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Exploring digital divide in India: A framework for inclusive Information Communication

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Abstract

The surge of cheap internet access and digital devices in India, especially for the rural population, has transitioned India into the second-level digital divide from access to effective use and digital skill. Here, the divide emerges based on quality of use, digital skill and usability. Review of secondary literature suggests that gender, socio-cultural norms, economic disparity, geographical location (rural-urban), level of education, age and language play a key role in creating digital disparity. To address this, we tried to map the disparities among the Indian states. We constructed a digital skill index, which explains how the people residing within states are comfortable in performing some basic digital tasks like copy and paste file, use MS Word/Excel, send email with attachment, etc. By mapping the digital skills across states, we can better understand the regional disparities, benchmarking state performance and designing targeted interventions. In this paper we found, Substantial disparities exist in terms of digital skills among the Indian states like Mizoram and Kerala which showed higher digital skill efficiency. This study provides empirical evidence that the digital skill is important and there is a requirement of developing strategies state wise to improve the condition of digital skill among states.

Keywords: Information Communication; Digital Divide; ICT; Social Inclusion; Digital Skills

1. Introduction

Over the year inequality has persisted but is more prominent in current time (Kumar et al., 2021). The pandemic intensified the gap even further, when everything moved online (Mahendru et al., 2022; Fouillet et al., 2021). This highlighted the inequality in multiple domains, one of which is "Digital Divide", which describes the disparity in access to information and communication technology (ICT), such as device availability, internet connectivity and digital infrastructure, amongst people, communities and geographical areas. Traditionally, this divide has been understood as the difference in access to hardware and the internet, often measured by device penetration rates and network coverage.

In today's context, the digital divide also incorporates discrepancies in digital skills and the capability to use technology effectively for personal, educational and economic advancement. This has affected access to health, education and financial services (Ramsetty & Adams, 2020; Lai and Widmar, 2020). The UN Secretary General had expressed "the digital divide is now a

matter of life and death" (United Nations, 2020). In the post-pandemic period, progress has remained uneven. The differences in online education access in India, especially between urban and rural areas, reflect the issues seen in the online world (Mandal, 2025).

The digital divide perpetuates inequality and is one of the key factors of poverty (Lythreatis et al., 2022). It also affects online learning which was observed during pandemic (Mathrani et al., 2021). It has been proven in earlier studies that digitization has improved entrepreneurship in rural India, improving agricultural productivity and hiring in non-agricultural sector (Aleksandrov and Fedorova, 2019; Fu and Akter, 2016; Lio and Liu, 2006; Qiu et al., 2021). Availability and technology access can improve economic output, job availability and overall development of region or country (Zhang, 2024) and to access these technologies there is a requirement of availability of devices and the knowledge required to use digital technologies effectively. Cheap and affordable devices like mobile phone, has reduced the gap in regards to access. The gap in terms of digital skill i.e. the knowledge of using the technology or devices, still persist.

Now, if we examine India's current data, the country is expected to have over 900 million internet users by 2025. More users are coming from rural areas (Kantar, 2025). Internet users spend an average of 90 minutes per day online. Urban users spend more time online compared to rural users. There are more internet users in rural areas than in urban ones. The gender gap has been narrowing over the years. In 2024, there are 870 million internet users, which is 98% of total users, who have accessed the internet in Indic languages. Additionally, 57% of internet users in Urban India say they prefer accessing content in Indic languages.

From Kantar ICUBE 2024 survey data it has been observed that around 25% of the user from non-active internet user group reported unawareness of the internet as the top factor for not using internet followed by unavailability of internet access. It was also found that around 20% of people from non-active internet user feel difficulties in understanding and using. recent evidence continues to indicate, the first and second level of digital divide yet to be overcome.

In India, rapid digitization has transformed education, governance, healthcare and economic opportunities, amplifying the importance of digital inclusion. Persistent disparities in digital skills and access broaden the existing social inequalities associated to caste, gender, rural-urban divides and income (Tewathia et al., 2020). Digital inclusion safeguards that all individuals and societies have the information technology capacity required for full contribution in society, democracy, and the economy (Mandal, 2025). Prior studies consistently identify these determinants. The present study builds upon this literature by focusing on their combined outcome regional digital capability rather than modelling each determinant separately.

However, gaps in infrastructure and access still exist. For example, schools often have inadequate accessibility of computers and internet resources, which hinders the effectiveness of digital learning initiatives. Research shows that both teachers and students face difficulties such as poor infrastructure, lack of devices and inadequate training in digital teaching methods (Hota, 2022). These challenges are often influenced by social identity, power dynamics and local contexts, highlighting the need for inclusive and context-aware policy design (Choudhary, 2025).

Digital technologies have significantly transformed daily life. They offer benefits like better academic work, access to global knowledge, savings in time and money and chances for online transactions and social connections. Still, problems like digital illiteracy, high device costs, unequal access and information overload limit how effectively people can use these technologies (Chaudhuri, 2024; Guha & Mukerji, 2021). Researchers suggest the need for

targeted actions. These include developing skills, regional policies, promoting digital skill for women and expanding digital education infrastructure.

The rise in demand of smartphones and smart devices has been crucial in improving access to digital technologies across different income groups. Even people with varying income levels now rely on smartphones to access apps, educational resources and other online services. Devices such as smartphones, tablets and personal computers, along with reliable internet, are essential for encouraging digital skill and participation. These technologies help share knowledge, exchange culture and access both educational and entertainment content. This shows the need for developed digital infrastructure to support a digitally literate society (Shabbir & Porwal, 2025).

Even with improved access, people with inadequate digital skills often do not benefit fully from digital transformation efforts. Studies show that digital skill training programs can greatly improve both economic and social empowerment, specifically among marginalized groups like women living in poverty (Mahendru et al., 2022; Fouillet et al., 2021; Aissaoui, 2022). For example, training in digital skills has been found to increase job-seeking opportunity, educational participation and entrepreneurial activities. It also boosts self-confidence and self-efficacy through hands-on skill use (Mukherjee et al., 2024). These findings show the importance of not just access but also acquiring and using skills effectively.

These findings have also been highlighted in earlier studies. The digital divide has evolved from a simple question of physical access to digital technologies into a multidimensional phenomenon encompassing access, capability, and outcomes. Van Dijk (2005) and Van Deursen and Van Dijk (2014) conceptualize this evolution through three interrelated levels. The first-level digital divide concerns inequalities in access to devices and internet connectivity. As connectivity expands, disparities increasingly emerge in individuals' abilities to effectively operate digital technologies, commonly referred to as the second-level digital divide. These differences include operational, information navigation, communication, content creation, and problem-solving skills required for meaningful participation in digital environments. The third-level digital divide extends beyond skills to unequal social, educational, and economic benefits derived from digital technology use. Thus, digital skills act as a critical mechanism linking access with tangible socio-economic outcomes. Consequently, measuring digital capability provides an essential step toward understanding both second-level inequalities and the foundations of third-level disparities.

Various initiatives have substantially improved digital infrastructure and internet accessibility across the country. However, as digital technologies become increasingly integrated into governance, education, healthcare, financial services, and employment, the challenge has shifted from ensuring access to developing citizens' ability to effectively use these technologies. Consequently, digital skills have emerged as a fundamental determinant of meaningful digital participation and social inclusion (Choudhary & Matin, 2025). As government service delivery increasingly relies on digital platforms, inadequate digital skills limit the ability of individuals to benefit from these initiatives, thereby reinforcing existing socio-economic inequalities (Kirty, 2025).

Recent evidence suggests that digital skills have become a prerequisite for effective public service delivery in India. Common Service Centres (CSCs), established under the Digital India programme, serve as critical intermediaries connecting rural citizens with digital government services. However, the effectiveness of these centres depends not only on technological infrastructure but also on citizens' digital capability. Persistent deficiencies in digital literacy, regional disparities in infrastructure, and socio-economic inequalities continue to constrain the

inclusive delivery of digital public services, particularly in rural and marginalized communities (Choudhary & Matin, 2025).

Digital skills are equally critical in improving healthcare accessibility. The increasing adoption of telemedicine, online health consultations, electronic medical records, and mobile health applications requires individuals to possess adequate digital health literacy. Patel et al. (2024) found that only about one-fifth of older adults in Telangana demonstrated adequate digital health literacy, with education, smartphone ownership, and prior experience using digital technologies emerging as significant determinants. These findings indicate that expanding digital healthcare services alone is insufficient unless accompanied by initiatives that strengthen citizens' digital capabilities. However, the benefits of these platforms are unequally distributed because disadvantaged populations often lack the digital competencies required to engage effectively with online systems. Consequently, the persistence of second-level digital divide limits equitable participation in governance despite improvements in digital infrastructure (Kirty, 2025).

Several studies conducted in the Indian context consistently identify education, gender, rural–urban residence, language proficiency, and network connectivity as key determinants of digital capability. For example, Chaudhuri (2024) reported that inadequate network connectivity, English language barriers, gender disparities, and geographical location significantly contribute to digital inequalities, particularly in rural areas. These findings suggest that digital exclusion in India increasingly reflects disparities in digital capability rather than simple differences in physical access to digital technologies.

Overall, the existing literature demonstrates that digital skills represent the critical link between digital access and meaningful digital outcomes. While India's digital infrastructure has expanded rapidly, substantial regional disparities remain in citizens' ability to effectively use digital technologies for education, employment, governance, healthcare, and economic participation. Existing Indian research has primarily examined determinants of digital literacy, digital governance, educational technology adoption, and sector-specific digital competencies. Comparatively limited attention has been devoted to developing a comprehensive, state-level measure of functional digital skills using nationally representative data. By constructing a Digital Skill Index based on task-oriented ICT competencies, the present study addresses this gap and contributes to the growing literature on the second-level digital divide by providing a robust empirical framework for comparing digital capabilities across Indian states.

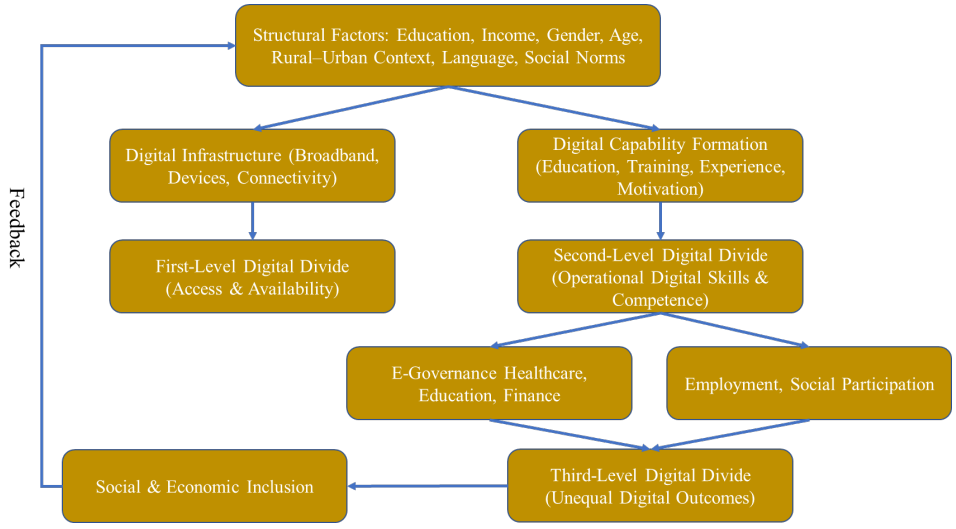


Figure 1: Conceptual Diagram of the Digital Divide

Source: Prepared by authors

While previous studies have looked closely at what affects digital access and more recently at the role of digital skill, there is still a significant gap in understanding how digital skills are spread out and measured. Most studies either focus on access indicators, like device ownership and connectivity or they look at digital skill through small surveys. They do not produce a composite index that shows differences across regions. Additionally, not much attention has been paid to linking the measurement of digital skills with regional inequalities, especially at the state level in India (Arora & Sapre, 2025). This study explains where digital capability is concentrated, how regional digital capability clusters emerge, and why digital capability should be viewed as a capability-development problem rather than merely an infrastructure problem.

The study is structured into six sections, the first section provides the background, motive and findings from earlier works. The second section describes the gaps and objectives of the study. The Third section deals with the methodology and data; it describes the source of data and method used in the studies. The fourth section is the result section; it describes the outcome of the study. The following section discusses the finding and also tried to connect it to earlier studies. The sixth section we put out concluding statements by summarising the key points and highlighted the areas to be explored in future research.

2. Contributions of the Study

This study contributes significantly to the discussion on digital skill and digital inequality.

Development of a State-Level Digital Skill Index:

This study reconceptualises India's second-level digital divide as a problem of regional capability formation rather than infrastructure access. The Digital Skill Index operationalises this conceptual shift by measuring functional digital capability across states using nationally representative task-based indicators.

Measurement of Functional Digital Competencies:

The study includes various aspects of digital skills, such as operational, communication, content creation, and technical configuration skills. This gives a clearer understanding of digital capability compared to simple measures of internet or device access.

Policy Relevance for Digital Inclusion:

The findings show that closing the digital divide requires more than just expanding infrastructure. The study points out the importance of educational achievement, skill development, and improving human capabilities for encouraging meaningful digital participation. This provides useful insights for digital inclusion policies in India.

Overall, the study enriches the growing literature on the second-level digital divide by establishing a solid empirical framework for measuring and comparing digital skills at the subnational level in India.

3. Objectives

Earlier studies mainly measure the digital divide through access indicators like internet connectivity or device ownership. In contrast, this study focuses on actual digital skills, which relates to second-level digital divide research. Many studies use proxies like education or income to estimate digital capability. This study directly measures task-based digital skills, offering a clearer assessment of digital skill. Most studies look at the digital divide at the national level, hiding regional differences. This study introduces state-wise mapping, showing spatial inequalities in digital skill. The study pursues two specific objectives:

1. To construct a composite measure of digital capability across Indian states based on digital skill.
2. To rank states in terms of digital divide intensity (or digital efficiency).

Building on previous research, the study seeks to establish the importance of digital skill in the current time.

4. Methodology

4.1 Data Source and Unit of Analysis

The study uses secondary data collected from the 78th round of National Sample Survey, published in 2023. The NSS 78th Round Multiple Indicator Survey (MIS) covered 276,409 households and 1,163,416 individuals across rural and urban India. State-level weighted proportions were computed using the NSS person-level multiplier supplied in the unit-level dataset. For the present analysis, observations with missing responses on ICT skill variables were excluded, resulting in an effective analytical sample of 1,099,343 individuals. This study follows a quantitative, cross-sectional research design to focus on measurement and spatial comparison of digital skills.

The study focuses on the second-level digital divide, the disparities in individuals' ability to effectively use digital technology, which is beyond mere access to digital devices or internet connectivity. The analytical sample consisted of 1,099,343 individuals across various states India, comprising 61.1 and 38.9 percent of households located in rural and urban sectors respectively. State-level digital skill indicators were computed as weighted proportions of respondents reporting the ability to perform selected ICT-related tasks. These were then converted into state and UT level data having 37 observations. We acknowledge that factor analysis with small sample sizes can lead to instability. However, given the very high communalities, strong inter-item correlations, and theoretical unidimensionality of digital skills, PCA is used here as a data reduction technique rather than a latent variable model. Results are therefore interpreted cautiously. The indicators are described below.

4.2 Measurement of Digital Skills

The secondary digital divide represents a fundamental shift in understanding digital inequality, moving beyond simple access metrics to examine the complex patterns of digital competence, usage behaviours, and skill differentials that characterize contemporary digital societies. This comprehensive analysis reveals that secondary digital divide indicators encompass multidimensional frameworks measuring not just whether individuals can access digital technologies, but how effectively they can utilize these tools for meaningful participation in economic, educational, and social activities. Drawing ideas from prior works (Audrin et al., 2024; Fan & Wang, 2022; Van Deursen & Van Dijk, 2008; Vuorikari et al., 2022), the investigation identifies a set of variables for the digital skill measurement.

Table 1: NSS 78th Round MIS ICT Skill variables Used for Construction of the Digital Skill Index

Variable	NSS MIS Item	Digital Skill Indicator
whether able to copy or move a file or folder	b5q9	Copy and paste (X1)
whether able to use the copy and paste tools to duplicate or move information within a document	b5q10	Duplicate or move within document (X2)
whether able to send e-mails with attached files (e.g. document, pictures and video)	b5q11	Send emails with attachments (X3)
whether able to use basic arithmetic formulae in a spreadsheet	b5q12	Use spreadsheets (X4)

whether able to connect and install new devices (e.g. modem, camera, printer)	b5q13	Install new devices (X5)
whether able to create electronic presentations with presentation software (including text, images, sound, video or charts)	b5q15	Create presentations (X6)
whether able to find, download, install and configure software	b5q14	Configure software (X7)

Source: NSS 78th Round Multiple Indicator Survey (MIS)
Note: *Original NSS coding: Yes = 1, No = 2. Variables were recoded as Yes = 1 and No = 0 before aggregation. State-level values represent weighted percentages of respondents able to perform each digital task.*

The Digital Skill Index was constructed using seven ICT skill items from Block 5 of the NSS 78th Round (2020–21) Schedule 25.2. Original responses coded as Yes = 1 and No = 2 were recoded into binary variables (Yes = 1, No = 0). State-level weighted proportions were calculated using NSS sampling weights and subsequently used as input variables for the Principal Component Analysis (PCA). The analysis included all 37 States and Union Territories, with rural and urban observations combined through survey weighting to generate comparable population-representative estimates at the sub-national level.

4.3 Analytical Tools

All statistical analyses were conducted using STATA. The procedures included reliability testing, factorability assessment, principal component extraction, and index construction.

4.4 Index Construction Procedure

The construction of the Digital Skill Index (DS Index) followed a systematic multi-step procedure to ensure methodological transparency, comparability, and robustness.

Step 1: Indicator Selection

Seven indicators representing functional digital skills were selected based on prior literature and data availability. These include abilities such as file management, communication (email use), content creation (spreadsheets and presentations), software configuration, and device installation. Each indicator reflects a distinct but related dimension of operational digital competence.

Step 2: Aggregation to State Level

The indicators were computed as the proportion of respondents within each state reporting the ability to perform the respective digital task. This aggregation converts large-scale household-level data into comparable state-level measures, resulting in a dataset comprising 37 States and Union Territories.

Step 3: Data Standardization

To remove scale differences and ensure comparability across indicators, all variables are usually standardized using z-score transformation:

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j}$$

where X_{ij} signifies the value of indicator j for state i, and μ_j, σ_j denotes the mean and standard deviation of indicator j, respectively. Because all indicators were measured as percentages, PCA was performed using the correlation matrix, which standardizes variables internally. Therefore, separate z-score transformation was not required prior to extraction.

Step 4: Assessment of Factorability

Prior to index construction, the suitability of the data for dimensionality reduction was assessed using:

- Kaiser-Meyer-Olkin (KMO) measure
- Bartlett's Test of Sphericity

The results confirmed adequate sampling adequacy and significant inter-item correlation structure, supporting the application of Principal Component Analysis (PCA).

Step 5: Principal Component Extraction

Principal Component Analysis (PCA) was applied to the seven digital skill indicators to identify the underlying structure of digital skills. The analysis revealed a dominant first component explaining over 85% of total variance, indicating a strong unidimensional construct. The component loadings were relatively uniform across indicators, suggesting balanced contributions of each skill dimension. The PCA-derived and equal-weight indices produced nearly identical rankings ($\rho = 0.998$), indicating that digital skills constitute a highly coherent construct. PCA was nevertheless retained because it provides an empirically derived weighting structure and facilitates comparability with previous composite-index studies.

Step 6: Index Construction

The Digital Skill Index was computed using the scores of the first principal component:

$$DL_i = \sum_{j=1}^{k} w_j \, Z_{ij}$$

where wj represents the PCA-derived weights and Zij represents the observed state-level indicator value.

Step 7: Normalization

To facilitate interpretation and comparison across states, the PCA scores were normalized using min-max scaling:

$$DL_i = \frac{DL_i - \min(DL)}{\max(DL) - \min(DL)}$$

This transformation rescales the index to a range between 0 and 100, where higher values indicate greater digital skill capability.

Step 8: Ranking of States

States were ranked based on their normalized DS Index scores. This ranking enables the identification of relative disparities in digital capability and highlights regional patterns of the second-level digital divide.

5. Results

The state-level analysis reveals substantial variation in digital skill levels across Indian States and Union Territories, indicating the persistence of a pronounced second-level digital divide. The PCA-based Digital Skill Index demonstrates that digital capabilities are unevenly distributed, with a small group of states achieving consistently high scores while several others lag considerably behind. The descriptive statistics and PCA results suggest that digital skills constitute a coherent but multifaceted construct encompassing a range of operational and information-processing competencies. Although all seven indicators contribute positively to the Digital Skill Index, the relatively lower prevalence of advanced digital tasks such as

spreadsheet use, software installation, presentation creation, and device configuration indicates that higher-order digital competencies remain less widespread than basic operational skills. This pattern suggests that digital engagement extends beyond mere access to technologies and increasingly depends on the ability to effectively utilize digital tools for diverse purposes.

The ranking results further highlight significant regional disparities in digital capability. States such as Mizoram, Kerala, and Chandigarh occupy the highest positions in the Digital Skill Index, whereas Bihar, Assam, and Madhya Pradesh rank among the lowest. The substantial gap between the highest- and lowest-performing states reflects considerable differences in digital capability across regions and underscores the uneven nature of digital skill development in India. Taken together, these findings demonstrate that digital inequality in India is not solely a question of access to digital technologies but also involves disparities in the skills required to use such technologies effectively. The results therefore provide empirical evidence that the second-level digital divide remains an important dimension of digital inclusion across Indian States and Union Territories.

5.1 Descriptive Overview of Digital Skills

As shown in the indicator proportions, states such as Mizoram, Kerala, Sikkim, Himachal Pradesh, and Tamil Nadu consistently report higher levels of digital competency across multiple ICT-related tasks, including copying and managing files, spreadsheet usage, software configuration, presentation preparation, and installation of digital devices. For example, Mizoram recorded the highest proportions across most indicators, including copying and pasting files (43.5%), spreadsheet usage (23.1%), presentation software use (23.5%), and installation of new devices (23.3%). Similarly, Kerala and Sikkim exhibited comparatively high performance across advanced digital skill categories.

In contrast, states such as Bihar, Assam, Madhya Pradesh, Jharkhand, and Uttar Pradesh reported substantially lower proportions across most functional digital skill indicators. Bihar, in particular, recorded the lowest values across nearly all categories, including spreadsheet use (2.3%), software configuration (1.1%), and device installation (3.9%). These disparities indicate that access to digital infrastructure alone does not necessarily translate into effective digital capability.

Table 2 presents the descriptive statistics of the digital skill indicators used to create the Digital Skill Index. Because all variables were transformed using z-score standardization, each indicator has a mean close to zero and a standard deviation of one. The minimum and maximum values highlight significant differences in digital skills across India. Higher-level digital skills, like sending emails with attachments and using spreadsheets, have larger ranges, indicating greater disparities among states in these advanced abilities. In contrast, basic skills like copying or moving files show less variation. Overall, the descriptive statistics reveal important differences across states and support the use of these indicators for building the index and for comparative analysis.

Table 2: State-wise Proportions of Digital Skill Indicators (%)

States and UT	Copy pastes file	Duplicate or move within document	e-mails with attached	Spreadsheet Formula	Software Installation	Presentation Creation	Device Connection
Andaman & Nicobar Islands	19.74	14.67	9.06	9.00	5.25	10.41	9.45
Andhra Pradesh	16.98	14.11	4.75	5.71	3.80	8.37	7.23
Arunachal Pradesh	28.11	21.10	12.22	11.99	6.48	11.61	12.51
Assam	11.90	7.02	1.63	3.51	1.96	5.62	6.89
Bihar	10.07	6.29	1.58	2.33	1.10	4.08	3.94
Chandigarh	45.13	41.09	8.51	20.27	9.55	22.72	12.00
Chhattisgarh	15.49	9.46	1.96	3.06	1.49	4.83	7.29
Dadra & Nagar Haveli	14.63	11.84	3.78	4.33	1.81	8.99	4.88
Daman & Diu	25.62	16.29	2.73	1.33	2.36	15.81	8.24
Delhi	33.32	26.21	15.21	13.97	11.28	20.45	19.36
Goa	29.85	23.09	9.36	10.33	9.19	15.87	13.90
Gujarat	24.76	14.92	5.72	7.19	4.90	11.20	11.01
Haryana	25.53	15.31	5.57	5.98	2.71	12.33	12.38
Himachal Pradesh	32.10	22.39	9.36	11.67	8.10	19.34	17.48
Jammu & Kashmir	25.58	11.07	3.30	4.13	2.11	7.15	18.49
Jharkhand	12.91	7.82	3.33	3.93	1.84	5.81	8.15
Karnataka	27.60	19.79	7.04	9.87	9.36	11.44	14.32

Kerala	35.42	27.87	17.85	17.58	13.34	22.23	22.96
Ladakh	28.20	20.06	6.96	6.33	3.04	9.32	15.20
Lakshadweep	37.90	21.30	7.85	14.29	6.63	22.33	17.44
Madhya Pradesh	12.26	8.37	2.67	3.24	2.09	5.54	4.70
Maharashtra	25.60	17.86	7.69	9.38	5.82	14.51	14.10
Manipur	32.85	25.92	8.98	13.46	6.92	11.28	19.93
Meghalaya	23.83	10.77	1.72	3.56	0.88	9.88	13.36
Mizoram	43.51	27.98	13.07	23.13	12.05	23.54	23.32
Nagaland	25.29	15.56	3.31	6.51	4.36	15.13	16.96
Odisha	14.10	8.80	2.64	3.16	2.22	6.76	7.79
Puducherry	34.76	30.45	12.51	12.93	10.93	24.37	17.24
Punjab	23.76	12.95	5.59	4.61	3.21	12.19	12.24
Rajasthan	15.65	11.80	4.11	4.53	2.41	7.19	7.36
Sikkim	38.04	25.82	9.98	14.66	7.41	21.89	20.51
Tamil Nadu	30.87	23.02	8.92	15.05	11.10	19.98	20.30
Telangana	22.32	18.95	6.15	7.59	5.34	11.67	11.03
Tripura	12.69	10.91	6.51	6.93	4.74	4.58	5.53
Uttar Pradesh	12.58	7.70	2.13	3.19	1.46	6.92	6.74
Uttarakhand	22.61	13.70	5.13	6.48	2.57	11.98	11.55
West Bengal	20.02	10.99	4.08	4.66	3.44	7.07	12.32

Source: Calculated by authors

A Pearson correlation analysis was conducted to examine the relationships among the seven digital skill items: copy and paste, duplicating or moving files, sending emails with attachments, using spreadsheets, configuring software, creating presentations, and installing new devices. The results indicate that all variables are positively and strongly correlated, with coefficients ranging from 0.703 to 0.922 ($p < .001$).

Table 3: Descriptive statistics of indicators

Indicator	Mean	SD	Min	Max
Copy and Paste Files	24.64	9.28	10.07	45.13
Duplicate or Move Files within document	17.11	7.88	6.29	41.09
Send Emails with Attachments	6.57	4.02	1.58	17.85
Use Spreadsheet Formulae	8.38	5.37	1.33	23.13
Install Software or Applications	5.22	3.57	0.88	13.34
Create Electronic Presentations	12.55	6.20	4.08	24.37
Connect and Install Devices	12.65	5.42	3.94	23.32

Source: Calculated by authors using Stata

The high magnitude of correlations suggests substantial overlap among the items, indicating that they likely measure a common underlying construct, namely digital skill or digital skills proficiency. This strong interrelatedness also provides preliminary support for scale reliability and dimensionality. Although inter-item correlations are high, each indicator represents a distinct operational domain of digital skills. The high correlations reflect the cumulative nature of digital capability rather than pure redundancy.

Table 4: Correlation Matrix of Digital Skills Items

Variable	1	2	3	4	5	6	7
1. Copy and Paste Files	1.000						
2. Duplicate or Move Files within document	0.922***	1.000					
3. Email Attachments	0.742***	0.802***	1.000				
4. Spreadsheet Formulae	0.872***	0.898***	0.855***	1.000			
5. Software Installation	0.791***	0.859***	0.907***	0.909***	1.000		
6. Presentation Creation	0.908***	0.872***	0.759***	0.836***	0.828***	1.000	
7. Device Connection	0.851***	0.703***	0.724***	0.753***	0.747***	0.768***	1.000

*Note: *** $p < 0.001$*
Source: Calculated by authors using NSS 78th round data

5.2 Reliability and Measurement Validation

To examine the reliability of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were conducted. The KMO value was 0.808, indicating meritorious sampling adequacy. Bartlett's test was statistically significant (χ^2 (21) = 366.518, $p < .001$), discarding the null hypothesis that the correlation matrix is an identity matrix. These results confirm that the dataset is appropriate for factor analysis and that meaningful latent structures can be extracted.

In addition, reliability analysis using Cronbach's alpha indicated excellent internal consistency among the selected digital skill indicators ($\alpha = 0.9677$). Although Cronbach's alpha exceeds the conventional threshold of 0.95, all indicators were retained because they represent conceptually distinct dimensions of digital capability and the robustness analyses confirmed that no single indicator dominated the index.

Table 5. Tests of Sampling Adequacy and Factorability

Test	Statistic
Kaiser-Meyer-Olkin (KMO)	0.808
Bartlett's Test χ^2	366.518
Degrees of Freedom	21
p-value	<0.001
Determinant of Correlation Matrix	<0.001

Source: Calculated by authors using NSS 78th round data

5.3 Principal Component Analysis and Digital Skill Index

Principal Component Analysis (PCA) was employed to examine the underlying dimensional structure of the seven digital skill indicators and to construct a composite Digital Skill Index. As reported in Table 6, the first principal component exhibited a dominant eigenvalue of 5.950 and accounted for 85.0% of the total variance in the data. All remaining components had eigenvalues below one and individually explained only a small proportion of the variance, indicating that the indicators are strongly associated with a single latent dimension.

Table 6. Principal Component Analysis

Component	Eigenvalue	Variance Explained (%)	Cumulative (%)
PC1	5.950	85.00	85.00
PC2	0.407	5.81	90.81
PC3	0.313	4.47	95.28
PC4	0.141	2.01	97.30
PC5	0.101	1.44	98.74
PC6	0.069	0.99	99.73
PC7	0.019	0.27	100.00

Source: Calculated by authors using NSS 78th round data

Table 7: Component Loadings for Digital Skill Index

Indicator	Loading
Spreadsheet Formulae	0.390
Copy and Paste Files	0.387
Duplicate or Move Files within document	0.386
Software Installation	0.384
Presentation Creation	0.380
Email Attachments	0.368
Device Connection	0.351

Source: Calculated by authors using NSS 78th round data

The component loadings for the first principal component ranged from 0.351 to 0.390 (Table 7), demonstrating that all seven digital skill indicators contribute positively and relatively evenly to the underlying digital skill construct. The highest loading is observed for Spreadsheet Formulae (0.390), followed closely by Copy and Paste Files (0.387) and Duplicate/Move Files (0.386). Indicators related to Software Installation (0.384) and Presentation Creation (0.380) also exhibit strong contributions to the principal component. While Email Attachments (0.368) and Device Connection (0.351) have comparatively lower loadings, they remain substantial and contribute meaningfully to the overall construct.

The small variation in loadings suggests that digital skills represent a balanced and integrated competency rather than being dominated by any single task. This finding supports the use of a composite Digital Skill Index, as all indicators capture complementary dimensions of digital capability. These findings are further supported by the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (0.808) and the statistically significant Bartlett's test of sphericity ($\chi^2 = 366.52$, $p < 0.001$), confirming the suitability of the data for dimension reduction.

Given the clear dominance of the first principal component and the strong intercorrelations among the indicators, the factor scores derived from the first component were used to construct the Digital Skill Index (DSI). The resulting index captures the overall level of digital skills across Indian States and Union Territories and serves as the basis for subsequent ranking and comparative analyses.

5.4 State-wise Ranking of Digital Skill Capability

The PCA-derived factor scores were normalized to a 0–100 scale to facilitate interpretation and comparison across States and Union Territories. The normalized scores were subsequently used to rank states according to their overall level of digital skills.

The results reveal substantial regional disparities in digital capability across India. Mizoram emerged as the highest-performing State/UT with a Digital Skill Index score of 100.00, followed by Kerala (96.85) and Chandigarh (88.81). Other high-ranking regions included Puducherry, Delhi, Sikkim, and Tamil Nadu, all of which recorded relatively strong digital skill outcomes. These findings suggest that higher-performing states and Union Territories have been more successful in translating access to digital technologies into meaningful digital competencies.

At the other end of the distribution, Bihar recorded the lowest score (0.00), followed by Assam (6.71), Madhya Pradesh (6.99), Uttar Pradesh (7.87), and Chhattisgarh (8.95). These states exhibited substantially lower levels of digital proficiency, highlighting persistent inequalities in the acquisition and use of digital skills. The wide gap between the highest- and lowest-ranked states underscores the uneven nature of digital capability development across the country.

Overall, the ranking pattern indicates that digital skills are concentrated in a relatively small group of states and Union Territories, while a large number of regions continue to lag behind. The findings point to the existence of a pronounced sub-national digital skills divide in India, suggesting that policies aimed at improving digital inclusion should focus not only on access to digital technologies but also on strengthening the educational, institutional, and infrastructural conditions that support the development of digital competencies.

Table 8: State-wise Digital Skill Index Ranking

State/UT	DSI Score	DSI Rank	Copy pastes file	Duplicate or move within document	e-mails with attached	Spreadsheet Formula	Software Installation	Presentation Creation	Device Connection
Mizoram	100	1	1	1	12	2	6	3	21
Kerala	96.85	2	2	3	3	1	2	2	1
Chandigarh	88.81	3	3	7	6	5	10	6	3
Puducherry	82.65	4	4	11	13	6	12	4	9
Delhi	82.53	5	5	4	1	3	1	5	2
Sikkim	76.7	6	6	2	4	9	5	1	10
Tamil Nadu	73.95	7	7	5	2	7	3	7	6
Lakshadweep	68.54	8	8	6	10	8	11	20	5
Himachal Pradesh	65.5	9	9	10	8	11	9	9	8

Manipur	63.62	10	10	9	11	4	4	8	4
Goa	59.91	11	11	8	7	12	8	10	15
Arunachal Pradesh	54.92	12	12	13	16	21	23	24	12
Karnataka	51.49	13	13	12	5	10	13	18	17
Maharashtra	47.32	14	14	14	15	13	7	19	13
Ladakh	40.17	15	15	17	30	37	27	11	26
Nagaland	39.59	16	16	16	14	14	14	13	14
Telangana	38.32	17	17	27	29	28	29	28	7
Andaman & Nicobar Islands	36.71	18	18	19	21	22	24	14	18
Gujarat	35.53	19	19	18	28	19	19	12	11
Haryana	34.04	20	20	20	19	17	17	21	24
Punjab	31.14	21	21	30	35	30	37	23	16
Uttarakhand	30.62	22	22	24	20	25	22	15	20
Jammu & Kashmir	27.87	23	23	23	22	20	25	16	22
Daman & Diu	26.65	24	24	15	18	16	15	17	23
West Bengal	23.38	25	25	28	25	24	21	29	19
Andhra Pradesh	22.83	26	26	21	9	15	16	22	25
Meghalaya	21.26	27	27	22	23	23	20	26	31
Tripura	19.04	28	28	26	24	26	26	27	29
Rajasthan	16.74	29	29	31	34	35	34	35	30
Dadra & Nagar Haveli	14.41	30	30	25	26	27	33	25	35
Odisha	11.37	31	31	32	32	34	28	31	28
Jharkhand	10.74	32	32	34	27	29	32	32	27
Chhattisgarh	8.95	33	33	29	17	18	18	36	34
Uttar Pradesh	7.87	34	34	35	33	33	35	30	33
Madhya Pradesh	6.99	35	35	33	31	32	30	34	36
Assam	6.71	36	36	36	36	31	31	33	32
Bihar	0	37	37	37	37	36	36	37	37

Source: Calculated by authors using Stata

Higher-ranked states generally exhibit stronger educational attainment, higher literacy, greater ICT exposure, and better digital ecosystems. Conversely, lower-ranked states tend to face multiple structural constraints, including lower educational achievement, weaker digital infrastructure, lower household incomes and limited digital training opportunities.

Table 9: Rank Stability Across Weighting Schemes

Statistic	Value
Spearman Rank Correlation (PCA vs Equal Weight)	0.998
p-value	<0.001
Mean Absolute Rank Difference	0.38
Maximum Rank Difference	2
Number of States with Rank Change > 2	0

Source: Calculated by authors using Stata

The rank stability analysis demonstrates a remarkably high degree of robustness in the Digital Skill Index. Comparison of the PCA-based index with the equal-weighted index reveals an almost perfect correspondence in state rankings, with a Spearman rank correlation coefficient of 0.998 ($p < 0.001$). The average rank change across States and Union Territories is less than one position, and no state experiences a substantial shift in its relative standing. These findings indicate that the observed pattern of digital skill disparities is highly stable and largely insensitive to alternative weighting schemes.

The strong consistency between PCA-derived and equal-weighted rankings suggests that the index is driven by the underlying structure of the data rather than by methodological choices concerning variable weights. This result reflects the high degree of coherence among the digital skill indicators, as evidenced by their strong intercorrelations and similar component loadings. At the same time, the stability of the rankings should not be interpreted as evidence of redundancy among the indicators. Rather, the indicators capture distinct yet complementary dimensions of digital capability, including information management, communication, software use, content creation, and device operation. Together, these dimensions contribute to a common latent construct while preserving the multidimensional nature of digital skills.

Overall, the rank stability results provide strong support for the validity and reliability of the Digital Skill Index, demonstrating that the identification of high- and low-performing States and Union Territories is robust to alternative assumptions regarding index construction. The findings also suggest that policy interventions should move beyond infrastructure provision toward capability development. For lower-performing states such as Bihar, Assam, Madhya Pradesh, and Uttar Pradesh, priority should be given to integrating digital competency into school curricula, strengthening teacher digital pedagogical skills, expanding community digital resource centres under programmes such as PMGDISHA, and providing localized multilingual digital training for adults and marginalized populations. In contrast, higher-performing states may serve as policy laboratories from which successful implementation strategies can be adapted to local contexts.

5.5 Interpretation of State Rankings

The Digital Skill Index reveals substantial interstate heterogeneity in functional digital capability across India, reflecting the persistence of the second-level digital divide beyond differences in internet access or device ownership. Rather than representing isolated state-specific outcomes, the observed rankings reveal broader regional patterns associated with educational development, socio-economic conditions, and institutional capacity. States with higher Digital Skill Index scores generally exhibit stronger educational systems, higher literacy rates, greater digital ecosystem maturity, and wider adoption of information and communication technologies. Conversely, lower-ranked states continue to face structural constraints that limit the acquisition and effective use of digital skills.

A clear geographical pattern emerges from the analysis. Southern states, including Kerala and Tamil Nadu, together with several northeastern states such as Mizoram, Sikkim, and Manipur, consistently demonstrate relatively high levels of operational digital competence across

multiple ICT tasks. These regions have historically invested in education, human development, and community-based digital initiatives, creating favourable environments for developing digital capability. Their relatively stronger performance suggests that investments in human capital and institutional capacity facilitate the translation of digital access into meaningful digital use.

In contrast, many states in central and eastern India, including Bihar, Assam, Madhya Pradesh, Jharkhand, Chhattisgarh, and Uttar Pradesh, occupy the lower end of the Digital Skill Index. These states consistently report lower levels of proficiency across advanced ICT tasks such as spreadsheet use, software installation, and presentation development. The findings suggest that although digital infrastructure has expanded considerably across India, disparities in educational attainment, digital literacy, language barriers, and socio-economic opportunities continue to constrain the development of higher-order digital competencies. These results are consistent with previous studies that identify education, income, gender, and rural–urban disparities as key determinants of digital capability in India (Chaudhuri, 2024; Hota, 2022). These determinants are synthesised to develop the conceptual framework rather than empirically tested because the objective of this paper is measurement rather than explanation.

The ranking also indicates that digital skills develop progressively rather than uniformly across competencies. Basic operational tasks, including file management, are relatively widespread across states, whereas more advanced competencies involving productivity software, digital content creation, and software configuration remain concentrated in higher-performing regions. This progression is consistent with digital competence frameworks, which distinguish between foundational operational skills and more advanced competencies required for effective participation in digital environments (Van Deursen & Van Dijk, 2014; Vuorikari et al., 2022).

Importantly, the policy interpretation should not focus on small differences in individual state rankings but rather on the broader spatial distribution of digital capability. The robustness analyses demonstrate that the ranking remains highly stable under alternative weighting schemes and leave-one-out sensitivity analyses (Spearman's $\rho = 0.992–0.998$), indicating that the observed interstate differences reflect substantive variation rather than methodological artefacts. Consequently, the Digital Skill Index should be interpreted primarily as a benchmarking tool that identifies broad categories of digital capability across states rather than as a precise ordinal ranking.

Overall, the interstate comparisons suggest that reducing India's second-level digital divide requires differentiated policy responses that address regional disparities in educational opportunity, digital training, institutional support, and socio-economic development. While high-performing states may provide examples of effective digital capability development, lower-performing states require sustained investments in digital education, teacher capacity building, community-based digital training, and localized multilingual digital services to translate digital access into meaningful digital participation.

5.6 Digital Skill and Human Development Indicators

Digital Skills and Human Development Indicators

To further assess the external validity of the Digital Skill Index (DSI), its relationship with broader human development outcomes was examined using the Subnational Human Development Index (SHDI) and its constituent dimensions, namely the Health Index, Education Index, and Income Index. This analysis provides insight into whether regional variations in digital skills are associated with broader patterns of socio-economic development and human capability.

Correlation Analysis

Table 10 presents the correlation matrix between the Digital Skill Index and selected human development indicators. The results indicate positive associations between digital skills and all dimensions of human development, although the strength and statistical significance of these relationships vary. The strongest association is observed between the Digital Skill Index and the Education Index ($r = 0.420$, $p < 0.01$), suggesting that states with higher educational attainment tend to exhibit greater levels of digital capability. Positive but statistically insignificant correlations are observed with the Subnational Human Development Index ($r = 0.317$), Income Index ($r = 0.319$), and Health Index ($r = 0.190$).

Table 10: Correlation Matrix

Variable	DSI	SHDI	Health	Education	Income
DSI	1.000				
SHDI	0.317	1.000			
Health Index	0.190	0.983***	1.000		
Education Index	0.420***	0.986***	0.947***	1.000	
Income Index	0.319	0.991***	0.965***	0.968***	1.000

Source: Calculated by authors using Stata

The findings suggest that education is more closely linked to the development of digital skills than the other dimensions of human development. This result is consistent with the view that digital competence is strongly dependent on educational opportunities, cognitive skills, and learning environments that enable individuals to acquire and effectively utilize digital technologies.

At the same time, the human development indicators exhibit extremely high correlations with one another, ranging from 0.947 to 0.991. This reflects the strong interdependence of health, education, income, and overall human development outcomes across Indian States and Union Territories.

Bivariate Association Analysis

To further examine these relationships, a series of bivariate regression models were estimated with the Digital Skill Index as the dependent variable and each human development indicator entered separately as an explanatory variable. Separate models were preferred because the very high correlations among the human development indicators generated severe multicollinearity when included simultaneously in a multivariate specification (Mean VIF = 18.66).

Table 11: Separate bivariate regressions

Predictor	Coefficient (β)	Std. Error	t-value	p-value	R^2
Health Index	30.733	26.861	1.14	0.260	0.036
Education Index	78.122**	28.548	2.74	0.010	0.176
Income Index	53.497†	26.900	1.99	0.055	0.102

Source: Calculated by authors using Stata

***Notes: p < 0.05**, † p < 0.10.*

The positive associations observed between the Digital Skill Index and human development indicators should be interpreted with caution. These relationships do not necessarily imply causality and may partly reflect conceptual overlap among the underlying constructs. In particular, educational attainment and broader human development measures capture dimensions of human capability that are inherently related to the acquisition and effective use of digital technologies. Consequently, part of the observed association between digital skills

and human development indicators may reflect shared socio-economic and institutional conditions rather than independent causal relationships.

Moreover, the cross-sectional nature of the analysis precludes identification of the direction of influence. Higher levels of human development may facilitate the acquisition of digital skills through better educational opportunities, improved infrastructure, and greater exposure to technology. Conversely, enhanced digital capability may contribute to improved educational, economic, and social outcomes. The relationship is therefore likely to be mutually reinforcing rather than unidirectional.

The regression results, presented in Table 11, reinforce the findings from the correlation analysis. The Education Index exhibits a positive and statistically significant association with digital skills ($\beta = 78.12$, $p = 0.010$), explaining approximately 17.6% of the variation in digital skill levels across States and Union Territories ($R^2 = 0.176$). In contrast, the Health Index shows a positive but statistically insignificant relationship with digital skills ($\beta = 30.73$, $p = 0.260$), accounting for only 3.6% of the variation ($R^2 = 0.036$). Similarly, the Income Index demonstrates a positive association ($\beta = 53.50$) that is only marginally significant at the 10% level ($p = 0.055$), explaining approximately 10.2% of the variation in digital skills ($R^2 = 0.102$).

Overall, the results indicate that education constitutes the most important human development dimension associated with digital capability. While income and health may contribute indirectly to digital participation, educational attainment appears to play a more direct role in shaping the distribution of digital skills across Indian States and Union Territories.

The observed relationships should nevertheless be interpreted with caution and not as evidence of causality. Human development and digital skills are mutually reinforcing processes that may be influenced by a range of underlying social, economic, and institutional factors. Moreover, the Education Index captures dimensions of human capability that are inherently related to the acquisition and use of digital technologies. Consequently, part of the observed association between educational attainment and digital skills may reflect shared underlying capabilities rather than a direct causal effect. Despite these limitations, the findings provide evidence that digital capability is closely connected to broader patterns of human development, particularly educational development, across India.

The purpose of the HDI analysis is exploratory and intended to assess the external validity of the Digital Skill Index rather than establish causal relationships. Given the cross-sectional nature of the data and the absence of suitable instruments at the state level, formal endogeneity testing was not undertaken. The observed relationships should therefore be interpreted as associations rather than causal effects.

6. Discussion

The findings from this study provide strong empirical evidence for the unidimensional nature of digital skills, supporting the conceptualization of digital skill as a coherent and integrated construct. The high inter-item correlations and strong factor loadings indicate that basic digital competencies, ranging from simple operations such as copy-paste to more advanced tasks like configuring software are closely interconnected. Although contemporary frameworks such as DigComp conceptualize digital competence as comprising multiple domains (information, communication, content creation, safety, and problem solving), the present study finds that these operational skill indicators behave empirically as a single latent dimension at the state level. This does not imply that digital competence is theoretically one-dimensional. Rather, the selected functional ICT tasks are sufficiently interrelated that they collectively represent a common underlying level of operational digital capability. Thus, the unidimensional index

should be interpreted as a parsimonious empirical representation of overall digital proficiency rather than a replacement for broader multidimensional competence frameworks.

The first principal component explained 85.0% of the total variance, providing strong evidence of a unidimensional digital skill construct and reinforces the argument that digital skills should not be treated as fragmented abilities but rather as part of a unified skill set. This aligns with existing literature on digital competence frameworks, which conceptualize digital skill as a composite capability involving multiple but interrelated competencies. Prior research consistently establishes that digital skills are a crucial determinant of a person's ability to effectively use digital technologies and meaningfully utilise its benefits from them.

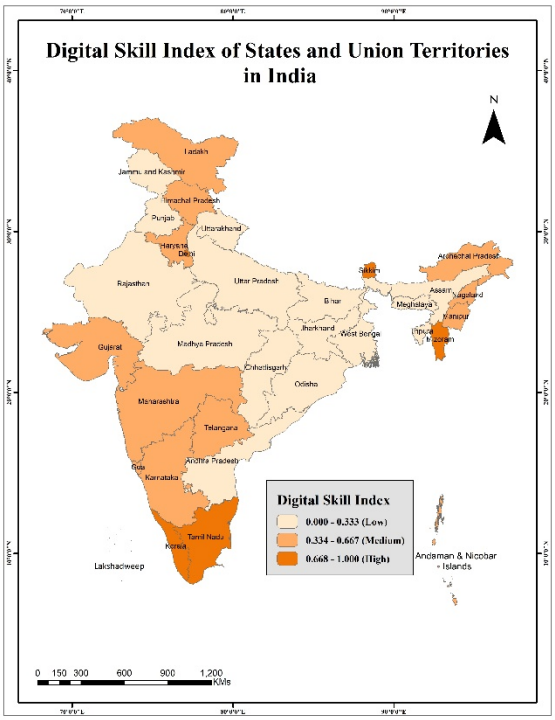


Figure 2: Map of the Digital Skill Index

Source: Prepared by authors using QGIS

The state-by-state analysis shows significant regional differences in digital skill. States like Mizoram and Kerala, which have a history of strong education and social development, also have higher levels of digital skill. This suggests an association between human development factors and the ability to gain digital skills. In contrast, states with lower rankings, like Bihar and Assam, struggle with challenges such as limited access to digital infrastructure, lower education levels and socio-economic issues (Arora, & Sapre, 2025; Mandal, 2025).

The study adds to the literature by defining digital skills as a single, measurable concept, which was verified using Principal Component Analysis (PCA). The findings show that various digital skills, which range from basic tasks to more complex operations, create a clear structure. This offers a strong method for building a Digital Skill Index that future research can replicate. Second, the study broadens the understanding of the digital divide by combining measurement with spatial analysis. While earlier research focused on socio-economic factors, it rarely looked at how digital skills differ by region. By mapping digital skill across states, this study illustrates the geographical aspect of the second- and third-level digital divide. It reveals how differences in skills lead to unequal opportunities and results.

Beyond theoretical contributions, this study has important implications for policy design and implementation. First, the findings show that digital inclusion policies need to go beyond

focusing only on access. Government initiatives often prioritize expanding infrastructure and improving connectivity. However, this study reveals that gaps in digital skills are a major barrier. Without the right skills, simply having access to technology may not result in meaningful participation in the digital economy. This limits the effectiveness of such policies.

Second, the state-wise Digital Skill Index created in this study offers a data-driven tool for targeting policies. By identifying states that perform well and those that do not, policymakers can plan specific interventions for each region instead of using the same strategies nationwide. This is crucial in a country like India, where educational, infrastructural, and socio-economic differences are significant.

Third, the study emphasizes the need to link digital skill with broader socio-economic policies. Therefore, efforts to close the digital divide must also tackle deeper issues like gaps in education and economic opportunities. The analysis suggests that educational attainment is more closely associated with digital skills than the other dimensions of human development. While positive relationships were observed with health, income, and overall human development, these associations were comparatively weak and statistically insignificant. This finding aligns with the capability approach, which highlights how individual skills can turn access into real benefits. The results show that tackling the second-level digital divide needs actions beyond just improving infrastructure. While access is still important, improving education, health outcomes, and human capital is essential for fostering effective digital engagement. Overall, the external validation confirms that the Digital Skill Index is well-founded both in theory and in practice. It captures important differences in digital capability that are closely related to broader socio-economic development, making it relevant for policy creation and targeted actions.

The observed regional variations found in this study, reflect broader socio-economic and educational inequalities highlighted in digital divide literature. States with relatively stronger educational outcomes, higher human development levels, and better digital ecosystems tend to demonstrate greater functional digital proficiency, whereas economically and educationally disadvantaged regions continue to face challenges in acquiring higher-order digital skills. These findings reinforce the argument that the second-level digital divide in India is closely associated with differences in educational opportunity, technological exposure, and broader developmental conditions rather than simple access to digital devices or internet connectivity alone.

The positive associations observed between the Digital Skill Index and human development indicators should be interpreted with caution. These relationships do not imply causality and may partly reflect conceptual overlap among the underlying constructs. In particular, educational attainment and broader human development measures capture dimensions of human capability that are inherently related to the acquisition and effective use of digital technologies. Consequently, part of the observed correlation between digital skills and human development indicators may reflect shared socio-economic and institutional conditions rather than independent causal relationships.

Moreover, the cross-sectional nature of the analysis precludes identification of the direction of influence. Higher levels of human development may facilitate the acquisition of digital skills, while greater digital capability may also contribute to improved educational, economic, and social outcomes. The findings should therefore be interpreted as evidence of association rather than causation. Future research using longitudinal or causal inference approaches may help clarify the dynamic relationship between digital capability and human development.

The findings also suggest that digital skill and human development are closely interconnected dimensions of social development. Rather than viewing digital skills as an outcome of human development alone, it is more appropriate to conceptualize the relationship as one of mutual reinforcement. States with stronger educational systems, higher incomes, and better health outcomes may provide environments that facilitate the development of digital skills, while greater digital capability may, in turn, enhance access to information, learning opportunities, public services, and economic participation. Future research employing longitudinal data or causal inference approaches would be valuable in disentangling these dynamic relationships.

6.1 Robustness Checks

To assess the reliability and robustness of the Digital Skill Index (DSI), a series of complementary robustness and sensitivity analyses were conducted. Given that the Principal Component Analysis (PCA) was performed on aggregated State and Union Territory-level observations (N = 37), it was important to evaluate whether the resulting index and rankings were sensitive to alternative weighting schemes, the exclusion of individual indicators, or potential methodological assumptions underlying the PCA approach.

Sensitivity to Weighting Scheme

The robustness of the index to alternative weighting assumptions was assessed by constructing an equal-weighted Digital Skill Index and comparing it with the PCA-based index. The results indicate an exceptionally high degree of correspondence between the two approaches. The Spearman rank correlation between the PCA-based and equal-weighted indices was 0.998 ($p < 0.001$), demonstrating near-identical ranking patterns across States and Union Territories. Moreover, the mean absolute rank difference was only 0.38 positions, while the maximum observed change in rank was limited to two positions.

These findings suggest that the spatial distribution of digital skills is driven primarily by the underlying data structure rather than by the specific weighting methodology employed. The high level of agreement between the two indices also reflects the relatively balanced contribution of all digital skill indicators to the latent construct.

Leave-One-Out Sensitivity Analysis

To evaluate the influence of individual indicators on the Digital Skill Index, a leave-one-out sensitivity analysis was conducted by sequentially excluding each digital skill indicator and recomputing the PCA-based index. The resulting rankings were then compared with the baseline index.

The analysis revealed consistently high levels of rank preservation. Spearman rank correlations between the baseline index and the leave-one-out indices ranged from 0.992 to 0.998. The lowest correlation was observed when the Device Connection indicator was excluded ($\rho = 0.992$), while the highest correlations were recorded when Spreadsheet Formulae and Software Installation were omitted ($\rho = 0.998$). Across all specifications, the resulting state rankings remained highly stable, indicating that no individual indicator exerted a disproportionate influence on the overall index.

These findings provide strong evidence that the Digital Skill Index captures a broad and coherent measure of digital capability rather than being driven by any single dimension of digital skills.

Stability of PCA Structure

The stability of the underlying PCA solution was further assessed through examination of sampling adequacy, factorability, and component structure. The Kaiser-Meyer-Olkin (KMO)

statistic of 0.808 indicates good sampling adequacy, while Bartlett's test of sphericity was highly significant ($\chi^2 = 366.52$, $p < 0.001$), confirming the suitability of the data for dimension reduction.

Across all model specifications, the first principal component remained dominant, explaining approximately 85.0% of the total variance. In addition, the component loadings remained consistently high and relatively balanced across indicators, supporting the existence of a strong unidimensional structure underlying digital skills. The persistence of this structure under alternative specifications further strengthens confidence in the validity of the index construction procedure.

Table 12: Robustness Checks Summary

Robustness Check	Result
Overall KMO	0.808
Bartlett's Test p-value	<0.001
Variance Explained by PC1	85.0%
PCA vs Equal Weight Spearman Correlation	0.998
Mean Rank Difference	0.38
Maximum Rank Difference	2
Leave-One-Out Minimum Spearman Correlation	0.992
Leave-One-Out Maximum Spearman Correlation	0.998
Conclusion	Highly Robust

Source: Calculated by authors using Stata

Table 13: Leave-One-Out Correlations

Excluded Indicator	Spearman Correlation
Copy and Paste Files	0.996
Duplicate or Move Files within document	0.998
Email Attachments	0.997
Spreadsheet Formulae	0.998
Software Installation	0.998
Presentation Creation	0.995
Device Connection	0.992

Source: Calculated by authors using Stata

Taken together, the robustness checks provide strong evidence for the reliability and stability of the Digital Skill Index. The high degree of rank preservation under alternative weighting schemes, the minimal sensitivity to the exclusion of individual indicators, and the stability of the PCA structure collectively demonstrate that the index is not driven by arbitrary methodological choices. Rather, the Digital Skill Index captures a consistent and robust pattern of digital capability disparities across Indian States and Union Territories.

Although formal confidence intervals for state rankings were considered, the relatively small number of aggregated State and Union Territory observations limits the reliability of bootstrap-based interval estimation. Consequently, uncertainty was assessed through a series of complementary robustness analyses, including comparison with an equal-weighted index and leave-one-out sensitivity testing. The exceptionally high rank correlations observed across alternative specifications ($\rho = 0.992–0.998$) indicate that the Digital Skill Index is highly stable and not unduly influenced by any single indicator or weighting assumption. These findings suggest that the observed interstate differences in digital skills reflect substantive variation rather than methodological artefacts arising from index construction.

7. Policy Implications

The findings of this study have important implications for digital inclusion policies in India. While considerable progress has been made in expanding digital infrastructure through initiatives such as Digital India, BharatNet, Common Service Centres (CSCs), and the Pradhan Mantri Gramin Digital Saksharta Abhiyan (PMGDISHA), the results demonstrate that expanding access alone is insufficient to eliminate digital inequalities. The substantial variation in Digital Skill Index (DSI) scores across Indian States and Union Territories indicates that the second-level digital divide remains a significant barrier to achieving meaningful digital inclusion. Consequently, future policy efforts should place greater emphasis on developing citizens' digital capabilities alongside continued investments in digital infrastructure.

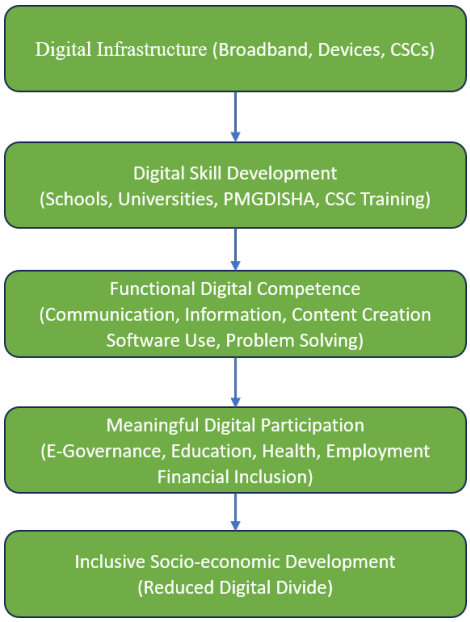


Figure 3: Policy Framework

Source: Prepared by authors

Shift from Access-Oriented to Capability-Oriented Digital Policies

The findings support a transition from infrastructure-centric policies toward capability-oriented digital inclusion strategies. While first-generation digital policies primarily focused on expanding internet connectivity and device ownership, contemporary policy frameworks must emphasize the acquisition of functional digital skills that enable citizens to effectively use digital technologies. National digital inclusion programmes should therefore incorporate structured digital competency training covering operational, communication, information management, content creation, and problem-solving skills, consistent with internationally recognised digital competence frameworks.

State-Specific Digital Skill Development Strategies

The considerable interstate variation observed in the Digital Skill Index suggests that uniform national interventions may not adequately address regional disparities. States with relatively lower digital skill levels, including Bihar, Assam, Madhya Pradesh, Uttar Pradesh, Jharkhand, and Chhattisgarh, require targeted investments that reflect their socio-economic and educational contexts. State governments should develop localized digital skill strategies aligned with regional needs, demographic characteristics, and existing educational capacities rather than relying solely on national programmes. The Digital Skill Index developed in this study provides a practical benchmarking tool that can assist governments in identifying priority

regions, monitoring progress, and evaluating the effectiveness of digital inclusion initiatives over time.

Strengthening Digital Skills through Formal Education

Educational institutions should become the primary platform for developing digital competencies. Rather than limiting digital education to basic computer literacy, school and higher education curricula should integrate practical digital tasks such as document management, spreadsheet analysis, digital communication, presentation development, cybersecurity awareness, and responsible information use. Equally important is strengthening teachers' digital pedagogical competencies through continuous professional development programmes, ensuring that digital technologies are effectively integrated into classroom instruction.

Expanding Community-Based Digital Capacity Building

Community-based digital learning centres can play an important role in reducing digital inequalities among adults and disadvantaged populations. Existing Common Service Centres (CSCs), public libraries, Panchayat Resource Centres, and community institutions may be strengthened as local digital capability hubs offering structured digital skills training, particularly for women, older adults, unemployed youth, and marginalized communities. Such community-level interventions are likely to complement formal education while extending digital learning opportunities to populations outside the traditional education system.

Promoting Inclusive and Multilingual Digital Ecosystems

The persistence of regional and socio-cultural disparities suggests that digital inclusion policies should address barriers beyond technological infrastructure. Digital platforms should support multilingual interfaces, simplified navigation, accessibility features, and culturally appropriate content to accommodate India's linguistic and educational diversity. Improving the usability of digital government services may substantially enhance effective technology adoption among first-generation digital users and populations with limited formal education.

Monitoring Digital Capability Beyond Connectivity Indicators

Current digital development indicators largely emphasize measures such as internet penetration, broadband subscriptions, or mobile ownership. While these indicators remain important, they provide limited information regarding citizens' ability to effectively utilize digital technologies. Governments should therefore complement infrastructure indicators with regular monitoring of functional digital skills. Incorporating Digital Skill Index-type measures into national surveys would enable policymakers to evaluate whether improvements in digital access translate into meaningful digital participation and socio-economic benefits.

Integrating Digital Skills into Broader Human Development Policies

The positive association observed between digital skills and educational development suggests that digital capability should be treated as an integral component of broader human development strategies. Investments in education, lifelong learning, vocational training, and digital capacity building are likely to generate mutually reinforcing improvements in digital participation, employment opportunities, financial inclusion, healthcare accessibility, and civic engagement. Consequently, digital skill development should be mainstreamed across national education, employment, health, and rural development programmes rather than being implemented as an isolated ICT initiative.

8. Conclusion

This study established a composite Digital Skill Index to measure state-level effective digital capability using multiple indicators of practical technology use. The index established a strong reliability and construct validity, supported by excellent internal consistency, high sampling adequacy and a clear unidimensional structure identified through principal component analysis. Empirical evidence shows that digital skill significantly improves people's engagement with online platforms and increases the access to economic, social and informational opportunities. From a structural viewpoint, digital skills are shaped by both demand-side and supply-side factors.

Overall, prior studies highlight that digital skills are fundamental to addressing both the second-level digital divide (skills gap) and the third-level digital divide (outcome disparities), making them a critical area of investigation. The state ranking reveals considerable inter-state discrepancies in digital capability. While several states exhibit advanced digital competencies, others remain significantly constrained in their ability to effectively use digital technologies.

9. Limitation and Future direction

This study has some limitations. The measure of digital skills relies on seven functional indicators and may not capture higher-level skills like critical thinking or awareness of cybersecurity. The cross-sectional design restricts our understanding of changes over time. Also, the quantitative approach might not fully capture the context or behaviour related to skill use. A limitation of the study is that the Principal Component Analysis was performed on aggregated State and Union Territory-level observations (N = 37) rather than individual-level data.

Although the underlying NSS dataset is based on a large nationally representative sample, aggregation reduces the effective sample size available for dimensional reduction. Consequently, the PCA results should be interpreted as capturing sub-national patterns of digital capability rather than individual-level latent traits. To mitigate this concern, a series of robustness checks, including KMO and Bartlett diagnostics, equal-weight sensitivity analysis, and leave-one-out PCA analysis were conducted. The consistently high rank correlations across alternative specifications suggest that the Digital Skill Index is robust to reasonable variations in index construction and weighting assumptions. Along with that absence of longitudinal data restricts broader interpretation. Future research should incorporate micro-level modelling and temporal analysis.

Furthermore, state-level aggregation may hide differences within states, and the index centres on skills instead of actual outcomes, which offers limited insight into the third-level digital divide. Also, analysis is based on aggregated State and Union Territory-level data (N = 37), which may limit statistical stability. Along with that high inter-item correlations may indicate redundancy, although robustness checks suggest index stability. With respect to uncertainty estimation, we explicitly acknowledge the limitations associated with deriving formal inferential standard errors and confidence intervals from a highly aggregated state-level dataset with only 37 observations.

Formal endogeneity testing was not undertaken in the present study. The primary purpose of the analysis was exploratory and focused on assessing the external validity of the Digital Skill Index rather than establishing causal relationships. Given the cross-sectional design, the aggregated state-level nature of the data, and the absence of suitable instrumental variables at the sub-national level, conventional approaches for addressing endogeneity would be difficult to justify and interpret. Accordingly, the results are presented as descriptive associations rather than causal effects.

Although the present study focuses on constructing a state-level Digital Skill Index using aggregated state-level estimates, we have explicitly identified subgroup analyses based on gender, rural–urban residence, age, and educational categories as an important direction for future research. Such analyses would provide additional insights into within-state digital inequalities.

Furthermore, the ICT skill variables used in the NSS are self-reported measures rather than performance-based assessments. Consequently, responses may be affected by recall errors, social desirability bias or differences between perceived and actual digital competence. Although the NSS provides nationally representative estimates, future research should complement self-reported measures with task-based assessments of digital performance.

References

Aissaoui, N. (2022). The digital divide: A literature review and some directions for future research in light of COVID-19. *Global Knowledge, Memory and Communication*, *71*(8/9), 686–708. https://doi.org/10.1108/GKMC-06-2020-0075

Aleksandrov, I. N., & Fedorova, M. Yu. (2019). Digital economy and green economy: Rural unemployment and territorial self-development in Russia. *E3S Web of Conferences*, *110*, 02019. https://doi.org/10.1051/e3sconf/201911002019

Arora, R., & Sapre, N. (2025). Rural–Urban Digital Divide: Evidence From Indian States. *International Journal of Finance & Economics*, *31*(2), 2912–2932. https://doi.org/10.1002/ijfe.70045

Bansal, N., & Choudhary, H. (2024). Fostering digital equity: Evaluating impact of digital literacy training on internet outcomes in rural marginalised communities in India. *International Journal of Lifelong Education*, *43*(5), 473–493. https://doi.org/10.1080/02601370.2024.2347327

Chaudhuri, A. (2024). *Analysing the digital divide factors: Evidence of a rural–urban comparison from an Indian district*. *Journal of Scientific Research and Reports, 30*(5), 243–250. https://doi.org/10.9734/JSRR/2024/v30i51939

Choudhary, A., & Matin, A. (2025). *Digital India at the grassroots: The changing landscape of public service delivery through Common Service Centres*. *Journal of Science Innovations and Nature of Earth, 5*(3), 46–48. https://doi.org/10.59436/jsiane.438.2583-2093

Choudhary, H. (2025). From margins to mainstream: Paving the way to digital equity through digital literacy training programs. *Evaluation and Program Planning*, *109*, 102533. https://doi.org/10.1016/j.evalprogplan.2024.102533

Fouillet, C., Guérin, I., & Servet, J.-M. (2021). Demonetization and digitalization: The Indian government's hidden agenda. *Telecommunications Policy*, *45*(2), 102079. https://doi.org/10.1016/j.telpol.2020.102079

Fu, X., & Akter, S. (2016). The Impact of Mobile Phone Technology on Agricultural Extension Services Delivery: Evidence from India. *The Journal of Development Studies*, *52*(11), 1561–1576. https://doi.org/10.1080/00220388.2016.1146700

Guha, A., & Mukerji, M. (2021). Determinants of digital divide using demand-supply framework: Evidence from India. *Australasian Journal of Information Systems*, *25*. https://doi.org/10.3127/ajis.v25i0.3029

Hota, S. P. (2022). Digital Education and Literacy in India: An Overview. *Splint International Journal of Professionals*, *9*(4), 257–263. https://doi.org/10.5958/2583-3561.2022.00030.3

Kantar, & Internet and Mobile Association of India (IAMAI). (2025). *Internet in India 2024*. https://www.iamai.in/sites/default/files/research/Kantar_%20IAMAI%20report_2024_.pdf

Kirty. (2025). *Digital India and democratic accountability: A critical assessment*. *Research Review Journal of Indian Knowledge Systems,* *2*(2), 165–178. https://doi.org/10.31305/rrjiks.2025.v2.n2.017

Kumar, R., Balasubramanian, S., & Loungani, P. (2021). *Inequality and locational determinants of the distribution of living standards in India* [Working paper]. SSRN. https://ssrn.com/abstract=3654494

Lai, J., & Widmar, N. O. (2021). Revisiting the Digital Divide in the COVID -19 Era. *Applied Economic Perspectives and Policy*, *43*(1), 458–464. https://doi.org/10.1002/aepp.13104

Lio, M., & Liu, M. (2006). ICT and agricultural productivity: Evidence from cross-country data. *Agricultural Economics*, *34*(3), 221–228. https://doi.org/10.1111/j.1574-0864.2006.00120.x

Lythreatis, S., Singh, S. K., & El-Kassar, A.-N. (2022). The digital divide: A review and future research agenda. *Technological Forecasting and Social Change*, *175*, 121359. https://doi.org/10.1016/j.techfore.2021.121359

Mahendru, A., Dutta, M., & Mishra, P. R. (2022). *Digital divide: India inequality report 2022*. Oxfam India. https://www.oxfamindia.org/knowledgehub/workingpaper/india-inequality-report-2022-digital-divide

Mandal, B. (2025). Digital Divide in Online Education: A Statewise Survey of Internet Accessibility and Usage Patterns in India. In Digital Crossroads: Integrating Humanities, Science and Technology Edition 1 (pp. 135–151). https://doi.org/10.9734/bpi/mono/978-93-48859-10-5/CH12

Mathrani, A., Sarvesh, T., & Umer, R. (2022). Digital divide framework: Online learning in developing countries during the COVID-19 lockdown. *Globalisation, Societies and Education*, *20*(5), 625–640. https://doi.org/10.1080/14767724.2021.1981253

Mukherjee, T., Ilavarasan, P. V., & Kar, A. K. (2024). Empowering through digital skills training: An empirical study of poor unemployed working-age women in India. *Information Technology for Development*, *30*(3), 562–583. https://doi.org/10.1080/02681102.2023.2292739

Patel, S., Sreelal, B. S., Kalyani, S., Joy, S. G., Pravalika, T., Ramya, T., Khan, S., Archana, V., & Gandhi, A. P. (2024). Digital health literacy among the ageing population: A comparative cross-sectional study between rural and urban Telangana, India. *Medical Journal Armed Forces India,* *80*(3), 313–319. https://doi.org/10.1016/j.mjafi.2023.09.006

Qiu, L., Zhong, S., & Sun, B. (2021). Blessing or curse? The effect of broadband Internet on China's inter-city income inequality. *Economic Analysis and Policy*, *72*, 626–650. https://doi.org/10.1016/j.eap.2021.10.013

Ramsetty, A., & Adams, C. (2020). Impact of the digital divide in the age of COVID-19. *Journal of the American Medical Informatics Association*, *27*(7), 1147–1148. https://doi.org/10.1093/jamia/ocaa078

Shabbir, N., & Porwal, S. (2025). DIGITAL LITERACY: A NECESSITY IN THE 21ST CENTURY FOR INDIA. *Information Technologies and Learning Tools*, *105*(1), 222–231. https://doi.org/10.33407/itlt.v105i1.5883

Tewathia, N., Kamath, A., & Ilavarasan, P. V. (2020). Social inequalities, fundamental inequities, and recurring of the digital divide: Insights from India. *Technology in Society*, *61*, 101251. https://doi.org/10.1016/j.techsoc.2020.101251

United Nations. (2020, June 11). *Digital divide 'a matter of life and death' amid COVID-19 crisis, UN chief warns*. UN News. https://news.un.org/en/story/2020/06/1066132

Zhang, H. (2024). The Impact of Technological Innovation on Economic Growth: A Study Based on Relevant Cases. *Advances in Economics, Management and Political Sciences*, 139, 130–136. https://doi.org/10.54254/2754-1169/2024.19289