International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2025, 15(6), 433-441.

# Determinants of Behavioral Intention toward Digital Health Services in India: A PLS-SEM Study on the e-Sanjeevani Application

**Amar[1]*, Komal Malik[2], Namita Srivastava[3], Neha Parashar[4]**

[1]Amity University, Uttar Pradesh, Lucknow, India, [2]Amity Business School, Amity University, Lucknow, Uttar Pradesh, India, [3]St. John's College, Agra, Uttar Pradesh, India, [4]Raja Balwant Singh Management Technical Campus, Agra, Uttar Pradesh, India. *Email: amar@s.amity.edu

**Received:** 17 February 2025 **Accepted:** 15 September 2025 **DOI:** https://doi.org/10.32479/irmm.19007

**ABSTRACT**

The rapid digitization of healthcare services has driven the adoption of telemedicine platforms, particularly in developing countries like India. The e-Sanjivani application, a government-backed telemedicine service, has gained prominence, yet the determinants influencing user behavioral intention toward its adoption remain underexplored. This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to investigate key factors—performance expectancy, effort expectancy, social influence, price value, and user satisfaction—that shape users' behavioral intention to use the e-Sanjivani application. The study is based on survey data collected from a diverse sample across urban and semi-urban regions of India. Findings indicate that performance expectancy, effort expectancy, social influence, and price value significantly influence user satisfaction, which, in turn, is a strong predictor of behavioral intention. While effort expectancy plays a role, its impact is relatively lower. The study highlights the necessity of enhancing the application's usability, affordability, and social endorsement to drive widespread telemedicine adoption. Policymakers and healthcare providers can leverage these insights to optimize digital health strategies, ensuring equitable and sustainable telemedicine integration in India. Future research should explore longitudinal trends and extend the scope to rural populations to refine telemedicine implementation strategies further.

**Keywords:** Telemedicine, e-Sanjivani, Behavioral Intention, PLS-SEM, Healthcare Digitization, User Satisfaction, India
**JEL Classifications:** I11, I18, C38, D91

## 1. INTRODUCTION

The proliferation of digital technologies has profoundly transformed the healthcare landscape, giving rise to innovative telemedicine services that offer individuals convenient and accessible medical care. In India, the e-Sanjivani application, a government-sponsored telemedicine platform, has emerged as a prominent player in this evolving digital health ecosystem. Understanding the factors that shape users' behavioral intention toward telemedicine services is crucial for enhancing the adoption and sustainability of these transformative technologies (Call et al., 2015).

Existing research has explored the technical and socio-political factors that influence the capabilities and implementation of telemedicine in India. Studies have also examined the role of trust, perceived usefulness, and privacy concerns in the continuance of use of online doctor consultation platforms. However, a comprehensive analysis of the determinants of behavioural intention toward telemedicine services, particularly the e-Sanjivani application, remains limited (Bakshi and Tandon, 2022).

To address this research gap, this study aims to investigate the key factors that influence users' behavioral intention toward the e-Sanjivani telemedicine application in India. Employing a partial least squares structural equation modeling approach, the study will explore the impact of compatibility, computer self-efficacy, technical support, and training on users' behavioral intention to use the e-Sanjivani application. the telemedicine capabilities in India and the potential for their advancement and sustainability (Mathur et al., 2017). Additionally, the study will examine the moderating effect of privacy concerns on the relationship between these factors and behavioral intention.

In today's increasingly digital healthcare landscape, understanding the determinants of behavioral intention toward telemedicine services is crucial for driving user adoption and ensuring the long-term success of these transformative technologies. The intention to use and recommend the e-Sanjivani application will be critical in shaping the future of telemedicine in India and informing the development of similar digital health solutions. Adoption of telemedicine services can help address the country's healthcare challenges, particularly in underserved rural areas, and contribute to the enhancement of overall healthcare accessibility and quality (Rastogi et al., 2022). The telehealth services delivered through the e-Sanjivani application can serve as a valuable resource for individuals seeking convenient, accessible, and affordable medical care, especially during times of crisis, such as the COVID-19 pandemic.

The ease and accessibility of telehealth services can be instrumental in bridging the rural-urban divide in healthcare. The e-Sanjivani application has the potential to play a significant role in expanding the reach of healthcare services across India, particularly in regions with limited physical infrastructure and healthcare resources (Hassibian and Hassibian, 2016). The telehealth application can serve as a vital link, connecting patients in remote areas with medical professionals, and facilitating timely and effective healthcare delivery (Kifle et al., 2010).

The determinants of user behavioral intention toward the e-Sanjivani telemedicine application will provide valuable insights for policymakers, healthcare providers, and technology developers to enhance the adoption, usage, and sustainability of such digital health solutions. The findings of this study can guide the design and implementation of effective strategies to promote the use of telemedicine services, addressing the unique needs and concerns of users in the Indian context.

## 2. REVIEW OF LITERATURE

### 2.1. Performance Expectancy of Telemedicine

Performance expectancy, which refers to the degree to which an individual believes that using the system will help them attain gains in job performance, has been identified as a significant predictor of behavioral intention toward telemedicine services (Wu et al., 2021). Studies have shown that users are more likely to adopt telemedicine if they perceive it as a useful and effective tool for healthcare delivery, particularly in terms of improved access to healthcare, reduced travel time and costs, and better health outcomes (Kohnke et al., 2014) (Call et al., 2015). Telehealth applications have demonstrated their potential to enhance healthcare accessibility and efficiency in underserved areas of India (Mathur et al., 2017).

### 2.2. Effort Expectancy of Telemedicine

Effort expectancy, which refers to the degree of ease associated with the use of the system, is another important factor in the adoption of telemedicine services (Kohnke et al., 2014). Individuals are more likely to use telemedicine if they find it easy to navigate and use, with minimal technical complexity (Kifle et al., 2010). Ensuring user-friendly interfaces and providing adequate training and support can help enhance the effort expectancy of telemedicine, thereby increasing its adoption (Dixit et al., 2022). The development of user-friendly telemedicine platforms and the provision of appropriate training for healthcare providers and patients can help overcome the challenges related to effort expectancy (Sharma and Prashar, 2019). telemedicine adoption in India has been hampered by the lack of digital literacy and technical skills among some users, highlighting the need for targeted interventions to address these barriers (Dixit et al., 2022).

### 2.3. Social Influence of Telemedicine

Social influence, which refers to the degree to which an individual perceives that important others believe they should use the system, has also been found to influence the adoption of telemedicine services (Rahi et al., 2021). Positive recommendations and endorsements from healthcare providers, family members, and peers can increase the perceived value and legitimacy of telemedicine, leading to higher rates of adoption (Wade et al., 2014). The social influence of telemedicine is particularly relevant in the Indian context, where social norms and community perceptions play a significant role in healthcare-related decisions (Call et al., 2015) (Mathur et al., 2017). Telemedicine has the potential to address the social stigma associated with certain health conditions and promote its acceptance among the wider community (Irfanahemad et al., 2018).

### 2.4. Price Value of Telemedicine

The price value of telemedicine, which refers to the perceived trade-off between the monetary cost of using the service and the benefits derived, is another important factor (Licurse and Mehrotra, 2018). Users are more likely to adopt telemedicine services if they perceive the benefits, such as reduced travel costs and improved access to healthcare, to outweigh the monetary costs associated with the service (Gilman and Stensland, 2013) (Russo et al., 2016).

### 2.5. User Satisfaction with Telemedicine

User satisfaction with telemedicine services is a crucial determinant of behavioral intention, as it reflects the overall experience and perceived value of the service. Factors such as the quality of the healthcare services provided, the ease of use of the technology, and the responsiveness of the healthcare providers can all contribute to user satisfaction and, in turn, influence the likelihood of continued use of telemedicine services (Wang et al., 2023) (Edoh et al., 2018). The successful implementation of telemedicine in India will depend on ensuring high levels of user satisfaction through the provision of quality healthcare services and a positive user experience (Mishra et al., 2009). The seamless integration of telemedicine into the existing healthcare system and the development of robust patient-provider communication channels can help enhance user satisfaction and drive the adoption of telemedicine (Haleem et al., 2021). The satisfaction of patients with telemedicine services has been identified as a key factor in determining its long-term sustainability and success.

### 2.6. Behavioural Intention of Telemedicine

Behavioral intention, which refers to the likelihood of an individual using telemedicine services, is the ultimate outcome variable in this review. The factors discussed above, such as performance expectancy, effort expectancy, social influence, price value, and user satisfaction, are all expected to positively influence the behavioral intention of users toward telemedicine services in India (Zhang and Zaman, 2020). The intention to adopt telemedicine services in India is influenced by a complex interplay of technological, social, and economic factors (Bakshi and Tandon, 2022). Addressing these factors through targeted interventions and policies can help promote the widespread adoption and sustained use of telemedicine services, ultimately improving healthcare access and outcomes in the country (Kifle et al., 2010).

## 3. RESEARCH METHODOLOGY

### 3.1. Participants

The participants in this study were e-Sanjivani telemedicine service users across various demographic and geographical backgrounds within India. To capture a diverse and representative sample, participants were recruited from urban, semi-urban, and rural regions across multiple states. Selection of participants was aimed at including users from diverse age groups, education levels, and socioeconomic backgrounds to understand broader user perceptions. Age groups ranged from 18 to above 48 years, all participants were either active or potential users of telemedicine services and were aware of or had previously accessed the e-Sanjivani platform.

### 3.2. Procedure

A quantitative research approach was employed, using a structured survey method to gather data on behavioral intentions and determinants affecting telemedicine usage. Data collection was carried out online, using a self-administered survey distributed through various digital channels such as email, social media, and health forums to reach a large and geographically diverse participant base. Each item on the survey was measured on a 5-point Likert scale, allowing participants to express the degree of their agreement or disagreement. The structured survey approach aligns with the methods suggested by Churchill (1979) for collecting standardized data across multiple constructs.

### 3.3. Questionnaire Development

The questionnaire was developed by adapting and refining constructs from existing literature to ensure that it was contextually relevant to telemedicine services, specifically the e-Sanjivani application. The survey was organized into five main sections, corresponding to each construct in the study. The first section included demographic information, such as participants' age, gender, education level, and place of residence, to analyze any demographic differences in responses. The second section, focused on Performance Expectancy, assessed participants' perceptions of the utility of e-Sanjivani in daily health management. The third section, addressing Effort Expectancy, evaluated the ease of use and learning associated with the e-Sanjivani application. The fourth section, on Social Influence, explored the role of peers, family, and colleagues in influencing participants' use of telemedicine. The fifth section on Price Value assessed perceptions of the financial cost-benefit of using the service, while the final section, User Satisfaction, measured overall satisfaction with the platform's interface, service quality, and efficiency leading to the *Behavioral intention*. The measurement items for each construct in the SEM-PLS model are detailed in Table 1. These items were adapted from previous studies and refined to fit the context of this research.

### 3.4. Hypothesis Development

EE → US: Effort expectancy significantly impacts user satisfaction
PE → US: Performance expectancy significantly impacts user satisfaction
PV → US: Price value significantly impacts user satisfaction
SI → US: Social influence significantly impacts user satisfaction
US → BI: User satisfaction significantly impacts behavioral intention

### 3.5. Sampling

Purposive sampling was employed to select participants familiar with or likely to use the e-Sanjivani telemedicine application. This approach allowed the study to focus on individuals with relevant telemedicine experience, capturing insights across diverse demographic backgrounds, including age, gender, and location.

### 3.6. Data Collection and Sample Size

Data were collected in two phases: September to November 2024 and December to January 2025. This approach covered both early and established users, ensuring varied experiences were captured. Using Cochran's formula (Cochran, 1997), the sample size was set at 475 participants, sufficient to support SEM analysis and achieve statistical reliability.

### 3.7. Data Analysis

Data collected from the surveys was analyzed using partial least squares structural equation modeling (PLS-SEM) to explore the relationships among the constructs: Performance expectancy, effort expectancy, social influence, price value, user satisfaction, and behavioral intention. PLS-SEM was chosen for its effectiveness in analyzing complex models with multiple latent variables and smaller sample sizes. Statistical analysis was performed using software SmartPLS.

## 4. DATA ANALYSIS AND RESULTS

The demographic profile of the study sample, as presented in Table 2, highlights a balanced distribution across gender, age, city of residence, and educational qualifications. The sample consisted of 240 males (51%) and 235 females (49%), ensuring near-equal gender representation. In terms of age, the majority of participants fell within the 28-37 years category (30.7%), followed by those aged 38-47 years (28%), 18-27 years (25.1%), and 48 years and above (16.2%). Participants were recruited from six major cities in India, with Kolkata contributing the highest proportion (20%), followed by Mumbai (18%), Delhi (18%), Bengaluru

**Table 1: Scale**

| Construct | Statement | References |
|---|---|---|
| Performance expectancy | Using the e-Sanjivani telemedicine service application is useful in my daily life. | (Pramudita et al., 2023) |
| | Using the e-Sanjivani telemedicine service application allows me to access health services faster. | |
| | Using the e-Sanjivani telemedicine service application increases my opportunity to achieve important health goals. | |
| | Using the e-Sanjivani telemedicine service application improves my ability to manage my daily health. | |
| | Using the e-Sanjivani telemedicine service application improves my overall health. | |
| Effort expectancy | It is easy for me to operate the e-Sanjivani telemedicine service application. | (Pramudita et al., 2023) |
| | Learning how to use the e-Sanjivani telemedicine service application is easy for me. | |
| | My interactions with the e-Sanjivani telemedicine service application are clear. | |
| | My interactions with the e-Sanjivani telemedicine service application are easy to understand. | |
| | It is easy for me to acquire the skills to use the e-Sanjivani telemedicine service application. | |
| Social influence | People who are important to me think that I should use the e-Sanjivani telemedicine service application. | (Pramudita et al., 2023) |
| | People around me who use the e-Sanjivani telemedicine service application appear more proactive about their health. | |
| | My colleagues recommend that I use the e-Sanjivani telemedicine service application. | |
| | People whose opinions I value prefer that I use the e-Sanjivani telemedicine service application. | |
| | Most people around me use the e-Sanjivani telemedicine service application. | |
| Price value | The e-Sanjivani telemedicine service offers a reasonable price. | (Pramudita et al., 2023) |
| | The e-Sanjivani telemedicine service is good value for money. | |
| | At the current price, the e-Sanjivani telemedicine service provides good value for money. | |
| | The price of the e-Sanjivani telemedicine service suits me. | |
| | Regardless of the price, the e-Sanjivani telemedicine service consistently provides quality. | |
| User satisfaction | The e-Sanjivani telemedicine service application meets my expectations. | (Pramudita et al., 2023) |
| | I am satisfied with the e-Sanjivani telemedicine service application's user interface. | |
| | I am satisfied with the service quality of the e-Sanjivani telemedicine service application. | |
| | I am satisfied with the efficiency of the e-Sanjivani telemedicine service application. | |
| | Overall, I am satisfied with the services provided by the e-Sanjivani telemedicine service application. | |
| Behavioral intention | I intend to use the e-Sanjivani telemedicine service application in the future. | (Pramudita et al., 2023) |
| | I will always try to use the e-Sanjivani telemedicine service application whenever I need health services in my daily life. | |
| | I plan to continue using the e-Sanjivani telemedicine service application frequently. | |
| | I prefer to use the e-Sanjivani telemedicine service application when I need health services in the future. | |
| | The e-Sanjivani telemedicine service application is my first choice when I need health services in the future. | |

**Table 2: Demographic profile**

| Demographics | Subcategory | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 240 | 51 |
| | Female | 235 | 49 |
| Age | 18-27 years | 119 | 25.1 |
| | 28-37 years | 146 | 30.7 |
| | 38-47 years | 133 | 28 |
| | 48 years, above | 77 | 16.2 |
| City of residence | Bengaluru | 71 | 15 |
| | Delhi | 84 | 18 |
| | Chennai | 70 | 15 |
| | Hyderabad | 67 | 14 |
| | Mumbai | 85 | 18 |
| | Kolkata | 98 | 20 |
| Education qualification | Undergraduate | 120 | 25.26 |
| | Graduate | 118 | 24.84 |
| | Postgraduate | 123 | 25.89 |
| | Others | 114 | 24 |

(15%), Chennai (15%), and Hyderabad (14%). Educational qualifications were evenly distributed, with the highest percentage of respondents holding postgraduate degrees (25.89%), followed by undergraduates (25.26%), graduates (24.84%), and others (24%). Overall, the sample demonstrates diverse demographic characteristics, providing a comprehensive dataset for examining behavioral intentions toward telemedicine services in India.

Figure 1 represents the gender distribution of participants in the pie chart. Male respondents make up 51% of the total sample (240 participants), while female respondents account for 49% (235 participants). This nearly equal representation between genders ensures a balanced perspective and reduces the likelihood of gender bias in the study's findings.

In Figure 2 the city-wise distribution of participants is shown in the bar chart. Kolkata contributes the highest number of respondents, accounting for 20% (98 participants). Mumbai and Delhi follow closely, each comprising 18% of the sample (85 and 84 participants, respectively). Other cities, including Bengaluru (15%), Chennai (15%), and Hyderabad (14%), have slightly lower but comparable participation. This distribution ensures representation from key tier 1 cities in India, providing insights from diverse urban populations.

In Figure 3 the bar chart illustrates the age distribution of the participants. The largest age group is 28-37 years, which constitutes 30.7% of the sample (146 participants). This is closely followed by the 38-47 years group at 28% (133 participants) and the 18-27 years group at 25.1% (119 participants). Participants aged 48 years and above form the smallest group, accounting for 16.2% (77 participants). This varied age range ensures a comprehensive understanding of perceptions across different life stages.

In Figure 4 the bar chart highlights the educational qualifications of the participants. Postgraduate respondents form the largest group, comprising 25.89% of the total sample (123 participants).

This is followed closely by undergraduate respondents at 25.26% (120 participants). Graduate respondents make up 24.84% of the sample (118 participants), while the "Others" category, which may include vocational or specialized training qualifications, accounts for 24% (114 participants). This balanced distribution across education levels ensures diverse perspectives from individuals with varying academic backgrounds, enriching the study's overall insights.

**Figure 1:** Gender distribution

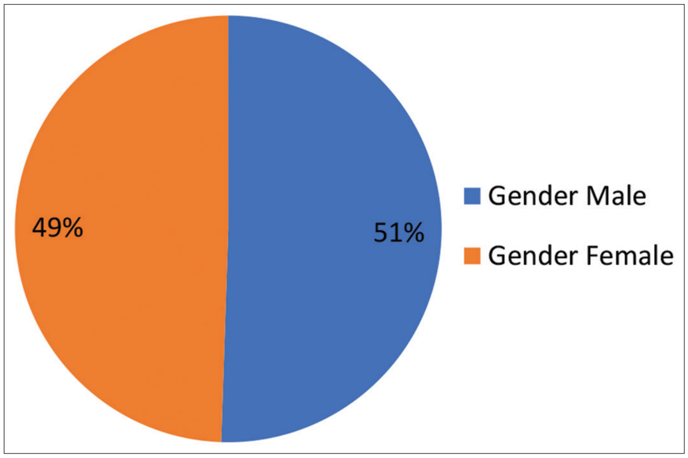


**Figure 2:** City of residence

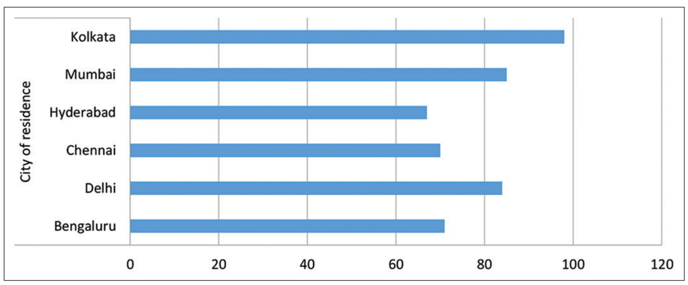


**Figure 3:** Age

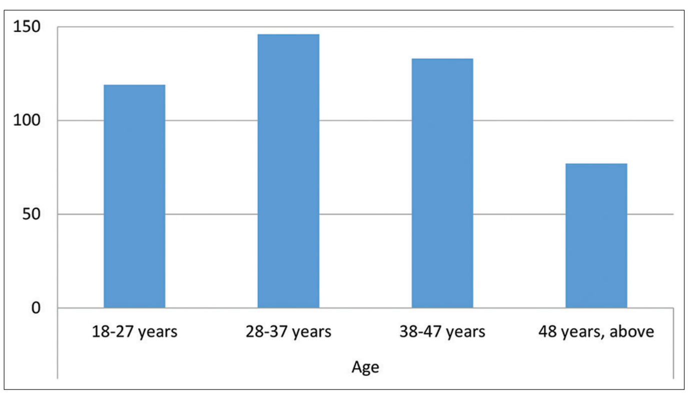


**Figure 4:** Educational qualifications

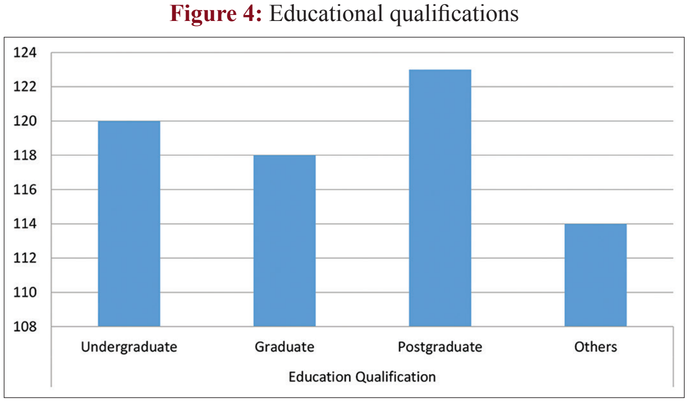


Table 3 provides an analysis of the measurement model, demonstrating reliability and validity metrics for the constructs behavioral intention (BI), effort expectancy (EE), performance expectancy (PE), price value (PV), social influence (SI), and user satisfaction (US). Each construct's reliability, validity, and multicollinearity are assessed through various indicators, including composite reliability (CR), average variance extracted (AVE), Cronbach's alpha, and variance inflation factor (VIF). behavioral intention (BI): This construct has five items (BI1 to BI5) with loadings ranging from 0.781 to 0.886, which indicates strong item reliability. The composite reliability for BI is 0.836, showing consistent measurements, and the Cronbach's alpha is also 0.836, indicating good internal consistency. The average variance extracted (AVE) is 0.509, suggesting moderate convergent validity. The VIF values for BI items, ranging from 1.612 to 2.155, suggest minimal multicollinearity concerns. The loadings for EE items range from 0.701 to 1.095, with a composite reliability of 0.815 and a Cronbach's alpha of 0.847, indicating acceptable reliability. The AVE is 0.527, demonstrating reasonable convergent validity. VIF values, spanning from 1.267 to 2.531, remain within acceptable limits, indicating low multicollinearity among EE items.

**Table 3: Measurement model**

| Construct | Item Code | Construct Loadings | Composite Reliability | AVE | Cronbach Alpha | VIF |
|---|---|---|---|---|---|---|
| Behavioral intention | BI1 | 0.822 | 0.836 | 0.509 | 0.836 | 2.102 |
| | BI2 | 0.811 | | | | 1.983 |
| | BI3 | 0.834 | | | | 1.891 |
| | BI4 | 0.886 | | | | 2.155 |
| | BI5 | 0.781 | | | | 1.612 |
| Effort expectancy | EE1 | 0.917 | 0.815 | 0.527 | 0.847 | 2.41 |
| | EE2 | 1.095 | | | | 2.531 |
| | EE3 | 0.745 | | | | 1.822 |
| | EE4 | 0.766 | | | | 2.167 |
| | EE5 | 0.701 | | | | 1.267 |
| Performance expectancy | PE1 | 0.764 | 0.899 | 0.642 | 0.898 | 1.431 |
| | PE2 | 0.828 | | | | 2.407 |
| | PE3 | 0.871 | | | | 2.902 |
| | PE4 | 0.812 | | | | 2.023 |
| | PE5 | 0.722 | | | | 2.761 |
| Price value | PV1 | 0.73 | 0.875 | 0.583 | 0.873 | 1.493 |
| | PV2 | 0.797 | | | | 2.353 |
| | PV3 | 0.749 | | | | 2.936 |
| | PV4 | 0.786 | | | | 2.382 |
| | PV5 | 0.754 | | | | 1.486 |
| Social influence | SI1 | 0.778 | 0.876 | 0.588 | 0.881 | 2.3 |
| | SI2 | 0.71 | | | | 2.436 |
| | SI3 | 0.703 | | | | 2.03 |
| | SI4 | 0.708 | | | | 2.519 |
| | SI5 | 0.914 | | | | 1.57 |
| User satisfaction | US1 | 0.791 | 0.769 | 0.542 | 0.769 | 1.788 |
| | US2 | 0.886 | | | | 1.881 |
| | US3 | 0.832 | | | | 1.986 |
| | US4 | 0.725 | | | | 1.789 |
| | US5 | 0.724 | | | | 1.786 |

Performance expectancy (PE) with loadings between 0.722 and 0.871, PE demonstrates strong item reliability. The CR for PE is 0.899, and Cronbach's alpha is 0.898, both reflecting high reliability. The AVE of 0.642 suggests good convergent validity, and the VIF values range from 1.431 to 2.902, showing no significant multicollinearity issues. Price Value (PV) construct includes five items with loadings from 0.73 to 0.797. The composite reliability is 0.875, and Cronbach's alpha is 0.873, indicating high internal consistency. The AVE is 0.583, suggesting adequate convergent validity. VIF values, ranging from 1.486 to 2.936, indicate that multicollinearity is not a concern.

The loadings for social influence (SI) items vary from 0.703 to 0.914, with a composite reliability of 0.876 and Cronbach's alpha of 0.881, confirming the construct's reliability. The AVE of 0.588 suggests moderate convergent validity, while VIF values between 1.57 and 2.519 indicate low multicollinearity. User satisfaction (US) construct has five items with loadings between 0.724 and 0.886. The composite reliability and Cronbach's alpha are both 0.769, showing acceptable reliability, and the AVE of 0.542 indicates moderate convergent validity. VIF values for US items, which range from 1.786 to 1.986, confirm that multicollinearity is minimal.

All constructs in the measurement model demonstrate adequate reliability, with composite reliability and Cronbach's alpha values meeting accepted thresholds. The AVE values confirm satisfactory convergent validity across constructs, while VIF values indicate that multicollinearity is not an issue. This assessment supports the reliability and validity of the constructs used in the study.

Table 4 presents the discriminant validity of the constructs in the model, using the Fornell-Larcker criterion. Discriminant validity is assessed by comparing the square root of the Average Variance Extracted (AVE) for each construct, which is shown on the diagonal, with the correlations between constructs, which are shown off-diagonal. For adequate discriminant validity, each construct's square root of the AVE should be higher than its correlations with other constructs.

Behavioral Intention (BI): The square root of the AVE for BI is 0.713, which is higher than its correlations with effort expectancy (0.671), performance expectancy (0.598), price value (0.861), social influence (0.576), and user satisfaction (0.902). However, BI's correlation with user satisfaction (0.902) exceeds 0.713, indicating a potential issue with discriminant validity between these two constructs. Effort expectancy (EE) has a square root of AVE of 0.726, which is greater than its correlations with other constructs: BI (0.671), PE (0.078), PV (0.123), SI (0.033), and US (0.004). This shows that EE discriminates well from other constructs. Performance expectancy (PE)'s square root of AVE is 0.801, higher than its correlations with BI (0.598), EE (0.078), PV (0.705), SI (0.624), and US (0.531), confirming that PE has satisfactory discriminant validity. The square root of AVE for PV is 0.864, which is greater than its correlations with BI (0.861), EE (0.123), PE (0.705), SI (0.751), and US (0.761). PV's correlation with BI (0.861) is close to its AVE value, suggesting a slight concern for discriminant validity between these two constructs. Social influence (SI) has a square root of AVE of 0.767, higher than its correlations with BI (0.576), EE (0.033), PE (0.624), PV (0.751), and US (0.657), confirming its discriminant validity from other constructs. The square root of AVE for US is 0.632, which is lower than its correlation with BI (0.902) and close to its correlations with PV (0.761) and SI (0.657). This indicates that user satisfaction may not fully achieve discriminant validity, particularly in relation to BI.

Table 5 presents the discriminant validity of the constructs in the model using the Heterotrait-Monotrait (HTMT) criterion. Discriminant validity is evaluated by comparing HTMT ratios, which should generally be below 0.85 or 0.90 to confirm that constructs are distinct.

The values show that behavioral intention (BI) has HTMT ratios with other constructs ranging from 0.068 (with effort expectancy) to 0.696 (with user satisfaction), all below the threshold, indicating adequate discriminant validity. Effort expectancy (EE) maintains particularly low HTMT values with all constructs, with values such as 0.064 (with performance expectancy) and 0.043 (with social influence), confirming its clear distinction from other constructs. Performance expectancy (PE) also shows acceptable discriminant validity, with HTMT values below 0.85 about all other constructs, such as 0.6 with BI and 0.705 with Price Value.

Similarly, price value (PV) demonstrates satisfactory discriminant validity, with HTMT values including 0.569 with BI, 0.746 with Social Influence, and 0.663 with user satisfaction, below 0.85. Social influence (SI) has HTMT values ranging from 0.043 with EE to 0.746 with PV, supporting its distinctness from other constructs. Lastly, user satisfaction (US) has HTMT values below 0.85 with all constructs, with the highest being 0.696 with BI, confirming that it is distinguishable from other constructs.

Overall, the HTMT analysis indicates that all constructs in the model satisfy the discriminant validity criterion, supporting each construct's distinctiveness.

### 4.1. Research Model

As shown in Figure 5, the structural model indicates that performance expectancy (PE), effort expectancy (EE), social

**Table 4: Discriminant validity of Fornell and Larker**

| | BI | EE | PE | PV | SI | US |
|---|---|---|---|---|---|---|
| BI | 0.713 | | | | | |
| EE | 0.671 | 0.726 | | | | |
| PE | 0.598 | 0.078 | 0.801 | | | |
| PV | 0.861 | 0.123 | 0.705 | 0.864 | | |
| SI | 0.576 | 0.033 | 0.624 | 0.751 | 0.767 | |
| US | 0.902 | 0.004 | 0.531 | 0.761 | 0.657 | 0.632 |

**Table 5: Discriminant validity of the HTMT criterion**

| | BI | EE | PE | PV | SI | US |
|---|---|---|---|---|---|---|
| BI | | | | | | |
| EE | 0.068 | | | | | |
| PE | 0.6 | 0.064 | | | | |
| PV | 0.569 | 0.08 | 0.705 | | | |
| SI | 0.568 | 0.043 | 0.518 | 0.746 | | |
| US | 0.696 | 0.11 | 0.63 | 0.663 | 0.648 | |

**Figure 5:** SEM model

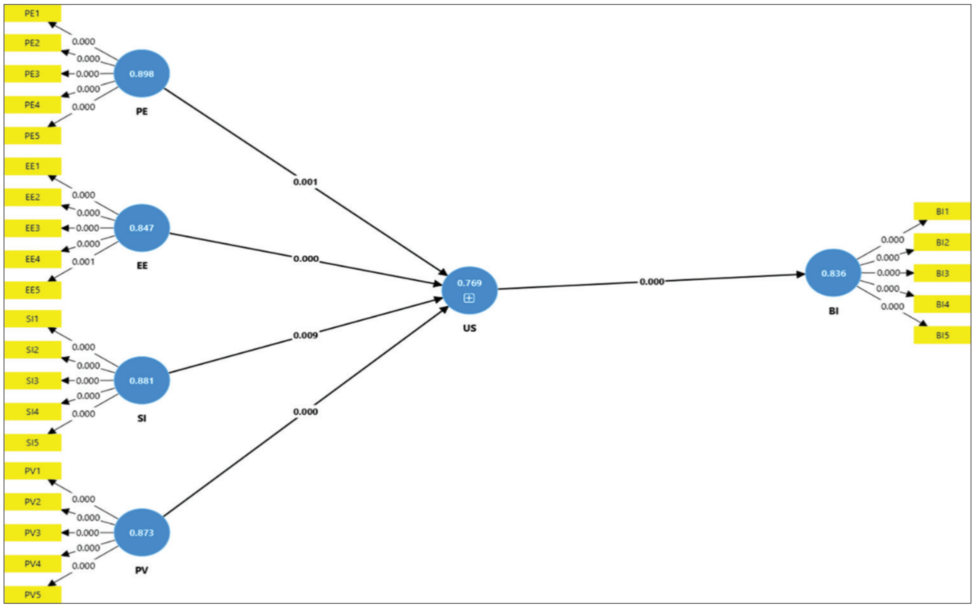


**Table 6: Structural model hypothesis testing and results**

| Hypothesis | Path | Path co-efficient | SD | T statistics | P-values | Result |
|---|---|---|---|---|---|---|
| $H_1$ | EE->US | −0.06 | 0.035 | 1.828 | 0 | Accepted |
| $H_2$ | PE->US | 0.056 | 0.041 | 3.183 | 0.001 | Accepted |
| $H_3$ | PV->US | 0.796 | 0.051 | 10.528 | 0 | Accepted |
| $H_4$ | SI->US | 0.029 | 0.047 | 2.619 | 0.009 | Accepted |
| $H_5$ | US->BI | 0.902 | 0.022 | 33.724 | 0 | Accepted |

influence (SI), and price value (PV) significantly influence user satisfaction (US). Additionally, the (US) has a strong predictive effect on behavioral intention (BI), with a path coefficient of 0.836 ($P < 0.001$). All relationships are statistically significant at $P < 0.05$.

Table 6 outlines the hypothesis testing results for the structural model, indicating the relationships between constructs and their significance levels. Each hypothesis is evaluated using path coefficients, standard deviations (SD), t-statistics, and P-values, with P-values below 0.05 considered significant.

$H_1$ (effort expectancy to user satisfaction) reveals a path coefficient of −0.06, a t-statistic of 1.828, and a significant P-value of 0, indicating a slight negative relationship between effort expectancy and user satisfaction, which is statistically significant, so $H_1$ is accepted. $H_2$ (performance expectancy to user satisfaction) shows a path coefficient of 0.056, a t-statistic of 3.183, and a P-value of 0.001. This positive, significant relationship suggests that higher performance expectancy enhances user satisfaction, thus supporting $H_2$. $H_3$ (price value to user satisfaction) has a strong positive path coefficient of 0.796, a t-statistic of 10.528, and a highly significant P-value of 0, indicating a substantial positive impact of price value on user satisfaction. Consequently, $H_3$ is accepted. $H_4$ (social influence to user satisfaction) is supported with a path coefficient of 0.029, t-statistic of 2.619, and a P-value of 0.009, showing a positive and significant influence of social influence on user satisfaction, making $H_4$ accepted. $H_5$ (user satisfaction to behavioral intention) exhibits the strongest positive effect with a path coefficient of 0.902, an exceptionally high t-statistic of 33.724, and a P-value of 0, highlighting a highly significant impact of user satisfaction on behavioral intention. Thus, $H_5$ is accepted.

## 5. DISCUSSION

The findings of this study provide valuable insights into the determinants influencing behavioral intentions toward telemedicine services, specifically the e-Sanjivani application. The demographic profile highlights a balanced representation across gender, age, city of residence, and education, ensuring the generalizability of results to diverse user groups in India. The analysis of key constructs such as performance expectancy, effort expectancy, social influence, price value, user satisfaction, and behavioral intention reveals significant relationships that drive telemedicine adoption.

Performance expectancy emerged as a critical factor, indicating that users perceive telemedicine as a useful and efficient solution for accessing healthcare services. Effort expectancy also played a significant role, emphasizing the importance of user-friendly interfaces and clear instructions in encouraging adoption. Social influence was another key determinant, reflecting the role of societal and peer opinions in shaping telemedicine usage. Price value had a moderate impact, suggesting that while affordability is important, the perceived value of services matters more. User satisfaction was found to be a strong predictor of behavioral intention, reinforcing the need for consistent service quality to retain users and encourage repeated use.

Overall, the findings align with existing literature, highlighting the growing acceptance of telemedicine as a convenient and effective healthcare solution. The study underscores the importance of focusing on user experience, affordability, and social acceptance to increase telemedicine adoption in India.

## 6. CONCLUSION

This study examined the factors influencing behavioral intentions toward telemedicine services, using the e-Sanjivani application as a case study. The results demonstrate that performance expectancy, effort expectancy, social influence, price value, and user satisfaction significantly impact users' behavioral intentions. The findings suggest that telemedicine is perceived as a reliable, user-friendly, and valuable tool for healthcare delivery in India, especially among urban populations.

The study also highlights the importance of social and cultural factors, such as peer influence and affordability, in shaping user behavior. By addressing these determinants, healthcare providers and policymakers can develop targeted strategies to enhance telemedicine adoption, improve service quality, and bridge healthcare accessibility gaps across diverse user groups.

### 6.1. Implications

The findings have several theoretical, practical, and policy implications: As Theoretical Implications, this study contributes to the growing body of research on telemedicine adoption by identifying and analyzing key determinants through PLS-SEM. It provides a framework for future research to explore behavioral intentions toward healthcare technologies in similar contexts. Also, the Practical Implications are that Healthcare providers should focus on optimizing user interfaces, simplifying processes, and enhancing service reliability to improve user satisfaction. Additionally, strategies to promote affordability and showcase the value of telemedicine services can drive wider adoption. Policymakers should prioritize awareness campaigns to normalize telemedicine usage, particularly in rural and semi-urban areas, while ensuring affordable pricing models and equitable access to technology infrastructure.

### 6.2. Limitations and Future Research

Despite its contributions, this study has certain limitations. First Geographic Scope; The study primarily focused on urban areas, limiting its applicability to rural populations, where telemedicine adoption may face additional challenges. Future research should include a broader geographical scope to explore rural-specific barriers. Second Sample Size; While the sample size was adequate for statistical analysis, a larger and more diverse sample could enhance the robustness of the findings. Third Cross-sectional Design; The study used a cross-sectional approach, capturing user perceptions at a specific point in time. Longitudinal studies are needed to understand how user attitudes evolve with increased telemedicine adoption. And the Limited Constructs This study examined a defined set of constructs. Future research could explore additional factors, such as trust in technology, data privacy concerns, and cultural differences, to provide a more comprehensive understanding.

By addressing these limitations, future studies can further advance our understanding of telemedicine adoption and contribute to the development of inclusive and sustainable healthcare solutions.

## 7. ACKNOWLEDGMENT

I would like to express my sincere gratitude to Dr. Namita Srivastava for their insightful contributions to this research.

## REFERENCES

Bakshi, S., Tandon, U. (2022), Understanding barriers of telemedicine adoption: A study in North India. Systems Research and Behavioral Science, 39(1), 128-142.

Call, V.R.A., Erickson, L.D., Dailey, N.K., Hicken, B.L., Rupper, R., Yorgason, J.B., Bair, B. (2015), Attitudes toward telemedicine in urban, rural, and highly rural communities. Telemedicine and E-Health, 21(8), 644-651.

Cochran, W.G. (1997), Sampling Techniques. 3rd ed. New York: John Wiley & Sons. p76-78.

Dixit, N., Van Sebille, Y., Crawford, G.B., Ginex, P.K., Ortega, P.F., Chan, R.J. (2022), Disparities in telehealth use: How should the supportive care community respond? Supportive Care in Cancer, 30(2), 1007-1010.

Edoh, T., Pawar, P.A., Kora, A.D. (2018), Evaluation of telemedicine systems user satisfaction in developing countries: The case of Mali and Senegal. International Journal of E-Health and Medical Communications, 9(3), 62-78.

Gilman, M., Stensland, J. (2013), Telehealth and medicare: Payment policy, current use, and prospects for growth. Medicare and Medicaid Research Review, 3(4), a04.

Haleem, A., Javaid, M., Singh, R.P., Suman, R. (2021), Telemedicine for healthcare: Capabilities, features, barriers, and applications. Sensors International, 2, 100117.

Hassibian, M.R., Hassibian, S. (2016), Telemedicine acceptance and implementation in developing countries: Benefits, categories, and barriers. Razavi International Journal of Medicine, 4(3), 38332.

Irfanahemad, A.S., Nandakumar, B.S., Radhika, K. (2018), Use of unified theory of acceptance and use of technology model for telemedicine services: An exploratory study. International Journal Of Community Medicine And Public Health, 5(9), 4112.

Kifle, M., Payton, F.C., Mbarika, V., Meso, P. (2010), Transfer and adoption of advanced information technology solutions in resource-poor environments: The case of telemedicine systems adoption in ethiopia. Telemedicine and E-Health, 16(3), 327-343.

Kohnke, A., Cole, M.L., Bush, R. (2014), Incorporating UTAUT predictors for understanding home care patients' and clinician's acceptance of healthcare telemedicine equipment. Journal of Technology Management and Innovation, 9(2), 29-41.

Licurse, A.M., Mehrotra, A. (2018), The effect of telehealth on spending: Thinking through the numbers. Annals of Internal Medicine, 168(10), 737-738.

Mathur, P., Srivastava, S., Lalchandani, A., Mehta, J.L. (2017), Evolving role of telemedicine in health care delivery in India. Primary Health Care Open Access, 7(1), 1000260.

Mishra, S.K., Kapoor, L., Singh, I.P. (2009), Telemedicine in India:

Current scenario and the future. Telemedicine and E-Health, 15(6), 568-575.

Pramudita, E., Achmadi, H., Nurhaida, H. (2023), Determinants of behavioral intention toward telemedicine services among Indonesian Gen-Z and Millenials: A PLS-SEM study on Alodokter application. Journal of Innovation and Entrepreneurship, 12(1), 68.

Rahi, S., Khan, M.M., Alghizzawi, M. (2021), Factors influencing the adoption of telemedicine health services during COVID-19 pandemic crisis: An integrative research model. Enterprise Information Systems, 15(6), 769-793.

Rastogi, S., Singh, N., Pandey, P. (2022), Telemedicine for ayurveda consultation: Devising collateral methods during the COVID-19 lockdown impasse. Journal of Ayurveda and Integrative Medicine, 13(1), 100316.

Russo, J.E., McCool, R.R., Davies, L. (2016), VA telemedicine: An analysis of cost and time savings. Telemedicine and E-Health, 22(3), 209-215.

Sharma, R.K., Prashar, R. (2019), Feasibility of ehealth implementation in India learning from global experience. Asia Pacific Journal of Health Management, 14(3), 1-12.

Wade, V.A., Eliott, J.A., Hiller, J.E. (2014), Clinician acceptance is the key factor for sustainable telehealth services. Qualitative Health Research, 24(5), 682-694.

Wang, B., Asan, O., Mansouri, M. (2023), Systems approach in telemedicine adoption during and after COVID-19: Roles, factors, and challenges. IEEE Open Journal of Systems Engineering, 1, 38-49.

Wu, D., Gu, H., Gu, S., You, H. (2021), Individual motivation and social influence: A study of telemedicine adoption in China based on social cognitive theory. Health Policy and Technology, 10(3), 100525.

Zhang, X., Zaman, B.U. (2020), Adoption mechanism of telemedicine in underdeveloped country. Health Informatics Journal, 26(2), 1088-1103.