# IMPACT OF DIGITAL HEALTH & AI ON JOB SATISFACTION OF DOCTORS IN PRIVATE TERTIARY CARE HOSPITALS IN THIRUVANANTHAPURAM DISTRICT IN KERALA, INDIA.

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Dr. Azarudeen Mohamed

Student ID – 58690

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APPROVED BY

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<Milica Popović Stijačić, PhD>, Chair

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<Member’s Name, Degree>, Committee Member

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<Member’s Name, Degree>, Committee Member

RECEIVED/APPROVED BY:

<Associate Dean’s Name, Degree>, Associate Dean

**DEDICATION**

I am eager to extend my deepest appreciation to Dr. Hemant Palivela, my dedicated DBA supervisor, whose unwavering guidance and invaluable assistance were instrumental in navigating me through the journey of research completion. Additionally, I am filled with profound gratitude towards my circle of friends, coworkers, and cherished family members, without whom the successful culmination of my research journey would not have been achievable. Beyond this, I wish to convey my heartfelt thanks to the esteemed doctors who graciously devoted their precious time and expertise to participate in this significant study, reaffirming the importance of their contributions to the research process. Their collective support has truly been a cornerstone in driving the successful completion of this study, and for that, I am immensely grateful.

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## ABSTRACT

**Introduction :** The healthcare landscape in the state of Kerala in India is undergoing a significant transformation with the increasing adoption of digital health technologies and AI. Research conducted in different parts of the state shows doctors in Kerala are facing job stress due to the growing work pressure, administrative demands, and evolving healthcare environment. Since digital health and AI technologies are progressing in an unprecedented manner in healthcare, there are possibilities that work satisfaction issues could be made worse by the advent of these technologies, or they could also present chances to increase job satisfaction.

**Objective :** This research aims to systematically investigate and analyze the impact of digital health and AI on job satisfaction of doctors working in private tertiary care hospitals in Thiruvananthapuram district in Kerala and to draw conclusions from the study with ultimate objective of improving strategies for policy makers, regulators, providers and technology developers for improving job satisfaction of doctors, ultimately improving the working environment resulting in better patient care.

**Methodology :** This cross sectional study included 110 doctors as samples selected using convenience sampling method from 5 private tertiary care hospitals in Thiruvananthapuram district in the state of Kerala in India. A modified version of TAM questionnaire was used as the research instrument for primary data collection. For data analysis, sorting of data and data visualization, SPSS software and Microsoft Excel were utilized. Regression modeling, hypothesis testing, and principal component analysis were used to arrive at the conclusion.

**Results:** Out of the selected sample 76.4% of doctors expressed over all job satisfaction which however varied across gender and age. Hypothesis testing reveals that differences across the age and gender are not statistically significant. Through the regression modelling

the major factors that were affecting the job satisfaction includes work performance ( exp (β) 6.665, P value- 0.008, β = 1.897), Effectiveness at work (exp (β) 11.208, P value- 0.002, β = 2.417), Ease of use (exp(β ) 6.665, P value- 0.008, β = 1.897), Variety of purposes (exp(β) 1.735, P value- 0.000.047, β = 1.735)

**Conclusion:** The widespread adoption of digital health and AI technologies among doctors working in tertiary care hospitals in this study is evidenced by the fact that over three-quarter of them expressed job satisfaction using digital health and AI technologies. However, compared to young doctors and male doctors, older and female doctors were less inclined to the usage of digital health technologies. It is anticipated that the findings of this study will assist policymakers, regulators, healthcare providers, planners, and technology developers in creating solutions for improving doctors job satisfaction that will enhance the efficacy and efficiency of healthcare delivery for the benefit of human life.

**Recommendation:** Based on the findings, healthcare providers should invest in digital health technology and AI to improve job satisfaction of doctors. However, considering the fact that still a good number of all doctors especially old and female doctors tends to be less receptive to new technologies, while introduction of new technologies, it is highly recommended that the users gets trained before implementation of new technologies in healthcare facilities. Future research should look on the long-term impact of digital health technology and AI on doctors. Policymakers and practitioners can utilize these findings to help establish policies and interventions that encourage the successful use of digital health technologies.

**Limitations:** This cross- sectional study may not have fully represented the intricacy of the investigated phenomenon because it was based on a specific theoretical framework. To improve the findings' generalizability, future research could try to enlist a bigger and more varied sample and mixed-methods technique and also investing more time to give more understanding of the phenomenon being studied. Data was collected over a period of 4 months and the short timeframe for this study may have affected the scope and depth of the investigation.

**Key words:** Digital health, AI (Artificial Intelligence), tertiary care hospitals, job satisfaction, TAM questionnaire, healthcare, doctors, quantitative research, regression analysis, hypothesis testing, principal component analysis, SPSS

# CHAPTER -1

# INTRODUCTION

## 1.1. Statement of the Problem

The health standards of Kerala are now on par with developed countries in the world. Compared to other Indian states, the health metrics such as the infant mortality rate, maternal mortality, birth rate, death rate, life expectancy, etc are far better and on line with those of industrialized and developed countries worldwide (Aaditya et al, 2024).

The "Kerala model of health" refers to Kerala's health accomplishments despite its low per capita income. The Kerala model of health is characterized by low costs, quick accessibility, and availability of healthcare, even for the most impoverished segments of society. The well-known Kerala health model is currently facing a number of difficulties. The healthcare landscape in the state of Kerala in India is undergoing a significant transformation with the increasing adoption of digital health technologies and AI (Aaditya et al, 2024). AI and digital health together have the potential to completely transform healthcare delivery, making it more patient-centred, effective, and efficient. However, the impact of these technologies on the job satisfaction of doctors in Kerala remains a topic of concern.

Healthcare workers' well-being, productivity, and retention are all significantly impacted by job satisfaction. Doctors in Kerala are dealing with a lot of difficulties that may have an impact on their job satisfaction due to the increase in work pressure, administrative demands, and evolving healthcare environment (Ramaswamy, S. 2024). These issues could be made worse by the advent of AI and digital health technology, or they could present chances to increase job satisfaction.

Motivated health workforce and technology are some of the key building blocks of a healthcare system (WHO Report, 2016). Among the health workforce, in terms of professionals, doctors are a burnout-prone occupational group with affected professionals potentially struggling with emotional exhaustion, cynicism, and a low sense of personal accomplishment from work (Nwosu, et al. 2020). Motivated health workforce especially doctors are very important for effective and efficient functioning of healthcare system and for the amelioration of human life (WHO Report, 2016). Many studies shows that there is a definite link between doctors' attitudes and patient satisfaction. If doctors are unhappy or dissatisfied, despite their best efforts, it is difficult for them to conceal this factor when interacting with patients and other staff members. One of the primary reasons for evaluating job satisfaction of doctors is to identify problems and try to resolve them before they impact on patient care and treatment. Healthcare employers around the world are trying various methods for motivating health workers especially doctors to improve the effectiveness and efficiency of the healthcare delivery process for better health outcomes. Researches conducted in different parts of the world shows that burnout among doctors is raising and job satisfaction is declining in an undeviating manner among doctors. Also it is a proven fact that money cannot be the only factor for motivating doctors. ( Sachin R, et al. 2018). There are many factors related to job satisfaction and there are myriad potential contributors to burnout in healthcare. Several studies shows that the usage of technologies like Digital Health and AI have been increasingly implicated with burnout of doctors. Now we face a cognitive era of Digital Health and AI with a great expansion of information accompanied by new information tools that impact care decisions. Machine learning, predictive analytics, pharmacogenomics, remote monitoring data, and so on, are all poised to create new capabilities but also new complexities, with each new tool carrying "the promise of positive change and the risk of further increasing clinicians' work stresses and burnout. (Koon, S. 2021) In this scenario this research aims to find out whether the usage of digital health and Artificial Intelligence among doctors working in private tertiary care hospitals in Trivandrum district in the state of Kerala will have any role in motivating their working environment so that strategies can be developed by providers, regulators, policy makers and developers of technologies for improving the job satisfaction of doctors through which the effectiveness and efficiency of healthcare delivery can be improved for the amelioration of human life.

### 1.2. Significance of the study

There are significant implications for a number of stakeholders from this study on the effects of digital health and artificial intelligence (AI) on job satisfaction of doctors working in private tertiary care hospitals in Kerala, India. One of the major issues that the Indian healthcare system continues to face is with motivating healthcare workers, particularly doctors (Kasthuri A, 2018). We live in a technological era and the speed at which technology is developing globally is unprecedented. As more aspects of daily life become digital, so too does the health sector, which depends on technology not just to revolutionize health care but also to continue and maintain its services and products at a level that is deemed acceptable by society. Artificial intelligence (AI) along with information and communication technologies, has the potential to fundamentally change the healthcare industry ( World Economic Forum, 2023 ).

Since a majority of the doctors are not very adept at using technology, the expanding and unavoidable usage of digital health and artificial intelligence is reported to increase work stress, despite the fact that there are many other causes for doctors' demotivation at work, including extreme stress at work, job pressure, poor leadership, poor systems, and lack of opportunity for professional development (Hararika, 2020 ). It is need of the hour and crucial to understand the causes that influence doctors' productivity and job satisfaction if healthcare systems are to remain viable. Job stress, burnout, and job dissatisfaction among doctors are problems that need to be fixed, challenges that need to be solved, and serious questions that exist in academic literatures and in practice that call for thoughtful analysis and research.

This study on the impact of Digital Health and AI on doctors' job satisfaction can contribute to existing knowledge base in several ways. Using the modified version of Technology Acceptance Model (TAM) questionnaire as an instrument for data collection, Principal component analysis, hypothesis testing and regression analysis this study investigates how technology like digital health and AI impact the job satisfaction of doctors working in private tertiary care hospitals in Thiruvananthapuram district in Kerala, India. For this research, to collect more valuable inputs and gather data from the users, the researcher used a modified version of The Technology Acceptance Model (TAM) questionnaire. To make this instrument better suited for this research, some modifications were made. The TAM questionnaire typically makes predictions about a user's future propensity to utilize a product.

The questions in the modified version of TAM used for this study cover 15 questions under 4 sections

(i) Perceived Use

(ii) Perceived ease of use

(iii) User Acceptance and

(iv) User Recommendation.

To measure doctors' propensity to advocate for Digital Health and AI technologies, serving as a proxy for happiness, a question was added mentioning how likely would they recommend these technologies to others under user recommendation. Without changing the original content of the data collection, this research study has assessed the variables for similarities and employed data reduction procedures to prevent repetition and duplication. The results of the study can guide the creation of theoretical frameworks that clarify the connections between AI, digital health, and healthcare workers' job satisfaction and can be applied to other areas and professions that are similar in order to determine the degree of satisfaction among healthcare workers and to raise the level of satisfaction in the current system.

In order for providers, policymakers, regulators and technology developers to develop strategies for motivating doctors and improving the effectiveness and efficiency of healthcare delivery for the betterment of human life, the research's findings can help determine whether the use of digital health and artificial intelligence by physicians in private tertiary care hospitals in Kerala's Trivandrum district will have any role in enhancing their working environment.

The results of this study can mainly help policy makers and healthcare providers understand how AI and digital health affect doctors' job satisfaction, allowing them to create plans for continuous improvement. Hospitals can maximize the use of AI and digital health to enhance patient care and results by knowing how these technologies affect doctors' job satisfaction. The results of the study can particularly assist decision makers of hospitals in better allocating resources by giving priority to investments in digital health technologies for job satisfaction. Overall, this study on the effects of AI and digital health on doctors' job satisfaction can contribute to the theoretical frameworks, conceptual discussions, and theoretical debates while offering important insights into how these technologies affect the delivery of healthcare through influencing the satisfaction of doctors.

**1.3. Research Questions**

Before creating the research questions, the following important factors were carefully taken into account. A well-crafted research question was created to guarantee that the study is targeted, pertinent, and significant because it serves as the cornerstone of the research study and is essential in directing the entire research process. These questions are thought to give a clear outline of the researcher's goals and serve as a guide for the entire investigation.

By keeping the researcher on task and preventing needless digressions, a well stated research topic was in need to help the study stay on course and meet its goals. It must be acknowledged that a research question guarantees the significance and relevance of the investigation. (J.E. Dodgen, 2020)

Effective research questions were required to justify this study and point out the problems and knowledge gap that has to be solved. This was also considered to guarantee that the research work has applications and adds to the corpus of current knowledge.

The selection of study design, data collection techniques, and sample techniques are all influenced by the research questions. A well-written research question guarantees that the methodology is suitable for answering the issue and accomplishing the goals of the study. (J.E. Dodgen, 2020)

Also, the validity and reliability of the research investigation are improved by a research question. A clear research question increases validity by ensuring that the study measures what it is supposed to assess. Additionally, it encourages uniformity in the gathering and evaluation of data, which improves dependability. The transmission and distribution of research findings are facilitated by a research question. A succinct and unambiguous research question summarizes the goals of the study and facilitates the dissemination of the results to all interested stakeholders. Determining the target audience and adjusting the dissemination method appropriately are also beneficial. (J.E. Dodgen, 2020). In order to improve strategies for motivating the work environment of doctors, the research systematically investigates and analyses the impact of digital health and artificial intelligence on job satisfaction of doctors in tertiary care hospitals in Thiruvananthapuram district in South Kerala. Also, the developers of technologies like AI and digital health products will gain insights from this to create technologies that influence doctors' daily routines and ultimately enhance the working environment. Considering all the above-mentioned facts, this research study has developed the following questions to find out

(i) Whether the usage of digital health and AI contributes towards job satisfaction of doctors working in private tertiary care hospitals in Thiruvananthapuram district in Kerala, India.

(ii) Whether age of doctors influences the usage of Digital Health and AI

(iii) Whether gender of doctors influence the usage of Digital Health and AI

The sample is confined to allopathic doctors working for more than five years in private tertiary care hospitals in Thiruvananthapuram district in Kerala.

### 1.4. Hypothesis Testing

Considering the major issue of job satisfaction experienced by different categories of doctors, the following null and alternate hypothesis were tested for this study.

The null hypothesis is that there is no difference of job satisfaction among different background of respondents namely.

(i) Gender – Male Vs Female

(ii) Age – Young (<50) Vs Old (>50)

(iii) Young Male Vs Young Female

(iv) Old Male Vs Old Female

Thus, four set of null hypotheses were tested against the alternative hypothesis of significant variance in the job satisfaction.

A total of 15 response variables have been enumerated as part of the study which reflects the job satisfaction of doctors. All the response variables have been combined together for each group of explanatory variables by taking the average of satisfaction level.

(i) Sex Vs Satisfaction Level: The following null hypothesis was tested against alternative hypothesis.

- Null : There is no difference in the satisfaction level of male and female doctors
- Alternate : There is significance difference in the satisfaction level of male and female doctors

(ii) Age Vs Satisfaction Level: The following null hypothesis was tested against alternative hypothesis.

- Null : There is no difference in the satisfaction level of young and old doctors
- Alternate : There is significance difference in the satisfaction level of young and old doctors

(iii) Young and Gender Vs Dissatisfaction Level: The following null hypothesis was tested against alternative hypothesis.

- Null : There is no difference in the satisfaction level of young male and young female doctors
- Alternate : There is significance difference in the satisfaction level of young male and young female doctors

(iv) Old and Gender Vs Dissatisfaction Level: The following null hypothesis was tested against alternative hypothesis.

- Null : There is no difference in the satisfaction level of old male and old female doctors
- Alternate : There is significance difference in the satisfaction level of old male and old female doctors

## 1.5. Limitations, delimitations, and assumptions

### 1.5.1. Limitations

Self-reported surveys were used to gather the data for this research, which could have biases and limitations. It is possible that the doctors working in private tertiary care hospitals in Thiruvananthapuram district in Kerala, in India gave socially acceptable answers or struggled to remember particular details. To triangulate the results, future research can think about employing a variety of data collection techniques, such observations or interviews. This study may not have fully represented the intricacy of the investigated phenomenon because it was based on a specific theoretical framework. To provide a more comprehensive view of the subject topic, future studies can think about integrating multiple perspectives or employing alternative theoretical frameworks. The study's sample size could not be entirely typical of the general population. Furthermore, the convenience-based nature of the sample might have added biases. To improve the findings' generalizability, future research could try to enlist a bigger and more varied sample. The quantitative methodology used in this study might not have adequately reflected the participants' complex and contextualized experiences. A mixed-methods technique might be used in future study to give a more thorough understanding of the phenomenon being studied. The cross-sectional study design may have affected the scope and depth of the investigation. Longitudinal studies may be considered in future study since they can offer insightful information that helps researchers understand how factors change over time.

### 1.5.2. Delimitation

Doctors employed by the private tertiary care hospitals are the subject of this study. Without careful adjustments, the results might not apply to doctors in community health centers, public hospitals, rural hospitals, other nations etc.

The impact of digital health and AI on job satisfaction of doctors is the main emphasis of this study. The impact of other technologies is not examined in this study. This study looks at how technology like digital health and AI affects job satisfaction over a four-month period. The results might not fully account for how technology affects job satisfaction over the long run. To investigate the connection between use of digital health and AI and job satisfaction, this study takes a quantitative approach, using surveys and statistical analysis. To acquire more detailed information about doctors' experiences, the study does not use qualitative techniques like focus groups or interviews.

### 1.5.3. Assumptions

The assumption which forms the basis for this research are mainly based on Ontological assumptions regarding the nature of reality, epistemological presumptions regarding the nature of the knowledge, axiological presumptions regarding the significance and worth of research and methodological presumptions regarding the procedures and methods that are acceptable under the paradigm. The sample used in this study is thought to be representative of the Thiruvananthapuram district’s greater medical community. Additionally, it is expected that respondents would answer the survey questions truthfully and accurately. The study is predicated on the validity and reliability of the survey instrument as well as the accuracy, completeness, and error-free nature of the data. Furthermore, the study makes the premise that the statistical tests will satisfy the independence, homogeneity of variance, and normality

**1.6. Definitions**

i) Digital health

Digital health is the application of digital technologies in healthcare such as digital platforms for managing patient communication, Apps for mobile health (mHealth), electronic health records (EHRs), electronic medical records (EMRs), wearable technology, telehealth, telemedicine, clinical decision support systems, robotics, artificial intelligence (AI) etc ( Chang, A, 2023)

ii) Artificial intelligence (AI)

Artificial intelligence (AI) is the term used to describe computer programs and devices that are capable of perceiving, reasoning, and making decisions tasks that normally require human intelligence. In healthcare AI technologies are applied in clinical, diagnostic, rehabilitative, surgical, and prognostic techniques etc ( Chang, A, 2023)

iii) Job Satisfaction

The feeling of pleasure and achievement that one experience in their job when they know that their work is worth doing, or the degree to which their work gives them this feeling.( Kaur, S, 2009)

iv) Tertiary care Hospitals

Tertiary care hospitals are hospitals with specialized care settings typically for patients with life-threatening or extremely complicated medical illnesses that demand for sophisticated procedures, treatment for cancer, organ transplants, plastic surgery, neurosurgery, perinatology (high-risk pregnancies), neonatology intensive care unit (high-risk newborn care), trauma surgery, etc ( Britto, JJ, 2022 ).

v) Technological Acceptance

The degree to which and individual perceives a technology as useful and easy to use ( Davis,1989)

vi) Perceived Usefulness (PU)

Perceived usefulness (PU) refers to a user's subjective probability that using a different system or technology will increase his or her job performance (Davis, 1989).

vii) Perceived ease of use

Perceived ease of use is determined when a user believes that using a system is free of effort. (Davis, 1989)

viii) Descriptive statistics

Descriptive statistics are brief informational coefficients that summarize a given data set, which can be either a representation of the entire population or a sample of a population. Descriptive statistics are broken down into measures of central tendency and measures of variability (spread). Measures of central tendency include the mean, median, and mode, while measures of variability include standard deviation, variance, minimum and maximum variables, kurtosis, and skewness. (Hinton, P.R, 2014).

ix) Inferential statistics

Inferential statistics enables one to make descriptions of data and draw inferences and conclusions from the respective data. Inferential statistics uses sample data because it is more cost-effective and less tedious than collecting data from an entire population. It allows one to come to reasonable assumptions about the larger population based on a sample's characteristics. (Hinton, P.R, 2014).

x) Principal component analysis

Principal component analysis (PCA) reduces the number of dimensions in large datasets to principal components that retain most of the original information. It does this by transforming potentially correlated variables into a smaller set of variables, called principal components. (Hinton, P.R, 2014).

xi) Hypothesis testing

Hypothesis testing is a structured method used to determine if the findings of a study provide evidence to support a specific theory relevant to a larger population. Hypothesis testing is a type of statistical analysis in which you put your assumptions about a population parameter to the test. It is used to estimate the relationship between 2 statistical variables. (Hinton, P.R, 2014).

xii) Binary regression modelling

Binary regression modelling, also known as binary logistic regression, is a statistical technique that estimates the relationship between a binary dependent variable and one or more independent variables. (Hinton, P.R, 2014).

# CHAPTER-2

# REVIEW OF LITERATURE

## 2.1. Introduction

The purpose of this literature review is to investigate the data currently available regarding the effects of AI and digital health on the job satisfaction of doctors working in private tertiary care hospitals. A thorough analysis of the literature on the effects of AI and digital health on physicians' job satisfaction at private tertiary care institutions was necessary, despite the expanding corpus of research in this area. By offering a thorough analysis of the current literature, spotting trends and themes, and emphasizing potential topics for further research, this review aims to close this gap.

Relevant literatures were reviewed through bibliographical databases such as Google Scholar, PubMed, Medline, Emerald Insight and Research Gate. By analysing the main conclusions, research methods, and theoretical frameworks used, this review of the literature seeks to summarize the body of knowledge regarding the effects of artificial intelligence and digital health on the job satisfaction of physicians working in tertiary care hospitals.

## 2.2. Inclusion criteria

Carefully considered inclusion criteria were used during the literature review to make sure the earlier studies chosen for analysis were legitimate, pertinent, and in line with the goals of the study. As a result, it was guaranteed that this detail and systematic literature review offered valuable and reliable insights into the study subject. The following inclusion criteria were adopted to choosing the right literature;

1. Most relevant and related topic: How artificial intelligence and digital health influence medical doctors job satisfaction in tertiary care hospitals
2. Peer-reviewed studies,
3. Reports published during the previous 15 years
4. English-language
5. Adequate information and data,
6. Research that is not heavily biased,
7. Research employing a quantitative approach,
8. Research with a sample size of over 100.

### 2.3. Clear organizing theme - Literatures reviewed

With the above inclusion criteria, the following literatures were reviewed for this study.

One of the most relevant research studies identified in this area was conducted by Zaresani and Scott (2020) as a cross-sectional study in clinical practice settings in Australia to investigate the relationships between physicians' usage of digital health technologies and their job satisfaction and work-life balance. Study samples of this research were doctors practicing in hospitals in both the public and private sectors. To investigate the relationship between using digital health technology and the likelihood of having high job satisfaction and a healthy work-life balance, a cross-sectional nationally representative survey of physicians and probit regression models were utilized. Instrumental variable analysis was used to control for bias from unobservable confounders and reverse causality. Models included a rich set of covariates, including the personality traits of doctors. This study offered fresh data on the ways in which physicians' usage of digital health technology enhances their work-life balance and job satisfaction. It made use of distinctive and detailed data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey, as well as characteristics of doctors. Reverse causality problems and unobserved confounding variables were taken into consideration using instrumental variables. This Cross-sectional survey results necessitate careful interpretation because there may be additional unobserved factors that were not taken into account. This study offered fresh, pertinent data regarding the relationship between physician job satisfaction and work-life balance and the use of digital health technology. This study recommends that physician education initiatives that aim to promote use of digital health should emphasize convincing them of the advantages of using digital health technology and assuring adequate IT support. However, the results imply that for physicians who employed digital health technology, it was more of a work resource than a work demand.

Emani et al (2022) carried out research on the viability and effectiveness of incorporating AI systems into actual clinical practice, particularly from the viewpoints of clinicians who utilize such technologies. This study examines how doctors feel about Watson for Oncology, an AI tool utilized in a variety of settings to treat cancer, as well as how satisfied they are with it. This research also aims to show how AI can be both helpful and problematic for cancer management internationally, especially for low-middle income nations, by focusing on the development of an AI-based clinical decision support system for oncology. Also, this study emphasizes the need for additional user experience research and the distinctive social, cultural, and political obstacles that must be overcome for AI to be successfully used to the treatment of cancer in low- and middle-income nations. It is obvious from this study that if cancer specialist doctors practicing in low- and middle-income countries need to be convinced with the usage of AI they require all the extra assistance they can get for user support. The use of AI tools, like WfO, in various settings has shown that having access to a clinical decision support system resource for a second opinion, concise scientific evidence, and global clinical guidelines can help doctors feel more confident in their ultimate treatment decisions. The outcome of this study shows that experiences and happiness of doctors who use these tools, especially those in Low and Middle income Countries, must be examined in greater detail in order to increase the therapeutic utility of AI tools like WfO. These viewpoints are especially crucial for shaping AI systems for use in actual clinical contexts . Naturally, these viewpoints are influenced by the local social, cultural, and political LMIC contexts in which AI is used and by the ways in which local circumstances might influence how AI is used. This research demonstrates that we are acquiring expertise in the application of AI tools, such WfO, in actual cancer therapy situations and reveals that there are several issues that need to be resolved in the "final mile" of implementation of AI in healthcare, particularly those pertaining to local contexts.

A comprehensive review was undertaken by Nguyen et al (2020) to determine the causes and remedies for the effects of electronic health records on physicians' wellbeing. The two goals of this research are to identify intriguing possible EHR advancements that have been suggested by physicians and to examine the multilevel organizational, physician, and information technology (IT) elements connected to EHR-related consequences on physician well-being and burnout. In order to help health system executives, policy makers and EHR suppliers improve professional wellbeing, this review highlights the current body of research on predictors of and potential remedies for EHR-related physician burnout. This study suggests that a number of intricate aspects play a role in physicians' well-being in relation to EHRs. These included overall EHR time, after-hours EHR time, on-site EHR support, perceived EHR usability, in-basket burden, and documentation burden. This analysis demonstrates that most of the doctors using Digital Health are having suggestions for changes to technology, organizational policies, and government legislation. From this review it can be understood that future studies should evaluate multifaceted strategies that target these characteristics, according to this review's recommendation. Additionally, it can be recommended that in order to ensure compatibility with physician requirements and clinical processes, physicians who are the modifications' key stakeholders should be involved in developing and implementing them.

Kissi et al. (2019) used the technology acceptance model (TAM) to assess doctors' satisfaction with the adoption and use of digital health products like telemedicine services. Data was gathered from participants in four distinct government health facilities using a standardized questionnaire based on the notion of technology acceptance model. Healthcare experts from a range of medical specialties were chosen using convenience and purposeful sampling strategies. The data was analyzed using structural equation modeling. Physicians' behavioral intentions were found to be influenced by their perceptions of the telemedicine services' value and convenience of use. Physician satisfaction with telemedicine services increased as a result, as did efficiency and the quality of services and patient care delivered. According to this study, the degree to which doctors and patients are satisfied with digital health products like telemedicine services is a determining factor in their adoption in clinical settings. By determining the critical predictive elements influencing physicians' satisfaction with telemedicine services, the study advances empirical knowledge.

A conceptual framework for assessing doctors' satisfaction with telemedicine services was created for this study. Additionally, among other ideas, prior research on technology acceptance demonstrated that TAM is a perfect model for assessing consumers' acceptance of technology in healthcare contexts. Physician satisfaction with telemedicine services was found to be positively correlated with behavioral intention, perceived usefulness, and ease of use. Once more, the study revealed that physician Behavioral intention is a crucial component in the adoption of telemedicine services, and that perceived usefulness and perceived ease of use are predicted factors in telemedicine service acceptance. Physician satisfaction with the use of telemedicine services is significantly influenced by these prognostic factors. After reading this study, it is clear that more user dimensions should be added to the model and that policies that actively maintain these predictive factors should be developed for future research on doctors' satisfaction with digital technologies like telemedicine services.

A study by Shanafelt et al. (2016) assessed the relationships among burnout, clerical stress, and the electronic environment among US physicians. Between August and October 2014, a survey of physicians in the United States was conducted in all disciplines. Physicians gave information about using computerized physician order entry (CPOE), electronic patient portals, and electronic health records (EHRs). Validated metrics were used to measure burnout. It is clear from the study's findings that 5389 (84.5%) of the 6375 responding doctors who were actively practicing said they used electronic health records.

4858 (82.5%) of the 5892 doctors who said CPOE was pertinent to their specialty reported using it. According to univariate analysis, physicians who used CPOE and EHRs reported higher burnout rates and were less satisfied with the amount of time spent on administrative duties. After controlling for age, sex, specialty, practice setting, and weekly hours worked, doctors who used EHRs (odds ratio [OR]=0.67; 95% CI, 0.57-0.79; P<.001) or CPOE (OR=0.72; 95% CI, 0.62-0.84; P<.001) were less likely to be satisfied with the amount of time spent on clerical tasks, according to multivariable analysis.

After controlling for these same characteristics, using CPOE was similarly linked to an increased risk of burnout (OR=1.29; 95% CI, 1.12-1.48; P<.001). In adjusted models that controlled for CPOE and other variables, burnout was not linked to the use of EHRs. Nonetheless, doctors' satisfaction with their CPOE and EHRs was typically low in this sizable nationwide study. Physicians who used CPOE and EHRs were more likely to experience professional burnout and were less happy with the amount of time spent on clerical task and administrative duties.

Given the numerous unfavourable effects of physician burnout, such as a detrimental effect on patient care delivery and career satisfaction, Cook et al. (2018) investigated whether electronic health records (EHRs) could hasten physician burnout by increasing physician workload. In order to evaluate physician stress and satisfaction related to EHR, a nationwide survey of adult congenital heart disease (ACHD) physicians was carried out. Using the Adult Congenital Heart Association directory, they conducted a survey on physician burnout.

The Maslach Burnout Inventory (MBI) was used to quantify burnout in order to better understand the elements that lead to EHR satisfaction and work-life balance. Between February and April of 2017, 383 physicians were given the survey. All answers were anonymous, and participation was entirely voluntary. For statistical analysis, the Wilcoxon Rank Sum and chi-square tests were employed. Results: 110 (28.7%) of the 383 invited physicians filled out the surveys; most of them (n=88, 80.7%) reported working for an academic medical institution. Those with high scores on the MBI subscales measuring emotional weariness and/or depersonalization were considered to be burned out.

There was significant disagreement regarding the amount of time spent on clerical chores linked to direct ($p=0.0043$) or indirect ($p=0.0004$) patient care when comparing the 40% ($n=44$) who fulfilled burnout criteria with those who did not. Additionally, there was substantial disagreement about whether the patient portal or EHRs enhanced patient care ($p=0.0215$) or efficiency ($p=0.006$). Finally, individuals who satisfied the burnout criteria scored lower on personal accomplishments ($\chi 2=6.6759$, $p=0.0355$).

The findings imply that the amount of time spent using EHRs leads to clerical strain, which in turn aggravates physician burnout. By diverting attention away from the doctor-patient relationship, doctors' high levels of emotional weariness and depersonalization may lower the overall quality of patient care. It is also clear from this study that further research is necessary to determine the extent of burnout directly related to EHR in patient care and how it can impact doctors' general work-life balance.

In a most recent study in 2023, Virtanen et al. investigated the relationships between physicians' workplace stress and the quantity of digital work they do and how they perceive changes in their jobs as a result of digitalization. For these correlations, the moderating effect of work experience duration was examined. This study made use of representative survey data from 2021 regarding the experiences of Finnish physicians ($N = 4271$) with digitalization. Perceptions of statements on work transformations in line with digitalization objectives, as well as the degree to which information systems and teleconsultations were used, were among the independent factors.

The dependent variables were psychological stress, time pressure, and stress related to information systems (SRIS). As can be observed, multivariable linear and logistic regressions were used in this study to analyze the associations. On a scale of 1 to 5, respondents' mean SRIS score was 3.5, and their mean time pressure score was 3.7, according to the data. Sixty percent reported experiencing psychological stress. Disagreements with claims that digitalization speeds up clinical interactions (b =.23 [95% CI:.16–.30]), makes patient information easier to obtain (b =.15 [.07–.23]), and aids in decision-making (b =.11 [.05–.18]) were among the perceptions linked to greater SRIS.

Opinions linked to increased time pressure included disagreement with quicker clinical encounters (b =.12 [.04–.20]), agreement with patients' more active engagement in care (b =.11 [.04–.19]), and agreement with interprofessional collaboration (b =.10 [.02–.18]). Higher psychological stress was linked to disagreement with supported decision-making (OR = 1.26 [1.06–1.48]) and agreement with patients' active role (OR = 1.19 [1.02–1.40]). On the other hand, occupational stress seems to be reduced by the perception of increases in the speed of clinical interactions and access to patient data. Furthermore, there was a continuous correlation between increased strain and extensive digital labour.

When we analyse the results of this study, we can see that respondent with less than six years of work experience and those who conducted teleconsultations routinely expressed the highest levels of time pressure. Frequent teleconsultations and work that falls short of digitalization targets appear to be taxing doctors. It can be vital for the wellbeing of doctors to increase their job satisfaction with digitalization by providing training tailored to their career stage and system development. It is understood form this study that planning and allocating time for digital work can help to avoid stress associated with reaching the objectives of digitalization.

A study by Elder et al. (2010) sought to determine the relationship between career satisfaction among primary care physicians (PCPs) and specialty physicians and health information technology (HIT). They used the Community Tracking Study Physician Survey, 2004–2005, to conduct a retrospective, cross-sectional examination of physician career satisfaction. Multivariate logistic regression was used to analyze nine distinct forms of HIT as well as the general uptake of HIT in the practice. The findings indicated that doctors who employed seven to nine (OR = 1.47) or five to six (odds ratio [OR] = 1.46) categories of HIT were more likely to be "very satisfied" with their professions than doctors who employed zero to two types of HIT.

Career satisfaction was positively correlated with the use of information technology for emailing patients (OR = 1.35) and corresponding with other doctors (OR = 1.31). The likelihood of professional satisfaction was lower for PCPs who used technology to write prescriptions (OR = 0.67) and for specialists who used technology to write notes (OR = 0.75). The study found that the largest positive indicator of doctors being extremely satisfied with their work was using more information technology. It is clear from this study that healthcare organizations and practitioners should think about investigating how to incorporate different types of HIT into practice.

A research by Srinivan M. et al. (2025) evaluated the UC Davis Health System's shift to digital radiology. Physician satisfaction surveys, workflow and cost evaluations conducted before and after PACS, and self-recorded radiological encounters by on-call residents were also part of the study. The study's findings were noteworthy. Physicians were unsatisfied with radiological services prior to the PACS installation and spent one to three hours every day looking for films. Following deployment, pictures were easily accessible, and doctors reported feeling more satisfied and were more willing to study and analyze photographs themselves. Residents saw studies with radiologists 90.2 percent less frequently as a result of real-time reporting. From 16 to 2 minutes, the average image search time was reduced, saving 21.5 physician years and $1,034,150 yearly.

Film printing (73.4%) and file clerk full-time equivalents (50.3%) were reduced, resulting in an annual savings of $1,001,452 and the release of 2,018,320 square feet of hospital and 8,108 warehouse space. The digital radiology system at UCDHS therefore enhanced clinician workflow and satisfaction, raised clinician image viewing, and reduced clinician interaction with radiologists. Implementing the system saved $2 million a year and 21 physician years.

Conducting a thorough analysis of existing literature is very crucial to identifying potential research gaps. By scrutinizing available data, researchers can unveil underlying patterns, trends, and disparities that could signify untapped areas for further exploration and conduct further researches. In the context of this study, an identified research gap is the scarcity of empirical studies focusing on the unique challenges and opportunities encountered by doctors working in private tertiary care hospitals in the state of Kerala specifically concerning the adoption of digital health and AI technologies. In general, while there has been considerable research devoted to examining how digital health technologies impact the job satisfaction of doctors, a notable gap emerges in the specific investigation of how digital health and artificial intelligence (AI) affect physicians' job satisfaction within the context of private tertiary care hospitals in a developing country like India. Prior studies have predominantly concentrated on AI and digital health applications in Western countries and other countries, with limited attention paid to India. Furthermore, private tertiary care hospitals have largely been understudied in the existing literature compared to other types of healthcare facilities, highlighting the need for more comprehensive exploration in this specific setting. It is crucial to address this gap to enhance our understanding of how digital health tools and AI impact job satisfaction among physicians in private tertiary care hospitals in the state of Kerala, ultimately contributing to the improvement of healthcare practices and the well-being of doctors in the region.

Furthermore, it is noteworthy to highlight that in previous research endeavors, there has been a predominant focus dedicated to the isolated examination of specific health technologies, such as Electronic Health Records (EHR), Telemedicine, and Artificial Intelligence (AI). In contrast, the primary objective of this present study is to present a comprehensive and holistic analysis that transcends these individual silos. To achieve this, this study has strategically targeted doctors with a wealth of experience exceeding five years within the realm of private tertiary care hospitals. These selected doctors have established a habitual usage pattern, engaging with a minimum of three distinct digital health applications on a weekly basis. This meticulous selection process not only ensures a diverse pool of participants but also lays the foundation for a more meticulous investigation into the integration of digital health solutions within the medical landscape. By focusing on individuals who possess a considerable tenure in the field, the study aims to tap into the nuanced insights and perspectives that stem from prolonged interaction with digital health tools. Noteworthy is the acknowledgment of the inherent challenges and initial hurdles encountered by physicians when embracing novel technologies. It is with this awareness that the study aims to dissect and comprehend the intricate web of transitions that occur as doctors navigate the landscape of adopting new technologies.

By deliberately pinpointing and engaging with experienced doctors who have weathered the storm of technological assimilation, the study architects a channel for extracting enriched and more profound insights. This tailored approach not only amplifies the clarity of the findings but also sets the stage for a robust and well-rounded exploration of the complexities that underpin the amalgamation of digital health technologies within the professional realm of seasoned physicians.

Numerous studies have delved into the intricate relationship between digital health technologies and the often-elusive concept of job satisfaction. Despite this extensive exploration, there remains a notable gap in research focusing on this dynamic within the distinctive healthcare landscape of Kerala. This scenic state, nestled in the serene southwest of India, presents an intriguing backdrop where the adoption of digital technologies is steadily rising while concurrently being juxtaposed against the backdrop of considerable work stress experienced by the dedicated cadre of doctors who serve the populous with unwavering dedication.

Moreover, the multifaceted interplay of variables such as age and gender while acknowledged in other contexts, stands as an untouched frontier within the specific realm of private tertiary care hospitals in the district of Thiruvananthapuram. Consequently, the nuanced analysis of how these factors intersect and potentially influence the delicate equilibrium of job satisfaction among healthcare professionals in this region remains a compelling avenue for further exploration and scholarly scrutiny. By unravelling these intricate webs of influence, we can garner crucial insights into enhancing the well-being and professional fulfilment of those at the forefront of healthcare delivery in the captivating domain of Kerala's healthcare landscape

In the existing body of literature, a notable gap persists concerning the investigation of the correlation between the socio-economic background of medical practitioners and their levels of job satisfaction. This current research endeavour, therefore, stands poised to rectify this void by meticulously formulating pertinent questions and extracting invaluable insights from survey participants. Methodologically, the study aims to leverage the utility of both descriptive statistics and inferential analysis to unravel key trends and patterns. Moreover, a recurrent issue in prior studies revolves around the handling of redundant responses in assessing job satisfaction, as maintaining data integrity is of paramount importance. Recognizing this limitation, the present study is intent on streamlining the process by implementing effective statistical techniques to streamline data while safeguarding the integrity of the core findings. Through this approach, the research endeavours to bridge the existing gaps and contribute meaningfully to the literature on this vital subject matter.

While earlier studies extensively utilized models such as the probit model and structural equation model, the researcher has determined that the binomial logit model stands out as particularly well-suited to the unique nature and objectives of this specific study. This choice is driven by several key factors, including the model's widespread acceptance within the academic community, its ease of interpretation, and its direct relevance to the policy recommendations that will be drawn from the study's findings. The existing facilities under study present a critical context for the application of the binomial logit model, as the study aims to enhance their practical utility and effectiveness within the healthcare framework.

By adopting the binomial logit model, the researcher aims to ensure that the study's outcomes are not only robust and reliable but also directly actionable and comprehensible for the stakeholders involved, such as healthcare administrators and policymakers. This strategic approach is grounded in a commitment to making the study's results accessible and relevant to those who hold decision-making authority in the healthcare sector. Through the lens of the binomial logit model, the researcher anticipates generating insights that can drive meaningful improvements in the operational strategies and policy frameworks governing the existing facilities.

Moreover, the emphasis on increasing the applicability of the study's findings underscores a proactive effort to bridge the gap between theoretical insights and practical implications. By aligning the analytical framework with the specific context of the study, the researcher sets the stage for translating quantitative data into actionable strategies that can directly inform decision-making processes. This alignment not only enhances the overall relevance of the study but also reinforces its potential to drive positive change within the healthcare landscape.

In essence, the choice of the binomial logit model as the primary analytical tool reflects a deliberate strategy to maximize the study's impact and relevance within the broader healthcare community. By focusing on the interpretability, applicability, and policy implications of the model, the researcher paves the way for a comprehensive and actionable analysis that can resonate with key stakeholders and drive tangible improvements in healthcare administration and policymaking.

The identified gaps in the existing research not only underscore the critical importance of recognizing and addressing understudied areas but also emphasize the invaluable contributions that come from delving into unexplored territories. These gaps serve as beacons guiding research endeavors towards the forefront of knowledge within a particular domain, enriching the discourse with innovative perspectives and profound insights that were previously obscured. The significance of meticulously filling these gaps extends beyond theoretical advancements, delving into the realm of practical problem-solving and the refinement of current methodologies. By bridging these voids in knowledge, researchers pave the way for transformative breakthroughs and a deeper understanding that transcends conventional boundaries.

Furthermore, the profound impact that results from the diligent pursuit of research initiatives aimed at bridging disparate fields of study extends well beyond the confines of academic circles, reverberating throughout the domain of policymaking and the formulation of strategic decisions. Research endeavors that actively involve the connection of these fragmented areas assume a pivotal role in shaping policies that are anchored in evidence, thereby guiding stakeholders towards more knowledgeable and effective strategies. As researchers navigate the landscape of these unexplored territories, each instance of bridging a gap not only represents a crucial step forward in the quest for knowledge but also serves as a beacon of progress for society as a whole. This journey towards filling research lacunae not only signifies intellectual maturation but also embodies the collective endeavor towards advancing knowledge and fostering meaningful societal change, with each gap closed drawing us closer to a future built on solid empirical foundations and informed decision-making.

The rapid progress of digital health and artificial intelligence (AI) technologies in private tertiary care hospitals in Kerala has significantly transformed the healthcare landscape. As these advancements continue to revolutionize the way medical services are delivered, one key area that warrants further exploration is the impact of these technologies on job satisfaction among doctors. By delving deeper into this aspect, we aim to shed light on the relationship between the adoption of digital health and AI and the overall job satisfaction levels of doctors working in private tertiary care hospitals in Thiruvananthapuram district, Kerala.

By addressing this particular research gap, the study aspires to provide a deeper understanding of the multifaceted factors influencing job satisfaction among doctors in this specific setting, contributing to a more nuanced comprehension of the dynamics at play. This study seek to address some pivotal research questions that will help us better understand the dynamics at play. Firstly, this study aims to investigate whether the usage of digital health and AI technologies directly contributes towards enhancing the job satisfaction of doctors in private tertiary care hospitals in Thiruvananthapuram district in Kerala. Additionally, this study explores how factors such as the age of doctors may influence their adoption and utilization of these innovative tools. Furthermore, this study will examine whether gender plays a role in determining the extent to which doctors engage with digital health and AI solutions within their professional practice.

By exploring these research questions in depth, it is hoped to provide valuable insights into how the usage of digital health and AI technologies impacts the job satisfaction of doctors, thereby paving the way for future advancements and improvements in healthcare delivery within private tertiary care hospitals in Thiruvananthapuram district, Kerala, India.

## 2.4. Summary of Literature review

The comprehensive literature review delves into the intricate and diverse ways in which AI and digital health technologies influence the job satisfaction of doctors. Among the studies reviewed, a spectrum of effects emerges, ranging from positive outcomes that enhance job satisfaction to negative impacts that include technostress and burnout. Interestingly, there is a subset of studies that view these technologies through a more neutral lens, perceiving them as resources rather than imposing demands on healthcare professionals. The overall assessment of job satisfaction resulting from the integration of digital health and AI tools showcases a wide range of perspectives, with varying degrees of scale and significance across different research findings. In essence, the research landscape elucidates a nuanced interplay between technology adoption and its repercussions on doctors' job satisfaction levels.

In analyzing the research gap, numerous deficiencies have come to light. Firstly, there is a glaring absence of literature concentrating on doctors within tertiary care hospitals who utilize various digital health technologies concurrently. This lacuna extends to the dearth of similar studies conducted in the specific context of India, with a particular focus on regions like Kerala. Notably, the absence of an in-depth empirical investigation involving doctors having over five years of expertise in tertiary care settings and utilizing more than three digital health applications has been glaring. Moreover, upon closer examination, it becomes apparent that the data collection instrument employed in previous research could be further refined to ensure simplicity and effectiveness. Improving the questionnaire's design will not only streamline data collection but also yield more comprehensive information. Additionally, there is a recognized need to simplify the analysis process of past research endeavors to enhance ease for medical professionals working within the healthcare industry. By refining methodologies and enhancing clarity in the analytical approach, the research findings can be more readily understood and applied by physicians actively involved in healthcare provision.

In light of the various factors taken into consideration, the research questions developed for this study revolve around the impact of digital health and artificial intelligence (AI) on the job satisfaction of doctors working in private tertiary care hospitals in Thiruvananthapuram district, Kerala, India. The first question investigates whether the utilization of digital health and AI tools contributes significantly to the job satisfaction levels of these medical professionals. The second research query delves into the potential correlation between the age of doctors and their adoption of digital health and AI technologies. Lastly, the third question explores whether there is a noticeable difference in the usage of digital health and AI based on the gender of the doctors. These research questions aim to provide valuable insights into the factors influencing the integration of technology in healthcare settings and its implications on the well-being and efficiency of medical practitioners in the specified region.

# CHAPTER 3

# METHODOLOGY

## 3.1. Introduction

This chapter describes the research methods used to assess the impact of Digital health and AI on job satisfaction of doctors working in private tertiary care hospitals in Trivandrum district, Kerala, India.

The research methodology adopted provides a systematic and structured approach to data collection and analysis, ensuring that the study's objectives are met. This chapter discusses the research design, sampling strategy, data gathering methods, and data analysis methodologies adopted in the study.

In order to improve strategies for motivating the work environment of doctors, the research systematically investigates and analyses the impact of digital health and artificial intelligence on job satisfaction of doctors in tertiary care hospitals in Thiruvananthapuram district in Kerala.

Also, the makers of AI and digital health products will gain inspiration from this to create items that influence doctors' daily routines and ultimately enhance the working environment. Accordingly, this research study aims to find out

(i) Whether the usage of digital health and AI contributes towards job satisfaction of doctors working in private tertiary care hospitals in Thiruvananthapuram district in Kerala, India

(ii) Whether age of doctors influences the usage of Digital Health/AI

(iii) Whether gender of doctor influence the usage of Digital Health and Artificial intelligence

The scope of the research is confined to allopathic doctors working for more than five years in private tertiary care hospitals in Thiruvananthapuram district in Kerala.

## 3.2. Research Design

As per the information gathered from the Health and Family Welfare Department, Govt of Kerala/ Local Authorities, presently there are 5 private tertiary care hospitals in Thiruvananthapuram district in Kerala. This research was done using a cross-sectional study design and was conducted in these five tertiary care hospitals. According to the Two-Factor Theory of job satisfaction, job satisfaction is a multidimensional phenomenon and it is composed of many intrinsic and extrinsic factors. The intrinsic factors include things like type of work they do, the tasks that make up the job, task significance, task identity, personal fulfilment, passion etc and extrinsic factors include salary, monetary incentives, recognition, status, job security, career prospects, fringe benefits, work life balance, leadership style, coworkers etc. The primary aim of this research was to investigate the utilization of Digital health and Artificial intelligence among doctors and its impact on their job satisfaction levels. A methodical approach was taken, with a focus on realistic sampling techniques and the selection of suitable statistical tools to evaluate the research hypothesis. The analysis involved hypothesis testing and regression modelling to determine the relationship between the use of Digital health and Artificial intelligence in healthcare and doctors' job satisfaction. By employing these statistical methods, the study was able to draw meaningful conclusions regarding the factors influencing doctors' satisfaction with their work. It was believed that the findings shed light on the potential benefits of integrating digital technologies into medical practices and the implications for enhancing overall job satisfaction among medical professionals.

### 3.3. Population and Sample

Population considered for the study: The selection of a tertiary care hospital for the research study is based on a comprehensive analysis of various factors. One crucial consideration is that tertiary hospitals specialize in handling complex and intricate cases, which often require a higher level of expertise and advanced medical interventions. Consequently, the stress levels experienced by doctors working in private tertiary care institutions are notably elevated compared to those in other healthcare settings.

Private tertiary care facilities distinguish themselves from public hospitals by their strong emphasis on maximizing efficiency and embracing technological advancements in healthcare delivery. This drive for efficiency is largely fueled by the constant quest to enhance patient outcomes and elevate the overall quality of care provided. By incorporating digital health technologies and artificial intelligence solutions into their practice, private tertiary care hospitals not only streamline processes but also empower patients to take a more active role in managing their health.

The increasing prevalence of digital health technologies and artificial intelligence in tertiary care settings reflects a broader trend within the healthcare industry. These innovative solutions are not only cost-effective but also significantly enhance the overall effectiveness of patient care. Moreover, they play a crucial role in fostering improved communication between patients and healthcare providers, ultimately leading to more informed decision-making and better healthcare outcomes for all involved.

As per the information gathered from Health and Family Welfare Department, Govt of Kerala/ Local Authorities there are about 5 tertiary hospitals in the district which employ a total of 700 doctors who constituted the population for the present study.

Sample size: Accordingly, a total of 700 doctors employed at private tertiary hospitals within the Thiruvananthapuram district were considered as population for this study. Subsequently, a representative sample of 200 doctors from five select tertiary hospitals was chosen using a convenience sampling approach. This sampling method was based on various predetermined criteria. Firstly, the selected doctors had to be practitioners of the allopathic system of medicine, ensuring homogeneity within the sample. Additionally, these doctors were required to possess a minimum work experience of more than five years, reflecting a certain level of expertise and knowledge in their respective fields. Furthermore, another essential criterion stipulated that the doctors had actively used at least three digital health applications in their daily healthcare practices, showcasing a proclivity towards technological integration in their clinical routines. Finally, the doctors included in the study had to voluntarily agree to participate, ensuring the absence of any external pressures. By meticulously delineating these selection criteria, the study aimed to create a cohesive and representative sample reflective of experienced and tech-savvy medical professionals dedicated to advancing healthcare with digital solutions.

## 3.4. Data collection and Instrumentation

### 3.4.1. Data collection

In selecting the method for drawing samples for the study, convenience sampling was deemed the most suitable due to the unique circumstances present in tertiary care hospitals. Typically, doctors in these hospitals are heavily burdened with demanding schedules and the unpredictable nature of their working environment. This makes it challenging and time-consuming to gather their responses through random sampling which is a probability sampling method.

Therefore, the researcher made a deliberate choice to employ convenience sampling to optimize the collection process and ensure a timely and efficient outcome. By focusing on the willingness of the respondent doctors to participate and their accessibility, the researcher was able to streamline the sampling process and engage with those individuals who could readily contribute valuable insights to the study. Consequently, this approach not only facilitated data collection but also enhanced the overall quality and reliability of the research findings by engaging with doctors who were more willing and accessible for participation.

During the trial phase of the study, it was observed that a significant portion of the participants harboured apprehensions about divulging information pertaining to their workplace environment. This highlighted the importance of ensuring the confidentiality of the data collected. One of the key steps taken to address this concern was the implementation of a robust system that guaranteed anonymity for all participants who took part in the survey.

By safeguarding the confidentiality and privacy of the participants, it was able to create a safe space where individuals felt secure in sharing their insights and experiences. This was achieved by removing any personal identifying information from the questionnaires, thereby upholding the integrity of the study and protecting sensitive data against potential breaches. In addition to fostering trust and confidence among the participants, this meticulous approach also underscored our commitment to upholding ethical standards in research and maintaining the highest level of integrity throughout the entire process.

Questionnaires aimed at gathering valuable insights were meticulously prepared and distributed to a cohort of 200 doctors through various channels, including social networks and email correspondence. Evidently, the response rate from the medical professionals were significant, with a total of 120 doctors actively engaging with the surveys. Further scrutiny revealed that, among the responders, a select group of 110 doctors successfully met the predefined selection criteria, signifying the quality and relevance of the obtained data. It is noteworthy that this detailed data collection process spanned over an extensive timeframe, encompassing a thorough observation period spanning four months from August 2024 to November 2024, ensuring a comprehensive and robust dataset for analysis and interpretation.

### 3.4.2. Survey Instrumentation

The researcher researched from previous similar studies to find an ideal instrument for collecting data from doctors. For this research, the researcher used a modified version of the Technology Acceptance Model (TAM) questionnaire, which proved to be an ideal tool for gathering data from doctors. To make this instrument better suited for this research, some modifications were made. The TAM questionnaire typically makes predictions about a user's future propensity to utilize a product. Ratings of likelihood are used in the questionnaire. There are seven response alternatives in the original TAM format, with "Likely" on the left and "Unlikely" on the right. To make it simpler for doctors and to make it more suitable for this study, this was modified with five options in ascending order from Strongly agree to Strongly disagree. The modified version of the Technology Acceptance Model (TAM) questionnaire questions covered 15 questions under 4 sections

(i) Perceived Use

(ii) Perceived ease of use

(iii) User Acceptance and

(iv) User Recommendation.

| MODIFIED VERSION of TECHNOLOGY ACCEPTANCE MODEL QUESTIONNAIRE | |
|---|---|
| | **PERCIEVED USE** |
| 1 | Using Digital Health and Artificial Intelligence technologies at work helps me to accomplish tasks more quickly |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 2 | Using Digital Health and Artificial Intelligence technologies improves my work performance |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 3 | Using Digital Health and Artificial Intelligence technologies increases my work productivity |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 4 | Using Digital Health and Artificial Intelligence technologies enhances my effectiveness at work |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 5 | Using Digital Health and Artificial Intelligence technologies makes it easier to do my work |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 6 | Using Digital Health and Artificial Intelligence technologies is useful in my work |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| | **PERCEIVED EASE OF USE** |
| 1 | Learning to operate the Digital Health and Artificial Intelligence technologies has been easy for me |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 2 | I find it easy to get the Digital Health and Artificial Intelligence technologies to do what I want it to do |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 3 | My interaction with Digital Health and Artificial Intelligence technologies is clear and understandable |

| | |
|---|---|
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 4 | I find Digital Health and Artificial Intelligence technologies to be flexible to interact with |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 5 | It is easy for me to become skilful at using Digital Health and Artificial Intelligence technologies |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 6 | I find the Digital Health and Artificial Intelligence technologies easy to use |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| | **USER ACCEPTANCE (UA)** |
| 1 | I use Digital Health and Artificial Intelligence technologies very frequently (many times per week) |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| 2 | I use Digital Health and Artificial Intelligence technologies for a variety of purposes (clinical notes, reports, medical info, etc.) |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |
| | **USER RECOMMENDATION** |
| 1 | Considering your experience in using Digital Health and Artificial Intelligence technologies, how likely are you to recommend this to your friend or colleague? |
| | (i) Strongly Agree (ii) Agree (iii) Neutral ( iv ) Disagree ( v) strongly disagree |

To measure doctors' propensity to advocate for Digital Health and AI technologies, serving as a proxy for happiness a question was added mentioning how likely would they recommend these technologies to other similar professionals under user recommendation.

A theory of information systems serves as the foundation for the technology acceptance model (TAM), which simulates how people adopt and utilize new technologies. As per TAM, the adoption of technical innovation is contingent upon an individual's attitude towards its usage, which is predicated on two beliefs: perceived usefulness (PU) and perceived ease of use (PEU). In the realm of information systems, the TAM model is a commonly utilized theoretical model. It has been employed in numerous studies including studies on the level of acceptance of digital health technologies among medical professionals. (Al-Adwan and Berger, 2015).

Because the Technology Acceptance Model (TAM) questionnaire is a popular instrument for evaluating consumers' adoption and use of technology, the researcher chose to utilize it. Construct validity, or the degree to which the TAM questionnaire assesses the theoretical constructs it is intended to measure, has been thoroughly examined. The TAM questionnaire has strong construct validity, according to numerous studies. A measure of internal consistency that shows how well the questionnaire's items connect to one another is the Cronbach's alpha coefficient. High Cronbach's alpha values for the TAM questionnaire have been recorded in studies, suggesting that it has good internal consistency. Convergent validity, or the degree to which the TAM measures the same constructs as other comparable questionnaires, has been demonstrated to be good. The TAM survey sheds light on the variables influencing users' adoption and use of technology. ( Gagnon, MP et al 2012 ).

Understanding how to encourage technology adoption and enhance user experience is essential for organizations. Organizations may create more user-friendly and user-friendly technologies by knowing the elements that affect technology adoption. Organizations can detect potential obstacles to technology adoption by using the TAM questionnaire to anticipate users' intention to use technology. The TAM questionnaire can be used to compare how different groups like age, gender, or occupation accept technology. Technology implementation tactics can be informed by the TAM questionnaire's insights on the elements that impact technology acceptance.

Although the TAM questionnaire's limitations were carefully considered before reaching a final decision, it was acknowledged that the questionnaire primarily focuses on the individual's viewpoint, neglecting critical organizational and environmental factors that could influence the adoption of technology. Despite occasional adjustments, the TAM questionnaire fundamentally operates under the assumption that consumers' attitudes and intentions serve as the primary catalysts for technological adoption. Nevertheless, given its widespread use and reliability, the TAM questionnaire remains a favoured tool for assessing user acceptance and utilization of technology. Despite its limitations, it was deemed pertinent for this study due to its effectiveness in understanding technology uptake and informing implementation strategies.

In addition to the examination of job satisfaction responses, comprising 15 proxy variables as previously described, the study also encompassed an assessment of doctors' profiles concerning both their gender and age. This holistic approach sought to provide a comprehensive understanding of how these factors interplay with technological adoption behaviour within healthcare settings, enhancing the overall robustness and depth of the research findings.

### 3.5. Data Analysis Procedures

The collected data underwent a thorough analysis by utilizing a range of appropriate statistical tools and quantitative techniques. Both descriptive statistics, aiming to provide a comprehensive overview of the data, and inferential statistics, serving to draw meaningful conclusions and predictions beyond the data sample, were skilfully employed to extract vital inputs for the study. In terms of descriptive statistics, the analysis encompassed a detailed examination of the respondents' profiles, their perspectives on job satisfaction, and the presentation of findings through well-crafted tables, graphs, and charts. Additionally, inferential statistics played a crucial role by focusing on hypothesis testing and regression modelling.

Specifically, for hypothesis testing, various socio-economic characteristics of the respondents were carefully selected as explanatory variables and juxtaposed against the employees' responses, which included a mix of quantitative and qualitative variables to ensure a robust analysis of the data. Through these meticulous statistical analyses, the study was able to delve deep into the data, uncover patterns, relationships, and insights that greatly enriched the overall research findings.

In the conducted study, a thorough analysis was carried out using a variety of statistical tools to draw accurate conclusions and test proposed hypotheses. Initially, essential measures such as frequency tables, mean, standard deviation, and z-test were computed to provide a comprehensive overview of the data. Subsequently, advanced statistical techniques including the Chi Square test and Correlation Test were employed to further explore the relationships between variables and validate the research hypotheses. In order to streamline the analysis process, data reduction techniques were implemented, specifically Principal Component Analysis, which effectively reduced the number of variables from 15 to one. Both MS Excel and SPSS were utilized extensively for data processing and statistical analysis in the research project. The inferential statistical tools utilized played a crucial role in deriving meaningful insights and drawing reliable conclusions from the gathered data, showcasing the robust methodology adopted to ensure the accuracy and validity of the study results.

### 3.3.1 Principal component analysis

In data analysis, principal component analysis, or PCA, is used since this was essential, especially when working with big datasets that have a lot of variables. By reducing the original set of variables into a smaller set without significantly sacrificing information, PCA can be used to effectively reduce the dimensionality of such datasets. Simplifying complex data structures and improving the manageability and interpretability of the ensuing analysis require this reduction in dimensionality.

Finding the principal components from the original data requires a number of crucial phases in the PCA computation process. These procedures provide information about the computation of the primary components and their relationship to the original dataset. Gaining an understanding of this procedure is vital to understanding PCA's underlying mechanics and its capacity to identify the key patterns and variations seen in the data.

To put it simply, PCA was used in this study for data analysis because this is an effective method for more succinctly and meaningfully examining and displaying high-dimensional data. PCA helps analysts to better understand the underlying structures and relationships in the data by recognizing and keeping the most important information while eliminating less important details. Condensing complicated information into a more palatable format not only makes further analysis easier, but it also makes it easier to make better decisions using the insights that are gleaned. ( Hinton PR 2014)

All things considered, the process of using PCA in this research study highlights the value of dimensionality reduction strategies in contemporary data analysis procedures, showing how these approaches can improve the comprehension and application of sizable datasets in a variety of domains, from business intelligence to research.

(i) Step1-Standardizing the range of continuous initial variables: Since PCA can bias towards specific features, it is important to evaluate whether normalization of data is needed.

Data should reflect a normal distribution with a mean of zero and a standard deviation of one. In this step, the mean values of the variables are calculated and subtracted from the original dataset so that each variable contributes equally to the analysis. This value is then divided by the standard deviation for each variable so that all variables use the same scale.

(ii) The second step involves computing the covariance matrix to identify correlations: Covariance (cov) measures how strongly correlated two or more variables are. The covariance matrix summarizes the covariances associated with all pair combinations of the initial variables in the dataset. Computing the covariance matrix helps identify the relationships between the variables–that is, how the variables vary from the mean with respect to each other. This data matrix is a symmetric matrix, meaning the variable combinations can be represented as $d \times d$, where d is the number of dimensions. For example, for a 3-dimensional dataset, there would be $3 \times 3$ or 9 variable combinations in the covariance matrix. The sign of the variables in the matrix tells us whether combinations are correlated:

- Positive (the variables are correlated and increase or decrease at the same time)
- Negative (the variables are not correlated, meaning that one decreases while the other increases)
- Zero (the variables are not related to each other)

(iii) In the third step, the eigenvectors (principal components) and eigenvalues of the covariance matrix are computed: As eigenvectors, the principal components represent the directions of maximum variance in the data. The eigenvalues represent the amount of variance in each component. Ranking the eigenvectors by eigenvalue identifies the order of principal components.

(iv) Selecting the principal components will be forth step: Which components will have to be kept and which to be discarded will be decided in this step. Components with low eigenvalues typically will not be as significant. Scree plots usually plot the proportion of total variance explained and the cumulative proportion of variance. These metrics help one to determine the optimal number of components to retain. The point at which the Y axis of eigenvalues or total variance explained creates an "elbow" will generally indicate how many PCA components that we want to include.

(v) The fifth and last step will transform the data into the new coordinate system: Finally, the data is transformed into the new coordinate system defined by the principal components. That is, the feature vector created from the eigenvectors of the covariance matrix projects the data onto the new axes defined by the principal components. This creates new data, capturing most of the information but with fewer dimensions than the original dataset.

The data sets thus reduced to the minimum will be put through hypothesis testing and regression modeling to assess the impact of gender and age of the doctors on their job satisfaction.

### 3.3.2 Hypothesis testing

Hypothesis testing is a statement about a population which is to be tested on the basis of result obtained from a random sample. It is a statement about a population parameter evolved from a sample statistic. The hypothesis should possess the following characteristics.

(i) It should be clear and precise

(ii) It should be capable of testing

(iii) It should state relationships among variables.

For testing the hypothesis, two set of variables namely (i) explanatory variables and (ii) response variables need to be defined and categorized. An explanatory variable is a type of independent variable. When a variable is independent, it is not affected at all by any other variables.

The response variable, on the other hand, is the focus of a question in a study or experiment. An explanatory variable is one that explains changes in that variable. It can be anything that might affect the response variable. It explains the underlying phenomena of the response variables which could be either quantitative or categorical.

Variables whose values result from counting or measuring something area called quantitative variables while categorical variable is a variable that can take on one of a limited, and usually fixed, number of possible values, assigning each individual or other unit of observation to a particular group or nominal category on the basis of some qualitative property.

Various combinations of hypothesis will be tested which will include the response variables on on side and explanatory variables on the other side.

The response variable will be the job satisfaction represented by the following 15 variables grouped under four categories.

| Broad category | Sub-category | |
|---|---|---|
| 1. PERCIEVED USE of digital health and AI | 1 | Tasks accomplished quickly |
| | 2 | Work performance improved |
| | 3 | work productivity increased |
| | 4 | Work effectiveness enhanced |
| | 5 | Work made easier |
| | 6 | Work usefulness |
| 2. PERCIEVED EASE OF USE (PEU) | 1 | Learning to operate technologies is quite easy |
| | 2 | Easy to get technologies to do what I want it to do |

| | | |
|---|---|---|
| | 3 | My interaction with technologies is clear and understandable |
| | 4 | Technologies found to be flexible to interact with |
| | 5 | Becoming skilful at technologies |
| | 6 | Quite easy to use |
| 3. USER ACCEPTANCE (UA) | 1 | Frequently used |
| | 2 | Multi-purpose usage (clinical notes, reports, medical info, etc.) |
| 4. USER RECOMMENDATION | 1 | Recommending to other users |

The above response variables will be reduced to three or more representative variables based on principal component analysis. On the other hand, the following explanatory variables will be studied for the purpose of hypothesis testing.

1. Gender (male/ female)
2. Age group

### 3.3.3 Regression modeling Using SPSS Software

A binomial logit model, also commonly referred to as binary logistic regression, stands as a widely used statistical technique designed to replicate the relationship between a binary dependent variable and one or more independent variables. This method is used in this study because it is most effective when the dependent variable involves defining outcomes in terms of two distinct categories such as success or failure, yes or no, or accept or reject. Its robustness and versatility make it a favored tool across various disciplines including the social sciences, business, medicine, and education sectors. By enabling researchers to analyze and predict binary outcomes accurately, the binomial logit model plays a crucial role in generating valuable insights and driving informed decision-making processes in complex and dynamic environments.

Its application extends to scenarios where clear-cut distinctions and precise predictions become essential for understanding and influencing outcomes effectively. Furthermore, in order to ensure its validity and reliability in diverse contexts, the model allows for the inclusion of multiple independent variables, thereby enabling a comprehensive and nuanced analysis of the relationships at play. The model's significance is further underscored by its capability to provide insights into how different factors interact and influence the likelihood of specific outcomes occurring, thereby empowering researchers and practitioners alike to make informed and data-driven decisions. Overall, the binomial logit model represents a powerful and versatile statistical tool that continues to be instrumental in uncovering patterns, trends, and relationships within binary data, thereby facilitating a deeper understanding of the underlying mechanisms governing various phenomena across a wide array of fields. (Hinton, P.R, 2014).

Binomial logit model is used because this is particularly well-suited to the nature and objectives of this study. The dependent variable in this research is binary (e.g., job satisfaction: satisfied or not satisfied), and the binomial logit model is specifically designed to model the relationship between a binary outcome and multiple independent variables. The binary logit was particularly selected based on the following

The model uses a logistic function to model the probability of an event (in this case, job satisfaction) occurring, which ensures that the predicted probabilities are constrained between 0 and 1, a critical requirement for binary dependent variables. It provides coefficients that can be transformed into odds ratios, offering a clear and meaningful interpretation of the impact of independent variables (e.g., perceived ease of use, variety of purpose use etc ) on the likelihood of job satisfaction.

The logit function, a fundamental component of logistic regression, plays a crucial role in capturing complex, nonlinear connections among predictors and the log-odds of outcomes. This feature distinguishes logistic regression from simplistic linear regression models that oversimplify relationships by assuming linearity. By considering potential nonlinear patterns, the logit function enhances the modeling process, enabling practitioners to analyze data more effectively and accurately. Its flexibility helps accommodate diverse datasets with intricate interactions and dependencies among variables, allowing for a more nuanced understanding of the underlying phenomena. As a robust statistical tool, the logit function empowers researchers to delve deeper into the dynamics of their data, uncovering hidden patterns and insights that may not be detectable through traditional linear modeling approaches. Furthermore, its ability to model complex relationships contributes to the overall predictive power and reliability of logistic regression analysis, making it a valuable tool in various fields such as healthcare, finance, and social sciences where accurate predictions are crucial for decision-making and problem-solving

When evaluating different methodologies for analyzing factors influencing job satisfaction, the binomial logit model emerges as a distinct choice compared to approaches like decision tree methods, random forest methods, probabilistic modelling, and other machine learning models. The key strength of the binomial logit model lies in its focused emphasis on identifying and understanding the significance and strength of relationships between variables. This methodological preference directly aligns with the primary objective of the study, which is to uncover and analyze the various elements influencing job satisfaction levels among individuals.

Furthermore, contrasting the binomial logit model with these previously mentioned complex methods, one notable advantage that stands out in favor of the binomial logit model is its notable computational efficiency. This efficiency aspect becomes crucial given the vast amounts of data that need to be processed and interpreted in job satisfaction studies. Moreover, the simplicity and ease of implementation associated with the binomial logit model, especially when utilizing widely available software tools including SPSS, further enhance its attractiveness as a methodology choice for researchers embarking on similar studies.

Another significant point in Favor of the binomial logit model is its minimal requirement for parameter tuning compared to its more intricate counterparts. This attribute not only saves valuable time during the data analysis process but also reduces the likelihood of potential errors that may arise from intensive parameter adjustments. With the binomial logit model's strong alignment with fundamental principles of hypothesis testing and regression modelling, researchers can have increased confidence in their study's theoretical foundation and ensure the robustness of their analytical approach.

In essence, selecting the binomial logit model as the primary analytical tool for investigating job satisfaction influences offers a well-rounded method that efficiently captures the intricate relationships present within the data while maintaining a robust theoretical underpinning. This choice not only streamlines the analytical process but also enhances result interpretation and overall research outcomes.

Additionally, the decision to utilize the binomial logit model over other potential methods for analysis, like probit regression, was based on multiple factors. These included the model's widespread acceptance within the research community, its capacity for straightforward interpretation, and its direct relevance to offering policy recommendations, given the existing nature of the facilities under investigation. This choice was paramount in ensuring that the findings of the study could be effectively translated into actionable insights for stakeholders, including healthcare administrators and policymakers.

By employing the binomial logit model through the use of SPSS software, the study was able to effectively examine questionnaire survey data obtained from doctors working in private tertiary care hospitals in the Thiruvananthapuram district. The dataset was comprised of a single binary dependent variable and a set of 15 independent variables that were meticulously gathered through a structured questionnaire. The ultimate aim of this analysis was to explore the impact that the independent variables had on the probability of observing one of the two potential outcomes for the dependent variable. Through this rigorous approach, the study sought to provide valuable insights that could inform decision-making processes and enhance the overall applicability of the research findings.

The binomial logit model predicts the log-odds of the dependent variable as a linear combination of independent variables.

Mathematically, it can be expressed as:

$$\log(P / (1 - P)) = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta kXk$$

Where:

P: Probability of the dependent variable being 1.

$\beta 0$: Intercept of the model.

$\beta 1, \beta 2, \ldots, \beta k$: Coefficients of the independent variables X1, X2, …, Xk.

The probability of the dependent variable being 1 is obtained through the logistic function:

$P = 1 / (1 + e^{-(\beta 0 + \beta 1X1 + \ldots + \beta kXk)})$

The coefficients (β) represent the change in the log-odds of the dependent variable for a unit change in the corresponding independent variable. When exponentiated, these coefficients yield odds ratios, which are easier to interpret in practical terms.

Before running the binomial logit model in SPSS, the following steps are essential:

- Data Entry: Enter the survey data into SPSS. Ensure that the dependent variable is coded as 0 and 1, representing the two categories.

- Variable Types: Define all variables appropriately in the "Variable View" tab. Continuous variables should remain numeric, while categorical variables must be appropriately coded (e.g., dummy coding).

- Multicollinearity: Perform a preliminary analysis (e.g., variance inflation factor, VIF) to identify multicollinearity among independent variables, which can adversely affect model estimates.

The various steps used for modelling process through SPSS is:-

1. Accessing the Module: Navigate ` Analyze > Regression > Binary Logistic in SPSS.

2. Model Setup:

✓ Select the dependent variable from the variable list.

✓ Add the 15 independent variables to the covariates box.

✓ If categorical independent variables are present, define their reference categories through the "Categorical" button.

✓ Options: Enable options such as Hosmer-Lemeshow test and confidence intervals for odds ratios for better insights into model fit and results. If desired, include interaction terms to examine combined effects of predictors.

SPSS provides a comprehensive output with several tables and statistics. Key outputs include:

Variables in the Equation Table: Displays estimated coefficients (β), standard errors, Wald statistics, and p-values.

❖ Significance of p-values ($p < 0.05$) indicates whether an independent variable is a significant predictor.

❖ Odds Ratios ($e^\beta$) show the multiplicative change in odds for a one-unit increase in the predictor. For example, an odds ratio of 1.5 indicates a 50% increase in odds

❖ Provides measures such as -2 Log Likelihood, Cox & Snell $R^2$, and Nagelkerke $R^2$. These metrics assess the explanatory power of the model. Higher $R^2$ values indicate a better fit of the model to the data.

❖ A non-significant result ($p > 0.05$) suggests that the model fits the data well.

The advantages of the Binomial Logit Model are:-

- Flexibility: Handles both continuous and categorical predictors.
- Non-Linearity: Models non-linear relationships between predictors and the outcome through the logit transformation.
- Interpretability: Odds ratios provide an intuitive measure of predictor impact.
- Diagnostics: Offers various tools to evaluate model fit and performance.

The Limitations of the model are:-

- Linearity Assumption: Assumes a linear relationship between predictors and log-odds, which might not always hold.
- Sample Size: Requires a sufficiently large sample for stable estimates and reliable inferences.
- Multicollinearity: Strong correlations among predictors can distort coefficients.

The binomial logit model, implemented via SPSS, is a robust method for analyzing the impact of multiple independent variables on a binary dependent variable. The ability to predict probabilities, calculate odds ratios, and assess model fit makes it an invaluable tool for researchers. By leveraging SPSS's user-friendly interface and comprehensive output, researchers can derive meaningful insights, validate hypotheses, and inform decision-making processes effectively.

### 3.6 Data analysis Limitations

Although anonymity was maintained, the initial reluctance of participants to share information about their workplace may have affected the depth or honesty of responses. The modified TAM questionnaire focuses primarily on individual perspectives, potentially overlooking organizational or environmental factors influencing technology adoption and job satisfaction. The data analysis for the study has been carried using the best statistical tools which have been tested over a time period. However, limitations exist when applying the same in certain contexts. In the present study, data reduction techniques have been used to avoid repetitiveness in the responses and evolve into more cohesive form without scarifying the major data contents. This might have caused deletion of some important variables which may have otherwise relevance to the study. PCA assumes that the principal components are a linear combination of the original features. If this is not true, PCA will not give sensible results.

In the same way, hypothesis testing is prone to two types of errors namely

(i) Type I error by which a false positive, which occurs when the null hypothesis is incorrectly rejected. This means that the researcher concludes there is a significant effect when there is not.

(ii) Type II error: A false negative, which occurs when the null hypothesis is incorrectly retained. This means that the researcher misses a significant effect that is actually there.

Type I and type II errors are inversely related, meaning that when one increases, the other decreases. Type II errors are generally considered more serious than type I errors.

Binary logistic regression assumes linear relationships between predictors and log-odds, which may not fully capture the complexities of the studied variables. Here, MS Excel and SPSS were used for analysis, these tools may have limitations depending on datasets while performing advanced modelling, compared to more sophisticated statistical software.

### 3.6. Ethics related to human subject participation

This research study was conducted in strict accordance with the principles, policies, and guidelines meticulously outlined by the Swiss School of Business & Management, Geneva. Before engaging in the study, all aims, potential risks, benefits, as well as the responsibilities and entitlements of the participants were thoroughly elucidated and discussed with the volunteers. Prior to their involvement, clear assurances and guarantees of both anonymity and confidentiality were provided to the participants. Rigorous measures were in place to closely restrict access to the securely stored data, ensuring the utmost protection of information. It was emphasized that participation in the study was entirely voluntary, with participants retaining the freedom to withdraw from the study at any given point without facing any financial implications or losing any associated benefits. Every participant was comprehensively briefed on the potential advantages that the study could offer, ensuring they were fully informed and conscious of what to expect. Access to the study's valuable data was meticulously restricted to solely those individuals with proper authorization, ensuring the utmost level of security and confidentiality throughout. Upon the successful culmination of this thesis, the data will be promptly and responsibly removed from all systems and records, guaranteeing full compliance with ethical research practices.

Participants were given the autonomy to withdraw from the research at any juncture or refrain from responding to any inquiries presented to them, fostering a sense of comfort and respect within the study framework. Notably, no financial rewards was offered to participants, underlining the voluntary and altruistic nature of their involvement in the research endeavour. Furthermore, particular attention was paid to safeguarding vulnerable populations, by excluding them from the study to maintain ethical integrity and protect their rights. The participant-researcher dynamics were consistently characterized by a demeanour of professionalism and courtesy, ensuring a conducive and respectful environment for the exchange of information and insights. Importantly, the researcher ensures transparency by openly acknowledging any potential conflicts of interest that could have influenced the study results, thus upholding the research's credibility and objectivity. Lastly, the invaluable support and contributions provided by the participants are duly recognized and appreciated by the researcher, acknowledging their pivotal role in enriching the study's outcomes and significance.

### 3.7. Summary

The methodology for the study consisted of a well-researched and documented series of tasks consisting of selection of sample from the population through convenience sampling, design of research questionnaire, collection of data through social media, application of statistical tools like principal component analysis, hypothesis testing and regression modelling for evolving meaningful outputs.

Population for the study consisted of allopathic doctors working in five tertiary hospitals in the district of Thiruvananthapuram in Kerala State. Questionnaires for the study were evolved from TAM. They consisted of social profile of doctors like gender and age and 15 variables representing job satisfaction in five-point Likert scale under four broad headings. They were sent to about 200 doctors through social media and correct entries numbering 110 out of 120 were received. The data collected were subjected to descriptive and inferential statistics. Under descriptive statistics, the data were tabulated under different headings with responses summarized to represent job satisfaction in the form of tables, charts and figures. To draw inferences on the descriptive statistics, the 15 variables collected for the study were reduced to minimum number of principal components so as to avoid duplication without compromising on the data contents. They were further subjected to hypothesis testing with null hypothesis implying no variation in the satisfaction level among doctors in respect of age and gender against significant variation in it. Z statistics was used for testing the hypothesis.

The data were again put for binary regression modelling where satisfaction level was tested against responses received under 15 different variables.

# CHAPTER 4:

# RESULTS

## 4.1. Introduction

Broad findings from the study were obtained through data collection, data compilation, analysis and interpretation. Various statistical tools were employed for the purpose of data compilation and analysis.

## 4.2. Organization of data analysis

The data collected from the respondents were processed for eliminating inappropriate and illogical data sets. It was followed by detailed data analysis and statistical inferences to draw the findings of the study and arrive at suitable recommendations for enhancing job satisfaction among medical professionals. Analysis of data pertaining to job satisfaction and profile of doctors were obtained through both descriptive and inferential statistics. Descriptive statistics consisted of tabulation and summarization with appropriate tables, charts, and figures. MS excel software was extensively used for descriptive statistics. They were statistically tested for accuracy, reliability and inferring necessary outputs for the study. Apart from MS excel, SPSS was also used for the data analysis.

## 4.3. Survey findings through Descriptive Statistics

Data analysis through descriptive statistics were carried out to draw conclusions on the following inputs.

(i) Profile of respondents – Gender and age

(ii) Characteristics of responses

(iii) Setting respondents profile versus their responses

### 4.3.1. Profile of Respondents

Profile of respondents was assessed to ascertain their socio-economic background so as to relate their responses to their profile and arrive at statistically amenable outputs. Brief profile of the respondents is presented below.

**(i)** Gender of respondents: Out of 110 respondents for the study, 57 were males and 53 were females (Figure 4.1).

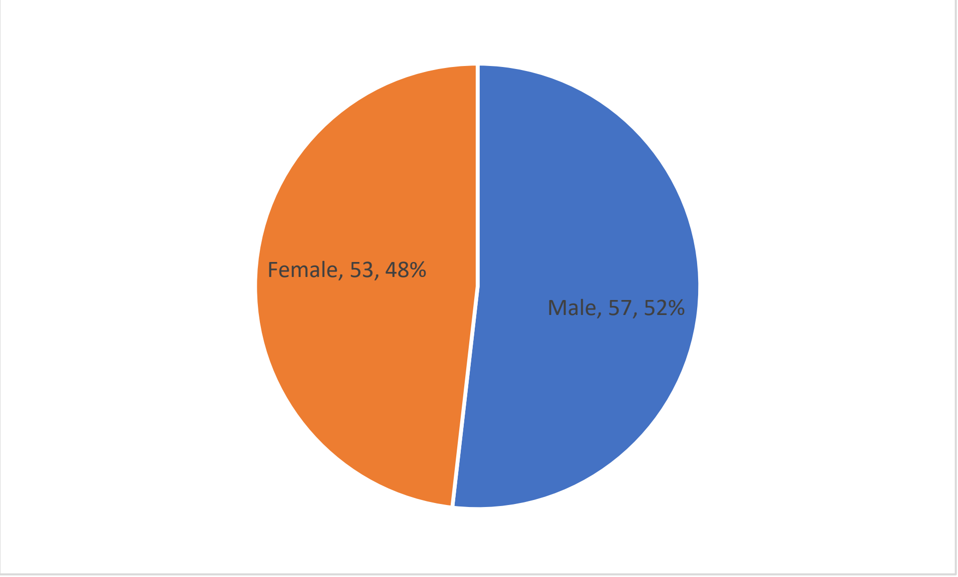


Figure 4.1: Gender profile of respondents

**(ii)** Age of respondents: It is seen that one third of the respondents had their age between 40 and 50, and the rest of them almost equally distributed among other age groups of ‘less than 40’, ‘50-60’ and ‘>above 60’ (Figure 4.2)

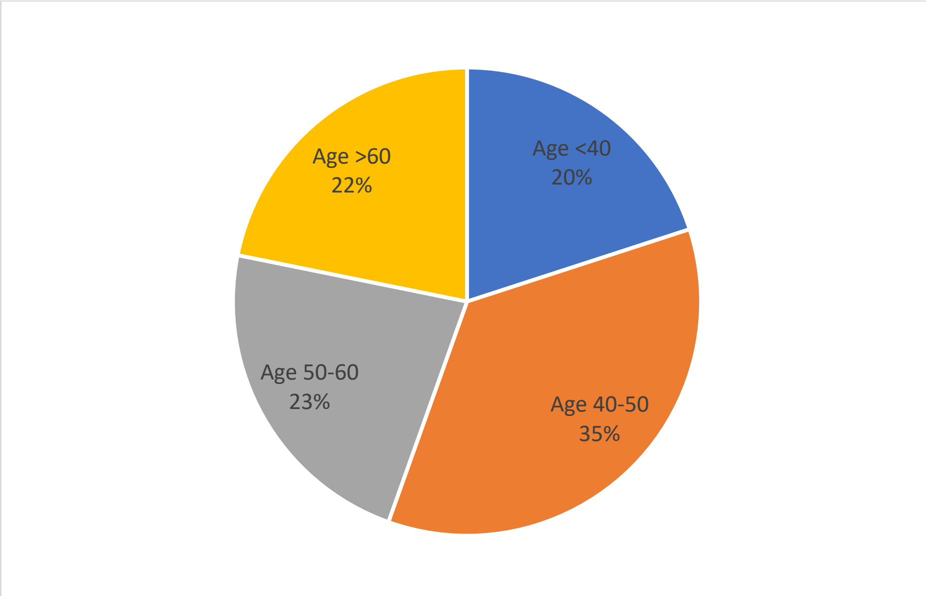


Figure 4.2: Age profile of Respondents

**(iii)** Gender Vs Age of respondents: It could be seen that male respondents dominated the older age group (above 60) while female doctors were the maximum in young age group below 40 (Figure 4.3). More or less same number of male and female doctors represented the middle age group between 40 and 60.

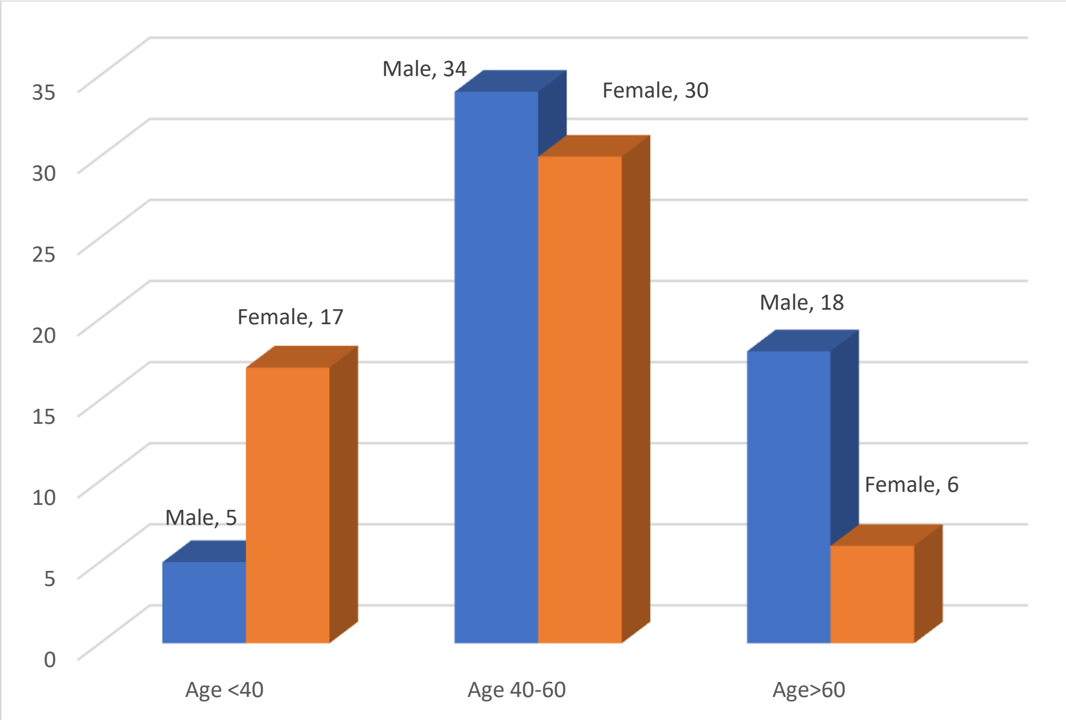


Figure 4.3: Gender Vs age of respondents

### 4.3.2. Responses Related to Job satisfaction

Instead of asking study participants directly if they were satisfied with their jobs, a total of 15 indirect questions (proxy variables) were presented to them under three main topics in order to get information on their job satisfaction:

(i) Perceived use of digital health and AI – six questions

| | |
|---|---|
| 1 | Tasks accomplished quickly |
| 2 | Work performance improved |
| 3 | work productivity increased |
| 4 | Work effectiveness enhanced |
| 5 | Work made easier |
| 6 | Work usefulness |

(ii) Perceived ease of use – six questions

| | |
|---|---|
| 7 | Learning to operate technologies is quite easy |
| 8 | Easy to get technologies to do what I want it to do |
| 9 | My interaction with technologies is clear and understandable |
| 10 | Technologies found to be flexible to interact with |
| 11 | Becoming skilful at technologies |
| 12 | Quite easy to use |

(iii) User acceptance – two questions

| | |
|---|---|
| 13 | Frequently used |
| 14 | Multi-purpose usage (clinical notes, reports, medical info, etc.) |

(iv) User recommendation – one question.

15. Recommending to other users

The responses were measured in five- point Likert scale namely

(i) Strongly agree

(ii) Agree

(iii) Neutral

(iv) Disagree

(v) Strongly disagree

In order to quantify the job satisfaction, percentage of satisfied were taken as the criteria and the following steps were taken to establish the same;

As a first step in this regard, scaling of responses to the variables were adopted. The first two responses generally reflect on the satisfaction level while the last two point to the dissatisfaction of respondents to their job satisfaction. The adopted scales were as follows;

(i) Strongly agree 1.00 (Fully satisfied)

(ii) Agree 0.90 (90% accounted)

(iii) Neutral 0.50 (only half accounted)

(iv) Disagree 0.10 (only one tenth is accounted)

(v) Strongly disagreed 0 (None is satisfied)

In the second step, proportion of satisfied was estimated by summing up the number of respondents with weightages assigned to each response in the Likert scale and taking the average. It was also computed for different age and gender groups. The following formula was used in this regard;

$$P\text{-}S_{ij} = \sum Rep_{ijk} * Wt_k / N_{ij}$$

Where $P\text{-}S_{ij}$ = Proportion of satisfied for each group (i) and variable (j)

$Rep_{(ijk)}$ = Number of respondents under each group (i), variable (j) & scale (k)

$Wt_k$ = Weightage assigned to each scale (k)

$N_{ij}$ = No. of respondents under the group (i) and variable (j)

Following above steps, the overall satisfied to the 15 variables individually as well as on average are computed as summarized in Table 4.1. It could be interpreted that 76.4% of doctors on the whole were satisfied with the use of digital health and AI applications in their 'day to day' job functions. It was found to be high in the indicators among user

acceptance, perceived use and recommendation to others (above 70%) and lower among perceived ease of use ranging between 64% and 73%.

Table 4.1: Responses to Job satisfaction

| **Responses** | | | **Total respondents** | **Satisfied** | |
|---|---|---|---|---|---|
| No. | **Details** | | | **No.** | **Percent** |
| 1 | Perceived use | Tasks accomplished quickly | 110 | 86 | 78.27 |
| 2 | | Work performance improved | 110 | 85 | 77.09 |
| 3 | | work productivity increased | 110 | 77 | 70.27 |
| 4 | | Work effectiveness enhanced | 110 | 91 | 82.55 |
| 5 | | Work made easier | 110 | 85 | 76.91 |
| 6 | | Work usefulness | 110 | 99 | 89.73 |
| 7 | Perceived ease of use | Learning to operate technologies is quite easy | 110 | 71 | 64.18 |
| 8 | | Easy to get technologies to do what I want it to do | 110 | 71 | 64.18 |
| 9 | | My interaction with technologies is clear and understandable | 110 | 80 | 72.73 |
| 10 | | Technologies found to be flexible to interact with | 110 | 71 | 64.55 |
| 11 | | Becoming skilful at technologies | 110 | 76 | 69.36 |
| 12 | | Quite easy to use | 110 | 75 | 68.18 |
| 13 | User Acceptance | Frequently used | 110 | 89 | 80.45 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 110 | 102 | 92.55 |

| | | | | | |
|---|---|---|---|---|---|
| 15 | Recommen - dation | Recommending to other users | 110 | 88 | 80.36 |
| | | Average | | | 76.40 |

### 4.3.3. Respondents' Background Vs Their Responses

Job satisfaction level among medical professional depend on many factors. In the present study, two socio economic background of the respondents were studied namely

(i) Gender

(ii) Age

The above explanatory variables alone and in combination are set against the job satisfaction level measured through 15 proxy variables discussed above to evolve meaningful insights into their behaviour pattern. Summary of satisfaction level among doctors measured in terms of gender and age are provided in Table 4.2.

Table 4.2: Job satisfaction level due to use of digital health among doctors

| | Gender | | |
|---|---|---|---|
| Age group | Male | Female | All |
| <40 | 83.42 | 83.28 | 83.31 |
| 40-60 | 81.95 | 72.22 | 77.39 |
| >60 | 68.65 | 63.81 | 67.44 |
| All | 77.88 | 74.81 | 76.40 |

The following inferences can be made from the above table.

(i) With increase in age, dissatisfaction level decreases.

(ii) More male doctors were satisfied with the use of digital health technologies than female doctors

(iii) In the lower age group (<40years), both male and female exhibited similar job satisfaction

(iv) At other age groups, female doctors tended to be more dissatisfied with the use of digital health technologies.

Detailed analysis of the job satisfaction level among different categories of doctors are given in Tables 4.3 to 4.15.

**Table 4.3: Responses from Male doctors**

| Responses | | | Response Type from Males | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | | **Details** | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Strongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 29 | 14 | 7 | 6 | 1 |
| 2 | | Work performance improved | 21 | 20 | 12 | 3 | 1 |
| 3 | | work productivity increased | 13 | 22 | 12 | 10 | 0 |
| 4 | | Work effectiveness enhanced | 22 | 22 | 11 | 2 | 0 |
| 5 | | Work made easier | 18 | 24 | 9 | 6 | 0 |
| 6 | | Work usefulness | 26 | 28 | 3 | 0 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 14 | 16 | 17 | 10 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 9 | 20 | 16 | 11 | 1 |
| 9 | | My interaction with technologies is clear and understandable | 14 | 22 | 15 | 6 | 0 |
| 10 | | Technologies found to be flexible to interact with | 6 | 21 | 23 | 6 | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 11 | | Becoming skilful at technologies | 14 | 20 | 18 | 5 | 0 |
| 12 | | Quite easy to use | 11 | 23 | 17 | 6 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 13 | User Acceptance | Frequently used | 20 | 24 | 9 | 4 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 28 | 27 | 1 | 1 | 0 |
| 15 | Recom men-dation | Recommending to other users | 18 | 26 | 11 | 2 | 0 |
| | | **Average** | | | | | |

This table provides an overview of male participants' responses regarding perceived use, ease of use, user acceptance, and recommendations for technologies. The data reveals trends in agreement levels across various aspects, reflecting positive feedback on tasks, productivity, and usability.

**Table 4.4: Responses of doctors Age (<40)**

| Responses | | | Response Type from <40 | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | Perceived use | Tasks accomplished quickly | 9 | 9 | 4 | 0 | 0 |
| 2 | | Work performance improved | 4 | 13 | 4 | 1 | 0 |
| 3 | | work productivity increased | 4 | 13 | 4 | 1 | 0 |
| 4 | | Work effectiveness enhanced | 9 | 11 | 2 | 0 | 0 |
| 5 | | Work made easier | 9 | 10 | 3 | 0 | 0 |
| 6 | | Work usefulness | 8 | 14 | 0 | 0 | 0 |
| 7 | Perceived ease of use | Learning to operate technologies is quite easy | 1 | 12 | 7 | 2 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 3 | 9 | 8 | 2 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 9 | | My interaction with technologies is clear and understandable | 5 | 12 | 4 | 1 | 0 |
| 10 | | Technologies found to be flexible to interact with | 4 | 12 | 4 | 2 | 0 |
| 11 | | Becoming skilful at technologies | 8 | 9 | 2 | 3 | 0 |
| 12 | | Quite easy to use | 6 | 10 | 4 | 2 | 0 |
| 13 | **User Acceptance** | Frequently used | 10 | 9 | 3 | 0 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 10 | 9 | 2 | 1 | 0 |
| 15 | **Recom men-dation** | Recommending to other users | 11 | 6 | 5 | 0 | 0 |
| | | **Average** | | | | | |

This table illustrates responses from participants under 40 regarding perceived use, ease of use, and acceptance of technologies. Younger individuals show stronger agreement on performance and productivity aspects, indicating a generally positive outlook towards using such technologies.

**Table 4.5: Responses from Male doctors (<40)**

| **Responses** | | | **Response Type from male <40** | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 2 | 3 | 0 | 0 | 0 |
| 2 | | Work performance improved | 0 | 4 | 0 | 1 | 0 |
| 3 | | work productivity increased | 0 | 4 | 0 | 1 | 0 |
| 4 | | Work effectiveness enhanced | 2 | 3 | 0 | 0 | 0 |
| 5 | | Work made easier | 1 | 4 | 0 | 0 | 0 |
| 6 | | Work usefulness | 2 | 3 | 0 | 0 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 7 | Perceived ease of use | Learning to operate technologies is quite easy | 0 | 4 | 1 | 0 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 0 | 4 | 0 | 1 | 0 |
| 9 | | My interaction with technologies is clear and understandable | 3 | 0 | 1 | 1 | 0 |
| 10 | | Technologies found to be flexible to interact with | 1 | 2 | 2 | 0 | 0 |
| 11 | | Becoming skilful at technologies | 2 | 2 | 0 | 1 | 0 |
| 12 | | Quite easy to use | 1 | 3 | 1 | 0 | 0 |
| 13 | User Acceptance | Frequently used | 3 | 1 | 1 | 0 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 3 | 1 | 0 | 1 | 0 |
| 15 | mmen - | Recommending to other users | 3 | 1 | 1 | 0 | 0 |
| | | **Average** | | | | | |

Responses from males under 40 reveal their perceptions of technology use. Most agree that technologies enhance productivity and are easy to use, though a few remain neutral or disagree. The data highlights a mix of positive experiences and learning curves.

**Table 4.6: Responses from Female doctors (<40)**

| **Responses** | | | **Response Type from female <40** | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | Perceived use | Tasks accomplished quickly | 7 | 6 | 4 | 0 | 0 |
| 2 | | Work performance improved | 4 | 9 | 4 | 0 | 0 |
| 3 | | work productivity increased | 4 | 9 | 4 | 0 | 0 |
| 4 | | Work effectiveness | 7 | 8 | 2 | 0 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | enhanced | | | | | |
| 5 | | Work made easier | 8 | 6 | 3 | 0 | 0 |
| 6 | | Work usefulness | 6 | 11 | 0 | 0 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 1 | 8 | 6 | 2 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 3 | 5 | 8 | 1 | 0 |
| 9 | | My interaction with technologies is clear and understandable | 2 | 12 | 3 | 0 | 0 |
| 10 | | Technologies found to be flexible to interact with | 3 | 10 | 2 | 2 | 0 |
| 11 | | Becoming skilful at technologies | 6 | 7 | 2 | 2 | 0 |
| 12 | | Quite easy to use | 5 | 7 | 3 | 2 | 0 |
| 13 | **User Acceptance** | Frequently used | 7 | 8 | 2 | 0 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 7 | 8 | 2 | 0 | 0 |
| 15 | **Recomm en- dation** | Recommending to other users | 8 | 5 | 4 | 0 | 0 |
| | | **Average** | | | | | |

Responses from females under 40 highlight their perspectives on technology. Strong agreement is observed for productivity and usefulness, while a few respondents report challenges in understanding or interacting with technologies. Overall, responses reflect favorable attitudes towards technology use.

**Table 4.7: Responses from All Female doctors**

| Responses | | | Response Type from Females | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | | **Details** | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 23 | 13 | 10 | 7 | 0 |
| 2 | | Work performance improved | 14 | 20 | 14 | 5 | 0 |
| 3 | | work productivity increased | 14 | 16 | 17 | 6 | 0 |
| 4 | | Work effectiveness enhanced | 20 | 21 | 8 | 4 | 0 |
| 5 | | Work made easier | 18 | 17 | 12 | 6 | 0 |
| 6 | | Work usefulness | 19 | 26 | 7 | 1 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 3 | 21 | 20 | 8 | 1 |
| 8 | | Easy to get technologies to do what I want it to do | 5 | 22 | 18 | 7 | 1 |
| 9 | | My interaction with technologies is clear and understandable | 4 | 27 | 19 | 3 | 0 |
| 10 | | Technologies found to be flexible to interact with | 3 | 24 | 17 | 9 | 0 |
| 11 | | Becoming skilful at technologies | 7 | 22 | 14 | 10 | 0 |
| 12 | | Quite easy to use | 5 | 22 | 17 | 9 | 0 |
| 13 | **User Acceptance** | Frequently used | 15 | 23 | 12 | 3 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 24 | 26 | 3 | 0 | 0 |
| 15 | **Recomm en-dation** | Recommending to other users | 16 | 19 | 16 | 2 | 0 |
| | | **Average** | | | | | |

This table outlines responses from all female participants, emphasizing perceived usefulness and ease of technology use. High agreement is observed for productivity and interaction ease, with occasional disagreements reflecting areas needing attention or improvement in usability.

**Table 4.8: Responses of doctors Age (40-50)**

| Responses | | | Response Type from 40-50 | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 21 | 8 | 5 | 5 | 0 |
| 2 | | Work performance improved | 14 | 13 | 8 | 3 | 1 |
| 3 | | work productivity increased | 11 | 11 | 12 | 5 | 0 |
| 4 | | Work effectiveness enhanced | 17 | 13 | 6 | 3 | 0 |
| 5 | | Work made easier | 13 | 15 | 6 | 5 | 0 |
| 6 | | Work usefulness | 16 | 18 | 4 | 1 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 4 | 16 | 16 | 3 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 4 | 18 | 12 | 5 | 0 |
| 9 | | My interaction with technologies is clear and understandable | 5 | 16 | 17 | 1 | 0 |
| 10 | | Technologies found to be flexible to interact with | 3 | 14 | 17 | 5 | 0 |
| 11 | | Becoming skilful at technologies | 5 | 18 | 12 | 4 | 0 |
| 12 | | Quite easy to use | 5 | 18 | 11 | 5 | 0 |
| 13 | **User Acceptance** | Frequently used | 11 | 16 | 10 | 2 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 20 | 17 | 2 | 0 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 15 | Recommen-dation | Recommending to other users | 12 | 17 | 8 | 2 | 0 |
| | | **Average** | | | | | |

Participants aged 40-50 express their views on technology. Responses show moderate agreement on productivity, with occasional neutrality or disagreement in ease of use and flexibility. This suggests some challenges with adapting to technology but overall positive feedback.

**Table 4.9: Responses from Male doctors (40-50)**

| **Responses** | | | **Response Type from male 40-50** | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 9 | 3 | 0 | 2 | 0 |
| 2 | | Work performance improved | 8 | 4 | 0 | 1 | 1 |
| 3 | | work productivity increased | 6 | 5 | 1 | 2 | 0 |
| 4 | | Work effectiveness enhanced | 9 | 2 | 2 | 1 | 0 |
| 5 | | Work made easier | 8 | 4 | 0 | 2 | 0 |
| 6 | | Work usefulness | 8 | 5 | 1 | 0 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 3 | 5 | 5 | 1 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 2 | 6 | 4 | 2 | 0 |
| 9 | | My interaction with technologies is clear and understandable | 3 | 6 | 5 | 0 | 0 |
| 10 | | Technologies found to be flexible to interact with | 3 | 2 | 8 | 1 | 0 |
| 11 | | Becoming skilful at technologies | 4 | 5 | 5 | 0 | 0 |
| 12 | | Quite easy to use | 5 | 5 | 3 | 1 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 13 | User Acceptance | Frequently used | 5 | 5 | 4 | 0 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 7 | 6 | 1 | 0 | 0 |
| 15 | Recomm en-dation | Recommending to other users | 6 | 6 | 1 | 1 | 0 |
| | | **Average** | | | | | |

Male participants aged 40-50 provide insights into their technology experience. Responses show satisfaction with productivity enhancements, but a few highlight difficulties in flexibility and becoming skilful with technologies. Positive trends dominate despite some usability concerns.

**Table 4.10: Responses from Female doctors (40-50)**

| **Responses** | | | **Response Type from female 40-50** | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 12 | 5 | 5 | 3 | 0 |
| 2 | | Work performance improved | 6 | 9 | 8 | 2 | 0 |
| 3 | | work productivity increased | 5 | 6 | 11 | 3 | 0 |
| 4 | | Work effectiveness enhanced | 8 | 11 | 4 | 2 | 0 |
| 5 | | Work made easier | 5 | 11 | 6 | 3 | 0 |
| 6 | | Work usefulness | 8 | 13 | 3 | 1 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 1 | 11 | 11 | 2 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 2 | 12 | 8 | 3 | 0 |
| 9 | | My interaction with technologies is clear and understandable | 2 | 10 | 12 | 1 | 0 |
| 10 | | Technologies found to be flexible to interact with | 0 | 12 | 9 | 4 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 11 | | Becoming skilful at technologies | 1 | 13 | 7 | 4 | 0 |
| 12 | | Quite easy to use | 0 | 13 | 8 | 4 | 0 |
| 13 | User Acceptance | Frequently used | 6 | 11 | 6 | 2 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 13 | 11 | 1 | 0 | 0 |
| 15 | Recomm en-dation | Recommending to other users | 6 | 11 | 7 | 1 | 0 |
| | | **Average** | | | | | |

Responses from females aged 40-50 indicate varying levels of agreement on productivity and usability. While most find technologies beneficial, neutrality in some aspects reflects potential challenges with ease of use or flexibility. Recommendations are generally positive.

**Table 4.11: Responses from Male doctors (50-60)**

| **Responses** | | | **Response Type from male 50-60** | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 11 | 5 | 2 | 1 | 1 |
| 2 | | Work performance improved | 8 | 6 | 5 | 1 | 0 |
| 3 | | work productivity increased | 4 | 8 | 4 | 4 | 0 |
| 4 | | Work effectiveness enhanced | 7 | 10 | 2 | 1 | 0 |
| 5 | | Work made easier | 5 | 11 | 3 | 1 | 0 |
| 6 | | Work usefulness | 9 | 10 | 1 | 0 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 8 | 5 | 4 | 3 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 6 | 6 | 6 | 1 | 1 |
| 9 | | My interaction with technologies is clear and understandable | 6 | 10 | 3 | 1 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 10 | | Technologies found to be flexible to interact with | 2 | 12 | 5 | 0 | 1 |
| 11 | | Becoming skilful at technologies | 6 | 9 | 5 | 0 | 0 |
| 12 | | Quite easy to use | 4 | 10 | 5 | 1 | 0 |
| 13 | User Acceptance | Frequently used | 8 | 10 | 1 | 1 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 9 | 11 | 0 | 0 | 0 |
| 15 | Recommen-dation | Recommending to other users | 5 | 10 | 5 | 0 | 0 |
| | | **Average** | | | | | |

Male participants aged 50-60 reflect on their technology experiences, with most agreeing on productivity and usefulness. However, responses indicate challenges in interacting with or becoming proficient in technologies. There is a mix of satisfaction and areas needing focus.

**Table 4.12: Responses from Female doctors (50-60)**

| **Responses** | | | **Response Type from female 50-60** | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | Perceived use | Tasks accomplished quickly | 2 | 1 | 0 | 2 | 0 |
| 2 | | Work performance improved | 2 | 0 | 1 | 2 | 0 |
| 3 | | work productivity increased | 2 | 0 | 0 | 3 | 0 |
| 4 | | Work effectiveness enhanced | 3 | 1 | 1 | 0 | 0 |
| 5 | | Work made easier | 2 | 0 | 1 | 2 | 0 |
| 6 | | Work usefulness | 2 | 1 | 2 | 0 | 0 |
| 7 | Perceived ease of use | Learning to operate technologies is quite easy | 0 | 2 | 0 | 3 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 0 | 2 | 1 | 2 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 9 | | My interaction with technologies is clear and understandable | 0 | 2 | 2 | 1 | 0 |
| 10 | | Technologies found to be flexible to interact with | 0 | 2 | 1 | 2 | 0 |
| 11 | | Becoming skilful at technologies | 0 | 2 | 1 | 2 | 0 |
| 12 | | Quite easy to use | 0 | 2 | 1 | 2 | 0 |
| 13 | User Acceptance | Frequently used | 2 | 1 | 1 | 1 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 2 | 3 | 0 | 0 | 0 |
| 15 | Recommen-dation | Recommending to other users | 2 | 0 | 3 | 0 | 0 |
| | | **Average** | | | | | |

Responses from females aged 50-60 showcase a balanced view of technology use. While many acknowledge usefulness and productivity, neutral or negative feedback on ease of use and interaction highlights areas for improvement. Recommendations are cautiously optimistic.

**Table 4.13: Responses of doctors Age (>60)**

| **Responses** | | | **Response Type from >60** | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 9 | 4 | 6 | 5 | 0 |
| 2 | | Work performance improved | 7 | 8 | 8 | 1 | 0 |
| 3 | | work productivity increased | 6 | 6 | 9 | 3 | 0 |
| 4 | | Work effectiveness enhanced | 6 | 8 | 8 | 2 | 0 |
| 5 | | Work made easier | 7 | 5 | 8 | 4 | 0 |
| 6 | | Work usefulness | 10 | 11 | 3 | 0 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 4 | 2 | 10 | 7 | 1 |
| 8 | | Easy to get technologies to do what I want it to do | 1 | 7 | 7 | 8 | 1 |
| 9 | | My interaction with technologies is clear and understandable | 2 | 9 | 8 | 5 | 0 |
| 10 | | Technologies found to be flexible to interact with | 0 | 5 | 13 | 6 | 0 |
| 11 | | Becoming skilful at technologies | 2 | 4 | 12 | 6 | 0 |
| 12 | | Quite easy to use | 1 | 5 | 13 | 5 | 0 |
| 13 | **User Acceptance** | Frequently used | 4 | 11 | 6 | 3 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 11 | 13 | 0 | 0 | 0 |
| 15 | **Recomm en-dation** | Recommending to other users | 4 | 12 | 6 | 2 | 0 |
| | | **Average** | | | | | |

Participants over 60 share their views on technology. Responses highlight perceived usefulness and productivity, though significant neutral or negative feedback appears in ease of use and flexibility. These responses emphasize the need for age-friendly technology designs.

**Table 4.14: Responses from Male doctors (>60)**

| Responses | | | Response Type from male>60 | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 7 | 3 | 5 | 3 | 0 |
| 2 | | Work performance improved | 5 | 6 | 7 | 0 | 0 |
| 3 | | work productivity increased | 3 | 5 | 7 | 3 | 0 |
| 4 | | Work effectiveness enhanced | 4 | 7 | 7 | 0 | 0 |
| 5 | | Work made easier | 4 | 5 | 6 | 3 | 0 |
| 6 | | Work usefulness | 7 | 10 | 1 | 0 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 3 | 2 | 7 | 6 | 0 |
| 8 | | Easy to get technologies to do what I want it to do | 1 | 4 | 6 | 7 | 0 |
| 9 | | My interaction with technologies is clear and understandable | 2 | 6 | 6 | 4 | 0 |
| 10 | | Technologies found to be flexible to interact with | 0 | 5 | 8 | 5 | 0 |
| 11 | | Becoming skilful at technologies | 2 | 4 | 8 | 4 | 0 |
| 12 | | Quite easy to use | 1 | 5 | 8 | 4 | 0 |
| 13 | **User Acceptance** | Frequently used | 4 | 8 | 3 | 3 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 9 | 9 | 0 | 0 | 0 |
| 15 | **mmen -** | Recommending to other users | 4 | 9 | 4 | 1 | 0 |
| | | **Average** | | | | | |

Male participants over 60 provide feedback on technology use. While agreement on productivity is common, significant challenges with usability and interaction ease are evident. Neutral and negative responses suggest room for improving technology accessibility for older users.

**Table 4.15: Responses from Female doctors (>60)**

| Responses | | | Response Type from female>60 | | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Details** | | **Strongly agree** | **Agree** | **Neutral** | **Disagree** | **Stongly disagree** |
| 1 | **Perceived use** | Tasks accomplished quickly | 2 | 1 | 1 | 2 | 0 |
| 2 | | Work performance improved | 2 | 2 | 1 | 1 | 0 |
| 3 | | work productivity increased | 3 | 1 | 2 | 0 | 0 |
| 4 | | Work effectiveness enhanced | 2 | 1 | 1 | 2 | 0 |
| 5 | | Work made easier | 3 | 0 | 2 | 1 | 0 |
| 6 | | Work usefulness | 3 | 1 | 2 | 0 | 0 |
| 7 | **Perceived ease of use** | Learning to operate technologies is quite easy | 1 | 0 | 3 | 1 | 1 |
| 8 | | Easy to get technologies to do what I want it to do | 0 | 3 | 1 | 1 | 1 |
| 9 | | My interaction with technologies is clear and understandable | 0 | 3 | 2 | 1 | 0 |
| 10 | | Technologies found to be flexible to interact with | 0 | 0 | 5 | 1 | 0 |
| 11 | | Becoming skilful at technologies | 0 | 0 | 4 | 2 | 0 |
| 12 | | Quite easy to use | 0 | 0 | 5 | 1 | 0 |
| 13 | **User Acceptance** | Frequently used | 0 | 3 | 3 | 0 | 0 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 2 | 4 | 0 | 0 | 0 |
| 15 | **mme n- datio** | Recommending to other users | 0 | 3 | 2 | 1 | 0 |
| | | **Average** | | | | | |

Female participants over 60 highlight mixed responses to technology. While some agree on usefulness and productivity, others report challenges in interaction and ease of use. Neutral and disagreeing responses suggest the need for better support and adaptation to technology.

## 4.4. Inferences from data analysis

Statistical inference is the process of using data analysis to infer properties of an underlying distribution of probability. Inferential statistical analysis infers properties of a population, for example by testing hypotheses and deriving estimates. It is assumed that the observed data set is sampled from a larger population.

Inferential statistics can be contrasted with descriptive statistics. Descriptive statistics is solely concerned with properties of the observed data, and it does not rest on the assumption that the data come from a larger population. In machine learning, the term *inference* is sometimes used instead to mean "make a prediction, by evaluating an already trained model”. In this context inferring properties of the model is referred to as *training* or *learning* (rather than *inference*) and using a model for prediction is referred to as *inference* (instead of *prediction*).

Whatever presented in the earlier sections provide description of properties observed from the sample data without subjecting them to statistical scrutiny. Statistical scrutiny helps in establishing their reliability, accuracy, and variability. Accordingly, principal component analysis, hypothesis testing and regression modeling are used in the present study.

### 4.4.1. Principal component analysis

The data collected for the study consists of the profile of respondents and information on the job satisfaction level represented by 15 proxy variables as discussed earlier. It has to be seen how far the responses to these 15 variables differ from each other and whether data uniformity occurs in these data sets. Accordingly, principal components analysis is used to reduce the data sets without affecting the prime data contents. SPSS was used to reduce the data. The results of the data analysis reveals that 15 Based on the evaluation of the PCA, it is decided to condense the 15 variables to four principal components as defined earlier. These four principal components are further subjected to hypothesis testing to arrive at alternate inferences. For the purpose of the same, original data set of responses to 15 variables were recast to four components by taking the average value of the responses.

variables studied for the study could be reduced to two principal components based on correlation among the variables and principal components considering the cutoff point of 0.45. Details of 15 variables and the principal components obtained from the PCA are presented in Table 4.16 and detailed output are enclosed at Appendix 4.1.

Table 4.16: Principal components arrived from data analysis

| Sl. No. | Name of original variable | | Principal Component | |
|---|---|---|---|---|
| | | | 1 | 2 |
| 1 | Perceived use | Tasks accomplished quickly | 0.16 | 0.73 |
| 2 | | Work performance improved | 0.12 | 0.81 |
| 3 | | work productivity increased | 0.15 | 0.72 |
| 4 | | Work effectiveness enhanced | 0.13 | 0.68 |
| 5 | | Work made easier | 0.16 | 0.78 |
| 6 | | Work usefulness | 0.19 | 0.76 |
| 7 | Perceived ease of use | Learning to operate technologies is quite easy | 0.82 | 0.13 |
| 8 | | Easy to get technologies to do what I want it to do | 0.80 | 0.27 |
| 9 | | My interaction with technologies is clear and understandable | 0.81 | 0.25 |
| 10 | | Technologies found to be flexible to interact with | 0.80 | 0.16 |
| 11 | | Becoming skilful at technologies | 0.90 | 0.15 |

| | | | | |
|---|---|---|---|---|
| 12 | | Quite easy to use | 0.85 | 0.17 |
| 13 | User Acceptance | Frequently used | 0.65 | 0.53 |
| 14 | | Multi-purpose usage (clinical notes, reports, medical info, etc.) | 0.30 | 0.45 |
| 15 | Recommen - dation | Recommending to other users | 0.48 | 0.66 |

Based on the evaluation of the PCA, it is decided to condense the 15 variables to four principal components as defined earlier. These four principal components are further subjected to hypothesis testing to arrive at alternate inferences. For the purpose of the same, original data set of responses to 15 variables were recast to four components by taking the average value of the responses.

### 4.4.2. Hypothesis Testing

In a hypothesis test, conclusion is based on the probability value which comes from a normal model of the sampling distribution of differences in samples.  In the first step of hypothesis testing, a null hypothesis and alternate hypothesis are formulated with preset values for the sample statistics.

The null hypothesis is a hypothesis about the value of the population parameter on the basis of the sampling distribution. The alternative hypothesis usually reflects the claim in the research question about the value of the parameter. The alternative hypothesis says the parameter is "greater than" or "less than" or "not equal to" the value what is assumed to true in the null hypothesis. (Hinton, P.R, 2014).

The next step of hypothesis testing is to assess the evidence by using a simulation or a mathematical model to examine the results from random samples selected from the population described by the null hypothesis. It should be figured out whether results similar to the data are likely or unlikely which implies that this step requires some kind of probability calculation. The probability depends on how much variability there is in random samples of this size from this population.

The next step in the hypothesis testing is to draw conclusion about the null hypothesis. Then one of two outcomes can occur:

- One possibility is that results similar to the actual sample are extremely unlikely. This means that the data do not fit in with results from random samples selected from the population described by the null hypothesis. In this case, it is unlikely that the data came from this population, and it is viewed as strong evidence against the null hypothesis.
- The other possibility is that results similar to the actual sample are fairly likely (not unusual). This means that the data fit in with typical results from random samples selected from the population described by the null hypothesis. In this case, there is no
- evidence against the null hypothesis, and it cannot be rejected it in Favor of the alternative hypothesis.

A small P-value indicates that it is unlikely that the actual sample data came from the population described by the null hypothesis. More specifically, a small P-value says that there is only a small chance that we will randomly select a sample with results at least as extreme as the data if $H_0$ is true. The smaller the P-value, the stronger is the evidence against $H_0$.

P value is compared with a value called ‘significance level’ for the test, and when is P value is less than or equal to significance level, the difference is concluded to be statistically significant (unlikely to have occurred solely by chance).

Z statistics is used to test the validity of hypothesis which is given as

$$Z = \frac{\mathrm{x1} - \mathrm{x2}}{\mathrm{SE}}$$

Where $x_1$ is the proportion of variable 1 and $x_2$ is the proportion of variable 2

SE = Standard deviation = =SQRT $((p_0*q_0*((1/ N_1) +(1/ N_2))))$

Where $p_0$ = probability of occurrence of variable 1

$Q_0$ = probability of occurrence of variable 2

$N_1$ = number of samples of variable 1 and

$N_2$ = number of samples of variable 2

Considering the major issue of job satisfaction experienced by different categories of doctors, it is proposed to test the following null and alternate hypothesis for the present study.

The null hypothesis is that there is no difference of job satisfaction among different background of respondents namely.

(i) Gender – Male Vs Female

(ii) Age – Young (<50) Vs Old (>50)

(iii) Young Male Vs Young Female

(iv) Old Male Vs Old Female

One response qualitative variable is indicated by a large number of 15 job satisfaction variable. For the ease of comparison, these variables enumerated as part of the study were combined into a single variable by using weighted average method. Thus, four set of null hypotheses were tested against the alternative hypothesis of significant variance in the job satisfaction.

A total of 15 response variables have been enumerated as part of the study which reflects the job satisfaction of doctors. All the response variables have been combined together for each group of explanatory variables by taking the average of satisfaction level.

(v) Sex Vs Satisfaction Level: The following null hypothesis was tested against alternative hypothesis.

- Null : There is no difference in the satisfaction level of male and female doctors
- Alternate : There is significance difference in the satisfaction level of male and female doctors

The following data were used for testing the hypothesis.

| Sub-category | Sample size | Proportion of Satisfied |
|---|---|---|
| Male | 57 | 0.80 |
| Female | 53 | 0.77 |
| $P_0$ | | 0.79 |
| $Q_0$ | | 0.21 |
| SE | | 0.08 |
| Z | | 0.40 |

Since the computed Z value of 0.40 is less than 1.96, the critical value of Z at 5% level of significance, the null hypothesis that there is no significant variation in job satisfaction among male and female doctors is accepted.

(vi) Age Vs Satisfaction Level: The following null hypothesis was tested against alternative hypothesis.

- Null : There is no difference in the satisfaction level of young and old doctors
- Alternate : There is significance difference in the satisfaction level of young and old doctors

The following data were used for testing the hypothesis.

| Sub-category | Sample size | Proportion of Satisfied |
|---|---|---|
| Young | 61 | 0.81 |
| Old | 49 | 0.76 |
| $P_0$ | | 0.79 |
| $Q_0$ | | 0.21 |
| SE | | 0.08 |
| Z | | 0.62 |

Since the computed Z value of 0.62is less than 1.96, the critical value of Z at 5% level of significance, the null hypothesis that there is no significant variation in job satisfaction among young and old doctors is accepted.

(vii) Young and Gender Vs Dissatisfaction Level: The following null hypothesis was tested against alternative hypothesis.

- Null : There is no difference in the satisfaction level of young male and young female doctors

- Alternate : There is significance difference in the satisfaction level of young male and young female doctors

The following data were used for testing the hypothesis.

| Sub-category | Sample size | Proportion of Satisfied |
|---|---|---|
| Young Male | 19 | 0.84 |
| Young female | 42 | 0.80 |
| $P_0$ | | 0.81 |
| $Q_0$ | | 0.19 |
| SE | | 0.11 |
| Z | | 0.33 |

Since the computed Z value of 0.33 isles than 1.96, the critical value of Z at 5% level of significance, <u>the null hypothesis that there is no significant variation in job satisfaction of young male and young female is accepted</u>.

(viii) Old and Gender Vs Dissatisfaction Level: The following null hypothesis was tested against alternative hypothesis.

a. Null : There is no difference in the satisfaction level of old male and old female doctors

b. Alternate : There is significance difference in the satisfaction level of old male and old female doctors

The following data were used for testing the hypothesis.

| Sub-category | Sample size | Proportion of Satisfied |
|---|---|---|
| Male | 38 | 0.79 |
| Female | 11 | 0.67 |
| $P_0$ | | 0.76 |
| $Q_0$ | | 0.24 |
| SE | | 0.15 |
| Z | | 0.80 |

Since the computed Z value of 0.80 is less than 1.96, the critical value of Z at 5% level of significance, the null hypothesis that there is no significant variation in job satisfaction among old male and old female doctors is accepted.

### 4.4.3. Regression modeling

In this study, a binary logistic regression model was applied to examine the relationship between three dependent variables and a set of independent variables. The initial set of independent variables consisted of 15 potential predictors, which were selected based on their theoretical relevance and prior research. These predictors included various demographic, behavioural, and economic factors that could influence the dependent variables. However, before fitting the logistic regression model, a critical step was taken to reduce potential multicollinearity among the independent variables and enhance the interpretability of the model.

To achieve this, a correlation analysis was conducted using SPSS software, a powerful statistical tool commonly used for such purposes. The correlation matrix helped identify pairs of independent variables that were highly correlated with each other. Variables that exhibited high correlations were considered redundant, as their information overlapped. To avoid multicollinearity, which can distort the coefficients and significance of variables in the regression model, a set of four independent variables was selected. These four variables showed minimal correlation with each other, ensuring that they were independent enough to provide unique contributions to the model. Furthermore, these variables were chosen based on their ability to explain the variance in the dependent variables effectively.

After the reduction process, a binary logistic regression model was fitted using the four selected independent variables. Logistic regression was chosen due to the binary nature of the dependent variables, where the outcomes are categorical with two possible values. SPSS was used to perform the logistic regression analysis, which provided insights into the relationship between the predictors and the dependent variables, as well as the significance of these relationships. The output from SPSS included key statistics, such as odds ratios, p-values, and the model's overall goodness-of-fit indicators.

The binary logistic regression model in SPSS was assessed for its adequacy using several measures. These included the Hosmer-Lemeshow test, which evaluates how well the model fits the observed data, and the classification table, which provides the accuracy of the model's predictions. Additionally, the odds ratios were examined to understand the strength and direction of the relationship between each independent variable and the probability of the outcome occurring. For example, an odds ratio greater than 1 indicates that as the independent variable increases, the likelihood of the dependent variable taking the value of interest also increases.

The use of SPSS software greatly facilitated the analysis process, allowing for efficient handling of large datasets and providing clear, interpretable results. The reduction of independent variables via correlation analysis helped simplify the model without sacrificing explanatory power, making it easier to draw meaningful conclusions about the factors influencing the dependent variables. The final logistic regression model, with its reduced set of predictors, offered valuable insights into the key drivers of the outcomes and provided a more efficient and focused analysis of the dataset.

Overall, this approach ensured that the model remained both robust and interpretable, with the results offering actionable insights for decision-making. The correlation-based reduction of independent variables and the use of SPSS for the regression analysis allowed for a more streamlined and accurate understanding of the relationships between the variables, contributing to the overall success of the project. Detailed processes are presented in Appendix 4.2.

#### 4.4.3.1 Dependent and Independent Variables

The dependent variable is the variable that is being predicted or explained, while the independent variable is the variable that is used to predict or explain the dependent variable:

Dependent variable is also known as the response variable or outcome variable, the dependent variable is what is being studied or analyzed. In a linear regression equation, the dependent variable is represented by the letter "Y".

Independent variable is known as the explanatory variable, predictor variable, or exogenous variable, the independent variable is what is used to predict or explain the dependent variable. In a linear regression equation, the independent variable is represented by the letter "X".

The dependent and independent variable based on the study is given below:-

| Notation | Variables | Scale |
|---|---|---|
| | Dependent variables | |

| | | |
|---|---|---|
| $Y_1$ | Satisfaction of doctors | Yes/No (0 and 1) |
| Independent Variables | | |
| $X_1$ | Task Efficiency | Strongly Agree- 5<br>Agree- 4<br>Neutral- 3<br>Disagree- 2<br>Strongly Disagree- 1 |
| $X_2$ | Work Performance | |
| $X_3$ | Work Productivity | |
| $X_4$ | Work Effectiveness | |
| $X_5$ | Ease of Work | |
| $X_6$ | Work Usefulness | |
| $X_7$ | Learning Ease | |
| $X_8$ | Tech Control | |
| $X_9$ | Interaction Clarity | |
| $X_{10}$ | System Flexibility | |
| $X_{11}$ | Skill Usability | |
| $X_{12}$ | Ease of Use | |
| $X_{13}$ | Usage Frequency | |
| $X_{14}$ | Multipurpose Use | |
| $X_{15}$ | Recommendation Likelihood | |

**4.4.3.2 Correlation Matrix**

From the collected sample size of 110. The correlation matrix of the 15 independent variable is given below at Table 4.17:-

Table 4.17: Correlation Matrix

**Correlation**

| | x1 | x2 | x3 | x4 | x5 | x6 | x7 | x8 | x9 | x10 | x11 | x12 | x13 | x14 | x15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| x1 | 1 | .651** | .418** | .330** | .572** | .466** | .209* | .384** | .328** | .200* | .269** | .266** | .460** | .254** | .581** |
| x2 | .651** | 1 | .598** | .369** | .576** | .568** | .261** | .386** | .259** | .245** | .234* | .228* | .434** | .330** | .566** |
| x3 | .418** | .598** | 1 | .505** | .592** | .494** | .270** | .328** | .255** | .332** | .274** | .255** | .417** | .198* | .432** |
| x4 | .330** | .369** | .505** | 1 | .501** | .587** | .181 | .239* | .327** | .284** | .200* | .241* | .417** | .383** | .399** |
| x5 | .572** | .576** | .592** | .501** | 1 | .527** | .252** | .337** | .358** | .281** | .284** | .250** | .492** | .226* | .568** |
| x6 | .466** | .568** | .494** | .587** | .527** | 1 | .248** | .346** | .360** | .257** | .293** | .293** | .529** | .407** | .509** |
| x7 | .209* | .261** | .270** | .181 | .252** | .248** | 1 | .782** | .724** | .577** | .667** | .597** | .515** | .226* | .431** |
| x8 | .384** | .386** | .328** | .239* | .337** | .346** | .782** | 1 | .726** | .635** | .677** | .605** | .548** | .292** | .521** |
| x9 | .328** | .259** | .255** | .327** | .358** | .360** | .724** | .726** | 1 | .584** | .705** | .652** | .607** | .342** | .527** |
| x10 | .200* | .245** | .332** | .284** | .281** | .257** | .577** | .635** | .584** | 1 | .767** | .708** | .571** | .257** | .411** |
| x11 | .269** | .234* | .274** | .200* | .284** | .293** | .667** | .677** | .705** | .767** | 1 | .816** | .651** | .288** | .526** |
| x12 | .266** | .228* | .255** | .241* | .250** | .293** | .597** | .605** | .652** | .708** | .816** | 1 | .694** | .317** | .550** |
| x13 | .460** | .434** | .417** | .417** | .492** | .529** | .515** | .548** | .607** | .571** | .651** | .694** | 1 | .513** | .671** |
| x14 | .254** | .330** | .198* | .383** | .226* | .407** | .226* | .292** | .342** | .257** | .288** | .317** | .513** | 1 | .525** |
| x15 | .581** | .566** | .432** | .399** | .568** | .509** | .431** | .521** | .527** | .411** | .526** | .550** | .671** | .525** | 1 |

**4.4.3.3 Logistic Regression Analysis Results**

Now based on the correlation matrix different combinations of independent variables that were significantly less correlated with each other were found out and regression test was run on each of the combinations. Now based on higher $R^2$ value, the following combination was used for regression (X2), (X4), (X8) and(X14). The test results based on the regression is given below at

Table 4.18:-Test results of regression modelling

| Variable | Coefficient (β) | Odds Ratio (Exp(β)) | p-value |
|---|---|---|---|
| X2: Work Performance | 1.897 | 6.665 | 0.008 |
| X4: Effectiveness | 2.417 | 11.208 | 0.002 |

| | | | |
|---|---|---|---|
| X8: Ease of Use | 2.532 | 12.585 | 0.007 |
| X14: Variety of purposes | 1.735 | 5.672 | 0.047 |

Here is the logistic regression equation written in terms of the coefficient and independent variables.

$$\log\left\{\frac{P(Y_1 = 1)}{P(Y_0 = 0)}\right\} = \beta 0 + \beta 1x2 + \beta 2x4 + \beta 3x8 + \beta 4x14$$

Substituting the values from the model:

$$\log\left\{\frac{P(Y_1 = 1)}{P(Y_0 = 0)}\right\} = -\ 30.824 + 1.897\mathrm{X}2 + 2.417\mathrm{X}4 + 2.532\mathrm{X}8 + 1.735\mathrm{X}14$$

Here,

P(Y1=1) : Probability of doctors being satisfied with digital health and AI technologies.

P(Y1=0) : Probability of doctors not being satisfied.

- β0=−30.824 : Intercept.
- β1, β2,β3,β4 : Coefficients of the independent variables X2,X4,X8,X14 respectively.

The probability of satisfaction (P(Y1=1) can be calculated as:

$$\mathrm{P(Y1{=}1)} = \frac{1}{1+e^{(-30.824+1.897\mathrm{X}2+2.417\mathrm{X}4+2.532\mathrm{X}8+1.735\mathrm{X}14)}}$$

This equation provides the likelihood of satisfaction based on the values of the independent variables.

#### 4.4.3.4 Validation of the Model

Data validation is a critical step in preparing data for logistic regression modelling, as the quality of the data directly affects the performance and interpretability of the model. The validation of the model was done in MS Excel. Out of the total samples, 20% is used for model validation. For validation, the probability of selecting one parking choice over the others are found out from Eq. (5.4).

**Probability of choosing a mode =** $\frac{e^{u}}{1+\sum e^{u}}$

Where, ‘u’ is the utility function of each preference

The prediction accuracy of the model is shown in Table 5.10.

Table 5.10 Validation of model

| Sample size | Matched predictions | Unmatched predictions | Prediction accuracy (%) |
|---|---|---|---|
| 22 | 18 | 4 | 81.82 |

The choices obtained by the model was compared with the choices given by the doctors. Thus, the number of choices that matched with respect to total number of choices gave the percentage of accuracy. The accuracy of prediction was found out as 81.82%. Since, the prediction accuracy is greater than 80%, the model is significant. The low value is however due to low sample size.

#### 4.4.3.5 Theoretical Inference of the Model

The logistic regression model aims to predict doctors' satisfaction with digital health and AI technologies (dependent variable, Y1), based on four critical independent variables. Below is a thorough interpretation of how each independent variable influences the likelihood of satisfaction:

- Work Performance (X2)

`The coefficient for X2 is 1.897, with an odds ratio (Exp(β) of 6.665 and a p-value of 0.008. This result highlights the importance of perceived efficiency in driving satisfaction. When doctors believe that these technologies enhance their work performance, they are more likely to be satisfied. This may stem from reduced workload, faster task completion, or improved accuracy in tasks like diagnosis and patient monitoring. Organizations looking to increase adoption and satisfaction levels might focus on showcasing measurable improvements in performance through real-world examples and feedback.

- Effectiveness at Work (X4)

The coefficient for X4 is 2.417, with an odds ratio of 11.208 and a p-value of 0.002. This variable indicates that satisfaction is strongly tied to how effectively these technologies assist doctors in achieving desired outcomes. For example, technologies that provide decision support, clinical insights, or aid in complex procedures contribute significantly to perceived effectiveness. Doctors who feel empowered and effective are more likely to adopt these innovations enthusiastically and recommend them to their peers. Therefore, emphasis on training and showcasing effectiveness improvements can further increase satisfaction.

- Ease to Perform Desired Tasks (X8)

The coefficient for X8 is 2.532, with an odds ratio of 12.585 and a p-value of 0.007. Ease of use is critical in technology adoption and satisfaction. If doctors find it intuitive and straightforward to use these systems, they are more likely to integrate them into their workflows. Complex systems requiring excessive training or those prone to errors could lead to dissatisfaction. This finding underscores the need for user-friendly interfaces, seamless integrations with existing workflows, and robust support systems to address usability issues promptly. The remarkable odds ratio shows that this is the strongest driver of satisfaction in this model. Ease of use can thus act as a "make-or-break" factor for the acceptance of digital health technologies.

- Use of Digital Health and AI Technologies for Variety of purposes (X14)

The coefficient for X14 is 1.735, with an odds ratio of 5.672 and a p-value of 0.047. This result indicates that doctors appreciate versatile tools that can be applied to multiple tasks, such as clinical notes, reports, or accessing medical information. The ability to use a single platform for various purposes reduces the need for switching between systems, enhances productivity, and improves overall satisfaction. Highlighting the multifunctionality of these technologies can thus serve as a key marketing strategy for developers and implementers.

The model as a whole exhibits excellent predictive performance, as indicated by:

- Nagelkerke R2=0.777, suggesting that 77.7% of the variance in satisfaction is explained by the predictors.

- Classification accuracy = 93.1%, demonstrating strong predictive power.

All four independent variables are statistically significant ($p<0.05$, confirming their relevance in predicting satisfaction. The variable X8 (ease of use) emerged as the most influential predictor, reflecting the importance of usability in driving satisfaction with digital health technologies.

### 4.5. Summary

In this chapter, the job satisfaction among doctors working in private tertiary care hospital in Thiruvananthapuram district regarding the use of digital health and AI technologies was analyzed. Data from 110 respondents were statistically processed using tools like SPSS and MS Excel. Key findings revealed that 76.4% of doctors were satisfied overall, with satisfaction varying by gender, age, and task-specific experiences. Satisfaction was higher for user acceptance and work usefulness but slightly lower for ease-of-use metrics.

Inferential analyses, including hypothesis testing, showed no significant satisfaction differences based on gender or age categories. Logistic regression identified four significant predictors of satisfaction: work performance, work effectiveness, ease of use, and multifunctionality of tools, with ease of use being the strongest driver. The regression model achieved 81.82% prediction accuracy, emphasizing the importance of intuitive, effective, and versatile technologies. The findings highlight critical areas for improving adoption and satisfaction among medical professionals through tailored technological interventions and user-friendly designs.

# CHAPTER -5

# DISCUSSION

The research outcomes indicate that digital health and AI creates a positive impact on job satisfaction of doctors working in private tertiary care hospitals in Thiruvananthapuram district in Kerala, India. This finding aligns harmoniously with previous researches that have similarly highlighted how the incorporation of digital health technologies can significantly enhance the overall quality of patient care and foster an uptick in job satisfaction levels among medical practitioners (Kissi et al., 2019; Vitanen et al., 2023). Furthermore, the study underscores the influential role of four key satisfaction variables in elucidating the positive impact of artificial intelligence and digital health on physicians' job satisfaction. These key variables, namely Work performance, work effectiveness, ease of use, and multifunctionality of tools, collectively contribute to nurturing a favourable work environment for healthcare professionals, with particular emphasis placed on the paramount significance of ease of use as the primary driving force behind the observed positive effects of digital health and AI technologies on doctors' job satisfaction levels.

The findings of this study shed light on the immense potential that digital health technologies and artificial intelligence hold in revolutionizing the landscape of job satisfaction among doctors working in private tertiary care hospitals in Kerala. This is of utmost significance, especially when considering the unique healthcare landscape of Kerala, where there exists a substantial demand for delivering superior quality healthcare services to the population. Through the integration and utilization of digital health platforms and AI-driven solutions, hospitals in Kerala can make significant strides in elevating the standard of care provided, while concurrently managing costs efficiently and enriching the overall patient journey.

Moreover, the transformative influence that digital health and artificial intelligence exhibit on doctors' job satisfaction levels can play a pivotal role in mitigating burnout instances among medical professionals and bolstering retention rates within the healthcare workforce in Kerala. By embracing these cutting-edge technologies, hospitals can cultivate an environment that not only enhances the well-being and fulfilment of physicians but also reinforces the foundation for sustainable growth and development within the healthcare sector in the region. This paradigm shift towards leveraging digital innovations is poised to bring about a tangible and long-lasting positive impact on the quality of healthcare delivery and the holistic experience of both patients and healthcare providers alike in Kerala.

This study adopted a well-thought-out cross-sectional research design combined with a convenient sampling approach to delve into the profound effects of digital health and artificial intelligence on the job satisfaction experienced by doctors working within private tertiary care hospitals. It is worth highlighting the remarkable advantages associated with utilizing these particular methodologies. Cross-sectional studies have a distinctive edge in their ability to facilitate quick and efficient data collection, a particularly desirable feature when exploring cutting-edge subjects such as digital health and AI. By utilizing this design, researchers can capture a precise snapshot that effectively portrays the current state of job satisfaction among doctors, thus providing invaluable insights into how digital health and AI are influencing this vital aspect. Although the sample size is not exhaustive, it nonetheless accurately represents a spectrum of doctors within private tertiary care hospitals, thereby allowing for meaningful extrapolations and generalizations to be made to similar healthcare settings with required adjustments.

This study approached the research issue systematically by thoroughly examining prior work in the field and pinpointing research gaps from the outset. The review process delved into a range of deficiencies, notably focusing on the inadequacies in questionnaire design, such as the absence of crucial socio-economic data and insufficiencies in the content of responses expected from participants. Furthermore, the review highlighted the lack of an improved methodological approach in the study, particularly emphasizing the need for implementing more appropriate statistical tools to effectively analyse the compiled data. By uncovering these gaps and areas for enhancement, the review laid a strong foundation for the subsequent research efforts to bridge these gaps and produce a more comprehensive and robust study outcome.

Accordingly, a new methodology was developed to effectively address the identified research gaps leveraging a judicious approach that carefully navigated the established discrepancies. The formulation of this methodology was guided by incorporating pertinent questions into the instrumentation process, specifically focusing on capturing the socio-economic profiles of the participants and various other key variables derived from a comprehensive review of Technology Acceptance Model (TAM) questionnaire.

The TAM questionnaire utilized in this research study is meticulously crafted to evaluate an individual's attitudes and behaviours towards utilizing a specific technology. The modified version of the questionnaire has been tailored to be highly pertinent for investigating doctors' acceptance of digital health technologies. This adaptation of TAM places a strong emphasis on the concepts of perceived usefulness and ease of use, which directly correlates with the primary concerns and priorities of medical professionals. Given that doctors often require a swift and seamless integration of new technologies into their daily practices, the TAM questionnaire stands out as a valuable instrument for probing into their acceptance patterns. Through extensive validation and reliability testing across diverse studies, including those involving healthcare practitioners, TAM has consistently demonstrated its capacity to accurately gauge technology acceptance within the medical community.

The straightforward and user-friendly nature of TAM renders it particularly convenient for administration to busy doctors who are constantly pressed for time. Moreover, the modified version of the questionnaire has been thoughtfully designed to accommodate individual variations in how doctors perceive usefulness, ease of use, user acceptance, and user recommendation. This nuanced approach allows researchers to capture the distinct perspectives and experiences of doctors, enriching the depth and scope of data gathered during the study.

By using the modified TAM questionnaire in this investigation, researcher stand to gain profound insights into the critical factors influencing doctors' willingness to embrace and adopt digital health technologies. This enhanced understanding not only sheds light on the complexities of technology integration within medical settings but also paves the way for developing targeted strategies aimed at improving overall healthcare outcomes. The robustness and versatility of TAM as a research tool further instil confidence in its efficacy for accurately assessing technology acceptance among doctors, thus empowering researchers to make informed decisions based on solid empirical data.

The ensuing data obtained from the respondents underwent a meticulous analysis encompassing both descriptive and inferential statistical techniques. Within the realm of descriptive statistics, a nuanced approach was taken to evaluate the extent of job satisfaction among the sample population. This evaluation involved assigning weightages to different response scales and subsequently aggregating the values obtained from the 15 variables. These computed values were then analysed across all the doctors in the study, while also comparing them based on gender and age categories to draw meaningful insights from the data collected.

As the analysis progressed, it became evident that a significant portion of the various variables elicited comparable responses. This observation led to the decision to employ principal component analysis, a statistical method used to condense a large set of variables into a more manageable and simplified form, while still retaining the essential information they convey. However, an important drawback that surfaced during the analysis was the potential risk associated with data reduction techniques. There was a concern that in the process of reducing the data, certain variables, no matter how seemingly trivial, might have been inadvertently eliminated, potentially affecting the integrity and completeness of the study's results. Despite the inherent benefits of streamlining the variables, this cautionary note underscored the need for thorough evaluation and consideration when applying such techniques.

The data analysis involved in the study comprised hypothesis testing utilizing z statistics to evaluate the variance present within the gender and age categories. Subsequently, a logit regression model was selected as the primary method to establish relationships between multiple variables and the satisfaction levels, thereby deriving meaningful insights. While alternative techniques like probit regression could have been considered, the decision to employ the binomial logit model was based on its widespread acceptance, ease of interpretation, and its appropriateness for policy recommendations. This specific choice was particularly valuable given that the focus of the study was on enhancing the applicability of existing healthcare facilities. By adopting this methodological approach, the findings generated from the analysis ensure that they are not only actionable but also easily comprehensible for key stakeholders, including healthcare administrators and policymakers. The emphasis on employing a model that aligns with the existing infrastructure underscores the practical implications of the study, emphasizing the important role it plays in informing decision-making processes in the healthcare domain. Additionally, the utility of the chosen logit regression model lies in its ability to provide insights that can be directly translated into policy recommendations, enhancing the potential for real-world application and effectiveness. Ultimately, the thorough consideration given to the selection of the statistical methods ensures that the results derived are not only robust but also relevant and beneficial for guiding future decision-making and strategic planning efforts within the healthcare sector.

The collected data gathered from the participants underwent a comprehensive and insightful analysis encompassing a thorough examination via both descriptive and inferential statistical procedures. The utilization of descriptive statistics facilitated the transformation of raw data into visually accessible formats such as charts, graphs, and tables to enable a more effective interpretation. As a result of this meticulous analysis, pertinent findings emerged, shedding light on various aspects of job satisfaction, particularly delineating differences in satisfaction levels between male and female doctors as well as younger and older practitioners. Notably, the study revealed that a significant majority of doctors expressed satisfaction with the integration of digital technology in their work practices. Nevertheless, the scrutiny also brought to light notable disparities based on gender and age, underscoring the importance of considering these factors in understanding the diverse perspectives within the medical profession. Further exploration into the correlations between job satisfaction and demographic variables delineated valuable insights that underscored the need for targeted interventions to address the nuanced needs of different physician cohorts. This reflective analysis not only deepened our comprehension of the prevailing trends in job satisfaction among medical professionals but also highlighted the importance of incorporating a multi-dimensional approach to grasp the complexities inherent in workforce dynamics within the healthcare sector.

In exploring the dynamics of digital technology adoption among healthcare professionals, it became apparent that male doctors and younger practitioners exhibited a greater openness to integrating such tools into their practice. Conversely, female and older doctors showcased distinct tendencies, indicating a divergence from their counterparts. This observation underscores the ongoing evolution of digital technologies and the nuances of how various demographics interact with them. Particularly noteworthy is the recognition that doctors who may be young and tech-savvy today could find themselves navigating a more challenging landscape as these technologies continue to advance. As such, it becomes imperative to approach this demographic with bespoke training initiatives to facilitate their transition and ensure their proficiency with new technological developments. Moving forward in our analysis, given the robust sample size drawn from a diverse pool of healthcare professionals, the next step entailed a meticulous examination to ascertain the significance of the disparities observed across different age groups and gender categories within the sample. This rigorous evaluation sought to provide deeper insights into the diverse responses and receptivity levels towards digital technology, shedding light on the nuanced interactions between demographic factors and technological integration within the healthcare sector.

By conducting hypothesis testing using z statistics, it was concluded that there was no statistically significant variation observed in the relationships between gender and satisfaction, as well as age and satisfaction. This analysis provided a foundation for further exploration into the impact of job satisfaction on a range of response variables by employing logistics regression modelling techniques. The results of this extended analysis identified four key predictors of satisfaction: work performance, work effectiveness, ease of use, and the multifunctionality of tools, with ease of use emerging as the most influential factor. The practical implications of these findings suggest that investments in digital health technologies by hospitals and other healthcare institutions could lead to improvements doctor’s job satisfaction and patient care. To enhance the generalizability of these findings, future research endeavours may consider expanding the sample size, incorporating a more diverse participant pool, utilizing mixed-methods approaches, and dedicating additional time to delve deeper into the intricacies of the phenomenon under study.

# CHAPTER 6:

# CONCLUSIONS AND IMPLICATIONS

## 6.1 Introduction

The study's findings suggest that usage of Digital health and AI impacts the job satisfaction of doctors in Kerala, India. These results are consistent with many of the previous studies on the advantages of digital health and AI tools in medical environments. The study also emphasizes the need for more research into how digital health technologies affect doctors' satisfaction in various settings and scenarios. According to the study's practical implications, hospitals and other healthcare institutions can enhance patient care and physician satisfaction by investing in digital health technologies.

The study's theoretical implications add to the body of knowledge regarding the advantages of digital health technologies in medical environments. The study's policy implications advise policy makers to create laws and rules that encourage the use of digital health technologies in medical facilities. Methodological restrictions and possible biases are among the study's main limitations. Future studies should examine how digital health technologies affect physician satisfaction in various settings and scenarios. To sum up, this study adds to the body of knowledge regarding the advantages of digital health technologies in healthcare environments and emphasizes the need for additional research on how these technologies affect physician satisfaction.

## 6.2 **Summary of the study and finding Conclusions**

This section describes the essence of the research, emphasizing the findings' significance and their implications for digital health and AI technologies in enhancing job satisfaction among doctors in private tertiary care hospitals in Trivandrum, Kerala.

The study's primary objective was to evaluate how digital health and artificial intelligence (AI) technologies impact job satisfaction among doctors. This research is significant in Kerala's context, known for its exemplary healthcare standards but also facing challenges in adapting to evolving technologies. Digital health and AI offer promising opportunities to enhance efficiency, reduce administrative burdens, and improve clinical outcomes. However, they also pose challenges, including technology-induced stress and the need for adaptability.

The study revealed that 76.4% of doctors expressed overall satisfaction with using digital health and AI technologies in their professional roles. The satisfaction levels varied across different demographic segments, particularly concerning gender and age. Younger doctors (below 40) demonstrated similar satisfaction levels regardless of gender. However, satisfaction decreased with age, and female doctors, especially those above 50, exhibited relatively lower satisfaction levels. These findings highlight that demographic factors significantly influence how digital technologies are perceived and adopted in healthcare settings.

Using a modified version of the Technology Acceptance Model (TAM), the study identified four major factors influencing job satisfaction:

- Perceived Usefulness: This encompasses how effectively the technologies enhanced job performance, including accomplishing tasks quickly, improving productivity, and ensuring work usefulness. Notably, over 80% of respondents reported high satisfaction with how technologies made their tasks more manageable and effective.
- Ease of Use: While satisfaction was high in this category, it lagged behind perceived usefulness. Respondents pointed out challenges such as the time needed to learn and adapt to technologies. Around 64–73% of doctors agreed that the systems were intuitive and straightforward to operate, indicating room for improvement.
- User Acceptance: The technologies were well-received, with over 80% of doctors frequently using them for multiple purposes, including clinical notes, diagnostic tools, and patient management systems.
- Recommendation Likelihood: The majority expressed willingness to recommend these tools to colleagues, showcasing their positive attitude toward integrating digital health into clinical practice.

The research provided deeper insights into satisfaction levels using principal component analysis, hypothesis testing, and regression modelling. Notably, gender and age did not significantly impact overall satisfaction statistically, but qualitative differences were observed. Logistic regression modelling identified ease of use, task efficiency, work effectiveness, and tool versatility as critical predictors of satisfaction. Among these, ease of use emerged as the most influential factor, with the strongest odds ratio.

The findings of the study underscore the transformative potential of digital health and AI technologies in modern healthcare. By simplifying workflows, enhancing task efficiency, and providing multifunctional capabilities, these tools can alleviate job stress and foster a more conducive working environment. However, the study also highlights the need for tailored interventions to address demographic disparities. Female doctors and older professionals may require additional support, including training programs and user-friendly interfaces.

The research emphasizes the importance of intuitive design, robust support systems, and policy-level interventions to maximize the benefits of digital health technologies. For technology developers, the findings stress the need to prioritize usability and adaptability in system designs. For policymakers, fostering an environment that encourages the adoption of digital tools is vital.

The recommendations of the study are as follows: -

- Ongoing and continuous education programs tailored to demographic needs can bridge the skill gap and ensure seamless technology adoption.
- Developers should focus on creating doctors-friendly or healthcare workers – friendly systems with minimal learning curves.
- Policymakers and regulators should implement guidelines that promote the equitable use of digital health tools and address gender and age-specific challenges.

- Hospitals should establish feedback loops to identify and address challenges doctors face in using these technologies.
- Encouraging technology adoption through incentives and recognition can motivate doctors to embrace innovations.
- Highlighting the multifunctional nature of digital tools can enhance their perceived value and acceptance.

While the study provides valuable insights, it is not without limitations. The cross-sectional design limits the ability to establish causal relationships. The convenience sampling method may introduce bias, and the sample size, though adequate, may not fully represent the larger population. Future research should adopt longitudinal designs and include diverse geographic and institutional settings to generalize findings.

## 6.3 Implications, applications and future research

### 6.3.1 Implications and Applications

There are several significant implications associated with this study that explores the effects of digital health and artificial intelligence on the job satisfaction of doctors practicing in private tertiary care hospitals in Thiruvananthapuram district in Kerala. From a theoretical perspective, the study delves into how advancements in technology are reshaping the healthcare landscape and influencing the professional experiences of physicians. Practically, the findings may offer valuable guidance on optimizing the integration of digital health tools and AI solutions within private healthcare settings in Kerala, potentially leading to enhanced efficiency and quality of care delivery.

Moreover, at a policy level, the study can shed light on the need for regulatory frameworks that foster innovation while ensuring the well-being of healthcare professionals. Exploring the societal implications, the research may highlight the broader effects of digitization in healthcare, including implications for healthcare accessibility, equity, and quality. By examining the impact of digital health and AI on doctor-patient relationships, the study could provide crucial insights into how these technologies influence communication, trust, and the overall patient experience.

Furthermore, exploring the concept of technostress within the context of this research could offer a nuanced understanding of how the increasing reliance on technology affects doctors' well-being and job satisfaction. By evaluating the potential stressors associated with technology adoption and the strategies to mitigate technostress, the study aims to contribute to a comprehensive understanding of the challenges and opportunities that emerge with the digital transformation of healthcare. Ultimately, this research seeks to enrich the current discourse on the evolving role of technology in healthcare and its implications for the job satisfaction and well-being of doctors in private tertiary care hospitals in Kerala.

The study's findings play a vital role in shaping strategies aimed at enhancing the well-being of doctors, mitigating burnout, and fostering job satisfaction within the medical field. Moreover, these findings are instrumental in offering valuable insights that can guide the successful integration of digital health and artificial intelligence (AI) technologies within private tertiary care hospitals. Such guidance holds significant importance as it aims to streamline operational processes while ensuring minimal disturbances to doctors' workflows. Furthermore, these findings have the capacity to support the development of comprehensive training programs designed to equip doctors with the necessary skills and knowledge to effectively leverage digital health and AI tools in their daily practice. By providing evidence-based recommendations and actionable insights, this study serves as a key resource in advancing healthcare practices and improving overall patient outcomes through the strategic utilization of technology in the medical sector.

The study's findings play a crucial role in shaping the regulatory landscape concerning the integration of digital health and artificial intelligence (AI) within the healthcare sector. Furthermore, the study's outcomes shed light on the imperative for increased investments in enhancing digital health infrastructures that incorporate AI capabilities. Such financial commitments are pivotal in establishing robust and interconnected systems that can seamlessly integrate with existing healthcare structures, aiming to elevate care quality and accessibility for all individuals. Moreover, by outlining the evolving requirements for healthcare professionals, specifically doctors, to embrace digital health tools and AI technologies, the study underscores the necessity for ongoing workforce education and training programs. This strategy ensures that medical practitioners are equipped with the requisite knowledge and competencies to leverage these innovative solutions effectively, thereby enhancing patient care outcomes and fostering a culture of technological proficiency within the healthcare workforce. Ultimately, the study's findings hold the promise of revolutionizing healthcare practices by streamlining processes and optimizing resources through the strategic deployment of digital health and AI advancements. By harnessing these insights and implementing evidence-based strategies, healthcare systems can significantly enhance their efficiency, quality of care, and overall patient outcomes.

The study's analysis delves deep into the intricate ways that the integration of digital health and AI technologies can revolutionize the patient experience, paving the way for heightened levels of patient satisfaction and engagement. By shedding light on innovative strategies that leverage these technologies, the study's insights play a crucial role in addressing existing health inequities, particularly with a keen eye on bridging the gap when it comes to access to digital health and AI tools. These profound implications underscore the significant value of the study, showcasing its potential to not only offer theoretical insight but also serve as a practical guide for policymakers looking to shape the future of healthcare. Moreover, the study's findings are poised to drive societal advancements that can potentially reshape the landscape of digital health and AI applications in healthcare, ushering in a new era of transformative progress.

### 6.3.2 Recommendation

In order to increase doctors' job satisfaction, healthcare organizations are advised to invest in AI and digital health technology, according to the study's conclusions. In order for doctors in tertiary care hospitals to successfully employ and incorporate digital health technology into their practices, they should be trained and supported.

In order to increase engagement and adherence, developers of these technologies should also take into account the demands and preferences of doctors when designing digital health solutions. This study suggests that governments and healthcare institutions create rules and regulations to encourage the use of digital health technologies. Governments and healthcare institutions should fund AI and digital health infrastructure and encourage doctors to be digitally literate.

In addition, this study suggests that future research look into how doctors' satisfaction is affected over the long run by digital health technologies. Future research should look at how vulnerable groups of doctors, those living in rural locations, and those with low levels of IT literacy are affected by digital health technologies. To enhance patient outcomes and save healthcare expenditures, future research should create and evaluate digital health solutions. By putting these suggestions into practice, academics, politicians, and healthcare organizations may collaborate to fully utilize digital health technologies' promise to enhance patient outcomes and lower healthcare expenses.

According to the study's findings, 76.4% of the sample is leaning toward using AI and digital health. It is imperative that policymakers, providers, and technology developers focus on how to make all doctors technologically savvy, even though this is a positive outcome when we consider the future, when all doctors will need to be tech-savvy.

However, technology adoption in healthcare necessitates a planned strategy to guarantee that all physicians are tech-savvy. A methodical approach to accomplishing this would be to begin with Leadership and Governance by creating a thorough digital health plan that complements the objectives of the company. Then, to manage digital health projects, a chief medical information officer (CMIO) or any position similar to it should be appointed. To ensure stakeholder engagement and direct choices regarding digital health, a committee or working group ought to be formed.

To educate physicians about new technology and digital health tools, healthcare institutions should regularly host workshops, online courses, and training sessions.

Additionally, they must to stress the value of user-centred design and offer instruction on the proper use of digital health products. It is legitimate to urge doctors to learn from one another's experiences and to cultivate a culture of information sharing. Healthcare organizations must make sure that its technological infrastructure is current and facilitates the use of digital health technologies.

They also need to provide specialized technical assistance to assist physicians in resolving problems and making the most of these tools. This can be accomplished by setting up a help desk or support hotline to give doctors prompt assistance. The advantages of digital health tools and how they might enhance patient care and results should be made explicit by healthcare organizations. Address reluctance to change and promote candid communication. Honor and commemorate the accomplishments of medical professionals who have embraced digital health resources. Offer incentives to physicians who exhibit competence with digital health tools, such as prizes or recognition. Find and honour medical professionals who are advocates for digital health and who can encourage others to embrace new technologies. To motivate physicians to give digital health skills top priority, incorporate digital health competences into performance reviews. Keep an eye on how digital health tools are being adopted and used. To help guide future decisions, ask physicians for their opinions on digital health solutions. Assess the success of digital health projects on a regular basis and adjust as necessary. Healthcare organizations may foster an environment that supports and motivates physicians to use digital health tools by adhering to this methodical approach, which will ultimately improve patient care results and work satisfaction.

The key takeaway is that, as emerging technologies continue to alter the morphology of the healthcare landscape of Kerala , it is significantly and indisputably contributing for doing the right thing at the right time in the right way for the right person right the first time. No one can halt the advancement of technology. The potential of healthcare technologies will eventually transform every aspect of our life. As a result, healthcare professionals must keep their minds open to the idea that technology could alter the way that healthcare is now delivered and their minds should be adaptive and versatile for changes. In order to manage technological improvements, healthcare personnel must now keep up with the latest developments, not the other way around. Working together with clinicians and technology will be essential to providing high-quality healthcare in the future so that it can adjust to changes in the healthcare sector and stay relevant for many years to come.

### 6.3.3 Future Research Directions

Due to the difficulties encountered in gaining access to doctors who operate in tertiary care hospitals, where intricate cases and a complex atmosphere prevail, a non-probability sampling approach employing convenience sampling was chosen for data collection. The decision to use this method was influenced by the inherent challenges of reaching out to medical professionals working in such specialized settings. However, it is important to note that future research endeavours could benefit from employing probability sampling techniques for a more comprehensive approach to data collection. By doing so, potential biases can be minimized, enhancing the overall quality and validity of the research findings. Therefore, while the current study opted for a convenient sampling method, there is scope for future investigations to explore more rigorous and methodical sampling strategies for a deeper insight into the subject matter and to ensure the reliability and generalizability of the research outcomes.

In addition to utilizing cross-sectional studies, conducting longitudinal studies in the future can offer a more comprehensive understanding of the subject matter. Longitudinal studies provide insights into how variables change over time and can help identify trends and patterns that may not be evident in cross-sectional studies alone. Furthermore, exploring comparative studies can further enrich our understanding of the impact of digital health and artificial intelligence on doctor job satisfaction by analysing differences across various regions. By comparing data from different geographic areas, researchers can gain valuable insights into how contextual factors may influence the relationship between technology adoption and job satisfaction among medical professionals. Therefore, incorporating both longitudinal and comparative study designs can enhance the depth and breadth of knowledge in this field, ultimately contributing to more informed decision-making and policy development in healthcare settings.

In addition to digital health technologies, various other technological advancements are playing a significant role in shaping the levels of job satisfaction experienced by doctors. It is crucial that the impact of all types of technologies is thoroughly examined in future studies in order to gain a comprehensive understanding of their effects on the healthcare workforce. Moreover, it is essential to recognize that the influence of technology on job satisfaction is not limited to doctors alone, all healthcare professionals across different roles and specialties should be considered. By broadening the scope of future research to encompass the perspectives of various healthcare professionals, an inclusive and holistic view can be obtained, leading to more informed decisions and policies in the healthcare industry. Therefore, a comprehensive approach that incorporates all relevant technologies and healthcare professionals will be vital in advancing our understanding of how technology intersects with job satisfaction in the healthcare sector. This expanded perspective will lay a solid foundation for driving positive changes that enhance the overall well-being and job satisfaction of healthcare professionals in the modern technological landscape.

6.4 .**Summary** The study was carried out with the primary objective assessing the job satisfaction level of doctors working in private tertiary hospitals in Thiruvananthapuram district due to the impact of digital health and AI technologies. A total of 110 doctors selected on convenience sampling basis were contacted through social media for the purpose of study. The data collected for the study included social profile of doctors and job satisfaction level. Job satisfaction level was measured through 15 proxy variables which were evolved through modified TAM questionnaire.

The study finds that 76.4% of doctors reported job satisfaction which were evaluated based on descriptive analysis of data compiled. There were considerable variances among female/ male doctors and old/ young doctors. Female doctors and aged doctors were a little less adoptive to modern technologies of digital health care when compared to the male and young doctors. The statistical tool of principal component analysis was used to reduce the data pertaining to 15 variables to major principal components so as to avoid duplication in data sets without losing the major contents. A Hypothesis testing was carried out to test whether the variations observed among different categories of doctors were statistically significant or not and the results indicate the variations were not substantial. Regression modeling carried out as part of the study confirmed ease of use and work effectiveness as the most influential predictors of job satisfaction. The study listed the limitations arising from the methodological, theoretical and implementation aspects of digital health technologies. It is recommended that the technologies should be adopted in full measure without any let up. However, adequate orientation and training programs should be conducted on continuous basis to transform the young, old, male and female doctors to be adoptive to the new technologies considering the generational and gender gap in adopting the technologies.

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# 8 APPENDICES

**Appendix 4.1**

Detailed output of Principal component Analysis

**Notes**

| | | |
|---|---|---|
| Output Created | | 05-DEC-2024 14:31:49 |
| Comments | | |
| Input | Data | C:\Users\User\Downloads\Data 04.08.20rc3_1.sav |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| Syntax | | ALTER TYPE ALL(A=AMIN). |
| Resources | Processor Time | 00:00:00.02 |
| | Elapsed Time | 00:00:00.06 |

**Altered Types**

| | | |
|---|---|---|
| Name of Respondent | A45 | AMIN |
| Designation Address | A90 | AMIN |
| Place of Residence | A57 | AMIN |

```
DATASET NAME DataSet1 WINDOW=FRONT.
DATASET ACTIVATE DataSet0.
FACTOR
  /VARIABLES Variable1 Variable2 Variable3 Variable4 Variable5 Variable6 Variable7 Variable8
    Variable9 Variable10 Variable11 Variable12 Variable13 Variable14 Variable15
  /MISSING LISTWISE
  /ANALYSIS Variable1 Variable2 Variable3 Variable4 Variable5 Variable6 Variable7 Variable8
    Variable9 Variable10 Variable11 Variable12 Variable13 Variable14 Variable15
  /PRINT INITIAL EXTRACTION ROTATION
```

/CRITERIA MINEIGEN(1) ITERATE(25)

/EXTRACTION PC

/CRITERIA ITERATE(25)

/ROTATION VARIMAX

/METHOD=CORRELATION.

**Factor Analysis**

**Notes**

| | | |
|---|---|---|
| Output Created | | 05-DEC-2024 14:55:02 |
| Comments | | |
| Input | Active Dataset | DataSet0 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 110 |
| Missing Value Handling | Definition of Missing | MISSING=EXCLUDE: User-defined missing values are treated as missing. |
| | Cases Used | LISTWISE: Statistics are based on cases with no missing values for any variable used. |

| | | |
|---|---|---|
| Syntax | | FACTOR<br><br>/VARIABLES Variable1 Variable2 Variable3 Variable4 Variable5 Variable6 Variable7 Variable8<br><br>Variable9 Variable10 Variable11 Variable12 Variable13 Variable14 Variable15<br><br>/MISSING LISTWISE<br><br>/ANALYSIS Variable1 Variable2 Variable3 Variable4 Variable5 Variable6 Variable7 Variable8<br><br>Variable9 Variable10 Variable11 Variable12 Variable13 Variable14 Variable15<br><br>/PRINT INITIAL EXTRACTION ROTATION<br><br>/CRITERIA MINEIGEN(1) ITERATE(25)<br><br>/EXTRACTION PC<br><br>/CRITERIA ITERATE(25)<br><br>/ROTATION VARIMAX<br><br>/METHOD=CORRELATION. |
| Resources | Processor Time | 00:00:00.00 |
| | Elapsed Time | 00:00:00.03 |
| | Maximum Memory Required | 28528 (27.859K) bytes |

**Communalities**

| | Initial | Extraction |
|---|---|---|
| Tasks accomplished quickly | 1.000 | .554 |
| Work performance improved | 1.000 | .663 |
| work productivity increased | 1.000 | .544 |
| Work effectiviness enhanced | 1.000 | .477 |
| Work made easier | 1.000 | .641 |
| Work usefulness | 1.000 | .616 |
| Learning to operate technologies is quite easy | 1.000 | .689 |
| Easy to get technologies to do what I want it to do | 1.000 | .709 |
| My interaction with technologies is clear and understandable | 1.000 | .720 |
| Technologies found to be flexible to interact with | 1.000 | .673 |
| Becoming skilful at technologies | 1.000 | .825 |
| Quite easy to use | 1.000 | .756 |
| Frequently used | 1.000 | .699 |
| Multi-purpose usage (clinical notes, reports, medical info, etc.) | 1.000 | .291 |
| Recommending to other users | 1.000 | .663 |

Extraction Method: Principal Component Analysis.

**Total Variance Explained**

| | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| Component | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 7.184 | 47.892 | 47.892 | 7.184 | 47.892 | 47.892 | 5.031 | 33.541 | 33.541 |
| 2 | 2.337 | 15.581 | 63.473 | 2.337 | 15.581 | 63.473 | 4.490 | 29.932 | 63.473 |
| 3 | .998 | 6.650 | 70.123 | | | | | | |
| 4 | .846 | 5.640 | 75.764 | | | | | | |
| 5 | .646 | 4.307 | 80.071 | | | | | | |
| 6 | .538 | 3.584 | 83.655 | | | | | | |
| 7 | .452 | 3.016 | 86.671 | | | | | | |
| 8 | .391 | 2.610 | 89.281 | | | | | | |
| 9 | .322 | 2.144 | 91.425 | | | | | | |
| 10 | .287 | 1.910 | 93.335 | | | | | | |
| 11 | .248 | 1.653 | 94.988 | | | | | | |
| 12 | .236 | 1.572 | 96.560 | | | | | | |
| 13 | .191 | 1.273 | 97.834 | | | | | | |
| 14 | .176 | 1.174 | 99.007 | | | | | | |
| 15 | .149 | .993 | 100.000 | | | | | | |

Extraction Method: Principal Component Analysis.

## Appendix 4.2- Development of Binomial Logistic Model

| Gender | res1 | res2 | res3 | res4 | res5 | res6 | res7 | res8 | res9 | res10 | res11 | res12 | res13 | res14 | res15 | Total score | Satisfied | Yes/ No |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 3 | 3 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 5 | 5 | 3 | 4 | 4 | 4 | 51 | 68.00 | 1 |
| 1 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 5 | 4 | 5 | 5 | 5 | 5 | 57.4 | 76.53 | 1 |
| 1 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 5 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 54.1 | 72.13 | 1 |
| 1 | 4 | 4 | 4 | 3 | 4 | 4 | 5 | 4 | 4 | 3 | 5 | 4 | 4 | 5 | 4 | 48.2 | 64.27 | 1 |
| 1 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 3 | 3 | 4 | 4 | 3 | 4 | 5 | 44.9 | 59.87 | 1 |
| 2 | 5 | 4 | 5 | 3 | 5 | 4 | 3 | 3 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 46.2 | 61.60 | 1 |
| 2 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 50.7 | 67.60 | 1 |
| 1 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 5 | 5 | 5 | 4 | 4 | 56.3 | 75.07 | 1 |
| 1 | 5 | 5 | 5 | 5 | 5 | 5 | 3 | 3 | 3 | 5 | 5 | 5 | 5 | 5 | 5 | 54.2 | 72.27 | 1 |
| 1 | 5 | 4 | 3 | 3 | 4 | 5 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 4 | 4 | 49.7 | 66.27 | 1 |
| 1 | 5 | 5 | 5 | 4 | 5 | 5 | 5 | 4 | 5 | 4 | 5 | 4 | 5 | 4 | 5 | 55 | 73.33 | 1 |
| 2 | 4 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 50.9 | 67.87 | 1 |
| 1 | 5 | 5 | 5 | 4 | 4 | 5 | 5 | 5 | 5 | 4 | 5 | 4 | 5 | 5 | 5 | 56 | 74.67 | 1 |
| 1 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 4 | 5 | 4 | 4 | 4 | 4 | 5 | 4 | 49.7 | 66.27 | 1 |
| 2 | 5 | 4 | 3 | 4 | 4 | 4 | 5 | 4 | 5 | 3 | 5 | 4 | 5 | 5 | 5 | 51.6 | 68.80 | 1 |
| 1 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 46.4 | 61.87 | 1 |
| 1 | 5 | 5 | 4 | 5 | 5 | 4 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 56 | 74.67 | 1 |
| 1 | 5 | 5 | 5 | 5 | 5 | 5 | 3 | 4 | 4 | 3 | 3 | 3 | 4 | 4 | 4 | 48.2 | 64.27 | 1 |
| 1 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 3 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 44.8 | 59.73 | 1 |
| 2 | 4 | 5 | 5 | 5 | 5 | 5 | 4 | 5 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 53.4 | 71.20 | 1 |
| 2 | 4 | 4 | 4 | 4 | 4 | 5 | 4 | 5 | 4 | 4 | 4 | 5 | 4 | 5 | 5 | 51.4 | 68.53 | 1 |
| 2 | 3 | 3 | 3 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 4 | 45.3 | 60.40 | 1 |
| 1 | 5 | 4 | 4 | 4 | 5 | 4 | 5 | 5 | 5 | 4 | 5 | 5 | 5 | 5 | 5 | 55.4 | 73.87 | 1 |
| 2 | 5 | 4 | 4 | 5 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 49.3 | 65.73 | 1 |
| 1 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 2 | 2 | 3 | 2 | 3 | 3 | 2 | 3 | 36.3 | 48.40 | 0 |
| 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 42.2 | 56.27 | 0 |
| 2 | 5 | 4 | 4 | 3 | 3 | 4 | 3 | 4 | 4 | 3 | 3 | 3 | 3 | 4 | 4 | 42.4 | 56.53 | 0 |
| 2 | 3 | 4 | 3 | 3 | 4 | 4 | 4 | 4 | 3 | 3 | 4 | 4 | 4 | 3 | 4 | 42.6 | 56.80 | 0 |
| 2 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 43 | 57.33 | 0 |
| 1 | 5 | 5 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 56.2 | 74.93 | 1 |
| 1 | 5 | 4 | 4 | 5 | 5 | 4 | 5 | 4 | 5 | 3 | 3 | 4 | 4 | 5 | 5 | 51.2 | 68.27 | 1 |
| 1 | 5 | 4 | 3 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 45.8 | 61.07 | 1 |
| 1 | 3 | 4 | 3 | 3 | 4 | 4 | 5 | 5 | 4 | 3 | 3 | 3 | 4 | 4 | 3 | 43.3 | 57.73 | 1 |
| 1 | 3 | 4 | 3 | 3 | 3 | 4 | 3 | 3 | 3 | 2 | 3 | 3 | 4 | 4 | 4 | 38.8 | 51.73 | 0 |
| 2 | 5 | 4 | 3 | 3 | 4 | 4 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 41.7 | 55.60 | 0 |
| 2 | 3 | 3 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 3 | 3 | 3 | 3 | 4 | 4 | 40.2 | 53.60 | 0 |
| 1 | 5 | 3 | 4 | 4 | 5 | 5 | 3 | 3 | 4 | 1 | 3 | 3 | 4 | 4 | 4 | 43 | 57.33 | 0 |
| 2 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 2 | 3 | 3 | 3 | 3 | 3 | 4 | 3 | 36.3 | 48.40 | 0 |
| 1 | 4 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 45.8 | 61.07 | 1 |
| 2 | 4 | 3 | 4 | 5 | 5 | 5 | 4 | 3 | 4 | 4 | 5 | 4 | 5 | 4 | 5 | 50.5 | 67.33 | 1 |
| 2 | 5 | 5 | 5 | 5 | 4 | 5 | 4 | 5 | 5 | 4 | 4 | 4 | 5 | 5 | 5 | 55.1 | 73.47 | 1 |
| 1 | 4 | 3 | 4 | 3 | 3 | 4 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 5 | 3 | 40.2 | 53.60 | 0 |
| 2 | 5 | 4 | 4 | 4 | 3 | 4 | 3 | 3 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 50 | 66.67 | 1 |
| 2 | 5 | 4 | 5 | 5 | 5 | 5 | 3 | 4 | 4 | 3 | 3 | 3 | 4 | 4 | 4 | 47.5 | 63.33 | 1 |
| 1 | 5 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 5 | 57.4 | 76.53 | 1 |
| 2 | 5 | 5 | 5 | 4 | 5 | 5 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 56.7 | 75.60 | 1 |
| 1 | 5 | 5 | 3 | 4 | 5 | 5 | 3 | 3 | 4 | 3 | 4 | 3 | 4 | 5 | 4 | 47 | 62.67 | 1 |
| 1 | 2 | 3 | 2 | 3 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 4 | 3 | 34.7 | 46.27 | 0 |
| 2 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 54.2 | 72.27 | 1 |
| 1 | 5 | 3 | 3 | 5 | 4 | 5 | 5 | 5 | 5 | 4 | 5 | 5 | 5 | 5 | 4 | 53.7 | 71.60 | 1 |
| 2 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 4 | 3 | 4 | 4 | 4 | 5 | 5 | 4 | 47.4 | 63.20 | 1 |
| 1 | 5 | 5 | 2 | 2 | 4 | 5 | 2 | 3 | 3 | 4 | 4 | 4 | 5 | 5 | 5 | 46.1 | 61.47 | 1 |
| 1 | 2 | 1 | 2 | 2 | 2 | 3 | 2 | 2 | 3 | 2 | 3 | 2 | 3 | 3 | 2 | 27 | 36.00 | 0 |
| 2 | 2 | 3 | 3 | 2 | 2 | 3 | 5 | 4 | 4 | 3 | 3 | 3 | 3 | 4 | 2 | 36.4 | 48.53 | 0 |
| 2 | 4 | 3 | 3 | 3 | 3 | 4 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 4 | 3 | 36.8 | 49.07 | 0 |
| 2 | 2 | 3 | 2 | 3 | 2 | 3 | 2 | 3 | 3 | 3 | 3 | 2 | 2 | 4 | 3 | 31.7 | 42.27 | 0 |
| 2 | 4 | 5 | 5 | 4 | 5 | 5 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 5 | 4 | 46.1 | 61.47 | 1 |
| 2 | 5 | 5 | 4 | 5 | 5 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 53.5 | 71.33 | 1 |
| 1 | 4 | 5 | 4 | 4 | 4 | 4 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 42.2 | 56.27 | 0 |
| 1 | 5 | 5 | 5 | 5 | 5 | 5 | 3 | 3 | 3 | 3 | 3 | 3 | 5 | 5 | 4 | 48.4 | 64.53 | 1 |
| 1 | 3 | 3 | 4 | 4 | 2 | 4 | 2 | 2 | 2 | 3 | 3 | 2 | 2 | 4 | 2 | 32.6 | 43.47 | 0 |
| 2 | 5 | 4 | 2 | 4 | 2 | 4 | 3 | 3 | 3 | 2 | 2 | 2 | 3 | 5 | 3 | 36.9 | 49.20 | 0 |
| 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 2 | 32.5 | 43.33 | 0 |
| 1 | 4 | 4 | 3 | 5 | 5 | 5 | 3 | 3 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 49.8 | 66.40 | 1 |
| 2 | 5 | 5 | 3 | 5 | 5 | 5 | 2 | 4 | 3 | 2 | 2 | 2 | 3 | 5 | 4 | 42.8 | 57.07 | 0 |
| 2 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 2 | 2 | 2 | 2 | 3 | 2 | 3 | 3 | 27.1 | 36.13 | 0 |
| 1 | 4 | 2 | 2 | 4 | 4 | 5 | 4 | 4 | 5 | 4 | 4 | 4 | 5 | 5 | 5 | 48.7 | 64.93 | 1 |

**Table 1: Coding of Data**

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4 | 5 | 2 | 5 | 3 | 5 | 4 | 4 | 4 | 3 | 4 | 4 | 5 | 5 | 4 | 48.2 | 64.27 | 1 |
| 1 | 3 | 3 | 3 | 4 | 4 | 4 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 4 | 4 | 33.7 | 44.93 | 0 |
| 2 | 5 | 5 | 4 | 4 | 4 | 4 | 3 | 3 | 3 | 3 | 3 | 2 | 3 | 4 | 4 | 42.1 | 56.13 | 0 |
| 2 | 2 | 2 | 2 | 4 | 2 | 4 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 4 | 3 | 30.9 | 41.20 | 0 |
| 1 | 3 | 3 | 2 | 3 | 3 | 4 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 4 | 3 | 31.5 | 42.00 | 0 |
| 1 | 1 | 2 | 2 | 4 | 2 | 3 | 2 | 1 | 2 | 3 | 3 | 3 | 3 | 5 | 3 | 31.2 | 41.60 | 0 |
| 1 | 5 | 4 | 4 | 4 | 4 | 4 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 5 | 4 | 43.1 | 57.47 | 0 |
| 1 | 2 | 4 | 3 | 4 | 4 | 5 | 4 | 2 | 4 | 3 | 3 | 3 | 4 | 5 | 3 | 41.7 | 55.60 | 0 |
| 1 | 5 | 3 | 2 | 5 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 2 | 2 | 4 | 3 | 36.5 | 48.67 | 0 |
| 1 | 5 | 4 | 4 | 5 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 54.6 | 72.80 | 1 |
| 2 | 4 | 4 | 4 | 4 | 4 | 4 | 2 | 3 | 4 | 3 | 3 | 3 | 3 | 4 | 3 | 40.5 | 54.00 | 0 |
| 1 | 5 | 5 | 5 | 5 | 4 | 5 | 3 | 2 | 2 | 2 | 2 | 2 | 4 | 4 | 4 | 41.9 | 55.87 | 0 |
| 2 | 3 | 3 | 3 | 5 | 4 | 4 | 4 | 3 | 4 | 4 | 2 | 2 | 3 | 4 | 3 | 39.9 | 53.20 | 0 |
| 1 | 5 | 5 | 3 | 3 | 3 | 4 | 2 | 3 | 3 | 2 | 3 | 3 | 2 | 4 | 4 | 38.3 | 51.07 | 0 |
| 1 | 2 | 4 | 4 | 5 | 2 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 4 | 46 | 61.33 | 1 |
| 2 | 3 | 3 | 3 | 5 | 3 | 5 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 52.6 | 70.13 | 1 |
| 2 | 4 | 2 | 2 | 5 | 3 | 3 | 2 | 2 | 3 | 2 | 2 | 2 | 4 | 4 | 3 | 33.9 | 45.20 | 0 |
| 2 | 3 | 3 | 5 | 4 | 3 | 4 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 5 | 4 | 43.5 | 58.00 | 1 |
| 2 | 2 | 2 | 3 | 2 | 3 | 3 | 1 | 1 | 2 | 2 | 2 | 2 | 3 | 4 | 3 | 27.8 | 37.07 | 0 |
| 2 | 5 | 5 | 5 | 5 | 5 | 5 | 2 | 2 | 3 | 2 | 2 | 2 | 4 | 5 | 5 | 44.5 | 59.33 | 1 |
| 1 | 5 | 5 | 2 | 3 | 2 | 5 | 5 | 4 | 4 | 3 | 3 | 3 | 4 | 5 | 5 | 46.1 | 61.47 | 1 |
| 2 | 5 | 5 | 4 | 5 | 5 | 4 | 3 | 3 | 4 | 2 | 3 | 4 | 5 | 5 | 5 | 48.8 | 65.07 | 1 |
| 2 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 54.2 | 72.27 | 1 |
| 2 | 5 | 5 | 5 | 5 | 5 | 5 | 2 | 2 | 3 | 2 | 2 | 2 | 4 | 5 | 5 | 44.5 | 59.33 | 1 |
| 2 | 5 | 3 | 3 | 4 | 4 | 4 | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 3 | 41.5 | 55.33 | 0 |
| 2 | 3 | 5 | 5 | 5 | 5 | 5 | 2 | 2 | 3 | 3 | 2 | 3 | 4 | 5 | 3 | 42.7 | 56.93 | 0 |
| 2 | 4 | 3 | 3 | 5 | 4 | 4 | 3 | 4 | 3 | 4 | 4 | 3 | 4 | 5 | 3 | 44 | 58.67 | 1 |
| 1 | 3 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 4 | 4 | 5 | 4 | 5 | 5 | 5 | 54.4 | 72.53 | 1 |
| 1 | 4 | 3 | 5 | 5 | 3 | 5 | 2 | 2 | 3 | 3 | 2 | 4 | 5 | 5 | 4 | 43.3 | 57.73 | 1 |
| 1 | 5 | 4 | 4 | 5 | 5 | 5 | 4 | 4 | 5 | 3 | 5 | 4 | 5 | 5 | 5 | 53.6 | 71.47 | 1 |
| 1 | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 50.6 | 67.47 | 1 |
| 1 | 2 | 2 | 2 | 5 | 2 | 5 | 3 | 2 | 5 | 3 | 4 | 5 | 3 | 4 | 3 | 39.5 | 52.67 | 0 |
| 1 | 2 | 3 | 4 | 5 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 5 | 3 | 44.9 | 59.87 | 1 |
| 2 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 3 | 3 | 43.7 | 58.27 | 1 |
| 2 | 4 | 4 | 4 | 4 | 4 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 47.9 | 63.87 | 1 |
| 1 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 47.1 | 62.80 | 1 |
| 2 | 5 | 5 | 4 | 5 | 5 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 5 | 4 | 4 | 50.1 | 66.80 | 1 |
| 1 | 5 | 5 | 4 | 4 | 3 | 5 | 3 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 3 | 45.2 | 60.27 | 1 |
| 1 | 4 | 5 | 4 | 4 | 5 | 4 | 3 | 3 | 4 | 4 | 3 | 3 | 4 | 4 | 4 | 45.4 | 60.53 | 1 |
| 2 | 2 | 4 | 5 | 5 | 2 | 5 | 4 | 4 | 4 | 4 | 4 | 3 | 4 | 4 | 3 | 44.7 | 59.60 | 1 |
| 2 | 5 | 4 | 4 | 4 | 3 | 4 | 3 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 3 | 43.8 | 58.40 | 1 |
| 2 | 5 | 4 | 3 | 4 | 4 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 4 | 49.7 | 66.27 | 1 |
| 2 | 4 | 4 | 4 | 4 | 5 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 47.9 | 63.87 | 1 |

| | res1 | res2 | res3 | res4 | res5 | res6 | res7 | res8 | res9 | res10 | res11 | res12 | res13 | res14 | res15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 4.05 | 3.91 | 3.69 | 4.10 | 3.92 | 4.30 | 3.46 | 3.44 | 3.69 | 3.42 | 3.63 | 3.56 | 4.00 | 4.42 | 3.99 |
| | 1.09 | 0.96 | 1.00 | 0.88 | 0.98 | 0.67 | 0.97 | 0.97 | 0.84 | 0.86 | 0.95 | 0.90 | 0.88 | 0.61 | 0.84 |
| | 0.7 | 0.7 | 0.7 | 0.7 | 0.7 | 0.7 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.9 | 0.9 | 1 |

**Regression by Binomial Logit Modelling Using SPSS- Final Model**

LOGISTICREGRESSIONVARIABLESY1

/METHOD=ENTERX2 X4 X8 X14

/CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).

# Logistic Regression

**Notes**

| | | |
|---|---|---|
| Output Created | | 07-DEC-2024 22:05:50 |
| Comments | | |
| Input | Data | C: \Users\hp\OneDrive\Desktop\Dr. Azad\Coding Final Y1, .sav |
| | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 87 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing |
| Syntax | | LOGISTIC REGRESSION VARIABLES Y1 /METHOD=ENTER X2 X4 X8 X14 /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5). |
| Resources | Processor Time | 00:00:00.05 |
| | Elapsed Time | 00:00:00.02 |

**Case Processing Summary**

| Unweighted Cases[a] | | N | Percent |
|---|---|---|---|
| Selected Cases | Included in Analysis | 87 | 100.0 |
| | Missing Cases | 0 | .0 |
| | Total | 87 | 100.0 |
| Unselected Cases | | 0 | .0 |
| Total | | 87 | 100.0 |

a. If weight is in effect, see classification table for the total number of cases.

**Dependent Variable Encoding**

| Original Value | Internal Value |
|---|---|
| 0 | 0 |
| 1 | 1 |

# Block 0: Beginning Block

**Classification Table[a,b]**

| Observed | | | Predicted Y1 0 | Predicted Y1 1 | Predicted Percentage Correct |
|---|---|---|---|---|---|
| Step 0 | Y1 | 0 | 0 | 22 | .0 |
| | | 1 | 0 | 65 | 100.0 |
| | Overall Percentage | | | | 74.7 |

a. Constant is included in the model.

b. The cut value is .500

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 0 | Constant | 1.083 | .247 | 19.291 | 1 | .000 | 2.955 |

**Variables not in the Equation**

| | | | Score | df | Sig. |
|---|---|---|---|---|---|
| Step 0 | Variables | X2 | 23.157 | 1 | .000 |
| | | X4 | 22.406 | 1 | .000 |
| | | X8 | 21.455 | 1 | .000 |
| | | X14 | 19.713 | 1 | .000 |
| | Overall Statistics | | 45.156 | 4 | .000 |

# Block 1: Method = Enter

**Omnibus Tests of Model Coefficients**

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| Step 1 | Step | 65.014 | 4 | .000 |
| | Block | 65.014 | 4 | .000 |
| | Model | 65.014 | 4 | .000 |

**Model Summary**

| Step | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| 1 | 33.378[a] | .526 | .777 |

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

**Classification Table[a]**

| Observed | | | Predicted Y1 0 | Predicted Y1 1 | Percentage Correct |
|---|---|---|---|---|---|
| Step 1 | Y1 | 0 | 19 | 3 | 86.4 |
| | | 1 | 3 | 62 | 95.4 |
| | Overall Percentage | | | | 93.1 |

a. The cut value is .500

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | X2 | 1.897 | .717 | 6.994 | 1 | .008 | 6.665 |
| | X4 | 2.417 | .784 | 9.492 | 1 | .002 | 11.208 |
| | X8 | 2.532 | .942 | 7.234 | 1 | .007 | 12.585 |
| | X14 | 1.735 | .874 | 3.942 | 1 | .047 | 5.672 |
| | Constant | -30.824 | 8.445 | 13.323 | 1 | .000 | .000 |

a. Variable(s) entered on step 1: X2, X4, X8, X14.

**Regression by Binomial Logit Modelling Using SPSS- Trial Model with Different Combination 1**

LOGISTICREGRESSIONVARIABLESY1

/METHOD=ENTERX1 X4 X12 X14

/CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).

# Logistic Regression

**Notes**

| | | |
|---|---|---|
| Output Created | | 07-DEC-2024 21:52:35 |
| Comments | | |
| Input | Data | C: \Users\hp\OneDrive\Desktop\Dr. Azad\Coding Final Y1.sav |
| | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 88 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing |
| Syntax | | LOGISTIC REGRESSION VARIABLES Y1 /METHOD=ENTER X1 X4 X12 X14 /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5). |
| Resources | Processor Time | 00:00:00.03 |
| | Elapsed Time | 00:00:00.02 |

**Case Processing Summary**

| Unweighted Cases[a] | | N | Percent |
|---|---|---|---|
| Selected Cases | Included in Analysis | 88 | 100.0 |
| | Missing Cases | 0 | .0 |
| | Total | 88 | 100.0 |
| Unselected Cases | | 0 | .0 |
| Total | | 88 | 100.0 |

a. If weight is in effect, see classification table for the total number of cases.

**Dependent Variable Encoding**

| Original Value | Internal Value |
|---|---|
| 0 | 0 |
| 1 | 1 |

# Block 0: Beginning Block

**Classification Table**[a,b]

| Observed | | | Predicted Y1 0 | Predicted Y1 1 | Percentage Correct |
|---|---|---|---|---|---|
| Step 0 | Y1 | 0 | 0 | 36 | .0 |
| | | 1 | 0 | 52 | 100.0 |
| | Overall Percentage | | | | 59.1 |

a. Constant is included in the model.

b. The cut value is .500

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 0 | Constant | .368 | .217 | 2.877 | 1 | .090 | 1.444 |

**Variables not in the Equation**

| | | | Score | df | Sig. |
|---|---|---|---|---|---|
| Step 0 | Variables | X1 | 19.483 | 1 | .000 |
| | | X4 | 16.972 | 1 | .000 |
| | | X12 | 42.968 | 1 | .000 |
| | | X14 | 24.719 | 1 | .000 |
| | Overall Statistics | | 54.859 | 4 | .000 |

# Block 1: Method = Enter

**Omnibus Tests of Model Coefficients**

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| Step 1 | Step | 85.299 | 4 | .000 |
| | Block | 85.299 | 4 | .000 |
| | Model | 85.299 | 4 | .000 |

**Model Summary**

| Step | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| 1 | 33.770[a] | .621 | .837 |

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

**Classification Table[a]**

| Observed | | | Predicted Y1 0 | Predicted Y1 1 | Percentage Correct |
|---|---|---|---|---|---|
| Step 1 | Y1 | 0 | 34 | 2 | 94.4 |
| | | 1 | 4 | 48 | 92.3 |
| | Overall Percentage | | | | 93.2 |

a. The cut value is .500

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | X1 | 1.142 | .513 | 4.946 | 1 | .026 | 3.133 |
| | X4 | 1.737 | .690 | 6.335 | 1 | .012 | 5.678 |
| | X12 | 3.812 | .996 | 14.644 | 1 | .000 | 45.235 |
| | X14 | 1.838 | .884 | 4.320 | 1 | .038 | 6.285 |
| | Constant | -31.421 | 7.940 | 15.659 | 1 | .000 | .000 |

a. Variable(s) entered on step 1: X1, X4, X12, X14.

**Regression by Binomial Logit Modelling Using SPSS- Trial Model with Different Combination 2**

LOGISTICREGRESSIONVARIABLESY1

/METHOD=ENTER X2 X3 X7 X10 X15

/CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).

# Logistic Regression

**Notes**

| | | |
|---|---|---|
| Output Created | | 07-DEC-2024 21:28:53 |
| Comments | | |
| Input | Data | C: \Users\hp\OneDrive\Desktop\Dr. Azad\Coding Final Y1.sav |
| | Active Dataset | DataSet0 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 88 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing |
| Syntax | | LOGISTIC REGRESSION VARIABLES Y1 /METHOD=ENTER X2 X3 X7 X10 X15 /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5). |
| Resources | Processor Time | 00:00:00.03 |
| | Elapsed Time | 00:00:00.02 |

**Case Processing Summary**

| Unweighted Cases[a] | | N | Percent |
|---|---|---|---|
| Selected Cases | Included in Analysis | 88 | 100.0 |
| | Missing Cases | 0 | .0 |
| | Total | 88 | 100.0 |
| Unselected Cases | | 0 | .0 |
| Total | | 88 | 100.0 |

a. If weight is in effect, see classification table for the total number of cases.

**Dependent Variable Encoding**

| Original Value | Internal Value |
|---|---|
| 0 | 0 |
| 1 | 1 |

# Block 0: Beginning Block

**Classification Table**[a,b]

| Observed | | | Predicted Y1 0 | Predicted Y1 1 | Percentage Correct |
|---|---|---|---|---|---|
| Step 0 | Y1 | 0 | 0 | 36 | .0 |
| | | 1 | 0 | 52 | 100.0 |
| | Overall Percentage | | | | 59.1 |

a. Constant is included in the model.

b. The cut value is .500

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 0 | Constant | .368 | .217 | 2.877 | 1 | .090 | 1.444 |

**Variables not in the Equation**

| | | | Score | df | Sig. |
|---|---|---|---|---|---|
| Step 0 | Variables | X2 | 19.288 | 1 | .000 |
| | | X3 | 20.510 | 1 | .000 |
| | | X7 | 30.105 | 1 | .000 |
| | | X10 | 36.220 | 1 | .000 |
| | | X15 | 45.241 | 1 | .000 |
| | Overall Statistics | | 56.384 | 5 | .000 |

# Block 1: Method = Enter

**Omnibus Tests of Model Coefficients**

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| Step 1 | Step | 91.414 | 5 | .000 |
| | Block | 91.414 | 5 | .000 |
| | Model | 91.414 | 5 | .000 |

**Model Summary**

| Step | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| 1 | 27.655[a] | .646 | .871 |

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

**Classification Table[a]**

| Observed | | | Predicted Y1 0 | Predicted Y1 1 | Predicted Percentage Correct |
|---|---|---|---|---|---|
| Step 1 | Y1 | 0 | 32 | 4 | 88.9 |
| | | 1 | 4 | 48 | 92.3 |
| | Overall Percentage | | | | 90.9 |

a. The cut value is .500

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | X2 | 1.451 | .835 | 3.017 | 1 | .082 | 4.266 |
| | X3 | 1.590 | .740 | 4.610 | 1 | .032 | 4.903 |
| | X7 | 3.006 | 1.269 | 5.613 | 1 | .018 | 20.197 |
| | X10 | 2.427 | 1.247 | 3.784 | 1 | .052 | 11.321 |
| | X15 | 4.278 | 1.779 | 5.786 | 1 | .016 | 72.131 |
| | Constant | -46.221 | 15.197 | 9.250 | 1 | .002 | .000 |

a. Variable(s) entered on step 1: X2, X3, X7, X10, X15.

| x1 | x2 | x3 | x6 | Y1 |
|---|---|---|---|---|
| 3 | 5 | 3 | 4 | 0 |
| 5 | 3 | 3 | 4 | 0 |
| 4 | 5 | 4 | 5 | 1 |
| 3 | 5 | 5 | 5 | 1 |
| 2 | 5 | 2 | 4 | 0 |
| 3 | 4 | 3 | 5 | 1 |
| 2 | 2 | 1 | 4 | 0 |
| 5 | 5 | 2 | 5 | 1 |
| 5 | 3 | 4 | 5 | 1 |
| 5 | 5 | 3 | 5 | 1 |
| 5 | 5 | 4 | 5 | 1 |
| 5 | 5 | 2 | 5 | 1 |
| 3 | 4 | 3 | 4 | 0 |
| 5 | 5 | 2 | 5 | 0 |
| 3 | 5 | 4 | 5 | 1 |
| 5 | 5 | 4 | 5 | 1 |
| 3 | 5 | 2 | 5 | 1 |
| 4 | 5 | 4 | 5 | 1 |
| 5 | 5 | 4 | 4 | 1 |
| 2 | 5 | 2 | 4 | 0 |
| 3 | 5 | 3 | 5 | 1 |
| 4 | 4 | 4 | 4 | 1 |

| U1 | Eu1 |
|---|---|
| 1.488 | **4.42823** |
| 0.448 | **1.565179** |
| 7.652 | **2104.851** |
| 8.287 | **3971.901** |
| -2.941 | **0.052813** |
| 0.806 | **2.238934** |
| -12.724 | **2.98E-06** |
| 4.485 | **88.67695** |
| 4.715 | **111.6088** |
| 7.017 | **1115.435** |
| 9.549 | **14030.66** |
| 4.485 | **88.67695** |
| -0.929 | **0.394948** |
| 4.485 | **88.67695** |
| 5.755 | **315.7655** |
| 9.549 | **14030.66** |
| 0.691 | **1.99571** |
| 7.652 | **2104.851** |
| 7.814 | **2475.011** |
| -2.941 | **0.052813** |
| 3.223 | **25.10332** |
| 3.5 | **33.11545** |

81.81818

| Z0 | Z1 |
|---|---|
| **0.184222** | **0.815778** |
| **0.389836** | **0.610164** |
| **0.000475** | **0.999525** |
| **0.000252** | **0.999748** |
| **0.949836** | **0.050164** |
| **0.308744** | **0.691256** |
| **0.999997** | **2.98E-06** |
| **0.011151** | **0.988849** |
| **0.00888** | **0.99112** |
| **0.000896** | **0.999104** |
| **7.13E-05** | **0.999929** |
| **0.011151** | **0.988849** |
| **0.716872** | **0.283128** |
| **0.011151** | **0.988849** |
| **0.003157** | **0.996843** |
| **7.13E-05** | **0.999929** |
| **0.333811** | **0.666189** |
| **0.000475** | **0.999525** |
| **0.000404** | **0.999596** |
| **0.949836** | **0.050164** |
| **0.038309** | **0.961691** |
| **0.029312** | **0.970688** |