Impact of Per Capita on School Life Expectance and Gender-Base Literacy Rate

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Abstract

The main aim of the study is to evaluate the relationship between per capita GDP and gender-based literacy rates as well as school life expectancy. The study approach is described in filled, along with each step of instrumental growth and expansion, and the benefits and drawbacks of the selected strategy are also covered. The study looks at how per capita GDP affects gender-based literacy rates and how it relates to school life expectancy using quantitative approaches. The study uses statistical analysis to produce observations and insights, and it is based on SPSS data that the university has provided. In analyzing the effect of per capita GDP on gender-based literacy rates and school life expectancy, the present paper effectively applies statistical methodologies and provides insightful information on the research issue and study methodology as a whole. The research's results suggest that differences in per capita GDP did not appear to have a significant effect on gender-specific literacy or educational duration because the models utilized for regression did not find statistical relevance in per capita GDP.

Keywords: *Per Capita GDP, School Life Expectancy, Gender-Based Literacy Rate, Socioeconomic Dynamics, Educational Development*

Introduction

Global society's progress and growth are largely dependent on education. In the field of education, per capita GDP—that is, the average income per person in a nation—becomes apparent as a critical element impacting some aspects of educational performance. Examining how per capita GDP influences that is gender-based rates of literacy and academic durations sheds light on the connection between economic achievement and educational opportunities.

The concept of per capita GDP and the amount of money available for schooling are similar. A country with a higher GDP per person has the means to upgrade its educational system.

These enhancements include recruiting qualified teachers, constructing fresher more efficient school facilities, and providing classrooms with the supplies they need. Consequently, these costs enable children to attend school for extended periods, so fostering a more comprehensive and meaningful educational experience.

In terms of gender-specific educational attainment, per capita GDP has a greater effect. Richer nations are more prepared to implement policies and initiatives that ensure women and men have equal learning opportunities. Higher rates of proficiency for both boys and girls serve as evidence that gender parity in education is positively connected with per capita Gross Domestic Product. This transformative effect raises the community's overall intellectual vibrancy as well as the level of personal independence.

The purpose of the study

To evaluate the relationship between school duration and gender-based levels of literacy and the gross domestic product (GDP) per capita.

Literature Review

In a sense, per capita GDP acts as a catalyst for educational progress. By making improvements in facilities, social, and schooling, nations may establish environments where everybody, despite race, can receive better educational opportunities. Although it measures a nation's overall socioeconomic health and affects how much of its finances are allocated to education, the per capita GDP has an important influence on the standard of schooling. A growing per capita GDP, according to Appiah (2017), is indicative of improved financial expansion, which typically means increased funding for education. Many research have consistently shown a link between per capita GDP and school life expectancy. Mitchell et al. (2019), for example, found that countries with larger economies generally invest more in education, providing more learning opportunities for pupils. According to a 2019 study by Yaroslav Kuzminov and colleagues, there seems to be a favorable correlation between higher learning and economic development. For instance, the median length of official schooling seems to be more powerful in cultures with greater economic growth concentrations. It also means that providing funding for educational institutions can have a beneficial affect on a country's general growth in the economy.

The idea behind human capital is that investing in education raises worker productivity, which in turn helps a nation's economy flourish (Rangongo & Ngwakwe, 2019). In a similar vein, the human resource development perspective maintains that industrialized nations have more financial means to allocate to education, leading to a population that is more educated and promotes economic growth (Bawono, 2021). According to the 'Education Pays' hypothesis, obtaining an education increases one's employability while simultaneously promoting economic growth (Anca Andreeatefãnescu, 2022). Furthermore, studies have demonstrated that a rise in per capita GDP gives people more money to spend on education, which raises literacy rates and lengthens school lifespans (Adel Ifa & Imène Gutat, 2018). These results highlight how important it is to fund education in order to support economic development and progress.

Moreover, the rates of literacy for all sexes are significantly impacted by per capita GDP. In commercially emerging economies, it is imperative to guarantee that both men and women are given access to quality education (Wodon et al., 2018). Even so, because of a wide range of factors related to culture and society, women and girls commonly encounter more challenges to obtaining higher education than males. On the contrary present, Grigion et al. (2017) observed that the variation in the level of education of makes and females reduces in parallel with a rise in per capita GDP. Several variables support the closure of the gender gap in literacy rates as per capita GDP rises. Yoga Affandi et al., (2019) described that economic development contributes to better infrastructure, such as schools and educational institutions, which makes education more accessible to girls. Additionally, families usually have more spare income to devote to their daughters' education when per capita GDP increases. In order to close the gender gap, initiatives that support girls' schooling as well as gender equality are crucial.

Tran, & Buckman, (2017) conceded that a fixed-effects regression model can be used to analyze panel data to compensate other factors that could influence educational performance, including government policy, healthcare spending, and social development programs. Gregory & Fergus, (2017) stated that school life expectancy and gender-based literacy rates can be strongly influenced by societal attitudes towards education, gender roles, and traditional conventions.Stoilova, &Ilieva-Trichkova, (2022)described that cultural views and gender biases may limit educational chances for girls in some societies, especially in countries with high per capita GDP. Similarly, Ghai, (2018)asserted that despite economic prosperity, deeply rooted societal norms and discriminatory practises can stymie girls' educational opportunities. To overcome thecultural barriers, a multifaceted approach that combines community participation, awareness campaigns, and policy actions to promote gender equality in education is required.

Furthermore, Parker (2020) argued that the standard of schooling received matters just as much as the availability of knowledge. Nonetheless, per capita GDP does not ensure high-quality learning, even though it has a positive relationship with longer educational expectations, according to Adel Ifa and ImèneGuetat (2018). Barrett et al. (2019) acknowledged that in order to ensure that learners obtain excellent schooling, there is an obligation to engage sufficiently in educational facilities, teacher planning, and the development of curriculum. Furthermore, Appiah (2017) stated that it is critical to understand that there is a two-way relationship between per capita GDP and academic achievement. According to Diebolt, and Hippe, (2019), financial development encourages education, but education itself is the engine of economic advancement. Additionally, Chankseliani et al. (2021) claimed that by equipping people with abilities and expertise, learning increases employment prospects, fosters innovation, and encourages advancement in society, all of which contribute to greater financial growth.

Hypothesis H1: In regard to school life expectancy, there is a significant association between per capita GDP and gender-based literacy rates.

Hypothesis H0: There is no appreciable relationship between per capita GDP, length of schooling, and gender-based literacy rates.

Methodology

Positivist, interpretative, and Realism are the three research philosophy approaches (Davies & Fisher, 2018). The researcher employed positivist research methodologies because of the quantitative integrity of the data that were offered for this investigation. Positive data is considered more truthful, dependable, and significant in the eyes of positivists due to its accurate measurements and mathematical evaluation abilities. Prasad (2017) claims that positivism is a helpful methodology for analyzing how per capita GDP affects gender-based literacy rates and school life expectancy. It provides objective, quantifiable data through quantitative evaluation, thus enabling statistical association validation. There were difficulties in using positivism in research, such as potential comprehension gaps regarding social context and subjective experiences.

The two main approaches used in research are deductive and inductive rational thinking (Huang, 2023). The technique of deductive reasoning is used in this study since it helps professional judgments, models, and visual aids connected to research (Staff, 2018). Research Methodology (2017) states that based on theories and literature regarding the connection between a child's reading behavior and intellectual development—including shading and letter recognition, counting abilities, and cognitive skills—deductive reasoning has aided in the construction of a well-defined and scientifically testable hypothesis. There were some difficulties when using a deductive technique in research, such as potential rigidity and little exploration of novel concepts. The inductive method was not used in this study since it cannot produce accurate predictions or reasonable conclusions in a variety of scenarios. Sileyew (2019) asserts that problems with the initial assumptions' validity arise in deductive research, requiring modification and possibly contributing inaccuracies. The researcher can encourage the use of excellent procedures and offer straightforward explanations to get beyond these obstacles.

Pan et al. (2022) define methodologies for research as the organized approaches—qualitative or quantitative—that researchers employ throughout an investigation. Rafe, Elliott, and Flannagan (2022) contend that because quantitative research reduces bias among investigators by enabling accurate measurements and analysis of statistical data, it is more objective. Quantitative data is useful in assessing how per capita GDP affects gender-based literacy rates and school life expectancy. Additionally, Feehan et al. (2018) found that quantitative data guarantees accurate and consistent outcomes, offers an independent examination, helps researchers with statistical analysis, facilitates generalization, and allows for comparability and predictions. However, qualitative data was not used because of its variability. The challenge of validating quantitative research methods can be addressed by leveraging one of its advantages, such as the capacity to extrapolate results to a broader population (André Queirós et al., 2017).

The researcher's data set was used in this investigation, which was conducted using the SPSS format. Since the investigator gathered the data set on her own, statistical sampling was done. The researchers were solely accessing the data file for research purposes in order to address ethical issues. Furthermore, after the research was finished, the data set's contents were completely deleted and never shared with someone else.

Data Analysis and Findings

The typical socioeconomic contribution capital per person in the sample is 3522.70, according to the descriptive analysis of per capita GDP. There is a significant amount of data volatility around the mean, as indicated by the hefty 5257.70 standard deviation. With SPSS, two variables—the rates of literacy for men and women—were converted into the variable GENER_IR, yielding a mean value of 27.4525 and a standard deviation of 22.54901. This implies that the data values for the modified variable GENDER_IR are distributed around the mean. Furthermore, the sample presented has an average school life expectancy of 10.50 years, which indicates the length of time people anticipate attending school. All things considered, these results shed light on the state of the economy, characteristics pertaining to gender, and expectations for schooling within the dataset under analysis. A standard deviation of 3.301 is found in the school life expectancy analysis, demonstrating variation in the number of years people anticipate attending school. Skewness measures the shape of the distribution; positive values (per capita GDP: 2.767, GENDER_IR: 0.499, school life expectancy: 0.015) indicate an extended right tail, and a negative value indicates a longer left tail. Additionally, kurtosis, which assesses tail form, has relatively elevated values (8.364 for school life expectancy, -1.142 for GENDER_IR, and -1.136 for per capita GDP). These findings imply that the distribution of school life expectancy and GENDER_IR have slightly shorter tails than the per capita GDP distribution, which has a wider right tail. In general, the values of skewness and kurtosis offer valuable information on the consistency and form of the variations for the variables analyzed.

Table 1 Descriptive Statistics

	Per Capita GDP ($US)	Gender IR	School Life Expectancy (Years)
Valid	20	20	20
Missing	0	0	0
Mean	3522.7	27.4525	10.5
Std. Deviation	5257.107	22.54901	3.301
Skewness	2.767	0.499	0.015
Std. Error of Skewness	0.512	0.512	0.512
Kurtosis	8.364	-1.142	-1.113
Std. Error of Kurtosis	0.992	0.992	0.992

The results of the analysis's coefficient of correlation (R) show that there is a moderately strong positive association (0.424) between GDPs per capita and school duration. The R Square coefficient, which stands at 0.180, indicates that 18% of the difference in school life expectancy can be explained by GDP per capita. In comparison to R Square, Adjusted R Square, which takes the number of variables into account, is comparatively low at 0.134. The precision of the model's predictions as measured by the accepted error of the estimate is 3.701. An additional 18% of the variability in school life expectancy may be explained by an increase in per capita GDP, according to the R Square change of 0.180. This rise in GDP is statistically significant, as indicated by the F change value of 3.945.

Table 2 The Direction and Strength of the Predictor and Dependent Variables

Model Summary		
R		0.424
R Square		0.18
Adjusted R Square		0.134
Std. Error of the Estimate		0.3071
R Square Change		0.18
Change Statistics	F Change	3.945
	df1	1
	df2	18
Sig. F Change		0.062
Durbin Watson		2.258

a. Predictors: (Constant), Per Capita GDP ($US)
b. Dependent Variable: School Life Expectancy (Years)

A regression approach for estimating school life expectancies based on per capita GDP's variability and its statistical importance is revealed by the ANOVA analysis. The variable that is the dependent variable's variance explanation is shown by the regression's sum of squares, which is 37.208. The ANOVA table's mean square, also with one degree of independence, is 37.208. With a mean square of 9.433, the residual, which represents unaccounted variation, has a total of squares of 169.792 and 18 degrees of uncertainty. With 19 degrees of freedom, the entire sum of squares represents the whole range in school life expectancy, which comes out to 207.000.

The correlation between the variable that is dependent (school life expectancy) and the variable that serves as a predictor (per capita GDP) is evaluated using the F statistic, which has been computed as 3.945. At the standard relevance level of 0.05, the non-significant p-value of 0.062 indicates that there is not a statistically significant relationship between per capita GDP and school life expectancy. Based on the ANOVA table analysis, the null hypothesis (H0), which states that there is no significant association between per capita GDP and school life expectancy, is thus accepted.

Table 3 ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	37.208	1	37.208	3.945	0.062b
Residual	169.792	18	9.433		
Total	207.000	19			

When the independent variable (Capita Per GDP) is zero, the corresponding constant in the above table shows an informal coefficient of 9.562, which represents the contents of the dependent variable. The estimated coefficient's volatility is indicated by the constant's Std. error of.833. The informal coefficient of.000 for the independent variable, capita per GDP, shows how the dependent variable, school life expectation, changed. The coefficient's standard error is.000, indicating that the computed coefficient has little variation. Capita Per GDP's standardized coefficient (Beta) is.424, and the t-value is used to determine the relevance of this coefficient. At the 0.05 level, Per Capita GDP is not of statistical significance, according to the corresponding p-value (Sig.) of.062. The constant term's 95% confidence interval spans 7.811 to 11.313, indicating a likely range of values for the actual population coefficient. Patience and VIF (Variance Inflation Factor) are taken into consideration when assessing multicollinearity among predictor variables. Tolerance and VIF for Per Capita GDP are both 1.000, indicating that multicollinearity problems are not present.

Table 4 Coefficients

Model		Constant	Per Capita GDP ($US)
Unstandardized Coefficient	B	9.562	0.833
	Std. Error	0.000	0.000
Standardized Coefficient Beta			0.424
T		11.474	1.986
Sig.		0.000	0.062
	Lower Bound	7.811	0.000

95.0% Confidence Interval for B	Upper Bound	11.313	0.001
Collinearity Statistics	Tolerance		1.000
	VIF		1.000

The association between the independent variable (per capita GDP) and possible multiple linearity in the model of regression estimating the dependent variable (school life expectancy) can be seen in the Collinearity Diagnostics table. Per capita GDP and the amount that remains constant are the two variables that make up the number of variables listed in the table. The variance in each dimension is measured by eigenvalues; dimension 1 has an eigenvalue of 1.567 and dimension 2 has an eigenvalue of 0.433. When multiple linearity exceeds 30, the Condition Index, a measure of its presence, is 1.000 for Dimension 1 and 1.901 for Dimension 2, meaning there are no multicollinearity problems. According to variance proportions, the constant accounts for 22% of the variance in Dimension 1 and 78% of the variance in Dimension 2, respectively.

Table 5 Collinearity Diagnostics: The information related to multicollinearity

Model		**1**	
Dimension		1	2
Eigenvalue		1.567	0.433
Condition Index		1	1.901
Variance Proportion	Constant	0.22	0.78
	Per Capita GDP ($US)	0.22	0.78

a. Dependent Variable: School Life Expectancy (Years)

A moderately positive association between Per Capita GDP and GENDER_IR is shown by the regression model's overview table's correlation coefficient (R) of 0.403. The percentage of variability in the variable that is explained is indicated by the R square value of 0.116. R square adjustment stays at 0.116. The estimate's standard error, or Std. The error is 21.20085, which represents the average predictor error. The independent variable, GENDER_IR, was significantly impacted by the predictors, Constant and Per Capita GDP, as indicated by the R Square change of 0.163. The predictive model overview table, which sheds light on the link between GENDER_IR and Per Capita GDP, highlights a moderately favorable correlation between the variables that predict and the dependent variable.

Table 6 Gender

Model Summary	
R	0.403
R Square	0.163
Adjusted R Square	0.116
Std. Error of the Estimate	21.200085
R Square Change	0.163

Change Statistics	F Change	3.493
	df1	1
	df2	18
Sig. F Change		0.078
Durbin Watson		2.115

a. Predictors: (Constant), Per Capita GDP ($US)
b. Dependent Variable: Gender IR

The sum of the Square in the ANOVA table for the regression Model is 1570.135. It provides information about the amount of variation in GENDER_IR. The fd (gf degree of freedom 1 indicates the number of predictors. The mean Square is 1570.135, and the F-statics is 3.493, which calculates the ratio of explained variance to unexplained variance. The (sig.) p-value is .078, which shows no significant relationship between the two variables (GENDER_IR and Per Capita GDP). The sum of the Square of the residual is 8090.567, which shows the unexplained variation in GENDER_R. The df for the residual is 18, demonstrating the number of observations. The mean Square of the residual is 449.476, and the total sum of Square is 9660.702, showing the total variation in the dependent variable.

Table 7 ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1570.135	1	1570.135	3.493	0.078b
Residual	8090.567	18	449.476		
Total	9660.702	19			

a. Dependent Variable: GENDER IR
b. Predictors: (Constant), Per Capita GDP ($US)

The continuous coefficients in the coefficient table, 33.544, indicate the estimated values of GENDER_IR in the case of zero per capita GDP. The alteration in GENDER_IR for each unit rise in Per Capita GDP is indicated by the coefficient of variation for Per Capita GDP, which is -0.002. For a given constant, the standard error is 5.753; for the per capita GDP, it is 0.001. The normalized effect of per capita GDP on GENDER_IR is indicated by the normalized coefficient (Beta) of -0.403. The link between Per Capita GDP and GENDER_IR appears to lack any statistical significance, as indicated by the t-value of -1.869 and the associated p-value of 0.078. The coefficient's 95.0% range of assurance spans from -0.004 to 0.000. In terms of collinearity, the table's Tolerance and VIF values are both 1.000, suggesting that there are no problems with mutual dependence between the independent variables.

Table 8 Coefficients

Model		Constant	Per Capita GDP ($US)
Unstandardized Coefficient	B	33.544	-0.002
	Std. Error	5.753	0.001

Standardized Coefficient Beta			-0.403
t		5.831	-1.869
Sig.		0.000	0.078
95.0% Confidence Interval for B	Lower Bound	21.458	-0.004
	Upper Bound	45.630	0.000
Collinearity Statistics	Tolerance		1.000
	VIF		1.000

a. Dependent Variable: Gender IR

Measurements 1 and 2 are shown in the Collinearity Diagnostics table. Each dimension's their eigenvalue, which measures the amount of variance it explains, is 1.567 for dimension 1 and 0.433 for Dimension 2. The Condition Index in Dimension 1 is 1.000, indicating that multicollinearity problems are not present. On the other hand, the Condition Index in Dimension 2 is 1.901, suggesting a slight occurrence of multicollinearity. According to Dimension 1's variance proportions, the Constant shares 0.22 of the variance with Gender_IR. Within Dimensions 2, 0.22 of the variances is explained by the Constant, while an additional 0.78 is explained by Per Capita GDP. Although Dimension 2 has a slight problem with multicollinearity, the table shows no significant issues with the relationship between the steady state and per capita GDP. All things considered, the Collinearity Diagnostics shed light on the variance explained and multicollinearity that exists in the regression framework that includes the constant, GDP per capita, and gender_IR.

Table 9 Collinearity Diagnostics: Gender IR

Model		**1**	
Dimension		1	2
Eigenvalue		1.567	0.433
Condition Index		1	1.901
Variance Proportion	Constant	0.22	0.78
	Per Capita GDP ($US)	0.22	0.78

a. Dependent Variable: Gender IR

Discussion

Given that the per capita GDP coefficient was not highly significant ($p > 0.05$), it is plausible that rises in per capita GDP had no discernible impact on school life expectancy. We conclude there is no significant relationship between each of the variables in the data set at hand since the null hypothesis (H0) cannot be ruled out. In each of the regression models that were looked at, the per capita GDP coefficient was not significantly different from zero, meaning that modifications to per capita GDP had no discernible impact on gender-based literacy rates or school life expectancy.

According to the investigation done, the regression model examining the relationship between GENDER_IR and Per Capita GDP offers the subsequent results. The results indicate a somewhat positive link between GENDER_lR and per capita GDP, with a correlation coefficient (R) of 0.403. Based on the coefficient of prediction (R Square), 16.3% of the variability in GENDER_lR can be explained by the per capita GDP. It is noteworthy to observe that the adjusted R Square, which is significantly less at 0.116, suggests that adding more predictor variables could improve the model's prediction ability.

Previous research on the relationships between economic factors, educational measures, and inequality by gender has produced contradictory findings. Measurements of educational achievement and gender equality are positively correlated with economic advancement as indicated by the GDP per person (Vignoles, 2016). Results show that greater financial resources can lead to greater involvement in education and improved access to learning opportunities for all genders. (Da Costa, 2021) found a similar link between per capita GDP and school life expectancy. Nonetheless, this study did find a positive correlation between the gender-based literacy rate and per capita GDP, indicating that greater economic output is associated with better rates of literacy for both sexes.

(Abdullah Hisam Omar & Inaba, 2020) state that there is a negligible or poor relationship between financial variables and academic metrics. These investigations stress the complex structure of this connection and indicate that variations in level of education may not be fully explained by monetary variables. Inequalities between sexes and academic possibilities can be significantly impacted through additional psychological, cultural, and political considerations such as governance, social norms, and roles associated with gender. Other research, depending on the subject, indicated a weak or no association, demonstrating the complex nature of the relationship between economic situations and educational markers.

Conclusion

The null hypothesis (H0), which suggests that there is no significant relationship between the variables in the sample under investigation, was accepted because the per capita GDP coefficient did not reach statistical significance ($p > 0.05$).

With a correlation value (R) of 0.403, the investigation of the association between gender-based literacy rates and per capita GDP revealed a somewhat positive relationship. The coefficient of determination (R Square) showed that the variation in gender-based literacy rates could only be explained by per capita GDP to the extent of about 16.3%. The smaller corrected R Square of 0.116 suggests that incorporating more variables to predict could enhance the model's predictive power. These results show the intricate relationship between per capita GDP and gender-based rate of literacy, with financial variables explaining a comparatively tiny amount of the observed difference.

The findings add to the continuing conversation on the intricate relationships between factors related to gender inequity, schooling, and the economy. The present study offers an additional complicated image, despite several previous studies suggesting a favorable association between per capita GDP and educational achievement. Vignoles (2016) and Da Costa (2021) have shed light on contradictory findings from earlier research, emphasizing the complex interplay among a political issue, and interpersonal, cultural, and financial factors that impact educational attainment and gender differences. Abdullah Hisam Omar & Inaba (2020) claim that there is little to no correlation between economic and educational indices. This highlights the need to take into account a variety of factors in addition to economic situations in order to fully comprehend the differences in educational attainment.

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