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Evaluating the Role of Maternal Income in Mediating the Effect of Mother's Education on under Five Child Mortality in Kenya

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

Aims/ Objectives: The study identified the role of maternal income in mediating the effect of a mother's education level on UFCM.
Study Design: We sourced secondary data from a 2014 Kenya Health Demographic Health Survey (KHDS). We analyzed data to determine mortality among the under-five children.
Place and Duration of Study: Department of mathematics and Actuarial science, the Catholic University of Eastern Africa, Nairobi, Kenya.
Methodology: We then conducted regression with mediation to assess the effect of a mother's education on UFCM in the presence of a mediator, "mothers income." We also determined the direct, total and indirect effects of the independent variable in the presence of mediation.
Results: The results indicate that maternal education is directly important on UFCM. Maternal education level also channeled its effects through maternal income. Change from no education level to primary education level would reduce the number of deaths by 1.9 deaths per 1000 children. Of this decrease, 0.5 fewer deaths were attributed to the maternal income pathway representing 26 percent of the total effect.

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Conclusion: If an intervention could improve, the maternal income of mothers at no education level to that of mothers at higher education level while keeping the other aspects of social deprivation constant we could eliminate 26% of the education level effect.

Keywords: Mediation; Aalen additive model; child mortality; total effect.

2010 Mathematics Subject Classification: 53C25; 83C05; 57N16.

1 Introduction

One of the great indicators of health of a country is the under-five child mortality rate. Kenya, just like other Sub-Saharan countries, have recorded high cases of under-five deaths. The Sustainable Development Goal(SDG) number 3, target 3.2 has not been achieved in Kenya,with 43.2 deaths per 1000 live births being reported in the year 2019(UNICEF,2019) which is way above the 25 deaths per 1000 that is expected. This work therefore aims at evaluating determinants of Under Five Child Mortality(UFCM) using appropriate statistical models and assumptions. We have in this case applied regression with mediation and appropriate survival analysis models to conduct this analysis, taking into account the rarely considered aspect of a possibility of mediators on some useful UFCM determinants.

The past two decades has seen great achievements made globally towards reducing deaths [1]. 99% of the annual under-five deaths are registered in the low and middle income countries (LMICs), while 50% of such deaths are recorded in the Sub-Saharan Africa alone [1]. Consequently, there is a need to have more efforts to reduce these numbers so as to meet one of the pillars of the sustainable development goal (SDGs), which is prevention of under five child mortality and achieve below 25/1000 child deaths for all nations [1]. One of the country's socio-economic development measure on quality of maternal life is the child mortality [2].

Demographics and child mortality indicators are represented in demographic and health surveys (DHS), which are series of national representative surveys. These data sets help health stakeholders understand the environmental, demographics, social, economic, environmental, community and health risk–factors. The data collected include broad scope of risk factors of UFCM.

DHS data sets have previously been used by [3, 4, 5] studying the risk factors of under-five mortality in SSA. Among the significant predictors of child survival indicators are based in the risk factors that may include living in remote areas, short preceding birth intervals, high parity, male children, high number of births and low mother's education.

A study on determinants of under five child mortality on rural and urban Kenya used the 2008-2009 KHDS data and found out that determinants of UFCM differ in rural and urban areas in Kenya. Poverty was also identified as a key predictor for mortality in rural areas [6].

Education level of individual reflects their health awareness, thus the more an individual is educated, the more he becomes health privy. Therefore, education level is associated with life expectancy since educated individuals participate and promote better health behaviors. The education level of a mother indicates the child's likelihood of survival whenever a complex health problem exists [7]. Education level raises the mothers skills and self-confidence. This is because educated mothers are more exposed to information compared to their uneducated counterparts. Therefore, the way an educated mother would respond to child health issues will be different from uneducated mother. An educated mother possess better child care traits due to the difference in social and economic class. Education aids women to stun barriers set by societal norms which may harm their children. Transformation through education can be achieved through policy intervention. Increasing women's education level helps in reducing the child mortality [8].

In order to improve child care practices and reduce early childhood mortality, health stakeholders have focused on improving the mothers education level. Besides, education improves the mothers' domestic management skills, which are crucial in basic health care and promote modern medical services [9]. Under-five mortality child mortality is also caused by unplanned pregnancies, thus, a need to increase contraceptive coverage is essential to manage high risk-births. This explains why increasing access to education and economic empowerment among mothers within sub-Saharan Africa could help achieve multiple improved health benefits [10].

Understanding under-five mortality in Uganda, the determinants or risk factors were found to be; mother's educational level, mother's age group, type of residence, education level of partner, birth status ,gender of child, wealth index, children ever born, birth order ,religion, type of toilet facility, mothers occupation, births in the past one year, children below five years in household, gender of head of the household, source of drinking water and age of mother at first birth [5].It is clear that such factors affect UFCM.

A child's mother traits are significant in affecting the child growth and well-being. Parental socio-economic status is crucial in the child's' healthy living and as such determines the progress towards common childhood illnesses [11]. A study in Kenya [13] sought to comprehend the factors affecting UFCM between 1990 and 2015 towards fast-tracking the progress in Kenya by 2030. The analysis employed hierarchical multivariate linear regression. They analyzed KHDS data between 1989 and 2014. Household wealth, maternal literacy, reproductive health of mother and nutrition were found to be some of the determinants.

Daniel et al[12] studied determining factors of infant and child mortality in Kenya using Cox-Proportional hazards model via 2008/09 KHDS data. The findings of the study established that child mortality is related to education, occupation of mother, age, among others.

Studies examining the mediation among risk factors related with under-five mortality in Kenya are limited. Most of these methods do not consider other factors effects. These various studies on UFCM mortality leave a question on how factors are mathematically related to the mortality rate in the presence of mediation. The incidence of comparatively higher proportion of SSA validates the need to categorize and analyze mathematically the major influencers of infant mortality in the presence of mediation.

Epidemiological research values investigations of this kind since they link the causal pathways between exposure and the outcome. Interventions or preventive strategies are crucial decision making processes among the health stakeholders that could help protect the patients or population subgroups [14]. Several studies on under five child mortality proposed use of different modelling tools. Majority of those methods are not applied on survival data.

Researchers and health practitioners have used traditional approach based on estimated hazard ratios from Cox models to assess the magnitude of the pathways from mothers education through maternal income to child mortality. This is achieved using both with or without adjusting for maternal income, the potential mediator. Education changes via mediation alters hazard ratios, which might have some severe shortcomings [15]. These changes, which are based on hazard ratios cannot be given a casual interpretation.Proportional hazards assumptions can also never be satisfied for both models with or without the mediator.

Additive models complement the known proportional hazards model by describing the relationship of covariates and failure times. This was measured by finding the risk difference instead of the risk ratio. Univariate or multivariate approach can be used to perform mediation analysis. Univariate analysis means that each mediator is analyzed separately[16]. Multivariate analysis indicate that the effect of mediation are not examined distinctly, but inclusive of the contemplation of other variables [17]. The Aalen additive model is regularly used in mediation analysis and expansively used in survival data. The Aalen additive model do not assume proportional hazards that are used in most classical survival analysis tools, or more so the influence of time varying co variates. The Aalen additive model has its strength on its ability to estimate non-negative change in the rate during comparison of an assumed exposure group to the reference group.

The main objective is to evaluate the function of maternal income in mediating the effect of mother's education on under-five child mortality in Kenya. A univariate mediation analysis, on the role of maternal income in mediating the effects of education on mortality in the KHDS survival data is carried out.An Aalen additive model is used to determine the effect of maternal education on UFCM and decomposition on additive hazards scale in estimating total, direct and indirect effects is done. This study has three main contributions:

- Run a regression of maternal income on education
- To formulate an Aalen additive model determining how maternal income mediates the effect of maternal education on under five child mortality.
- Total, direct and indirect effects are estimated via decomposition of additive hazards scale.

Lang and Hansen [16] published a paper focusing on survival context in terms direct and indirect effects , which is related to the current study.

We propose to use the results from this study to enlighten and reinforce existing national policies and intervention strategies whose aim is to reduce under-five mortality in the country. The rest of the paper is outlined as follows: Section 2 presents the methods. Section 3 presents data analysis, findings and results. Section 4 discusses the results and the findings. Section 5 presents a conclusion of the research.

2 Methods

The mediation models are concerned with seeking answers to the relationship between two variables based on how, or why questions. We hypothesize M as an intervening or mediating variable to show the relationship between X and Y. Where X is an independent variable, and Y is a dependent variable or outcome. The test for statistical mediation has been supported by recent studies based on regression equation's coefficients from two or more equations as follows:

$$Y = i_1 + cx + e_1 \tag{2.1}$$

$$Y = i_2 + c'x + bm + e_2 \tag{2.2}$$

$$M = i_3 + ax + e_3 \tag{2.3}$$

Mediation analysis uses a mediator to investigate the effect of an exposure on an outcome through a mediator. A vast discussion on mediation analysis can be found in Martinussen and Sheike by [18]. The Aalen additive model being additive ,is directly suitable to incorporating the role of mediation as opposed to other forms of survival regression models. Besides the additive models allows for the effect of covariates to vary with time which is not the case for basic forms of multiplicative survival regression models, such as the Cox PH model. The method helps in obtaining a simple and intuitive understanding of mediation measure, such as the per unit time additional cases [16]. When compared to relative measures, absolute effect measures are predominantly applicable for public policies and public health interventions [14]. This is due to their clarity on matters of public health impact, thus easily intervening on the mediator and exposure interest.

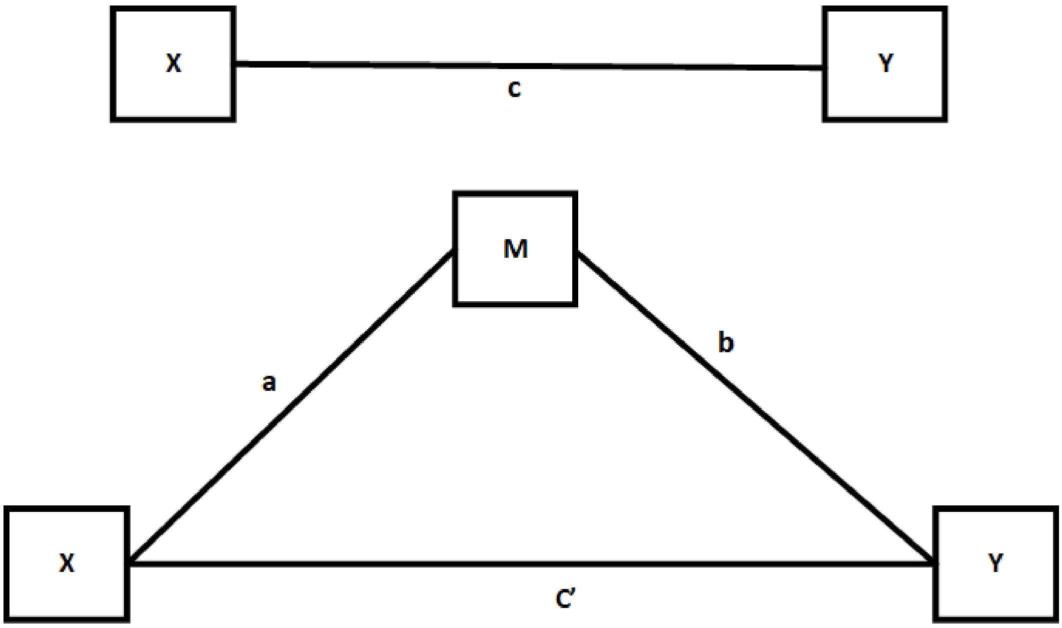

Fig. 1. Where X= the independent variable, Y= the dependent variable, and M= the mediating variable. c is the overall effect of the independent variable on Y; c' is the effect of the independent variable on Y controlling for M; b is the effect of the mediating variable on Y; a is the effect of the independent variable on the mediator; i_1, i_2, and i_3 are the intercepts for each equation; and e_1, e_2, and e_3 are the corresponding residuals in each equation [19].

Numerous research have presented different mediation analysis methods [20, 19, 21, 20]. Lange and Hansen [16] suggested a univariate method analyzing mediation using a survival context as a case study. The model framework proposed contained the survival time T, either the interest time, or the time of censoring and X a binary exposure, that is equated to 1 in the presence of exposure and 0 otherwise. M represents the potential mediators while Z represent other baseline covariates.

2.1 Aalen additive model

This is a semi-parametric model estimating the hazard time t as a linear function of unspecified baseline hazard and covariates [14]. In this semi-parametric model, the baseline hazards are additive for the effects of covariates (constant or variable effect). We can use this model to determine the relation between hazard function and failure time T_i with p-dimensional vector X(covariates).

The Aalen additive hazards model expresses the hazards rate at time t of the ^{ith} of n individuals with vector of covariates $X_i(t) = (X_{i_1}, X_{i_2}, ...X_{i_p})'$, that is given by

$$h(t|X_i(t)) = \beta_0(t) + \beta_1(t)X_{i_{1(t)}} + ...\beta_p(t)X_{i_{p(t)}} \tag{2.4}$$

where $\beta_i(t) = (\beta_0(t), \beta_1(t), ...\beta_p(t))'$ is the vector of parameter functions that may be estimated and $\beta_0(t)$ is the base line hazard(Aalen 1989).

2.2 Aalen additive model with mediation

Decomposition estimates will be derived based on Aalen additive hazard model. The additional cases per unit time can be obtained,which is a to simple and intuitively understandable the measure of mediation. These can be obtained by adapting Aalen additive hazard model [16]. This measure is based on counterfactuals and measures the natural direct and indirect effects. The technique permit a casual explanation of mediated effect (based on rate of additional cases).

The probability of experiencing an event at time t is measured within the next unit of time, suppose an individual has no prior experience before time t is measured by the rate at time t [16, p. 576]. The Cox regression can be used to estimate the number of times the rate is greater in the existence of the exposure X relative to the reference X = 0 (hazard ratio). Lange and Hansen [16] used an Aalen additive hazard model to estimate the rate, as the ratio modeled by Cox is not related to an absolute number of events. The results based on the Aalen additive hazard model , estimated the absolute change in the rate during comparison of a given exposure group to the reference group [16, p. 576]. It does not assume a proportional hazards, and can include time-varying covariate effects, which is an advantage compared to the Cox model.

The Aalen model specifies that the rate as a function of mediator (m), other baseline covariates (z) and exposure (x) is

$$\gamma(t; x, m, z) = \lambda_0(t) + \lambda_1(t)x + \lambda_2(t)z + \lambda(t)m \tag{2.5}$$

Where$\gamma(t; x, m, z)$ is the rate, which is written as function of mediator (m), other baseline covariates (z) and exposure (x). $\lambda_j(t)$ are potentially time –dependent functions. A simple linear regression can be used to model the mediator,assuming that it is as a normal variable. Therefore,given other covariates (z) and exposure (x) the mediator is given by

$$M = \alpha_0 + \alpha_1 x + \alpha_2 z + e. \tag{2.6}$$

where e is normally distributed error with zero mean and its variance σ^2. The parameters $\alpha_0, \alpha_1, \alpha_2, \sigma^2$ and the collection of functions $\lambda_0(t), ..., \lambda_3(t)$ is estimated using the "timereg" package in R programming. Suppose the exposure is set to X and the mediator to M, then we can denote the counterfactual rate for the event by $\gamma(t; x, m, c)$ in the presence of other baseline covariates. The rate difference scale at time t is used to measure the total casual effect of changing the exposure from x^* to x is

$$\begin{aligned} \gamma(t; x, M^x) - \gamma(t; x*, M^{x^*}) &= \\ \gamma(t; x, M^x) - \gamma(t; x*, M^{x^*}) + \gamma(t; x*, M^x) - \gamma(t; x*, M^{x^*}) \\ &= \lambda_1(t)(x - x^*) + \lambda_3\alpha_1(t)(x - x^*), \end{aligned}$$

that is $TE(t) = DE(t) + IE(t)$ where IE, DE and TE denote natural indirect effect, natural direct effect and total effect respectively. The number of deaths that can be attributed to mediation through the mediator is the indirect effect. The direct effect is the deaths attributed to the direct path (or to the mediators excluded in the analysis). The total effect is the deaths caused by changing the exposure and is given by the summation of direct and indirect effects [16].

Aalen additive model provides platform for directly obtaining confidence intervals for the direct effects. Combining the covariance matrices for parameter estimates of the regression and the Aalen model via simulation permits attainment of confidence intervals for the indirect and total effects. The assumptions of the model is that there are no confounding of the relationship between (i) Exposure and mediator, (ii) Mediator and outcome, and (iii) Exposure and outcome upon conditioning pre-exposure con founders [22].

2.3 Data

A secondary data set from the nationwide2014 Kenya Demographic health survey (KHDS) was used for this analysis. KHDS data sourced from a random sample of 20964 respondents gathered as part of the KHDS was analyzed. The data set provides information on under-five children. Such information may include sex, survival status, birth interval, birth status and weight. Other information may include household and community characteristics, such as health coverage, maternal and antenatal care, infant feeding practices and immunization coverage. The dependent variable was time until child mortality and event status. The status was dead within 0-59 months (coded 1) or alive at 5 years (coded 0) and representing censoring status. Right censored data is vastly discussed by[23]. Survival data concepts have been widely presented by numerous scholars.

2.4 Variables

The risk factors examined in the study were selected based on results from already published articles. They include sex of child, age of mother, mother's level of education and maternal income. Mother's education level is the exposure and maternal income is the mediator. Education is grouped in four categories; no education, primary education, secondary education and higher education. Household wealth level was used for maternal income. The wealth level was derived from an index computed using data on ownership. The outcome variable is mortality status and month of death. Status was recorded and subsequently coded according to whether the child is alive or not, with 0 for being alive while 1 for being dead within the first 5 years. Age at death is given in months. The covariates included in the model were sex of child and age. One exposure, one mediator and two covariates were considered. To investigate whether the total effect of mother's education level and the effect of mother's education level through maternal income varied by mother's education level, we repeat the analysis stratified by mother's education level (according to the data). In assessing mediation, we estimate natural direct effects or pure direct effects which is the variation in the predicted number of deaths per 1000 children-months per unit level change in mother's education level when the mediator maternal income is set at a value it would take at the reference level of mother's education level. Natural indirect effect is the difference in predicted number of deaths per 1000 children-months when the exposure mother's education level is kept constant but the mediator is changed.

The first step is to run a regression of maternal income on education adjusted for age and sex of child. This is used to examine associations of maternal income and education. The next step is to fit the Aalen additive model on mortality with sex of child, age, maternal income and education as covariates. This is to explore potential underlying mechanisms in these associations. The difference between the two is the effect of the mediator.

Confidence intervals are also provided for the proportion of mediation and the effect measure can be directly construed as the number of added cases of mortality due to variation in education levels and the number due to direct effects. Descriptive statistics are presented in Table 1. All analysis was conducted in R.

3 Results

In the present paper we adopt the ordinary least squares (OLS) in approximating the parameters. This was achieved via R-programming using the package 'timereg'. [16] discusses this technique widely. Descriptive statistics on mortality, mother's education, maternal income and covariates are presented in Table 1.

3.1 Descriptive characteristics

A total of 20964 children were identified in the 2014 KHDS data.Of these 871 had died and 20,093 were alive. Table 1 shows the descriptive characteristics of some the variables included in the study. Around 34 per cent of those dead were living in urban areas and 66 percent in rural areas. Among the dead children 54.6 percent were male and 45.4 percent were female.

Table 1. Descriptive characteristics of demographic and variables determining under five child mortality in Kenya,2014

	0 (N = 20093)	1 (N = 871)	TRUE (N = 20964)
Residence			
Urban	6532(32.5%)	296(34.0%)	6828(32.6%)
Rural	13561(67.5%)	575(66.0%)	14136(67.4%)
Education level			
No Education	4406(21.9%)	179(20.6%)	4585(21.9%)
Primary Education	10551(52.5%)	504(57.9%)	11055(52.7%)
Secondary Education	3857(19.2%)	146(16.8%)	4003(19.1%)
Higher education	1279(6.4%)	42(4.8%)	1321(6.3%)
Religion			
Roman Catholic	3706(18.4%)	139(16.0%)	3845(18.3%)
Protestant	12405(61.7%)	553(63.5%)	12958(61.8%)
Muslim	3364(16.7%)	156(17.9%)	3520(16.8%)
No religion	521(2.6%)	20(2.3%)	541(2.6%)
Other	59(0.3%)	3(0.3%)	62(0.3%)
Missing	38(0.2%)	0(0%)	38(0.2%)
Wealth index			
Poorest	6893(34.3%)	285(32.7%)	7178(34.2%)
Poorer	4154(20.7%)	194(22.3%)	4348(20.7%)
Middle	3334(16.6%)	163(18.7%)	3497(16.7%)
Richer	3001(14.9%)	130(14.9%)	3131(14.9%)
Richest	2711(13.5%)	99(11.4%)	2810(13.4%)
Sex			
Male	10157(50.6%)	476(54.6%)	10633(50.7%)
Female	9936(49.5%)	395(45.4%)	10331(49.3%)
Age group			
15-19	1024(5.1%)	28(3.2%)	1052(5.0%)
20-24	4773(23.8%)	210(24.1%)	4983(23.8%)
25-29	6143(30.6%)	250(28.7%)	6393(30.5%)
30-34	4009(20.0%)	179(20.6%)	4188(20.0%)
35-39	2659(13.2%)	117(13.4%)	2776(13.2%)
40-44	1164(5.8%)	69(7.9%)	1233(5.9%)
45-49	321(1.6%)	18(2.1%)	339(1.6%)
Birth type			
Single Birth	19596(97.5%)	784(90.0%)	20380(97.2%)
1st of multiple	240(1.2%)	52(6.0%)	292(1.4%)
2nd of multiple	257(1.3%)	35(4.0%)	292(1.4%)
No of children			
0	586(2.9%)	251(28.8%)	837(4.0%)
1	7415(36.9%)	372(42.7%)	7787(37.1%)
2	8314(41.4%)	198(22.7%)	8512(40.6%)
3	3086(15.4%)	38(4.4%)	3124(14.9%)
4	570(2.8%)	8(0.9%)	578(2.8%)
5	98(0.5%)	3(0.3%)	101(0.5%)
6	19(0.1%)	1(0.1%)	20(0.1%)
7	5(0.0%)	0(0%)	5(0.0%)

3.2 Regression of maternal income on education adjusting for age and sex

Table 2 suggests that on average mothers in higher education level have an income of 2.9 units higher than mothers in no education level, when adjusted for age and sex. Mothers in secondary education level have an income of 1.98units higher than mothers in no education level. Mothers in primary level have an income of 0.99 units higher than mothers in no education level .

Table 2. Parameter Estimates and Standard Errors fSES for the regression of maternal income on education adjusting for Age and sex

Coefficients	Estimate	Std. Error	t value	$Pr(>\|t\|)$
(Intercept)	1.281	0.048	26.565	$< 2e-16^{***}$
Age	0.005	0.001	3.942	$8.09e-05^{***}$
Sex	0.013	0.016	0.810	0.418
Primary education	0.987	0.021	47.064	$< 2e-16^{***}$
Secondary education	1.980	0.026	76.482	$< 2e-16^{***}$
Higher education	2.896	0.037	77.901	$< 2e-16^{***}$

Signif. codes: $0^{***}, 0.001^{**}, 0.01^{*}, 0.05^{\cdot}, 0.11$

Table 3. Parameter Estimates and Standard Errors from the Aalen additive model adjusting for maternal income , Education level, age and Sex.

Education level	Estimate(S.E) $x10^{-3}$
No education	0.00(0.00)
Primary education	-1.45(0.057)
Secondary education	-2.30(0.812)
Higher education	-2.75(0.26)
Maternal income	-2.16(0.728)

3.3 Aalen additive model adjusting for maternal income, education level, age and sex

Table 3. shows that children born of mother's in higher education level have a mortality rate that is $2.75X10^{-3}$ units lower than those of mothers in no education level adjusted for age and sex. Children born of mothers in secondary education level have a mortality rate that is $2.30X10^{-3}$units lower than those of mothers in no education level. Children born of mothers in primary education level have a mortality rate that is $1.45X10^{-3}$ units lower than those of mothers in no education level .

3.4 Mediation Analysis

Table 4. Mediation analysis of maternal income on mothers education level for Under Five Child Mortality

Outcomes	Total effect	Direct effect	Indirect effect
$0-1$	-1.9	-1.4	-0.5
0-II	-2.5	-2.3	-0.2
0-III	-3.5	-2.8	-0.7

As expected[10] high education level leads to a lower rate of child mortality.The effect of mothers education level has two components,direct effect without maternal income and mediation effect of maternal income.

Change from no education level to higher education level would reduce the number of deaths by 3.5 per 1000children$\beta = -3.5$ of this decrease 0.7 fewer deaths ($\beta = -0.7$) resulted from maternal income pathway(natural indirect effect)representing 20 percent of the total effect . This means that if, an intervention could enhance maternal income of no education level one to higher education level without affecting other features of social deprivation 20% of the education level effect could be eliminated.

Change from no education level to secondary level, would reduce the number of deaths by 2.5 per 1000children$\beta = -2.5$ of this decrease 0.1 fewer deaths($\beta = -0.1$)were attributed to maternal income pathway(natural indirect effect)representing 4% percent of the total effect . This shows that if, an intervention could enhance maternal income of education level one to secondary level without affecting other features of social deprivation 4% of the education level effect could be eliminated. Change from no education level to primary level would reduce the number of deaths by 1.9 per 1000children $\beta = -1.9$ of this decrease 0.5 fewer deaths($\beta = -0.5$) were attributed to maternal income pathway (natural indirect effect) representing 26% percent of the total effect. This implies that,suppose an intervention could improve maternal income of no education level to primary level while other aspects of social deprivation remain unchanged, 26% of the education level effect could be eliminated.

4 Discussion

Kenya is one of the countries in the region with high UFCM rates. Identifying factors leading to mortality among children under 5 years is crucial problem that needs consideration. This could help inform health and intervention strategies. The objective if this study was to identify the role played by maternal income in mediating the effect of mothers education level on UFCM. This work contributes to existing body of research on how to determine the effects of mediators in epidemiological literature.

The proposed study has used statistical modelling tools specifically linear regression and Aalen additive model to evaluate the role of maternal income in mediating the effect of mother's education on under five child mortality in Kenya. We adapted Aalen's additive model to help us make a simplified comprehensible measure which deviates from risk additivity in survival analysis. We are also able to directly estimate the absolute deviation from additivity of effects based on incidence rates with corresponding confidence intervals. In the analysis, the selection of covariates is alike that of Soe *et al.* [24].

The analysis indicated that maternal income is a mediator between maternal education and under five child mortality. Our study found out that education was inversely associated with UFCM and maternal income was a partial mediator of the relationship. For the regression model mothers in higher education level have an income of 2.58 units higher than mothers in no education level when adjusted for age and sex. The Aalen additive model shows that children born of mother's in higher education level have a mortality rate that is $2.75X10^{-3}$units lower than those of mothers in no education level adjusted for age and sex. From the confidence intervals high education level leads to a lower rate of child mortality. Change from no education level to primary education level would reduce the number of deaths by 1.9 per week per 1000 children. Of these cases 0.5 can be attributed to pathway through maternal income (natural indirect) as expected. Change from no education level to secondary level would reduce the number of deaths by 2.4 per week per 1000 children. Of these cases 0.1 can be attributed to pathway through maternal income as expected. Change from no education level to higher education level would reduce the number of deaths by 3.5 per week per 1000 children. Of these cases 0.7 can be attributed to pathway through maternal income as expected. This implies that, an intervention could improve maternal income of no education level to higher education level while other aspects of social deprivation remain unchanged 20% of the education level effect could be eliminated. Likewise, if an intervention that could improve maternal income of no education level to secondary level without affecting other features of societal deprivation 4% of the education level effect could be eliminated. An intervention that could improve maternal income of no education level to primary level while other aspects of social deprivation remain unchanged, then we could eliminate 26% of the education level effect.

Similarly, other studies within India and Sub-saharan Africa hinted at the crucial role the socio economic position plays on aiding the decision making on childhood illnesses. Thus, having a better education is regarded to increase a child healthy living. Kenya has recorded higher under-five children years mortality rate. The need to reduce under five child mortality which lies under one of the Social development Goals, has promoted use of modelling to understand effects of variables and their mediators. The Sustainable Development Goal (SDG) number 3, target 3.2 has not been achieved in Kenya, with 43.2 deaths per 1000 live births being reported in the year 2019(most recent world bank data). There is still a need to have more efforts in order to prevent and manage the neonatal child mortality. This will help boost the realization of the sustainable development goal, which is to achieve below 25/1000 child deaths in every nation (Unicef,2015).

Evaluation of mediators and interactions is vital in guiding the public health interventions, clinical decision making and health planning policy. The interventions are designed to change mediating variables that are hypothesized to be casually related to the outcome variable. By attempting to use varied techniques in analysis, more insights into the data becomes clearer thus development of better analysis.

5 Conclusion

The study involves quantification of mediation in a survival context. We applied an easier and interpretable measure of natural and indirect effects in addition to their confidence intervals. The additive hazard scale are used to calculate the effects. This helps in direct translation of expected no of extra cases. The method is illustrated by analysis of the linkage among education, maternal income and under-five mortality previously examined in the study of [24]. The results points to initial analysis which suggested that the effect of education on child mortality is mediated through maternal income. Our analysis also indicate confidence intervals for mediated proportion and the effect measure can be directly interpreted as the number of reduced cases due to differences in maternal income and the number due to direct effects. If an intervention could improve maternal income of mother's without affecting other features of societal deprivation the education level effect could be reduced. This means that if the interventions improve maternal income, then the rate of UFCM could be reduced.

The results of this study may contribute to improve relevant interventions for UFCM among children in Kenya. It will help Kenya government, non-governmental organizations and other partners in health sector to know and understand the important areas they need to focus on in order to develop policies and programmed projects to reduce UFCM, which is part of the SDGs and Presidents Big Four Agenda. The future research needs to extend the approach to incorporate interactions among covariates.

Competing Interests

Authors have declared that no competing interests exist.

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