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DETERMINANTS OF ACCESS TO PRIMARY EDUCATION DURING COVID-19 LOCKDOWN AMONG SCHOOL GOING CHILDREN IN UGANDA

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ABSTRACT

The main objective of this research was to find the determinant factors of access to education during covid-19 lockdown among primary school going children in Uganda. This study utilized statistical figures from the cross-sectional survey which was carried-out in December 2020 under the auspices of the Forum for African Women Educationalists Uganda (FAWEU). The study targeted boys and girls of age group 10-24 years, Children involved were from a sample of 25 out of 134 districts of Uganda and these were 6,394 young people, drawn from 3,201 households in 200 parishes. A total of 4,195 primary learners sampled were included for analysis of which 1,754 learners had access to education during lockdown while 2,441 did not. The hypothesized predictors considered were; sex, age, learner's education level, learner's disability status, region of origin, time spent on household chores, household size, household main source of income, and who the learner stayed with using a mixed effects logistic model to identify the determinant factors of access to education during lockdown in Uganda.

The attributes of access to learning/education at primary level during Covid-19 lockdown were household source of income, average time spent on house chores, learner's education level and interaction between household size and it's source of income. It was found out that learners whose parents were non-farmers had a probability three times greater to access learning/education as compared to learners whose parents were farmers. Learners from households with more than 9 members and whose parents were non-farmers had reduced odds of accessing education during schools' closure compared to those whose parents were non-farmers and from households with less than 5 members. Learners in upper primary were 3 times more likely to access education during lockdown as compared to their counterparts in lower primary.

In order to have a large number of learners accessing education during pandemics like the COVID-19 pandemic, government and education supporting partners should invest and provide learners in Uganda with training programs on how to spend time during pandemics and holidays. Furthermore, support to household to engage in economic activities should be prioritized to increase access to education in Uganda. Also, government and the reproductive health supporting partners should formulate programmes aimed at sensitizing and mind change for citizens in Uganda about the importance of family planning and having fewer children.

KEYWORDS: Access to Primary Education, teaching and learning approaches used, Covid-19 pandemic/Emergency situation.

1. INTRODUCTION

Background

The Covid-19 pandemic had significant repercussions / consequences for education systems around the world, resulting in the widespread closure of schools in almost all affected countries; by March 2020, an estimated 1.7 billion learners were not attending school because of school shutdown/closure. In Uganda, following the president's directive to close all education institutions, on March 20, 2020, and according to the Ministry of Education and Sports, more than 73,000 learning institutions closed and as a result 15 million learners and 600,000 refugee students were out of school. (Simeon et al., 2022; Tumwesige, 2020.). According to UNESCO, (2021), the dwindling incomes due to prolonged lockdown was expected to cause about 24 million learners from returning to the classroom, based on evidence that prolonged school closure without educational engagement increases the likelihood of exposure to violence, sexual assaults, child marriages, child labour, prostitution and other life-threatening criminal activities. The UNESCO monitoring reports confirmed that, over 100 countries to have implemented a national wide closure of learning centers / education institutions in efforts to control the transmission of Covid-19, affecting more than 91% of global student population. (Tumwesige, 2020).

Since 2019, the global coronavirus outbreak interrupted all human activities, forcing people to adopt the new norm of social distancing, which has had a direct impact on the physical normal class learning and teaching in the vast majority of educational institutions. Uganda's lockdown was longer than anywhere else in the world, and this, combined with underlying challenges in education service provision, may have made the pandemic's impact on education in Uganda more concerning than elsewhere. Closing schools had far-reaching economic and societal consequences, not just for students, teachers, and families (Mukherjee & Maity, 2022; Simeon et al., 2022). The lockdown due to coronavirus pandemic not only affected the global economy, but it also resulted in travel restrictions and cancellations, as well as the prohibition of mass gatherings. The lockdown posed an economic challenge for a number of households, prompting families to consider the financial and opportunity costs of education.

In Uganda, through MoES, various government agencies and institutions, non-government organizations, and private partners in education investigated a number of different forms that could permit continuity of learning during school lockdown. These included the development of e-learning platforms like the introduction of online classes, Radio and Television lessons, and the distribution of home learning materials. The closure of schools during lockdown prompted the government to distribute self-study material to all learners in the country and halt the 12% tax on internet data that was introduced in July 2018 with the strong directive intervention of introducing "Learn from Home student internet data bundles" by all internet providers. However, in some remote areas, learners' access to education through online learning was limited due to slow and unreliable connectivity, inadequate ICT skills of both teachers and learners, the high cost of Wi-Fi, and inequality over these new technologies (Bwire et al., 2020; Tumwesige, 2020). In the twenty-first century, an innovative and distance approach to education is synonymous with learning using technologies. Learning technologies facilitate the continuation of education in situations where traditional learning has been interrupted, and they also create opportunities to address geographical barriers and limitations of conventional educational systems. (Gulati, 2008; Lalima & Lata Dangwal, 2017). In Uganda, a significant challenge arises due to the fact that 80% of school-age children and youth reside in rural areas including refugee hosting districts. These areas are often marked by insufficient basic living resources and poorly developed educational infrastructure. As a result, evaluating learning technologies and understanding the digital divide between affluent and dis advantaged categories becomes increasingly difficult. This situation ultimately exacerbates the existing educational disparities. (Tumwesige, 2020).

Solano, Cabrera, Ulehlova, & Espinoza, (2017) stated that technological advancements are being implemented to enhance education across all levels Thus, effective use of technological innovations can promote and improve teaching and learning. As a supplement to home learning materials supplied by the government of Uganda and its partners, E-learning was used to manage, plan, deliver, and track the learning and teaching process during school closures. (Hassan, 2020). However, obstacles to achieving digital inclusion include inadequate infrastructure, low income, user competency, digital literacy, and incentives for access, relevant content, and social acceptanceare all hurdles to internet access (van Deursen, 2020). Similar hurdles exist in Uganda inclusive of the refugee hosting districts. Digital inclusion purposely serves to address issues related to access, knowledge and skills or expertise at the level of digitalization (Hamburg & Lütgen, 2019).

Understanding the primary hurdles that e-learning systems encounter, the distribution challenges of home learning materials, technical support needed and the learners' perception about the adopted aspects of teaching was critical for the success of learning during schools' closure (Segbenya et al., 2022).

This study aimed to test the following hypotheses: Access to education is not influenced by the learner's demographics; there is no significant relationship between household income and access to education; household size has no effect on access to education during the COVID-19 lockdown; and there is no relationship between the learner's time spent on household chores and access to education during lockdown.

2. METHODOLOGY AND DATA SOURCES

This research utilized data from a cross-sectional Survey conducted in December 2020 under the auspices of the Forum for African Women Educationalists Uganda (FAWEU). This targeted boys and girls of age group 10-24 years, from 25 of 134 districts of Uganda. The study ultimately interviewed 6,394 young people from 3,201 households in 200 parishes. A total sample-size of 4,195 primary learners were included for analysis. The dependent variable is access to education during Lockdown period. According to the survey, respondents were asked whether they were engaged in any form of learning while at home during Covid-19 schools' closure. The Outcome variable is a binary outcome as those who accessed education were recoded as one (1) and the ones who never accessed education were recoded zero (0). Determinants for access were hypothesized as; individual level determinants (learner's sex, age, education level, disability and relationship to the household head) and household level determinants (household size, household main source of income and time spent on household chores and a community level determinant which is region of origin for the learners). Multivariate analysis was done using a mixed effects logistic regression model. All data analysis was done using STATA 15.0 statistical package. The statistical significance level was set at 5% ($p<0.05$).

Table 3.1: Study of variables and their description

Variable	Nature of variable	Categories and coding
Dependent Variable		
Access to education during COVID-19 pandemic	Binary	Never accessed education Access education
Independent Variables Individual level determinants		
Age	Ordinal	0. 10-14 1. 15-19 2. 20-24
Sex	Binary	Female Male
Learner's Education level	Ordinal	Lower Primary Upper Primary
Place of residence	Binary	Rural Urban
Learner staying with Biological Parents (How is the Main Care giver)	Nominal	Biological Mother Biological Father Guardian
Learner's disability status	Binary	Learner has no disability Learner has disability
Household level determinants		
Average time spent on house chores	Nominal	less than 1 hour Between 1-3 hours Between 4-6 hours More than 6 hours
HH main source of income	Nominal	Farming Non farming
Learner's involvement in economic activity	Binary	No Yes
Region	Nominal	Central Western Eastern Northern
Household Size	Ordinal	Less than 5 members Between 5 to 9 members More than 9 members

At univariate analysis, descriptive statistics were presented for the selected independent variables; this was mainly to explore each variable separately. Frequency distribution tables were constructed to show the distribution of each variable in the study.

Chi-square tests were done to test associations between two variables at Bivariate level of analysis. Since the outcome of interest (access to education) is a binary outcome, contingency tables were employed. Contingency tables use a Pearson chi-square test as the test for independence between two variables. The study used observed frequencies of access to education during COVID-19 pandemic to calculate the expected number of learners that accessed education during COVID-19 pandemic in Uganda.

The chi-square statistics value depends on the discrepancies measured by the difference between the observed (Oij) and expected (Eij) frequencies in cells of the contingency table ($Oij - Eij$). That is, the greater the discrepancies, the more evidence that the variables are against the null hypothesis. The chi-square statistics is presented as;

$$2 \quad \sum^{r} \sum^{c} \quad (Oij{-}Eij) \quad \ldots\ldots 3.1$$

Where; $j = 1, 2 \ldots\ c$.

$i = 1, 2 \ldots\ r$

Oij = Observed number of learners

Eij = Expected number of learners that accessed education during lockdown.

c = Number of categories of the dependent variable (access to education).

r = Number of categories of the independent variable.
Rejection of null hypothesis

The underlying theory states that the null hypothesis is rejected if $\chi^2_c > \chi^2_t$, where χ^2_t is the tabulated chi-square value with $(r - 1)\ (c - 1)$ degrees of freedom at 5% level of significance and χ^2_c is a computed chi-square value.

At the multivariate level of analysis**,** the analysis was to determine how each independent variable affects the dependent variable. The multilevel mixed-effects model was fitted to determine the effect of the covariates on access to education during the COVID-19 pandemic. The advantages of the mixed effects regression model is an example of a multilevel modelling approach are; enables the estimation of both fixed and random effects simultaneously since it handles clustered or grouped data to study the random effects and deals with data in which the times of the measurements vary from subject to subject to measure the fixed effects (Buxton, 2008).The model clearly tell us the total variability in access to education during COVID-19 pandemic that is attributable to both learner level factors and region level factors.

The mixed-effects logistic model was appropriate for this analysis because the outcome variable is a binary outcome that indicates whether a learner accessed education during the COVID-19 pandemic or not. The assumption in this analysis is that the probability of learners from the same regions accessing education during the COVID-19 pandemic is similar due to the shared region environment. Similarly, region's characteristics that influence access to education are more similar in one region. The model was fitted for the presence of a relationship between the dependent and independent variables. The independent variables used at this level of analysis were those that showed a strong association with access to education at the bivariate level of analysis (p-value < 0.05). The odds ratio was used to indicate the risk of a learner not accessing education in relation to the variable's reference category.

Multilevel analysis is a general term referring to statistical methods appropriate for the analysis of data sets comprising several types of units of analysis. The levels in the multilevel analysis are another name for the different types of units of analysis.
For the i^{th} observation (learner) in the j^{th} region, we observe a dichotomous response:
$Yij = 1$, for a learner who accessed education during COVID-19 pandemic 0, otherwise. We assume that;
$Yij = Bernouli(Pij)$ ……………………………………………………………………………3.2
Independently for $i = 1, \ldots\ldots\ldots\ldots, nj$ and $j = 1,2, \ldots \ldots, M$
Where;

$Pij = Pr(Yij = 1)$ The probability that i^{th}observation (learner) has accessed education.
Therefore, considering a two-level model, where a series of M=4 independent regions, and conditional on a set of random effectsuj.

$Pr(Y_{ij} = 1|X_{ij} , u_j) = H(X_{ij} \beta + z_{ij}u_j)$..3.3

For $j = 1, . . . , M$ regions, with region $j$consisting of $i = 1,$ $, n_j$ observations (learners). The $1 \times p$row vector $X_{ij}$are
the covariates for the fixed effects each with regression coefficients (fixed effects)β. The $1 \times q$ vector z_{ij} are the covariates corresponding to the random effects which can also be used to represent both random intercepts and random coefficients. For example, in a random-intercept model, z_{ij} is simply the scalar 1. The random effects u_j are M realizations from a multivariate normal distribution with mean 0 and $q \times q$variance matrix$\sum$. $H(.\ )$Is the logistic cumulative distribution function, which maps the linear predictor to the probability of a success (accessed education during lockdown)($Y_{ij} = 1$), so that; $H(v) = exp(v)/(1 + exp(v))$

Equation 3.3 can also be stated in terms of a latent linear response, where only $Y_{ij} = I(Y_{ij}{}^* > 0)$ is observed for the latent,

$Y_{ij}{}^* = X_{ij}\beta + z_{ij}u_j + \varepsilon_{ij}$……………………………………………………………3.4

Limitations of the study

The study only covered 25 districts out of the 134 districts (18 percent) of which 200 parishes were sampled out and 2 villages per parish which may not give a general picture for the whole country regarding access to education due to the heterogeneity between districts. And also, did not capture the different partners how supported education which is very important while exploring the impact of COVID-19 lockdown of access to education.

1.1.1 RESULTS AND DISCUSSION

1.2 Results

The study's findings show that 41.8% (1,754) learners had access to education during the lockdown, while 58.2% (2,441) did not. Furthermore, the findings revealed that household source of income, average time spent on house chores, learner's education level, and the interaction between household size and source of income were all determinants of access to primary education during the Ugandan lockdown. It was discovered that learners whose parents were non-farmers were three times more likely to access education than those whose parents were farmers. Learners from households with more than 9 members and non-farming parents had a lower chance of accessing education during school closures than those whose parents were non-farmers and lived in households with fewer than 5 members. Learners in upper primary were three times more likely to access education during lockdown than their counterparts in lower primary.

1.2.1 Distribution of learners' characteristics by access to education during Lockdown:

Table 4.2 indicates that almost equal number of female and male learners had accessed education during schools' closure (50.2% vs. 49.8%). Furthermore, results from table 4.2 show that 79% of learners who accessed education did not work for money during school closures. The results show that the majority (35.1%) of learners who did not access education during school closures were from the northern region, while the central region had the lowest proportion (17.7%) of the learners who did not access education.

Table 4.2 also showed that 96% of the learners who accessed education had no disability. The majority of students (64.5%) who received education during school closures were in upper primary. In addition, 79% of the learners who accessed education were between the ages of 10 and 14. 45% of students who did not attend school during the closure spent 1 to 3 hours doing household chores. In addition, 56.3% of learners who did not receive an education lived in rural areas. Households with 5 to 9 members had the highest percentage (71.6%) of learners who accessed education. According to Table 4.2, 46% of learners who did not access education were cared for primarily by their biological fathers. Furthermore, the majority of the learners (71.0%) who did not access education during school closures were from households whose main source of income was farming.

1.2.2 Relationship between access to education and learner's factors:

Cross tabulations were used to determine the relationship between each learner factor and access to education during the COVID-19 lockdown period. The chi-square statistic was used to assess associations. Table 4.2 shows that region, education level, learner age, average time spent on house chores, household size, caregivers, and household source of income were all significant at the 5% level. This indicates that region, learner's education level, learner's age, average time spent on house chores, household size, type of caregiver, and household source of income had a significant effect on learner's access to education during the COVID-19 lockdown.

Table 4.2: Relationship between access to education during lockdown and learner's factors

Did not access learning			Accessed learning			
Variable	**Percentage**	**N**	**Percentage**	**N**	**P-Value**	**Chi-square Value**
Gender					0.760	0.0934
Male	50.3	1,228	49.8	874		
Female	49.7	1,213	50.2	880		
Worked for money during Lockdown					0.073	3.2151
No	81.0	1,978	78.8	1,382		
Yes	19.0	463	21.2	372		
Region					0.000	43.2701
Central	17.7	433	25.5	447		
Western	25.4	621	22.6	398		
Eastern	21.8	531	17.2	301		
Northern	35.1	856	34.7	608		
Learner disability					0.093	2.8200
Had no disability	95.3	2,326	96.4	1,690		
Had disability	4.7	115	3.6	64		
Education level					0.000	186.2862
Lower primary	56.9	1,388	35.5	623		
Upper primary	43.1	1,053	64.5	1,131		
Age of learner					0.000	22.5860
10-14	84.6	2,065	79.3	1,390		
15-19	14.9	363	20.4	358		
20-24	0.5	13	0.3	6		
Average time spent on house chores					0.000	65.7696
less than 1 hour	12.4	302	20.1	353		
Between 1-3 hours	45.4	1,108	46.1	809		
Between 4-6 hours	34.9	851	25.9	455		
More than 6 hours	7.4	180	7.8	137		
Place of residence					0.300	1.0762
Rural	56.3	1,374	54.7	959		
Urban	43.7	1,067	45.3	795		
Household size					0.000	15.4074
< 5	13.5	330	15.6	274		
5-9	69.5	1,696	71.6	1,255		
>9	17.0	415	12.8	225		
Care giver					0.000	29.9796
Biological Mother	42.3	1,033	47.5	833		
Biological Father	46.3	1,131	38.1	668		
Guardian	11.4	277	14.4	253		
Household source of income					0.000	128.9041
Farmer	71.0	1,732	53.9	945		
Non-Farmer	29.0	709	46.1	809		

1.2.3 Determinants of access to education during Covid-19 lockdown in Uganda:

To investigate the effect of each covariate on access to education during Covid-19 lockdown in Uganda, a mixed effects logistic regression model was fitted with random effects for each region.

Table 4.3 shows that learners in the upper primary were three times more likely to access education during COVID-19 lockdown than their counterparts in the lower primary (OR= 2.515, P=0.000). Additionally, learners who spent more than one-hour doing household chores were less likely to access education during the COVID-19 lockdown than those who spent less than one hour. However, a study conducted in Sri Lanka among Sri Lankan undergraduate students found that workload and time had no impact on online education (Sriyalatha & Kumarasinghe, 2021). This finding could be as result that many learners/students might have been overwhelmed with household chores during schools' closure leaving little or no time to concentrate on the learning platforms that were availed during schools' closure. Furthermore, majority of learners in Uganda had limited access to offline learning assets (Tumwesige, 2020) which might have forced parents to occupy their children with household chores, limiting their accessibility to education.

Table 4.3 also shows that learners whose parents were non-farmers had more odds of accessing education compared to learners whose parents were farmers (OR=2.689, P= 0.000). Furthermore, table 4.3 indicates that learners from households with more than 9 members and non-farming parents had a reduced likelihood of accessing education during school closures than those with non-farming parents and households with fewer than 5 members (OR=0.520, P=0.010). Table 4.5 also indicates that learners aged 15-19 years were more likely to access education during school closures than those aged 10-14 years (OR= 1.195, P= 0.053; 10% C.I).

A study by (Alzahrani & O'Toole, 2017), proved that learners who had online gadgets like computers and phones had significantly more positive attitudes towards accepting e-learning programmes which implies that students could access any online platforms to engage in learning if there was a need. This result is also consistent with other studies by (Maarop & Embi, 2016; Mayora, 2006; Oluniyi, 2011) showed that online device accessibility had a positive effect on student attitudes toward using them. When students have the necessary internet devices and can use them for online learning, they will accept to participate in online learning programs (Leszczyński et al., 2018). Similarly, (van Deursen, 2020) showed that material internet access contributes positively to all uses and outcomes, and skills access has a positive relationship with education related information. This can be as a fact that learners with access to offline assets like Televisions and radios are experienced and used to the assets thus making it easier for education access usage in times of crisis like the COVID-19 pandemic.

The intra-region correlation coefficient (ICC) in variance components model is *ICC*= 0.0156, implying that 2% of the total variability in learner's access to education during COVID-19 lockdown is significantly attributable to the region level factors, whereas the remaining 98% is attributable to learner's level factors. Table 4.3 also shows no significant association between learner's age, household size and access to education during COVID-19 lockdown.

Table 4.3: **Mixed effects logistic regression of access to education and learner's factors**

Variable	**Odds Ratio**	**Standard Error (SE)**	**P-Value**	**ıfidence Interval 95% (C.I)**
Education level*				
Lower primary Upper primary	- 2.515	-	- 0.000	-
		0. 179		2.187 - 2.892
Age of learner**				
10-14	- 1.195	-	- 0.053	-
15-19	0.451	0. 110	0.127	0. 998 - 1.432
20-24		0. 235		0. 162 - 1.253
Average time spent on house chores*				
less than 1 hour Between 1-3 hours	-	-	- 0.000	-
Between 4-6 hours More than 6	0 .599	0 .058	0.000	0.495 - 0.724
hours	0 .409	0 .043	0.000	0.332 - 0.503
	0 .507	0 .075		0.379 - 0.678
Household size				
< 5	- 1.113	- 0.146	- 0.415	-
5-9	0.917	0.149	0.594	0.860 - 1.440
>9				0.667 - 1.261
Household source of income*				
Farmer	- 2.689	- 0.477	- 0.000	-
Non-Farmer				1.899 - 3.807
Household size## Household source of income*				

<5# Non-Farmer	- 0.713	- 0.139	- 0.083	-
5-9# Non-Farmer	0.520	0.131	0.010	0.486 - 1.045
>9# Non-Farmer				0.317 - 0.853
Constant	0.584	0.111	0.005	0.402 - 0.848
Random-effects Parameters				
Region				
var(_cons)	0.052	0.041		0.011 - 0.244

LR test vs. logistic model: chi2 (2) = 27.82 Prob > chi2 = 0.0000
Significant at 5% confidence interval, **significant at 10% confidence interval

1.3 CONCLUSION AND RECOMMENDATIONS

1.4 Conclusion

The main objective of this study was to identify the determinants of access to education during Covid-19 lockdown among primary school going children in Uganda. Results from the mixed effects logistics regression shows that Age of Learners, Learner's education level, Average time spent on house chores, Household source of income and Household size with Household source of income interaction significantly had determined access to learning Covid-19 lockdown in Uganda.

Regarding research hypotheses, results have shown that; access to education during Covid-19 lockdown in Uganda was attributable to the learner's demographic factors. Furthermore, results indicated that there was a significant relationship between household size and access to education/learning during lockdown in the sampled 25 districts of Uganda. And also, household source of income had an effect on access to education during Covid-19 lockdown in Uganda.

1.5 Recommendations

Findings from this study add to the knowledge of access to education during the lockdown in Uganda. Using the mixed effects logistic model, evidence about the determinants of access to education during lockdown was obtained and policy makers and education partners were facilitated with baseline information vital for designing interventions for access to education in Uganda during pandemics which could lead to schools' closure.

To have a large number of learners accessing education during pandemics like the COVID-19 pandemic, government and education supporting partners should invest and provide learners in Uganda with training programs on how to spend time during pandemics and holidays. Furthermore, support of household to engage in economic activities should be prioritized to increase access to education in Uganda. Also, government and the reproductive health supporting partners should formulate programmes aimed at sensitizing and mind change for citizens in Uganda about the importance of family planning and having few children.

According to the diffusion of innovations theory and the theory of technological adoption (Network Intelligence Studies, 2020.; Understanding Diffusion of Innovations 2, 2018.), the adoption of 50 percent online learning policy at university education should also be adopted at early stages of education based on learners and teachers' willingness to try new technologies as a way of "leverage technology to enhance education delivery" and in case of any immersion that will lead to the closure of education institutions, education can still go on.

Future studies should focus on identifying data sources in Uganda that would allow analyzing the extraneous determinants that were not included in this study and elucidate how they contributed to the observed access to education during COVID-19 lockdown in Uganda.

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Bio-data

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Annex

2.1 Regression diagnostics results:

Using the variance inflation factor, autocorrelation problems amongst the variables can be identified. As a rule of thumb, a variable whose VIF values are greater than 10 may merit further investigation and a tolerance value lower than 0.1 is comparable to a VIF of 10. It means that the variable could be considered as a linear combination of other independent variables.

Table 8.4 indicates that autocorrelation problems amongst the variables; region, education level, age of learner, average time spent on house chores, household size, Care givers and Household source of income with access to education during COVID-19 pandemic does not exist since their variance inflation factor is less than 10 for each factor. The variables were maintained for the mixed effects logistic regression analysis.

Table 8.4: Multicollinearity test

Variable	VIF	1/VIF
Region		1.040.9618
Average time spent on house chores		1.040.9624
Education level		1.130.8874
Age of learner		1.150.8666
Household size		1.010.9884
Care giver		1.010.9919
Household source of income		1.020.9838
Mean VIF		1.06

The Hosmer-Lemeshow test (HL test) is a goodness of fit test for logistic regression. Results from table 8.5 shows a small chi-squared value with a p-value = 0.9779. Therefore, at $\alpha = 0.05$ we fail to reject the hypothesis that the data fit the model and conclude that the model provides adequate fit.

Table 8.5: Hosmer-Lemeshow's test for goodness of fit

Hosmer- Lemeshow's test	**RESULTS**
Number of groups	10
Hosmer-Lemeshow's chi2(8)	2.10
Prob.>chi2	0.9779