Journal of Economics and Public Finance
ISSN 2377-1038 (Print) ISSN 2377-1046 (Online)
Vol. 6, No. 1, 2020
www.scholink.org/ojs/index.php/jepf

Original Paper

The Over-Searching Accidents Causative Factors in Ghana: The Role of Policyholders Education Levels

Azaare Jacob[1*], Zhao Wu[1], Bright Nana Kwame Ahia[2] & Edward Amankwah[3]

[1] School of Management and Economics, University of Electronic Science and Technology of China, No. 2006, Xiyuan Ave, West High-Tech Zone, Chengdu 611731, China

[2] School of Management and Economics, University of Electronic Science and Technology of China, Chengdu, China

[3] Sichuan Urban Vocational College, Chengdu, China

[*] Azaare Jacob, School of Management and Economics, University of Electronic Science and Technology of China, No. 2006, Xiyuan Ave, West High-Tech Zone, Chengdu 611731, China

Received: August 1, 2019 Accepted: August 13, 2019 Online Published: January 13, 2020

doi:10.22158/jepf.v6n1p28 URL: http://dx.doi.org/10.22158/jepf.v6n1p28

Abstract

Available statistics indicates that about 90% of all claims or accident in Ghana is caused by human behavior. Therefore, policyholders' errors are categorized depending on the severity and extend of casualties caused as a result of misinterpretation of road traffic control devices based on their education levels. Hence, in order to ascertain all the possible causes within the human element to reduce the increasing trend of yearly claims, this study report on the influence of education levels on accident/claims frequency and severity drawing upon a purposive sample of 203 policyholders who have experienced at least one accident in a year using structural equation modeling (SEM). The findings from our regression weights gave enough evidence to reject most of our hypotheses with few ones being supported. This study provides enough evidence that education generally to perspective policyholders influence accidents/claims occurrence. However, in terms of education levels of policyholders, we did not have enough evidence in support of any of these levels either causing or reducing claims/accident frequency. Besides accident/claim frequency, we extended our regression analysis on claim severity and also included some well know auto insurance rating factors to ascertain their impacts on accident frequency. Consequently, it was revealed that most of the severe claims or accidents that results into deaths and serious injuries on yearly basis are caused by policyholders or drivers with medium level of education in Ghana with its frequency driving mostly by rating factors such as the vehicle's age, cubic capacity, mileage, etc.

Keywords

structural equations modeling, accidents minimization, priori homogenous variables, historic accident records, education levels

1. Introduction

Due to an increase per capital of income globally, automobile is almost becoming available in every household for either commercial or private purpose. This has increased its associated risk in insuring as a result of variable degree of independent rating factors (Stojaković & Jeremić, 2016; Yazan, 2016). The rate of accident occurrence worldwide affect population with varied contributing factors influencing the causes in different region particularly developing country like Ghana Mends-Brew et al. (2019). According to World health organization (WHO), 1.6 million people are perished in road traffic accident globally and an estimated 20 to 50 million are disabled from its effects, a menace which if not properly checked would be the third cause of mortality and morbidity by 2020. Statistics has shown that, the number of fetal accidents in Ghana keeps increasing on yearly basis with its negative impact on families, government and insurers (Albert, 2014). See also Figure 1 for more details on the yearly trend of people killed since 1991 from road accidents. Available data from the Ghana motor traffic and transport department (MTTD) of the Ghana of police service and the National road safety commission (NRSC) indicates that, as at the first quarter of 2019, a whopping total of 696 Souls have already been perished through road accidents. This figure is an overwhelming increment of 17.57% for that of 2018 which recorded 592 casualties in the first quarter. On semiannual basis, the number has rose by 3.3% from 1,212 in the first half of 2018 to 1,252 during the first six months of 2019, a menace which needs an urgent attention Mends-Brew et al. (2019).

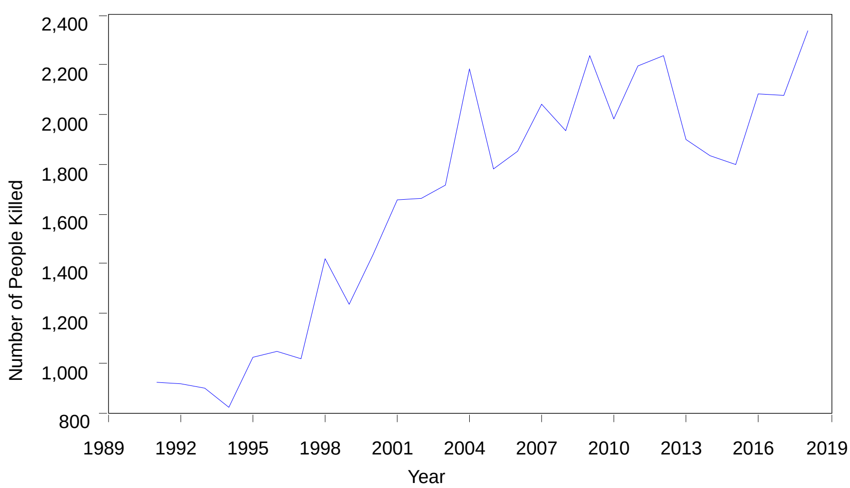

Figure 1. Yearly Trend of People Killed in Road Accidents since 1991 in Ghana

In order to ensure safety driving, auto insurers in predicting risk usually based on priori homogenous variables such as the vehicle's age, its mileage, cubic capacity, experience of the policyholder or the driver etc. and also historic accident records to obtain optimal premiums. The purpose of this risk categorization is to proportion driver's bad accident records to their premium in order to deter them from reckless driving. Despite these homogenous groupings, swiftness of reflexes, aggressiveness at the back of the wheel, or information on road safety regulations which have impact on frequency and severity of claims are always difficult to deal with by risk forecasters because of their heterogeneous nature (Brouhns et al., 2003; Ibiwoye et al., 2011; Kafkova & Krivankova, 2014; Kafková, 2015; Pinquet, 2000; Renshaw, 1994; Walhin & Paris, 1997). Policyholders or drivers also contributions to minimizing these risks are also in doubt since their level of understanding for instance road safety regulations, may highly depend on their level of education (Adedeji et al., 2016; Ibiwoye et al., 2011; Mock et al., 1999; Smart & Mann, 2002). To this effect, recent extensive study conducted by Al-Reesi et al. (2013) essentially confirmed that risky driving and aggressively violation of road traffic laws in particular are the main risk factors for claims occurrences. In view of this (Mends-Brew et al., 2019; Plankermann, 2013; Smith, 2005) found that knowledge of drivers' behavior, attention to road safety and auto is very important and therefore concluded that human element is the pivotal factor for claims occurrence. In addition, Atubi and Onokala (2009), Feachem et al. (1992), Hazen and Ehiri (2006), Smith and Barss (1991) categorized driver error depending on the severity and extend of casualties caused as a result of misinterpretation of road traffic control devices leading to 90% of all road traffic accident. Aside human element, global trend on road traffic accidents are also well known to be influenced by factors such as unfavorable weather conditions, poor roads network, vehicular factors, and so on, which previous researchers have always based to providing solutions (Afukaar et al., 2003; Mends-Brew et al., 2019). However, it's an acknowledged fact that there is still an alarming rate of this menace in Ghana as indicated in Figure 1 despite all the efforts made (Mock et al., 1999; Mends-Brew et al., 2019).

Therein, we draw upon the findings from Adedeji et al. (2016), Al-Reesi et al. (2013), Ibiwoye et al. (2011), Mends-Brew et al. (2019), Mock et al. (1999), Plankermann (2013), Smart and Mann (2002), Smith (2005) and consider education, education levels as an independent and very uncommon variables for premium rating with the reason that Ghana have majority of road users with different levels of education. Education is the process of facilitating learning, or acquisition of knowledge, skills, values and habits or simply put is the process of helping someone to do things. Education enhances the number of potentially ideas to increases knowledge on road safety regulations and can reduce the occurrence of possible accidents (Adedeji et al., 2016; Mock et al., 1999). This is because having strong prior technical knowledge allows process more information on the type of motor at hand and road safety regulations which helps reduce uncertainty (Atubi & Onokala, 2009; Feachem et al., 1992; Hazen & Ehiri, 2006; Plankermann, 2013; Smith & Barss, 1991; Smith, 2005). The level of policyholder's education level might have very significant role to play when it comes to occurrence of accidents and therefore the need to consider it within the human factor which have proven to be the pivotal cause. The levels being categorized as high, medium and low serves as independent variables against claims occurrence and claims size to ascertain the magnitude of impact each level impose. We maintained in our model following Rumar (1999) some well-known rating factors often used by automobile insures during pricing to compare the results with our newly introduced variables in order to make meaningful deductions on the various contributory factors that influences claims frequency. To drive hypotheses on education levels and their effects on claims frequency and severity, we draw from multivariate linear regression (MLR) in structural equation modeling (SEM) methods to explore the relationship in our latent variable construct. Several models such as Autoregressive (AR), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Exponential and Polynomial methods, specifically the sixth-order polynomial model have been considered by Mends-Brew et al. (2019).

We draw upon a purposive sample of 203 motor users in Ghana who have experienced at least one accident in a year to test a set of hypotheses derived from our MLR. This research adds to the literature on rating factors impacting on frequency and severity of claims/accidents in motor insurance in several ways. First in drawing upon MLR and SEM, we provide parsimonious explanation the effect of education on claims occurrence. Second, we explicitly model the actual contributions of each level of education (high, medium and low) in determination of claim size and frequency. This research is to help policy makers especially those in the insurance sector and Driver and Vehicle Licensing Agency (DVLA) in Ghana to decide respectively on; 1) Inclusion of education level as a rating variable in determination of premium for policyholders. 2) The kind of training to be given to driving license applicants and possibly setting up minimum educational qualification for driving license acquisition.

To this end, we based on Afukaar et al. (2003), Atubi and Onokala (2009), Al-Reesi et al. (2013), Mends-Brew et al. (2019), Plankermann (2013) and derive out hypotheses as follows;

H_1: Education background has positive influence on claims/accident frequency reduction

H_2: a) Higher education level lower claim/accident occurrence.

b) Medium level of education causes frequent claims/accidents.

c) Low or no education background significantly causes frequent claims/accidents.

H_3: a) High level of education positively reduces Severity of claims.

b) Medium education level leads to severe claims.

c) Low level of education causes severe claims.

H_4: Automobile rating factors are the real causes of claims/accident.

The rest of the paper is organized as follows: Section 2 describes the materials and methods. In section 3, we present how our data was analyzed and the findings. We discuss the results in section 4 and conclude in section 5.

2. Materials and Methods

2.1 Data Sample

In exploring the influence of policyholders' education backgrounds and levels on claims frequency and severity, questionnaire was developed and the survey included 265 individual drivers who have experienced at least one accident in a year. Due to available statistics which indicates high accident rate in Greater Accra and Ashanti region, we took our sample from these two regions. See Mends-Brew et al. (2019) for details. Out of the 265 questions distributed to respondents, a total of 206 were retrieved constituting 77.74%. We removed three cases out of the 206 due to the fact that the respondents somewhat agreed to every likert scale item leaving a total of 203 cases made up of 168 males and 35 females. We also observed two missing values in both education levels and claims severity. We checked at the surrounding values of the other indicators for the variable education levels and claims severity, and we used the mode value for the respondent to impute the missing values. Shown in Table 1 are the various characteristics about the 203 respondent and their auto information.

Table 1. Characteristics of 203 Respondents and Their Auto Information

	Frequency(n=203)	**%**
Gender		
Male	168.0	82.8
Female	35.0	17.2
Age group		
18-30	45.0	22.2
31-45	124.0	61.1
46-60	32.0	15.8
+60	2.0	1.0
Occupation		
Professional driver	25.0	12.3
Government worker	55.0	27.1
Private worker	108.0	53.2
Others	15.0	7.1
Vehicle insured		
Yes	203.0	100.0
No	0.0	0.0
Insurer		
SIC	39.0	19.2
Hollard	39.0	19.2
Vanguard	34.0	16.7
GUA	18.0	8.9
Others	73.0	36.0
Involved in an accident before		
Yes	203.0	100.0
No	0.0	0.0

Vehicle model		
Toyota	78.0	37.9
Hyundai	22.0	10.8
Nissan	15.0	7.4
Others	88.0	43.3
Vehicle cubic capacity(CC)		
1000-2500	150.0	73.9
>2500	53.0	26.1
Vehicle manufacturing year range		
1999-2000	9.0	4.4
2001-2010	118.0	58.1
2011-2019	76.0	37.4
Vehicle use		
Private/ Corporate	160.0	78.8
Commercial	42.0	20.7
Others	1.0	0.50
Education level of policyholder		
Bachelor or Above	38.0	18.7
Secondary/Diploma	140.0	69.0
Basic/Not at all	25.0	12.3

2.2 Measurement of Variables

Each of the constructs was measured by original measurement items designed by the authors. Education was measured on (Knowledge in road signs, background information on accident, driving school training). Education level was measured on (driving years, High education certificate (bachelor and above), Medium education certificate (diploma and high school) and Low or no education at all). Rating factors in auto insurance maintained in our model were (auto cubic capacity, Mileage, auto age, auto use, Profession of policyholder and experience). Claims frequency was measured on (possibility of the accident occurring, different claims reporting, multiple times occurrence). Finally, claims severity was measured on (degree of damages on auto, degree of casualties, and level financial distress to insurers or government). The questions were asked on a 5-point Likert scale in which 1 indicates strongly disagree, 2 indicates disagree, 3 represents neutral, 4 represents agree, and 5 indicates strongly agree. The motive behind using this Likert scale items is due to the fact that most drivers were reluctant in disclosing actual claim records.

2.3 Research Tools

In exploring the relationship in each of our latent variable construct, multivariate data analysis was deemed necessary in two stages. With the first stage, we extracted factor structure of our conceptual framework by using the principal component analysis (PCA). The PCA was used to minimize sets of variables into a convenient set of scales. In considering the underlying dimensions, the PCA with Varimax rotation was conducted. Still on this stage, we explored the convergent validity (AVE) and reliability via the Cronbach alpha test. The second stage of this analysis constituted exploring the relationship between our factors. We employed the structural equation modeling (SEM) in finding this relationships with our AMOS SPSS software**.** Blow is our MLR models explaining our hypothesis in section 1.

$$\left\{\begin{array}{l} CF_i = \alpha_0 + \alpha_1 edu + \alpha_2 rf + \mu \\ CF_i = \beta_0 + \beta_1 Hedu_i + \beta_2 Medu_i + \beta_3 Ledu_i + v \\ CS_i = \beta_0 + \beta_1 Hedu_i + \beta_2 Medu_i + \beta_3 Ledu_i + v \end{array}\right\} \quad (1)$$

Where, CF is claims/accident frequency, edu is education, SC is claims severity. Hedu, Medu and Ledu represents high, medium and low/no education levels respectively.

3. Analysis and Findings

Reliability analysis was first performed to check inter- item level consistency of responses on the various subscales under consideration. The composite Cronbach alpha on each of our five (5) latent variables indicated a suitable level of internal consistency amongst the scale items because all the values were above the lower threshold of 0.70. Also, our AVE values above the 0.50 threshold show that our data satisfies the principle of convergent validity as shown in Table 2. See Lowry and Gaskin (2014) for more details.

Table 2. Reliability and Validity Test

Variables	Cronbach Alpha	Convergent Validity (AVE)
Education	0.907	0.782
Education levels	0.919	0.745
Rating factors	0.939	0.725
Claims frequency	0.888	0.735
Claims severity	0.837	0.634

In Table 3, orthogonal extraction with varimax using principal component analysis (CPA) was considered appropriate because it was deemed necessary to large number of variables to a minimum set of uncorrelated variables. Specifically, varimax rotation was employed to minimize variables with high factor loadings to augment the interpretation of factors. Eventually, we retained five factors in the principal component analysis with eigenvalue > 1.0 explaining a total variance of 80.344% in our dataset. The KMO is a statistic measure of sampling adequacy. We performed this test to ascertain how adequate our sample size is to represent the population we are dealing with. As found in Table 4, our data gave a KMO value of 0.881 which clearly indicates that the sample under consideration is very adequate as generally any KMO values above 0.50 is considered acceptable. In Table 5, we also show the loading for all our factors considered. This table depicts that all factors are significant ranging from 0.825 to 0.934 with p-values <0.05.

Table 3. Factor Analysis Total Variance Explained

	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
Component	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	6.104	32.128	32.128	6.104	32.128	32.128	4.662	24.539	24.539
2	3.334	17.546	49.674	3.334	17.546	49.674	3.263	17.172	41.710
3	2.235	11.764	61.438	2.235	11.764	61.438	2.566	13.507	55.217
4	1.873	9.856	71.294	1.873	9.856	71.294	2.477	13.036	68.253
5	1.719	9.050	80.344	1.719	9.050	80.344	2.297	12.091	80.344
6	0.498	2.621	82.964						
7	0.406	2.139	85.103						
8	0.385	2.024	87.127						
9	0.325	1.712	88.838						
10	0.301	1.585	90.424						
11	0.268	1.409	91.833						
12	0.263	1.383	93.215						
13	0.240	1.262	94.477						
14	0.226	1.191	95.669						
15	0.204	1.074	96.743						
16	0.176	0.924	97.667						
17	0.166	0.872	98.539						
18	0.147	0.775	99.314						
19	0.130	0.686	100.00						

Table 4. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.851
Bartlett's Test of Sphericity (BTS)	Approx. Chi-Square	2832.502
	Df	171
	Sig	0.000

Table 5. Factor Loadings

	Factor				
	1	2	3	4	5
Knowledge			0.934		
Education background			0.873		
Driving school training			0.880		
Driving years		0.894			
High Education level		0.900			
Medium Education level		0.840			
Low or No		0.874			
Cubic Capacity	0.908				
Mileage	0.862				
Auto Age	0.825				
Auto Use	0.841				
Profession	0.874				
Experience	0.847				
Possibility				0.886	
Different claims				0.872	
Multiple times				0.886	
Damages					0.867
Casualties					0.843
Financial distress					0.864

3.1 Confirmatory Factor Analysis (CFA)

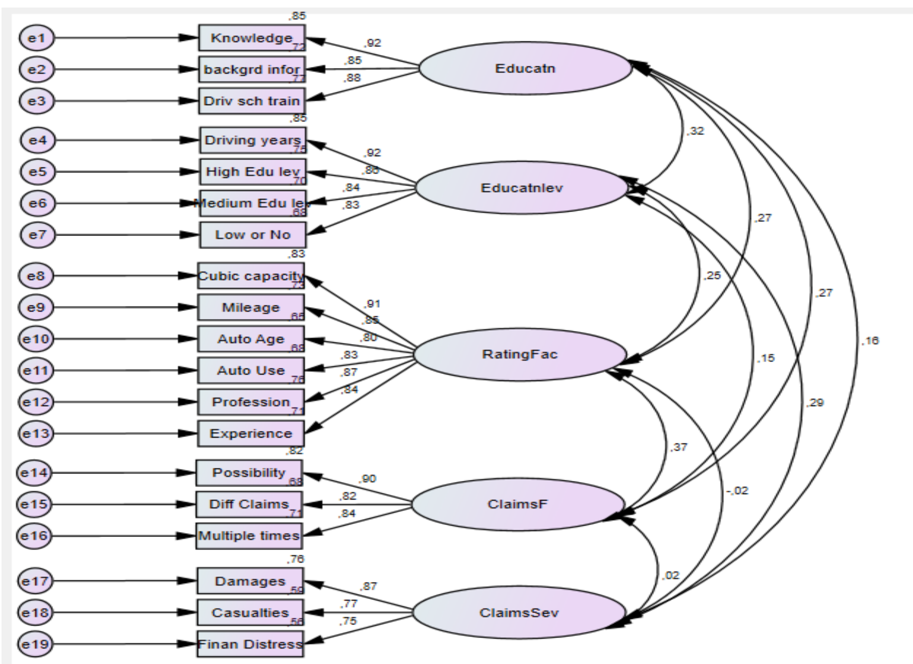

Figure 2. SEM Confirmatory Factor Analysis

Figure 2 represents the confirmatory factor analysis (CFA) derived from our AMOS software. The factor loading from each of our constructs depicted very high loadings and hence the reason to maintain all in our final model. Table 6 shows our unstandardized regression weights indicating that all the values in our construct was significant with p-values <0.04.

Table 6. Regression Weights: Maximum Likelihood Estimates

			Estimate	S.E.	C.R.	P
Driving sch. Train.	<---	Education	1.00			
Background infor.	<---	Education	1.13	0.07	1.95	***
Knowledge	<---	Education	1.40	0.08	1.80	***
Low or No	<---	Education lev	1.00			
Medium Edu lev	<---	Education lev	1.08	0.08	14.28	***
High Edu lev	<---	Education lev	1.08	0.07	14.99	***
Driving years	<---	Education lev	1.39	0.08	16.44	***
Experience	<---	Rating Factors	1.00			
Profession	<---	Rating Factors	0.97	0.06	15.98	***
Auto Use	<---	Rating Factors	0.86	0.06	14.58	***
Auto Age	<---	Rating Factors	0.95	0.07	13.96	***
Mileage	<---	Rating Factors	0.97	0.06	15.35	***
Cubic capacity	<---	Rating Factors	1.22	0.07	17.15	***
Multiple times	<---	Claims Freq	1.00			
Diff Claims	<---	Claims Freq	1.01	0.07	13.72	***
Possibility	<---	Claims Freq	1.33	0.09	14.95	***
Financial Distress	<---	Claims Sev	1.00			
Casualties	<---	Claims Sev	1.07	0.11	10.14	***
Damages	<---	Claims Sev	1.33	0.13	10.49	***

We then moved to Table 7 to depict goodness-of-fit indices performed using the maximum likelihood estimation. This goodness-of-fit index was conducted using the variance-covariance matrix obtained by ensuring correspondence with the sample. The λ^2/degree of freedom value of 1.495 corresponds with the general rule of $1< \lambda^2/df<5$ with the value indicating a better fit. The CFI (comparative fit index), NFI (normed fit index), RFI (relative fit index), IFI (incremental fit index) and TLI (tucker-Lewis fit index) all reported a very good fit because the values were all closer to 1. Finally, the RMSEA value of 0.050<0.08 also depicts a good model fit. Readers may refer to Lowry and Gaskin (2014) for more details.

Table 7. Goodness-of-fit Indices

Goodness of Fit	Construct	Reference Value
λ^2/degree of freedom	1.495	$1< \lambda^2/df<5$
CFI (comparative fit index)	0.970	0.95<CFI<1
NFI (normed fit index)	0.930	0.90<NFI<1
RFI (relative fit index)	0.910	0.90<RFI<1
IFI (incremental fit index)	0.970	0.95<IFI<1
TLI (tucker-Lewis fit index)	0.970	0.95<TLI<1
RMSEA (root mean square error)	0.050	RMSEA<0.08

Our model also shows in Table 8 that the standardized residual covariance of our data has a standard normal distribution with most of the values < two (2) in absolute terms.

Table 8. Standardized Correlation Results

	Dm	Cas	FD	Pos	DC	MuT	CC	Mile	AuA	AuU	Prof	Exp	Driy	HeL	MeL	L/N	Kno	Bagd	Drist
Dam	.000																		
Cas	-.006	.000																	
FD	.001	.010	.000																
Pos	.-058	.078	.098	.000															
DC	.-072	.089	.092	.-004	.000														
MuT	.-088	-.011	.051	.000	.005	.000													
CC	.018	.018	.211	.-046	.-044	.-073	.000												
Mile	.-121	.-094	.013	.003	.-047	.-007	.008	.000											
AuA	.-002	.-065	.144	.056	.019	.102	.006	.-010	.000										
AuU	.-032	.-038	.084	.036	.026	.032	.007	.014	.031	.000									
Prof	.-061	.-074	.097	.014	.-008	.017	.016	.-036	.013	.-038	.000								
Exp	.-011	.-034	.092	.025	.-047	.027	.-031	.028	.-055	.-005	.045	.000							
Driy	.056	.020	.-032	.116	.034	.-081	.-071	.-032	.-037	.066	.-022	.018	.000						
HeL	.-016	.-125	.-106	.043	.-041	.-033	.-078	.-013	.-014	.053	.023	.079	.-004	.000					
MeL	.058	.004	.057	.006	.-029	.-089	.014	.025	.087	.070	.060	.067	.026	.-034	.000				
L/N	.023	.-010	.-048	.041	.-048	.-094	.-057	.-011	.-107	.-023	.010	.072	.-027	.055	.-014	.000			
Kno	.-084	.045	.-019	.-007	.024	.-145	.030	.-024	.-047	.-115	.-085	.-040	.-036	.-082	.-096	.-059	.000		
Bagd	.-035	.015	.046	.044	.064	.003	.090	.024	.090	.014	.-005	.002	.076	.-026	.051	.025	.008	.000	
Drist	.041	.075	.011	.048	.057	.-027	.068	.011	.074	.-036	.-004	.048	.111	.034	.017	.006	.003	-.016	.000

Table 9. Structural Model Path Coefficients

Variables	Standardized Estimates	SE	P	Results
Education on claims/accident occurrence	0.220	0.06	0.00	Supported
Higher education level to claim/accident frequency	0.140	0.199	0.222	Not Supported
Medium education level to claim/accident frequency	-0.040	0.090	0.880	Not Supported
Low/No education level to claim/accident frequency	-0.020	0.110	0.699	Not supported
Higher education level to claims severity	-0.170	0.085	0.122	Not supported
Medium education level to claims severity	0.320	0.073	0.002	Supported

Low/No education level to claims severity	0.120	0.086	0.265	Not supported
Rating factors on claims/accident occurrence	0.280	0.067	0.00	Supported

These structured models measures the influence of education levels (High, Medium and low/ no), Education and rating factors on claims/accident frequency and severity. This theoretical scheme (research model) is presented in (1). Table 9 shows the standardized path estimates as well as the p-values for our structural models. Most of our hypotheses with p-values>0.05 were rejected with few being supported with p-values<0.05. According to the regression estimates and in support of Afukaar et al. (2003), Atubi and Onokala (2009), Al-Reesi et al. (2013), Mends-Brew et al. (2019), Plankermann (2013), education in general influences accident/claims occurrence. However, there was no enough evidence to prove that any of the education levels involvement in reducing or causing accident/claims. Automobile rating factors is seen as the most influential driver on claims/accident occurrence.

On the contrary, when it comes to causes of severe claims, both high and low/no education level have no evidence to prove either being involved in reducing or causing severe claims respectively. However, there was enough evidence against policyholders with medium education levels.

4. Discussions

Reducing Claims frequency and severity on our roads have been one of the major drawbacks in recent years for the government and people of Ghana. Available statistics indicates that about 90% of all claims or accident in Ghana is caused by human behavior. Therefore, policyholders' errors are categorized depending on the severity and extend of casualties caused as a result of misinterpretation of road traffic control devices based on their education levels. Education enhances the number of potentially ideas to increases knowledge on road safety regulations and can reduce the occurrence of possible accidents (Adedeji et al., 2016; Mock et al., 1991). This is because having strong prior technical knowledge allows process more information on the type of motor at hand and road safety regulations which helps reduce uncertainty. Based on this background, we analyzed the influence of education levels categorized as high (bachelor or above), Medium (diploma/ secondary) and low (basic/not at all) on claims frequency and severity. Tackling the structural equation model used for our confirmatory analysis, it was evident from our standardized correlation matrix that none of our variables have low factor loadings. This hinges on the fact that all our variables (education, education levels, rating factors, claims frequency and severity) have factor loadings above 0.70. Our standardized correlation weight in Table 8 showed evident of standard normal distribution because all the values satisfied the threshold of being less than two in absolute value. After satisfying the existence of normality in our correlation matrix, it was therefore viable to look into out model fit data in AMOS to check for our model fit indices. The λ^2/degree of freedom, CFI (comparative fit index), NFI (normed fit index), RFI (relative fit index), IFI (incremental fit index), TLI (tucker-Lewis fit index) and RMSEA (root mean square error) all showed the existence of good or better fit when compared to the reference value in Table 7.

In depicting the relationship between our dependent and independent variables, we resorted to regression in AMOS once again. Regression weights was found for all the variables under each of the constructs and recoded into one variable for all our five (5) observed variables. In order to ascertain the various levels of education influence on accident/claims and severity, we first tested to see if there exist relationship between accident/claim frequency and education in general. We obtained standard coefficient value of 0.220 with significant P- value of 0.00 depicting the existence of direct relationship between education and accident/claim frequency which satisfies our first hypothesis (reference). In our second hypothesis, our ultimate goal was to establish the contributions of the various levels of education (High, Medium and Low/not at all) in reducing or causing claims/accident frequency. In hypothesis 2 (a), we recorded a standard coefficient of 0.140 with P-value of 0.222 which did not give us enough evidence in support of hypothesis 2(a). This shows that policyholders with even high level of education can cause frequent claims. Again, both hypotheses 2(b) and (c) were not supported because we obtained respectively standard coefficient and P values of -0.040, 0.880 and -0.020, 0.699 which further concludes that claims/accident frequency does not depend on any level of education.

After establishing that claim or accident occurrence does not necessarily rely on policyholder's level of education, we then moved to hypotheses 3(a), (b) and (c) to determine whether any of these levels have direct relationship with claims severity. Therefore, as shown in Table 9 it was established that there was no enough evidence in support of both hypotheses 3(a) and (c) as both recorded standard coefficients and P- values of -0.170, 0.122 and 0.120, 0.265 respectively. However, with hypothesis 3(b), policyholders with medium education level (diploma/secondary) causing severe claim was significant with standard coefficient value of 0.320 and P- value 0.002. Though there was indirect relationship between medium level of education and claims frequency, there is enough evidence based on our regression weight that most of the severe claims or accidents that results into deaths and serious injuries on yearly basis with its negative impact on families, government and insurers are caused by policyholders or drivers with medium level of education in Ghana.

Finally, in hypothesis 4 we draw from Rumar (1999) and included some rating variables normally used by automobile insurers in determination of premiums. This hypothesis was supported with positive coefficient of 0.280 and P- value of 0.00. This indicates that frequent accident/claims in Ghana are mostly influenced by factors such as the age of the vehicle, its cubic capacity, what it's been used for, its mileage and so on which enhances mechanical faults leading to accidents (Mends-Brew et al., 2019; Rumar, 1999).

5. Conclusion

The rate of accident/claims occurrence worldwide affect population with varied contributing factors influencing the causes in different region particularly developing country like Ghana (mends). Available statistics indicates that about 90% of all claims or accident in Ghana is caused by human behavior. Therefore, policyholders' errors are categorized depending on the severity and extend of casualties caused as a result of misinterpretation of road traffic control devices based on their education levels. This study report on the influence of education levels on accident/claims frequency and severity drawing upon a purposive sample of 203 policyholders who have experienced at least one accident in a year using structural equation modeling (SEM). The findings from our regression weights indicated in Table 9 rejects most our hypotheses with few ones being supported. This study had enough evidence to confirm that education in general either being sensitization on road safety regulations or training given to perspective policyholders contributes to influence accidents/claims occurrence. However, in terms of education levels of policyholders, we did not have enough evidence in support of any of these levels either causing or reducing claims/accident frequency. Besides accident/claim frequency, we extended our regression analysis on claim severity and also included some well know auto insurance rating factors to ascertain their impacts on accident frequency. Consequently, it was revealed that most of the severe claims or accidents that results into deaths and serious injuries on yearly basis are caused by policyholders or drivers with medium level of education in Ghana with its frequency driving mostly by rating factors such as the vehicle's age, cubic capacity, mileage, etc.

5.1 Implications to Policymakers

The practical implications of this paper are straightforward. In order to minimize the rate of accidents in Ghana, the driving and vehicle licensing authority (DVLA), the MTTD, and the NRSC should term up with education programs for drivers. This should be in the form of periodic in-service trainings to perspective drivers or policyholders that involves the need to have seat belts in every vehicle and the driver's role to encourage passengers to use them, preventive measures whiles driving with respect of bad weather conditions, traffic conditions, road signs, etc. These periodic in-service trainings should be given to drivers after increasing the number of driving lessons and tests by DVLA for drivers prior to the driving license acquisition. The MTTD on the other hand should also intensify the control on speed and drunk driving on our highways to check the high incidence of traffic fatalities and injuries and possibly punish severely drivers found violating speed limits.

The study also found that severe accidents on our highways are caused by drivers with medium education levels. This means that policyholders with very high and very low education levels are mostly careful in driving. We therefore recommend the incorporation of education levels into policyholder's premium computations by the National insurance commission (NIC) in order that policyholders with medium levels of education pays premium higher to deter them from reckless driving to avoid severe claims occurrences.

Furthermore, as it's already known, the contributions of rating variables like the vehicle's cubic capacity, mileage, age, etc. can never be taken out in dealing with road accidents. Therefore, car dealers in Ghana and supervisory authorities should make sure that only vehicles in good conditions are imported into the country since there is no well-established company that manufactures vehicles in Ghana.

Funding

This work was supported by the National Science foundation of China (project No: 71871044).

References

Adedeji, J. A., Abejide, S. O., & Hassan, M. M. (2016). Effectiveness of Communication Tools in Road Transportation: Nigerian Perspective. *International Conference on Traffic and Transport Engineering*, 510-517.

Afukaar, F. K., Antwi, P., & Ofosu-Amaah, S. (2003). Pattern of road traffic injuries in Ghana: Implications for control. *Injury Control and Safety Promotion*, *10*, 69-76. https://doi.org/10.1076/icsp.10.1.69.14107

Albert, C. (2014). Road Traffic Accidents in Ghana: A Public Health Concern, and a Call for Action in Ghana (and the Sub- Region). *Open Journal of Preventive Medicine*, *4*, 822-828. https://doi.org/10.4236/ojpm.2014.411092

Al-Reesi, H. et al. (2013). Economic Growth, Motorization and Road Traffic Injuries in the Sultanate of Oman, 1985-2009. *Traffic Injuries Prevention*, *14*, 322-328. https://doi.org/10.1080/15389588.2012.694088

Atubi, A. O., & Onokala, P. C. (2009). Contemporary Analysis of Variability in Road Traffic Accidents in Lagos State, Nigeria. *Journal of African Geographical Review*, *28*, 11-41. https://doi.org/10.1080/19376812.2009.9756216

Brouhns, N., Montserrat, G., Denuit, M., & Pinquet, J. (2003). Bonus-Malus Scales in Segmented Tariffs with Stochastic Migration between Segments. *Risk and Insurance*, *70*, 577-599. https://doi.org/10.1046/j.0022-4367.2003.00066.x

Feachem, R. G. A., Kjellstorm, T., Murray, C. J. L., Over, M., & Philips, M. A. (1992). *The Health of Adults in the Developing World, London*. Oxford University Press.

Ghana, Ghanaweb.com. (2019). *MTTD, 1,252 perish in accidents between January to June 2019*. Retrieved from https://www.ghanaweb.com/GhanaHomePage/NewsArchive/Road-accidents-696-die-in-2019-first-quarter-747721

Ghanaweb.com. (2019). *The Number of People Killed in Road Accidents in Monday, March 25 2019*. Retrieved from https://www.mobile.ghanaweb.com/GhanaHomePage/NewsArchive/Accidents-46-284-killed-between-1991-and-2018-732939

Hazen, A., & Ehiri, J. E. (2006). Road traffic injuries: Hidden epidemic in less developed countries. *Journal of the National Medical Association*, *98*, 73-82.

Ibiwoye, A., Adeleke, I. A., & Aduloju, S. A. (2011). Quest for Optimal Bonus-Malus in Automobile Insurance in Developing Economies: An Actuarial Perspective. *International Business Research*, *4*, 74-83. https://doi.org/10.5539/ibr.v4n4p74

Kafková, S. (2015). Bonus-Malus Systems in Vehicle Insurance. *Procedia Economicand Finance*, *23*, 216- 222. https://doi.org/10.1016/S2212-5671(15)00354-8

Kafkova, S., & Krivankova, L. (2014). Generalized Linear Models in Vehicle Insurance. *Acta University. Agric. Silvic. Mendelianae Brune*, *60*, 383-388. https://doi.org/10.11118/actaun201462020383

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transaction on Professional Communication*, *57*, 123-146. https://doi.org/10.1109/TPC.2014.2312452

Mends-Brew, E., Dadzie, J., Apau, B. D., & Owusu, M. A. (2019). Modelling the Trend of Road Traffic Accidents in Accra. *Mathematical Modelling and Applications*, *3*, 1-8. https://doi.org/10.11648/j.mma.20180301.11

Mock, C. N., Forjuoh, S. N., & Rivara, F. P. (1999). Epidemiology of transport-related injuries in Ghana. *Accident Analysis and Prevention*, *31*, 359-370. https://doi.org/10.1016/S0001-4575(98)00064-5

Pinquet, J. (2000). Experience Rating Through Heterogeneous Models. In G. Dionne (Ed.), *Handbook of Insurance. Amsterdam Kluwer Academic* (pp. 459-500).

Plankermann, K. (2013). *Human Factors as Causes for Road Traffic Accidents in the Sultanate of Oman under Consideration of Road Construction Designs*.

Renshaw, A. E. (1994). Modelling the Claim Process in the Presence of Covariates. *Astin Bulletin*, *24*, 265-285. https://doi.org/10.2143/AST.24.2.2005070

Rumar, K. (1999). *Speed: A sensitive matter for drivers*. VTI Transport Development AB, Nordic Road and Transport Research. Transport and Research Laboratory.

Smart, R. E., & Mann, R. G. (2002). Death and Injuries from Road Rage: Cases in Canadian Newspapers. *Canadian Medical Association Journal*, *167*, 761-762.

Smith, D. J. (2005). *Center for Transportation Research and Education Iowa State University*.

Smith, G. S., & Barss, P. (1991). Unintentional Injuries in Developing Countries: The Epidemiology of a neglected problem. *Epidemiology Review*, *13*, 228-266. https://doi.org/10.1093/oxfordjournals.epirev.a036070

Stojaković, A., & Jeremić, L. (2016). Development of the Insurance Sector and Economic Growth in Countries in Transition. *Science Review Article*, *13*, 83-106. https://doi.org/10.5937/MegRev1603083S

Walhin, J. F., & Paris, J. (1997). Using Mixed Poisson Processes in Connection with Bonus-Malus Systems. *Astin Bulletin*, *29*, 81-99. https://doi.org/10.2143/AST.29.1.504607

World Health Organization. (1984). *Road Traffic Accidents in Developing Countries*. Geneva: WHO.

Yazan, I. (2016). Effect of driver's personal characteristics on traffic accidents in Tabuk city in Saudi Arabia. *Journal of Transport Literature*, *10*, 25-29. https://doi.org/10.1590/2238-1031.jtl.v10n3a5