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Examining the role of unequal access to technology in child nutritional inequalities in India: A change decomposition analyses

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Abstract:

Technological innovations and adoptions are key pathways for achieving SDGs, including eliminating child malnutrition and related inequalities. However, the role of unequal access to technology in increasing inequalities in child nutritional outcomes has not been widely studied. This study has two-fold objectives: (1) Using the earlier evidence put forth by Wagstaff (2002) and Deaton (2013), it theoretically discusses an 'inverted U-shaped relationship' between 'technology accessibility' and 'child nutritional inequalities'. (2) It estimates child nutritional inequalities and decomposes them to identify the role of technology in their current levels and changes over the period. Using data from five rounds of India's Demographic Health Surveys, we measured wealth-based child nutritional inequalities using Wagstaff's Corrected Concentration Index (CI). Further, the CI and the change in CI were decomposed to find the relative contribution of technology. Findings reveal that inequality in child undernutrition has increased between 1992-93 and 2019-21, despite a significant decrease in their averages. Unequal access to digital and non-digital assets explains about 50% of inequality in child undernutrition and it is a major contributor to the increase in nutritional inequalities. This study advances that unequal access to technology widens the child undernutrition gap and advocates state-policy attempts to reduce disparities in technological access in India.

Key Words: Technology, Digital assets, Child nutrition, Inequality, Decomposition Analyses, India

Highlights:

- The study theoretically explains the 'inverted U-shape relationship between 'technology accessibility and child nutritional inequality'
- To our knowledge, this study is the first attempt in the Indian context to estimate the role of technology in explaining child nutritional inequalities.
- Unequal access to technology explains a major part of inequality in child undernutrition consistently during all five survey points and widens it.
- Reducing unequal access to technological resources across populations is a key pathway to achieving SDGs 2.2 and 10: ending all forms of malnutrition and reducing inequalities, respectively.

1. Introduction

The 2030 Agenda for Sustainable Development has pledged to ensure "no one will be left behind"[1]. Sustainable Development Goals (SDGs) 1 aims towards 'no poverty', while Goals 2 and 10 aims towards 'zero hunger' and 'reduction of inequalities', respectively. However, the progress towards achieving these goals is very slow [2]. The International Telecommunication Union (ITU) and the United Nations Development Programme (UNDP) pointed out that digital technologies are strongly linked with SDG progress. The improvement in technology is estimated to contribute to achieving two-thirds of the SDG targets [3]. United Nations identified 'Science', 'Technology' and 'Innovation' as the key pathways for achieving SDGs by 2030 [4]. In particular, ITU and UNDP emphasised that new and emerging technological changes are drivers of poverty eradication, monitoring sustainable development targets, ensuring food security, social inclusion, access to quality education, and fostering clean energy solutions [5]. Despite considerable technological and digital advancement, access to them is not uniform across socio-economic groups and countries, and thus, the digital divide is widening [6] [7]. Currently, 3.7 billion people worldwide are not using the internet, accentuating the existing inequalities and amplifying systemic bias and discrimination [8]. Studies in the global south highlight that the existing technological access enables the advantageous groups to receive most of the benefits; conversely, the disadvantageous groups continue to be deprived of the same [9].

Angus Deaton, in his landmark book 'The Great Escape' in 2013, put forth that with the advent of every technological innovation resultant resources are first accessed more by richer people, thereby leading to widening inequalities. Although the spillover effect might bring diffusion in technological resources across populations, thereby reducing economic, health, and nutrition inequalities, such a catching-up process generally happens with a considerable time lag unless there is strong intervention from the state to narrow down the gap [10]. In his previous works, Deaton has specifically emphasised that an economic, social, and politically conducive environment may lead to the rapid diffusion of technologies among all populations [11] [12]. In another piece of work, he reaffirms that healthcare technologies and innovations are accessed first among the economically better-off and better-educated, resulting in better health outcomes for them and thereby leading to health inequalities. However, he says that inequalities are gradually eliminated through the spillover or state-mediated effect, and technology and innovations are accessible to those left behind, leading to the diffusion of better health care and reduction in health inequalities [13].

Similarly, Adam Wagstaff, along with his colleague Watanabe, empirically found that most countries have experienced a rise in economic inequalities in child nutritional indicators with improvement in their averages [14]. Later through his breakthrough study in 2002 'Inequalities in health in developing countries: swimming against the tide?', Wagstaff put forth that technological changes increase economic and health inequalities because new technologies do not reach everyone at the same time and better-off adopts the technology faster, and gradually with trickle-down effect, it reaches to the poor. He further highlighted that with technological changes, there is an overall improvement in averages of health outcomes among most of the countries, but the inequalities within the country increase [15]. Based on the hypotheses put forth by Deaton and Wagstaff in terms of the relationship between 'technological innovations and health inequalities', we attempt to assess the role of technological access on child nutrition inequalities in the Indian context using three decades of information from the National Family Health Survey (NFHS). Specifically, we hypothesise that unequal access to technological resources has led to widening inequalities in child nutritional status.

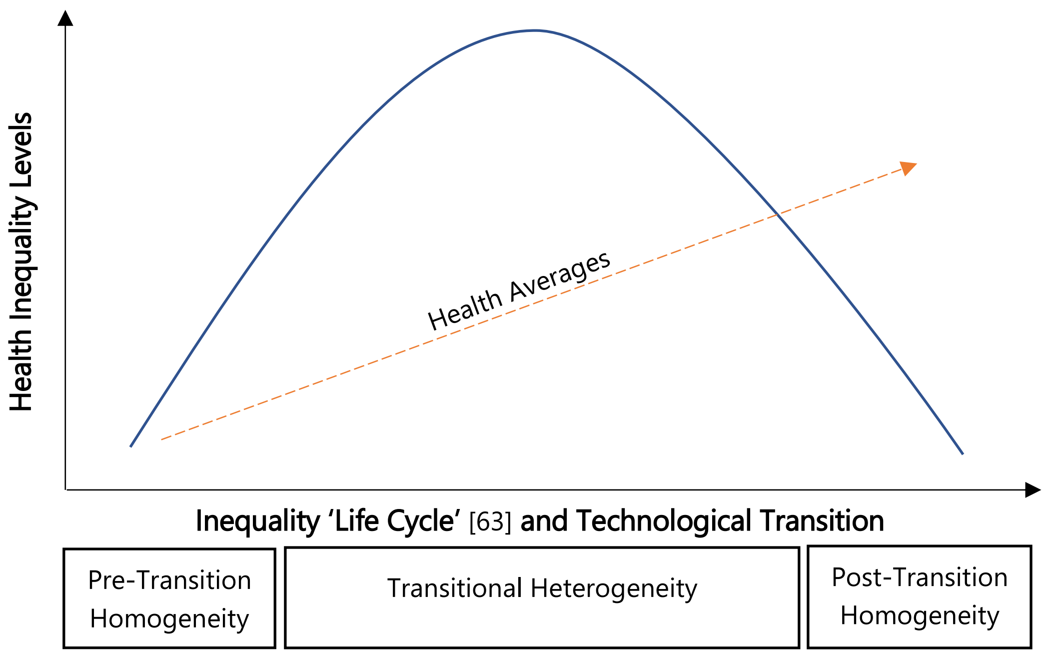
With its diverse socio-economic landscape, large population and faster economic growth, India is a compelling case for examining the nuanced effects of technological advancements on health outcomes. Nutritional indicators are a key measure of child well-being, reflecting broader socioeconomic conditions and the effectiveness of health and nutritional interventions. Despite economic advancements, India witnessed one of the highest burdens of child malnutrition in the world, with almost 35 per cent stunted children in 2019-21 [16]. Moreover, the literature has highlighted the concept of 'Indian Enigma', which points out that there is a higher prevalence of undernutrition in India relative to Sub-Saharan Africa, despite the higher levels of gross domestic product and food supply [17] [18]. This reflects that in India, the economic returns are not well translated into nutritional outcomes. India is witnessing two-fold challenges: reducing the malnutrition levels as well as ending the existing inequalities in malnutrition levels [19]. Although there has been a decline in the levels of child undernutrition, the tempo of decline is not sufficient for realising the SDGs, and the decline is largely concentrated in richer households, thus widening the economic inequality in child nutritional status [20] [21]. Therefore, there is a need to understand the emerging dynamics and new pathways such as the role of technology in explaining nutritional inequalities in India.

A large number of previous studies have assessed the socioeconomic determinants of inequality in the nutritional status of children in India and all of them found that undernutrition among children is disproportionately higher in poor households [19] [22] [23] [24] [25] [26]. Economic status, mother's education, mother's nutrition, and sanitation are found to be major contributors to the inequality in nutritional status in India [27] [28] [29] [30] [31] [32] [33]. However, in the era of modernisation and the increased penetration of digital and non-digital technologies, access to technological resources and their role in shaping nutritional outcomes must be incorporated into health service research. Digital technologies are important tools to deliver and transform food and nutrition security scenarios. The digital divide also leads to inequalities in public health outcomes because of the exclusion of those who experience the highest burden of poor health [34] [35]. There are major disparities in the adoption of technologies, particularly based on income, education, and household demographics in India [36]. India is undergoing a technological and digital transformation, but there is a notable digital divide as only 47 per cent of households receive electricity for more than 12 hours a day, and just 38 per cent of households are digitally literate [2]. Rajam et al. (2021) also put forth that the first-level digital divide, which pertains to having computers and the Internet, as well as the second-level digital divide, which concerns individuals' skills in using computers and the Internet, manifest in the disadvantaged caste groups through an interplay of caste-based socio-economic differences, resulting into digital divides [37].

With urbanisation, industrialisation and the digital India campaign, India is witnessing a significant increase in technological penetration among the population, which needs to be captured in the inequality analysis of the social and health sectors. The well-established hypotheses of Deaton and Wagstaff related to 'technological evolution and its association with health inequalities' are largely missing in nutrition literature in the Indian context. This study attempts to bridge that gap. Further, this study is motivated by the works of Wagstaff et al. (2003) to understand the inequalities in malnutrition in Vietnam, where he and his colleagues put forth an approach to decompose the change in inequalities of health outcome to estimate the relative contributions of its determinants [38]. None of the previous literature that studied child nutritional inequalities in India has tested Deaton and Wagstaff's hypotheses above. Moreover, this is the first study to reveal the contribution of digital and non-digital assets in determining child nutritional inequalities in India.

Therefore, in the given context, the present study attempts to test the hypothesis of "inverted 'U' shape relationship" between technology and inequality given by Wagstaff (2002) and Deaton (2013) (Figure 1) and then used a change decomposition model of Wagstaff et al (2003) [38] to determine the net contribution of digital and non-digital technological factors to the inequality in child nutritional status. India's stark regional and socio-economic disparities and the uneven pace of technological adoption provide a unique opportunity to assess whether technological advancements — have contributed to narrowing or widening nutritional inequalities. Analysing these trends will help understand whether the benefits of technological progress are equitably distributed or if certain groups continue to lag behind in accessing it. This insight is essential for policymakers to design targeted interventions that ensure equitable access to technological benefits, ultimately fostering better health outcomes for all population segments. This study will contribute valuable knowledge on the intersection of technology, economic inequality, and child nutrition, offering evidence-based guidance for addressing health disparities in India and similar contexts. To our knowledge, the present study is the first to apply change decomposition to examine the effect of access to technology on changing child health inequality in the Indian context. This study emphasises that technology is widening the gap in child undernutrition, so government interventions should be focused on bringing equality in technological penetration. India has yet to witness the entire 'cycle of inequality transition', so there is a scope for speeding up the trickling-down effect and diffusion process through state interventions.

Figure 1: Inverted U-shaped relationship between 'Technology' and 'Inequality'



Source: Authors constructed based on the works of Wagstaff (2002) [15] and Deaton (2013) [10]

2. Materials and Methods

2.1. Data Source

The present study is based on the five rounds of the National Family Health Survey (NFHS), which is equivalent to the Demographic Health Survey (DHS). The first NFHS was conducted in 1992-93, the second in 1998-99, the third in 2005-06, the fourth in 2015-16 and the most recent survey in 2019-21. NFHS is a nationwide, large-scale, multi-round cross-sectional survey which provides information on fertility, infant and child mortality, family planning, maternal and child health, reproductive health, nutrition, anaemia, utilisation and quality of health services for the Indian population. NFHS is conducted under the Ministry of Health and Family Welfare (MOHFW) of the Government of India, which has designated the International Institute for Population Sciences (IIPS) in Mumbai as the nodal agency responsible for coordinating and providing technical guidance for the survey. The details on the survey design, methodology, sample size and description of indicators for each round are available in the report (see, IIPS, 1995; IIPS and ORC Macro, 2000; IIPS and Macro International, 2007; IIPS and ICF, 2017; IIPS and ICF, 2021) [39] [40] [41] [42] [16].

In this study, we have utilised the information provided by mothers about themselves and their children born in the five years preceding the survey on health and socio-economic indicators and household characteristics. The data on child undernutrition is considered in terms of anthropometric measurements conducted by the trained NFHS team, where the child's height, weight and age of 0-59 months are measured. All anthropometric measures are standardised to WHO growth standards [43].

2.2. Variables

The major outcome variables are stunting (low height-for-age), wasting (low weight-for-height) and underweight (low weight-for-age). Stunting represents chronic undernutrition, wasting represents acute undernutrition, and underweight presents both chronic and acute undernutrition among children below five years of age. The major predictors are digital assets and non-digital assets. This study's digital assets include mass media exposure, radio, television, telephone, computer, mobile and internet. The non-digital assets include electricity, refrigerators, bicycles, motorcycles, cars, air conditioners/coolers and washing machines. Both categories resemble technology-related assets and, together, show the technological revolution. There has been a definitional change in defining digital and non-digital assets over the last thirty years based on the evolving nature of technological development. Table A1 provides a summary of assets according to these changing definitions over time. However, this would not affect our estimates of relative contributions derived from the decomposition models as they are not time-dependent.

Other covariates include socio-economic and demographic variables: sex of the child (female, male), place of residence (urban, rural), social group (Non-SC/ST, SC/ST), religion (Non-Muslims, Muslims), birth order (1-2, more than 2), Place of delivery (Home delivery, institutional delivery), Mother's Body Mass Index (Normal/overweight, underweight), Access to health insurance (yes, no), Water Sanitation and Hygiene (yes, no), Household Size (1-4 members, more than 4 members), Mother's Age at first birth (less than 20 years, 20 or more than 20 years), Mother's Education (less than 10 years schooling, 10+ years of schooling), and Type of House (kuccha/semi-pucca, pucca).

The economic status of households is measured using the wealth index, which is a cumulative measure of household standard of living. The wealth index is constructed using factor analyses of 33 household assets using data from the Household Questionnaire, which gathers information on various aspects such as ownership of consumer items (like televisions and cars), housing characteristics (such as flooring materials), drinking water sources, and sanitation facilities. Each type of asset is assigned a weight based on principal components analysis, and these weights are standardised to create asset scores with a mean of zero and a standard deviation of one. These standardised scores are then used to define wealth quintiles, which are categorised as Lowest (Poorest), Second (Poorer), Middle, Fourth (Richer), and Highest (Richest). The detailed method is available in Demographic Health Survey (DHS) reports [44].

2.3. Empirical Strategy

We analysed the data in four phases. Firstly, we conducted a univariate analysis using graphical methods to analyse the trends in outcome variables and major predictors. It is followed by calculating Wagstaff's corrected concentration index and employing decomposition and change decomposition analyses.

Wagstaff's corrected Concentration Index

The corrected concentration index (hereafter CI) is a measure of relative health inequality by socio-economic status [45]. CI is estimated to understand the level of inequality existing in child nutritional indicators by wealth status of households over the period of 1992 to 2021. It can be obtained using the following formulae:

$$Concentration\ Index = \frac{2}{n*\mu} * \sum(yi * Ri) - 1 \quad (1)$$

Where n is the total number of sampled children, μ is the mean of the outcome variable (stunting, wasting, underweight), yi is the value of the outcome variable for an i^{th} child, Ri is the fractional rank of the i^{th} child in the income distribution.

The value of CI '0' implies that there is no inequality in the distribution of child undernutrition by wealth status. A 'negative' implies a disproportionate concentration of child undernutrition among the poor, while a positive value implies a disproportionate concentration of child undernutrition among the rich. The CI is calculated separately for stunting, wasting and underweight for the years 1992-93, 1998-99, 2005-06, 2015-16 and 2019-21.

Decomposition Analysis

Decomposition analysis is used to measure the contribution of various predictors to the estimated inequality in health variables. We have adopted a decomposition approach proposed by Wagstaff et.al (2003) [38]. It assumes a linear relationship between the outcome variable and predictors and is calculated by the given formulae:

$$Concentration\ Index = \sum C_k \left(\frac{\overline{x_k} * \beta_k}{\mu}\right) + \frac{GC_e}{\mu} \quad (2)$$

Where, C_k is the CI of each of the predictor variables (x_k), $\bar{x}_k$ is the mean of each of the predictor variables (x_k), μ is the mean of the outcome variable (stunting, wasting and underweight), β_k is the regression coefficient for outcome variable by each predictor variable (x_k) and GC_e is the generalised concentration index for residuals. Equation 2 shows that the inequality in child undernutrition is composed of two parts: (1) explained component and (2) unexplained component. The decomposition analysis is conducted separately for stunting, wasting and underweight for the years 1992-93, 1998-99, 2005-06, 2015-16 and 2019-21.

Change Decomposition Analysis

Change decomposition analysis is used to understand the contribution of change in inequality in predictors over time to explain the change in health inequalities [38]. In other words, it tells how far the changes in inequality in health are caused by the changes in inequalities in determinants of health inequality. It is calculated using the given formulae:

$$\Delta C = \sum \eta_{kt} * (C_{kt} - C_{kt-1}) + \sum C_{kt-1} * (\eta_{kt} - \eta_{kt-1}) + \Delta \left({}^{GC_{et}}/_{\mu_t}\right) \quad (3)$$

Where, ΔC is the change in inequality in child undernutrition (y), C_{kt} is the concentration index of each of the predictor variables (x_k) for time 2019-21, C_{kt-1} is the concentration index of each of the predictor variable (x_k) for time 1992-93, η_{kt} and η_{kt-1} is the elasticity of variable on child nutrition with respect to predictor variable (x_k) for time 2019-21 and 1992-93 respectively. Separate models are run for stunting, wasting and underweight.

3. Results

In the era of technological revolution and modernisation, this study highlights the role of technological assets, i.e. digital and non-digital assets, in explaining the inequalities in undernutrition among children in India over the last thirty years.

3.1. Trends in Undernutrition among children and technological changes

Figure 2 shows that the percentage of underweight children has declined consistently by 22 percentage points between 1992-93 and 2019-21. The prevalence of stunted children, despite some variations in 2005-06, also declined during the study period. However, the prevalence of wasted children increased slightly between 1992-93 and 2019-21.

Figure 2: Trends in prevalence of undernutrition among children in India, 1992-2021

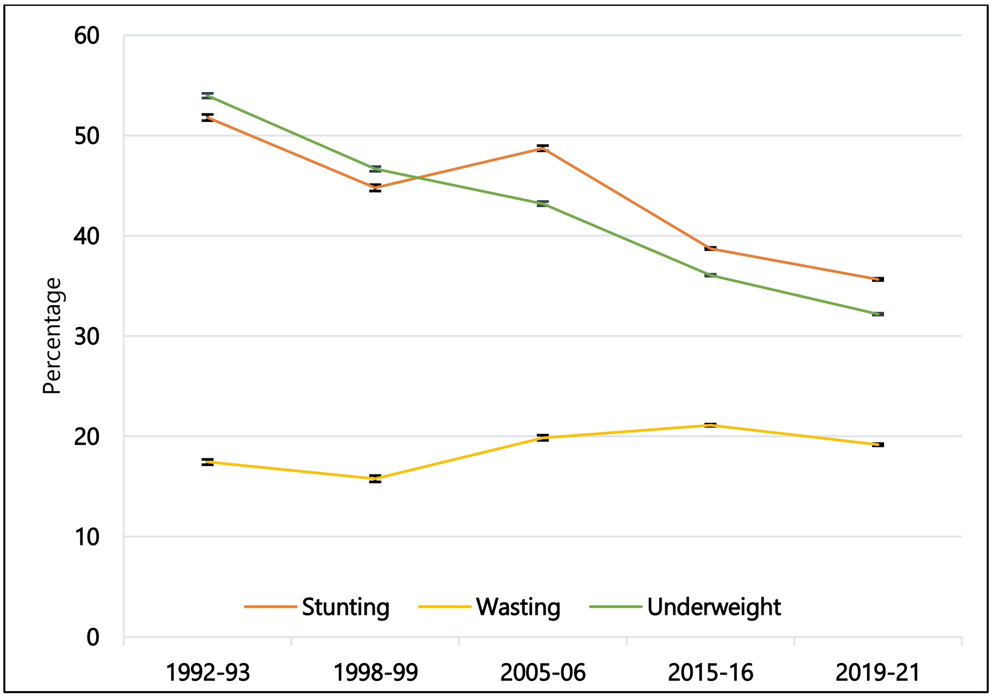
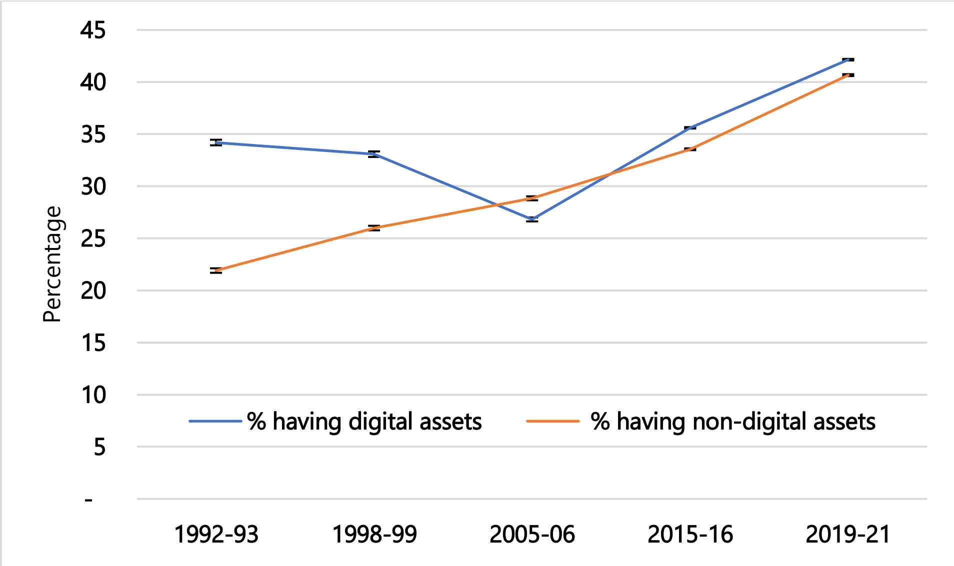


Figure 3 shows the trends in the adoption of technological assets in India. From these results, we found that the percentage of households having digital and non-digital assets consistently increased between 1992-93 and 2019-21 and almost nearly doubled. However, in the context of digital assets, there has been a deviation from the monotonic trends in the years 2005-06 (27 per cent) but then increased since 2015-16 from 36 per cent to 42 per cent in 2019-21.

Almost 29 per cent of households had non-digital assets in 2005-06, which increased to 34 per cent and 41 per cent in 2015-16 and 2019-21, respectively.

Figure 3: Trends in Adoption of Technological Assets in India, 1992-2021



3.2. Inequality in Child Nutritional Status

Table 1 indicates that the averages in child nutritional indicators are improving, but inequality persists. Inequality for children underweight increased substantially from 1992-93 (CI=-0.091, p<0.000) to 2015-16 (CI=-0.155, p<0.000), with a slight decrease in 2019-21 with a concentration index of -0.141 (p<0.000). This implies that the percentage of underweight children is decreasing in India but the rich-poor gap has increased over the last thirty years. Similarly, for child stunting and wasting also, it is observed that the inequality has increased between 1992-93 and 2019-21, with some deviations from the trend in 2005-06 for stunting.

Table 1: Trends in prevalence and inequality in child undernutrition in India, 1992-2021

	1992-93		1998-99		2005-06		2015-16		2019-21	
	Mean	CI	Mean	CI	Mean	CI	Mean	CI	Mean	CI
Stunting	0.52	-0.092	0.45	-0.130	0.49	-0.126	0.39	-0.149	0.36	-0.129
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Wasting	0.17	-0.059	0.16	-0.126	0.20	-0.119	0.21	-0.058	0.19	-0.064
	(0.002)	(0.007)	(0.002)	(0.008)	(0.002)	(0.006)	(0.001)	(0.002)	(0.001)	(0.003)
Underweight	0.54	-0.091	0.47	-0.137	0.43	-0.159	0.36	-0.155	0.32	-0.141
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)

Note: CI = concentration index to show inequality; standard errors are shown in parentheses ( )

The trends in averages and inequality for the predictor variables of child undernutrition between 1992-93 and 2019-21 are presented in Table A2-A3.

3.3. Decomposition of inequality in child undernutrition

Table 2 presents the percentage of contribution of selected predictors to the existing wealth-based inequality in child undernutrition. We found that the estimates of the relative contribution of not having digital and non-digital assets to stunting and underweight are itself more than half of the total explained inequalities in 2019-21. Digital and non-digital assets contribute more than 70 per cent for wasting. Other major contributors to this inequality are the mother's education, Water Sanitation and Hygiene Facility (WASH) and mother's Body Mass Index. Further, between 1998-99 and 2019-21, the contribution of non-digital assets to the inequality in stunting, wasting and underweight have increased. However, the contribution of digital assets exhibited variations. The marginal coefficients for each of the digital and non-digital assets, along with other predictors, are given in Table A4-A6. The marginal coefficients show an inverse relationship between access to digital and non-digital assets with child undernutrition.

Table 2: Relative contribution (%) of predictors to inequality (CI) in stunting, wasting and underweight in India, 1992-2021

Variables	Stunting					Wasting					Underweight				
	1992-93	1998-99	2005-06	2015-16	2019-21	1992-93	1998-99	2005-06	2015-16	2019-21	1992-93	1998-99	2005-06	2015-16	2019-21
Not having Digital Assets	21.39	30.55	23.94	20.87	21.71	41.16	27.31	17.22	33.28	20.90	24.99	27.86	24.39	27.42	23.06
	(0.008)	(0.012)	(0.009)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)	(0.004)	(0.004)	(0.007)	(0.010)	(0.009)	(0.005)	(0.005)
Not having Non-digital assets	35.73	16.97	22.74	27.00	30.96	27.86	28.13	19.73	4.57	51.27	30.69	25.83	22.34	18.19	33.00
	(0.013)	(0.013)	(0.009)	(0.004)	(0.004)	(0.010)	(0.009)	(0.007)	(0.003)	(0.003)	(0.012)	(0.013)	(0.009)	(0.003)	(0.003)
Male Child	0.00	0.06	-0.15	-0.15	-0.10	-0.08	-0.18	-0.40	-0.51	-0.25	0.00	0.18	0.01	-0.12	-0.11
	(0.006)	(0.006)	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.005)	(0.006)	(0.005)	(0.002)	(0.002)
Rural	-8.16	-7.22	-6.80	-2.27	-0.67	4.28	-7.61	-6.20	-8.94	-6.90	-4.76	-12.36	-3.86	-6.38	-3.24
	(0.008)	(0.009)	(0.006)	(0.003)	(0.003)	(0.006)	(0.007)	(0.005)	(0.002)	(0.003)	(0.007)	(0.009)	(0.006)	(0.003)	(0.003)
SC/ST	-0.78	2.14	2.12	1.36	2.89	2.78	0.71	4.28	2.92	1.12	-1.06	0.35	1.26	0.21	0.65
	(0.007)	(0.007)	(0.006)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.006)	(0.007)	(0.005)	(0.002)	(0.002)
Muslim	-0.42	-0.23	-0.01	-0.12	-0.05	0.64	0.71	0.00	0.39	-1.51	-0.21	0.08	0.00	0.01	-0.11
	(0.009)	(0.009)	(0.008)	(0.003)	(0.004)	(0.007)	(0.007)	(0.006)	(0.003)	(0.003)	(0.008)	(0.009)	(0.007)	(0.003)	(0.003)
Birth Order 3+	1.23	3.18	2.18	3.51	3.32	1.49	-0.17	5.44	1.37	0.81	0.90	3.34	3.51	2.79	2.84
	(0.007)	(0.007)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.006)	(0.007)	(0.006)	(0.002)	(0.003)
Not an Institutional Delivery	21.77	20.89	13.91	2.56	2.53	-2.76	1.93	-4.73	-4.66	-4.87	16.31	12.21	6.26	0.78	0.17
	(0.008)	(0.008)	(0.006)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)	(0.002)	(0.003)	(0.007)	(0.007)	(0.006)	(0.003)	(0.003)
Mother underweight	-	4.07	4.50	5.56	5.99	-	17.02	23.55	24.42	16.28	-	11.92	11.54	12.48	10.73
		(0.006)	(0.005)	(0.003)	(0.003)		(0.005)	(0.004)	(0.002)	(0.002)		(0.006)	(0.005)	(0.002)	(0.003)
No health insurance	-	-	-	0.15	0.10	-	-	-	-0.06	-0.06	-	-	-	0.00	0.09
				(0.003)	(0.003)				(0.003)	(0.002)				(0.003)	(0.002)
No WASH	9.55	12.37	14.11	16.90	8.34	11.95	9.67	35.97	52.59	20.64	8.43	10.42	17.31	26.96	13.49
	(0.008)	(0.008)	(0.007)	(0.003)	(0.004)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.007)	(0.008)	(0.007)	(0.004)	(0.004)
Household Size 5+	0.19	-0.07	0.24	0.03	-0.23	-0.44	0.11	-0.15	0.03	-0.09	0.00	0.05	0.10	0.03	-0.17
	(0.009)	(0.008)	(0.006)	(0.003)	(0.003)	(0.007)	(0.006)	(0.005)	(0.002)	(0.002)	(0.007)	(0.008)	(0.006)	(0.003)	(0.003)
Mother's Age at first birth below 20 years	6.42	6.62	4.74	1.93	3.12	3.22	3.60	-2.03	-1.29	-2.32	6.88	7.02	3.18	1.49	2.26
	(0.006)	(0.007)	(0.005)	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)	(0.006)	(0.007)	(0.005)	(0.002)	(0.002)
Mother's Education	13.74	9.45	12.51	16.31	14.57	15.82	5.56	10.81	2.19	6.32	14.65	7.58	11.76	14.41	13.91
	(0.011)	(0.009)	(0.008)	(0.003)	(0.003)	(0.008)	(0.006)	(0.006)	(0.002)	(0.002)	(0.010)	(0.008)	(0.008)	(0.003)	(0.003)
Not a pucca house	-0.65	1.21	5.97	6.35	7.53	-5.91	13.19	-3.49	-6.30	-1.35	3.17	5.52	2.21	1.74	3.43
	(0.009)	(0.008)	(0.007)	(0.003)	(0.003)	(0.007)	(0.006)	(0.005)	(0.002)	(0.002)	(0.008)	(0.008)	(0.006)	(0.003)	(0.002)

Standard Errors are shown in parentheses ( )

3.4. Change Decomposition Model

The change decomposition model shows that the majority of the increase in inequality in child undernutrition is attributed to the changes with respect to digital and non-digital assets, together constituting more than 50 per cent of the change in inequality (Table 3). It is followed by WASH, which has 13.6 per cent for stunting, 15 per cent for wasting, and 14 per cent for underweight. This implies that the heterogenous role of access to digital and non-digital assets in the last thirty years has resulted in the persisting increase in inequalities in stunting, wasting and underweight.

Table 3: Results of change decomposition model: Relative contribution of predictors to change in inequality in stunting, wasting and underweight in India between 1992 and 2021

Variables	Stunting	Wasting	Underweight
Not having Digital Assets	20.44 (0.008)	20.00 (0.006)	19.91 (0.007)
Not having Non-digital assets	34.12 (0.013)	34.19 (0.010)	33.19 (0.012)
Male Child	0.50 (0.006)	1.09 (0.004)	0.93 (0.005)
Rural areas	2.66 (0.008)	2.75 (0.006)	2.83 (0.007)
SCs/STs	4.13 (0.007)	4.42 (0.005)	4.09 (0.006)
Muslim	0.66 (0.009)	1.31 (0.007)	1.04 (0.008)
Birth Order 3+	2.82 (0.007)	2.95 (0.005)	3.01 (0.006)
Not an Institutional Delivery	7.88 (0.008)	5.63 (0.006)	6.75 (0.007)
No WASH	13.59 (0.008)	15.33 (0.006)	14.14 (0.007)
Household Size 5+	0.47 (0.009)	1.11 (0.007)	0.92 (0.007)
Mother's Age at first birth below 20 years	2.55 (0.006)	2.35 (0.005)	2.76 (0.006)
Mother's Education	3.99 (0.011)	2.94 (0.008)	4.21 (0.010)
Not a pucca house	6.21 (0.009)	5.93 (0.007)	6.22 (0.008)

Note: Standard Errors are shown in parentheses ( )

3.5. Robustness of Decomposition Model

The robustness of the decomposition model is examined through the total explained component of selected predictors. The results reveal that the selected predictors in the decomposition model explain more than 80 per cent of the total estimated inequality in stunting, wasting and underweight in all five periods of analysis (Table 4). The residuals for stunting remain below 10 per cent except in 1998-99 with 16 per cent. For wasting and underweight, the residuals are slightly higher in 2005-06 with 19 per cent and 1998-99 with 20 per cent, respectively. However, in 1992-93 and 2019-21, the residuals are below 10 per cent for all three indicators of child undernutrition. Overall, our model has relatively less unexplained components; thus, the models are robust.

Table 4: Explained and unexplained components of decomposition model

	Stunting			Wasting			Underweight		
	Estimated	Explained	Residuals	Estimated	Explained	Residuals	Estimated	Explained	Residuals
1992-93	-0.092	-0.085	-0.007	-0.059	-0.057	-0.002	-0.091	-0.083	-0.008
1998-99	-0.13	-0.108	-0.022	-0.126	-0.105	-0.021	-0.137	-0.11	-0.027
2005-06	-0.126	-0.116	-0.010	-0.119	-0.096	-0.023	-0.159	-0.134	-0.025
2015-16	-0.149	-0.138	-0.011	-0.077	-0.065	-0.012	-0.155	-0.142	-0.013
2019-21	-0.129	-0.121	-0.008	-0.068	-0.063	-0.005	-0.141	-0.129	-0.012

4. Discussion

Although technological advancement and nutritional status are well linked, the relationship between the existing disparities in access to technology and undernutrition levels has not been examined before. The interplay between technological advancement and child undernutrition presents a crucial area of investigation, particularly in rapidly developing countries like India. This study has provided empirical evidence on how inequalities in digital and non-digital assets contribute to widening inequalities in child undernutrition levels in India. This study shows that Adam Wagstaff's (2002) and Angus Deaton's (2013) hypotheses are well-applicable in the Indian context. The findings of this study reveal that the average prevalence rate of undernutrition among children in India is reducing; however, the inequality has widened between 1992 and 2021. Previous studies examining the inequalities in child undernutrition have reported similar results [21]. Further, the decomposition analysis has two important findings: firstly, the largest contributors to inequality in child undernutrition are digital and non-digital assets, and secondly, the change in the inequalities in having digital and non-digital assets caused the major increase in inequality in child undernutrition over time. These findings align with Adam Wagstaff's (2002) and Angus Deaton's (2013) hypothesis that technology initially exacerbates inequality before potentially reducing it. A crucial finding supporting Wagstaff's and Deaton's hypothesis is that in 2019-21, inequality in stunting and underweight slightly declined compared to 2015-16, possibly due to the beginning of the spillover effect of technological penetration among poor people. However, as this is the first-ever study to provide empirical evidence on the contribution of technology in exacerbating the inequalities in child nutritional status in India, specific pathways in which technology influences child nutritional inequalities can be a future scope of research.

Some global studies have attempted to establish possible pathways of the linkage between technology and nutrition. Evidence from developing countries has validated the importance of digitalisation in achieving a positive impact on public health [46] [47]. A review of evidence on the impact of digital technologies on health equity confirms that these technologies tend to exacerbate health disparities, particularly among individuals with lower levels of education and lower socio-economic status [48]. Health outcomes are significantly affected by the lack of access, skills and motivations for using digital technologies, and this digital exclusion directly (through lack of adequate information) and indirectly (i.e. inadequate employment and housing opportunities) leads to adverse health consequences [49]. In the same line, Jahnel et al. (2022) put forth that the role of digitalisation is not in isolation; it influences health inequities by its impact on all levels of determinants of health [50]. Further, a study in China shows that digital technology adoption increases protein consumption among the rural population, as it increases job opportunities and non-farm income and consequently improves nutrition [51]. Leveraging the technology, a self-learning expert system can be developed which provides nutritional knowledge to individuals, thus helping them monitor their food intake and health outcomes [52]. Such provisions of behavioural change techniques through digital media have potential consequences in ensuring healthy eating behaviour among children [53] [54], and monitoring the growth failures by mobile apps is effective in early detection and treatment [55]. However, apart from inequalities in access to technologies, there is a substantial need to improve these digital platforms as they lack uniform guidelines on child nutrition-related information [56] to reduce inequalities in child nutritional status. The United Nations Conference on Trade and Development (UNCTAD) highlight that the development of science and technology has a positive influence on each of the four dimensions of food and nutrition security: availability, accessibility, utilisation and stability and is an important facilitator in reducing the existing inequalities [57].

This study poses the utmost significance to the nutrition literature but has certain limitations. Firstly, over time, the indicators to define the digital and non-digital assets in NFHS have evolved with additional indicators; therefore, this study cannot apply a uniform definition of digital assets for better comparability. Secondly, NFHS is a cross-sectional study; it fails to capture the changes in technological advancement and nutritional status in the same household over a period of time. Thirdly, the bi-directional relation between poverty and technology adoption is beyond the scope of this study.

5. Conclusion

This study serves as a foundational contribution to the literature on nutritional inequalities by incorporating the role of the technological revolution in India. The findings of this study indicate that inequalities in access to technological assets are a major contributor to the widening inequality in children's nutritional status despite lowering the prevalence rates. Therefore, at the policy level, there is a substantial need to accelerate the diffusion process of technology to all segments of the population to ensure a faster reduction in nutritional inequalities among Indian children. Nutrition intervention policies should utilise the potential of technology to reduce malnutrition in India. Further, more empirically based research is needed to establish the pathways through which technologies exacerbate the existing inequalities in child undernutrition.

One most successful method to promote health by utilising technology is the *m-health* intervention which consists of two major aspects, firstly provision of mobile technology to frontline workers, increasing coverage, quality and coordination of services [58] and second, delivery of health knowledge through SMS messaging leading to decrease in child morbidities and mortalities and improving infant feeding practices [59]. User satisfaction, the functionality of the application, the ease with which users can learn and operate the application, and the quality of the information it delivers emerged as important factors of the m-Health application

[60]. Other emerging concepts are the Internet of Things (IoT) as a tool for health information exchange containing observatory portals and early warning systems [61] and the inclusion of Artificial Intelligence in Public Distribution System (PDS), ensuring effectiveness and transparency [62]. However, such supply support factors are not sufficient unless the demand side consumers are equipped with access to technological resources. Women need to be provided with access to smartphone technology as well as skills to use in order to expand the benefits of these technological interventions in health sectors to all segments of the population. Otherwise, the socioeconomic gaps will widen. So, policies that promote technological inclusivity—such as expanding internet access, electricity, and television in rural areas, subsidising digital devices for low-income families, and integrating digital literacy into educational curriculums—are essential to bridge the socioeconomic gap in undernutrition. These measures can enable more mothers to benefit from technological advancements, ultimately reducing their children's undernutrition and promoting overall child health and well-being.

Abbreviations:

SDG: Sustainable Development Goal; ITU: International Telecommunication Union; UNDP: United Nations Development Programme; NFHS: National Family Health Survey; DHS: Demographic Health Survey; MoHFW: Ministry of Health and Family Welfare; IIPS: International Institute for Population Sciences; WHO: World Health Organisation; SC: Scheduled Caste; ST: Scheduled Tribes; CI: Concentration Index; GC: Generalised Concentration Index; WASH: Water Sanitation and Hygiene; UNCTAD: United Nations Conference on Trade and Development

Authorship statement

AS: Conceptualisation, Data Curation and Analysis; Writing and Revising, Preparing manuscript, Approval for the final version; SG: Conceptualisation and Study Design, Supervision, Writing – review and editing, Approval for the final version.

Data Statement - Ethical Approval

This study used publicly available secondary sources of data from the Demographic Health Survey (DHS) available at www.dhsprogram.com. Thus, it does not require ethical approval.

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Competing Interest

The authors have no conflicts of interest to declare.

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