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Covariates of Digital Technology in Providing Effective Health Care Services: A Primary Study in India

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Abstract

This qualitative study seeks to understand the factors influencing the adoption and effectiveness of digital health services among Indian citizens. By collecting primary data through surveys distributed to public health staff across policy, district, and peripheral levels, the study explores how digital technology can be optimized to improve health outcomes in India. Descriptive and inferential statistics, including binary logistic regression and ANOVA, were employed to analyse the data, focusing on the digital health score and its associations with various independent variables. Data analysis was conducted using STATA and MS Excel. The results show varying levels of digital technology adoption for health services across different population groups. Mobile phone use for notifying disease outbreaks and tracking beneficiaries had the highest adoption rates. Bivariate analysis revealed significant regional differences in digital health scores, with central regions performing better than others. Regression analysis indicated that district and peripheral levels had higher odds of good digital health scores compared to the policy/program level. ANOVA confirmed statistically significant differences between group means, with the Central region notably differing from the national average. The adoption of digital health technologies is influenced by regional variations, timing, and implementation levels. Mobile technologies are prevalent, particularly for outbreak notifications and beneficiary tracking, indicating their crucial role in healthcare. Regional differences and data collection timing significantly impact digital health scores, with district and peripheral levels performing better than policy levels. These findings highlight the need for targeted, region-specific strategies to ensure equitable and effective digital health technology adoption.

Keywords: *Adoption, Beneficiary Tracking, Digital Health Score, District Level, Disease Outbreak, Digital Technology, Health, Healthcare, Healthcare Delivery, Health Outcomes, India, Mobile Health, Public Health, Policy Level, Peripheral Level, Qualitative, Regions, Regional Variations, Services.*

Introduction

The term "digital health" describes the increasing confluence of digital technology and healthcare provision. According to the World Health Organisation, "digital health" is a broad phrase that includes eHealth as well as recently developed fields like artificial intelligence, genomics, and the use of modern computing sciences to "big data." Thus, "tools and services that use information and communication technologies (ICT) for purposes connected to health" are included in the definition of "digital health," which may include bettering patient outcomes from treatments, making accurate diagnoses, and keeping a closer eye on chronic illnesses [1].

To achieve universal access to healthcare, the MoHFW published the National Health Policy ("NHP") in 2017, promoting the use of digital health initiatives in that context. By

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2025, the NHP has suggested creating a National Health Information Network and a Federated National Health Information Architecture to connect public and private health providers through electronic health records and Metadata and Data Standards (MDDS) [2]. The National Digital Health Mission (NDHM) is a state-wide campaign to develop an open digital ecosystem to improve the efficacy, efficiency, and transparency of health service delivery [3]. It was launched by the Government of India in 2020 as part of its primary programme, "Digital India". Every "citizen" will receive a unique Health ID as part of the goal, which will be generated using their basic personal information (such as a mobile number) or Aadhaar number. Additionally, each individual will receive a unique biometric-based identification number [4].

Nevertheless, despite technological advances, the adoption of eHealth systems in primary healthcare (PHC) has been sluggish because of challenges in integrating these technologies into conventional primary healthcare delivery procedures. Health programmes in India are currently supported by numerous digital platforms [5, 6]. However, the deployment of such systems is beset by issues with inadequate internet access, erratic electricity, software programme or device design flaws, and challenges with healthcare workers' (HCWs') comprehension and application of digital health technology [7, 8].

The adoption of digital technology frequently has wide-ranging effects that go beyond providing healthcare. They consist of the effects on organisations, the law, operations, psychology, and society [9]. Therefore, HCWs are a major source of adoption resistance. Physicians' use of information technology (IT) is thought to have the ability to raise the standard of care in underserved and rural areas. However, some medical professionals believe that the use of IT impedes communication between patients and doctors and heightens anxiety among medical professionals [10]. Medical professionals have expressed scepticism about the likelihood of a system failure and data loss. Due to potential conflicts with technology use, certain personal beliefs and professional values may potentially act as impediments to eHealth interventions [11].

In India, various methodologies have been used in the past for assessing the impact of digital health, including randomized control trials and mixed methods combining quantitative and qualitative approaches [12, 13]. By focusing on the covariates of digital technology in healthcare delivery, this present qualitative study seeks to understand the factors influencing the adoption and effectiveness of digital health services among Indian citizens. The goal is to provide insights into how digital technologies can be optimized to improve health outcomes and address the unique challenges faced in the Indian healthcare system.

Data and Methods

Data Collection

This research included the use of primary data-gathering methods. The objective of this study is to thoroughly examine the present state, impacts, and possible improvements in the implementation of various digital tools and methodologies. A Google form was disseminated via email to a broad spectrum of health staff within the public health sector in India, encompassing individuals operating at the policy/programme level, district level, and peripheral level. The form was designed to gather pertinent data points critical for our study. Figure 1 describes the flow chart of the process of qualitative data collection in the study.

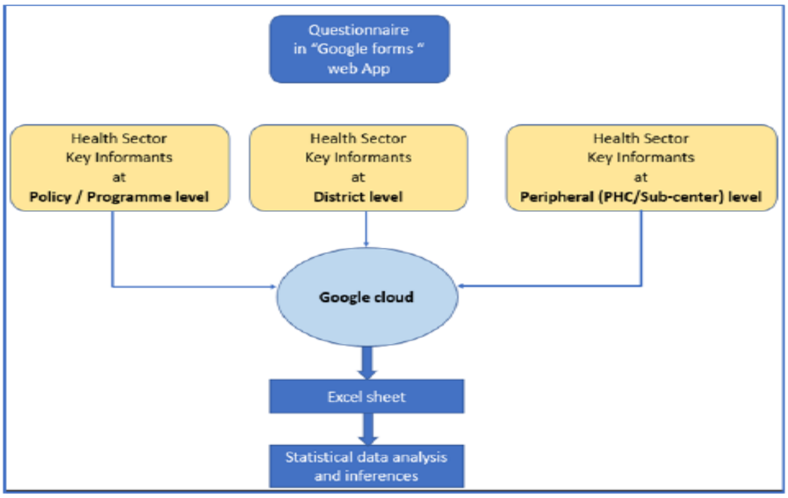

Figure 1. Flow-Chart of Qualitative Data Collection

Data Analysis

Upon receipt of the completed forms, a thorough validation process was conducted to ensure the accuracy and reliability of the data. This process involved checking for completeness, consistency, and correctness of the information provided. For analysis, data points with 'Don't know' responses were removed. The statistical techniques employed included descriptive statistics to summarize the basic features of the data, as well as inferential statistics to draw conclusions and make predictions based on the data.

Descriptive Statistics

We started our data analysis by univariate analysis which provided the profile of the respondents in the dataset. We also found individual prevalences and use of all the digital health technologies in the analysis.

Digital Health Score Generation

A digital health score was calculated with an additive method, which involved combining the following eight variables: (1) Birth/Death Notifications by mobile, (2) Blockchain apps for telemedicine, (3) Drone-based delivery of drugs, (4) Outbreak diseases notified by mobiles, (5) Apps for tracking interventions, (6) Health functionaries' skills monitoring for digital health interventions, (7) Mobile use by health functionaries for tracking beneficiaries and (8) Mobile use by population for health services.

The range of the score varied from a minimum of 8 to a maximum of 40. To make it a binary variable, the scores from 8 to 19 were clubbed and coded in the 'Poor' category while the scores from 20 to 40 were coded in the 'Good' category. The observed mean of the score was 25.61 and the standard deviation was 7.68. The variance observed was 59.06, the skewness observed was -.368 while the Kurtosis was 2.55. For the prevalence, class intervals of <10%, 11%-30%, 31% - 50%, 51% - 70%, >70% were used.

Bivariate Analysis

This digital health score was then used to examine the association with the other independent variables like Level (categorized as Policy/ Programme level, District level and Peripheral level), Regions (categorized as South, North, Central, West, West and National) and Month-wise data collection (categorized as September 2022, October 2022, November 2022, February 2023, March 2023 and April 2024).

Binary Logistic Regression Analysis

Binary logistic regression was used in this study to examine the association between the created digital health score and several independent variables like level, regions and month-wise data collection. A statistical technique called binary logistic regression is applied when the dependent variable is dichotomous (in our case Low and High) or has two alternative outcomes. This technique estimates the probability of a certain event occurring, allowing us to understand the influence of various predictor variables. The method is particularly useful for its ability to handle different types of predictor variables and for providing odds ratios that help interpret the effect size of each predictor. This approach was chosen for its robustness and suitability in modelling the binary outcomes relevant to our research.

ANOVA

Lastly, the Analysis of Variance (ANOVA) approach was utilised to investigate the variations in group means. ANOVA is a statistical method that evaluates possible mean variances among several groups so that any differences that are discovered can be determined to be statistically significant. ANOVA assists in determining whether at least one group's mean differs from the others by comparing the variances both within and between groups. To ensure a thorough analysis of the data gathered, ANOVA was used in this study to assess the impact of the independent factors on the dependent variable.

Software and Tools

The data was captured using Google Forms and the analysis was performed using a statistical software package named STATA (version 15) which facilitated efficient handling and analysis of the data. Tools such as MS Excel were employed for data cleaning, validation, and making tables and charts.

Table 1. Univariate Analysis of the Respondents in the Study

	Frequency	Percent	Total
Levels			
Policy level	68	48.23	48.23
District level	31	21.99	70.21
Peripheral level	42	29.79	100
State			
Andhra Pradesh	19	13.48	13.48
Arunachal Pradesh	1	0.70	14.18
Assam	6	4.26	18.44
Chandigarh	1	0.70	19.14
Chhattisgarh	44	31.22	50.36
Gujarat	4	2.84	53.20
Himachal Pradesh	7	4.96	58.16
Karnataka	11	7.8	65.96
Madhya Pradesh	1	0.70	66.66
Maharashtra	5	3.55	70.21
Odisha	19	13.48	83.69
At National level	23	16.31	100
Regions			
South	30	21.28	21.28
North-East	7	4.96	26.24
North	8	5.67	31.91
Central	45	31.91	63.83

West	9	6.38	70.21
East	19	13.48	83.69
At National level	23	16.31	100
Month-Wise Data Collection			
September, 2022	11	7.8	7.8
October, 2022	8	5.67	13.48
November, 2022	24	17.02	30.5
February, 2023	3	2.13	32.62
March, 2023	5	3.55	36.17
April, 2024	90	63.83	100

Results

Profile of the Respondents

Table 1 presents the results of the univariate analysis on the distribution of respondents across three different levels: Policy, District, and Peripheral. Policy level has the highest number of respondents with 68 cases, representing 48.23% of the total. This indicates that nearly half of the respondents taken in the analysis were operating at the policy level. There were 31 respondents at district level, making up 21.99% of the total. This shows that about one-fifth of the respondents were at the district level. The peripheral level includes 42 respondents, accounting for 29.79% of the total. This suggests that roughly one-third of the respondents are at the peripheral level.

The table also provides a breakdown of the respondents by state, indicating where these respondents were based. Chhattisgarh had the highest number of respondents, with 44, which is 31.21% of the total. This signifies that nearly one-third of all respondents were in Chhattisgarh. There were respondents at the national level, accounting for 16.31% of the total, showing a significant national presence. Andhra Pradesh and Odisha had 19 respondents each, each representing 13.48% of the total, indicating a notable presence in these regions. The remaining respondents were distributed among several states with lower frequencies, such as Karnataka (11 respondents, 7.8%), Himachal Pradesh (7 respondents, 4.96%), Assam (6 respondents, 4.26%), Maharashtra (5 respondents, 3.55%), and Gujrat (4 respondents, 2.84%). States like Arunachal Pradesh, Chandigarh, and Madhya Pradesh contributed less than 1% to the total.

With 45 responses, the Central Region accounts for 31.91% of the total. Thirty responders from the South Region make up 21.28% of the total. With 19 responses, the East Region accounts for 13.48% of the total. The percentage of respondents in the North-East, North, and West is lower, ranging from 4.96% to 6.38%. At the national level, 23 responders made up 16.31% of the total.

With 90 respondents or 63.83% of the total, in April 2024, data collecting is conducted at its highest frequency. In November 2022, there were 24 responders, or 17.02% of the total. The range of data collected in 2022–2023 for September, October, February, and March is 2.13%–7.8%.

Table 2. Usage of Digital Technologies Amongst the Respondents in the Study

Mobile use for Birth/Death Notifications by Population				
CI	**x**	**Frequency**	**xf**	**Percent (%)**
<10%	5	36	180	25.53
11%-30%	20	11	220	7.8
31% - 50%	40	19	760	13.48

51% - 70%	60	17	1020	12.06
>70%	85	23	1955	16.31
Total		**106**	**4135**	
Use of Blockchain for Telemedicine by Population				
CI	**x**	**Frequency**	**xf**	**Percent (%)**
<10%	5	39	195	27.66
11%-30%	20	25	500	17.73
31% - 50%	40	22	880	15.6
51% - 70%	60	16	960	11.35
>70%	85	16	1360	11.35
Total		**118**	**3895**	
Use of Drone-Based Delivery of Drugs by Population				
CI	**x**	**Frequency**	**xf**	**Percent (%)**
<10%	5	52	260	36.88
11%-30%	20	11	220	7.8
31% - 50%	40	10	400	7.09
51% - 70%	60	5	300	3.55
>70%	85	6	510	4.26
Total		**84**	**1690**	
Use of Outbreak Diseases Notified by Mobile Phone by Population				
CI	**x**	**Frequency**	**xf**	**Percent (%)**
<10%	5	12	60	8.51
11%-30%	20	13	260	9.22
31% - 50%	40	25	1000	17.73
51% - 70%	60	26	1560	18.44
>70%	85	59	5015	41.84
Total		**135**	**7895**	
Use of Apps for Tracking Interventions by Population				
CI	**x**	**Frequency**	**xf**	**Percent (%)**
<10%	5	24	120	17.02
11%-30%	20	18	360	12.77
31% - 50%	40	23	920	16.31
51% - 70%	60	30	1800	21.28
>70%	85	31	2635	21.99
Total		**126**	**5835**	
Use of Health Functionaries' Skills Monitoring for Digital Health Interventions				
CI	**x**	**Frequency**	**xf**	**Percent (%)**
<10%	5	28	140	19.86
11%-30%	20	21	420	14.89
31% - 50%	40	22	880	15.6
51% - 70%	60	32	1920	22.7
>70%	85	34	2890	24.11

Total		**137**	**6250**	
Mobile use by Health Functionaries for Tracking Beneficiaries				
CI	**x**	**Frequency**	**xf**	**Percent (%)**
<10%	5	11	55	7.8
11%-30%	20	14	280	9.93
31% - 50%	40	17	680	12.06
51% - 70%	60	30	1800	21.28
>70%	85	66	5610	46.81
Total		**138**	**8425**	
Mobile use by Population for Health Services				
CI	**x**	**Frequency**	**xf**	**Percent**
<10%	5	10	50	7.09
11%-30%	20	19	380	13.48
31% - 50%	40	21	840	14.89
51% - 70%	60	42	2520	29.79
>70%	85	47	3995	33.33
Total		**139**	**7785**	

CI – Class Interval; x – Quantiles of Certain Intervals Based on the Class Intervals

Table 2 provides data on the usage of mobile and other digital technologies for various health-related services by different population groups, categorized by the percentage of the population using these technologies.

1. The highest usage of mobile use for birth/death notifications (25.53%) is seen in the <10% CI category. The total population in this survey is 106, with a total xf (cumulative use frequency) of 4135.
2. The use of blockchain for telemedicine (27.66%) falls in the <10% CI category. The total population is 118, with a total xf of 3895.
3. The majority (36.88%) use of drone-based delivery of drugs falls in the <10% CI category. The total population is 84, with a total xf of 1690.
4. The highest usage (41.84%) of mobile phones to notify outbreak of diseases is seen in the >70% CI category. The total population is 135, with a total xf of 7895.
5. The usage of apps for tracking interventions is relatively distributed, with the highest (21.99%) in the >70% CI category. Significant usage (21.28%) is also seen in the 51%-70% category. The total population is 126, with a total xf of 5835.
6. The usage of health functionaries' skills to monitor digital health interventions is relatively distributed, with the highest (24.11%) in the >70% CI category. Significant usage (22.7%) is also seen in the 51%-70% category. The total population is 137, with a total xf of 6250.
7. The highest usage of mobiles for tracking beneficiaries (46.81%) is seen in the >70% CI category. Significant usage (21.28%) is also seen in the 51%-70% category. The total population is 138, with a total xf of 8425.
8. Use of mobile for population health services is highest (33.33%) in the >70% CI category. Significant usage (29.79%) is also seen in the 51%-70% category. The total population is 139, with a total xf of 7785.

Figures 2-9 also show that digital health technologies are widely used, with the highest usage often seen in the >70% category. Mobile phones for birth/death notifications and outbreak disease notifications have significant adoption, as do apps for tracking interventions and monitoring HF skills. While usage varies across services, a substantial portion of the population relies heavily on these technologies. Notably, the highest adoption rates are for mobile use in tracking beneficiaries and overall health services.

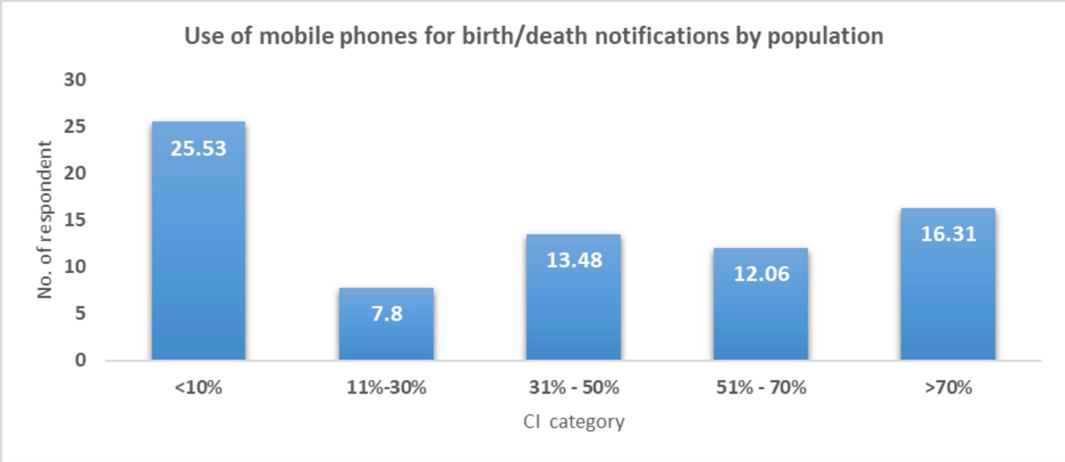

Figure 2. Use of Mobile Phones for Birth/Death Notifications

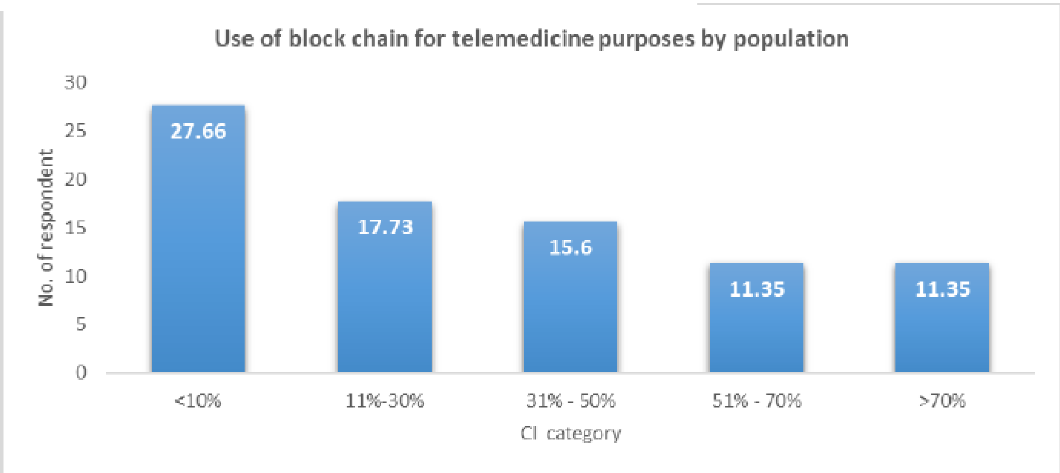

Figure 3. Use of Block Chain for Telemedicine Purposes

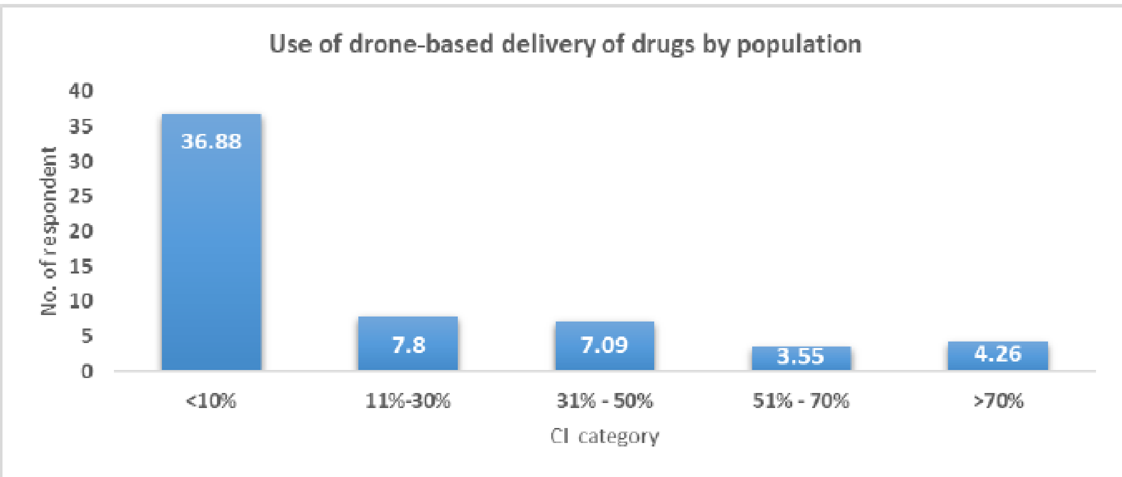

Figure 4. Use of Drone-Based Delivery of Drugs

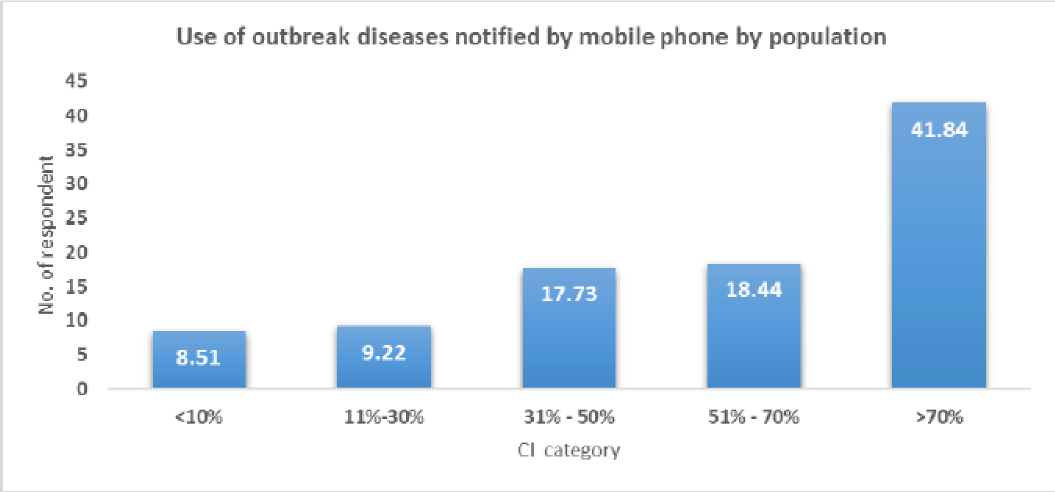

Figure 5. Use of Mobile Phone to Notify About Outbreak Diseases

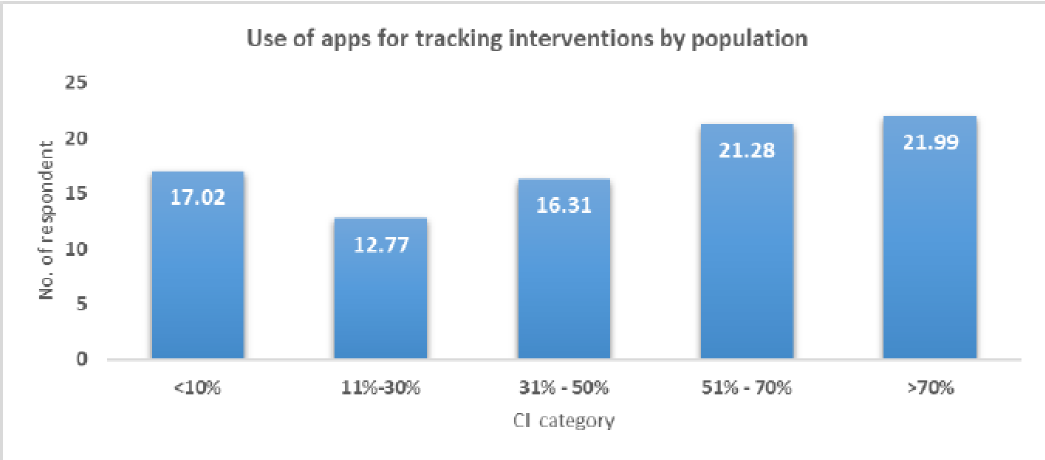

Figure 6. Use of Apps for Tracking Interventions

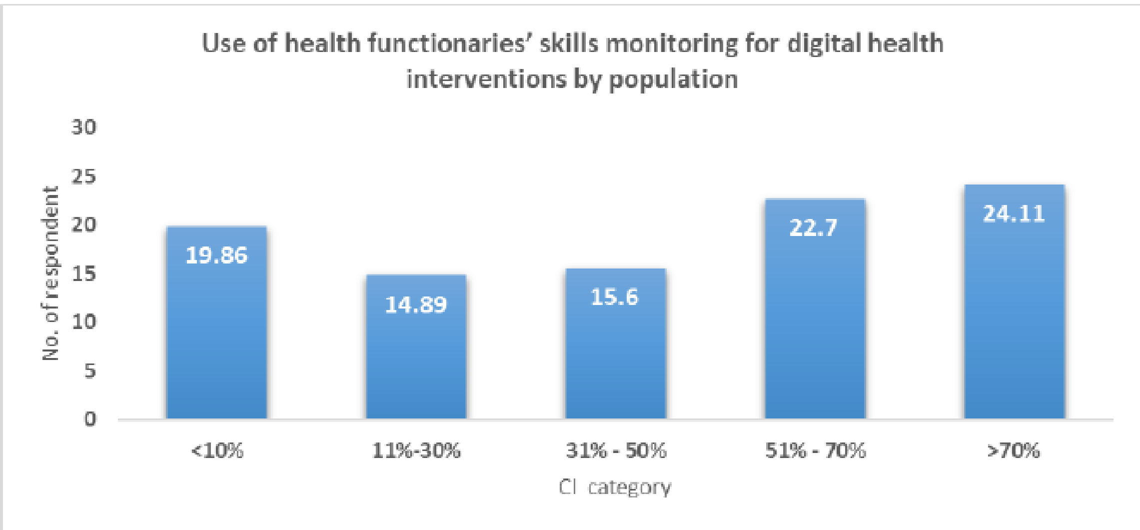

Figure 7. Use of Health Functionaries' Skills Monitoring for Digital Health Interventions

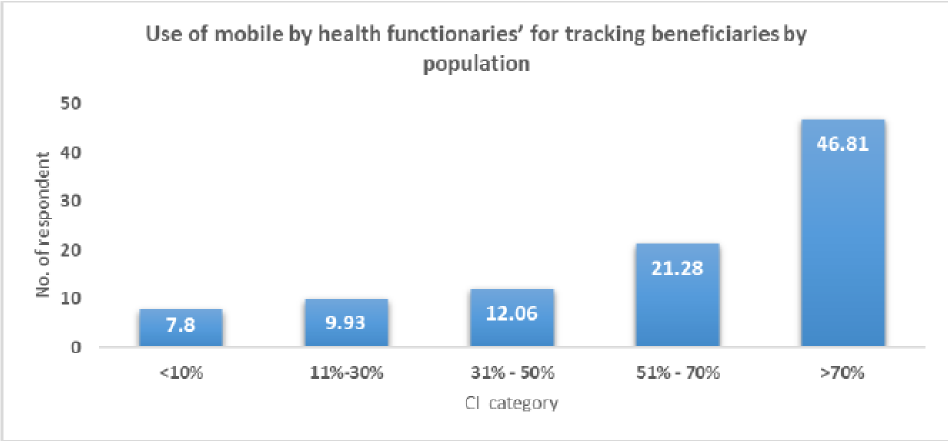

Figure 8. Use of Mobile by Health Functionaries for Tracking Beneficiaries

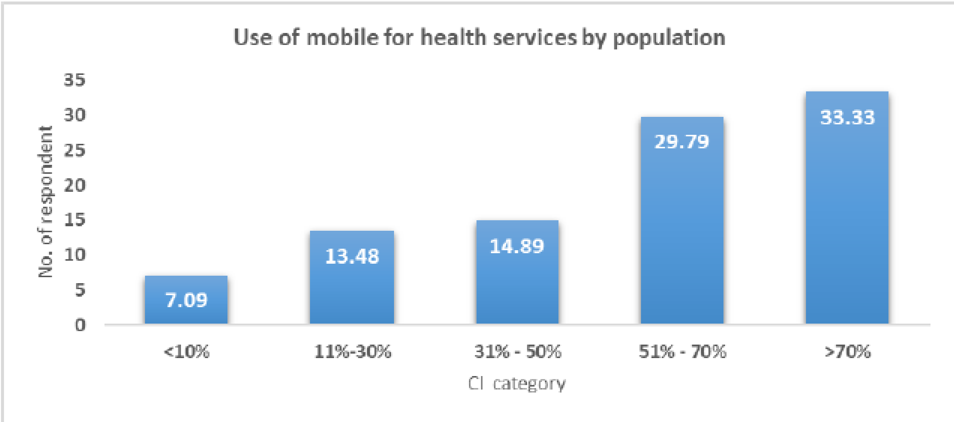

Figure 9. Use of Mobile for Health Services

Table 3. Prevalence of Digital Technologies Among the Respondents in the Study

S. No.	Indicator	Prevalence
1	Birth/Death notifications by mobile	39
2	Blockchain apps for telemedicine	33
3	Drone-based delivery of drugs	20
4	Outbreak diseases notified by mobile	58
5	Apps for tracking interventions	46
6	Health functionaries' skills monitoring for digital health interventions	46
7	Mobile use by Health functionaries for tracking beneficiaries	61
8	Mobile use by the population for health services	56

Prevalence of Various Digital Technologies

Table 3 provides the percentage of the population using various digital technologies for health-related services among the studied population. 39% of the surveyed population uses mobile phones to notify birth and death events. This indicates a moderate level of adoption for this service. 33% of the surveyed population utilizes blockchain applications for telemedicine. This suggests a relatively lower but significant adoption rate, indicating that blockchain technology in telemedicine is gaining traction but is not yet mainstream. 20% of the surveyed population uses drones for the delivery of drugs. This represents the lowest prevalence among the listed indicators, showing that drone technology for drug delivery is still in its early stages of adoption. 58% of the surveyed population uses mobile phones to notify about outbreak diseases. This highlights the critical role of mobile technology in managing public health emergencies and disease outbreaks. 46% of the surveyed population uses apps to track health interventions. This shows a high level of adoption, indicating that a significant portion of the population relies on apps to monitor health interventions. 46% of the surveyed population stated that health functionaries use mobile technology skills for digital health interventions. This suggests a robust adoption rate, reflecting the importance of monitoring and enhancing HF skills in digital health initiatives. 61% of the surveyed population uses mobile phones by health workers to track beneficiaries. This represents the highest prevalence among the indicators, indicating a widespread reliance on mobile technology by health facilities for beneficiary tracking. 56% of the surveyed population uses mobile phones for various health services. This high prevalence shows that more than half of the population integrates mobile technology into their health service interactions.

Table 4. Association Between Digital Health Score and Independent Variables

Bivariate Analysis			
	Digital Health Score	**P-value**	
Indicators	**Poor (<20)**	**Good (20+)**	
Level			0.289
Policy/Program Level	30	70	
District Level	9.09	90.91	
Peripheral (PHC/Sub-c)	16.67	83.33	
Regions			0.008
South	11.76	88.24	
North	50	50	
Central	5.26	94.74	
West	0	100	
East	66.67	33.33	
National	41.67	58.33	
Month-wise Data Collection			0.001
September, 2022	50	50	
October, 2022	20	80	
November, 2022	71.43	28.57	
Feb, 2023	100	0	
March, 2023	33.33	66.67	
April, 2024	7.69	92.31	

Association Between Digital Health Score and Independent Variables in the Study

Table 4 presents the bivariate analysis of the relationship between the Digital Health Score (categorized as Poor (<20) or Good (20+)) and various independent variables: Level, Regions, and Month-wise data collection. The p-values indicate the statistical significance of the relationships between these variables and the digital health score. The relationship between the level at which digital health initiatives are implemented (policy/program, district, peripheral) and the digital health score is not statistically significant. This suggests that the level of implementation does not have a strong impact on whether the digital health score is categorized as poor or good. The relationship between different regions and the digital Health Score is statistically significant. This indicates that regional differences significantly affect the digital health score. Some regions show a higher proportion of good scores compared to others. The relationship between the month of data collection and the digital health score is highly statistically significant. This suggests that the time of data collection has a significant impact on whether the digital health score is categorized as poor or good, with some months showing a higher prevalence of good scores than others.

Table 5. Binary Logistic Regression Estimates For Digital Health Score By Selected Independent Variables

Variables	**Odds Ratio**	**p-value**	**[95% Conf. Interval]**	
Category				
Policy/Program level	1			
District level	6.67	0.002	1.527	11.812
Peripheral (PHC/Sub-centre) level	4.59	0.003	0.239	8.938
Region				
South	1.00			
North	-1.97	0.711	-12.591	8.649
Central	1.27	0.001	-3.477	6.009
West	-0.14	0.975	-9.034	8.759
East	-7.64	0.027	-14.383	-0.891
(National)	-6.97	0.012	-12.327	-1.614

Estimates from Binary Logistic Regression

Table 5 The regression analysis table presents the odds ratios, p-values, and 95% confidence intervals for various variables impacting the outcome of interest (Digital Health Score). The odds of having a higher Digital Health Score (or the positive outcome being studied) are 6.67 times higher at the district level compared to the policy/program level. This relationship is statistically significant (p-value < 0.05). The odds of a higher digital health score are 4.59 times higher at the peripheral level compared to the policy/program level. This relationship is statistically significant (p-value < 0.05).

The negative odds ratio suggests lower odds of a higher digital health score in the North compared to the South, but this relationship is not statistically significant (p-value > 0.05). The Central region has higher odds of a better outcome compared to the South, and this relationship is statistically significant (p-value

< 0.05). There is no significant difference in the odds of a higher digital health score between the West and the South (p-value > 0.05). The East region has significantly lower odds of a higher digital health score compared to the South, and this relationship is statistically significant (p-value < 0.05). The National category has significantly lower odds of a higher Digital Health Score compared to the South, and this relationship is statistically significant (p-value < 0.05).

Table 6. Analysis of Variance- Between And Within Groups of Digital Health Score By Regions

Analysis of Variance					
Source	**SS**	**df**	**MS**	**F**	**Prob > F**
Between groups	767.114	5	153.42	3.06	0.0169
Within groups	2658.92	53	50.17		
Total	3426.03	58	59.07		
Bartlett's test for equal **Variances: chi2(5) = 2.5618**					
Prob>chi2 = 0.767					

Analysis of Variance

Table 6 presents the results of The Analysis of Variance (ANOVA) table which evaluates whether there are statistically significant differences between the means of different groups in the study. The source indicates the variability sources - between groups and within groups. The SS (Sum of Squares) measures the total variation. Between groups (767.114) is the variation due to differences between group means, while within groups (2658.92) is the variation within each group. The total variation in the data is 3426.03. df (Degrees of Freedom) reflects the number of independent values that can vary. The F-statistic (3.06) indicates the ratio of variance between groups to variance within groups. Since the p-value is less than 0.05 (0.0169), we reject the null hypothesis, indicating significant differences between group means.

The ANOVA results indicate that there are statistically significant differences between the means of the groups studied (p-value = 0.0169). Bartlett's test confirms that the assumption of equal variances holds (p-value = 0.767), supporting the validity of the ANOVA results.

Table 7. Analysis of Variance of Digital Health Score by Regions

Row Mean					
Col Mean	**South**	**North**	**Central**	**West**	**East**
North	-1.97059				
	1.000				
		3.2368			
Central	1.26625	4			
	1.000	1.000			
	0.13725	1.8333			
West	5	3	-1.40351		
	1.000	1.000	1.000		
		5.66667			
	-7.63725	7	-8.90351	-7.5	

East	0.409	1.000	0.145	1.000	
				6.8333	0.66666
India	-6.97059	-5	-8.23684	3	7
	0.176	1.000	0.040	1.000	1.000

Table 7 provides pairwise comparisons of means between regions using the results from the ANOVA. Each cell shows the difference between row and column means, along with the significance level of these differences. Row mean - col mean shows the difference between the mean of the row region and the column region. Numbers below the mean differences are the p-values indicating the statistical significance of the mean differences. The mean difference is statistically significant, indicating that the central region significantly differs from the national mean. However, most of the regional mean differences are not statistically significant, indicating that there are no substantial differences in the means between these regions, suggesting unique characteristics or performance in this region compared to the national average.

Discussion

The conversation about digital health technology in India is a significant step forward in the country's healthcare development since new developments have the potential to improve care quality, affordability, and accessibility. Through an assessment of data collected through this study, a thorough examination of how digital health is changing the way that healthcare is provided in India. The results are meant to add to the conversation about using technology to create a more just and healthy future.

Digital Health Technology Usage

The findings of the study suggest that there are notable variations in the adoption of digital health technologies among various areas and services. Significant distributions of respondents were also noted at the national level and in states such as Andhra Pradesh and Odisha, however, most respondents were concentrated in the state of Chhattisgarh and at the policy level. Based on this regional distribution, some areas may have more developed infrastructures or prioritise digital health projects more than others. These findings are aligned with the previous studies which have focused on the fact that India has a pronounced geographic variance in mobile phone ownership and digital services usage. For instance, a study that used data from the NFHS-4 survey to quantify geographic levels to comprehend how women in India are distributed in terms of SMS literacy and cell ownership. The findings showed that the central and eastern parts of India have low rates of mobile phone ownership. Women in the northeastern regions are more likely to be SMS literate [14]. The Digital Divide India Inequality Report 2022 highlights several significant issues related to digital access in India. Nearly 40% of mobile subscribers in India do not own smartphones. There is a 30% gap between men and women in phone ownership. Among salaried permanent workers, about 94% have phones, while less than 50% of unemployed individuals own a phone. Approximately 70% of the Indian population has poor or no access to digital services. Only 38% of households in India are digitally literate. These statistics illustrate the substantial disparities in digital access and literacy within the country [15].

High Usage Categories

The majority of services have utilisation percentages that fall into the >70% range, indicating that a sizable segment of the population is significantly dependent on these technologies. The relevance of integrating digital health tools into contemporary healthcare systems is highlighted by their broad acceptance. Nonetheless, the disparity in utilisation among various services suggests that whereas certain technologies are widely embraced, others might be more specialised or novel. Past studies have enlightened that due to epidemiological shifts during the previous three decades in India, there is currently an insufficient supply of comprehensive healthcare services for those with non-communicable diseases in particular. This is a significant contributing factor to the unequal use of primary care. The economically disadvantaged, the elderly, people living in rural areas of India, people with disabilities, those who bear the double burden of illness, and those with limited access to healthcare in India are among the vulnerable [16, 17].

Prevalence of Digital Health Technologies

The prevalence data offers a detailed picture of how widely different digital health technologies are being used by the questioned population. The highest adoption rates of mobile technology are shown in beneficiary tracking by health institutions (61%) and outbreak notifications (58%), highlighting their crucial roles in public health management and service delivery. The widespread use of mobile technology emphasises its function in recording and organising health data in the healthcare industry. Drone-based medication delivery, on the other hand, has the lowest prevalence (20%), indicating that this technology is still in its infancy. The reason for this lower adoption rate could be attributed to infrastructure deficiencies, legislative obstacles, or logistical difficulties. As this technology develops, it might become more widely used in isolated or difficult-to-reach places. Introducing job aids to improve the performance of community health workers is a common step in efforts to improve health knowledge and skills. Since 95% of people on the planet are now connected to a mobile network, mobile health (mHealth) solutions are becoming essential for enhancing the performance, knowledge, and abilities of health workers. It's crucial to understand, though, that a large body of research promoting mHealth tools concentrates on standard mobile phone usage, such as texting and making phone calls, rather than on particular apps for smartphones or tablets [18, 19].

Bivariate Analysis and Regional Differences

The results of the bivariate analysis show a strong correlation between the month of data collection and the digital health score as well as geographical variations. These results emphasise how crucial it is to take into account local settings and the time of data collection when assessing the efficacy and scope of digital health programmes. Higher-scoring regions in terms of digital health might profit from stronger infrastructure or better execution techniques. This finding goes in tune with the results of an earlier study as well which revealed noteworthy discovery of the concentration of mobile health (mHealth) solutions in a small number of states, almost excluding the others. These states included some of the most underserved areas, such as Jammu and Kashmir and the northeastern regions, where mHealth may be very effective. The Global Burden of Disease study group recently released a paper that highlighted the variation in risk factors and diseases among Indian states. The difficulty of providing last-mile healthcare is increased by interstate differences in the design and functionality of healthcare delivery systems. As a result, it's critical to test solutions in several states, particularly the underprivileged ones that stand to gain the most from revolutionary change [20].

On the other hand, there is no statistically significant correlation between the digital health score and the degree of implementation of digital health initiatives. This shows that, although administrative levels are significant, the timing of efforts and regional variables may be more crucial in influencing the effectiveness of digital health programmes.

Regression Analysis and Administrative Levels

The influence of administrative levels on digital health outcomes is further elucidated by the regression analysis. When comparing the district and periphery levels to the policy/program level, there is a much greater likelihood of achieving better digital health scores. Based on more individualised approaches and direct engagement with the target community, this research suggests that district- and localised implementation of digital health initiatives can produce superior results. The adoption and efficacy of SMART Health India, an AHSA-managed digital health initiative implemented in eighteen primary healthcare (PHC) clusters in rural India, vary widely, as a previous study reveals. The study also established five mechanism-based theories for how the intervention may have achieved its benefits, and we also highlighted crucial mechanisms of trust, acceptability, and risk awareness in our study environment [21].

There are also noticeable geographical variances. Higher odds of better results are seen in the Central region, but significantly lower odds are seen in the East and National categories as compared to the South. These discrepancies imply that to alleviate regional disparities in digital health outcomes, focused interventions could be required. For example, areas with lower odds might gain from more funding for resources, training, and digital infrastructure. The Public Health Foundation of India has converted this into a study titled "Mutual Learning Series on Digital Health Ecosystems." It was discovered that, despite the widespread agreement that integrating digital technology could improve access to healthcare, there is worry that certain demographic groups might be left behind as a result of the so-called "digital divide." As a result, there is increasing interest in creating treatments that try to lessen the disparities associated with larger initiatives to prevent digital exclusion [22].

Conclusion

The integration of digital health technologies in India has shown significant potential in improving healthcare quality, affordability, and accessibility, with considerable regional variations in adoption and usage.

Factors such as regional variations, timing, and implementation levels impact the adoption of digital health technology. Mobile technologies are particularly prevalent, highlighting their importance in modern healthcare. Most respondents are at the policy level and in Chhattisgarh, with significant numbers also from the national level and states like Andhra Pradesh and Odisha. Many services have high usage rates (>70%), indicating heavy reliance on these technologies. However, usage varies across services, with some being more widely adopted than others. Digital health technologies show varying adoption levels. Mobile technology is widely used, with high adoption for outbreak notifications (58%) and beneficiary tracking (61%). In contrast, drone-based drug delivery is less common (20%), indicating it is still emerging.

The study reveals that regions like Chhattisgarh, Andhra Pradesh, and Odisha have higher concentrations of respondents, indicating better infrastructure and prioritization of digital health projects. However, significant disparities persist, with mobile phone ownership and digital literacy particularly low in central and eastern regions. High adoption rates for mobile technology in beneficiary tracking and outbreak notifications highlight its critical role in public health management, though newer technologies like drone-based medication delivery remain underutilized. Bivariate and regression analyses suggest that localized, district-level implementation of digital health initiatives yields better outcomes, though regional disparities necessitate targeted interventions to bridge the digital divide and ensure equitable access to digital health services across India. These findings underscore the need for targeted, region-specific interventions to ensure equitable and effective adoption of digital health technologies. This analysis provides a basis for further research and policy development to optimize the implementation and impact of digital health programs.

Conflict of interest

The authors declare no conflict of interest.

Contribution

The corresponding author confirms sole responsibility for study conception and design, data collection, interpretation of results, and manuscript preparation. The second author (HS) did a literature search, data management and data analysis.

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