AMERICAN JOURNAL OF APPLIED STATISTICS AND ECONOMICS (AJASE)

ISSN: 2992-927X (ONLINE)

VOLUME 3 ISSUE 1 (2024)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Applied Statistics and Economics (AJASE)

Volume 3 Issue 1, Year 2024
ISSN: 2992-927X (Online)
DOI: https://doi.org/10.54536/ajase.v3i1.3686
https://journals.e-palli.com/home/index.php/ajase

Survival Regression Model Allowing for Exposure-Mediator Interaction: Analysis of Kenya Demographic Health Survey (KDHS) 2014 Data

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Article Information

Received: September 11, 2024

Accepted: October 15, 2024

Published: October 17, 2024

Keywords

Aalen Additive Model, Child Mortality, Mediation

ABSTRACT

Although infant and under-five mortality rates have decreased over the past decade, Kenya, like many other African nations, did not achieve the Millennium Development Goal (MDG) 4 target. To accelerate progress towards reaching Sustainable Development Goal 3 by 2030, it is essential to understand the factors influencing under-five child mortality (UFCM), taking into account all potential confounding variables and effect modifiers. The child mortality rate serves as a key health indicator for any country. This study used data from the 2014 Kenya Demographic and Health Survey (KHDS). This paper introduces the concept of decomposing the total effect of an independent variable into three components: a direct effect, an indirect effect, and an interactive effect. We attempt to account for the direct effect of an independent variable on the outcome, then proceed to check the effect of the presence of a possible mediator and, furthermore, the possible interactions between an exposure variable and a mediator variable. The outcome variable was UFCM, and the study was to determine the effect of mother's education on UFCM, in the presence of mediators such as mother's income and the effect via the interaction between mother's education and maternal income was estimated. To capture the effect of mediation and interactions in the context of survival analysis, an Aalen additive model, including a product term for the exposure and mediator term, was developed. The methods were further illustrated with practical approach to KDHS data. KDHS has data on a broad scope of risk factors for UFCM. Computations for all data sets was implemented using the freely available R-software package. This analysis suggests that while a significant portion of the impact of maternal education on UFCM is mediated by increasing maternal income, it is the interaction between maternal education and maternal income that leads to a reduction in UFCM. Interventions targeting an increase in income among mothers with no education level would yield a greater reduction in UFCM than interventions targeting mothers with a higher education level. The total effect was ascribed to an interaction between the mother's education level and maternal income, and part of it is attributable to pure indirect effect, and a given proportion is attributable to pure direct effect. The majority of the total effect (70%)is attributed to the interaction between change from no education level to primary education level and maternal income. 22% is associated with the pure direct effect, while 8% is linked to the pure indirect effect. Interventions with a given increase in income among those with no education level would yield a greater reduction in UFCM than interventions targeting mothers with a higher education level.

INTRODUCTION

Child mortality still remains a global problem despite many interventions going on, both in terms of health research and even at the level of government interventions. Despite the global and national decline in infant and under-five mortality rates over the past decade, Kenya, like many other African countries, failed to meet the target for Millennium Development Goal (MDG) 4. The analysis was conducted using house hold data from Kenya Demographic and Health Survey (KDHS) data. To accelerate progress towards achieving the Sustainable Development Goals (SDGs), effective interventions must be implemented in order to meet Goal number 3 by 2030. Determinants of child health, such as Under Five Child Mortality (UFCM) need to be understood in the context of all possible forms of confounding and/or effect moderation. Child mortality rate is one of the major health indicators for any country. Kenya, just like other Sub-Saharan countries, have recorded high cases of UFCM. The SDG, goal number 3, target 3.2 on neonatal and child mortality has not been achieved in Kenya, with 43.2 deaths per 1000 live births being reported in the year 2019 (Rod *et al.*, 2012) which is way above the 25 deaths per 1000 that is the target. Part of the Kenya government's previous mid term development plans, known as the "Big Four Agenda (2018-2022)" had universal healthcare as one of the key pillars, to align with the SDG's vision 2030. This work therefore aims at evaluating determinants of 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 and interactions among some useful UFCM determinants. Intervention strategies using statistical outcomes from regression type models, frequently encounter the task of dissecting the impact

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of an exposure into various causal pathways that operate through specific intermediary variables. The primary objective of conducting regression analysis is typically twofold: to gain insights into the underlying mechanisms and to then to propose potential intervention strategies. There is always a complex network surrounding decomposition of exposure effects in the presence of mediation and interactions. It's important to note that implementing mediation analysis methods can be complex, as they rely on stringent assumptions that must be satisfied to obtain valid and interpretable estimates. Exposure-mediator interaction is a potential source of bias, that if not carefully addressed, may lead to flawed conclusions in statistical analysis. Mediation analysis examines the effect of the exposure variable and how changes in the mediator variable subsequently affect the outcome. Therefore, controlling for exposure-mediator confounding, if it happens that such exist, is essential. Although a number of studies where the determinants of UFCM are of interest have been done without due consideration of the possible role of mediation or moderation, attempts have been done in that direction. VanderWeele (2013) developed findings on direct and indirect effects for linear and logistic regressions in the presence of exposure–mediator interaction. However, many studies have not considered the possibility that the exposure and mediator may interact in influencing the outcome. Including interaction effects in a model allows us to compare the relative importance of several pathways mediated by interdependent variables (Hougaard, 1999). Recent advancements in causal inference theory have introduced concepts for mediation analysis and effect decomposition, enabling the separation of a total effect into direct and indirect components. The indirect effect can be further broken down into a pure indirect effect and a mediated interactive effect, resulting in a three-part decomposition of the total effect (direct, indirect, and interactive). This three-way decomposition offers deeper insight by allowing us to determine how much of the total indirect effect is due to mediated interaction versus the pure indirect effect (VanderWeele, 2013).

This work makes use of the concept of decomposing the total effect into three components: a direct effect, an indirect effect, and an interactive effect. We perform this three-way decomposition using an additive regression type model. These additive hazard models have the potential to reveal intricate effects when examining the impact of various factors on UFCM in Kenya. Three-way decomposition also applies to additive hazard scales. An additive model including a product term for the exposure and mediator term was developed and R codes for decomposition expanded. The analysis was conducted using household data from the Kenya Demographic and Health Surveillance (KDHS) data. Results of the study shows that maternal education is recognised as a determinant of child health. The pathways linking maternal education level to UFCM are constrained by the statistical methods commonly found in the literature. To observe the complex pathways between maternal education and UFCM, we employed a statistical model that was able to accommodate interactions between the maternal education as an exposure and maternal income as a possible mediator.

MATERIALS AND METHODS

This section describes the datasets and the structure of a model with mediation and a model with possible exposure-mediator interaction. 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.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:

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

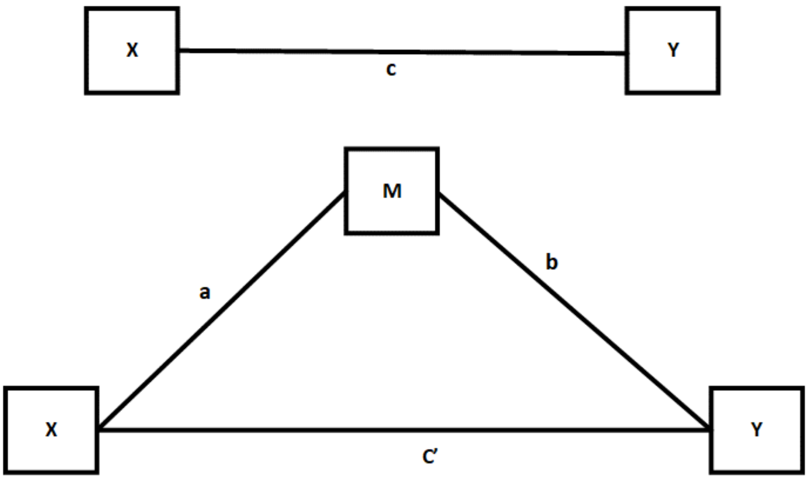

Figure 1: X= the independent variable, Y= the dependent variable, and M= the mediating variable. c is the overall effect of the independent variable on Y; c' is the effect of the independent variable on Y controlling for M; b is the effect of the mediating variable on Y; a is the effect of the independent 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 (Fairchild & MacKinnon, 2009)

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

$M= i_3+ax+e_3$ (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 (2006)The Aalen additive model being additive,is directly suitable to incorporating the role of mediation as opposed to other forms of survival regression models.

Survival Regression Model Incorporating One Mediator

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

$\gamma(t;x,m,z)= \lambda_0 (t)+\lambda_1 (t)x+\lambda_2 (t)z+\lambda_3 (t)m$ (4)

where $\gamma(t;x,m,z)$ represents the rate, expressed as a function of the mediator (m), other baseline covariates (z), and exposure (x). λ_j (t) denote potentially time-dependent functions. A straightforward linear regression can be employed to characterize the mediator, under the assumption that it follows a normal distribution. Thus, with other covariates (z) and exposure (x), the mediator is determined by:

$M= \alpha_0+\alpha_1 x+\alpha_2 z+e$ (5)

where e is normally distributed error with zero mean and its variance σ^2.The parameters are estimated using some statistical methods such as least squares method. Suppose the exposure is set to X and the mediator to M, then we can denote the counterfactual rate for the event by γ(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

$\gamma(t;x, M^x)-\gamma(t;x^*, M^x)=$

$\gamma(t;x, M^x)-\gamma(t;x^*, M^{x^*})+\gamma(t;x^*, M^x)-\gamma(t;x^*, M^{x^*}))$

$=\lambda_1(t)(x-x^*)+\lambda_3\, \alpha_1(t)(x-x^*),$

The equation TE(t) = DE(t) + IE(t) decomposes the effects into three distinct components: the natural indirect effect (IE), the natural direct effect (DE), and the total effect (TE). Each of these terms carries a specific interpretation. The indirect effect quantifies the number of deaths caused by mediation through the mediator, while the direct effect represents deaths due to the direct pathway (or through mediators not considered in the analysis). The overall effect, which accounts for the total deaths resulting from changes in exposure, is determined by combining the direct and indirect effects, as explained in Lange and Hansen (2011). When both the exposure and mediator exhibit no time-dependent effects in the Aalen model, with λ_1 (t) and λ_3 (t) remaining constant, Theorem 1 simplifies to:

$$\underbrace{\gamma(t;x,M^x)-\gamma(t;x^*,M^x)}_{total\quad effect} = natural\ \underbrace{\lambda_1(x-x^*)}_{direct}\ effect + natural\ \underbrace{\lambda_3\alpha_1(x-x^*)}_{indirect}\ effect \quad (6)$$

Therefore, both the direct and indirect effects can be represented by a single numerical value rather than being functions of time (t). The Aalen additive model offers a framework for directly deriving confidence intervals for the direct effects. The model assumes no confounding in the relationships between (i) exposure and mediator, (ii) mediator and outcome, and (iii) exposure and outcome, provided pre-exposure confounders are controlled for, as outlined in Nguyen *et al.* (2016).

Survival Regression Model Allowing for Exposure-Mediator Interaction

Even when there is interaction between the exposure and the mediator in its impact on the outcome, it is still possible to perform mediation analysis by breaking down the total effect into direct and indirect effects. The model for outcome including an exposure mediator interaction is

$E[Y|a, m, c]= \theta_0+\theta_1 a+\theta_2 m+\theta_3 am+\theta_4 c$ (7)

We once again fit a linear regression model for the mediator.

$E[M|a, c]=\beta_0+\beta_1 a+\beta_2 c$ (8)

If the models are accurately specified, and the assumptions related to confounding are met, then the estimates of direct and indirect effects resulting from a change in exposure from a level denoted as "a*" are provided as follows:

$DE=\theta_1+\theta_3 (\beta_0+\beta_1 a^*+\beta_2 a)(a-a^*)$ (9)

$IE=(\beta_1 \theta_2+\beta_1 \theta_3 a)(a-a^*)$ (10)

Standard errors for these equations are also calculated (Vanderweele TJ *et al.*, 2009). When there is no interaction between the exposure and mediator (i.e., when $\theta_3=0$), the equations simplify, with θ_1 representing the direct effect and $\beta_1 \theta_2$ representing the indirect effect.

As the explanatory variables are expressed on the additive hazards scale, product terms can be included to evaluate deviations from additive effects, similar to standard linear models. In the specified additive model, the rate is treated as a function of the mediator (m), baseline covariates (z), and the interaction between exposure (x) and the mediator (xm). This method is outlined in Rod *et al.* (2012) work .

$\gamma(t;x,m,z)=\lambda_0 (t)+\lambda_1 (t)x+\lambda_2 (t)z+\lambda_3 (t)m+\lambda_4 (t)xm$ (11)

where$\gamma(t;x,m,z)$ is the rate, which is written as a function of mediator (m), other baseline covariates (z) , exposure (x) and interaction (xm). λ_j (t) are potentially time-dependent functions.

Casual diagrams with exposure-mediator interaction representing a three-way decomposition.

The total indirect effect consists of both the pure indirect effect and the mediated interaction. The difference between the total indirect effect and the pure indirect effect serves as a measure of interaction, referred to as the mediated interactive effect (VanderWeele, 2013).

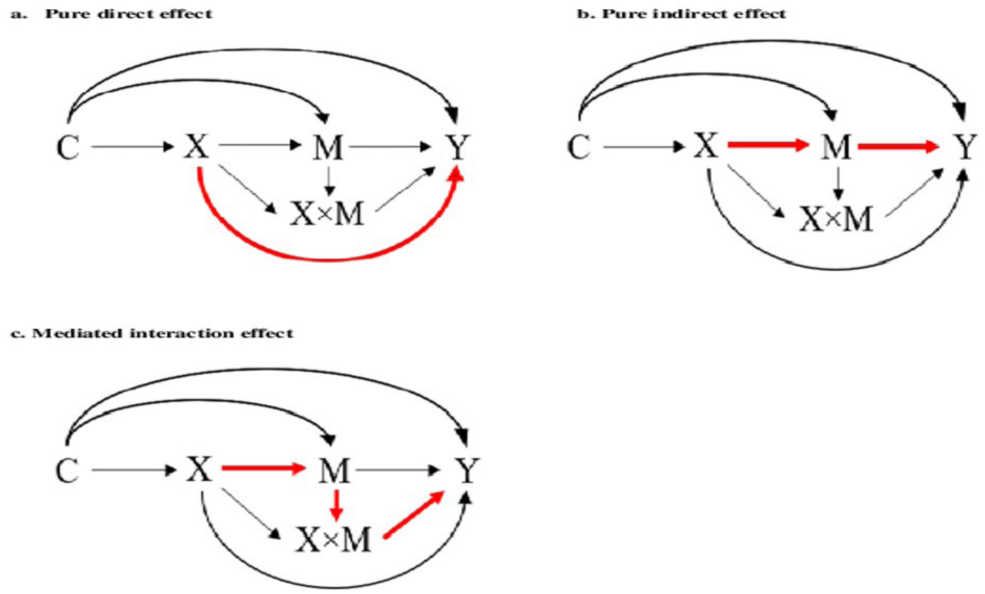

Figure 2: X is the exposure,M is the mediator and X*M is the interaction between the exposure and the mediator.Y is the outcome and C is a set of con founders.Red line shows each effect a.Pure direct effect b.pure indirect effect and c. Mediated interaction effect

Data

The research utilized data from the KDHS 2014 survey, collected from a random sample of 20,964 respondents. This data set offers comprehensive information about every child under five years old within households, including the child's gender, survival status, birth intervals, birth circumstances, and birth weight. In addition, the data set encompasses a wide range of information related to domestic and community characteristics, access to healthcare care, maternal and prenatal care, infant feeding practices, vaccination exposure, and more.

Our dependent variables include the time until a specific event occurs and the corresponding event status. In this context, the event status is coded as 1 for "dead" and 0 for "alive." All children still alive during data collection were considered right-censored, meaning their event status was unknown. The data used in this article was right-censored. Right censored data is vastly discussed by Hougaard (1999). Notable strengths of the KDHS data set include its large sample size, which represents the country's entire population, and its rigorous quality control measures (Manski, 2003).

Variables

The risk factors examined in the study were selected based on the results of articles already published. They include sex of the child, age of mother, mother's level of education, maternal income, and maternal health behavior. Maternal education is considered in this context as an exposure,while maternal income and health behavior are considered as mediators. Education is grouped in four categories; no education, primary education, secondary education, and higher education. The level of household wealth was used for maternal income. The wealth level was derived from an index calculated 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 the sex of the child and the age. Aalen additive model was used in the presence of mediation and interaction. It was used to assess mediation and interaction on two factors that are significant regulators of UFCM. Mediation analysis can still be conducted even when the exposure and mediator interact in their effect on the outcome, by dividing the total effect into direct and indirect components. An Aalen additive model was developed that incorporated a product term for the exposure and mediator, allowing the total effect to be broken down into three distinct components rather than just two.

1. The effect due to mediator only (maternal income).
2. The effect due to interaction (between maternal income and education)
3. The effect due to the exposure only (education)

RESULTS AND DISCUSSION

Through a model including a product term for the exposure and the mediator the total effect was decomposed into three distinct components (direct effect, pure indirect effect and the interactive effects). Additive hazard models are implemented in the software package R. 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'. The functions required for estimating and analyzing the additive hazards model are contained in the package.The model is fitted using the Aalen function.Lange and Hanssen (2011) discusses this technique widely. Descriptive statistics on mortality, mother's education, maternal income and adjusting factors are presented in table 1.

Descriptive Characteristics

A total of 20964 children were identified in the 2014

Table 1: Descriptive Statistics of Demographic Variables and other Determinants of Under Five-Child Mortality in Kenya, 2014

Width=tw			
	0 (N=20093)	**1 (N=871)**	**Total (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%)

KDHS data. Of these 871 had died within their first years of life 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 who died 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.There were more children born in the poorest households than the richest households. Almost 53% of the mothers had primary level of education, 22% no education, 19% secondary education and 6% higher education.

Bivariate Analysis between Maternal Education and Household Wealth Level

Table 2: Bivariate analysis between maternal education and household wealth level

Highest Education Level	Wealth index					
		Poorest	**Poorer**	**Middle**	**Richer**	**Richest**
	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.

Regression of Maternal Income on Education Adjusting for Age and Sex

Table 3: Parameter estimates and standard errors 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.,0.11*

Table 3 suggests that, on average, mothers at higher education levels have an income of 2.9 units higher than mothers at no education level when adjusted for age and sex. Mothers in secondary education have an income of 1.98 units 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.Mothers with higher education level in general have higher incomes compared to those with low education levels.

Aalen Additive Model Adjusting for Maternal Income, Education Level, Age and Sex

Table 4: Parameter estimates and standard errors(SE) from the Aalen additive model adjusting for maternal income, Education level, age and Sex

Education level	Estimate(SE) 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)

Table 4 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. The higher the education level for the mothers,the lower the mortality rate for their under-five children.

Mediation Analysis of Maternal Income on Mothers Education Level for Under Five Child Mortality

Table 5: Mediation analysis of maternal income on mothers education level for Under Five Child Mortality

Education level	Total effect	Direct effect	Indirect effect
0-I	-1.9	-1.4	-0.5
0-II	-2.5	-2.3	-0.2
0-III	-3.5	-2.8	-0.7

As in the findings of He *et al.* (2020) , 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 1000 childrenβ=-3.5 of this decrease 0.7 fewer deaths (β=-0.7) resulted from maternal income pathway(natural indirect effect)representing 20 percent of the total effect. This implies that if an intervention were able to increase the maternal income of individuals with no education to that of those with higher education, while leaving other aspects of social deprivation unchanged, then 20% of the effect associated with education level could be mitigated. A transition from having no education to attaining a secondary level of education is associated with a reduction of 2.5 deaths per 1000 children (β=-2.5). Among this decrease, 0.2 fewer deaths (β=-0.2) can be attributed to the maternal income pathway, considered the natural indirect effect. This represents 8% of the total effect. If an intervention were to elevate the maternal income of individuals with no education to the level of those with secondary education while keeping all other aspects of social deprivation constant, it could potentially eliminate 8% of the educational level's impact.

Estimation of the Interaction between Maternal Education and Maternal Income

Table 6: Mediation analysis of maternal income on mothers education level for Under Five Child Mortality

Education level	Total effect	Direct effect	Indirect effect	Interaction effect
0-1	-111.8	-25.1	-8.1	-77.8
0-II	-131,6	-119.7	18.5	-30.4
0-III	-345.6	-366.4	-26.8	47.6

The majority of the total effect 70%is attributed to the interaction between change from no education level to primary education level and maternal income. 22% is associated with the pure direct effect, while 8% is linked to the pure indirect effect. This analysis suggests that while a significant portion of the impact of maternal education on under-five child mortality (UFCM) is mediated by increasing maternal income, it is the interaction between maternal education and maternal income in most cases of mediation that leads to a reduction in UFCM.

Discussion

While conducting regression analysis, it is an important subject to attempt to decompose exposure effects in the presence of mediation and interactions. Evaluation of mediators and interactions is vital in guiding public health interventions, clinical judgment, and healthcare planning policies. By attempting to use varied techniques in analysis, more insights into the data becomes clearer leading to improved inference. This study used the Aalen's additive model which differs slightly from the Cox regression model. The latter approach involves modeling the hazard rate and assumes a proportional hazard structure, while the former employs an additive model, assuming a linear parametric structure for the hazard rate. Additive hazard models allow for the decomposition of effects into total, direct, and indirect components. The analysis utilized KHDS 2014 data to identify the determinants of UFCM. Kenya is one of the countries in the African 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 more appropriate health and intervention strategies. Using the Aalen additive models, we identified the total effects, direct effects, indirect effects and interactive effects between children's survival time, mother's education, maternal income and maternal health behaviour. We evaluated the effect of maternal income in mediating the impact of maternal education on child mortality among children under the age of five in Kenya. Our results confirm what has generally been found. In the analysis, the selection of covariates is linked to the findings in Nguyen *et al.* (2016). To assess interaction, we adopted a pragmatic approach grounded in the idea that interventions and preventive measures should target patients or specific subgroups of the population where most cases can be prevented. Interactions are typically evaluated by incorporating a product term into the regression model, a method that relies on the model's underlying scale (Martinussen, 2006). We evaluated interaction by calculating the deviation from the additivity of effects using a model incorporating a product term to account for the interaction between maternal education level and maternal income. The findings were as follows: UFCM was higher amongst mothers with no education level. Some of the differential effect of maternal income is most likely due to varying incomes across educational groups. A large percentage of the total effect (70%)was attributed to the interaction between change from no education level to primary education level and maternal income. Suppose we consider the observed relationships to be causal, that would imply that a specific intervention aimed at increasing income among uneducated individuals would result in a more significant reduction in UFCM than interventions directed toward mothers with a higher education level. Similarly, a universal intervention such as educating the mothers with the same increase in income in both groups would be expected to have a stronger effect on the reduction of UFCM in the no-education level group. Results from other researches concur with our findings. For example, Imbo *et al.* (2021) highlighted that mothers without any education had significantly higher odds of neonatal deaths, with an adjusted Odds Ratio (aOR) of 2.201, 95% CI: 1.43-4.15, p=0.049, when compared to mothers with higher levels of education. However, this study employed logistic regression, only adjusting for some specific covariates of interest. A similar study based on DHS data, conducted in Ethiopia showed that neonates born to fathers with secondary and higher education level (AOR=0.51; 95%CI: 0.22-0.88) had lower odds of neonatal mortality in Ethiopia. The analysis was conducted using multiple logistic regression and missed out on the possible role of mediation, moderation or interactions in directing the role of some of the defined exposure effects (Basha *et al.*, 2020). Another study in Ethiopia also made the following findings. Neonatal mortality was significantly associated with being born to a mother without formal education (AOR = 1.79, 95% CI: 1.12-2.88), a mother who did not participate in healthcare decision-making (AOR = 1.25, 95% CI: 1.14-1.79), and being part of a twin birth (AOR = 6.85, 95% CI: 3.69-12.70). The model used was a multivariable logistic regression model without any additional assumptions on covariate interactions or role of mediation, as is commonly done for such cross-sectional studies using DHS datasets. The main limitation of this study is that only a select few select variables were included in the final model, being the outcome variable (UFCM), the exposure variable (maternal education) and the mediator variables (maternal income and health characteristics). A more parsimonious model could be useful to illuminate even more realistic effect of the exposure variable on UFCM.

CONCLUSION

The study involves quantification of mediation in a survival context. We applied an easier and interpretable measure of natural direct, indirect effects, and interactive effects in addition to their confidence intervals. The additive hazard scale is used to calculate the effects. This helps in direct translation of expected no of extra cases. This study offers a simple and intuitive approach to evaluating deviations from additive effects in survival analysis by utilizing additive models in the context of mediation and interaction. In the absence of bias, deviations from risk additivity suggest that certain subgroups may experience greater absolute risk reduction than others. Additionally, a researcher might be interested in determining the extent to which a mediated effect depends on the combined influence of the exposure and the mediator. The method is illustrated by analysis of the linkage among education, maternal income and under-five mortality previously examined in the study of Soe *et al.* (2019). This paper contributes to the literature on mediation analysthe is as well as literature on the importance of education on UFCM. The influence of education on UFCM had different pathways in this study. Interventions with a given increase in income among those with no education level would yield a greater reduction in UFCM than interventions targeting mothers with a higher education level. The results of this study may contribute to improve relevant interventions for UFCM among children in Kenya. It will assist the Kenyan government, non-governmental organizations, and other health sector partners in identifying key focus areas and relevant statistical tools needed to formulate policies and implement projects aimed at reducing UFCM, which aligns with the Sustainable Development Goals (SDGs).
Future experimental studies are then necessary to provide more information on the implementation of mediation analysis methods in cases where the strong assumptions that need to be met are violated. Studies on statistical power to detect interactions and to incorporate additive hazard models into other conventional software package are required.

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