

Road Traffic Death Rate and Human Development Index in 2007-2016 at the Global Level: Trend Analysis

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Abstract

Background: Numerous studies working on the association between the human development index (HDI) and road traffic death rate (RTDR), merely focused on developed countries, have not thus far reflected on the relationship between the HDI components and RTDR. Therefore, this study aimed to analyze the trends of RTDR and their association with the HDI and its components from 2007 to 2016.

Methods: The RTDR data for 131 countries were imported into the unconditional latent growth model (LGM) to assess the trends of RTDR between 2007 and 2016. The impact of the HDI and its components (viz. education, income and life expectancy [LE viz]) on the trajectory of RTDR was also evaluated using the conditional LGM. Classification and regression trees (CARTs) were then applied to classify the countries based on the HDI and its components into downward or upward trends. The importance of the HDI components in the CART models was further extracted through random forests (RFs).

Results: The results of the unconditional LGM indicated an overall decreasing trend in RTDR. A total number of 106 and 25 countries also had a downward and upward trend of RTDR, respectively. Based on the conditional LGM, the outcomes revealed the negative effect of the HDI and its components on the model parameters. The accuracy of the CARTs was at least by 85%, indicating its high classification performance. According to the findings of RFs, LE was the most crucial variable in the CART models.

Conclusion: Overall, RTDR is concluded to be multifactorial. As this study showed, the HDI and its LE component are the main determinants of RTDR at the global level. In addition, legislative factors and sociocultural context of countries are assumed as important issues that should be considered by policy-makers to control RTD.

Background

Road traffic death (RTD) is the eighth leading cause of mortality among all people and the first cause of mortality in children and youngsters¹. Overall, RTD rate (RTDR) has experienced a reduction between 2007 and 2010, followed by an increasing trend in 2013². Africa and Southeast Asia regions have also faced RTDRs higher than the global average, while such values in Europe and America have been the lowest among the World Health Organization (WHO) regions¹. It is noticeable that, although high-income nations mostly have lower RTDR, in the Eastern Mediterranean Region (EMR), higher-income economies experience more RTD than lower incomes³.

As mentioned by the United Nations Development Programme (UNDP), gross national income (GNI) per capita per se cannot be sufficient to assess development in different countries. Hence, education and health status should be taken into account⁴. Thus, from 1990, the UNDP developed various measurement tools such as the human development index (HDI) and inequality-adjusted HDI (IHDI) to assess development among various nations. The HDI consists of three dimensions, viz. life expectancy (LE, years), education (years), and income as a standard of living (i.e., GNI per capita 2017 at the purchasing power parity [PPP] \$)⁵. South Asia, East Asia, the Pacific, and sub-Saharan Africa regions have accordingly had the most rapid growth in the HDI between 1990 and 2017. The Organisation for Economic Co-operation and Development (OECD) member countries has also experienced the least progress in HDI during this period⁴.

The relationship between RTDR and the HDI is not the same between countries with the HDI lower than 0.55 and those with higher HDI⁶. The association between RTDR and social, economic, and legislative factors in more than 100 countries has similarly revealed that the HDI has been strongly correlated with RTDR. Furthermore, considering the HDI components, education has been the most important dimension associated with RTDR, followed by income and LE⁷. In this respect, a study in OECD countries in 2009-2018 had confirmed that, even though the correlation between the HDI and road safety had not been clearly understood, developed countries had encountered more opportunities to invest in their infrastructure, education, health care system, and improvement of road-user behavior. As well, they had concluded that socioeconomic factors could play vital roles in RTD in developing and least developed countries than highly developed ones⁸. Melinder (2007), investigating the relationship between religion and wealth in 15 Western European countries, had found that non-wealthy Catholic nations had experienced more traffic accidents compared with wealthy ones, implying the importance of both religion and wealth in RTD⁹. Moreover, Bishai et al. (2006) had proposed four hypotheses regarding different behaviors about economic growth and road casualties in all countries, that is, first, more developed countries have a better institutional capacity to control externalities; second, there is a competing risk story in which developing countries prefer to reduce the risk of infectious and nutritional health risks rather than making investment in road safety; third, a vehicle mix story regards using safer vehicles in affluent countries instead of high-risk transportation such as motorized bicycles and roofed buses, and fourth, there is a medical technology story in which health care systems should be highly developed to deal with road trauma victims¹⁰.

Different studies have so far reflected on the relationship between income and RTDR. In 2003, Kopits and Copper, considering 88 countries between 1963 and 1999, had reported that RTDR had first increased following a rise in income per capita and then declined once reaching its peak¹¹. Another study in 2009 had demonstrated this relationship between motorcycle fatality and economic growth in 25 countries in 1970-1999. The turning point had reached in \$12,682 gross domestic product (GDP) per capita¹². Exploring RTDR among 60 countries between 1972 and 2004, Law et al. (2011) had found an inverted U-shape relationship between income per capita and RTDR. At the early stages of economic growth, road fatalities had also augmented, and a reduction trend had been observed by more growth in GNI per capita. Lowering corruption and improvements in medical care and technology could thus minimize RTDR¹³. Jafari et al. (2015), considering 22 factors related to RTD, had found that country's income level, existence of formal pre-hospital care system in a country, and some law enforcement factors, such as speed limits and use of motorcycle helmets, were among the most important factors which needed to be considered with regard to RTDR at the national level¹⁴.

Although many studies have thus far worked on the relationship between the HDI and RTDR, they have merely focused on a limited number of countries, mostly developed ones. Furthermore, they have not examined the association between the HDI components and RTDR, to the best of authors' knowledge.

Therefore, this study aimed to analyze the trends of RTDR and its link with the HDI and its components between 2007 and 2016 in order to classify the countries based on the HDI and its components into downward or upward trends.

Methods

Materials

The dataset included RTDR as well as the HDI and its components from 131 countries between 2007 and 2016. The initial dataset was comprised of 180 countries, which reduced to 131 cases after eliminating nations with missing data and those with less than one million population. The target variable, RTDR, was also collected from the Global Status Report on Road Safety published by the WHO^{1,3,15,16}. The covariates, HDI and its components, were further selected from the UNDP¹⁷.

Statistical Analysis

In this longitudinal study, the latent growth model (LGM) was used to assess the trends of RTDR over ten years. The LGM could thus estimate the outcome growth trajectory through analyzing development patterns in the data over time. This model was comprised of two growth parameters, namely, the initial point (i.e., intercept) and the rate of changes over time (viz. slope). The LGM could also allow estimating the effect of covariates on latent growth parameters¹⁸. First, the unconditional linear LGM was utilized to identify the trajectory of RTDR^{19,20}. Second, the impact of the HDI and its components on the trajectory of RTDR. Since the HDI and its components did not vary considerably over time, the mean of the HDI and its components were considered as time-invariant covariates. Third, the slopes from the unconditional linear LGM were used to determine the trends of RTDR in the countries concerned and a binary dependent variable was defined as follows: 0=countries with a downward trend of RTDR and 1=countries with an upward trend of RTDR. Fourth, as a machine-learning procedure, classification and regression trees (CARTs), were applied to identify the relationship between the defined binary variable and the HDI and its components.

Furthermore, to avoid the sensitivity of a single tree resulting from the CART models, the random forests (RFs) were used to extract the importance of the variable^{21,22}. As well, the root mean square error of approximation (RMSEA) and the comparative fit index (CFI) were recruited to assess the goodness-of-fit (GoF) of the LGM models. The CFI values greater than 0.95 accordingly indicated a good fit, while the RMSEA less than 0.08 suggested a good fit²⁰. The significance level of the parameter estimations of the LGM was set at 0.05. The LGM was also performed using the Mplus (ver. 7.0)²³. The CART and RF procedures were carried out using *rpar* and *randomForest* packages in the R (ver. 3.6.3)^{24,25}.

CARTs

As a machine-learning procedure, CARTs were based on the nature of the dependent variable, which could be applied for classification and regression. This tree-based procedure aimed to partition the dataset into homogeneous subsets (namely, terminal nodes) with regard to the dependent variable. Since the dependent variable was discrete (that is, binary), the CARTs could minimize the Gini index as a criterion to create the final optimal tree^{26,27}. The prediction performance of the classification trees was also assessed by accuracy, defined as follows:

$$Accuracy = \frac{\text{sum of true classified cases}}{\text{total number of cases}} * 100$$

RFs

Random forests (RFs) were a modification of the CARTs²¹. RFs could thus generate an ensemble of trees using bootstrap sampling and randomized subset of predictors to enhance prediction performance.

Results

Dataset

The common descriptive statistics are presented in Table 1. As can be seen, RTDR ranged from 2.7 to 42.37 per 100,000 population over ten years. The RTDR mean values in 2007, 2010, 2013, and 2016 were also by 19.79, 16.21, 16.97, and 16.51 per 100,000 population, respectively. According to the HDI analysis, among 131 countries, 39 cases were categorized as very high (HDI>=0.8), 35 countries as high (0.7<=HDI<0.8), 24 cases as medium (0.55<=HDI<0.7), and 33 countries as low development (HDI<0.55)⁴.

Table 1
Descriptive statistics of RTDR and HDI components of the total of 131 countries between 2007 and 2016

variable	Minimum				Maximum				Mean				Standard Deviation			
	2007	2010	2013	2016	2007	2010	2013	2016	2007	2010	2013	2016	2007	2010	2013	2016
RTDR ^a	4.3	2.96	2.8	2.7	41.6	42.37	36.2	35.9	19.79	16.21	16.97	16.51	10.18	7.781	8.994	8.936
HDI ^b	0.295	0.319	0.345	0.365	0.938	0.942	0.946	0.951	0.672	0.688	0.705	0.718	0.169	0.163	0.159	0.156
Education index	0.154	0.18	0.209	0.233	0.915	0.925	0.931	0.946	0.606	0.627	0.649	0.662	0.188	0.184	0.180	0.179
Income index	0.271	0.279	0.287	0.301	1	1	1	1	0.675	0.682	0.692	0.702	0.189	0.182	0.180	0.178
Life expectancy index	0.352	0.386	0.441	0.486	0.963	0.969	0.976	0.986	0.756	0.775	0.793	0.807	0.149	0.139	0.129	0.121

1. Road traffic death rate per 100,000 people
2. Human development index

Unconditional Linear LGM

The RMSEA and the CFI values were 0.024 and 0.983, respectively, representing an acceptable fit of the model. The estimated RTDR at the initial point was also 18.187, $p < 0.001$. Besides, the significant negative slope (-0.588, $p < 0.001$) implied a decreasing trend in RTDR. The trajectories of the unconditional linear LGM are illustrated in Figure 1.

Conditional LGM

An initial analysis was performed to compare the performance of the LGM model with the HDI as a time-invariant covariate to the LGM model with the IHDI as a time-invariant covariate. The fit indices also showed that the LGM model with the HDI as a time-invariant covariate outperformed the LGM model with IHDI as a time-invariant covariate (Additional file 1: Table S1). Therefore, the mean value was considered as a time-invariant covariate. The RMSEA and the CFI values were also equal to 0.037 and 0.975, respectively, suggesting an acceptable fit of the conditional LGM. The parameter estimations correspondingly implied the significant negative effect of the HDI on the intercept (-36.685, $p < 0.001$), denoting that countries with higher HDI had a lower initial value of RTDR. Moreover, the HDI had a significant negative effect on the slope (-2.568, $p < 0.001$), indicating a drop in RTDR, associated with an upsurge in the HDI.

To further investigate the role of the HDI in the trajectory of RTDR, the mean values of the HDI components were considered as time-invariant covariates. The results of the linear conditional LGM influenced by education, income and LE are summarized in Table 2. Since the mean of the HDI components were highly correlated with each other (namely, multicollinearity problem, Additional file 1: Table S2), the effect of each component on the LGM parameters was reported separately. The results revealed the negative effect of education, income and LE on the intercept and the slope. The results of the linear conditional LGMs with the HDI and its components as time-varying variables are provided in Additional file 1: Table S3-S6. Additionally, assessing the trends of RTDR and the influence of the HDI and its component on the LGM parameters in human development categories are reported in Additional file A: Table S7-S12.

Table 2
The parameter estimations of linear conditional LGM (HDI component as a time-invariant covariate).

Model (time-invariant covariate)	CFI	RMSEA	Effect on intercept	Effect on slope
Linear conditional LGM (Education)	0.981	0.027	-32.506*	-1.439*
Linear conditional LGM (Income)	0.976	0.032	-26.319*	-3.386*
Linear conditional LGM (Life expectancy)	0.963	0.046	-45.493*	-2.381*

*Significant at 0.05 level, CFI; comparative fit index, RMSEA; root mean square error of approximation

CARTs

The estimated slope of RTDR for each country from the linear unconditional LGM was used for determining the overall trends of RTDR. Accordingly, a total number of 106 and 25 countries had a downward and upward trend of RTDR, respectively. The categorical world map based on the trends of RTDR is illustrated in Figure 2, using the *rworldmap* package in the R (ver. 3.6.3)²⁸. The estimated slope of the countries is provided in Additional file 2. The CART analysis was further performed to assess the relationship between the dependent binary variable and the HDI and its components. Since the CART procedure could choose the best splitter, the issue of multicollinearity in the HDI components could be easily²⁹. Four models were also built using the CART procedure, that is, two models with the mean and the slope of the HDI as independent variables and the other two with the mean and the slope of the HDI components as independent variables.

In the first model, the CART outcomes with the mean value of the HDI as an independent variable are illustrated in Figure 3. The outcome was a tree with nine terminal nodes. As well, 63% of the countries were placed in terminal node 1, the CART classified these countries as a downward category, and only two

countries were misclassified (namely, the Kingdom of Saudi Arabia and Thailand). Moreover, 12% of the countries were classified as an upward category with two misclassified countries (viz. Honduras and Ethiopia). Of note, 13 countries were misclassified, which resulted in 90% accuracy.

Second, the CART result with an HDI slope as an independent variable is presented in Figure 4. The outcome was a tree having six terminal nodes in which 73% of the countries were classified in node 1 (the slope of HDI<0.0185) as a downward category. Thirteen countries were also classified as an upward category with four misclassified countries (namely, Bosnia and Herzegovina, Senegal, Niger, and Albania). Overall, the accuracy of the model was 85%.

Third, the outcome of the CARTs with the mean value of HDI components as independent variables was a tree comprised of eight terminal nodes (Figure 5). It was observed that 75% of the countries assigned to terminal nodes 1-3 were classified by CARTs as a downward category and only two countries were misclassified in these nodes (i.e., the Kingdom of Saudi Arabia and Thailand). CARTs also predicted the countries placed in the upward category in terminal nodes 4 and 8, consisting of 72% of the countries with an overall upward trend of RTDR, and only one country was misclassified (namely, Ghana) in these two nodes. Overall, CARTs misclassified eight countries. As a result, the accuracy of the CART model with the mean value of the HDI components as independent variables was 93.89%, indicating the high classification performance of the model.

Fourth, Figure 6 illustrates the CART results with the slope of the HDI components as independent variables. The slopes of the HDI components were calculated using the linear LGM. As can be seen in Figure 6, the outcome was a tree made up of eight terminal nodes. If the slope of LE of the countries ranged between 0.0025 and 0.0135, the CART could allocate these countries to terminal node 1, comprised of 56% of all countries and classified as a downward category. Moreover, the countries with the slope of LE equal to or more than 0.0305 were assigned to terminal node 8, which classified countries as an upward category and included the 32% of the countries with an overall upward trend of RTDR. The accuracy of the CART model with the slope of the HDI components as independent variables was 88.55%. The CART pruning rules, the mean value of RTDR, and the misclassified countries in each terminal node for all four models are provided in Additional file 1: Table S13-S16.

M. life expectancy=Mean of life expectancy, M. education=Mean of education, M. income=mean of income

S. life expectancy=Slope of life expectancy, S. education=Slope of education, S. income=Slope of income

Variable Importance

Variable importance measure, as one of the useful outputs of the tree-based models, could reflect the effect of the predictor variables on the model. The ranking of the variable importance in the RF model was more accurate than the CART³⁰. In this study, the independent variables from two CART models (with the mean and the slope of the HDI components) were entered into the RF model to produce a more accurate ranking. The variable importance based on the increase in node purity measure is displayed in Table 3. As observed, LE was the most important variable in these two models.

Table 3
Importance of variables in two CART models using random forest procedure.

Variable	Increases in node purities	
	The mean of the HDI components model	The slope of the HDI components model
Life expectancy	6.58	7.24
Income	6.18	4.05
Education	5.49	4.49

Discussion

This study revealed that the global trends of RTDR were decreasing over a 10-year period (from 2007 to 2016). However, such trends for 25 countries out of 131 cases examined were increasing. According to the conditional LGM, the results indicated the negative effect of the HDI and its components on the intercept and the slope. Furthermore, LE was the most important HDI component, negatively with RTDR in both mean and slope models. Moreover, countries with lower slope changes in the HDI and LE mainly had a downward trend in RTDR.

In line with these results, Slaehi et al. (2019), using LGMs in 2007, 2010, and 2013 in 181 countries, had demonstrated that the HDI had a significant negative impact on RTDR². On the other hand, although one other study had revealed that, LE, among the HDI components, had the least association with RTDR⁷, the time-trend analysis in the present study in both mean and slope models showed that the component concerned was the most important one. Another investigation had further deliberated that a decline in infant mortality rate (IMR) and a rising trend in physicians per thousand people were significantly associated with a decline in motorcycle mortality rate as one of the worldwide health care system-related factors¹². However, these factors were not assessed in the present study, considering that IMR might be an indirect indicator of LE.

Considering Figure 2, most countries with an ascending trend in RTDR were African or Southeast Asian ones. The results demonstrated that, among 131 countries, Egypt, Afghanistan, Lithuania, Qatar, Iran, and Slovakia had experienced the most reduction in RTDR between 2007 and 2016. On the other hand, Zimbabwe, Liberia, Central Africa, the Democratic Republic of the Congo, Malawi, and Thailand had faced the most increasing RTDR.

With regard to the relationship between the HDI and RTDR (Figure 3), all countries with the HDI higher than 0.6628, except for the Kingdom of Saudi Arabia and Thailand, had experienced a diminishing trend in their RTDR in these ten years (namely, 81 countries from 83). These countries were mostly classified in very high and high HDI categories. On the other hand, countries with the HDI between 0.482 and 0.4976 and those with a mean value of HDI lower than 0.4586 (except for Ethiopia) had experienced an upward trend in RTDR (viz. 11 countries among 12). All of these countries were categorized as low HDI ones.

Regarding the relationship between the slope of the HDI and RTDR (Figure 4), countries with slopes changing less than 0.0185 had the least mean of RTDR over these ten years (namely, 87 countries out of 96 cases). Among nine misclassified countries, Thailand also had a high mean of the HDI, El Salvador and Vietnam had a medium mean, and others had a low mean of this index. While the mean value of RTDR in countries with a slope lower than 0.0185 was 15.11, the mean of RTDR in other categories was at least 21.74.

Some studies had also assessed the relationship between the HDI and RTDR^{6,8}, but the relationship between the HDI components and RTDR had not been evaluated. Considering the relationship between the mean value of different components of the HDI and RTDR, with the model accuracy of 93.89%, the mean of LE was the most essential factor associated with RTDR. Based on this model, the mean value of LE, income, and education had influenced RTDR, respectively.

According to Figure 5, among countries with a higher mean LE, income, and education, except for the Kingdom of Saudi Arabia, 76 cases had experienced a diminishing RTD trend over these ten years. Moreover, countries in node 2 had a reduction trend of RTDR (viz. 13 countries with a mean value of RTD by 19.14). On the other hand, 23 countries with a mean LE, lower than 0.633, except for six countries named South Africa, Angola, Nigeria, Mali, Chad, and Niger, had encountered an increasing RTDR in these ten years. Thus, the policies in these six countries could be considered good examples for ones with low HDI to deal with RTD.

Besides, the present study analyzed the relationship between the rate of various components of the HDI and RTDR. In this regard, the accuracy of the model presented here was 88.55%. Considering the variable importance table, the slope of LE, education, and income was strongly correlated with RTDR, respectively. Based on Figure 6, node 1 consisted of 74 countries, except for four named El Salvador, Rwanda, Togo, the Democratic Republic of the Congo, which had a descending RTDR with a mean of 14.72. Node 2 also included seven countries, except for Timor-Leste, with a medium mean of HDI categorized in high and very high HDI countries.

Other 50 countries in nodes 3-8 had a mean value of RTD of more than 17.79. Among these nodes, nodes 3, 7, and 8 were predicted to increase RTDR in this period. Node 8 also consisted of 11 countries having a LE slope of more than 0.0305. In this node, three countries of Kazakhstan, Botswana, and South Africa had different behaviors than others and had experienced a diminishing RTDR. With an HDI mean near 0.8, Kazakhstan was categorized as a high HDI country, and the other two nations were categorized in the medium HDI.

Finally, comparing the mean and the slope of the CART models revealed that Kazakhstan and Botswana were in the first node of the mean model (with the means of LE, income, and education more than 0.633, 0.4926 and 0.6254, respectively) and in the eighth node of the slope model (LE slope more than 0.0305), facing a diminishing RTDR.

On the other hand, although Togo and the Democratic Republic of the Congo had experienced a rising RTDR in this period, in the mean model, they were in node 8 ($LE < 0.633$, $education \geq 0.2923$, and $income < 0.5823$), and in the slope model, they were in the first node (with LE slope between 0.0025 and 0.0135). Although the HDI increased at this period in these two countries, they remained in the low HDI category.

Besides, some countries had deviant behaviors compared with other nations in their own category. Among countries with very high HDI, the Kingdom of Saudi Arabia was the only case experiencing a rising RTDR in this period. In 2010, non-communicable diseases and road traffic injuries had the leading causes of disability and death in this country³¹, which could be explained with the suggestion by the WHO about affluent countries in the EMR, experiencing rapid economic development without sufficient investments in institutional capacities and interventions to deal with road collisions³. Moreover, people's non-adherence to road traffic law enforcement was a crucial factor related to RTDR in this Kingdom³¹. However, it should be noted that transport injuries in the Kingdom of Saudi Arabia had a descending trend from third to fifth of the cause of the disability-adjusted life years (DALYs) between 2010 and 2017³².

On the other hand, two deviated countries experiencing a diminishing trend in these ten years were Kazakhstan and Botswana. In this sense, Kazakhstan had promoted from a country with high HDI to a very high one over these years. Moreover, in 2008, this country had passed the Legislation of the Republic of Kazakhstan on Administrative Offences affecting people's road traffic behaviors³³. Therefore, both human development and legislative factors could be associated with a descending trend in RTD. The case of Botswana was a little different. This country had encountered its minimum RTDR in 2010, and then an increasing rate had been seen. It had also experienced one of the fastest-growing HDI and had moved up eight places from 2012 to 2017⁴. Although the Road Traffic Act of Botswana had been passed in 2008 and a decrease in RTDR had been experienced in 2010, an increasing trend in RTD could be observed from 2013. As Mphela (2011) mentioned, the ACT had little impact on reducing RTD³⁴. A study in this country had further demonstrated that night time travel and population density could lead to a growth in RTDR, while investing in road infrastructure could minimize it³⁵.

Overall, the present study showed the importance of changing HDI and LE in RTDR globally. Countries with a mean of the HDI more than 0.6628 or a change in their HDI slope smaller than 0.0185 could thus reduce RTDR between 2007 and 2016. Countries with a mean LE more than 0.633 had mainly controlled RTDR better than the ones with a lower index. As mentioned by the UNDP, there was a significant gap between LE at birth in 2017 among countries with different human development categories. LE at birth had been 60.8 and 69.1 years for the low and medium human development groups, respectively. On the other hand, countries with high and very high HDI had 76 and 79.5 years of LE, respectively⁴. Moreover, nations with more slight changes in LE from 2007 to 2016 had better association with reduced RTDR. Based on Bishai's hypothesis¹⁰ (mentioned earlier), it was concluded that countries with medium HDI had invested more in their high-ranked health risk factors such as infectious diseases and their nutritional status rather than road safety. Moreover, there was a lag between medical technology and dealing with road traumas in these countries. In addition to LE, Kazakhstan, the Kingdom of Saudi Arabia, and Botswana had shown the importance of sociocultural factors regarding people's driving behaviors in mitigating RTDR. These deviated cases revealed that increasing HDI and its components and legislating law enforcement could not be sufficient factors in minimizing RTDR. Therefore, countries are suggested to implement various interventions to change drivers' behaviors.

Among the main limitations of this study was lack of credible data at the global level (other than the HDI), which could be investigated for its association with RTDR. Furthermore, RTDR published were limited, while the prediction of RTDR in the future would be possible made through having access to more data.

Conclusion

Overall, RTDR is concluded to be multifactorial. As this study showed, the HDI and its LE component are the main determinants of RTDR at a global level. In addition, legislative factors and sociocultural context of countries are assumed as important issues that should be considered by policy-makers to control RTDR.

Abbreviations

HDI: human development index; RTDR: road traffic death rate; LE: life expectancy; CARTs: Classification and regression trees; RFs: random forests; RTD: Road traffic death; EMR: Eastern Mediterranean Region; IHD: inequality-adjusted human development index WHO: World Health Organization; UNDP: United Nations Development Programme; GNI: gross national income; PPP: purchasing power parity; OECD: Organisation for Economic Co-operation and Development; GDP: gross domestic product; LGM: latent growth model; RMSEA: root mean square error of approximation; CFI: comparative fit index; GoF: goodness-of-fit; IMR: infant mortality rate; DALYs: disability-adjusted life years.

Declarations

Ethics approval and consent to participate

All procedures performed in this study were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Since the data were collected from WHO and UNDP reports, which are publicly available on their website, consent to participate was not applicable to this study. This study was approved by the Research Ethics Committee of Shiraz University of Medical Sciences, Shiraz, Iran (code: IR.SUMS.REC.1399.1241).

Consent for publication

Not applicable.

Availability of data and materials

All data generated or analysed during this study are included in Additional file 2.

Competing interests

The authors declare no competing interests.

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None.

Authors' contributions

KBL, MRRH, SG and MS did the study design and conceptualization. MS and MRRH did the statistical analysis and wrote the original draft, with revisions by KBL, BH and SG. KBL, SG and BH supervised and validated the main study implementation. All authors reviewed and approved the final version of the manuscript.

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Figures

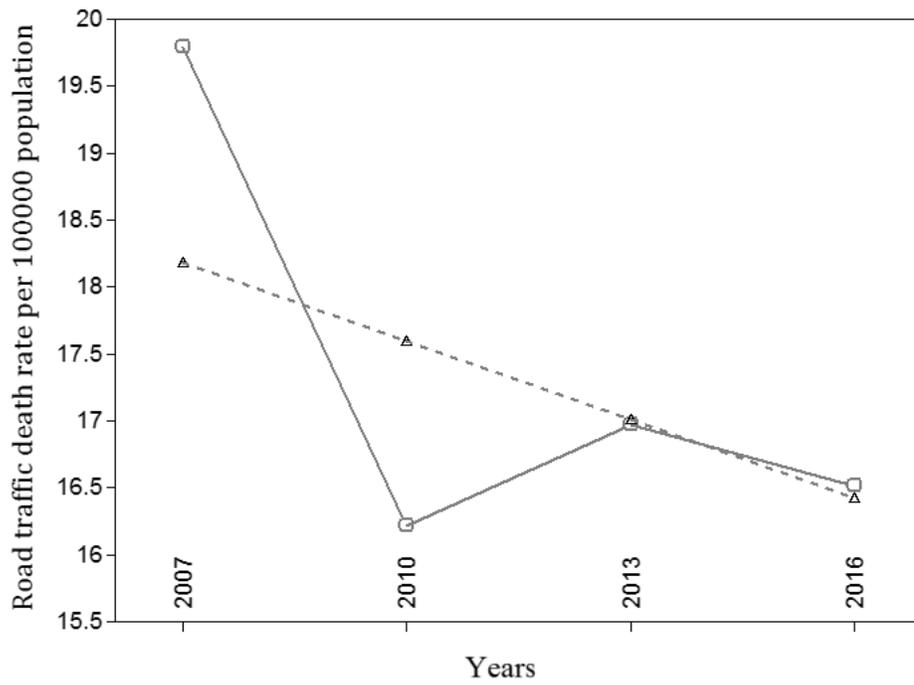


Figure 1

Observed overall trajectory (solid line) and estimated overall trajectory (dashed line) of unconditional linear LGM in 2007-2016

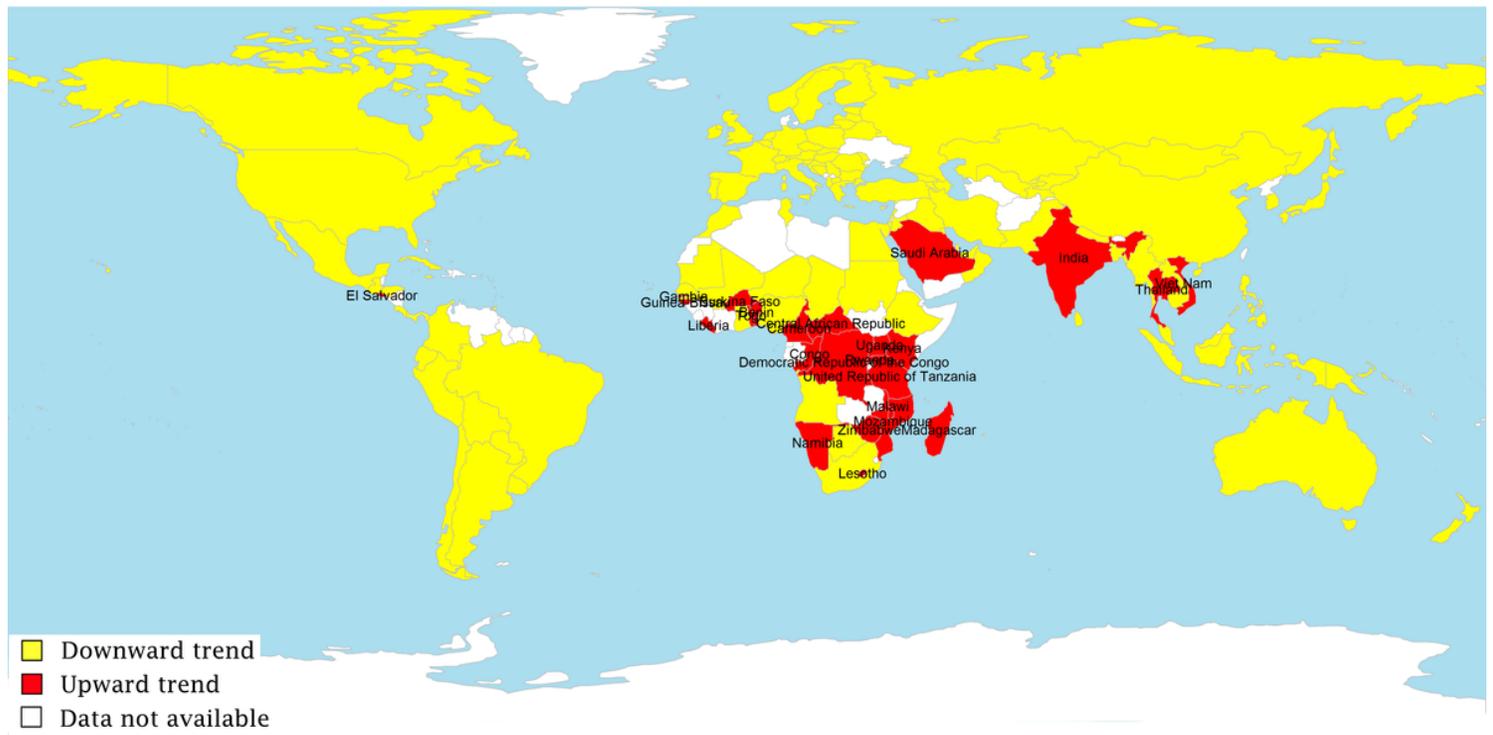


Figure 2

A global view of trends of RTDR in 2007-2016.

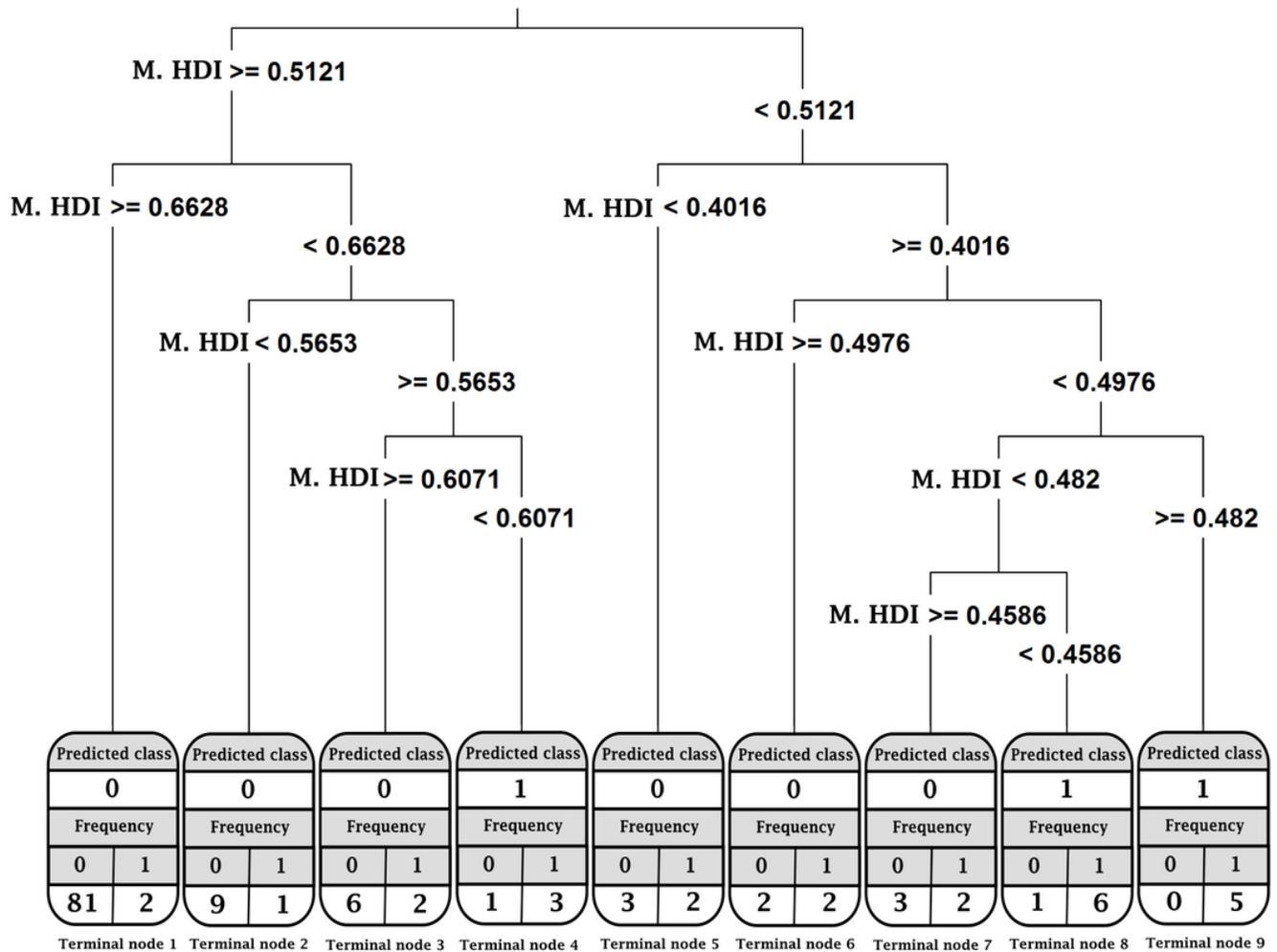


Figure 3
 Optimal tree created by CARTs (Mean values of HDI as independent variables). The predicted binary outcome and the number of countries at each category were shown at each terminal node. M. HDI=Mean value of the Human Development Index

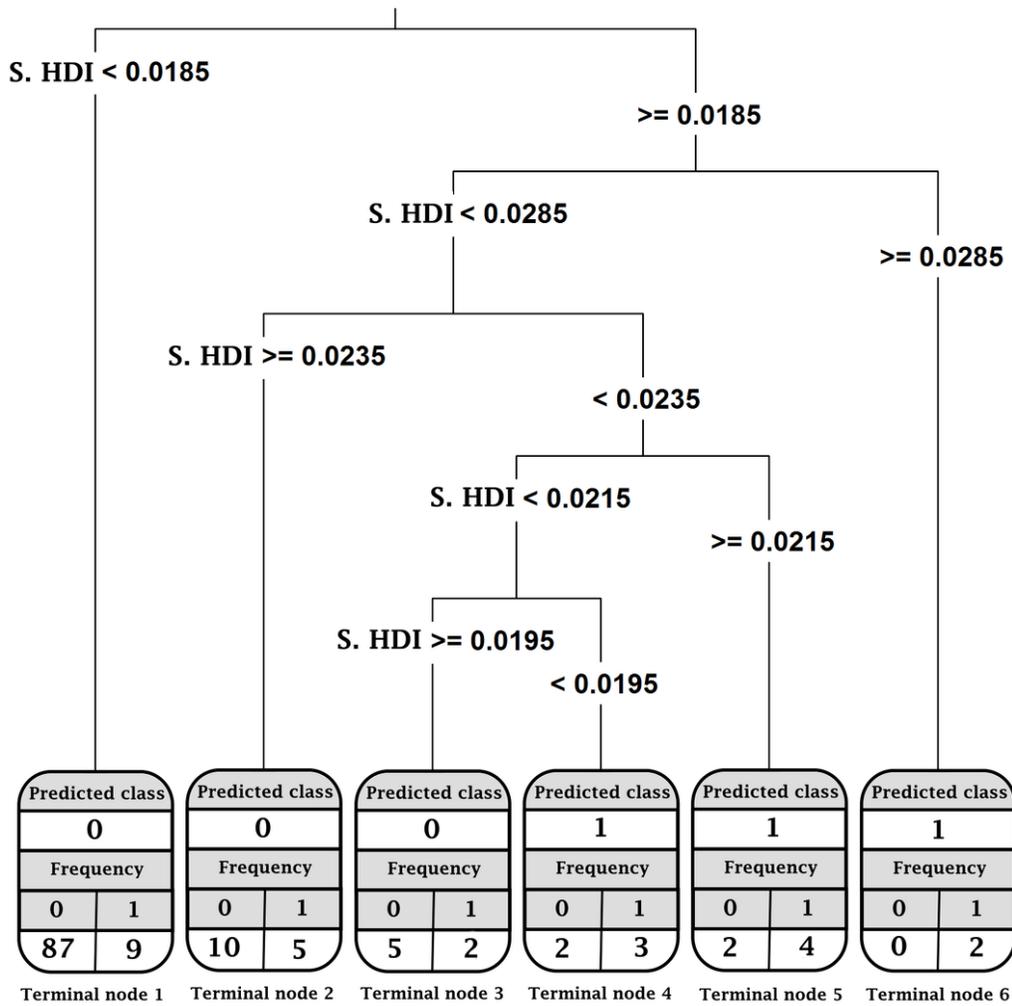


Figure 4

Optimal tree created by CART (Slope of HDI as independent variables). The predicted binary outcome and the number of countries at each category were displayed at each terminal node. S. HDI=Slope of Human Development Index

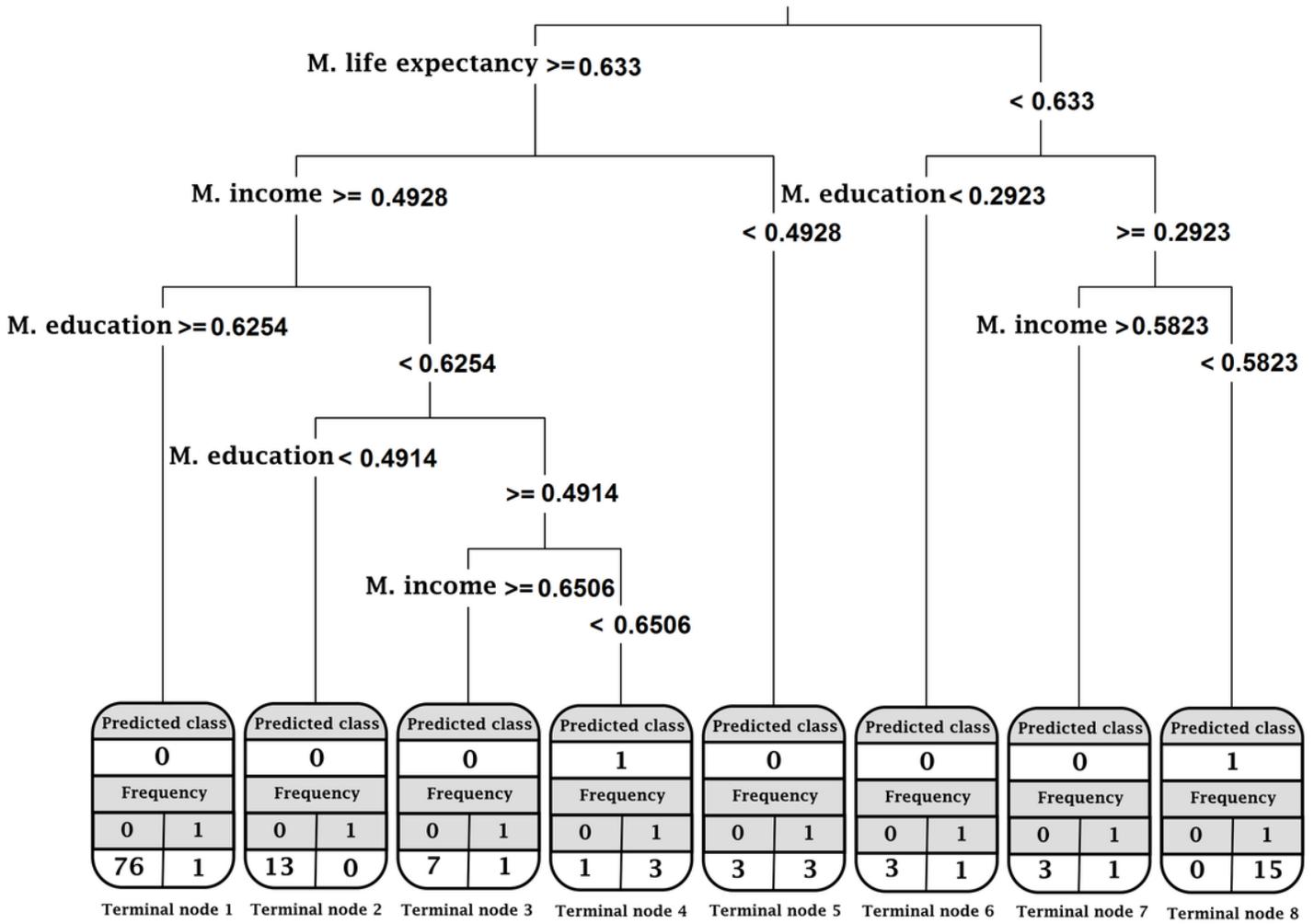


Figure 5
 Optimal tree created by CART (Mean of education, income and LE as independent variables). The predicted binary outcome and the number of countries at each category are shown in each terminal node.
 M. life expectancy=Mean of life expectancy, M. education=Mean of education, M. income=mean of income

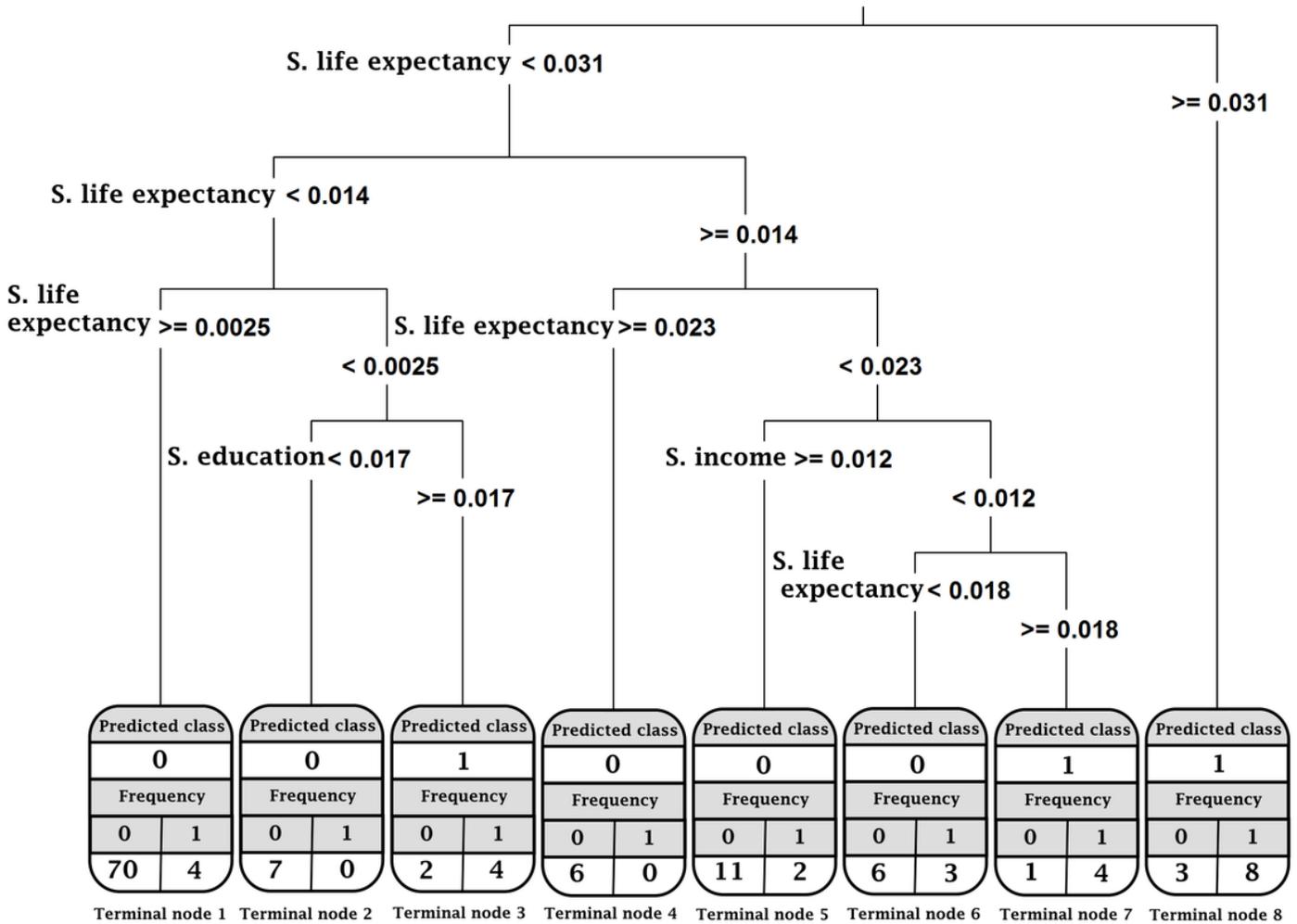


Figure 6
 Optimal tree created by CART (Slope of education, income, and LE as independent variables). The predicted binary outcome and the number of countries at each category are shown in each terminal node.
 S. life expectancy=Slope of life expectancy, S. education=Slope of education, S. income=Slope of income

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