examine the path coefficients, which indicate the strength of these relationships. We employ bootstrapping, a technique in which we repeatedly sample from our data to calculate standard errors and t-statistics for the path coefficients. We can determine if the relationships are statistically significant by comparing these t-statistics or the p-values to a significance level (usually 0.05). If a p-value is less than 0.05, we reject the null hypothesis (which states that there's no relationship) and accept the alternative hypothesis (which states that there is a relationship). This process helps us comprehend and confirm the strength and significance of the relationships in our theoretical model.

3.4.1 Proposed Research Model

The following research model is proposed to address the research objectives (see Figure 3.4).

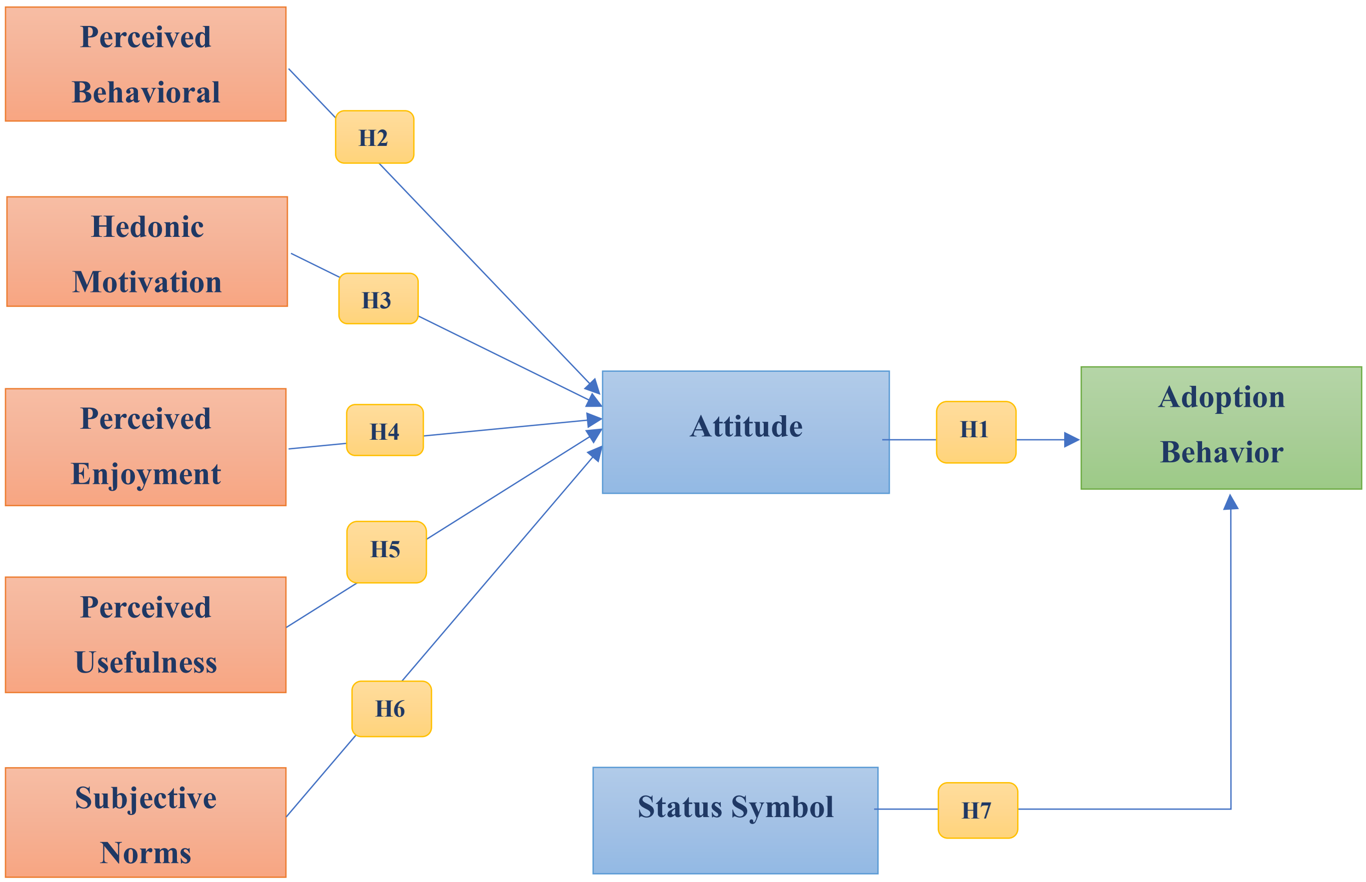

Figure 3.4: Proposed Research Model

Model Description:

Constructs:

1. Perceived Behavioral
2. Hedonic Motivation
3. Perceived Enjoyment

4. Perceived Usefulness
5. Subjective Norms
6. Attitude
7. Status Symbol
8. Adoption Behavior

Hypotheses:

- H1: Attitude → Adoption Behavior
- H2: Perceived Behavioral → Attitude
- H3: Hedonic Motivation → Attitude
- H4: Perceived Enjoyment → Attitude
- H5: Perceived Usefulness → Attitude
- H6: Subjective Norms → Attitude
- H7: Status Symbol → Adoption Behavior

Relationships:

1. Attitude serves as a mediator between several constructs (Perceived Behavioral, Hedonic Motivation, Perceived Enjoyment, Perceived Usefulness, Subjective Norms) and Adoption Behavior.
2. Status Symbol has a direct effect on Adoption Behavior.

Path descriptions:

1. Perceived Behavioral: This affects how people feel about something. If they think it will work well, it makes them more positive about it.

2. Hedonic Motivation: This is about how fun or enjoyable something is. If people find it fun, they will feel more positive about it.
3. Perceived Enjoyment: This is similar to hedonic motivation but focuses more on the actual enjoyment. If people enjoy something, they will feel more positive about it.
4. Perceived Usefulness: This is about how useful something is. If people think something will be useful to them, it makes them feel more positive about it.
5. Subjective Norms: This is about what people think others expect them to do. If people feel that others think they should do something, it makes them feel more positive about it.
6. Attitude: This is a general positive feeling towards something. It is influenced by perceived behavioral, hedonic motivation, perceived enjoyment, perceived usefulness, and subjective norms.
7. Adoption Behavior: This is about actually deciding to do something or use something. A positive attitude makes people more likely to adopt the behavior.
8. Status Symbol: This is about whether doing or using something makes people feel like they have a higher status. If people think it does, it makes them more likely to adopt the behavior.

How They Connect:

- Perceived Behavioral, Hedonic Motivation, Perceived Enjoyment, Perceived Usefulness, and Subjective Norms all lead to a more positive Attitude.
- A positive Attitude leads to Adoption Behavior, meaning people are more likely to do or use something.
- Status Symbol directly influences Adoption Behavior, meaning if people think something will boost their status, they are more likely to adopt it.

3.5 Implementation Requirements

I would like to use the Partial Least Squares (PLS) method to analyze the factors influencing the adoption of smartwatches. With an emphasis on variables like Perceived Utility (PU), Perceived Enjoyment (PE), Perceived Behavioral Control (FC), Subjective Norm (SN), Hedonic Motivation (HM), Attitude (ATT), and Status Symbol (SS). Firstly, using the literature as a guide, I will create a research framework and hypotheses. Secondly, I'll prepare and distribute the structured survey to collect information from an appropriate number of owners of smartwatches. The collected data will be cleaned and preprocessed to make the data suitable for PLS analysis. I will identify and estimate the measurement and structural models using statistical tools like SmartPLS, examining the path coefficients for their validity, significance, and reliability. A detailed report will present the results of the research, along with a discussion of the consequences for theory and practice. Furthermore, it is going to tackle the considerations regarding ethical points such as consent and participant confidentiality. With amazing clarity, this methodical approach will help pinpoint the elements contributing to the adoption of smartwatches and yield valuable insights in the field.

CHAPTER 4

Experimental Results and Discussion

4.1 Experimental Setup

The study's experimental framework has been carefully designed to examine the systematic effects of smartwatch adoption on everyday life. I will conduct a detailed online survey of 50 questions using a user-friendly platform like Google Forms. I will select 265 participants to form a diverse and representative sample by employing a well-planned sampling technique that considers populations and technological capabilities. Prioritizing participants' consent and confidentiality, the research team will be trained to ensure standardized processes and consistency. I will use SmartPLS, a specialized PLS-SEM software, for statistical analysis to gain insights into the complex interactions between variables. Quality control procedures and a specific timeframe will be implemented to ensure data accuracy. The results will be widely shared to enhance our understanding of smartwatch adoption dynamics while ensuring transparency and reliability through careful documentation of the procedure and analytical phases. Utilizing survey data and modern statistical methods, this approach guarantees a comprehensive and well-organized study of the research issue.

4.2 Experimental Results & Analysis

The experimental results and analysis provide valuable insights into the usage of smartwatches in everyday life.

4.2.1 Measurement Model:

Factor loading, or "indicator loading", is how much the construct influences the indicators. Moreover, it evaluates the amount of the indicator variable that is described by the corresponding latent variable. A loading value of at least 0.7 is considered satisfactory. A value of less than 0.5 indicates that the item has to be eliminated from the measurement model. The Variance Inflation Factor (VIF) is used in the Measurement Model analysis to analyze variation among indicators, ensuring that there is no excessive redundancy within the measurement constructs. Any VIF value higher than 10 should be rejected. Internal consistency reliability refers to the phenomenon where the indicator changes by the latent variable and can be assessed using composite reliability. The composite reliability value should be at least 0.7 to be acceptable. Validity is determined, when the measurement model correctly represents the desired dimensions of the constructs, ensuring that the instrument properly measures what it is designed to measure. Average variance extracted (AVE), which is the mean of the squared factor loadings of the set of items of a variable, is a frequently used convergent validity test. Furthermore, the suggested threshold value of AVE is 0.5. Discriminant validity is an important feature of measurement model analysis since it ensures that each construct in the study is diverse and different. This method allows a latent variable to share greater variance with the allocated indicators than for any other variable. Table 4.1 provides an overview of the validity standards used to assess a measurement model.

Table 4.1: Summary of Validity Standards for the Measurement Model

Validity and Reliability	Criteria	Threshold Value and Guideline
Indicator reliability	Factor loadings (FL)	FL > = 0.5
Indicator validity	Variance inflation factor (VIF)	VIF < = 5 or, VIF < = 10
Internal consistency reliability	Composite reliability (CR)	CR > = 0.7
Convergent validity	Average variance extracted (AVE)	AVE > = 0.5
Discriminant validity	Fornell and Larcker (1981)	The AVE of each variable has to be larger than the maximum squared correlation of any other variable

Indicator Reliability (Factor loading)

Factor loadings in PLS-SEM are crucial for evaluating the connections between observed variables (indicators) and their underlying latent variables (constructs). High factor loadings indicate that the indicator effectively represents the latent construct, demonstrating that the indicator accurately reflects and measures the desired construct. This contributes to the reliability and validity of the measurement model.

Table 4.2: Indicator Reliability

	AB	ATT	FC	HM	PE	PU	SN	SS
AB1	0.774							
AB2	0.746							
AB3	0.789							
ATT1		0.798						
ATT2		0.736						
ATT3		0.715						
ATT4		0.770						
FC1			0.839					
FC2			0.679					
FC3			0.724					
HM1				0.822				
HM2				0.758				
HM3				0.807				
PE1					0.794			
PE2					0.748			
PE3					0.747			
PE4					0.759			
PU1						0.813		
PU2						0.685		
PU3						0.705		
PU4						0.750		
SN1							0.861	
SN2							0.720	
SN3							0.792	
SS1								0.831
SS2								0.780
SS3								0.826

Table 4.2 shows the outer loading. The outer loadings table indicates that the measurement model is well-specified and that the indicators are measuring the latent constructs effectively.

Indicator Validity (Variance inflation factor)

The validity of the indicator is tested using the variance inflation factor (VIF). A high VIF indicates a high level of correlation among observed variables (indicators), which could impact the precision and reliability of regression coefficients.

Table 4.3: Indicator Validity

	VIF
AB1	1.358
AB2	1.220
AB3	1.306
ATT1	1.594
ATT2	1.377
ATT3	1.368
ATT4	1.509
FC1	1.394
FC2	1.163
FC3	1.251
HM1	1.530
HM2	1.308
HM3	1.414
PE1	1.635
PE2	1.409
PE3	1.462
PE4	1.440
PU1	1.600
PU2	1.364
PU3	1.335
PU4	1.388
SN1	1.597
SN2	1.277
SN3	1.426
SS1	1.572
SS2	1.393
SS3	1.514

Table 4.3 shows the variance inflation factor. The investigation has found that all elements of the measurement model have values less than 10 ranging from 1.163 to 1.635. According to the results, it can be determined that there are no multicollinearity issues.

Internal Consistency Reliability (Composite reliability)

The measurement model's internal consistency reliability is assessed by the application of composite reliability (CR) analysis. Strong internal consistency, as indicated by measures like composite reliability (CR), ensures high construct reliability, confirming that the indicators accurately represent the fundamental structures.

Table 4.4: Internal Consistency Reliability

	Composite Reliability
AB	**0.814**
ATT	**0.842**
FC	**0.793**
HM	**0.838**
PE	**0.847**
PU	**0.828**
SN	**0.835**
SS	**0.854**

Table 4.4 confirms that all the constructs have a CR of 0.793 to 0.854 and have exceeded the threshold value. This indicates that the model's internal consistency is sufficiently reliable.

Convergent Validity (Average variance extracted)

Convergent validity evaluates how different items correlate with instruments measuring various variables. The measurement model's convergent validity is evaluated using the average variance extracted (AVE) value.

Table 4.5: Convergent Validity

	Average Variance Extracted (AVE)
AB	**0.593**
ATT	**0.571**
FC	**0.563**
HM	**0.634**
PE	**0.581**
PU	**0.547**
SN	**0.629**
SS	**0.661**

Table 4.5 shows that all variables have an AVE of 0.547 to 0.661. These outcomes indicate that the model's convergent validity meets the requirements and that the threshold value of 0.5 is passed.

Discriminant Validity (Fornell and Larcker (1981))

The Fornell and Larcker (1981) criteria are used to assess the measurement model's discriminant validity. The square root of AVE is represented by the diagonal components; the squared correlations are represented by the other values.

Table 4.6 demonstrates discriminant validity by demonstrating that the diagonal values are greater than the corresponding row-column values.

Table 4.6: Discriminant Validity

	AB	ATT	FC	HM	PE	PU	SN	SS
AB	0.770							
ATT	0.807	0.756						
FC	0.696	0.756	0.750					
HM	0.682	0.741	0.579	0.796				
PE	0.766	0.812	0.708	0.675	0.762			
PU	0.752	0.800	0.712	0.709	0.808	0.740		
SN	0.743	0.753	0.650	0.679	0.758	0.693	0.793	
SS	0.709	0.676	0.574	0.660	0.722	0.670	0.731	0.813

In addition, Figure 4.1 shows the measurement model findings produced by the SmartPLS tool.

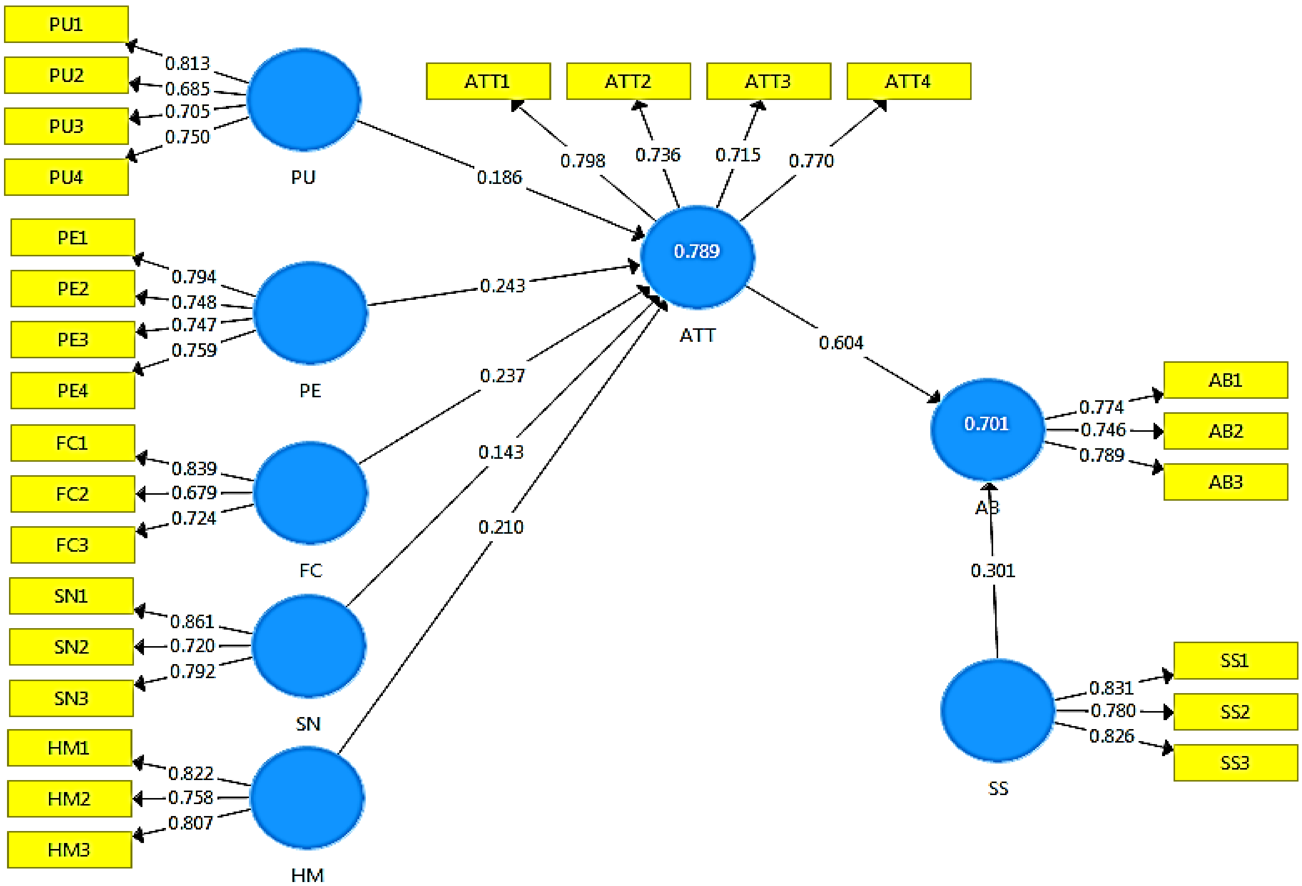

Figure 4.1: Measurement Model Results from SmartPLS Tool

The figure appears to show the path relationships between several latent constructs, represented by ovals, and their indicator variables, represented by rectangles. Arrows indicate the direction of the relationships, with some paths having associated path coefficients, represented by numbers next to the arrows.

4.2.2 Structural Model:

The Structural Model analysis produces analytical measures such as R^2, F^2, and Q^2, which provide an in-depth understanding of the model's explanatory power, effect size, and predictive importance. The R^2 value, which represents the amount of variance described by the endogenous(dependent) factors, shows the overall fit of the model. The F^2 represents the size of the effect, highlighting the practical importance of the linkages, whilst the Q^2 analyzes the model's predictive relevance, providing information about its ability to predict endogenous constructs. Furthermore, hypothesis testing with bootstrapping addresses confirms the importance and directionality of the defined associations, validating or questioning the established hypotheses and contributing to the

study's robustness. Table 4.7 provides a summary of the validity standards used to evaluate a structural model.

Table 4.7: Summary of Validity Standards for the Structural Model

Validity	Criteria	Threshold Value and Guideline
The validity of the model	Path coefficient (β)	β > 0.1 or, β > 0.2
	Coefficient of determination (R2)	Substantial→0.67, moderate→0.33, weak→0.19 or, Substantial→0.75, moderate→0.50, weak →0.25
	Cross-validated redundancy (Q2)	Q2 > 0
	Effect size (f2)	0.01<= *f2* < 0.02 → very small effect 0.02 <= *f2* < 0.15 → small effect 0.15 <= *f2* < 0.35 →medium effect *f2* >= 0.35 → large effect

Coefficient of Determination (R^2)

In structural equation modeling, the R^2 is an important metric. It shows the percentage of variation defined by the model in endogenous (dependent) constructs. Higher R^2 value means the model can better account for the variability observed in the dependent variables.

This statistic is important for assessing the model's overall clarity and its ability to capture the links between the constructs being studied. The R^2 in this study is computed using the SmartPLS tool. Table 4.8 displays the 70.1% and 78.9% model variances.

Table 4.8: Coefficient of Determination

	R^2	R^2 Adjusted
AB	0.701	0.699
ATT	0.789	0.785

Cross Validated Redundancy (Q^2)

Q square, an important statistic in PLS-SEM, evaluates the model's predictive value. It evaluates how effectively the model's latent variables predict endogenous constructs beyond the information available in external variables. A positive Q square value indicates good predictive performance, highlighting the model's capacity to identify and explain internal construct changes. The Q^2 values of AB and ATT are 40% and 43.4% which is greater than 0 and confirms that the model is correctly predicted (see Table 4.9).

Table 4.9: Cross Validated Redundancy

	SSO	SSE	Q^2 (=1-SSE/SSO)
AB	795.000	477.074	0.400
ATT	1060.000	599.535	0.434
FC	795.000	795.000	
HM	795.000	795.000	
PE	1060.000	1060.000	
PU	1060.000	1060.000	
SN	795.000	795.000	
SS	795.000	795.000	

Effect size (F^2)

In PLS-SEM, the F^2, also known as the effect size, provides important insights into the practical relevance of the connections within the structural model. The amount of the model's impact is reflected in F^2, which is the fraction of variation in the endogenous constructs described by the exogenous constructs. A higher F^2 indicates a more significant effect, emphasizing the identified associations' practical importance and real-world applicability. According to the result, five relationships have small effects, one with a medium effect, and one with a large effect (see Table 4.10).

Table 4.10: Effect size

	AB	ATT	FC	HM	PE	PU	SN	SS
AB								
ATT	**0.663**							
FC		0.113						
HM		0.089						
PE		0.072						
PU		0.044						
SN		0.035						
SS	**0.165**							

Path Coefficient (beta coefficient)

Path coefficient is the hypothesized association between the constructs known as a standardized beta coefficient or a weighted beta. To determine the significance level, t-statistics are constructed for all relationships. In addition, the sample mean, t-values, p-values, standard deviation, and path coefficient are shown in Table 4.11.

Table 4.11: Path Coefficient

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ATT -> AB	0.604	0.595	0.065	9.330	**0.000**
FC -> ATT	0.237	0.234	0.047	4.995	**0.000**
HM -> ATT	0.210	0.220	0.062	3.420	**0.001**
PE -> ATT	0.243	0.242	0.052	4.683	**0.000**
PU -> ATT	0.186	0.183	0.068	2.734	**0.006**
SN -> ATT	0.143	0.138	0.054	2.649	**0.008**
SS -> AB	0.301	0.310	0.059	5.066	**0.000**

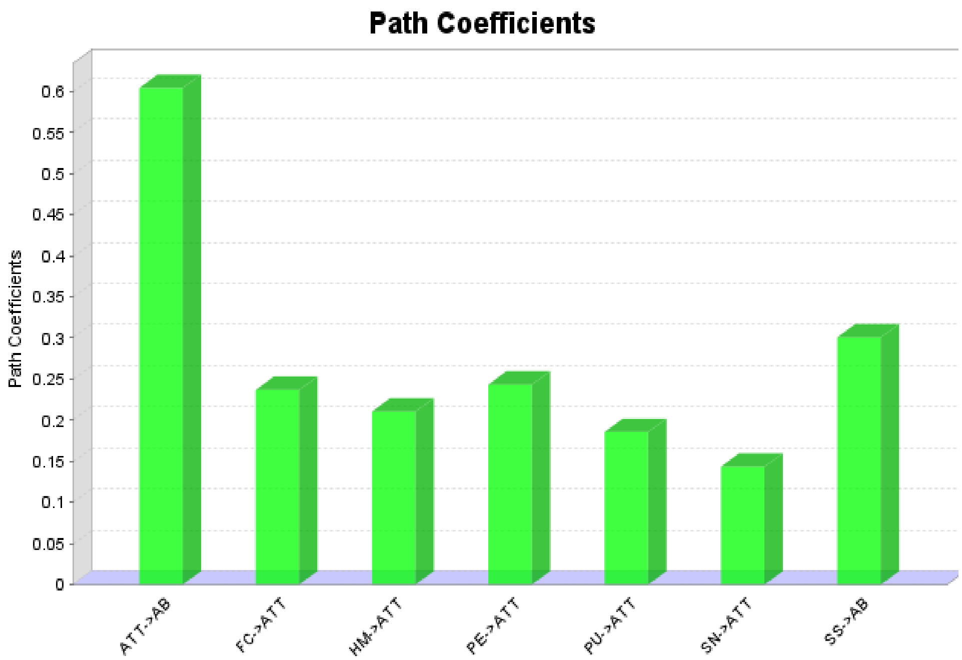

Figure 4.2: Bar chart, Path Coefficient

Hypotheses Testing

The seven hypotheses are proven to be significant, according to the findings from the SmartPLS tool. The intention is found to be significantly influenced by attitude (beta(O) = 0.604, $p<0.001$), perceived behavioral control (beta(O)= 0.237, $p<0.001$), hedonic motivation (beta(O)= 0.210, $p<0.01$), perceived enjoyment (beta(O) =0.243, $p<0.001$), perceived usefulness (beta(O) = 0.186, $p<0.01$), subjective norm (beta(O)= 0.143, $p<0.01$), and status symbol (beta(O)= 0.301, $p<0.001$). Besides, attitude, perceived behavioral control, hedonic motivation, perceived enjoyment, perceived usefulness, subjective norm, and status symbol are positively connected to adoption intention. According to the p-values, the intention is strongly influenced by attitude, perceived behavioral control, perceived enjoyment, status symbol, moderately influenced by hedonic motivation, perceived usefulness, and subjective norm. As a result, all hypotheses are supported

Table 4.12: Hypotheses testing

Hypothesis	Relationships	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P-Values	Remarks
H1	**ATT -> AB**	0.604	0.595	0.065	9.330	**0.000**	**Supported**
H2	**FC -> ATT**	0.237	0.234	0.047	4.995	**0.000**	**Supported**
H3	**HM -> ATT**	0.210	0.220	0.062	3.420	**0.001**	**Supported**
H4	**PE -> ATT**	0.243	0.242	0.052	4.683	**0.000**	**Supported**
H5	**PU -> ATT**	0.186	0.183	0.068	2.734	**0.006**	**Supported**
H6	**SN -> ATT**	0.143	0.138	0.054	2.649	**0.008**	**Supported**
H7	**SS -> AB**	0.301	0.310	0.059	5.066	**0.000**	**Supported**

ns = non-significant, *p<0.05, **p<0.01, ***p<0.001

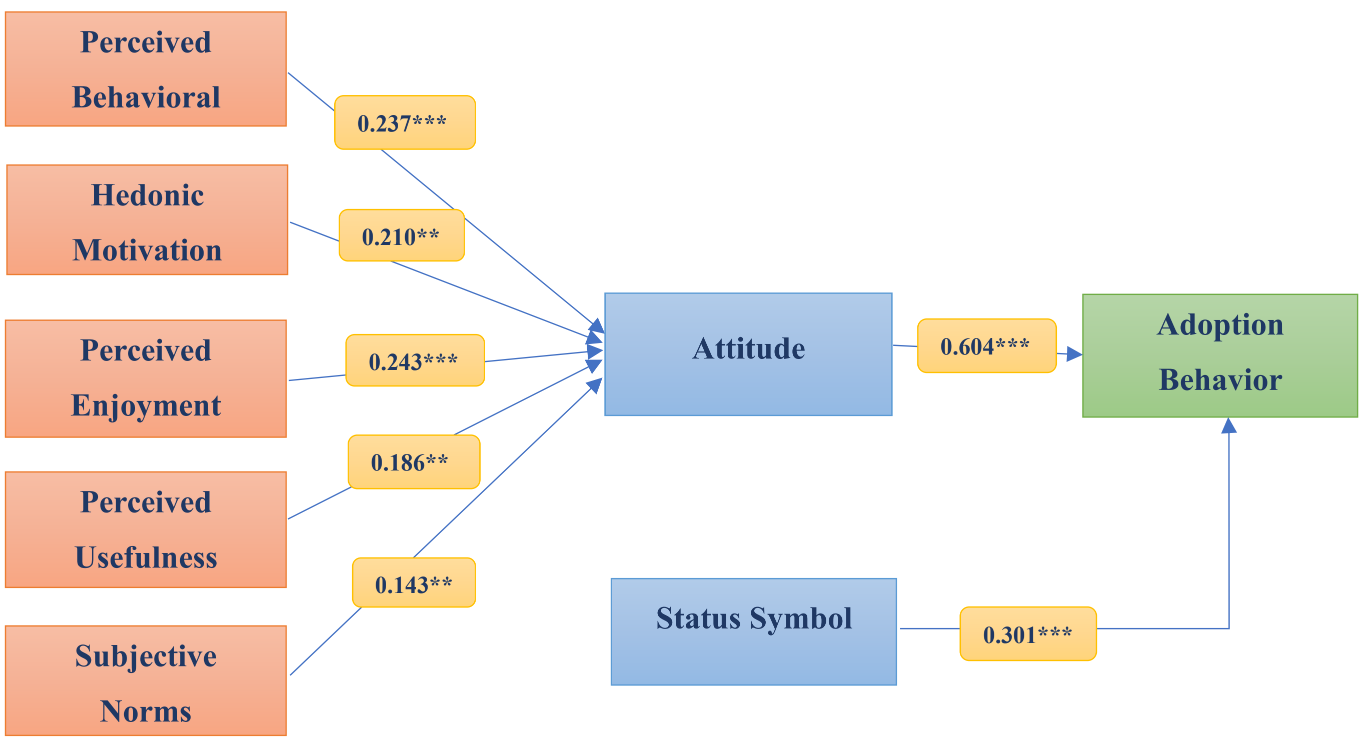

Figure 4.3: Hypotheses Testing Results

Figure 4.4 displays findings for the structural model obtained using the SmartPLS tool,

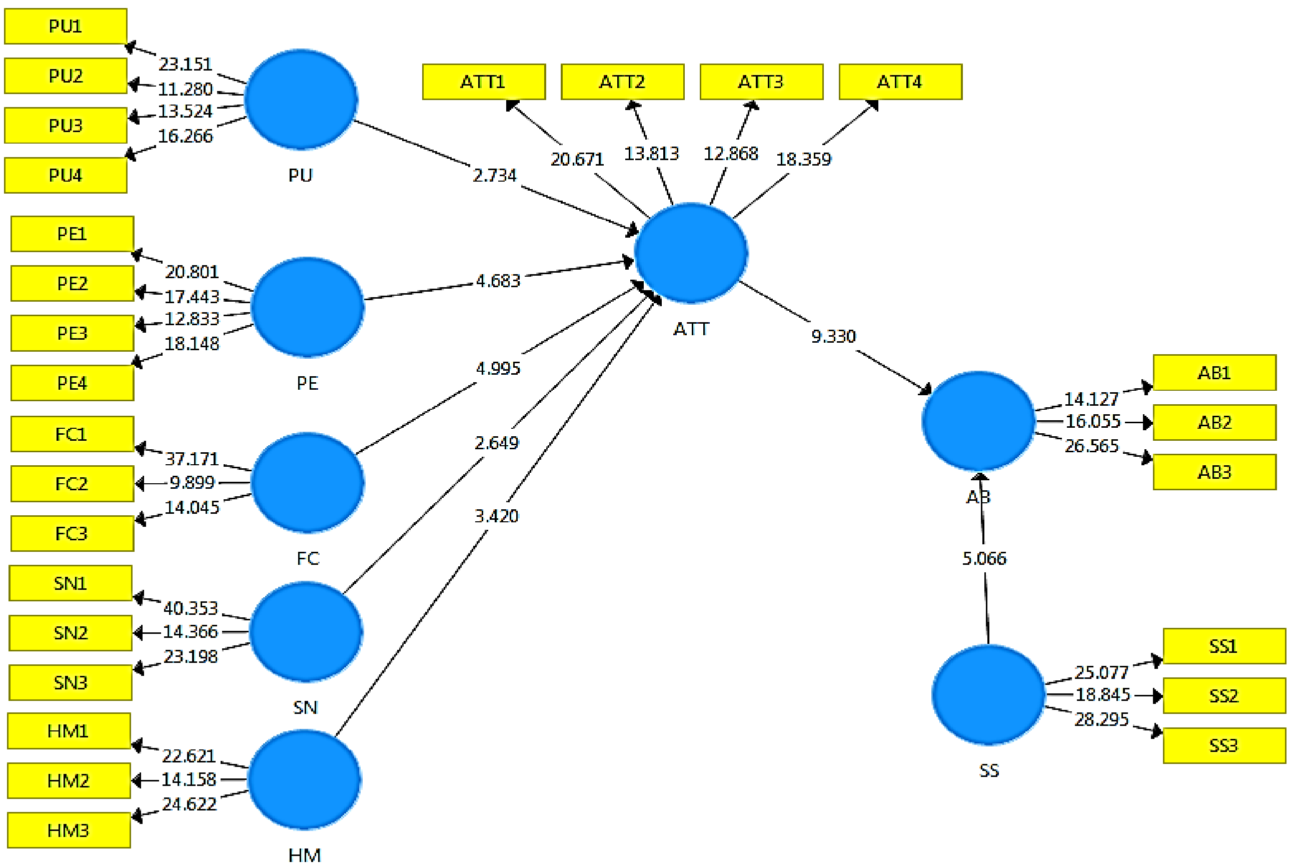

Figure 4.4: Structural Model Results from SmartPLS Tool

The figure of structural model results from SmartPLS appears to show the path relationships between several latent constructs, represented by ovals, and their indicator variables, represented by rectangles. Arrows indicate the direction of the relationships, with some paths having associated path coefficients, represented by numbers next to the arrows. This visual story encourages further investigation into path significance, effect size, and overall model fit to untangle the model's intricate symphony of relationships.

4.3 Discussion

This study gives a detailed look at what makes people use smartwatches daily. We used a thorough experimental setup and advanced statistical analysis with SmartPLS to determine what influences this adoption. The most important factor is people’s attitude toward smartwatches. This attitude is shaped by several key elements: how easy the smartwatch is to use (Perceived behavioral control- facilitating conditions (FC)), the fun and pleasure it provides (hedonic motivation (HM) and perceived enjoyment (PE)), how useful it is (perceived usefulness (PU)), and what people around them think (subjective norms (SN)). These factors help create a positive attitude toward smartwatches, making people more likely to adopt them.

We ensured our model was reliable and valid through rigorous checks. Most indicators effectively measured what they were supposed to, and there were no issues with multicollinearity. The internal consistency was strong, with composite reliability values above 0.7. Convergent validity was good, with AVE values above 0.5, and discriminant validity was confirmed using the Fornell and Larcker criterion.

The structural model showed high explanatory power, with 78.9% of the variance in attitude and 70.1% in adoption behavior explained by the model. The predictive relevance was also strong, supported by Q2 values. The effect size analysis showed that the relationships between factors varied, some small and others medium to large.

Path coefficient analysis revealed that attitude had the strongest direct effect on adoption behavior (beta= 0.604). perceived behavioral control (beta= 0.237), hedonic motivation (beta= 0.210), perceived enjoyment (beta= 0.243), perceived usefulness (beta= 0.186), and subjective norms (beta= 0.143) all significantly influenced attitude. Additionally, the status symbol (SS) had a significant direct impact on adoption behavior (beta = 0.301).

All seven hypotheses were supported, showing that practical and social factors are important in driving smartwatch adoption. These results suggest that improving user experience through better functionality, enjoyment, and social acceptance, along with leveraging the status symbol aspect, can significantly increase smartwatch adoption rates. This study offers valuable insights for marketers and developers, guiding them on where to focus to boost user engagement and adoption of smartwatches.

CHAPTER 5
Impact on Society, Environment and Sustainability

5.1 Impact on Society

This study on smartwatch adoption has some important impacts on society in shaping the way people use technology in daily life. By discovering what factors enhance or hinder smartwatch use developers and designers can develop more widely accepted and user-friendly products. Increasing users of smartwatches may mean that lots of things will be simplified, making life more productive and effective for a wide spectrum of consumers.

Additionally, as wearable technology and automation are becoming increasingly integrated into people's daily lives and smartwatches are becoming an essential component of it, the results of a study like this might encourage discussions on the wider social impacts. The public's perception of technology and wearables can be influenced by study findings on user experiences and attitudes, which may result in modifications to laws and regulations. This research goes beyond personal preference; it can change our interaction with technology and society. It promotes a more efficient, tech-savvy, and connected culture through the use and appeal of smartwatches.

5.2 Impact on Environment

Smartwatches can contribute to sustainability in several ways. They often promote healthier lifestyles, which can reduce the environmental impacts of healthcare. Some models have features that help users track and reduce their household energy consumption, leading to overall improved energy efficiency. Additionally, many companies are focusing on sustainable practices, such as reusing materials and creating more energy-efficient devices. However, the production of these devices requires the extraction of precious metals and other materials, which can result in habitat destruction and pollution. The manufacturing process itself uses a significant amount of water and energy, leading to chemical waste and carbon emissions. Additionally, the constant need to recharge smartwatch batteries contributes to energy consumption. When smartwatches are discarded, they contribute to the growing problem of electronic waste and, if not properly recycled, can release harmful materials. Ultimately, the lifecycle of a smartwatch from production to disposal leaves a carbon footprint and presents environmental challenges that require improved recycling techniques and sustainable practices to address.

5.3 Ethical Aspects

This study on smartwatch use in daily life is being conducted with ethical concerns in mind. In order to ensure the highest standards are followed, we will take the following critical steps: A simple, understandable informed consent process will be followed in collecting participant approval, ensuring that all subjects fully understand the aims, methods, risks, and benefits of this research. Strict monitoring of participant confidentiality will be implemented, along with data anonymization and safe storage practices to protect sensitive data. Prioritizing inclusivity and diversity in the study design will help achieve fair representation across populations and avoid bias. All stages of data handling will be done with strict ethical guidelines, ensuring safe collection, storage, and analysis. Eventually, the results of the study will be presented with the highest integrity; this will involve prioritizing accuracy and avoidance of any misrepresented results. Following these guidelines will help the research to maintain the highest levels of integrity and consideration of participant rights and data privacy.

5.4 Sustainability Plan

The research strategies that ensure continuous impact and relevance are outlined in a sustainability strategy. For example, transparency and reproducibility can be guaranteed by making thorough records of the procedure of data collection, statistical analysis, and research procedures. The collection will be stored safely and circulated to other scholars to encourage further research and validation of the results. Sharing research findings through publications, conferences, and workshops that ensure continuous communication between the academic and industrial sectors will be crucial. There will be a priority on collaboration with stakeholders, including policymakers and IT developers, in translating the research findings for the benefit of real-world applications that will last over a long period. To ensure the study's uninterrupted significance, regular updates on its impact on society and the environment will be communicated in a variety of forms.

CHAPTER 6
Summary, Conclusion,
and Future Study

6.1 Summary of the Study

The study "Factors Influencing the Adoption of Smartwatches: A PLS-SEM Analysis using SmartPLS" explores the factors that influence the adoption of smartwatches. Using Partial Least Squares Structural Equation Modeling to analyze survey data from a sample of 265 respondents, it discovered that perceived usefulness, enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol are some of the major determinants of smartwatch adoption. The results reveal that perceived usefulness and enjoyment are important predictors of adoption. The motivations of hedonic reasons and compatibility with users' lifestyles and devices are also very important factors. Attitudes such as social influences, perceived behavioral control, personal innovativeness, trust, and the status symbol of smartwatches all have significant impacts on adoption. All these insights are bound to be useful to technology developers and marketers, showing that emphasizing the utility and enjoyment of smartwatches and compatibility with other devices and leveraging social influences will improve adoption. Contributing to both academic research and practical applications, this study helps further understand the complex factors driving smartwatch adoption and promotes wearable technology.

6.2 Conclusion

The study, conducted on the adoption of smartwatches through Partial Least Squares Structural Equation Modeling, makes important contributions to understanding the factors that shape user behavior. The study identifies key elements from perceived usefulness to enjoyment, price value, hedonic motivation, compatibility, attitude, subjective norm, perceived behavioral control, personal innovativeness, trust, and status symbol as factors of utmost importance in the adoption process. This study improves the ability to forecast consumer behavior towards smartwatches using advanced computational methods. These findings can benefit stakeholders such as technology firms, policymakers, and marketers to understand consumer preferences and devise strategies for promoting smartwatch adoption. In the long run, the research study is meant to create awareness and assist consumers in making informed decisions about smartwatches, hence contributing to a deep understanding and wider acceptance of wearable technology.

6.3 Implication for Further Study

The current study lays a strong foundation for future research on smartwatch adoption dynamics. Future research could go deeper into certain demographic segments to identify potential differences in adoption trends. Including a more diverse group of participants, such as different age groups and cultures, will make the findings more universally applicable. As technology advances, examining how new features like improved health monitoring and battery life affect adoption will be valuable. Additionally, looking deeper into how individual personality traits and social influences impact decisions can provide richer insights. Comparing smartwatch adoption with other wearable technologies can highlight what makes certain devices more successful. Investigating how marketing strategies affect consumer choices will help companies promote smartwatches better. Understanding user satisfaction after purchase is crucial for improving long-term engagement. Lastly, addressing ethical and privacy concerns around data collection is essential for building user trust. Exploring these areas will enhance our understanding of smartwatch adoption and help make these devices more user-friendly and widely accepted.

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PLAGIARISM REPORT

Adoption of Smartwatches

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