

Determinants of Satisfaction in the Usage of Healthcare Information Systems by Hospital Workers in Hyderabad, India: Neural Network and SEM Approach

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ABSTRACT

This study focuses on the adoption of Healthcare Information System (HIS) in India's healthcare services, which has led to an increased use of HIS software for managing patient information in hospitals. The study aims to evaluate the factors that influence hospital workers' satisfaction with HIS usage and its impact on their intention to continue in the use of HIS. Primary data was collected through a survey questionnaire from 265 hospital workers. A new framework was developed, and Structural Equation Modeling (SEM) was used for analysis. Sensitivity analysis was also conducted on demographic data using an Artificial Neural Network (ANN) approach. The results indicated that all hypotheses were significant ($p < 0.05$). Effort expectancy was the most significant factor influencing hospital workers' satisfaction ($p < 0.01$). Sensitivity analysis showed that education (Model-A) and experience in use of HIS (Model-B) were the most important factors. The study contributes by proposing a new theoretical framework and extending the previous research on HIS usage satisfaction. Overall, the study highlights the importance of easiness and usefulness in predicting HIS usage satisfaction.

Keywords: Healthcare Information Systems, UTAUT, Artificial Neural Networks (ANN), Technology Adoption, Hospital Workers

I . Introduction

The healthcare industry undergone significant transformation in recent years due to the advancement of information technology (Gagnon et al., 2014).

These advancements helped in improvement of the quality of healthcare services in India. Healthcare Information System (HIS) is an all-encompassing term used to describe the use of technology to collect data on population health for analysis, sharing, and

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decision-making purposes (Iqbal et al., 2013). Various HISs has been implemented in both developed and developing countries, which helped to treat patients in hospitals while enhancing patient safety and reducing waiting time.

Healthcare information systems are defined and described the operational concerns by various organizations like Healthcare Information and Management Systems Society (HIMSS), and the American Medical Informatics Association (AMIA) to understand in details. Healthcare information systems are designed to manage healthcare data and assist healthcare providers in their daily clinical decision-making process, and patient care activities (WHO, 2008). HIS well known as the technology and tools to capture, store, analyze, and share healthcare information (HIMSS, 2021). HIS is the intersection of information science, computer science, and healthcare (AMIA, 2023).

The Ayushman Bharat Digital Health Mission (ABDHM) launched by the Indian Government in August 2020 aims to establish a comprehensive digital infrastructure for healthcare services in India (National Health Authority). It aims to create a National Digital Health Ecosystem (NDHE) that will leverage the power of information technology to provide universal health coverage to all citizens of India. The implementation of HIS in India has paved the way for the ABDHM initiative by providing a foundation for the digitalization of healthcare services. The digitalization of medical records through EMRs has allowed for the easy sharing of patient data across hospitals, which is essential for the success of the ABDHM.

HIS is instrumental in obtaining current healthcare information, which helps in processing and managing data across hospitals (Hennemann et al., 2017). Electronic Medical Records (EMRs) are a component of HIS that can be used to maintain patient in-

formation such as medical histories, diagnosis information, clinical epidemiology, and test results. Additionally, the Hospital Management Information System (HMIS), another component of HIS, can be utilized to manage information about bed availability and admission processes.

The workflow of healthcare providers is improving with the advancements of HIS in the healthcare industry. The steps of implementation of the technologies in hospitals are important for patients and also for healthcare providers in the process of treatment (Gagnon et al., 2014). Instead of the huge advantages of HIS in healthcare, some developing countries are poor in the implementation and adoption of HIS (Iqbal et al., 2013). In this digitalized world, paper-based medical records are not preferred because there are many constraints like imperfection and incompleteness when compared to HIS software. With these healthcare information technologies developments, the availability of information will increase which helps in the management of hospitals and other healthcare industries by doing research, analyzing, and planning actions according to the data (Wu et al., 2022). The adoption rate of HIS is relatively low instead of having huge expectations that HIS will help in the effectiveness of healthcare providers, further, evidence shows that fifty percent failed to maintain and use HIS (Hassan et al., 2019). There is a need to investigate the perceptions, and factors to estimate the intentions of the healthcare providers in adopting the HIS. This helps in the prediction of determinants influencing the intention to use HIS and helps in effective implementations of HIS.

The adoption of the HIS in hospitals is bounded by the satisfaction of the hospital workers while performing the activities in HIS instead of paper-based report collection. In the process of assessing the usage of HIS, user satisfaction is the important factor

(Almajali et al., 2016). This study took satisfaction as the dependent variable which is affected by performance expectancy (PE), effort expectancy (EE), and facilitating conditions (FC). Also, satisfaction is leading to the intention to use HIS by hospital workers (Hennemann et al., 2017). The previous studies follow the framework of UTAUT model. Whereas, less studies available by considering importance of satisfaction as the dependent variable. Literature shows that the unified theory of acceptance and usage of technology (UTAUT) is being used to estimate the behavior intention (BI) of the public in acceptance of technologies (Damberg, 2022; Rouidi et al., 2022), which suggests that factors in UTAUT are best in providing clear estimates between the factors of adoption and BI of customers on the technologies (Sadoughi et al., 2019). Also, some studies suggest that these factors can be used in making new frameworks in technology adoption studies and there is a need for an extension of UTAUT with new variables in different industries.

The chosen city Hyderabad (India) is emerging with healthcare facilities intending to provide medical tourism for global patients in addition to catering the local healthcare needs. Hence, healthcare providers are adopting HIS software to make healthcare delivery more effective. Therefore, this study aims to understand the factors influencing the satisfaction of hospital workers in the usage of HIS with a new framework of satisfaction leading to the intention to use HIS. In healthcare tools or technology adoption studies it is difficult to understand the relationships between different variables or components with traditional statistical techniques. For accurate and strong relationship results Neural Networks (NN) approach is considered the best technique (Ahmed et al., 2020). This study use structural equation modeling (SEM) in the process to test the hypothesis. As the demo-

graphics data is non-linear with its complex distribution, this study engaged Artificial Neural Networks (ANN) technique to find the influence strength of demographic data on the satisfaction of hospital workers in HIS usage.

The prior research indicates that HIS adoption rates remain low, often due to lack of user satisfaction and engagement. This study aims to address this issue by examining how various factors influence hospital workers' satisfaction with use of HIS. Specifically, it investigates the effects of performance expectancy, effort expectancy, and facilitating conditions on user satisfaction. It also explores how satisfaction in turn impacts workers' intentions to continue using HIS. Clarifying these relationships through the proposed conceptual framework can provide valuable insights into how to improve HIS implementation success by focusing on enhancements that maximize end user satisfaction.

II. Conceptual Background

2.1. Healthcare Information System (HIS)

Healthcare information systems are computerized systems that are used in the healthcare industry to manage and organize patient data, medical records, billing and financial data, and other administrative functions. These systems have become increasingly popular in recent years as the healthcare industry has become more digitized and technology-driven (Hennemann et al., 2017). The use of healthcare information systems has several benefits for both patients and healthcare providers. One of the main advantages is improved patient care. By having access to patient records, healthcare providers can make more informed decisions about patient care and

treatment. Additionally, these systems can help reduce medical errors and improve patient safety by providing real-time access to critical patient information (Maillet et al., 2015). Healthcare information systems also have benefits for healthcare providers. By automating administrative tasks, these systems can save time and reduce costs associated with paper-based systems. Electronic billing and claims processing, for example, can help reduce errors and improve the efficiency of the billing process. There are several types of healthcare information systems, including electronic medical records (EMRs), electronic health records (EHRs), and personal health records (PHRs) (Queen, 2021). EMRs and EHRs are used by healthcare providers to manage patient data and medical records, while PHRs are used by patients to manage their own health information. Overall, the use of healthcare information systems has revolutionized the way healthcare is delivered and managed. As technology continues to evolve, these systems will become even more advanced and offer even greater benefits to patients and healthcare providers alike.

2.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical model that helps in predicting the user acceptance of technology. In recent years, UTAUT has been widely used in healthcare to study the acceptance and utilization of healthcare technologies among healthcare providers and patients. UTAUT posits that performance expectancy, effort expectancy, social influence, and facilitating conditions are the major factors that affect users' acceptance and utilization of technology (Rouidi et al., 2022). Several studies have extended

the UTAUT model to understand users' continuance behavior towards digital health information systems (Dwivedi et al., 2019). The UTAUT model has also been utilized to investigate patients' behavior towards the adoption of contactless healthcare applications, such as telehealth. Moreover, UTAUT has been used to examine the factors that influence healthcare providers' acceptance and utilization of healthcare technologies, including electronic health records, clinical decision support systems, and telemedicine (Ahmed et al., 2020). The study of Hoque and Sorwar (2017) revealed that performance expectancy, effort expectancy, social influence, technology anxiety, and resistance to change significantly influenced the intention of elderly users to adopt mHealth services. Ifinedo (2012) employed a modified UTAUT model to explore the factors impacting IS acceptance among Canadian healthcare professionals. The study revealed significant influences of effort expectancy, social influence, compatibility, and organizational facilitating conditions on their intentions to use IS and usage behaviors. Utilization of UTAUT in healthcare has helped researchers and healthcare professionals to better understand the factors affecting the adoption and use of healthcare technologies, which can aid in developing effective strategies to improve healthcare outcomes. While the Unified Theory of Acceptance and Use of Technology (UTAUT) has gained significant popularity in research, it is important to acknowledge that the model has not been immune to criticism regarding its extensive usage (Blut et al., 2022). One approach to addressing the limitations of UTAUT and enhancing its applicability is by incorporating additional variables from other theoretical models (Bawack and Kala Kamdjoug, 2018). In our study, we recognized the need to explore the role of satisfaction as an extra variable in the context of technology adoption in healthcare. The

model's four major factors have provided a foundation for understanding the complex relationship between users and technology in healthcare settings.

2.3. Artificial Neural Networking (ANN)

ANN is the technique that is the imitation of the human brain neural network system containing the elements having the ability to store the given data and provide the information to use naturally (Haykin, 2007). ANN uses the three layers where the neurons are interconnected between each layer. The input layer is the first layer of the ANN technique and the hidden layer is the 2nd and middle layer which is having neurons and leading to the output layer the 3rd layer. In the output layer of this network, the values are obtained from the back propagation method and valued from 0 to 1 (Zakaryazad and Duman, 2016). An ANN model was built in the study of Huang (2010), to investigate the factors affecting the adoption of remote health monitoring. The study of Chan and Chong (2012) refers to the ANN model in its research methodology in the examination of the adoption of RosettaNet (inter-organizational system). Talukder et al. (2020) in their study of predicting the factors of wearable health technology adoption used the ANN model. The results of these studies show that ANN modeling is having high accuracy and more efficiency in finding the factors of adoption in different technologies in different industries (Khaldi et al., 2017; Staudenmayer et al., 2009). The literature suggests that leveraging artificial neural networks (ANN) can yield valuable insights into user intention. Sharma and Shafiq (2022) presents a comprehensive model for assessing intention using machine learning and deep learning techniques, effectively categorizing different purchase intention labels from text-based reviews on online platforms

and social media. Wang et al. (2021) highlights the significance of interpretability in artificial intelligence recommendation systems, positively influencing user trust, usefulness, and ease of use. Srinivas et al. (2018) proposes the application of machine learning methods, particularly ANN, to identify customers likely to be interested in achieving desired outcomes on e-commerce platforms. These findings underscore the value of ANN in understanding user intention and behavior.

2.3.1. Sensitivity Analysis

The literature indicates that sensitivity analysis of ANN can help identify the factors influencing user intention. Tan et al. (2014) employed a hybrid SEM-ANN methodology to identify the elements impacting the adoption of mobile learning, revealing the relevance of all determinants and assessing their normalized importance through sensitivity analysis. Maida et al. (2012) asserts that incorporating sensitivity analysis in recommender systems can enhance the reliability of recommendations, instilling user trust in the recommendation process and positively impacting their intention to utilize the system. The previous studies propose that employing sensitivity analysis of ANN can serve as a valuable instrument in pinpointing the factors influencing user intention.

III. Research Model and Hypothesis Formation

The aim of this study is to identify the factors that affect the satisfaction in the usage of Health Information Systems (HIS), and to develop a new framework for understanding the relationship between these factors. To achieve this, the researchers

have adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical base for the research.

Based on previous studies, the researchers identified five determinants to be included in the research model: Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Satisfaction (ST), and Behavioral Intention (BI).

PE refers to the usefulness of the HIS and the degree to which the worker feels that using the software will bring gains in their job performance. This variable has been widely studied in IT adoption research and is considered important in determining user behavior (Venkatesh et al., 2016; Vichitkraivin and Naenna, 2021). Therefore, if the user perceives the HIS system as useful and beneficial for their job performance, they are more likely to feel satisfied with the system (Sewandono et al., 2022). This is because the user's expectations are being met, and they are experiencing positive outcomes from using the system.

H1: Performance expectancy (PE) is positively related to Satisfaction (ST) in the use of HIS

EE refers to the ease of use of the HIS and the degree to which the worker feels that the system is easy to use and adopt. This variable has also been suggested by previous studies as a key determinant of user behavior, as it influences the adoption of the system (Venkatesh et al., 2012; Venkatesh et al., 2016). Therefore, if the user perceives the HIS system as easy to use and adopt, they are more likely to feel satisfied with the system (Wan et al., 2020). This is because the user's expectations of the system being easy to use are being met, and they do not experience any difficulties or frustrations while using the system.

H2: Effort expectancy (EE) is positively related to the Satisfaction in use of HIS

FC refers to the degree to which the worker feels that the hospital has all the necessary requirements for the smooth working of the HIS. This variable is important because it can affect the user's perception of the system and their willingness to use it (Zhou et al., 2019). Therefore, if the user perceives that the hospital has provided all the necessary requirements, they are more likely to feel satisfied with the system (Teo, 2014; Wu and Wu, 2018). This is because the user's expectations of the system being able to function smoothly are being met, and they are not experiencing any hindrances or obstacles while using the system.

H3: Facilitating Conditions (FC) is positively related to the Satisfaction in use of HIS

ST refers to the level of the worker's comfort and familiarity with the HIS software, and it refers to the fulfillment of requirements during the usage of the system. We need to understand that satisfaction is an important determinant of user behavior (Jaana and Paré, 2020; Kissi et al., 2020). When a user is satisfied with a system, they are more likely to use it in the future. Therefore, if a user is satisfied with the HIS system, they are more likely to have the intention to use it in their job.

H4: Satisfaction (ST) in the use of HIS is positively related to the Behavior Intention to use HIS

BI refers to the intention of the worker to use the HIS in their job. This variable is important because it reflects the user's behavioral intention towards the system, which is a key predictor of their actual

behavior.

Based on these determinants, the researchers developed a new framework for relating the factors of UTAUT differently and testing them. The research model is shown in <Figure 1>.

The hypotheses developed by the researchers suggest that if the user perceives HIS as useful (PE), easy to use (EE), and has access to the necessary resources and support (FC), they are more likely to be satisfied with the HIS usage (ST). This satisfaction will, in turn, lead to a stronger intention to use HIS (BI).

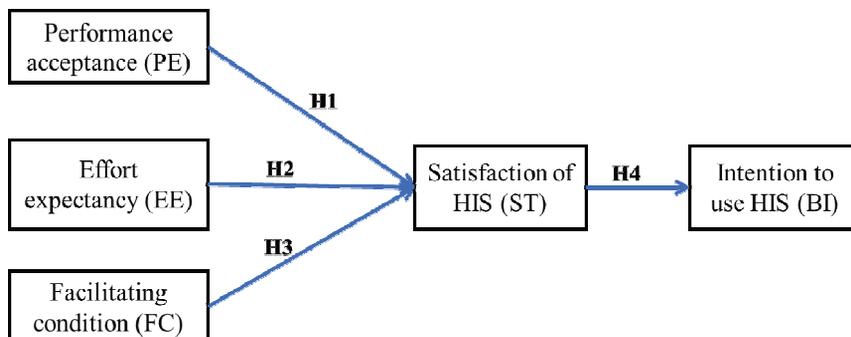
IV. Materials and Methods

4.1. Study Design and Data Collection

For this cross-sectional study multispecialty hospitals in Hyderabad with the implementation of HIS was considered and a questionnaire was forwarded to the hospital workers who use HIS in any form to deliver healthcare to the patients in the hospital. This study was conducted during the post-adoption phase of the healthcare information system. The post-adoption phase in healthcare information sys-

tems is critical as it influences system effectiveness, user satisfaction, and overall healthcare outcomes. Understanding how healthcare professionals adapt and interact with the system over time is crucial. It provides insights into long-term impacts on user behavior, productivity, and satisfaction. Additionally, the post-adoption phase helps identify areas for system improvement and optimization. This study was performed under ethical approval by the Institutional Ethical Committee.

The questionnaire was constructed to understand the hospital workers' perception of HIS usage in their daily job and their experiences with HIS. We received 280 responses out of 330 which were forwarded through online sources during the period of January 2022 to May 2022. From 280 samples we finalized 265 after filtering the collected data. Responses were collected from hospital workers from different departments of the hospital. These include administration staff, nurses, doctors, and floor managers. We explained about this study and asked everyone to fill it out, the participation in the survey was purely voluntary. The sample size was decided with the suggestions of researchers that the sample size can be 10 times the items used in the study (Hair et al., 2013).



<Figure 1> Research Model

4.2. Survey and Instrument Design

The survey included a diverse range of healthcare professionals to ensure a comprehensive representation of perspectives. Participants were recruited from multiple hospital departments, including the admission department, nurses, doctors, lab technicians, floor managers, and hospital management. The sample size consisted of 265 participants, representing various professional groups within the hospital. The survey questionnaire was designed with three parts, first is to know the demographics of the hospital workers (age, gender, education), the second part is to understand their experience with the job and HIS (Experience in Job, Experience in HIS usage) and final part is to determine their perceptions on PE, EE, FC, ST and BI to use HIS used in hospitals. Items for the variables are adapted from previous studies which are valid for the study (Ahmed et al., 2020; Limna et al., 2022; Rouidi et al., 2022). Every construct is measured with 3 items each and the items were scaled and measured with a 5-point Likert scale with the range of “1 - strongly disagree to 5 - strongly agree”.

4.3. Statistical Analysis

Structural Equation Modeling (SEM) is a statistical methodology used to test and estimate complex relationships among variables. It involves building a model that represents the underlying relationships among a set of variables and then testing the fit of the model to the data. SEM allows researchers to examine the direct and indirect effects of variables on each other, as well as the relative strength of those effects. Finalized data was analyzed by using the Statistical Package for the Social Sciences (SPSS) software version 26, which is widely used in social sciences

research. All the descriptive analysis on the demographics of hospital workers were done in SPSS and hypothesis testing was done in AMOS version 24. First, the reliability of the scales was tested and then the convergent and divergent validity of the collected data was tested. The proposed hypotheses of the study were tested for significance. The relation between the demographic data and satisfaction was measured using sensitivity analysis where the strength of the influence on the independent variable can be found. For this sensitivity analysis, we used the ANN approach in SPSS.

4.4. The ANN Sensitivity Analysis and Architecture

ANN is the best approach to deal with non-linear data in assessing the relationships between factors and dependent variables (Alam et al., 2021). While there are indeed other machine learning methods available, such as Support Vector Machines (SVM), Decision Trees, or Random Forests, each method has its strengths and limitations. In our Study, we found that ANN was well-suited for capturing the non-linear relationships between the demographic variables and satisfaction with the healthcare information system. Neural Networks are known for their ability to detect underlying patterns and relationships in large and complex datasets. Importantly, the Neural Network method enables sensitivity analysis, which further enhances our understanding of the relative importance and impact of different demographic variables on satisfaction. By measuring the strength of influence of various factors within the Neural Network model, we gain insights into the demographic profiles that have a more significant impact on satisfaction with healthcare information system usage. This information can guide healthcare

organizations in tailoring their strategies and interventions to address the specific needs of different user groups. An ANOVA test was conducted to determine if there were linear relationships between the variables. The results showed that out of the five relationships, only one (the relationships between experience in HIS and satisfaction) was found to be linear (Lee et al., 2020). The finding that most of the relationships were non-linear supports the need to use artificial neural network (ANN) analysis. Sensitivity analysis was engaged in analyzing the order of importance of demographic variables leading to Satisfaction of HIS usage.

Model in ANN analysis was built an algorithm called Multilayer Perceptron (MLP) method which is a feedforward artificial neural network. IBM statistics SPSS 26 version was used to run this ANN analysis. The best architecture for this analysis was automatically built by SPSS with three layers first layer is with Input variables, the second is the hidden layer and the third is the output layer of satisfaction. The details of the Models built by SPSS are been detailed in the <Table 6>. Activation functions were used to make a desirable output model in ANN.

The activation function used for the hidden layer is “hyperbolic tangent” which is also referred to as the TanH function, which is similar S shape same as the sigmoid activation function. The output values are ranged between -1 to 1. The mathematical equation for the hyperbolic tangent function is

$$\text{TanH} = (e^x - e^{-x}) / (e^x + e^{-x})$$

e - is the mathematical constant.

The activation function used for the output layer is the “identity function” which is the simplest function and is also referred to as the dummy activation

function. The mathematical equation for the identity function is

$$f(x) = x$$

The input variables for this analysis are in two types “Factors and Covariates”, categorical variables are called as factors and numeric scaled variables are called as covariates. Normalized Relative Importance (NRI) is the parameter estimated to order the variables. Two models were proposed depending on the different parts of survey design, Model-A (Age, Education, and Gender influence on ST) which is shown in <Figure 3> and Model-B (Experience in HIS and Job influence on ST) which is shown in <Figure 4>. The <Table 7> provides details about the summary of case processing for two models, Model-A and Model-B.

V. Results

<Table 1> displays data regarding the demographics of respondents. The majority of respondents were female, accounting for 54.3% of the total, while male respondents made up 45.7%. The age group with the highest number of respondents was 21-26 years, comprising 52% of the total, followed by the 27-35 years age group at 38%. Only 1.9% of respondents belonged to the 18-20 years age group.

In terms of job experience, the highest number of respondents, 69%, had less than 4 years of experience, while only 9.8% had 7 years or more of experience. With regard to HIS usage experience, the majority of respondents, 74%, had 1-3 years of experience, while 26% had more than 4 years of experience.

<Table 1> Socio-demographic Characteristics of the Responses

| | | Frequency | Percent (%) |
|-------------------|-------------------|-----------|-------------|
| Gender | Female | 144 | 54.3 |
| | Male | 121 | 45.7 |
| | Total | 265 | 100 |
| Age | 18-20 | 5 | 1.9 |
| | 21-26 | 140 | 52.8 |
| | 27-35 | 102 | 38.5 |
| | 36 and above | 18 | 6.8 |
| | Total | 265 | 100 |
| Education | Diploma | 15 | 5.7 |
| | Graduation | 104 | 39.2 |
| | PG | 146 | 55.1 |
| | Total | 265 | 100 |
| Experience in Job | 1-3 years | 183 | 69.1 |
| | 4-6 Years | 56 | 21.1 |
| | 7 years and above | 26 | 9.8 |
| | Total | 265 | 100 |
| Experience in HIS | 1-3 years | 195 | 74 |
| | 4 years and above | 70 | 26 |
| | Total | 265 | 100 |

5.1. Measurement Model Analysis

The reliability of the scale for the variables were tested and resulted that every scale's Cronbach's Alpha (α) was above 0.7 which says that all the scales are reliable for further analysis (Hair et al., 2013). The <Table 2> shows the results of every construct convergent validity (AVE) and loadings of each item. AVE for every construct is above 0.5 which says that there is convergent validity and data can be taken forward for analysis (Fornell and Larcker, 1981).

The Heterotrait Monotrait ratio of correlations (HTMT) test was used to check the discriminant validity in the data and this test was performed with the help of the plugin "Master Validity Tool" (Gaskin

et al., 2019). <Table 3> can show that every value was below the threshold which is 0.89 which says that constructs in the study form the required discriminant validity (Henseler et al., 2015) which can be considered in the analysis.

5.2. Structural Model Analysis

Fit indices for the proposed model were found with the help of the plugin "Model Fit Measures" in AMOS software (Gaskin and Lim, 2016). Hu and Bentler (1999), suggest that the model fit indices in the following ranges comparative fit index (CFI) > 0.95, standardized root mean square residual (SRMR) < 0.08. The authors also suggest that to strengthen the evidence you can present a

<Table 2> Scale Reliability and Convergent Validity

| Constructs | Items | Loadings | Cronbach's Alpha | Composite Reliability (CR) | Average Variance Extracted (AVE) |
|------------|-------|----------|------------------|----------------------------|----------------------------------|
| PE | PE3 | 0.84 | 0.762 | 0.768 | 0.525 |
| | PE2 | 0.646 | | | |
| | PE1 | 0.68 | | | |
| EE | EE3 | 0.676 | 0.734 | 0.698 | 0.537 |
| | EE2 | 0.635 | | | |
| | EE1 | 0.764 | | | |
| FC | FC3 | 0.787 | 0.89 | 0.892 | 0.734 |
| | FC2 | 0.88 | | | |
| | FC1 | 0.9 | | | |
| BI | BI1 | 0.664 | 0.806 | 0.829 | 0.619 |
| | BI2 | 0.878 | | | |
| | BI3 | 0.733 | | | |
| ST | ST1 | 0.646 | 0.757 | 0.864 | 0.761 |
| | ST2 | 0.813 | | | |
| | ST3 | 0.855 | | | |

<Table 3> HTMT Values for Discriminant Validity

| | PE | EE | FC | BI | ST |
|----|-------|-------|-------|-------|----|
| PE | | | | | |
| EE | 0.89 | | | | |
| FC | 0.407 | 0.654 | | | |
| BI | 0.619 | 0.588 | 0.434 | | |
| ST | 0.646 | 0.795 | 0.505 | 0.783 | |

root-mean-square error of approximation (RMSEA) which should be < 0.06. In this study, CFI is 0.90 which is less than the given range but this range can be acceptable for this model (Hu and Bentler, 1999). SRMR is under the suggested range, <Table 4> illustrates that the proposed model is having the fit indices in the range and a good fit of the model is evidenced positively.

5.3. Hypothesis Testing

The hypotheses proposed in this study were tested

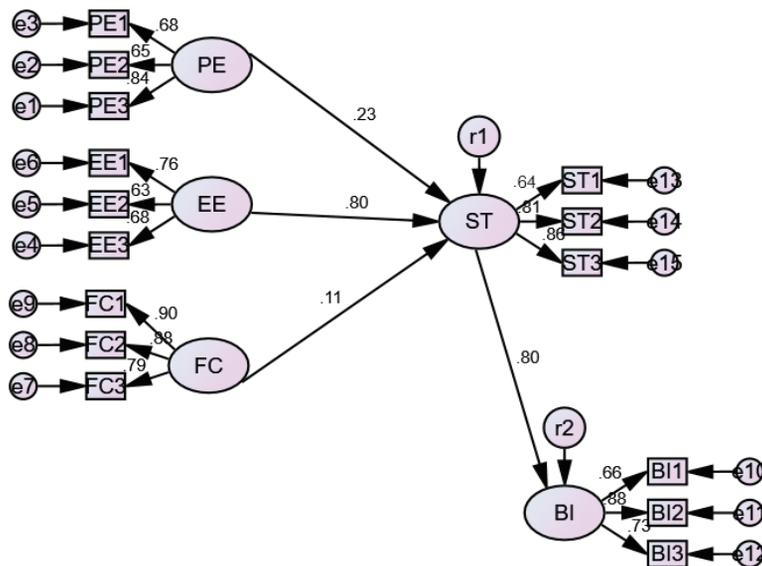
in AMOS and the <Figure 2> shows the structure model testing. <Table 5> illustrates the significance values of every hypothesis tested. PE and EE are showing positive significance relation with ST with $P < 0.01$, where H1 and H2 are accepted and FC is showing positive significance relation with ST with $P < 0.05$, where the H3 is accepted. Finally, the satisfaction leading to Behavior intention to use HIS is positively significant with $P < 0.01$ where the H4 has been accepted.

<Table 4> Model Fit Measures

| Measure | Estimate | Threshold | Interpretation |
|---------|----------|-----------------|----------------|
| CMIN/DF | 2.508 | Between 1 and 3 | Excellent |
| CFI | 0.907 | > 0.95 | Acceptable |
| SRMR | 0.056 | < 0.08 | Excellent |
| RMSEA | 0.076 | < 0.06 | Acceptable |

<Table 5> Hypothesis Relation Values

| Hypothesis Testing | C.R. | P | Significance |
|--------------------|-------|----------|--------------|
| ST < PE | 3.563 | 0.001*** | Supported |
| ST < EE | 6.024 | 0.001*** | Supported |
| ST < FC | 2.057 | 0.04* | Supported |
| BI < ST | 6.107 | 0.001*** | Supported |

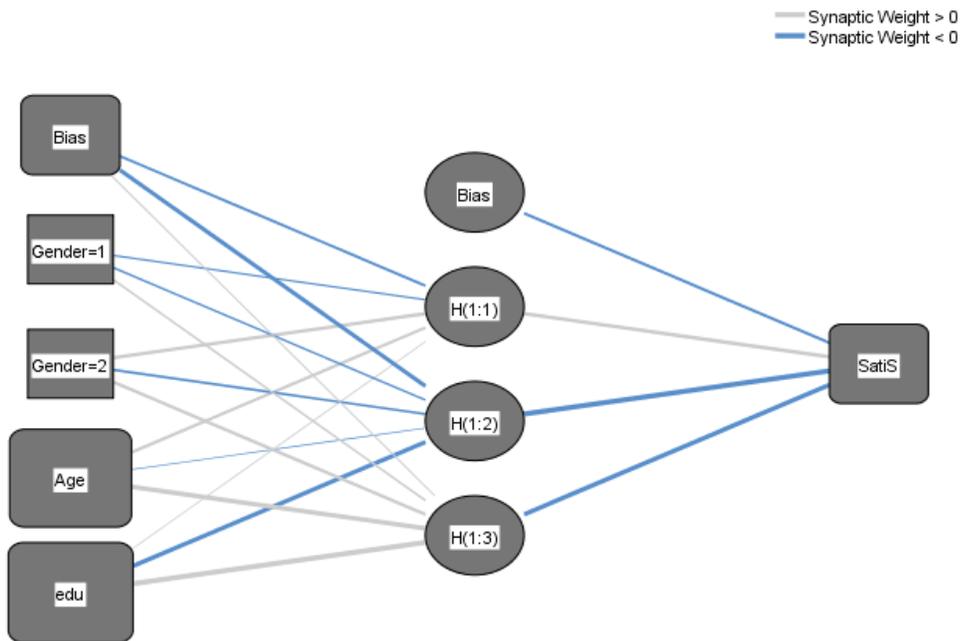


<Figure 2> Results of Structural Model from Smart PLS

5.4. Sensitivity Analysis of Demographical Data

Sensitivity analysis is an essential tool in decision-making processes, as it provides insights into the uncertainties and risks associated with different

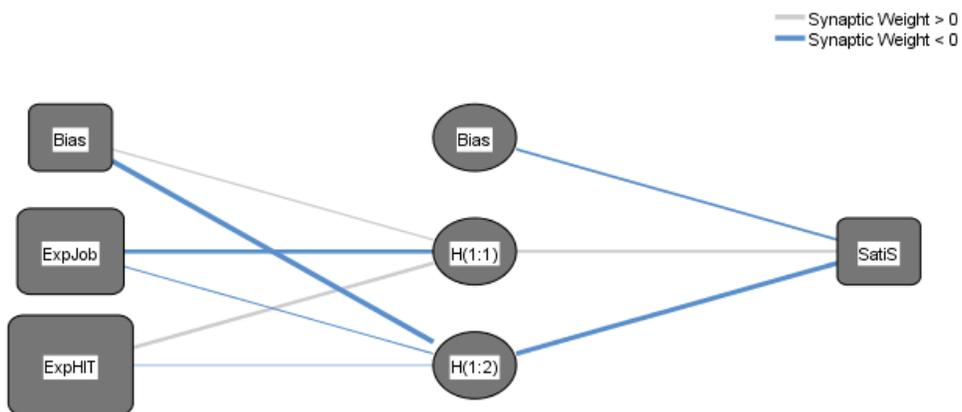
choices and helps to identify the critical factors that affect the outcomes of the decision. The data presented in <Table 8> indicates that education is the most important factor in predicting user satisfaction with HIS in Model-A, followed by age. This relationship is also visually represented in <Figure 5>. In



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

<Figure 3> Neural network for Model-A



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

<Figure 4> Neural network for Model-B

<Table 6> Details of Total Network of the Two Models

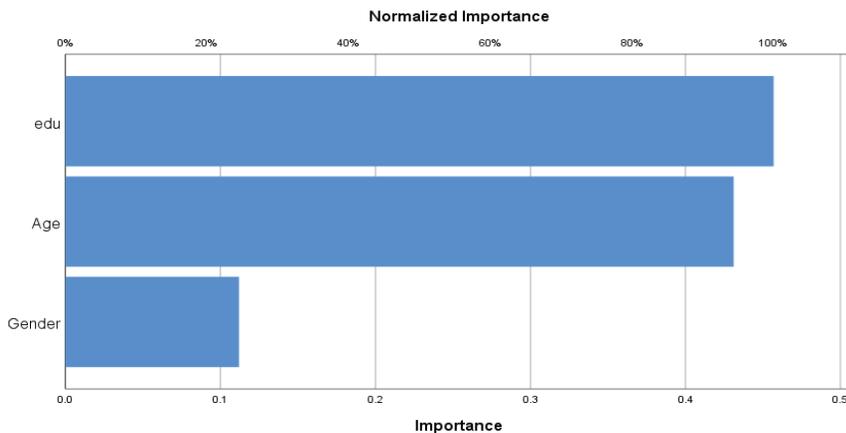
| Network Information | | | Model-A | Model-B |
|---------------------|-------------------------|---|--------------------|-----------------------|
| Input Layer | Factors | 1 | Gender | No Factors in Model-B |
| | Covariates | 1 | Age | ExpJob |
| | | 2 | Edu | ExpHIT |
| Hidden Layer(s) | Number of Hidden Layers | | 1 | 1 |
| | Activation Function | | Hyperbolic tangent | Hyperbolic tangent |
| Output Layer | Dependent Variables | 1 | SatiS | SatiS |
| | Activation Function | | Identity | Identity |

<Table 7> Details about the Sample in Training and Testing

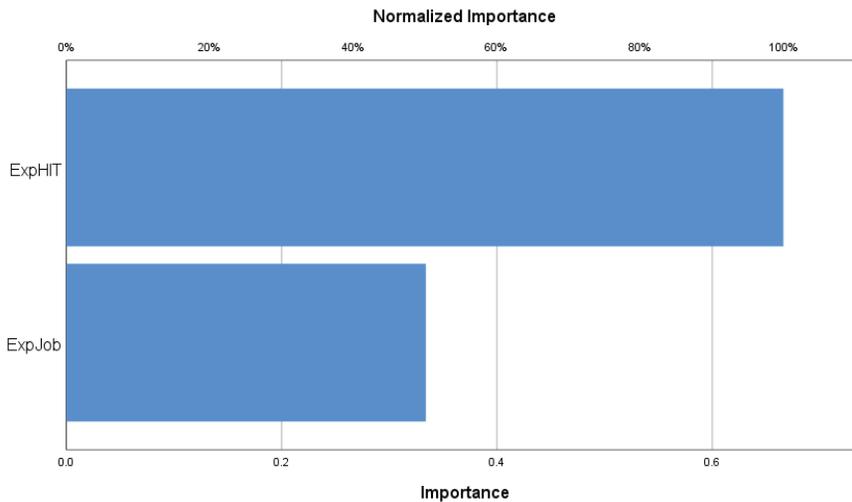
| Case Processing Summary | | Model-A | | Model-B | |
|-------------------------|----------|---------|---------|---------|---------|
| | | N | Percent | N | Percent |
| Sample | Training | 184 | 69 | 180 | 68 |
| | Testing | 81 | 31 | 85 | 32 |
| Valid | | 265 | 100 | 265 | 100 |

<Table 8> Sensitivity Analysis

| Independent Variable Importance | | | | | |
|---------------------------------|------------|-----------------------|---------|------------|-----------------------|
| | Model-A | | Model-B | | |
| | Importance | Normalized Importance | | Importance | Normalized Importance |
| Gender | 0.112 | 24.50% | ExpJob | 0.334 | 50.10% |
| Age | 0.431 | 94.40% | ExpHIT | 0.666 | 100.00% |
| Edu | 0.457 | 100.00% | | | |



<Figure 5> Sensitivity Analysis Model-A



<Figure 6> Sensitivity Analysis Model-B

Model-B, experience with HIS (ExpHIT) is the most significant predictor of user satisfaction, followed by job experience (ExpJob), which is illustrated in <Figure 6>. These findings suggest that demographic variables have varying degrees of influence on user satisfaction with HIS usage, depending on the specific model being analyzed.

VI. Discussion and Implications

6.1. Findings and Discussion

Implementing a Healthcare Information System (HIS) in a multispecialty hospital can be a challenging task, as it involves managing different departments' information and incurring significant implementation costs (Ostern et al., 2021). The success of HIS adoption depends on the satisfaction of hospital workers who use the system to deliver patient care, including appointment booking, admissions, billing, lab reports, nursing, treatment information handling, and bed management by floor managers.

As such, it is an essential area for research. This study aims to contribute to the existing literature on HIS adoption by exploring the five key components that influence hospital workers' satisfaction with HIS usage and their intention to adopt the system across different departments. The results presented in <Table 5> demonstrate that all proposed relationships in this study are statistically significant.

In addition to exploring the key components that influence hospital workers' satisfaction with HIS usage and their intention to adopt the system, this study is unique in that it utilized an Artificial Neural Network (ANN) model to measure the demographic importance of satisfaction in the use of HIS. By incorporating demographic variables into the ANN model, the study was able to assess how factors such as age, gender, education level, and work experience influence satisfaction with HIS usage. This analysis provided valuable insights into the different demographic factors that impact workers' satisfaction with the system, which can help healthcare organizations tailor their HIS implementation strategies to meet the specific needs and preferences of their workforce.

With the support of Hypothesis H1 acceptance, it is understood that the performance of HIS like usefulness in the job which increases the productivity in the job is influencing the satisfaction with the HIS, this result fits the implications from the research Holden et al. (2012), which says that the effectiveness and usefulness of healthcare technology influence the satisfaction of nurses. This suggests HIS software developers should look into the activities in the hospital and try to involve most of them in HIS system while developing and integrating (Sewandono et al., 2022). Hypothesis H2 acceptance indicate that easiness in the use of HIS will create interest in the hospital workers and make them satisfied with the HIS. The current study finding support the similar research by Hennemann et al. (2017) and Wan et al. (2020), as the ease of use of e-health systems in the health sector leads to the satisfaction of the user. As a result, the HIS software developers should develop the HIS system in a way that all the modules in the software are easy to understand and work on it. Also, IT managers in hospitals should look into training the workers to make them comfortable with the HIS systems.

The acceptance of Hypothesis H3 refers to the importance of facilitating conditions in the hospital regarding the HIS system leading to satisfaction in HIS usage. This hypothesis supports the study of Holden et al. (2012), on the nurse's acceptance of healthcare technology, which says that facilitating conditions like training and technical support will help in usage and this drives the nurses' satisfaction with healthcare technology usage (Teo, 2014; Wu and Wu, 2018). Therefore, managers in the hospitals have to make all the availabilities of the requirements of HIS like equipment required to use HIS, and the staff work on the issues of HIS in any situation. Finally, satisfaction with the usage of HIS will lead

to the intention to adopt the HIS by hospital workers, this has evidence by the approval of hypothesis H4. This hypothesis is similar to the hypothesis proposed in the study by Marinković et al. (2020) and Nwankpa and Roumani (2014). So, the ultimate goal of the managers of hospitals, and HIS software developers is to make the users (Hospital workers) satisfied with the use of HIS which will support and lead to the intention to adopt HIS by them.

Unlike previous studies, this study measured the effect of demographic details on the dependent variable which is Satisfaction (ST) with the technique of Sensitivity analysis with the help of the Artificial neural network approach in the SPSS software. This is the best contribution in the literature on healthcare technology adoption. This sensitivity analysis produced interesting results in which we measured the demographics in two models, in Model-A we see that Education is showing more strength in influencing the satisfaction of HIS usage followed by gender, and next is age. In Model-B, Experience is showing more strength in the influence of satisfaction in HIS usage than the experience in the job. These implications support that the workers with more experience with the HIS system are more into the intention to adopt HIS.

The findings of this study have important implications for HIS software developers, hospital managers, and policymakers. Developers should focus on designing HIS systems that are both useful and easy to use, and managers should provide the necessary facilitating conditions, such as training and technical support, to enhance satisfaction with HIS usage. Additionally, policymakers should promote the adoption of HIS systems by incentivizing hospitals to invest in these technologies and by providing guidelines for their implementation.

6.2. Implications

While previous studies have examined the factors influencing technology adoption using the Unified Theory of Acceptance and Use of Technology (UTAUT), this study extends the UTAUT framework by incorporating satisfaction as a key variable. By including satisfaction alongside the UTAUT variables, this study provides a comprehensive framework to better understand the factors influencing hospital workers' acceptance and utilization of HIS. The findings support the notion that satisfaction plays a significant role in technology adoption, as satisfied users are more likely to adopt and continue using the HIS. Also, this study introduces the use of an Artificial Neural Network (ANN) for sensitivity analysis, specifically to measure the effect of demographic details on satisfaction with HIS usage. The ANN approach allows for a deeper understanding of how factors such as age, gender, education level, and work experience influence satisfaction.

The findings of this study have important implications for healthcare organizations and policymakers. First, HIS software developers should design systems that are useful and easy to use for hospital workers, as this will increase their satisfaction with the system and their intention to adopt it. This can be achieved by involving hospital workers in the development and integration of the system and ensuring that all modules are easy to understand and work with.

Second, healthcare managers should provide facilitating conditions, such as training and technical support, to enhance satisfaction with HIS usage. This can be done by providing adequate equipment and staff support to ensure smooth usage of the system. Also, managers should ensure that the HIS system is integrated into all hospital activities to encourage

workers to use it more frequently.

Third, policymakers should incentivize hospitals to invest in HIS systems by providing guidelines for their implementation and promoting the adoption of these technologies. This can be done by providing financial support for the development and implementation of HIS systems and encouraging healthcare organizations to adopt them through educational campaigns.

The successful adoption of HIS systems in healthcare organizations will require collaboration between software developers, healthcare managers, and policymakers. By addressing the key components that influence workers' satisfaction with HIS usage and their intention to adopt the system, healthcare organizations can improve patient care and outcomes, reduce costs, and increase efficiency.

6.3. Limitations and Future Research Directions

The limitations of this study include a small sample size of 265 participants from multispecialty hospitals in a single city in India, which may limit generalizability to other healthcare settings. An inherent limitation of this study pertains to the demographics of the respondents. A significant majority of the participants (70%) reported having less than three years of experience in the usage of Healthcare IT. Given the skewed distribution of the respondents' experience level towards the beginner side, this could potentially influence the study outcomes. Future research could seek to address this issue by purposefully recruiting a more balanced sample in terms of experience level. Another limitation inherent in our study is the age distribution of our sample. The majority of our survey respondents (approximately 91.3%) fall within the age range of 21 to 35 years old. It

is important to acknowledge its potential impact on the generalizability of our findings. The study also relied on self-reported data, which may be subject to bias or social desirability effects. Future studies could address some of the limitations of this study by expanding the sample size to include a more diverse range of healthcare settings and participants. Future research could explore the inclusion of additional variables from other theoretical models. For example, incorporating variables from TAM, which emphasizes perceived usefulness and ease of use, or from IDT, which considers factors influencing the diffusion of innovations, could provide a more comprehensive understanding of technology adoption in healthcare settings.

VII. Conclusion

This study has successfully investigated the factors that influence the satisfaction and intention to adopt healthcare information systems (HIS) among hospital workers. By using the artificial neural network approach in the SPSS software, this study analyzed the impact of demographic details on satisfaction and intention to adopt HIS. The results of the study showed that usefulness and ease of use of HIS significantly influenced the satisfaction and intention to adopt HIS. The study also revealed that facilitating conditions, such as technical support and training, are essential for the effective use of HIS. The sensi-

tivity analysis conducted in this study showed that education and experience are critical factors that influence the satisfaction and intention to adopt HIS. In particular, workers with more experience with HIS are more likely to adopt it. These findings suggest that HIS software developers and hospital managers should focus on making the system more user-friendly and providing adequate training and technical support to ensure successful adoption of HIS. Overall, this study contributes to the literature on healthcare technology adoption by highlighting the importance of various factors in influencing satisfaction and intention to adopt HIS. The study's findings can assist healthcare organizations in making informed decisions when adopting HIS and help improve the quality of healthcare services provided to patients.

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