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Survival regression model incorporating two mediators for under five child mortality in Kenya: Analysis of Kenya demographic health survey (KDHS)

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Abstract
Kenya is among the nations where the rates of mortality for children under the age of five are alarmingly high. Under-five mortality rate in Kenya, as reported by the 2014 Kenya Demographic Health Survey, stood at 52 deaths per 1000 live births. It is crucial to tackle the significant issue of identifying the factors contributing to the mortality of children under the age of five, as this knowledge can inform health strategies and interventions. One method for determining these factors is by employing regression models that make different assumptions, including assuming the presence of mediation. Mediation analysis is frequently performed to deepen our comprehension of the underlying mechanisms in well-established cause-and-effect relationships. The primary objective of this analysis is to disentangle the indirect effect, which operates through a specific intermediary (or mediator), from the remaining direct effect. It also quantifies the contributions of these effects to the overall impact of the exposure. In most mediation analyses, even when the focus is on a single mediator, it is important to consider the possibility of multiple mediators. Incorporating additional mediators decreases the chances of overlooking alternative pathways that connect the exposure to the outcome. However, the development of mediation models involving multiple mediators is currently constrained or needs more extensive advancement. The Aalen additive hazard model with multiple mediators is used. Aalen additive hazard models are employed in mediation analyses to consider the influence of the disparity in hazard rates. When conducting causal mediation analyses of survival outcomes involving multiple mediators, additive hazard models are utilized with utility demonstrated in an under five child mortality study (UFCM). The study involved investigation of the effect of maternal education on child mortality, in the presence of two mediators: maternal income and maternal health behaviour. We initially conducted one-mediator analyses, to examine the effect of the maternal education on UFCM mediated through the maternal health behaviour. A two-mediator model investigating path-specific effects is then conducted with the exposure being education level(s), two mediators, one being maternal income (M_1) and the other mediator being maternal health behaviour (M_2) and the outcome being under five child mortality (Y).
The influence of education on UFCM had different pathways in this study. The effect mediated through maternal income M_1 and possibly through maternal health behaviour M_2, had stronger effects (-0.36) than $\Delta S \rightarrow M_2 \rightarrow Y$ the effect of education on the outcome mediated only through maternal health behaviour M_2 (-0.036) (i.e not through maternal income M_1). Health activities and information relating to maternal health behaviour will have a significant effect if maternal income is increased.

Keywords: Additive hazard model, multiple mediators, path specific effects, survival analysis, causal mediation model

Introduction

Kenya, in sub-Saharan Africa, grapples with high child mortality rates, especially under-five deaths. Mediation analysis helps understand cause-effect mechanisms. It dissects direct and indirect impacts. Sub-Saharan Africa records substantial child mortality rates, including Kenya. Mediation analysis with multiple mediator's aids understanding. The study uses an additive hazard model for multiple mediators. The aim is to comprehend maternal education's impact on under-five mortality, mediated by maternal income and health behavior. This research delves into path-specific effects, enhancing mechanistic insight. The approach is vital for designing effective interventions.

Methods

Multiple mediation analysis methods in this study are presented using the Aalen additive models. A mediator is a variable that explains or partially explains the association between a predictor and an outcome. It operates as an intermediary in the causal pathway between the independent and dependent variable [3, 20]. The effect mediated by the mediator is often referred to as the indirect effect, as it represents the independent influence of the predictor on the dependent variable through the mediating variable.

Single Mediator Model

$$Y = i_1 + cx + e_1 \quad (1)$$

$$Y = i_2 + c'x + bm + e_2 \quad (2)$$

$$M = i_3 + ax + e_3 \quad (3)$$

where c is the regression coefficient that quantifies the relationship between the independent variable and the dependent variable, while accounting for the influence of the mediator, is denoted as a. On the other hand, c' represents the regression coefficient that captures the association between the mediator and the dependent variable, adjusting for the influence of the independent variable

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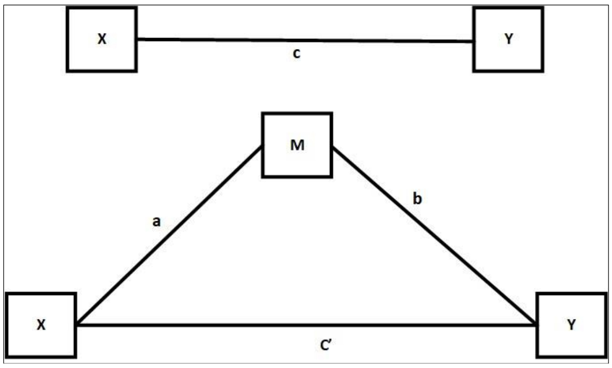

Fig 1: Figure, let us consider X as the independent variable, Y as the dependent variable, and M as the mediating variable.

The notation is as follows: c represents the overall effect of the independent variable X on the dependent variable Y, c' represents the effect of the independent variable X on the dependent variable Y while controlling for the mediating variable M. b signifies the effect of the mediating variable M on the dependent variable Y, and a represents the effect of the independent variable X on the mediating variable M. Additionally, i_1, i_2, and i_3 denote the intercepts for each equation, while e_1, e_2, and e_3 represent the corresponding residuals in each equation [9].

To identify the natural direct and indirect effects in mediation analyses involving an exposure variable X, a mediator M, and a survival outcome Y, a set of assumptions is necessary [24]. These assumptions can be stated as follows, given the presence of measured confounders X:

1. There is no confounding that affects the relationship between X and Y.
2. There is no confounding that affects the relationship between M and Y, conditional on X.
3. There is no confounding that influences the association between X and M.
4. There is no confounding of the relationship between M and Y that is caused by X.

These assumptions, conditional on measured confounders, are essential for accurately estimating and interpreting the natural direct and indirect effects in mediation analyses involving X, M, and Y.

Aalen additive hazard model

The Aalen additive hazards model describes the hazard rate at time t for the $i-th$ individual with vector covariates $Xt(t) = (X_{1i}, X_{2i}, \ldots, X_{pi})$. It is expressed as:

$$h(t|X_i(t)) = \beta_0(t) + \beta_1(t)x_i1(t) + \beta_2(t)x_i2(t) + \ldots + \beta_p(t)x_ip(t) \quad (4)$$

Here, $\beta_i(t)$ represents the vector of parametric functions, including $\beta_0(t)$ as the baseline hazard. These parametric functions can be estimated, and they capture the relationship between the covariates and the hazard rate at time t [1].

Aalen additive hazard model with one mediator

In the Aalen model, the rate, expressed as a function of the exposure (x), mediator (m), and other baseline covariates (z), can be represented as:

$$\gamma(t : x, m, z) = \lambda_0(t) + \lambda_1(t)x + \lambda_2(t)z + \lambda_3(t)m \quad (5)$$

Here, $\gamma(t : x, m, z)$ denotes the rate, and $\lambda_j(t)$ represents potentially time dependent functions. Assuming that the mediator follows a normal distribution and can be modeled through simple linear regression, the mediator (M) can be written as:

$$M = \alpha_0 + \alpha_1 x + \alpha_2 z + e \quad (6)$$

In this equation, e is a normally distributed error term with a mean of zero and a variance of σ^2. The "timereg" package is utilized to estimate the parameters $\alpha_0, \alpha_1, \alpha_2, \sigma^2$, as well as the collection of functions $\lambda_0(t), \ldots, \lambda_3(t)$. The parameter vector $\alpha = (\alpha_1, \ldots, \alpha_2)$ relates the independent variable to the mediating variables, while the parameter vector $\lambda = (\lambda_1, \ldots, \lambda_2)$ relates the mediators to the dependent variable, taking into account the effect of the independent variable [14].

Aalen additive hazard model with multiple mediators

The statistical methods for handling multiple mediators are a straightforward extension of the single mediator case. To test whether the mediators are significant predictors when both the independent variable and the mediators are included, the equation can be represented as:

$$Y = t'X + \beta_1 X_{M1} + \beta_2 X_{M2} + \ldots + \beta_i X_{Mi} + \epsilon_i \quad (7)$$

In this equation, the regression coefficients $\beta_1, \beta_2, \ldots, \beta_i$ represent the adjusted effects of each mediator. The coefficient t' denotes the regression coefficient that relates the independent variable to the dependent variable, accounting for the effects of the mediators. The term ϵ_i captures the unexplained variability.

Aalen additive hazard model for mediation analysis with one exposure and two mediators

In this section we present the Aalen additive hazard model method of mediation analysis involving a single exposure variable S, two mediators (M_1 and M_2), and a survival outcome, our methods can be applied. Furthermore, these methods can be readily extended to accommodate more than two mediators.

Specifically, we suggest utilizing two separate linear regression models, one for M_1 and another for M_2.

$$M_{1i} = \delta_x^T X_i + \delta_s S_i + \varepsilon_{m1i} \quad (8)$$

$$M_{2i} = \alpha_x^T X_i + \alpha_s S_i + \alpha_M M_{1i} + \varepsilon_{m2i}$$

Let X represent the covariates, where the initial element is 1 to account for the intercept. The error terms ε_{m1i} and ε_{m2i} are assumed to be independent and follow a normal distribution with a mean of zero. Their respective variances are denoted as $\sigma^2_{M_1}$ and $\sigma^2_{M_2}$. Our proposed model for the outcome Y, which is equivalent to $\lambda(t)$, is an additive hazard model defined as follows:

$$\lambda\left(\frac{t}{X_i}, S_i, M_{1i}, M_{2i}\right) = \lambda_t = \lambda_0(t) + \lambda_x^T X_i^* + \lambda_s S_i + \lambda'_{M1} M_{1i} + \lambda_{M2} M_{2i} \quad (9)$$

where λ_i is the hazard of dying for subject i; $\lambda_0(t)$ is the baseline hazard; and and $\lambda_X, \lambda_s, \lambda_{M1}$ and λ_{M2} are regression coefficients for the covariates $X*$ (X without the first element), education S, maternal income M_1 and maternal health behaviour M_2, respectively.

The estimation of δ_s and (α_s, α_m) can be carried out with ordinary least square estimator with respective variance/covariance, σ_δ^2 and $\sum_\alpha$, and the estimation of $\lambda_s, \lambda_{m1}, \lambda_{m2}$ can also be carried out in R library time reg with covariance estimate $\sum_\lambda$. The influence of mediators can be understood by examining specific effects along different paths. Causal mediation models can be represented using a directed acyclic graph (DAG), as demonstrated by [19]. In our study, we provide explicit mathematical expressions for the path-specific effects within the model, and these effects can be easily interpreted by referring to a causal diagram.

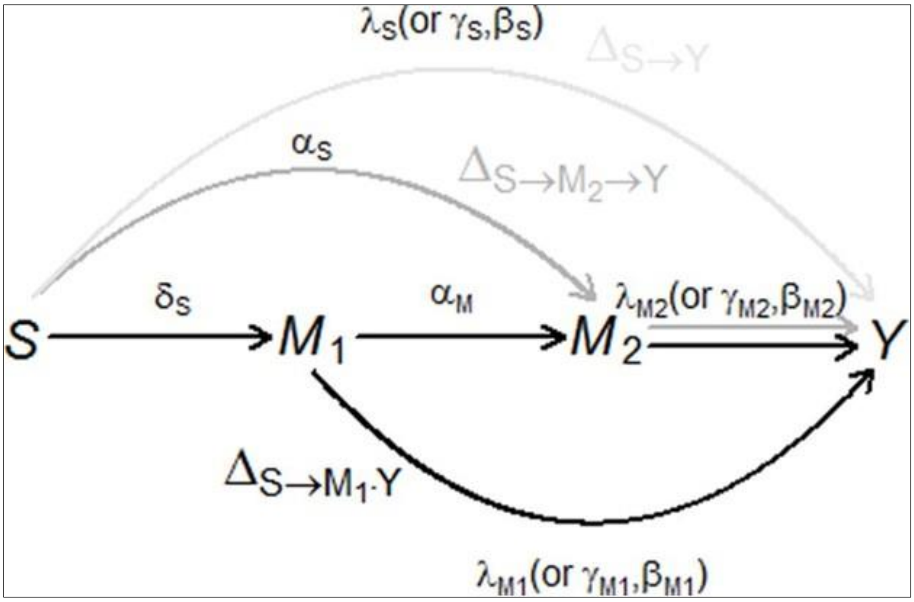

Fig 2: The path of $\Delta S \rightarrow Y$ has only one arrow with effect parameter $\delta S. \Delta S \rightarrow M_2 \rightarrow Y$ has two arrows: $S \rightarrow M_2$ and $M_2 \rightarrow Y$ with respective effect parameters being α_S and λ_{M2} and the path-specific effect is the product of the two parameters $\alpha S \lambda_{M2}. \Delta S \rightarrow M_1 Y$ contains two paths: $S \rightarrow M_1 \rightarrow M_2 \rightarrow Y$ and $S \rightarrow M_1 \rightarrow Y$. The path $S \rightarrow M_1 \rightarrow M_2 \rightarrow Y$ consists of three arrows: $S \rightarrow M_1, M_1 \rightarrow M_2$ and $M_2 \rightarrow Y$ with effect parameters being $\delta S, \alpha_M$ and λ_{M2}, respectively; the path $S \rightarrow M_1 \rightarrow Y$ consists of two arrows: $S \rightarrow M_1$ and $M_1 \rightarrow Y$ with effect parameters being δ_S and λ_{M1} respectively. The effect of $\Delta S \rightarrow M_1 Y$ is the sum of $\delta_S \alpha_M \lambda_{M2}$ and $\delta_S \lambda_{M1}$, which are the products of effect parameters along the two paths [12].

Data

The study was conducted using the KDHS 2014 data. Data obtained from a random sample of 20964 respondents collected as part of the KDHS was analyzed. The dataset contains details about each child under the age of five residing in the household. This includes information such as the child's gender, survival status, birth interval, birth order, and weight at birth. Additionally, the dataset provides data on various factors, including household and community characteristics, healthcare coverage, maternal and antenatal care, infant feeding practices, and immunization coverage, among others. The decision to consider the age range from 1 to 59 months was influenced by the need to accommodate certain survival analysis models that assume time (T) to be greater than zero ($T > 0$). In our study, the variables of interest are the time it takes for an event to occur and the status of the event. Time until child mortality was considered. The event status is represented by the code 1 for "dead" and 0 for "alive." It's important to note that the survival time data was subject to right censoring. The KDHS dataset possesses significant advantages, including its extensive sample size that accurately represents the entire population of the country. Additionally, the data is subjected to rigorous quality control measures. Table 1 provides a summary of descriptive statistics. All statistical analyses were performed using the R programming language, which is widely used for statistical computing.

Variables

This paper is motivated by a child mortality study where mediation by maternal income and maternal health behaviour in relation child mortality was investigated. The study was conducted using the KDHS 2014 data where the outcome is mortality status and time of death. A mediation model was proposed with the exposure being education level(s) and two mediators. The mediators were, maternal income (M_1) and maternal health behaviour (M_2). Under five child mortality (Y) was the outcome. Household wealth index which is a composite measure of household cumulative living standards was used for maternal income. It was used as a proxy of maternal income since KDHS did not collect income information. This was with the assumption that mother's level of education contributed to household wealth level. Maternal health behaviour was measured as the number of visits to the clinic. There are variables that are strongly associated with the dependent variable but are not associated with the study factor, these were sex and age. The risk factors examined in the study were selected based on results from already published articles. In this study three effects were considered. The three different effects have been termed as path specific effects which characterize mediation effects for various pathways through different mediators.

1. The effect of education on under five child mortality through maternal income and through maternal health behaviour(black).
2. The effect of under-five child mortality mediated through maternal behaviour but not through maternal income (the dark grey path).
3. The effect of education on under five child mortality not mediated by maternal income or maternal health behaviour (Light grey).

The outcome Y is $\lambda(t/x)$ in additive hazard model. Three specific path effects

$s \rightarrow Y$, the effect of education on the outcome (under five child mortality) independent of the mediators M_1 and M_2.

$s \rightarrow M_2 \rightarrow Y$, the effect of education on the outcome mediated only through maternal health behaviour M_2 (i.e not through maternal income M_1).

$s \rightarrow M_1 \rightarrow Y$ the effect mediated through maternal income and possibly through maternal health behaviour M_2.

The total effect can be expressed as sum of the three specific effects

$$\Delta_{TE} = \Delta_{S\rightarrow Y} + \Delta_{S\rightarrow M2\rightarrow Y} + \Delta_{S\rightarrow M_1\rightarrow Y} \quad (10)$$

To successfully identify the three path-specific effects within the scope of the UFCM study, it is imperative to make certain assumptions regarding the absence of unmeasured confounding [26, 11]. These assumptions can be briefly summarized as $A \coprod B\,|C$, which signifies that variable A is conditionally independent of variable B given variable C. Within this study, we present a set of six adequate conditions that facilitate the identification of path-specific effects (PSE). We express these assumptions as marginal exchangeability to simplify their understanding and implementation. Furthermore, extending this notion to encompass conditional exchangeability is possible by accounting for covariates X. By appropriately adjusting for known confounding factors like age and gender, we aim to establish exchangeability among the variables involved.

1. There is no confounding for the joint effect of maternal income and maternal health behaviour (M_1, M_2) on the time to death, conditional on mothers education level (S).
2. There is no confounding for the effect of mothers education level (S) on the time to death.
3. There is no confounding for the joint effect of (S, M_1), maternal income and mother's education level on maternal health behaviour (M_2).
4. There is no confounding for the effect of mother's education level (S) on maternal education (M_1).
5. There is no mother's education level (S) induced factor that can confound maternal income-survival time $(M_1 - T)$ and maternal health behaviour survival time $(M_2 - T)$ joint relation, where S^* and S^{**} are interventions for mother's education level with different values than S and each other.
6. There is no mother's education level-induced factor that confounds the $M_1 - M_2$ (maternal income vs. maternal health behaviour) association.

Results

This chapter presents the primary findings of our study. The descriptive analysis provides comprehensive summary statistics for the variables included. The bivariate analysis specifically examines the relationship between the independent and dependent variables. Furthermore, path analysis is conducted to investigate whether the influence of maternal education on UFCM is mediated through potential pathways.

Descriptive Statistics

A total of 20964 children were identified in the 2014 KDHS data. 871 deaths were reported while 20,093 cases survived. Table 1 shows the descriptive characteristics of some the variables included in the study. Around 34 per cent of deaths consisted of those living in urban areas and 66 percent were living in rural areas. 54.6 percent of the total deaths were male and 45.4 percent were female.

Table 1: Descriptive statistics for demographic and other variables perceived to determine UFCM in Kenya based on KDHS ,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(years)			
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%)

Bivariate analysis between maternal education and household wealth level

Table 2: Wealth index

		Wealth index				
		Poorest	Poorer	Middle	Richer	Richest
Highest Education Level	No Education	3690	306	186	229	174
		80.5 %	6.7 %	4.1 %	5.0 %	3.8 %
	Secondary Education	311	718	917	1096	961
		7.8 %	17.9 %	22.9 %	27.4 %	24.0 %
	Higher education	17	64	142	321	777
		1.3 %	4.8 %	10.8 %	24.3 %	58.8 %

Mothers residing in households with higher levels of wealth and affluence exhibited a greater level of educational attainment in comparison to mothers from economically disadvantaged households. Among the poorest families (80.5%) were at no education level. Among the richest households only (3.8%) were in the no education level. However only (1.3%) of the poorest households had a higher education level compared with (58.8%) from the richest households.

Multiple linear regression for maternal income on education adjusting for age and sex

Table 3: Parameter estimates and standard errors (SE) for regression of maternal income on education adjusting for age and sex

Coefficients	Estimate	SE	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 suggests that on average mothers in higher education level have a maternal income 2.9 times higher than mothers in no education level when adjusted for age and sex. Mothers in secondary education level have an income 1.98 units higher than mothers with no education level. Mothers in primary level have an income of 0.99 units higher than mothers in no education level.

Poisson regression model for maternal health behaviour on education adjusting for age and sex

Table 4: Parameter Estimates and Standard (SE) for the regression of maternal health behaviour on education adjusting for Age and sex

Coefficients	Estimate	Std. Error	t value	$Pr(>\|t\|)$
(Intercept)	1.061	0.024	43.366	$< 2e-16***$
Age	0.003	0.0006	4.743	$2.11e-06$
Sex	-0.012	0.0081	-1.522	0.128
Primary education	0.254	0.0122	20.83	$< 2e-16***$
Secondary Education	0.375	0.0137	27.383	$2e-16***$
Higher Education	0.599	0.017	36.03	$2e-16***$

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

Table 4 suggests that a primary education level mother is expected to make on average $e^{0.254} = 1.29$ times as many visits to the clinic (maternal health behaviour) as a no education level mother when adjusted for age and sex. A mother in secondary school level is expected to make on average 1.45 times as many visits to the clinic as a mother with no education level. A higher education level mother is expected to make on average 1.82 times as many visits to the clinic as a mother with no education level.

Poisson regression model for maternal health behaviour on education adjusting for maternal income, age and sex

Table 5: Parameter Estimates and Standard (SE) for the regression of maternal income on education adjusting for Age and sex

Coefficients	Estimate	Std. Error	t value	*Pr*(> |*t*|)
(Intercept)	0.961	0.249	38.563	$< 2e-16***$
Age	0.002	0.0006	3.961	$7.46e-05$
Sex	-0.013	0.0081	-1.600	0.11
Maternal Income	0.076	0.0033	822.78	$< 2e-16^{***}$
Primary education	0.170	0.0127	13.39	$< 2e-16***$
Secondary Education	0.217	0.0153	14.14	$2e-16***$
Higher Education	0.377	0.019	19.58	$2e-16***$

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

Table 5 suggests that on average mothers in higher education level have a maternal health behaviour (no. of visits) $e^{0.377}$= 1.5 times higher than mothers in no education level when adjusted for maternal income, age and sex. Mothers in secondary level have a maternal health behaviour (no. of visits) 1.3 units higher than mothers in no education level. Mothers in primary level have maternal health behaviour (no. of visits) 1.1 units higher than mothers in no education level.

Aalen additive model adjusting for maternal health behavior, education level, age and sex

Table 6: Parameter estimates and standard errors from the Aalen additive model adjusting for maternal health behaviour, education level, age and sex

Parametric terms	Coef.	SE	Robust SE	z	P-Val	lower2.5%
Sex	0.000210	6.80e-04	6.82e-04	0.308	7.58e-01	-0.001120
Age	-0.001660	5.08e-05	4.90e-05	-33.900	0.00e+00	-0.001760
Maternal health behaviour	-0.000274	4.32e-05	4.16e-05	-6.590	4.29e-11	-0.000359
Primary education	-0.012000	1.02e-03	1.06e-03	-11.400	0.00e+00	-0.010400
Secondary education	-0.015100	1.15e-03	1.18e-03	-12.800	0.00e+00e-11	-0.017400
Higher education	-0.013900	1.47e-03	1.50e-03	-9.250	0.00e+00	-0.016800

Table 6 shows that children born of mothers in higher education level have a mortality rate that is 13.9×10^{-3} units lower than those of mothers in no education level when adjusted for age, sex and maternal health behavior. Children born of mothers in secondary education level have a mortality rate that is 15.1×10^{-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 12.0×10^{-3} units lower that child born of mothers in no education level.

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

Table 7: Parameter estimates and standard errors from the Aalen additive model adjusting for maternal health behaviour maternal income, education level age and sex

Parametric terms	Coef.	SE	Robust SE	z	P-val	lower2.5%
Sex	0.000242	6.80e-04	6.84e-04	0.354	7.23e-01	-0.001090
Age	-0.001670	5.08e-05	4.92e-05	-33.800	0.00e+00	-0.001770
Maternal income	-0.003130	2.87e-04	2.88e-04	-10.900	0.00e+00	-0.003690
Maternal health behaviour	-0.000233	4.33e-05	4.06e-05	-5.730	1.02e-087	-0.000318
Primary education	-0.008430	1.07e-03	1.11e-03	-7.610	2.69e-14	-0.010500
Secondary education	-0.008620	1.30e-03	1.32e-03	-6.550	5.62e-11	-0.011200
Higher education	-0.004900	1.69e-03	1.72e-03	-2.850	4.31e-03	-0.008210

Table 7 shows that children born of mothers in primary education level have a mortality rate that is 8.4×10^{-3} units lower than those of mothers in no education level when adjusted for age, sex, maternal income and maternal health behavior. Children born of mothers in secondary education level have a mortality rate that is 8.6×10^{-3} units lower than those of mothers in no education level. Children born of mothers in higher education level have a mortality rate that is 4.9×10^{-3} units lower that children born of mothers in no education level.

Mediation Analysis

Table 8: Natural direct, natural indirect, and total effects of education level on under five child mortality mediated through maternal health behaviour

	Effect Estimate	95% Confidence Interval
Aalen; Effect scale: Difference in hazard (per 1000 births-year)		
Natural Direct Effect	−0.27	(-0.35, -0.019)
Natural Indirect Effect	-0.78	(-4.4, -7.4)
Total Effect	-1. 05	(-4.7, -7.7)

A change in maternal education level from no education to a higher level decreased the number of UFCM cases by a natural indirect effect of -0.27. This is the effect which is not through maternal health behaviour. The change decreased UFCM by a natural indirect effect of -0.78. This was the effect through maternal health behaviour. The total effect was -1.05. As expected Chikandiwa et.al (2018), high education level leads lower rate of mortality.

The effect of mothers education level has two components, direct effect (without mediators) and indirect effect (mediation effect of the mediators). Change from no education level to a higher education level would reduce the number of deaths by -1.05 deaths per 1000 births. Of this decrease -0.78 was attributed to maternal health behaviour pathway (natural indirect effect) representing 74% of the total effect. This implies that if an intervention could improve maternal health behaviour (number of visits) of no education level mothers to that of a higher education level mother,74% of the education level decrease effect could be achieved.

Path-specific effects and total effects of education level on UFCM (Y) mediated through maternal income (M_1) and maternal health behaviour (M_2)

Table 9: Path specific effects and total effects

Effect	Estimate	95% Confidence Interval
Aalen model; Effect scale: Difference in hazard (per 1000 births-year)		
$\Delta S_{\to Y}$	-0.024	(-0.032, -0.016)
$\Delta S_{\to M_2 \to Y}$	-0.036	(-0.047, -0.024)
$\Delta S_{\to M_1 Y}$	-0. 36	(-0. 48, -0.26)
ΔTE	-0.43	(-0. 52, -0.28)

The study utilized additive hazard models in R's timereg library. Path-specific effects' variability was estimated via resampling. When education improved from none to higher levels, UFCM decreased through $\Delta_{S \to Y}$ mechanism, hazard difference: -0.024 (-0.032, -0.016). Cases dropped via $\Delta S \to_{M1Y}$, mediated by maternal income and health behavior, hazard difference: -0.36 (-0.48, -0.26). Education also changed hazard via $\Delta_{S \to M2 \to Y}$, maternal health behavior mediation, hazard difference: -0.036 (-0.047, -0.024). Total effect: -0.43 (0.52, -0.28) i.e. sum of specific effects. Of the 43% UFCM decrease, 36% was mediated by income and health behavior. No-education level mothers could see 3.6% UFCM drop with clinic visit adjustments.

Discussion

In Sub-Saharan Africa, including Kenya, under-five child mortality (UFCM) remains high. Identifying drivers of child mortality is crucial for effective interventions. Mediation analysis unveils cause-effect mechanisms. This study explores dual mediators, maternal income, and health behavior, in relation to maternal education's impact on UFCM in Kenya. Policy options - enhancing education, income, and health behavior - are pivotal. This multimediator model, utilizing additive hazard models, uncovers distinct effects. Education reduces deaths directly (0.27) and indirectly via income (-0.78). Adverse education effects mediated by health behavior, countered by protective effects via income and health behavior ($\Delta S \to M_{1Y}$: -0.36 vs. $\Delta_{S \to M_2 \to Y}$: -0.036). Addressing this, promoting clinic visits among lower-educated mothers and improving maternal income, holds promise. Maternal education, crucial in reducing UFCM, links to health service utilization. Multi-mediator models mitigate confounding. Maternal income improvement and health behavior promotion are key takeaways.

Conclusion

This study contributes to mediation analysis and the education-UFCM link. Education's influence on UFCM varied here. Low education related to lower income, tied to higher UFCM. Maternal education affects child health via income and health behavior. Maternal education is vital for child health in this context. Policies should ensure equal education and healthcare access. Promoting health behaviors among girls/women with limited education and improving overall economy is crucial. Future experiments needed for mediation analysis with violated assumptions.

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