Final Report

on

Impact of Access to Digital Capital on Poverty Reduction in Bangladesh: Evidence from Household Income and Expenditure Survey 2016

Submitted by

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Abstract:

The study aims to portray the impact of digital capital on income and multidimensional poverty in Bangladesh by using the national level data- Household Income and Expenditure Survey (HIES) 2016. Both income and multidimensional poverty have been categorized into the upper-level and lower-threshold levels. Impact assessments have also been estimated by disaggregating the rural and urban population data. By implementing the Propensity Score Matching (PSM) method of impact assessment, the study wielded the three most widely used matching techniques for impact evaluation: the Nearest Neighbor Matching, Radius Matching, and Kernel Matching methods. Depending on the utilization of matching algorithms, the magnitude of the impact evaluation differs slightly. Obtained findings unveil that lower absolute income poverty at national level reduces by about 5% to 7% due to access to digital capital, while upper absolute income poverty decreases by about 9% to 11%, depending on the different matching algorithms. On the other hand, multidimensional poverty (lower threshold) reduces by about 2% to 3%, depending on the matching techniques. However, the obtained results are not statistically significant for the upper threshold of multidimensional poverty at the national level. On the other hand, reduction of urban poverty is found lower than rural poverty. For instance, lower income poverty reduces by about 9% to 11% at rural level, while about 2% to 4% are found at urabn level. The greatest magnitudes of poverty reduction are, however, observed for upper income poverty level (about 13% to 17% for rural level, and about 6% for urban level). Regarding multidimensional poverty, rural people reduced lower and upper multidimensional poverty by about 5% to 7% and 1% to 10% respectively. However, findings reveal that digital capital failed to reduce multidimensional poverty at both lower and upper level for urban people. The results suggest that policymakers should extend the horizon of digital resources to mass people in order to help eradicate the curse of poverty from the country.

Key Words: Digital Capital, Income Poverty, Multidimensional Poverty, Propensity Score Matching (PSM), Bangladesh

Section 1: Introduction

1.1 Background of the Study

Poverty is one of the world's fundamental problems, especially for developing economies like Bangladesh. Chen and Ravallion (2008) showed that about a quarter of the population in developing countries still remains as income poor. Poverty has severe consequences on poor peoples' personal, social, and economic behavior. It is generally defined as a lack of resources and is directly associated with hunger (Sen, 1987). However, it is not only simply the lack of resources; rather, it limits the abilities of full potentiality and prospects of an individual's welfare (Lybbert & Wydick, 2018; Sen, 1985). Therefore, the policymakers, especially of the developing and least developed countries, have placed eradication of poverty and inequality at the forefront of their development and nation-building strategy. The Government of Bangladesh (GoB) has also been relentlessly working to eliminate poverty since its independence in 1971.

The government of Bangladesh has taken many development strategies and policies like five-year plans, perspective plans, poverty reduction strategy papers, etc., to make a poverty-free nation. As a result, Bangladesh has achieved remarkable achievements in reducing poverty, especially extreme poverty. Laizu (2014) shows that more than 70% of the total population was below the poverty using the upper-income poverty line in 1971. However, over the passage of time, this upper poverty rate dropped to just around 24% in 2016-17 (World Bank, 2022). This extraordinary achievement in reducing poverty becomes possible due to sustained economic growth despite various constraints on physical and human capital (Maitra, 2018; Malek et al., 2022). In order to achieve sustained economic growth and speedy reduction of poverty, the government of Bangladesh emphasized the application of science and technology to promote economic advancement (International Monetary Fund, 2012).

Since the beginning of the 21st century, the application of digital resources (like smartphones, computers, information & communication technologies (ICT), and the internet) has been increasing to avail market access, decrease the economic cost of transactions, and increase the earnings of mass people (Chabossou et al. 2008; Mushtaq & Bruneau, 2019; Mora-Rivera & García-Mora, 2021). In fact, the usage of digital resources is now commonplace in every sphere of human social and economic life. As a result, people have increased efficiency by reducing the economic cost of transactions and saving time with increased labor productivity. Bangladesh has also adopted the application of digital resources to a wide range of economic activities that widen the employment opportunities for many young unemployed people and increase their income earnings. Using this mechanism, people are getting rid of the vicious cycle of poverty gradually.

Although many studies investigated the impact of access and usage of digital resources on the reduction of poverty worldwide, there are very few works that can be found in this field of research in Bangladesh (Akther et al., 2006; Bhavnani et al., 2008; Rahman, 2008; Rahman et al., 2013). However, though some studies can be found on the nexus between poverty reduction and digital capital, they did not use nationally representative data or appropriate theoretical perspective (Akther et al., 2006; Bhavnani et al., 2008; Rahman, 2008; Rahman et al., 2013; Mushtaq & Bruneau, 2019). Nevertheless, these studies mostly employed small samples or macro-based or followed the only income poverty line. To the best of the author's knowledge, no studies have been found on household-based analysis to investigate the causal impact of access to digital resources and multidimensional poverty reduction. This study investigates the nexus between the access and usage of digital resources and the reduction of multifaceted poverty in addition to income poverty based on household-level data using the appropriate econometric model.

1.2 Research Objectives

This study precisely investigated the following two objectives using national-level data.

i. To examine the determinants that induce households to get access to digital resources.

ii. To assess the impact of the access and usage of digital resources on the reduction of income and multidimensional poverty in Bangladesh using national-level household data.

Section 2: Review of the Literature

The impact of digital innovation on various aspects of an individual, social, and economic life has revolutionized the ways of thinking and policy adoption over time. It has gained increased attention in theoretical and applied perspectives (Mansell, 2017; Mora-Rivera & García-Mora, 2021) and converged to the concentration known as the 'digital divide' (Mansell, 2017; Mora-Rivera & García-Mora, 2021; van Deursen & van Dijk, 2019). Based on the digital divide concept, three categories of development for this concept are investigated (Mansell, 2017; Mora-Rivera & García-Mora, 2021). In the first level, the digital divide concept investigates access to digital resources. It implies that there is inequality in access to digital resources among people based on socioeconomic characteristics like age, gender, location, income, schooling, etc. (van Deursen & van Dijk, 2019; Mora-Rivera & García-Mora, 2021). The second feature of the concept of the digital divide focuses on the utilization of digital resources. The utilization of digital resources implies the skills to use digital resources efficiently. Finally, the third category concept of digital resources concentrates on the implications of the use of digital resources. The third level of the digital divide emphasizes the impact of digital resources on various social and economic aspects (van Deursen & van Dijk, 2019; Mora-Rivera & García-Mora, 2021).

The inability to access digital resources gears up the inequality in material commodities and increasing income inequality, too (van Deursen & van Dijk, 2019). On the other hand, access to digital resources decreases the disparity in material commodities and thus reduces income inequality too (van Deursen & van Dijk, 2019). Investigating the nexus between the use of digital resources and its implications in human life is getting accelerated among researchers as countries are adopting more and more applications of digital resources in their social and economic transactions. Among the various aspects of interest in the impact of digital resources on human life, labor productivity, transaction cost, efficiency gains, and poverty reduction are dominant fields of attention. Some studies showed that digital resources have a significant and very high probability of increasing long-term economic growth; thus, it is the driver of poverty reduction (Barro, 2000; Piatkowski, 2006). Investigating Mexico's national household income and expenditure data and using the propensity score matching (PSM) method, Mora-Rivera & García-Mora (2021) assessed the effect of the internet on 'income poverty' and 'multidimensional poverty'. They found that access to digital resources like the internet and other digital equipment significantly helps to reduce poverty in Mexico. They also found that the impact of digital resources on poverty reduction is stronger in rural areas than in urban areas.

Diga et al. (2013) examined the impact of information and communication technology on poverty reduction in some African countries. They have also found a positive and significant effect of digital resources on poverty reduction. They showed that using digital resources enhanced the economic capabilities of the poor and marginal people. In addition, Diga et al.

(2013) also found that human, social, and political capital are also essential in reducing poverty. Bhavnani et al. (2008) found a very high economic impact of mobile phones in Bangladesh. Akther et al. (2006) also found that the usage of telecommunication in rural areas of Bangladesh significantly impacts the livelihood of rural people. However, Bollou and Ngwenyama (2008) found a decreasing growth in the total factor productivity of ICT in West Africa. They also cautioned regarding future investment in the information and technology sector.

Although plenty of research works are available worldwide to derive the causal relationship between the use of digital resources, research works on this nexus are very limited in Bangladesh. Although some studies tried to work on related fields of digital resources and poverty reduction, to the best knowledge of the author, they did not try to find either a causal relationship or did not use nationally representative data (Akther et al., 2006; Bhavnani et al., 2008; Rahman, 2008; Laizu et al., 2010; Rahman et al., 2013). Therefore, in order to fill this research gap, this study aims to investigate the impact of digital resources on poverty reduction in Bangladesh using the national data with an appropriate econometric model. The findings from this study will help researchers study in the future in this fascinating research area and help policymakers make investment decisions in this sector.

Section 3: Data, Variable, and Methodology

3.1 Data

To investigate the causal effect of digital capital on poverty reduction in Bangladesh, we wielded the Bangladesh Household Income and Expenditure Survey (HIES)-2016. The HIES is national-level data fielded and surveyed by the Bangladesh Bureau of Statistics (BBS). The HIES is also a vital source of information on socioeconomic characteristics at the household level data in Bangladesh. The HIES 2016 collected data on 46,076 households, consisting of a total of 32096 rural households and 13980 urban households (BBS, 2019).

3.2 Definition of Digital Capital and Multidimensional Poverty

In order to estimate the impact of digital capital on income poverty and multidimensional poverty, this study wielded the propensity score matching (PSM) method. In a similar study, Mora-Rivera & García-Mora (2021) also tried to identify the causal relationship between access to the internet and poverty reduction in Mexico. However, this study added computers to the internet and broadened the concept as digital capital (DC). If a household has access to any of the two digital resources, computer and internet, the household is equipped with digital capital. After defining digital capital, the study focuses on the impact of digital capital on the reduction of income and multidimensional poverty. Income poverty is defined if the income falls below the income poverty line defined in the HIES 2016 (in the case of using income poverty, the income threshold has been proxied to the consumption level in the present study). On the other hand, as poverty is multidimensional (Sen, 1985; Alkire & Foster, 2011; Alkire et al., 2015), this study also concentrates on the impact of digital capital on multidimensional poverty. Multidimensional poverty developed by the United Nations Development Programme (UNDP) and Oxford University includes ten essential indicators from the three fundamental basic human need dimensions: education, health, and living standard of the people (UNDP, 2010; Alkire & Foster, 2011; Alkire et al., 2015). The details of all indicators are presented in Table 1.

Table 1: The approach to multidimensional poverty

Dimension	Indicators	Definition of Deprivation	Weights
Education	Years of schooling	If at least one Household (HH) member does not complete five years of education	1/6
	School attendance	If at least one HH member is not currently enrolled despite the age between 5-13	1/6
Health	Access to Health	If any HH member does not go to seek medical access despite the disease being serious	1/6
	Nutrition consequences	If any HH member suffers from heart disease, respiratory diseases, ulcers, cancer, blood pressure, diabetes	1/6
Living Standard	Electricity	If the household does not have electricity access	1/18
	Sanitation	If the household does not have improved or sanitary latrine	1/18
	Drinking water	If the household does have safe drinking water (tubewell)	1/18
	Roof condition	If the household does not have a tin or cemented roof	1/18
	Cooking condition	If the household cooks in a traditional way	1/18
	Assets ownership	If the household does not have more than one specific asset: Radio, TV, Mobile, Bicycle, Motorcycle/Scooter, Refrigerator/Freezer, and Motor car	1/18

Note: The definition of multidimensional poverty followed a similar approach of UNDP (2010).

UNDP (2010) used two indicators in the education dimension: years of schooling and school attendance; two indicators in the health dimension: child mortality and nutrition; and six indicators in the living standards dimension: electricity, sanitation, drinking water, roof condition, cooking condition, and assets ownership. However, due to the unavailability of data, child mortality has been substituted by general access to health, the consequence of nutrition has been substituted for nutrition indicator, and floor condition is substituted by roof condition (Table 1). Each dimension gets an equal weight (1/3), and each indicator within the dimension gets an identical weight (Table 1) in UNDP's definition.

The multidimensional index value is then calculated by aggregating each household's deprivation weights. In order to define a household as multidimensionally poor, a dummy variable is created for all households with multidimensional index values exceeding some thresholds. In this study, a household is identified as multidimensionally poor (lower level) if the index value exceeds one-third of the indicators (1/3). It means that a household is multidimensionally poor if deprived of three out of the ten indicators. In addition, severely multidimensionally poor households are those households that are deprived of at least five indicators (1/2). For income poverty, the absolute income poverty line is used. However, in this study, income is substituted by the overall consumption level to encompass the household's living standard. In case of income poverty, the national threshold for absolute lower and upper absolute poverty line Bangladesh Taka (BDT) 1944 and BDT 2273 have been used, respectively (Marzi, 2020)

3.3 Econometric Model

In order to estimate the impact of access to digital capital on poverty reduction, the study will wield the Propensity Score Matching Method (PSM). Mora-Rivera & García-Mora (2021) also followed the PSM method to identify the causal relationship between access to the internet and poverty reduction in Mexico. PSM technique has been used as it corrects the sample selection problem. One of the major problems in impact assessment studies is a potential bias in the sample selection. Because if the treatment group has some set of common features that differentiate them from the control group, then it is impossible to find out the net impact of the intervention on the treated group. Sample selection problem arises in cross-section data as one cannot observe the data for the treatment group (receiving digital capital) and control group simultaneously. PSM method incorporates this problem in estimating the causal effect of intervention in cross-section data by generating a counterfactual group representing the treatment group in terms of the common characteristics. In order to develop a counterfactual group similar to the treatment group, PSM depends on the conditional independence assumption (CIA) that guarantees unbiased causal effects (Rosenbaum & Rubin, 1983), and the matches are selected based on the condition of observability.

More precisely, the PSM method uses standard matching techniques (like Nearest Neighbor Matching, Radius Matching, Kernel Matching, etc.) for the control group with the treatment group. The difference between the outcome variable for the treatment and the counterfactual group can be identified as

$$\Delta Z_i = Z_{1i} - Z_{0i} \quad (1)$$

Where, ΔZ_i portrays the treatment effect. Though we cannot observe the data for the treated and control group at the same time in the cross-section data, we can find the treatment effect or Average Treatment Effect on Treated (ATT) by the following way

$$ATT = E(Z_{i1} - Z_{0i}|T_i = 1) = E(Z_{i1}|T_i = 1) - E(Z_{i0}|T_i = 1) \quad (2)$$

The ATT is the average treatment effect on the treated, and T_i is the treatment status. T_i takes the value one if an observation has access to the digital capital, while T_i takes 0 if the observation does not have access to the digital capital. The propensity score matching matches the treatment observations with the untreated based on the calculated probability of being treated. In the case of matching, matching is done on the probability of being treated instead of matching for each and every observation. The probability can be estimated as follows.

$$P(X) = P(T_i = 1|X) \quad (3)$$

$P(X)$ denotes the probability to propensity score, and X describes the socioeconomic variables (gender of the household head, age of the household head, age squared, religion, household size, household cultivable land, proportion of adult members in the household, location, education level of household head, migration status of household members, main profession of household hea, social security receiving status, shock experience). This propensity score or probability is calculated using the standard cumulative distribution function (CDF) or probit model. However, in order to estimate the propensity score, estimation depends on the conditional independence assumption (CIA). It implies that after conditioning the socio-economic characteristics, $\boldsymbol{X}$, the treatment allocation is completely random (Angrist & Pischke, 2008). More precisely,

$$E[Z_{i0}|X, T_i = 1] = E[Z_{i0}|X, T_i = 0] \quad (4)$$

For the matching of the non-treated group with the treated group, the nearest propensity score of the non-treated group is matched with the treated group; this study used the three most popular methods of matching: Nearest Neighbor Matching, Radius Matching, and Kernel Matching methods.

Despite other popular methods (difference in difference (DID), regression discontinuity (RD), etc.) of correcting sample selection bias problems being popular, the propensity score matching (PSM) technique is arguably deemed better in cross-section level data. Since the study dealt with cross-section data, the PSM method is used in this study.

Section 4: Results and Discussion

Table 2 portrays the household's categorization in their poverty status with respect to their digital capital access status. It shows that about 19% of the total households are income poor using lower income poverty level. On the other hand, 29% of the households are income-poor using the upper-income threshold level of poverty. These statistics are slightly above the reported statistics by (approximately 13% and 24%, respectively) HIES (2019), as the study used consumption data instead of income. On the other hand, Table 2 also presents that about 32% of the households in Bangladesh are deprived of about 3 out of 10 basic essential indicators.

Table 2: Summary of income and multidimensional poverty

Variable	All households (%)	Households without digital capital access (%)	Households with digital capital access (%)
Income poor (using the lower poverty line)	18.70	20.10	3.50
Income poor (using the upper poverty line)	28.80	30.80	6.10
Multidimensional poor (using 0.33 threshold level)	31.60	32.20	24.6
Multidimensional poor (using 0.50 threshold level)	2.80	2.90	1.70

Source: Author's calculation from HIES 2016 data

Visible differences in household poverty status, especially income poverty, regarding digital capital access can also be noticed in Table 2. It shows that a greater proportion of the households that do not have access to digital capital experience income poverty and multidimensional deprivation. Approximately 20% and 31% of the households without access to digital capital do not cross the lower and upper-income poverty threshold, respectively, while about only 4% and 6% of the households with access to digital capital are income-poor using lower and upper-income poverty threshold levels. A similar picture is observed for the multidimensional poor (Table 2).

Table 3 delineates the summary statistics of basic socio-economic characteristics used in this study for all households and also presents the summary of the basic socio-economic characteristics separately by disaggregating the households according to the status of having digital capital. In addition, the mean differences have also been tested through the *t* test. The t-test results reveal that the differences in socio-economic characteristics between the groups are highly statistically significant (last column of Table 3). It indicates that the households with the privileges of digital capital are different from their counterpart.

It is seen that about 8% of households are equipped with computers and the internet, and they use these digital resources. Azad (2015), however, found that about 10% of the total population used the internet in 2014. Although the number is still not very promising, the number is growing over time (4.8% of households had an internet connection in 2013, while 5.7 % of households had a computer in 2013 in Bangladesh (Saif, 2023)). Table 3 shows that 87.2% of the households in Bangladesh are male-headed, with an average age of 44.72 years. This statistic does differ much between the households without and with digital capital (87.4% and 84.7% respectively). The heads of households that have access to digital capital are approximately two years higher on average than the heads of households that do not have digital capital. The experienced heads of households are more likely to have digital resources.

An average Bangladeshi household having 4.04 members earns about BDT 16000 per month and expends about BDT 14000 per month. Although the household size is slightly higher for the households that have access to digital capital, average income and consumption are quite higher for those households (approximately double). Cultivable land in Bangladesh has been declining over time due to the higher population growth rate in Bangladesh. Table 3 shows that an average household possesses about ½ acre (about 50 decimal). Like household income and expenditure, the household's owning cultivable land is also about double for the household with digital capital.

Table 3: Descriptive Statistics

Variable	All households (Mean)	Households without digital capital access (Mean)	Households with digital capital access (Mean)	p-Value Diff = Mean (0) − Mean(1) Ho: diff = 0
Digital Capital (DC)(=1 if a household has access to digital capital)	0.080	-	-	-
Gender of the household head (male if gender=1 and 0 otherwise)	0.872	0.874	0.847	(0.028)***
Age of the household head (in years)	44.718	44.548	46.656	(-2.108)***
Age squared	2197.997	2184.54	2351.86	(-167.320)***
Religion (=1 if Islam and 0 otherwise)	0.870	0.869	0.886	(-0.017)***
Household size	4.041	4.016	4.334	(-0.318)***
Household monthly income (in BDT)	16043.638	15036.908	27526.166	(-12489.260)***
Household monthly expenditure (in BDT)	14352.309	13282.228	26557.401	(-13275.170)***
Household cultivable land (in acres)	0.478	0.447	0.836	(-0.389)***
Proportion of adult members in the household	0.662	0.658	0.708	(-0.050)***
Region (Urban if region=1 and 0 otherwise)	0.304	0.284	0.532	(-0.248)***
Education level of household head (in years)	7.215	6.887	9.756	(-2.869)***
Migration (=1 if any member of the household migrates in domestic or internationally)	0.085	0.077	0.174	(-0.097)***
Bank account (=1 if any member of the household has a bank account and 0 otherwise)	0.080	0.071	0.183	(-0.112)***
Profession (=1 if the profession of the household head belongs to nonagricultural sectors and 0 otherwise)	0.585	0.569	0.785	(-0.215)***
Social Security benefits (=1 if the household receives benefit from the social safety net program and 0 otherwise)	0.243	0.252	0.139	(0 .112)***
Shock experience (=1 if the household experiences any shocks and 0 otherwise)	0.139	0.142	0.109	(0.033)***

Note: Author's calculation from HIES 2016 data; Differences of mean are in parentheses; *** *p< 0.01, * p< 0.10*

About two-thirds of household members (66.2%) are over 18 years old in an average household in the country. However, the households with digital capital have more adult members in the household compared to their counterparts. Most people still live in the rural areas (70%). However, the more educated and digitally equipped people live in the urban areas and depend on nonagricultural professions (78.5%), while about 59% of total households' earnings come from the nonagricultural sectors. Migration tendency is also higher among digitally equipped people (17.4%). As digitally-equipped people are better informed and educated, a higher proportion of them have a bank account (18.3%). Table 3 also shows that digitally equipped households are less affected by any kind of shocks.

Table 4 delineates the determinants and factors that influence the household to access and own digital resources. The statistics are the probability of factors to have digital resouces. Table 4 shows that gender, age, age squared, education, major profession of the household head, religion,

Table 4: Determinant of access to Digital Capital (DC): Probit regression results

Dependent Variable: Access to Digital Capital (DC)	All households	Rural Households	Urban Households
	Marginal effects		
Gender of the household head (male if gender=1 and 0 otherwise)	-0.018 (0.011)*	-0.028 (0.012)**	-0.008 (0.020)
Age of the household head (in years)	0.008 (0.001)***	0.007 (0.001)***	0.007 (0.002)***
Age squared	-0.000 (0.000)***	-0.000 (0.000)***	-0.000 (0.000)**
Religion (=1 if Islam and 0 otherwise)	0.018 (0.006)***	0.017 (0.006)***	0.018 (0.011)*
Household size	0.019 (0.001)***	0.014 (0.001)***	0.028 (0.003)***
Household cultivable land (in acres)	0.001 (0.000)***	0.001 (0.000)***	0.002 (0.001) **
Proportion of adult members in the household	0.160 (0.011) ***	0.127 (0.012)***	0.222 (0.023)***
Region (Urban if region=1 and 0 otherwise)	0.056 (0.004)***	-	-
Education level of household head (in years)	0.013 (0.000)***	0.007 (0.001)	0.022 (0.001)***
Migration (=1 if any member of the household migrates in domestic or internationally)	0.048 (0.008)***	0.044 (0.007)***	0.020 (0.023)
Bank account (=1 if any member of the household has a bank account and 0 otherwise)	0.064 (0.006)***	0.051 (0.006)***	0.084 (0.012)***

Profession (=1 if the profession of the household head belongs to nonagricultural sectors and 0 otherwise)	0.033 (0.005)***	0.024 (0.004)***	0.058 (0.014)***
Social Security benefits (=1 if the household receives benefit from the social safety net program and 0 otherwise)	-0.014 (0.005)***	-0.006 (0.005)	-0.040 (0.014)**
Shock experience (=1 if the household experiences any shocks and 0 otherwise)	-0.005 (0.006)	-0.002 (0.005)	-0.006 (0.016)
Fitness of the Model			
Prob > chi2	0.000	0.000	0.000
Pseudo r-squared	0.160	0.108	0.145

Notes: Standard errors are in parentheses, and the standard errors derived from the delta method; *** *p< 0.01, ** p< 0.05, * p< 0.10*

household size, household cultivable land, adult members' proportion, location, migration status of household members, and social security receiving status are the statistically significant determinants of having digital resources. Among the determinants of digital capital, age, education, profession (in non-agriculture) of the household head, religion (being Muslim), household size, household cultivable land, adult members' proportion, location (urban), and migration status of household members positively influence the households to have and use digital capital. On the other hand, social security and male-headed characteristics negatively influence households to have digital capital.

Table 4 also depicts that the proportion of adult members increases by about 16% probability of having digital capital, and it has the largest magnitude among the determinants of digital capital. Urban households, migration status, having bank accounts, and nonagricultural sector professions have about 3% to 6% higher probability compared to having access the digital capital. On the other hand, the other determinants of digital capital have a probability of around 1% to 2% (Table 4). The determinants of digital capital in rural and urban areas behave in a similar way to the determinants in aggregate depiction. Some of the deviations are also noticed in rural and urban areas. For instance, the education of household heads and enjoying social safety net benefits are not statistically significant for rural households, but these are statistically significant for urban households. On the other hand, the gender of the household head plays a significant role in determining access to digital capital in rural households, though it is not statistically significant in urban areas.

Table 5 presents the impact of having access to digital capital on income and multidimensional poverty reduction. The statistics of the average treatment effect on the treated (ATT) for income and multidimensional poverty using the nearest neighbor matching, radius matching, and Kernel matching methods are reported in the table. The impact on upper and lower thresholds of poverty has also been estimated for both income and multidimensional poverty. All the reported statistics are statistically significant except for the upper threshold (0.5) of multidimensional poverty.

Access to digital capital reduces the probability in a range between 5% to 7%, depending on the use of matching methods (nearest neighbor, radius, and Kernel matching methods) for lower-income poverty. The largest impact in reducing poverty is evident in upper-income poverty. Table 5 shows that access to digital capital and its utilization decreases the probability of reducing poverty by about 9% to 11% for various matching algorithms. It shows that having access to digital capital and use of these digital resources robustly decreases income poverty in the country.

Table 5: Average Treatment Effect on Treated (ATT)-results from the Propensity Score Matching (PSM)

Dependent Variable	**Matching Algorithm**		
	Nearest neighbor matching	Radius matching	Kernel matching
Income poor (using the lower poverty line)	-0.050 (0.008)***	-0.070 (0.005)***	-0.060 (0.006)***
Income poor (using the upper poverty line)	-0.085 (0.011)***	-0.111 (0.000)***	-0.094 (0.007)***
Multidimensional poor (using 0.33 threshold level)	-0.006 (0.014)	-0.026 (0.010)***	-0.016 (0.010)*
Multidimensional poor (using 0.50 threshold level)	-0.002 (0.004)	-0.003 (0.003)	-0.002 (0.003)

Notes: Standard errors are in parentheses; *** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$

Obtained results also reveal that access to digital capital also reduces multidimensional poverty. According to the definition of UNDP, if people face deprivation of 3 out of 10 basic indicators from the three fundamental dimensions of basic human needs: education, health, and living standards, they are multidimensionally poor. Table 5 portrays that access to digital capital decreases the probability of being multidimensionally poor by about 2% to 3% using Kernel and radius matching methods, though the nearest neighbor matching method does not yield statistically significant results. The multidimensional approach to estimating poverty allows us to deduce that digital capital has positive impacts on education, health, housing, drinking water, and essential household assets for the people who use it. However, using the threshold of 5 out of the ten indicators, no estimation technique has statistically significant results, although the signs are negative.

Table 6 presents the disaggregate results of the impact of digital capital on income and multidimensional poverty for rural and urban areas. Similar to the results from aggregate data, almost all of the obtained results average treatment effects of treated (ATT) for rural areas are negative and statistically significant. However, although the average treatment effects on the treated (ATT) for income poverty are statistically significant in urban areas, the average treatment effects on treated (ATT) are not statistically significant for multidimensional poverty. In addition, the ATTs are surprisingly positive for the multidimensional poverty in urban areas.

Table 6 shows that digital capital assets decrease the probability of being poor using the extreme income poverty line by about 9% to 11%, depending on the different matching algorithms for rural people. On the other hand, the rate of poverty reduction is slower for the urban areas, and the range of probability reduction varies from 2% to 4% depending on the different methods in the same threshold for the urban people. The greatest rate of poverty reduction due to digital capital is noticed in the case of the upper poverty threshold, both for rural and urban areas. Using the upper poverty line definition, access to digital capital decreases the upper-income poverty in a range between 12% to 17% depending on the method of estimation technique for rural people, while urban areas people experience a lower rate of poverty reduction in the same threshold. In terms of magnitude and significance, this evidence is sound and robust for the purpose of policy prescription.

Table 6: Average Treatment Effect on Treated (ATT)-results from the Propensity Score Matching (PSM)

Dependent Variable	**Rural**			**Urban**		
	Nearest neighbor matching	Radius matching	Kernel matching	Nearest neighbor matching	Radius matching	Kernel matching

Income poor (using the lower poverty line)	-0.089 (0.015)***	-0.111 (0.008)***	-0.096 (0.009)***	-0.024 (0.008)***	-0.035 (0.006)***	-0.032 (0.006)***
Income poor (using the upper poverty line)	-0.128 (0.018)***	-0.168 (0.011)***	-0.143 (0.011)***	-0.060 (0.012)***	-0.063 (0.008)***	-0.057 (0.008)***
Multidimensional poor (using 0.33 threshold level)	-0.051 (0.022)***	-0.074 (0.015) ***	-0.061 (0.015)***	0.016 (0.018)	0.010 (0.013)	0.013 (0.014)
Multidimensional poor (using 0.50 threshold level)	0.010 (0.007)*	-0.010 (0.004)***	-0.008 (0.004)**	0.000 (0.004)	0.002 (0.003)	0.003 (0.004)

Notes: Standard errors are in parentheses; *** *p< 0.01, ** p< 0.05, * p< 0.10*

In terms of multidimensional poverty reduction, the impact of digital capital on rural populations is more promising than on urban populations. A similar finding is also seen in Mora-Rivera and García-Mora (2021). It is evident from Table 6 that access and use of digital capital reduces the probability of being multidimensionally poor (using threshold 0.33), varying from about 5% to 7% for rural areas. On the other hand, using a threshold of 0.5, the probability of reducing poverty due to access to digital capital is about 1%, though the nearest neighbor matching method yields a positive magnitude. We can argue, based on the obtained results, that digital capital brings positive impacts on education, health, housing, drinking water, and essential household assets for the rural people who use it. On the other hand, as all of the ATT results are not statistically significant, it is evident from the data that digital capital does not have any impact on urban people.

Therefore, analyzing all the obtained results, it can be argued that households with computer and internet facilities are more capable of reducing the vicious cycle of poverty than households without these accesses. This happens because these households are perhaps better informed and can get quicker access to other opportunities, like job market information, medical information, information on social safety net benefits, etc.

The common support and matching bias reduction graphs (with a matching bias reduction table for aggregate data) are reported in the appendix. These post-estimation results are estimated to specify the overall fitness of the model. Graph A1 describes the common support for aggregate data, while Graph A2 portrays the common support graphs of rural and urban areas. Almost all treated observations fall in on support region, but only very few observations fall in off support in rural areas. In addition to the common support region, matching bias reduction for the covariates as post-estimation has also been estimated. Matching bias reduction results are depicted in Table A1 and Graphs A3 and A4. Table A1 and Graph A3 contain information for aggregate data, whereas the first graph of Graph A4 explains the bias reduction of rural areas, and the second one presents the bias reduction of urban areas. In both the table and graphs, bias reduction is found to be very small on the matched observations (less than 5 percent). Hence, post-estimation results tell us that the matching technique used in the study explains the data very well. In addition, distribution of sample over the matching properties are also provided in table A2 in the appendix section.

Section 5: Conclusion and Policy Recommendations

Bangladesh is one of the most densely populated countries in the world, with about 180 million people in a small geographic area (56,977 square miles). Poverty has been a curse to the country since its birth in 1971. Relentless efforts and high priorities on poverty reduction in policy formulation from the governments played a significant role in reducing poverty substantially in Bangladesh. As a result, these efforts paved the way for substantial income poverty reduction from about 80% (1971) to only about 20% (2022) of the total population. Many factors, including the expansion of digitalization, obviously played a role in substantial poverty reduction. However, although absolute income poverty has been reduced substantially, multidimensional poverty is still moderately high in the country (around 32% found in this study). Therefore, evidence-based policies are very essential in further reducing absolute income as well as multidimensional poverty.

Since Bangladesh is experiencing steady increases in the use of digital technology and digital capital, most of the spheres of economic transactions have been highly dependent on digital resources and ICT knowledge. Therefore, the application of digital resources has an obvious impact on people's social and economic lives. Due to the decrease in economic transaction costs, the application of digital capital will ease people's lives and their poverty. This study confirms from the obtained findings that digital capital significantly reduces both absolute income and multidimensional poverty for the people who use it. As a result, the findings will help the researchers in this field to understand the nexus between digital capital and poverty reduction and help policymakers formulate evidence-based pragmatic policies.

Based on the obtained findings from the national level data, this study has some policy recommendations for reducing absolute income and multidimensional poverty. First, human capital development tools, for instance, education, should be emphasized, and quality of education should be ensured for all. More educated people are highly equipped with digital capital, and hence, they find effective ways through digital capital to reduce income and multidimensional poverty. Second, the horizon of the social safety net program should be expanded to encompass all the vulnerable people in society. In addition to the physical and financial support, social safety net programs should be extended by offering training to low and medium-skilled labor using computers and the internet so that they can find a way to get rid of the curse of poverty forever. This kind of training also paved the way for skilled labor migration from the country. That also helps the country to eradicate poverty, as there is substantial empirical evidence of migration and poverty reduction. Third, the financial sector should be digitalized completely, as the people who have an account in a bank are more prone to the use of digital capital. Transaction in the financial sector digitally reduces the cost of transactions and saves their productive time. Therefore, people are capable of higher earnings and thus reduce their poverty both income and multidimensional.

Although the obtained findings are very robust and significant in advocating policies in this field, the study, admittedly, has some limitations and constraints. For example, impact evaluation is best fitted when the data is perfectly experimental, and the obtained results from the experimental data are desired for the policy formulation. Unfortunately, the study did not have the luxury of experimental data and hence used the cross-sectional data with the quasi-experimental method. Future studies are needed to fill this gap of research and to provide policy prescriptions for policymakers. In addition, this study limited the concept of digital capital within the boundary of computers and the internet. Due to the context of the country and the availability of the data, this study has to exclude other forms of digital resources like wireless networks, cell phones, etc.

Section 6: References

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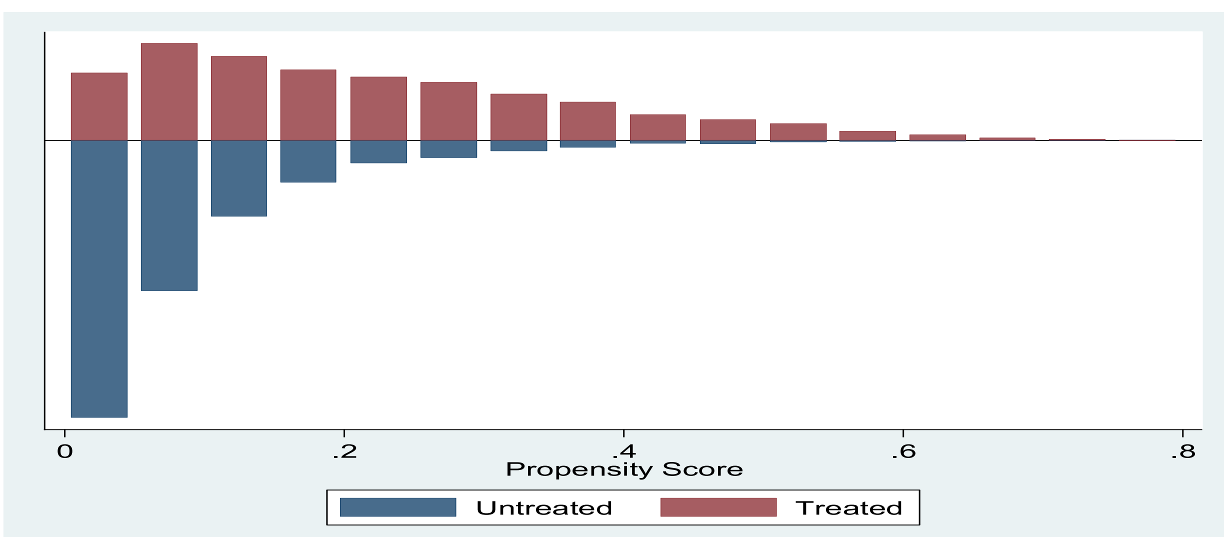
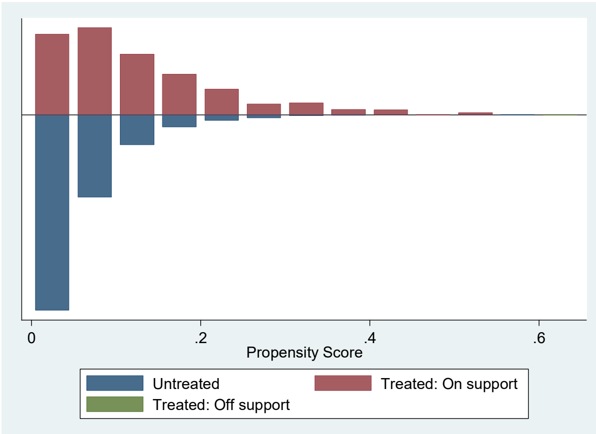
Section 7: Appendix:

Graph A1: Balancing Property Graph test-comparisons of treated and controls after matching (common support graph) -Aggregate sample



Graph A2: Balancing Property Graph test-comparisons of treated and controls after matching (common support graph) - Rural (first graph) and Urban (second graph)



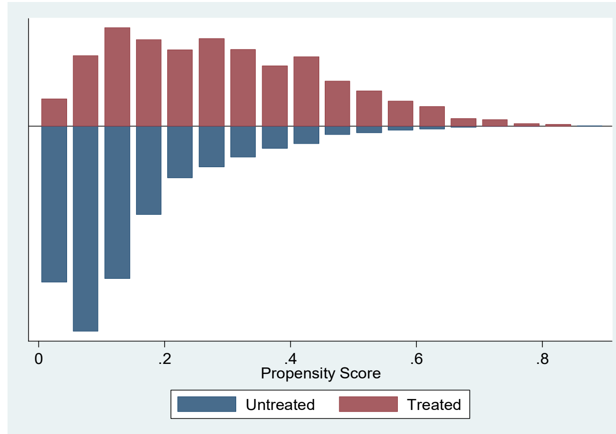
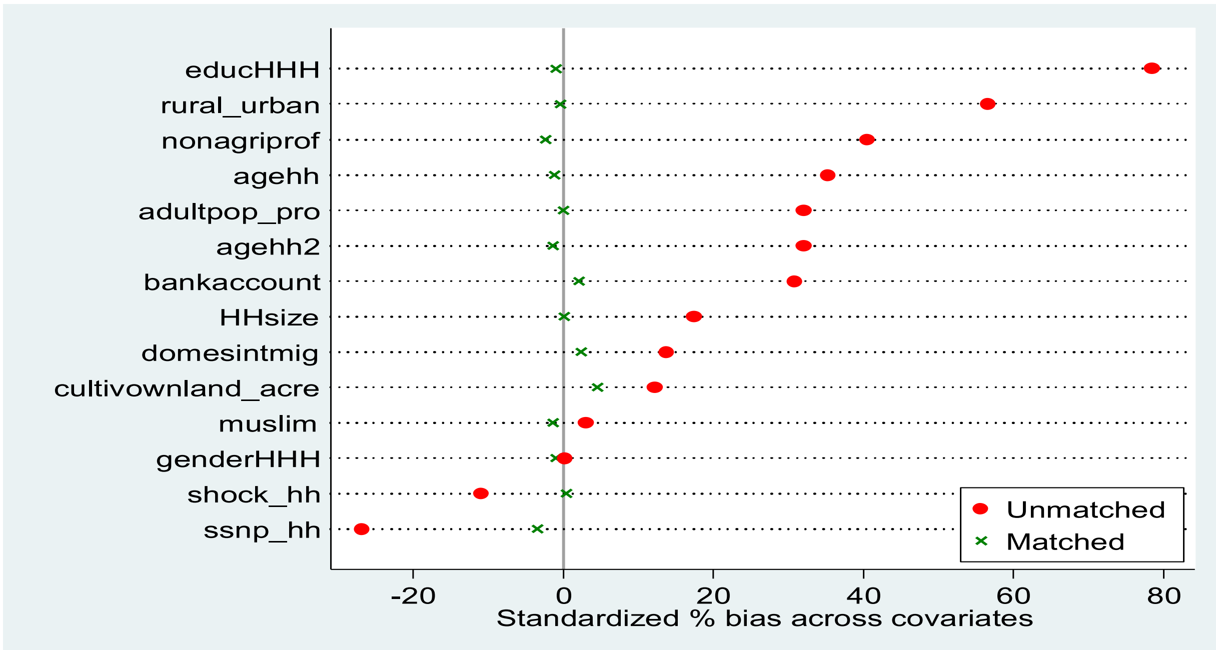


Table A1: Balancing property test-comparisons of treated and controls after matching

Variables	Mean			t-test
	Treated	Control	%bias	p>|t|
Gender of the household head (male if gender=1 and 0 otherwise)	.96851	.97023	-1.0	0.733
Age of the household head (in years)	44.824	44.96	-1.1	0.692
Age squared	2144.8	2159.9	-1.4	0.638
Religion (=1 if Islam and 0 otherwise)	.8654	.87015	-1.4	0.633
Household size	4.311	4.3102	0.1	0.985
Household cultivable land (in acres)	.91454	.75613	4.5	0.350
Proportion of adult members in the household	.71034	.71034	-0.0	1.000
Region (Urban if region=1 and 0 otherwise)	.60311	.60526	-0.4	0.881
Education level of household head (in years)	10.045	10.087	-1.0	0.751
Migration (=1 if any member of the household migrates in domestic or internationally)	.06644	.06126	2.4	0.471
	.18033	.17343	2.1	0.538
Profession (=1 if the profession of the household head belongs to nonagricultural sectors and 0 otherwise)	.82744	.83779	-2.4	0.345
Social Security benefits (=1 if the household receives benefit from the social safety net program and 0 otherwise)	.12597	.13891	-3.4	0.194

Shock experience (=1 if the household experience any shocks and 0 otherwise)	.09707	.09577	0.4	0.881

Graph A3: Matching bias reduction for different covariates-Aggregate sample



Graph A4: Matching bias reduction for different covariates-Rural (first graph) and Urban (second graph)

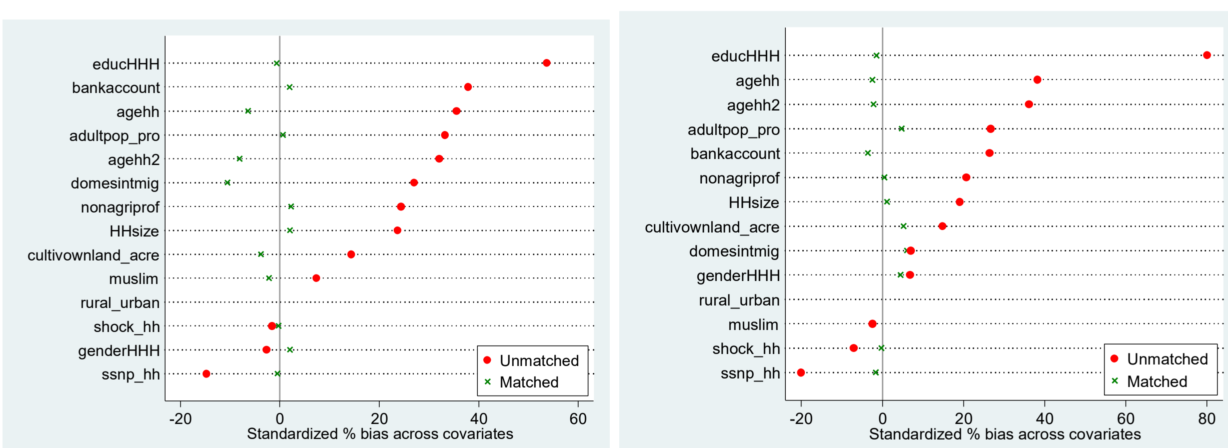


Table A2: Distribution of sample over the common support

Poverty Level	**Untreated**			**Treated**			**Grand Total**
	Common support (On	Common support (Off	Total	Common support (On	Common support (Off	Total	

		support)	support)		support)	support)		
National	Lower Income Poverty	20254	0	20254	2318	0	2318	22572
	Upper Income Poverty	20254	0	20254	2318	0	2318	22572
	Multidimensional Poverty (using 0.33 threshold level)	20254	0	20254	2318	0	2318	22572
	Multidimensional Poverty (using 0.50 threshold level)	20254	0	20254	2318	0	2318	22572
Rural	Lower Income Poverty	13547	0	13547	919	1	920	14467
	Upper Income Poverty	13547	0	13547	919	1	920	14467
	Multidimensional Poverty (using 0.33 threshold level)	13547	0	13547	919	1	920	14467
	Multidimensional Poverty (using 0.50 threshold level)	13547	0	13547	919	1	920	14467
Urban	Lower Income Poverty	6707	0	6707	1398	0	1398	8105
	Upper Income Poverty	6707	0	6707	1398	0	1398	8105
	Multidimensional Poverty (using 0.33 threshold level)	6707	0	6707	1398	0	1398	8105
	Multidimensional Poverty (using 0.50 threshold level)	6707	0	6707	1398	0	1398	8105

Source: Author's own calculation from the data