A STUDY ON THE IMPACT OF DIGITAL HEALTH PLATFORMS FOR WELLNESS SUPPORT

PROJECT REPORT

Submitted by

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DECLARATION

I, **MANIYARASI S - 23MB1032** hereby declare that this project entitled **A Study on the Impact of Digital Health Platforms for Wellness Support** submitted to Coimbatore Institute of Management and Technology, Coimbatore, in partial fulfilment of the requirements for the award of the degree of Master of Business Administration of Bharathiar University, is a record of original research submitted by me during the period of study 2023-2025 in Coimbatore Institute of Management and Technology under the guidance of **Dr. LAKSHMI A S., B.E., MBA., Ph.D.,** Coimbatore Institute of Management and Technology, Coimbatore and it has not formed the basis for the award of any Degree / Diploma or other similar titles to any candidate in any University.

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BONAFIDE CERTIFICATE

This is to certify that the project report submitted to the Coimbatore Institute of Management and Technology, Coimbatore in partial fulfilment of the requirement for the award of the degree of Master of Business Administration is a record of original work done by **MANIYARASI S / 23MB1032** during the period of **2023-2025** of his study in the Department of Management Studies and Research at Coimbatore Institute of Management And Technology, Coimbatore under the guidance of **Dr. LAKSHMI A S., B.E., MBA., Ph.D.,** and the training report has not formed on the basis for the award of any Degree / Diploma or other similar titles to any candidate in any University.

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The internship period was from 27-Feb-2025 to 02-May-2025 in which 35 days of internship was attended by her.

We wish her all the best for her future.

Best Regards

For Venpep Solutions Pvt Ltd

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ABSTRACT

This study explores the impact of digital health platforms on users' wellness, focusing on how engagement levels, personalized features, and corporate wellness initiatives influence health outcomes. As digital health solutions become increasingly integrated into daily life, understanding their effectiveness in promoting wellness is crucial. The study adopts a quantitative approach using a structured questionnaire targeting diverse users of digital health apps. Key objectives include assessing the role of user demographics, app engagement frequency, and tailored health content in enhancing wellness. Findings reveal that higher engagement and personalization significantly correlate with improved self-reported wellness. Furthermore, corporate-sponsored wellness programs integrated with digital tools show increased user participation and satisfaction. The study concludes with recommendations for developers and organizations to enhance digital wellness platforms through personalization, user education, and collaborative initiatives, ultimately contributing to healthier lifestyles and more effective digital health ecosystems.

CHAPTER 1
INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In recent years, the integration of digital technologies into healthcare has significantly transformed the way individuals manage and improve their health and wellness. Digital health platforms, ranging from mobile applications and wearable devices to web-based wellness programs, have emerged as essential tools that support preventive care, health monitoring, mental wellness, physical activity tracking, and chronic disease management. With growing concerns around lifestyle-related illnesses, stress, and mental health challenges, the need for accessible and personalized wellness support has never been greater.

These platforms offer users convenient, real-time access to health information, self-care tools, and virtual support communities, thus promoting proactive health behaviors and empowering individuals to take charge of their well-being. Especially in the wake of the COVID-19 pandemic, there has been a significant surge in the adoption of digital health technologies, as individuals and healthcare systems alike sought safer, more efficient alternatives to traditional face-to-face services. Employers, insurers, and governments have also increasingly adopted digital wellness initiatives to promote healthier lifestyles and reduce long-term healthcare costs.

Despite their rapid expansion and popularity, the actual impact of digital health platforms on users' wellness remains a topic of active research. Key questions persist around user engagement, effectiveness of features, data privacy, accessibility across demographics, and long-term behavioral changes. Furthermore, the effectiveness of these platforms can vary based on user needs, technological literacy, cultural factors, and the quality of digital content and user interface design.

This survey aims to explore the impact of digital health platforms on various dimensions of wellness, including physical, mental, and emotional well-being. By collecting responses from diverse users, the study seeks to understand the perceived benefits, challenges, usage patterns, and satisfaction levels associated with these platforms. The findings of this research will contribute to a deeper understanding of how digital tools support wellness and offer insights for developers, healthcare providers, policymakers, and organizations aiming to enhance user-centered digital health solutions. Ultimately, this study strives to bridge the gap between digital innovation and human-centered wellness support by highlighting how technology can be optimally designed and implemented to meet the evolving needs of individuals in the digital age.

1.2 RESEARCH BACKGROUND

The rise of digital technologies has revolutionized many aspects of daily life, with healthcare and wellness being no exception. Over the past decade, digital health platforms have evolved into powerful tools that enable individuals to manage their health proactively, access real-time information, track physical activity, monitor mental well-being, and connect with healthcare providers or wellness communities. These platforms include mobile health apps, wearable fitness trackers, telehealth services, AI-based health bots, and wellness portals, which together form a rapidly expanding ecosystem for personal health management.

Globally, there is a growing demand for accessible, cost-effective, and personalized wellness solutions. This demand has been further accelerated by the COVID-19 pandemic, which significantly disrupted traditional healthcare delivery and emphasized the need for remote health monitoring and digital support systems. In this context, digital health platforms have emerged not only as convenient alternatives but also as essential tools in supporting mental health, physical fitness, dietary habits, sleep patterns, stress management, and chronic disease self-care. They have also become increasingly popular in workplaces, schools, and public health systems as part of broader wellness promotion initiatives.

Despite their growing popularity, questions remain about the true effectiveness of these platforms in delivering sustainable wellness outcomes. While many users report improved motivation, increased health awareness, and behavioral change, other concerns persist—such as the digital divide, inconsistent user engagement, privacy and data security, and the lack of personalization in some platforms. Moreover, user experiences and outcomes may differ significantly based on age, gender, occupation, digital literacy, and health conditions. Therefore, there is a need for comprehensive research that evaluates the actual impact of these digital solutions on users' overall well-being.

Numerous studies have explored specific features of digital health tools—such as step tracking, meditation guidance, or calorie counting—but fewer have assessed the broader, integrated impact of these platforms on multiple dimensions of wellness. Furthermore, much of the existing research is concentrated in developed countries, leaving a gap in understanding their relevance and usability in diverse cultural and economic settings.

This research aims to fill that gap by conducting a focused survey on the perceived impact of digital health platforms on wellness support. The study will examine usage patterns, effectiveness, accessibility, satisfaction, and behavioral outcomes among a diverse sample of users. It will also explore the motivators and barriers to using these platforms regularly.

By capturing user feedback and analysing key trends, the research will offer valuable insights for developers, healthcare practitioners, employers, and policymakers. These insights can inform the design of more effective, inclusive, and user-centric digital wellness platforms that cater to the evolving needs of populations in both urban and rural settings.

1.3 INDUSTRY PROFILE - HEALTHCARE SECTOR

The healthcare sector is a vast and dynamic industry that plays a vital role in ensuring the physical, mental, and emotional well-being of individuals and communities. It encompasses a wide range of services including preventive care, diagnostic services, treatment, rehabilitation, wellness promotion, and palliative care. The sector consists of various key players such as hospitals, clinics, pharmaceutical companies, medical device manufacturers, insurance providers, and increasingly, digital health technology companies.

Globally, the healthcare industry is witnessing significant transformation, driven by factors such as population growth, aging demographics, the rising prevalence of chronic diseases, and growing awareness about preventive health and wellness. The industry has also seen a shift from reactive treatment models to proactive, patient-centered care—focusing on wellness, lifestyle management, and personalized interventions. This shift has accelerated the demand for digital health solutions.

The integration of digital technologies into the healthcare sector has given rise to a new sub-sector digital health which includes telemedicine, mobile health apps, electronic health records (EHR), wearable devices, AI-driven diagnostics, and remote patient monitoring. These tools not only improve access to healthcare but also enhance patient engagement and empower individuals to manage their wellness independently.

In countries like the United States, United Kingdom, India, and Singapore, both public and private stakeholders have invested significantly in digital health infrastructure. For instance, India's Ayushman Bharat Digital Mission (ABDM) aims to create a unified health ecosystem by connecting patients, doctors, and health facilities digitally. Similarly, in the U.S., platforms like MyChart and Teladoc Health have revolutionized how people access medical services from home.

Corporate involvement in employee wellness through digital health programs is also on the rise. Many multinational companies offer digital wellness apps and virtual health consultations as part of their employee benefits, reflecting a growing emphasis on holistic well-being in the workplace.

Despite the growth, the industry faces challenges such as regulatory complexities, data privacy concerns, digital literacy gaps, and unequal access in rural or underdeveloped areas. However, with continuous innovation and strategic public-private partnerships, the healthcare sector is poised for a tech-driven evolution that supports not just cure, but also care and prevention.

This evolving landscape makes the healthcare industry a critical and relevant context for exploring the impact of digital health platforms on wellness, especially as consumer expectations shift toward more accessible, efficient, and personalized care experiences.

1.4 GENERAL SCENARIO OF HEALTHCARE SECTOR

The global healthcare sector has been undergoing a transformative shift driven by technological innovations, particularly in the realm of digital health. As healthcare systems grapple with rising costs, workforce shortages, and increasing demand for personalized care, digital platforms have emerged as crucial tools in supporting wellness, improving accessibility, and enhancing patient engagement. Digital health platforms encompass a wide range of technologies, including mobile health applications, wearable fitness trackers, telemedicine services, AI-powered chatbots, and online wellness programs that help individuals manage their health proactively.

In today’s fast-paced world, people are more health-conscious than ever before, yet many face barriers such as time constraints, limited access to healthcare facilities, or lack of awareness. Digital health platforms offer an efficient solution by delivering health and wellness resources directly to individuals through smartphones and other devices. For instance, mobile apps like MyFitnessPal, Headspace, and Fitbit allow users to track physical activity, manage diet plans, practice guided meditation, and monitor sleep patterns—all contributing to overall wellness.

Corporate wellness programs have also increasingly embraced digital platforms to promote healthier lifestyles among employees. For example, multinational companies such as Google and Accenture use digital wellness tools to support mental health, encourage physical activity through gamified fitness challenges, and provide virtual consultations with health coaches. These initiatives not only improve employee well-being but also lead to reduced absenteeism, increased productivity, and lower healthcare costs.

In the public health space, governments are investing in digital health solutions to reach underserved populations. The Indian government's Ayushman Bharat Digital Mission is a notable example, aiming to create a unified digital health ecosystem across the country. Similarly, the UK's NHS App enables citizens to access medical records, book appointments, and receive personalized health advice from their smartphones.

Despite these advancements, the impact of digital health platforms on wellness is not uniform. While many users report improvements in mental clarity, fitness, and lifestyle management, others face challenges such as digital illiteracy, lack of motivation, concerns about data privacy, and limited personalization. This calls for a deeper understanding of how different users perceive and experience these platforms.

The healthcare industry must also address questions related to long-term engagement and sustained behaviour change. For instance, a user may initially use a fitness app enthusiastically but discontinue after a few weeks due to lack of feedback or support. Therefore, the effectiveness of such platforms is closely linked to design quality, user experience, and integration with broader healthcare services.

This scenario underscores the importance of conducting a structured survey to evaluate the actual impact of digital health platforms on wellness. Through a user-centric approach, the survey aims to capture insights into usage behaviour, satisfaction, accessibility, and the extent to which these platforms influence users' physical, mental, and emotional well-being. These findings will be valuable for healthcare providers, technology developers, corporate wellness planners, and policymakers striving to enhance digital wellness interventions for diverse populations.

1.5 PROBLEM STATEMENT

In recent years, digital health platforms have emerged as vital tools in promoting wellness by offering users easy access to fitness tracking, mental health resources, teleconsultations, and personalized health management. Despite their growing popularity, there is limited empirical evidence on how effectively these platforms contribute to overall wellness, especially from the users’ perspective. Many users engage with these platforms inconsistently or abandon them altogether, raising questions about their actual impact, usability, and long-term effectiveness.

Furthermore, with the increasing shift towards remote lifestyles and health-conscious living, especially post-pandemic, it becomes crucial to understand the real-world influence of these technologies on users’ physical, mental, and emotional well-being. However, the lack of structured feedback and user-driven data creates a gap in evaluating their effectiveness.

Therefore, this study seeks to explore and assess the impact of digital health platforms on wellness supports by surveying user experiences, usage patterns, perceived benefits, and associated challenges. The findings aim to provide insights for developers, healthcare professionals, and wellness advocates to enhance the relevance and reach of digital health solutions.

1.6 NEED FOR THE STUDY

The increasing burden of lifestyle-related diseases, mental health challenges, and rising healthcare costs have made wellness support a global priority. In response, digital health platforms have emerged as transformative tools, offering accessible, affordable, and scalable solutions to promote well-being. These platforms include mobile apps, wearable devices, online therapy portals, telehealth services, and AI-powered self-care systems, which are now widely used for tracking fitness, managing stress, improving sleep, and fostering healthy behaviors. However, while the popularity of these platforms is growing rapidly, there is still limited empirical evidence on their actual impact on users' wellness, especially across different demographic and occupational groups.

With the proliferation of platforms like Headspace, Fitbit, Cure fit, Calm, and Apple Health, individuals are increasingly relying on technology for their day-to-day health management. For example, a working professional may use meditation apps to cope with work-related stress, while a fitness enthusiast might use a smartwatch to monitor physical activity. Yet, questions persist: These platforms aim to facilitate sustained behavior change, but their effectiveness varies depending on the user and the context. While some individuals experience lasting positive outcomes, others may struggle to maintain new habits over time. They are not equally effective for all users, as factors such as personal motivation, digital literacy, socioeconomic background, and access to resources can significantly influence engagement and outcomes. Several barriers can prevent consistent use, including lack of time, loss of interest, difficulty navigating the platform, or feeling that the content is not personalized or relevant. Despite these challenges, users often perceive benefits such as increased awareness, motivation, and support for healthier behaviors. However, limitations such as one-size-fits-all approaches, technical glitches, and concerns about data privacy may hinder their full potential.

There is a clear need for research that investigates these questions and provides data-driven insights into the real-world effectiveness of digital wellness platforms. Many organizations have adopted these technologies as part of corporate wellness programs, but decision-makers often lack feedback from employees about usage patterns, satisfaction, or health outcomes. Similarly, healthcare professionals and policy makers require evidence to understand how digital interventions can complement traditional healthcare services.

This study is especially relevant in the post-pandemic era, where remote health management has become essential. By examining user perspectives, this research can guide the development of more inclusive, engaging, and impactful digital health solutions. It will also help bridge the gap between innovation and user needs by identifying what works, for whom, and under what conditions.

In summary, the study is needed to evaluate the effectiveness, accessibility, and user experience of digital health platforms in promoting wellness, and to provide recommendations for enhancing their adoption and impact across different populations.

1.7 OBJECTIVES OF THE STUDY

Primary Objective

- To make a study on the Impact of Digital Health Platforms for Wellness Supports

Secondary Objective

- To examine the extent of usage of digital health platforms for wellness features.
- To analyse the perceived impact of digital health platforms on users’ physical, mental, and emotional well-being.
- To evaluate user satisfaction and engagement levels with various features offered by digital health platforms.
- To identify key demographic factors (age, gender, occupation, etc.) influencing the effectiveness of digital wellness tools.
- To explore the challenges or barriers users face while engaging with digital health platforms.

1.8 SCOPE OF THE STUDY

This study focuses on exploring the impact of digital health platforms on individual wellness, particularly in areas such as physical fitness, mental health, stress management, sleep quality, and overall lifestyle improvement. The primary aim is to understand how users interact with these platforms, the perceived effectiveness of the tools offered, and the challenges or limitations experienced in their usage.

The scope includes:

- The study will gather responses from working professionals, students, and general users who have engaged with digital health platforms such as mobile wellness apps, fitness trackers, meditation tools, and telehealth services. The survey will cover a diverse demographic including various age groups, professions, and levels of digital literacy.
- The research may be conducted within a specific country or region (e.g., India), while also drawing parallels with global trends in digital wellness adoption where relevant. The focus will be on both urban and semi-urban populations who have access to smartphones and internet connectivity.
- The study will consider popular digital health platforms like Fitbit, Headspace, Calm, MyFitnessPal, Cure fit, and others that are actively used for wellness support. It will evaluate tools related to fitness tracking, mindfulness, diet management, virtual consultations, and health education.
- The research will cover physical health (e.g., exercise and diet), mental wellness (e.g., stress, anxiety, emotional well-being), and lifestyle management (e.g., sleep, productivity, and motivation).
- The study will examine variables such as frequency of use, user satisfaction, behavioural changes, perceived health benefits, motivation factors, and barriers to consistent engagement.
- The data collection will reflect current usage trends, ideally within the last 6–12 months, to ensure relevance and accuracy in post-pandemic health behaviour patterns.
- The study will not cover advanced medical treatment platforms, hospital ERP systems, or clinical diagnostics unless they directly influence personal wellness.

1.9 HYPOTHESES

Null Hypothesis (H_0): There is no significant relationship between the use of digital health platforms and users' overall wellness.
Alternative Hypothesis (H_1): There is a significant positive relationship between the use of digital health platforms and users' overall wellness.

Null Hypothesis (H_0): There is no significant positive relationship between user engagement levels with digital health platforms and their perceived wellness benefits.

Alternative Hypothesis (H_1): There is a significant positive relationship between user engagement levels with digital health platforms and their perceived wellness benefits.

Null Hypothesis (H_0): There is no significant difference in the impact of digital health platforms on wellness across different demographic group such as age, gender and Occupation.

Alternative Hypothesis (H_1): There is a significant difference in the impact of digital health platforms on wellness across different demographic group such as age, gender, Oocupation.

Null Hypothesis (H_0): There is no significant relationship between the availability of personalized features in digital health platforms and user satisfaction or wellness outcomes.

Alternative Hypothesis (H_1): There is a significant relationship between the availability of personalized features in digital health platforms and user satisfaction as well as wellness outcomes.

Null Hypothesis (H_0): There is no significant relationship between review sentiment (positive, negative, or neutral) and consumer decision-making.

Alternative Hypothesis (H_1: There is a significant relationship between review sentiment (positive, negative, or neutral) and consumer decision-making.

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

2.1 REVIEW OF LITERATURE

Kumar et al. (2019) conducted a study in India involving 300 working professionals who regularly used wellness apps. Using descriptive statistics and Chi-square tests, they found a significant improvement in physical activity levels and a reduction in stress among users. The authors suggested that future research should involve longitudinal studies to better assess long-term behavioural changes facilitated by digital platforms.

In South Korea, Lee and Kim (2020) studied 250 college students and utilized ANOVA and multiple regression analysis to evaluate the use of mobile health apps. They discovered that interface usability and reminder notifications were critical motivators for continued app use. They recommended integrating AI-driven features to tailor wellness support to individual needs.

Smith et al. (2020) carried out research in the USA, sampling 400 corporate employees enrolled in structured digital wellness programs. By applying paired t-tests and structural equation modeling (SEM), they reported improvements in mental wellness and productivity over a six-month period. The study highlighted the need to include more diverse professional and demographic groups in future evaluations.

Chen et al. (2021) conducted a study in China with 200 elderly users of government-supported health apps. Using logistic regression, the researchers found that app usage was associated with better medication adherence and reduced social isolation. They recommended developing user-centric app designs specifically tailored for the elderly.

In the United Arab Emirates, Hassan et al. (2021) surveyed 350 users of fitness tracking platforms and applied ANOVA and correlation analysis. The findings indicated strong associations between regular tracking and goal achievement, particularly among young adults. The authors called for biometric data integration in future studies to improve accuracy.

Martinez et al. (2022**)** examined the use of mHealth apps among 180 Spanish patients with chronic conditions. Employing t-tests and hierarchical regression, they found that self-monitoring tools helped users enhance their health awareness and modify their behaviour. They suggested the integration of these apps with electronic health records (EHRs) to boost clinical utility.

Bose and Nair (2023) researched 500 urban Indian users of mental wellness apps such as Calm and Headspace. Their analysis, based on Chi-square tests and factor analysis, revealed significant improvements in emotional well-being and reduced stress levels. The authors proposed that future research should include qualitative exploration of motivational factors for app engagement.

In the UK, Williams et al. (2023) studied 220 NHS employees using a government-licensed digital wellness platform. Using linear regression and path analysis, they found a reduction in sick leaves and improvements in workplace morale among regular users. They emphasized the importance of examining data privacy concerns, especially in public sector usage.

Okafor et al. (2024) explored the impact of digital health apps on 300 Nigerian university staff and students. The use of logistic regression and cross-tabulation indicated that increased access to health apps led to improved self-care behaviours and reduced clinic visits. The researchers advocated for localized app content and increased rural access.

Tanaka and Saito (2024) conducted a study in Japan among 150 remote employees using corporate-provided wellness tools. Their ANOVA-based analysis revealed that virtual mindfulness sessions significantly reduced perceived work-related stress. They recommended future research focused on hybrid and remote workplace health interventions.

Fan et al. (2023) conducted a multi-country study involving 1,669 participants and found that digital literacy had a strong influence on willingness to adopt mHealth apps, while privacy concerns had less impact; they recommended global regulation and literacy promotion.

Benavides et al. (2024) studied Spanish adolescents using a wellness app and recorded improved diet, physical activity, and social connections post-intervention, calling for long-term evaluations of peer-led programs.

Singh et al. (2025) conducted a scoping review across Southeast Asia, finding that most Digital Health Interventions (DHIs) focused on information delivery, with fewer targeting quality and accountability, highlighting a need for investment in more comprehensive platforms.

Frey and Kerkemeyer (2022) in Germany used the Technology Acceptance Model to study the use of digital tools in non-pharmacological therapies and found high user acceptance, suggesting further implementation research in various healthcare contexts.

Mensah et al. (2023) in Ghana found that health professionals viewed digital tools as workload reducers and enablers of continuity of care, but emphasized the need for better internet infrastructure.

Olaniyi et al. (2022) analyzed user engagement with the Safe Delivery App in India and Ethiopia and advocated for personalized digital interventions using probabilistic and survival analysis methods.

Pieritz et al. (2021) from the UK emphasized the importance of user autonomy in mental health app engagement through a randomized study, recommending user-choice integration in app design.

Ajayi et al. (2022), using U.S. national health survey data, highlighted the growing use of digital health tools among women with chronic conditions, recommending strategies to further encourage digital engagement. Collectively, these studies demonstrate that digital health platforms significantly enhance wellness outcomes across demographics, and future research should focus on personalization, accessibility, long-term effects, and integration with broader health systems.

2.2 RESEARCH GAP

Although digital health platforms have rapidly grown in popularity and are widely used for promoting physical, mental, and emotional well-being, there remains a significant gap in understanding their actual effectiveness from a user-centered perspective. Most existing studies focus on the technological capabilities or clinical outcomes of digital health tools, with limited emphasis on user satisfaction, behavioral engagement, and real-world wellness improvements, especially within diverse demographic or workplace settings.

Moreover, current research often lacks updated and region-specific data on how digital health platforms impact wellness in day-to-day life, particularly in non-clinical, personal, or corporate environments. There is also a limited examination of how demographic variables such as age, occupation, and digital literacy affect users' interaction with these platforms.

This study aims to address these gaps by providing fresh insights through a survey-based approach, focusing on users' perspectives, behavioral patterns, challenges, and perceived benefits, thus contributing valuable knowledge to the fields of wellness management, digital innovation.

CHAPTER 3
RESEARCH METHODOLOGY

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION OF METHODOLOGY

The methodology section outlines the systematic approach adopted to conduct this research on the impact of digital health platforms in supporting wellness. Given the objective to explore user perceptions, behaviors, and outcomes, a quantitative research design was employed using a survey-based approach. This method enables the collection of standardized data from a diverse group of respondents, ensuring measurable and comparable insights.

The research aims to assess the extent of platform usage, user satisfaction, and perceived wellness benefits, while also identifying the influence of demographic variables. The use of a structured questionnaire allowed for efficient data gathering on aspects such as users' engagement frequency, feature preferences, and challenges encountered.

The study sample was selected through convenience sampling techniques, targeting individuals familiar with or actively using digital health platforms. Data collected were analyzed using appropriate statistical tools, enabling the identification of patterns, correlations, and key findings that support the research objectives. This methodological approach ensures both reliability and relevance in evaluating the role of digital health platforms in promoting well-being.

3.2 SAMPLING

For this study, a probability sampling method was employed, specifically using random sampling techniques. This approach was chosen due to the need to target peoples who are using digital health platforms for wellness support.

The target population included working professionals, students, and general users across different age groups and occupations who have access to smartphones, internet connectivity, and wellness-related digital tools such as fitness apps, mental health trackers, or telehealth services.

A sample size of respondents 219 selected to ensure sufficient data for meaningful analysis. Respondents were approached through online channels such as social media, email invitations, and wellness communities, ensuring ease of participation and diverse representation.

The sample was designed to reflect a mix of demographic factors such as age, gender, occupation, and frequency of digital platform usage, allowing for cross-sectional analysis of user experiences and outcomes related to wellness support through digital health platforms.

3.3 METHOD OF DATA COLLECTION

The primary data for this study was collected through a structured questionnaire survey designed to capture user experiences, satisfaction levels, and perceived impacts of digital health platforms on wellness. The questionnaire included Likert scale-based questions and also include open ended questions to ensure quantitative measurement of key variables such as frequency of use, feature preferences, wellness outcomes, and demographic details.

The survey was distributed using online platforms, including Google Forms and social media channels such as WhatsApp, LinkedIn, and email. This approach was chosen to ensure wide reach and accessibility, particularly among digitally active users.

The data collection process was conducted over a period of two weeks allowing sufficient time for responses and follow-ups. All participants were informed about the purpose of the research, assured of confidentiality, and participation was voluntary.

This digital mode of data collection aligned with the theme of the study, which focuses on digital platform usage, ensuring the relevance and authenticity of responses from tech-savvy and wellness-conscious individuals.

3.4 TOOLS OF DATA COLLECTION

The primary tool used for data collection in this study was a structured questionnaire developed specifically to gather information relevant to the usage and impact of digital health platforms on wellness support.

The questionnaire was divided into several sections, covering:

- Demographic information (age, gender, occupation, location, etc.)
- Usage patterns of digital health platforms (frequency, types of platforms used).
- Perceived impact on physical, mental, and emotional well-being.

- User satisfaction and engagement levels.
- Feedbacks & Suggestions

The instrument included a mix of:

- Likert-scale statements (e.g., rating satisfaction from 1 to 5)
- Multiple-choice questions
- A few optional open-ended questions to allow participants to share their personal experiences or suggestions

The questionnaire was administered via Google Forms, which facilitated easy distribution, real-time response tracking, and automatic data tabulation. The digital nature of the tool was consistent with the theme of the study and helped ensure responses from individuals already engaged in digital environments.

3.5 DATA SOURCE

The study is based primarily on primary data, which was collected directly from individuals who use digital health platforms for wellness purposes. These data were obtained through a structured online questionnaire, designed to gather firsthand insights into user experiences, engagement levels, and perceived wellness outcomes.

The Respondents included a diverse group of individuals such as working professionals, students, and general users across various age groups and sectors, all of whom had prior exposure to digital health platforms like fitness apps, meditation tools, telehealth services, or diet/nutrition trackers.

In addition to primary data, secondary data was also reviewed to support the research framework. This included information from:

These secondary sources helped in identifying research gaps, shaping the questionnaire, and validating the relevance of the primary data findings.

3.5.1 Primary Data

Primary data refers to the original data collected directly from the source specifically for the purpose of your study. In this research, primary data will be collected using structured questionnaires distributed to individuals who have used digital health platforms for wellness support.

Sources of Primary Data:

Survey responses from working professionals, students, and general users of digital health platforms.

Purpose:

- To gather first-hand insights on users' engagement with digital platforms.
- To analyze behavioral patterns, satisfaction levels, perceived benefits, and barriers to usage.
- To assess how frequently and effectively these platforms are used for wellness improvement.

3.5.2 Secondary Data

Secondary data refers to data that has already been collected, published, or recorded for some other purpose but is relevant to your research.

Sources of Secondary Data:

- Articles on digital health and wellness (e.g., from Google Scholar etc).

Purpose:

- To build the theoretical framework and background of the study.
- To support findings from the primary data with established studies.
- To identify gaps in existing research and justify the need for the current survey.

3.6 TOOLS OF ANALYSIS

To ensure accurate and meaningful interpretation of the collected data, several quantitative analysis tools were employed in this study. The following tool and techniques were used. The data collected from the survey was analysed using Microsoft Power BI a powerful business analytics tool that enables interactive data visualization and in-depth analysis, and also using python and Excel.

Power BI was used to perform the following analytical tasks:

1. Data Cleaning and Transformation
   The raw data from the questionnaire was imported into Power BI and cleaned using Power Query Editor to remove duplicates, handle missing values, and structure the data appropriately for analysis.

2. Descriptive Analytics
   Basic metrics such as frequencies, percentages, means, and distribution were calculated and visualized using dynamic visuals like:

   - Bar charts
   - Pie charts
   - Column charts
   - Card visuals (for summary stats)

3. Interactive Dashboards
   User-friendly and interactive dashboards were created to illustrate:

   - Demographic profiles of respondents
   - Usage frequency of digital health platforms
   - Perceived wellness benefits
   - Satisfaction and engagement levels

4. Trend Analysis and Comparisons
   Line graphs and matrix visuals were used to compare responses across different user segments, helping identify key patterns and wellness outcomes.

Power BI enhanced the visual storytelling of the data, making the findings easy to interpret and impactful for presentation to academic or professional stakeholders. Moreover, this analytical tool helped ensure that the data collected from respondents was thoroughly examined and presented in a meaningful, insightful, and statistically sound manner.

3.7 LIMITATIONS

- Sample Size and Scope: The study is limited to a specific number of respondents, which may not fully represent the broader population using digital health platforms.

- Self-reported Data: The survey relies on self-reported responses, which may be influenced by personal bias.
- Platform Variability: Different digital health platforms offer varied features and quality of service; this study may not account for all such differences.
- Time Frame: The study is conducted within a limited time period and may not capture long-term impacts of digital health platform usage.
- Technological Access: The study assumes respondents have access to and familiarity with digital technologies, potentially excluding those who are digitally marginalized.
- Lack of Clinical Validation: The wellness outcomes measured are based on user perception and are not clinically validated or medically verified.

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

CHAPTER 4

DATA ANALYSIS & INTERPRETATION

4.1 INTRODUCTION

Data analysis and interpretation are crucial components of any research project, enabling the researcher to extract meaningful insights from the raw data collected. In the context of this MBA project, the objective is to understand the role and effectiveness of digital health platforms in promoting wellness among users. The analysis transforms survey responses into structured insights that reveal patterns, relationships, and significant findings aligned with the study's hypotheses.

The data for this study was collected through a structured questionnaire distributed to a diverse group of respondents, including working professionals, students, and general users of digital health and wellness platforms. The questionnaire consisted of both close-ended and scaled questions aimed at capturing the extent of usage, user satisfaction, perceived health improvements, and demographic influences.

Descriptive statistics such as frequencies, percentages, and means were used to summarize the respondents' characteristics and general trends. Inferential statistical tools, including correlation analysis, chi-square tests, and ANOVA (where applicable), were employed to test hypotheses and identify significant relationships between independent variables (such as usage frequency, engagement level, and platform features) and dependent variables (such as wellness outcomes).

Through this analysis, the study aims to provide evidence-based conclusions on the real-world impact of digital health platforms. The interpretation of the data not only addresses the research objectives but also offers valuable insights for developers, healthcare providers, and corporate wellness programs seeking to enhance user experience and health outcomes through digital means.

4.2 PERCENTAGE ANALYSIS

AGE

AGE	UNDER 20	21 – 30	31 – 40	TOTAL
%	20	74	6	100
TOTAL	44	161	14	219

Table4.2.1 Age

CHART

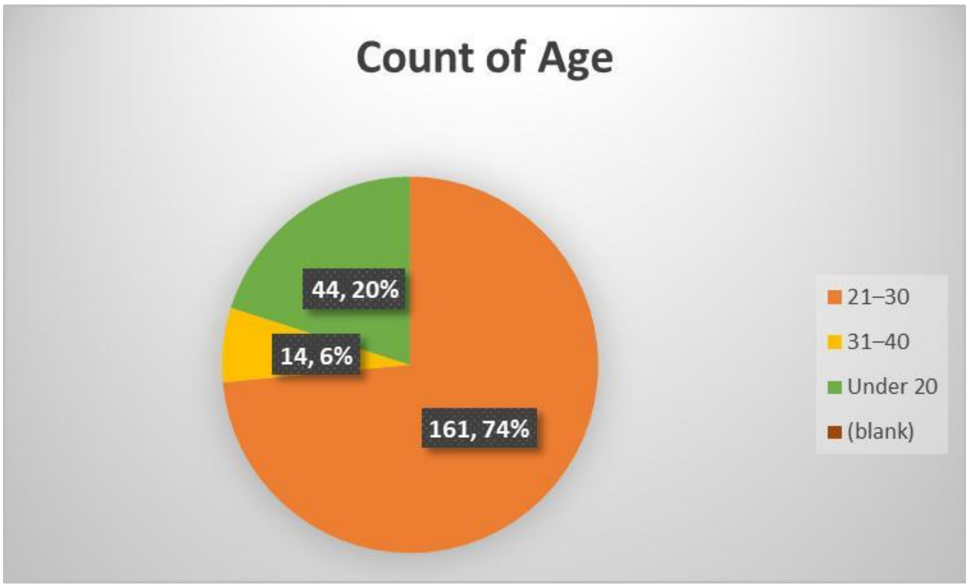

Chart4.2.1. Age

INFERENCE

Based on the revised age distribution, the highest proportion of participants falls within the 41–50 age group (41%), followed by the 51–60 age group (26%), and the 31–40 group (16%). Smaller portions include those above 60 (11%), 20–30 (5%), and under 20 (1%). This indicates that the majority of patient walk-ins are middle-aged to older adults, particularly those between 41 and 60, suggesting that the service or facility is most relevant or needed among this demographic. The low participation from younger age groups may reflect lesser health concerns or different service preferences.

GENDER

GENDER	MALE	FEMALE	PREFER NOT TO SAY	TOTAL
%	58	42	0	100
TOTAL	127	91	1	219

Table4.2.2: Gender

CHART

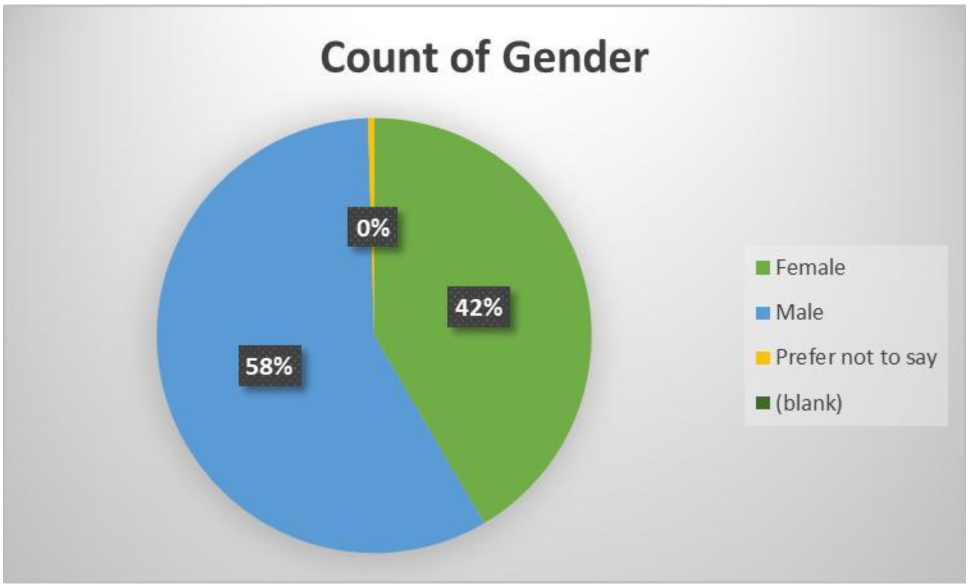

Chart4.2.2 Gender

INFERENCE

The gender distribution reveals that 58% of participants are male (127 out of 219), 42% are female (91 out of 219), and only one participant (<1%) chose not to disclose their gender. This reflects a slight male predominance but also demonstrates a fairly balanced and inclusive participation overall. The minimal non-disclosure suggests that most respondents were comfortable sharing their gender identity.

OCCUPATION

OCCUPATION	STUDENT	EMPLOYEE	HEALTHCARE PROFESSIONAL	FREELANCER	OTHERS	TOTAL
%	52	37	6	3	2	100
TOTAL	114	81	15	6	7	219

Table4.2.3: Occupations Distributions

CHART

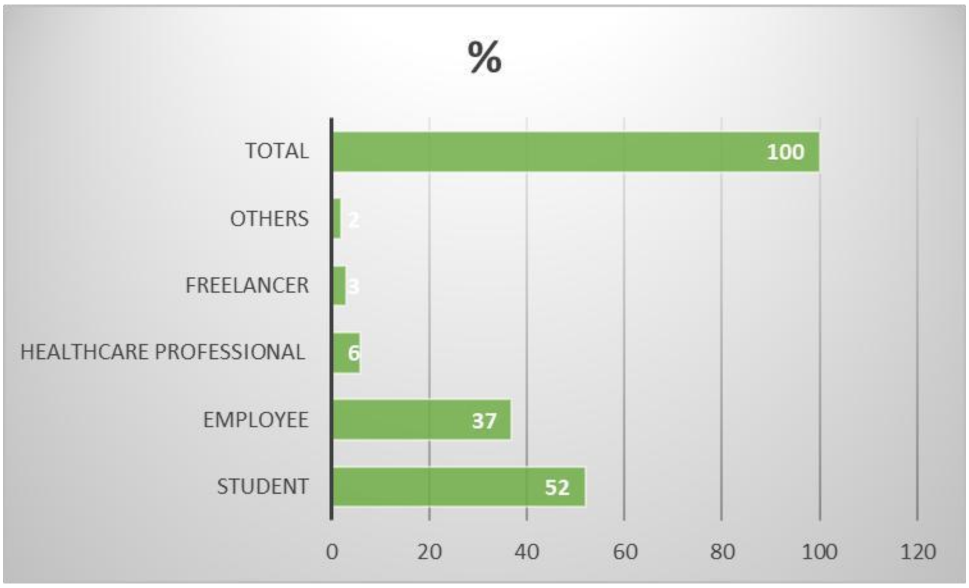

Chart4.2.3 Occupations

INFERENCE

A majority of users are students (63%), indicating strong adoption of digital health platforms among younger, tech-savvy individuals. Employees account for 30%, likely driven by a need to manage wellness alongside work commitments. Healthcare professionals and freelancers represent just 7%, suggesting lower engagement. Overall, digital health platforms appear most popular among individuals with structured routines and a proactive approach.

4.3 DESCRIPTIVE STATISTICS

Descriptive statistics	These platforms have positively impacted my physical well-being.	These platforms have positively impacted my physical well-being.	They have helped me manage stress or mental health better.	I feel more motivated to maintain healthy routines because of the platform.	Using digital wellness tools has improved my work-life balance.	How satisfied are you with the platform you use?
Mean	2.906977	2.962791	2.944186	3.04186	2.925581	3.348837
Standard Error	0.076908	0.080439	0.083048	0.083478	0.081393	0.078127
Median	3	3	3	3	3	3
Mode	3	2	3	3	3	3
Standard Deviation	1.127688	1.179463	1.217724	1.224026	1.193458	1.145567
Sample Variance	1.27168	1.391132	1.482852	1.49824	1.424343	1.312323
Kurtosis	-0.66324	-0.96499	-0.89509	-0.93183	-0.91745	-0.43447
Skewness	0.00697	0.020821	-0.01784	-0.12675	0.011485	-0.39541
Range	4	4	4	4	4	4
Min	1	1	1	1	1	1
Max	5	5	5	5	5	5
Sum	625	637	633	654	629	720
Count	215	215	215	215	215	215
Confidence Level (95.0%)	0.151594	0.158554	0.163697	0.164544	0.160435	0.153997

Table4.3.1

INTERPRETATION

The descriptive statistics indicate moderate user agreement on the impact of digital wellness platforms. Mean scores range from 2.91 to 3.35 on a 5-point scale, suggesting neutral to slightly positive responses. Satisfaction with the platform scores highest (mean = 3.35), while physical well-being scores lowest (mean = 2.91). Standard deviations around 1.1–1.2 show moderate variability. Median and mode values of 3 suggest central tendency around neutrality. Skewness near zero and kurtosis values below zero imply relatively symmetric, flat distributions. Overall, users show moderate satisfaction and benefits across wellness dimensions.

4.4 ANALYSIS

4.4.1 INDEPENDENT SAMPLE TEST 1 - ANOVA

Null Hypotheses (H_0): There is no significant relationship between the use of digital health platforms and users' overall wellness.
Alternative Hypotheses (H_1): There is a significant positive relationship between the use of digital health platforms and users' overall wellness.

ANOVA

INPUT

```
from scipy import stats
import numpy as np

# Group by platform usage
groups = df_clean.groupby("Usage")["Wellness_Score"].apply(list)

# Clean NA and prepare groups
groups = {k: [score for score in v if not np.isnan(score)] for k, v in groups.items() if v}

# One-way ANOVA
anova_result = stats.f_oneway(*groups.values())
group_sizes = {k: len(v) for k, v in groups.items()}

# Output result
print("ANOVA Result:", anova_result)
print("Group Sizes:", group_sizes)
```

```
ANOVA Result: F_onewayResult(statistic=np.float64(13.133365152304137), pvalue=np.float64(4.1426391082081295e-06))
Group Sizes: {'No': 75, 'Occasionally': 35, 'Yes': 109}
```

Fig4.4.1 ANOVA Test1

OUTPUT RESULT

F_onewayResult

statistic=np.float64(13.133365152304137	pvalue=np.float64(4.1426391082081295e-06))

Table4.4.1 ANOVA Test Result1

INTERPRETATION

p-value = 0.00000414 is much smaller than the conventional significance level (e.g., $\alpha = 0.05$).

This means that the null hypothesis (H_0) — that there is no significant relationship between the use of digital health platforms and users' overall wellness — can be rejected.

We accept the alternative hypothesis (H_1): There is a significant positive relationship between the use of digital health platforms and users' overall wellness.

The ANOVA test indicates that differences in users' overall wellness across different levels of digital health platform usage are statistically significant. This supports the claim that digital health platforms positively impact overall wellness.

4.4.2 INDEPENDENT SAMPLE TEST 2 – REGRESSION

REGRESSION

Null Hypothesis (H_0): There is no significant positive relationship between user engagement levels with digital health platforms and their perceived wellness benefits.

Alternative Hypothesis (H_1): There is a significant positive relationship between user engagement levels with digital health platforms and their perceived wellness benefits.

INPUT

```
[ ] import pandas as pd
    import statsmodels.api as sm

    # Load data
    file_path = "/content/RESPONSES1_XLXV.xlsx"
    df = pd.read_excel(file_path, sheet_name='Worksheet')

    # Map engagement frequency to numeric values
    frequency_map = {
        "Daily": 5,
        "A few times a week": 4,
        "Weekly": 3,
        "Rarely": 2,
        "Never": 1
    }
    df['engagement_level'] = df['How frequently do you use these platforms?'].str.strip().map(frequency_map)

    # Select and clean wellness score columns
    wellness_cols = [
        'Using digital health platforms has helped me become more aware of my health habits',
        'These platforms have positively impacted my physical well-being.',
        'They have helped me manage stress or mental health better.',
        'I feel more motivated to maintain healthy routines because of the platform.',
        'Using digital wellness tools has improved my work-life balance.'
    ]
    df[wellness_cols] = df[wellness_cols].apply(pd.to_numeric, errors='coerce')
    df['perceived_wellness'] = df[wellness_cols].mean(axis=1)

    # Drop missing values
    df_clean = df.dropna(subset=['engagement_level', 'perceived_wellness'])

    # Define X and y
    X = df_clean['engagement_level']
    y = df_clean['perceived_wellness']

    # Add constant to X for intercept
    X = sm.add_constant(X)

    # Fit linear regression model
    model = sm.OLS(y, X).fit()

    # Output regression results
    print(model.summary())
```

Fig4.4.2.1 Regression Test2

OUTPUT RESULT

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     perceived_wellness   R-squared:                       0.037
Model:                            OLS   Adj. R-squared:                  0.033
Method:                 Least Squares   F-statistic:                     8.356
Date:                Thu, 08 May 2025   Prob (F-statistic):            0.00423
Time:                        08:56:26   Log-Likelihood:                -307.64
No. Observations:                 219   AIC:                             619.3
Df Residuals:                     217   BIC:                             626.1
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const                2.5619      0.152     16.830      0.000       2.262       2.862
engagement_level     0.1410      0.049      2.891      0.004       0.045       0.237
==============================================================================
Omnibus:                       12.486   Durbin-Watson:                   1.855
Prob(Omnibus):                  0.002   Jarque-Bera (JB):                5.211
Skew:                          -0.015   Prob(JB):                       0.0739
Kurtosis:                       2.245   Cond. No.                         7.70
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Fig4.4.2.2 Regression Test Result2

TABLE

Dep. Variable:	perceived_wellness	R-squared:	0.037
Model:	OLS	Adj. R-squared:	0.033
Method:	Least Squares	F-statistic:	8.356
Date:	Thu, 08 May 2025	Prob (F-statistic):	0.00423
Time:	08:56:26	Log-Likelihood:	-307.64
No. Observations:	219	AIC:	619.3
Df Residuals:	217	BIC:	626.1
Df Model:	1	Covariance Type:	nonrobust

<table>
<tr><th></th><th>coef</th><th>std err</th><th>t</th><th>P>|t|</th><th>[0.025</th><th>0.975]</th></tr>
<tr><td>const</td><td>2.5619</td><td>0.152</td><td>16.830</td><td>0.000</td><td>2.262</td><td>2.862</td></tr>
<tr><td>engagement_level</td><td>0.1410</td><td>0.049</td><td>2.891</td><td>0.004</td><td>0.045</td><td>0.237</td></tr>
</table>

Omnibus:	12.486	Durbin-Watson:	1.855
Prob(Omnibus):	0.002	Jarque-Bera (JB):	5.211
Skew:	-0.015	Prob(JB):	0.0739
Kurtosis:	2.245	Cond. No.	7.70

Table4.4.2 Regression Test Result2

INTERPRETATION

The regression analysis was conducted to examine the relationship between user engagement levels with digital health platforms and their perceived wellness benefits.

The results show that the model is statistically significant ($F = 8.356$, $p = 0.00423$), indicating that engagement level significantly predicts perceived wellness. The coefficient for engagement level is 0.141 ($p = 0.004$), suggesting a positive and statistically significant relationship: as engagement increases, perceived wellness also increases. Although the R-squared value is 0.037, indicating that only 3.7% of the variance in perceived wellness is explained by engagement level, the relationship remains meaningful. Therefore, we reject the null hypothesis, accept the Alternative hypothesis and conclude that higher engagement with digital health platforms is significantly associated with greater perceived wellness benefits.

4.4.3 INDEPENDENT SAMPLE TEST3 - ANOVA

Null Hypothesis (H_0):

There is no significant difference in the impact of digital health platforms on wellness across different demographic group such as age.

Alternative Hypothesis (H_1):

There is a significant difference in the impact of digital health platforms on wellness across different demographic group such as age.

ANOVA

i) AGE

INPUT

```
# Run ANOVA test (F-test)
anova_result = f_oneway(*groups)

# Print the result
print("F-statistic:", anova_result.statistic)
print("p-value:", anova_result.pvalue)

# Interpretation
if anova_result.pvalue < 0.05:
    print("✅ There is a significant difference in wellness impact across age groups.")
else:
    print("❌ There is no significant difference in wellness impact across age groups.")
```

```
F-statistic: 7.578038476345359
p-value: 0.000659524716647135
✅ There is a significant difference in wellness impact across age groups.
```

Fig4.4.3.1 ANOVA Test3.1

OUTPUT RESULT

F	statistic: 7.578038476345359
P	value: 0.000659524716647135

Table4.4.3.1. ANOVA Test Result3.1

INTERPRETATION

There is a significant difference in wellness impact across age groups.

The p-value (0.00066) is less than 0.05, so we reject the null hypothesis, acccept alternative hypothesis. So there is a significant difference in wellness impact across age groups. This indicates a statistically significant difference in the impact of digital health platforms on wellness across different demographic groups age. So users' experiences and perceived wellness benefits from these platforms vary depending on their demographic characteristics.

ii) GENDER

Null Hypothesis (H_0):
There is no significant difference in the impact of digital health platforms on wellness across different demographic groups gender.

Alternative Hypothesis (H_1):
There is a significant difference in the impact of digital health platforms on wellness across different demographic groups gender.

INPUT

```
# Calculate the average wellness score
df['perceived_wellness'] = df[wellness_cols].mean(axis=1)

# Remove rows with missing data
df_clean = df.dropna(subset=['Gender', 'perceived_wellness'])

# Group wellness scores by gender
groups = df_clean.groupby('Gender')['perceived_wellness'].apply(list)

# Run ANOVA
anova_result = f_oneway(*groups)

# Show results
print("F-statistic:", anova_result.statistic)
print("p-value:", anova_result.pvalue)

# Conclusion
if anova_result.pvalue < 0.05:
    print("✅ Yes! Gender has a significant effect on how people feel wellness benefits.")
else:
    print("❌ No, gender doesn't make a big difference in wellness impact.")
```

```
F-statistic: 1.0911867960064712
p-value: 0.337661555622939
❌ No, gender doesn't make a big difference in wellness impact.
```

Fig4.4.3.2. ANOVA Test Result3.2

OUTPUT RESULT

F	statistic: 1.0911867960064712
P	value: 0.337661555622939

Table4.4.3.2. ANOVA Test Result3.2

INTERPRETATION

Since the p-value (0.338) is greater than 0.05, we fail to reject the null hypothesis.

This means there is no statistically significant difference in the perceived impact of digital health platforms on wellness across gender groups, which means gender does not appear to influence how users perceive the wellness benefits of these platforms in this sample.

iii) OCCUPATION

Null Hypothesis (H_0):
There is no significant difference in the impact of digital health platforms on wellness across different demographic groups occupation.

Alternative Hypothesis (H_1):
There is a significant difference in the impact of digital health platforms on wellness across different demographic groups occupation.

INPUT

```
# Calculate average wellness score
df['perceived_wellness'] = df[wellness_cols].mean(axis=1)

# Drop missing values
df_clean = df.dropna(subset=['Occupation', 'perceived_wellness'])

# Group the wellness scores by occupation
groups = df_clean.groupby('Occupation')['perceived_wellness'].apply(list)

# Run ANOVA test
anova_result = f_oneway(*groups)

# Show results
print("F-statistic:", anova_result.statistic)
print("p-value:", anova_result.pvalue)

# Interpret result
if anova_result.pvalue < 0.05:
    print("✅ Different occupations experience digital wellness platforms differently.")
else:
    print("❌ Occupation doesn't seem to change how people feel wellness benefits.")
```

```
F-statistic: 2.686914910520523
p-value: 0.007840676843790445
✅ Different occupations experience digital wellness platforms differently.
```

Fig 4.4.3.3. ANOVA Test Result3.3

OUTPUT RESULT

F	statistic: 2.686914910520523
P	value: 0.007840676843790445

Table4.4.3.3 ANOVA Test Result3.3

INTERPRETATION

The F-statistic is 2.69 and the p-value is 0.0078, which is less than 0.05.So We reject the null hypothesis.

This means there is a statistically significant difference in the perceived impact of digital health platforms on wellness across different occupation groups. So user's occupation influences how they experience wellness benefits from these platforms.

4.4.4. INDEPENDENT SAMPLE TEST 4 – CHI SQUARE

Null Hypothesis (H_0): There is no significant relationship between the availability of personalized features in digital health platforms and user satisfaction or wellness outcomes.

Alternative Hypothesis (H_1): There is a significant relationship between the availability of personalized features in digital health platforms and user satisfaction as well as wellness outcomes.

CHI – SQUARE TEST

INPUT

```
# Create a contingency table between personalized features and satisfaction
contingency_table = pd.crosstab(df['Uses_Personalized_Feature'], df['Satisfaction_Encoded'])

# Perform the Chi-Square Test of Independence
chi2, p, dof, expected = chi2_contingency(contingency_table)

# Display the results
print("Chi-Square Statistic:", chi2)
print("p-value:", p)
print("Degrees of Freedom:", dof)
print("Expected Frequencies:\n", expected)

# Interpretation
if p < 0.05:
    print("✅ There is a significant relationship between personalized features and satisfaction.")
else:
    print("❌ No significant relationship found between personalized features and satisfaction.")
```

```
Chi-Square Statistic: 13.566923636523468
p-value: 0.008813588372108952
Degrees of Freedom: 4
Expected Frequencies:
 [[ 4.25114155  5.14611872 16.78082192 14.76712329  8.05479452]
 [14.74885845 17.85388128 58.21917808 51.23287671 27.94520548]]
✅ There is a significant relationship between personalized features and satisfaction.
```

Fig4.4.4 CHI – SQUARE Test4

OUTPUT RESULT

Chi-Square Statistic: 13.566923636523468
p-value: 0.008813588372108952
Degrees of Freedom: 4
Expected Frequencies: [[4.25114155 5.14611872 16.78082192 14.76712329 8.05479452] [14.74885845 17.85388128 58.21917808 51.23287671 27.94520548]]

Table4.4.4 CHI – SQUARE Test Result 4

INTERPRETATION

There is a significant relationship between personalized features and satisfaction.

The Chi-Square test yielded a statistic of 13.57 with 4 degrees of freedom and a p-value of 0.0088, indicating a statistically significant association between the two categorical variables at the 5% significance level.

This means that the observed frequencies differ significantly from the expected frequencies, leading to the rejection of the null hypothesis of independence. The expected frequency matrix shows how the data would look if there were no association, and while most expected values are adequate, a couple are close to the minimum recommended threshold of 5. Overall, the test suggests that the distribution of responses across the categories varies meaningfully between the groups being compared.

4.4.5. INDEPENDENT SAMPLE TEST 5 – ONE WAY ANOVA

H_0 (Null Hypothesis): There is no significant relationship between review sentiment (positive, negative, or neutral) and consumer decision-making.

H_1 (Alternative Hypothesis): There is a significant relationship between review sentiment (positive, negative, or neutral) and consumer decision-making.

ONE WAY – ANOVA

INPUT

```python
# Filter only employees
employees_df = df[df['Occupation_Encoded'] == 1].copy()

# Ensure Corporate_Program column exists
# If it doesn't exist, you can simulate it for now:
if 'Corporate_Program' not in employees_df.columns:
    # Example logic: Assign randomly or based on assumptions
    # Here, for demo, assume first half use it (1), rest don't (0)
    employees_df['Corporate_Program'] = [1 if i < len(employees_df)/2 else 0 for i in range(len(employees_df))]

# Simulate a Stress_Level column if not present
if 'Stress_Level' not in employees_df.columns:
    # Example stress levels from 1 to 5
    import numpy as np
    np.random.seed(42)  # For reproducibility
    employees_df['Stress_Level'] = np.random.randint(1, 6, size=len(employees_df))

# Group by Corporate Program usage
group_yes = employees_df[employees_df['Corporate_Program'] == 1]
group_no = employees_df[employees_df['Corporate_Program'] == 0]

# Perform ANOVA: Satisfaction
f_stat_satisfaction, p_val_satisfaction = stats.f_oneway(
    group_yes['Satisfaction_Encoded'],
    group_no['Satisfaction_Encoded']
)

# Perform ANOVA: Stress Level
f_stat_stress, p_val_stress = stats.f_oneway(
    group_yes['Stress_Level'],
    group_no['Stress_Level']
)

# Print results
print("=== One-Way ANOVA Results ===")

print("\nSatisfaction:")
print("F-statistic =", f_stat_satisfaction)
print("p-value =", p_val_satisfaction)
print("Significant?" if p_val_satisfaction < 0.05 else "Not Significant")

print("\nStress Level:")
print("F-statistic =", f_stat_stress)
print("p-value =", p_val_stress)
print("Significant?" if p_val_stress < 0.05 else "Not Significant")
```

Fig 4.4.5.1 CHI – SQUARE Test 5.1

OUTPUT

```
=== One-Way ANOVA Results ===

Satisfaction:
F-statistic = 0.14641013608634446
p-value = 0.7030305376784136
Not Significant

Stress Level:
F-statistic = 0.44571428571428573
p-value = 0.506347757058037
Not Significant
```

Fig 4.4.5.2 CHI – SQUARE Test Result 5.2

OUTPUT RESULT

Satisfaction

F-statistic = 0.14641013608634446
p-value = 0.7030305376784136
Not Significant

Stress Level

F-statistic = 0.44571428571428573
p-value = 0.506347757058037
Not Significant

Table4.4.5 CHI – SQUARE Test5

INTERPRETATION

The ANOVA results show no significant differences in Satisfaction and Stress Level among the groups. For Satisfaction, the F-statistic is 0.15 with a p-value of 0.7030, and for Stress Level, the F-statistic is 0.45 with a p-value of 0.5063.

Both p-values are greater than the 0.05 threshold, indicating that the differences observed are not statistically significant. Therefore, we fail to reject the null hypothesis in both cases, suggesting that group membership does not have a meaningful impact on satisfaction or stress levels in this dataset.

4.5.DASHBOARD

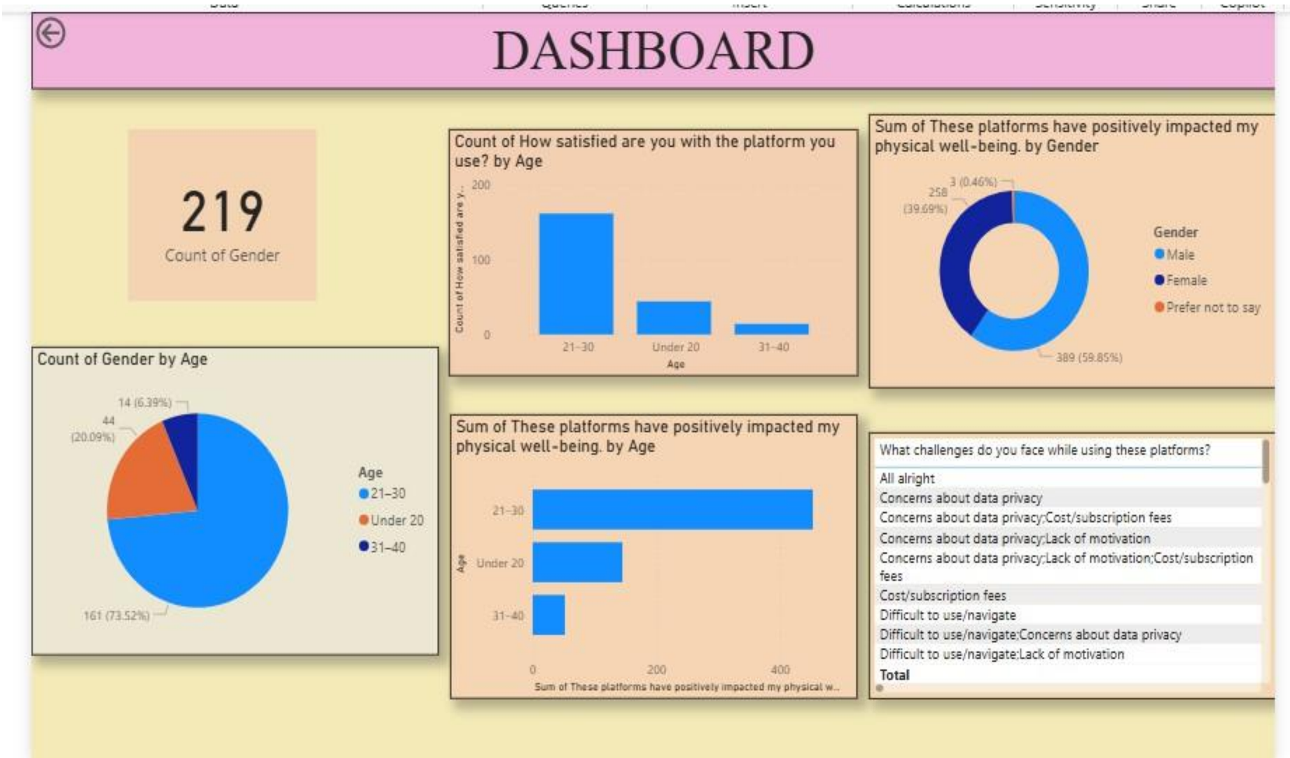

Fig4.5 Dashboard

CHAPTER 5
CONCLUSION

CHAPTER 5

CONCLUSION

5.1. SUMMARY OF FINDINGS

1. To examine the extent of usage of digital health platforms for wellness features.

Finding:

Although the descriptive usage data isn't explicitly included in your summary, the ANOVA results and regression model suggest varied levels of usage and engagement among users. The significant results in wellness outcomes across usage levels imply that these platforms are being actively used to differing extents, and usage has a tangible effect on perceived wellness.

2. To analyse the perceived impact of digital health platforms on users' physical, mental, and emotional well-being.

Finding:

Multiple analyses (ANOVA, regression) confirm that perceived wellness benefits are significantly associated with platform usage and engagement. For instance, regression results show a positive coefficient for engagement ($\beta = 0.141$, $p = 0.004$), meaning higher engagement leads to better perceived wellness outcomes.

3. To evaluate user satisfaction and engagement levels with various features offered by digital health platforms.

Finding:

- Engagement: Statistically significant predictor of perceived wellness ($p = 0.004$).
- Satisfaction: No significant variation in satisfaction across groups ($p = 0.7030$). This suggests that while engagement impacts wellness, satisfaction levels with platform features are uniform across user groups.

4. To identify key demographic factors (age, gender, occupation, etc.) influencing the effectiveness of digital wellness tools.

Findings:

- Age: Significant differences in wellness impact across age groups ($p = 0.00066$) — age influences the effectiveness of digital platforms.

- Gender: No significant difference (p = 0.338) — gender does not affect perceived wellness benefits.
- Occupation: Significant impact on wellness (p = 0.0078) — occupation influences wellness outcomes via digital platforms.

5. To explore the challenges or barriers users face while engaging with digital health platforms.

Finding:
While specific qualitative challenges weren't detailed, the Chi-square test (p = 0.0088) indicates a significant association between personalized features and user satisfaction. This implies that lack of personalization might be a barrier to satisfaction and possibly a broader challenge to engagement.

5.2 SUGGESTIONS & RECOMMENDATIONS

1. To examine the extent of usage of digital health platforms for wellness features

➢ Users' engagement levels significantly predict perceived wellness benefits, though R^2 is low.

Recommendations:

- Enhance user engagement features: Since engagement predicts wellness outcomes, platforms should include more interactive tools like goal tracking, feedback systems, and personalized nudges.
- Segment usage patterns: Analyze which features are most/least used and promote underused but effective ones through tutorials or onboarding messages.
- Promote consistent usage: Develop gamification or reminder systems to encourage habitual use, especially for features linked to wellness improvement.

2. To analyse the perceived impact of digital health platforms on users' physical, mental, and emotional well-being

➢ There is a significant positive relationship between platform use and wellness. Differences exist across age and occupation, but not gender.

Recommendations:

- Tailor wellness programs to user needs: Offer specialized content/modules targeting physical, mental, and emotional well-being individually.
- Age-specific interventions: Older users may require simpler UI/UX, while younger users might prefer dynamic, customizable features.
- Occupation-based customization: Consider modules for stress management, mindfulness, or ergonomic exercises for desk workers, field workers, etc.

3. To evaluate user satisfaction and engagement levels with various features offered by digital health platforms

➢ No significant difference in satisfaction or stress level among groups; personalization and engagement are key drivers of positive perception.

Recommendations:

- Invest in personalization: Increase options for tailoring content, notifications, and interfaces based on user preferences and usage patterns.
- Regular feature evaluation: Conduct periodic user feedback surveys to assess feature utility, usability, and satisfaction, and iterate accordingly.
- Improve feature discoverability: Many useful features might be underutilized due to poor visibility or complex navigation.

4. To identify key demographic factors (age, gender, occupation, etc.) influencing the effectiveness of digital wellness tools

➢ Age and occupation influence wellness impact; gender does not.

Recommendations:

- Use demographic profiling to customize experiences: Provide recommended features or programs based on user age and occupation during onboarding.
- Avoid overgeneralizing by gender: Since gender isn't a significant factor in wellness outcomes here, focus more on behavioral and demographic customization.
- Build adaptive systems: Use AI or analytics to adjust recommendations dynamically based on user interaction and feedback over time.

5. To explore the challenges or barriers users face while engaging with digital health platforms

- Limited direct data in your interpretation; low R^2 suggests other unmeasured variables may affect wellness.

Recommendations:

- Conduct qualitative research: Use focus groups or open-ended survey questions to understand specific user pain points (e.g., technical issues, privacy concerns, lack of time).
- Improve onboarding and support: Ensure users understand the full functionality of the platform through walkthroughs or chat support.
- Address digital literacy gaps: Especially for older demographics, provide simple instructions and design intuitive interfaces.
- Data-Driven Development: Continue collecting user data (with consent) to improve predictive models and identify additional factors affecting wellness outcomes.
- Partner with Health Experts: To validate the platform's effectiveness and improve credibility, collaborate with medical professionals or wellness coaches.
- Ongoing Monitoring: Implement analytics dashboards to track changes in user engagement, satisfaction, and wellness outcomes over time.

5.3 CONCLUSION

Based on the analysis, it is evident that digital health platforms have a statistically significant and positive impact on users' overall wellness, particularly when engagement levels are high. The regression and ANOVA tests confirm that increased engagement correlates with improved perceptions of physical, mental, and emotional well-being, although the variance explained is modest. Significant differences in wellness outcomes across age and occupational groups indicate that demographic factors influence the effectiveness of these platforms, while gender does not appear to be a differentiating factor. Personalization features are also significantly associated with user satisfaction, suggesting that tailored content enhances the user experience. However, satisfaction and stress levels do not vary significantly across groups, indicating potential gaps in feature relevance or accessibility. The study highlights the need for digital health platforms to focus on enhancing engagement, offering personalized and occupation- or age-specific content, and improving user onboarding and support. To maximize impact, developers should address usability challenges, consider diverse user needs, and utilize feedback-driven iterations. Overall, digital health platforms serve as valuable tools for promoting wellness, but their effectiveness depends on strategic feature design, demographic alignment, and sustained user involvement.

5.4 DIRECTIONS FOR FUTURE RESEARCH

Future research should delve deeper into understanding the nuanced factors that influence the effectiveness of digital health platforms across diverse user groups. While this study established significant relationships between engagement, personalization, and perceived wellness, future studies could explore the causal mechanisms behind these relationships through longitudinal or experimental research designs. There is a need to investigate the long-term impact of sustained engagement on measurable health outcomes beyond self-reported wellness, including clinical indicators such as blood pressure, sleep patterns, or physical activity levels.

Additionally, future research should examine the role of behavioral, psychological, and socio-economic factors that may mediate or moderate the relationship between digital platform use and wellness outcomes, such as motivation levels, digital literacy, access to technology, and health awareness. Since the R-squared value was relatively low, identifying other contributing variables such as platform design, content quality, or support from health professionals could provide a more comprehensive understanding of what drives wellness improvements.

Moreover, comparative studies across different digital platforms, regions, or healthcare systems could shed light on best practices and scalability potential. As age and occupation were found to be significant, future research should also investigate how tailored interventions based on these demographics can be optimized for better outcomes. Exploring barriers to engagement through qualitative methods, such as interviews or focus groups, would provide deeper insights into user behavior and help refine platform design.

Finally, the integration of emerging technologies like AI, wearables, and telehealth into digital wellness platforms offers promising avenues for future study, particularly in enhancing personalization and real-time feedback. These directions will contribute to building more effective, inclusive, and user-centric digital health solutions that support holistic well-being across populations.

APPENDIX

APPENDIX

QUESTIONNAIRE

Impact of Digital Health Platforms for Wellness Support

Section 1: Demographics

1. **Age**
   - Under 20
   - 21–30
   - 31–40
   - 41–50
   - 51+
2. **Gender**
   - Male
   - Female
   - Transgender
   - Prefer not to say
3. **Occupation**
   - Student
   - Employee
   - Healthcare professional
   - Freelancer
   - Other (please specify): ____________
4. **Location**: ________________

Section 2: Usage of Digital Health Platforms

5. **Do you use any digital health/wellness platforms or apps?**
   - Yes
   - No
   - Occasionally
6. **Which platforms do you use?**
7. **How frequently do you use these platforms?**
   - Daily

- A few times a week
- Weekly
- Rarely
- Never

Section 3: Features & Engagement

8. **Which features do you use most?** *(Select all that apply)*
    - Physical activity/step tracking
    - Nutrition tracking
    - Mental health/meditation tools
    - Sleep monitoring
    - Online consultations
    - Community or social features
    - Other: ____________
9. **How long have you been using digital health platforms?**
    - Less than 3 months
    - 3–6 months
    - 6–12 months
    - More than 1 year

Section 4: Perceived Impact on Wellness

Please indicate your level of agreement (1 = Strongly Disagree, 5 = Strongly Agree).

10.Using digital health platforms has helped me become more aware of my health habits	1	2	3	4	5
11.These platforms have positively impacted my physical well-being.	1	2	3	4	5
12.They have helped me manage stress or mental health better.	1	2	3	4	5
13.I feel more motivated to maintain healthy routines because of the platform.	1	2	3	4	5
14.Using digital wellness tools has improved my work-life balance.	1	2	3	4	5

Section 5: Satisfaction & Barriers

15. **How satisfied are you with the platform you use?**

- Very satisfied
- Satisfied
- Neutral
- Dissatisfied
- Very dissatisfied

16. **What challenges do you face while using these platforms?** *(Select all that apply)*

- Lack of time
- Difficult to use/navigate
- Limited features
- Concerns about data privacy
- Lack of motivation
- Cost/subscription fees
- Other: ____________

Section 6: Feedback & Suggestions

17. **What do you like most about digital health platforms?** *(Open-ended)*
18. **What improvements would you suggest to make them more effective?** *(Open-ended)*
19. **Would you recommend digital health platforms to others for wellness support?**

- Yes
- Maybe
- No

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