Original Research Article

Mechanistic Model for Predicting Accident Potential of Vehicle Transiting in Nigeria Road

Abstract: An accident prediction model was developed for determining the accident potential of a vehicle while on transit. The model identifies the various factors responsible for vehicle crashes with the help of accident data obtained from the database of the Nigerian Federal Road Safety Corps (FRSC), the percentage contribution of each factor is calculated. These accident-cause factors were further grouped into three distinct classes: Human factors (HF), Mechanical factors (MF) and Environmental factors (EF). Analysis of the accident data showed that HF is the chief cause of most road accidents recorded, followed by MF and EF with probabilities of 0.846, 0.138 and 0.016 respectively. Also, driver age, travel distance and maintenance frequency of the vehicle were considered in the development of the model. The model gives an output ranging from 0-1. Values close to 0 mean low accident probability while values close to 1 signify high accident probability. Application and adherence to this model will significantly reduce the frequency of road accidents. Finally, transport companies and fleet operators are therefore encouraged to embrace and use this innovation for safer operations.

Key words: Accident, Accident potential, Accident data, Vehicle crashes, Accident-cause factors.

1.0 Introduction

Road transport remains the chief universal means of transportation in Nigeria in comparison to air, rail, and water transport. Recent advances in technological development have resulted in the possible evolution of different types and models of modern and aesthetic vehicles with greater comfort and maneuverability; in contrast to the pre-colonial means of transportation such as the use of animals[1].The influx of these vehicles and the expansion of fleet operators in Nigerian have crowded the Nigerian motoring environment, thereby making road traffic a major challenge to combat in the country[2].These road traffic challenges in Nigeria often result in road traffic accidents, most times, with its attendant carnages. In the recent time, road traffic accident tolls have been on the increase in Nigeria. Several factors are responsible for this; they range from the drivers' attitude to the deplorable road network. The Nigerian roads have become death traps, with no protection for the users [2]. Travelers are often faced with the uncertainty of whether they would be able to reach their destinations and so become apprehensive of the journeys they make. This bothersome trend has great unfavorable effects on the nation's health system as well as her social and economic endeavors.

The ease in movement of human and items, notwithstanding, so many families have been bereaved of their breadwinners and loved ones by the menace of road traffic accidents in Nigeria. As reported the FRSC, over 88,520 road users lost their lives between the years 1991 and 2000 alone, most of the victims were below 40 years of age [3]. Between year 2012 and 2016 alone, about 57,894 road traffic accidents were recorded. Such factors as environmental, mechanical, human factors, etc. were responsible for the accidents[4].Considering the precarious nature of the Nigerian roads, the poor maintenance culture of most transport vehicles and the unwholesome attitudes of most drivers, there is a dire need to treat road accident as a major issue that requires urgent attention in order to prevent untimely deaths; reduce health risks, social and economic impacts it poses on the Nigerian road users in particular and the society at large.

Over 50 percent of the aggregate global road traffic deaths involve persons of ages 15 to 44; in their key productive years [5]. Furthermore, the disability load for this age group records about 60.0 percent of all disability-life years [5]. The consequences and costs of these losses are momentous. About 3/4 of the total deprived families who lost their ones in a traffic crash reported a decline in their livelihood, and about 61.0 percent reported that they had resorted to borrowing money for their daily expenses, consequent upon their loss [5]. World Bank report estimated that road traffic injuries cost between 2 percent to 3 per cent of the GDP of developing countries, or twice the total development aid given worldwide to developing countries [6].Though transport agencies often try to identify the most hazardous road spots, and put enormous efforts into protective measures, the yearly traffic crashes toll Has not hitherto appreciably reduced [6].

Road crash prediction models are crucial tools in highway safety, considering its ability to determine both the crash frequency and the degree of severity of crashes[7].Measures for useful interventions to trim down crash toll include design of safer road infrastructure and integration of road safety elements into land use and transport planning; upgrading of vehicle safety attributes; advancement of post-crash care for victims of road traffic crashes; and enhancement of driver behavior as well as raising public consciousness[7]. About 35,092 road traffic fatalities were documented in the US in 2015, an increase of 7.2% compared to the preceding year [7]. It is in consideration of these trends that the research is targeted at developing a model that could predict the probability of a transport vehicle to have accident while on transit. This prediction model would be used by transport agencies/fleet owners to increase knowledge of the safety of their vehicles [7].

2.0 Methodology

The study involves the use of road traffic accident data sourced from the robust database of the FRSC, a federal government agency saddled with the responsibility of managing road traffic in Nigeria, to develop an accident prediction model. Twenty accident-cause factors were considered responsible for the various road traffic accidents that occurred throughout the country during the period. The collected accident data covered a period of five years from 2012 to 2016 of accident occurrence (Table1). The accident data was analyzed to reflect the various accident-cause factors and their various probabilities. The data was then used to derive the respective accident occurrence probabilities for each of accident-cause factors.

Table 1: Road Traffic Accident Causes in Nigeria from 2012 to 2016

S/N	RTA CAUSES	2012	2013	2014	2015	2016
1.	**SPV**	2374	5495	3496	3195	3848
2.	**LOC**	1183	2928	2445	2770	1753
3.	**DGD**	1096	2082	1324	1137	969
4.	**WOT**	270	623	147	546	832
5.	**SLV**	3	333	905	1097	736
6.	**TBT**	623	1271	873	813	689
7.	**RTV**	165	582	513	524	591
8.	**BFL**	344	584	418	479	567
9.	**MDV**	158	450	226	197	316
10.	**OTH**	0	228	175	262	246
11.	**OBS**	116	85	181	167	182
12.	**DOT**	106	591	261	216	144
13.	**OVL**	46	165	114	82	99
14.	**SOS**	36	207	48	55	78
15.	**FTQ**	5	263	61	85	73
16.	**DAD**	36	179	93	63	57
17.	**UPWD**	26	77	32	38	32
18.	**NJR**	13	15	20	14	11
19.	**PWR**	4	40	28	16	27
20.	**BRD**	139	295	101	67	124

The twenty accident-cause factors presented in table 1 are further classified into the three chief accident-cause factors: Human factors *HF*, Mechanical factors *MF* and Environmental factors *EF*. With the above classification, an accident flowchart is developed as presented in Figure1.

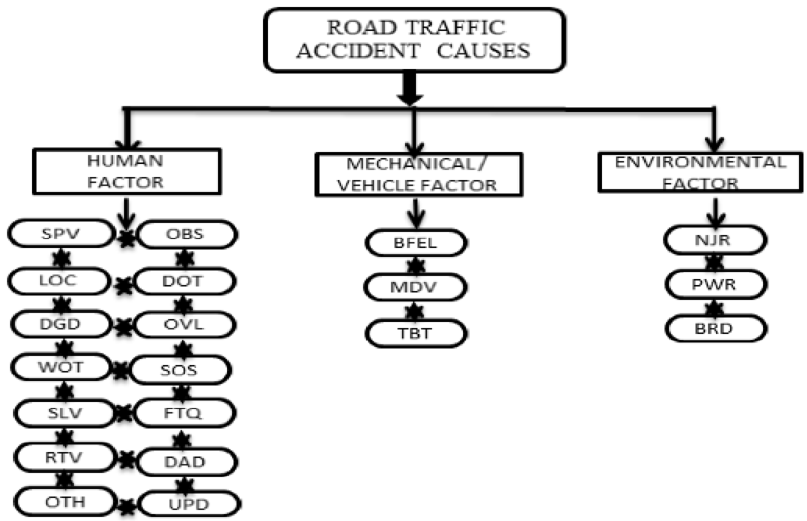

Fig. 1: Flowchart showing the causes of Road Transport Accident

Figure 1shows the summarized accident-cause factors responsible for accident occurrences during the five-year period. The accident flowchart makes it easier to appreciate the accident-cause factors at a glance.

Based on data from [7]; [8] and [9], and interactions from fleet operators and transport company workers, the *age group of the driver* A_i, *maintenance frequency of the vehicle* B_j and the *distance of travel* C_k were used as chief accident predictors. The various accident predictive factors (A_i, B_j and C_k) were scored based on their individual accident-cause load (the susceptibility to accident cause). These scores were utilized in computing the fractional scores. Table 2 shows the analysis of the accident predictive factors point scores as well as their respective fractional scores ($X_{i,j,k}$).. These fractional scores are integrated into the model for accident prediction.

Table 2: Analysis of the Accident Predictive Factors

Age of the Driver (A_i)			
	Class	**Score**	**Fractional Score, X_i**
Group A1	18-38	3	0.423
Group A2	39-59	2	0.282
Group A3	60+	1	0.141
			X_i= (score A_i÷ ∑score A_i) *0.846
Maintenance Frequency (B_j)			
	Class	**Score**	**Fractional Score, X_j**
Group B1	Regular	1	0.023
Group B2	Irregular	2	0.046
Group B3	Reactive	3	0.069
			X_j= (score B_j÷ ∑score B_j) *0.138
Distance of Travel (C_k)			
	Class	**Score**	**Fractional Score, X_k**
Group C1	**C**≤ 250 KM	1	0.0027
Group C2	250 ≤**C**≤ 500 KM	2	0.0053
Group C3	**C**≥ 500 KM	3	0.008
			X_k= (score C_k÷∑score C_k) *0.016

In the development of the desired accident prediction model, the accident data (Table 1) was further manipulated to obtain the respective accident-cause fractions (probabilities, *Pr*) which form the basis for the model development. The various accident-cause factors and their respective probabilities are presented in Table 3.

Table 3: RTA-Cause Factors and their probabilities

S/N	CAUSES OF RTA	2012	2013	2014	2015	2016	TOTAL	Pr.
1.	**SPV**	2374	5495	3496	3195	3848	**18408**	0.318
2.	**LOC**	1183	2928	2445	2770	1753	**11079**	0.191
3.	**DGD**	1096	2082	1324	1137	969	**6608**	0.114
4.	**WOT**	270	623	147	546	832	**2418**	0.042
5.	**SLV**	3	333	905	1097	736	**3074**	0.053
6.	**TBT**	623	1271	873	813	689	**4269**	0.074
7.	**RTV**	165	582	513	524	591	**2375**	0.041
8.	**BFL**	344	584	418	479	567	**2392**	0.041
9.	**MDV**	158	450	226	197	316	**1347**	0.023
10.	**OTH**	0	228	175	262	246	**911**	0.016
11.	**OBS**	116	85	181	167	182	**731**	0.013
12.	**DOT**	106	591	261	216	144	**1318**	0.023
13.	**OVL**	46	165	114	82	99	**506**	0.009
14.	**SOS**	36	207	48	55	78	**424**	0.007
15.	**FTQ**	5	263	61	85	73	**487**	0.008
16.	**DAD**	36	179	93	63	57	**428**	0.007
17.	**UPD**	26	77	32	38	32	**205**	0.004
18.	**NJR**	13	15	20	14	11	**73**	0.001
19.	**PWR**	4	40	28	16	27	**115**	0.002
20.	**BRD**	139	295	101	67	124	**726**	0.013
	TOTAL	**6743**	**16493**	**11461**	**11823**	**11374**	**57894**	**1.000**

The accident occurrence probabilities (*Pr)* for each accident-cause factor, is the ratio of the total accidents caused by a particular factor to the cumulative accident occurrence over the entire five-year period. *Pr* is therefore the quotient of 'row total' (*rt*) and the 'column total', (*ct*) as shown in table 3.

P_r for the three main accident cause factors as classified in Figure 1 was also computed from Table 3 and the results shown in Table 4.

Table 4: RTA-Causes and probabilities by the three main accident factors

	2012	2013	2014	2015	2016	Total	Pr.
Human Factor (HF)	5462	13838	9795	10237	9640	**48972**	**0.846**
Mechanical Factor (MF)	1125	2305	1517	1489	1572	**8008**	**0.138**
Environmental Factor (EF)	156	350	149	97	162	**914**	**0.016**
TOTAL	**6743**	**16493**	**11461**	**11823**	**11374**	**57894**	**1.000**

As the analysis is based on actual accident data, the summation of the product of the accident-cause factors and its respective probabilities is equal to unity; indicating a 100% certainty of accident occurrence. This scenario is represented in mathematical form by Equation 1:

$$\sum \{(\text{Accident Cause factor}) * (\text{Accident Probability})\} = 1 \qquad (1)$$

Therefore, it follows from Equation 1 that accident occurrence probability (according to Table 4) is expressed as

$$0.846HF + 0.138MF + 0.016EF = 1 \qquad (2)$$

Notice that Equation 2 is the fundamental accident equation which forms the basis for the advancement of the model:

Hence,

$$\mathrm{HF}pr_i + \mathrm{MF}pr_j + \mathrm{EF}pr_k = 1 \qquad (3)$$

Where:

pr_i ,pr_j and pr_k are accident-Cause probabilities of HF, ME and EF, respectively. Also, it is assumed that the coefficients HF, MF *and EF* are respectively equal to unity.

That is, HF = MF = EF =1

Where:

pr_i= 0.846, pr_j= 0.138and pr_k= 0.016 (Table 2)

Equation 1 is predicated on the assumption of 100% accident occurrence certainty, but in reality, this is not perfectly true. There exists as equal likelihood of no accident as there is likelihood of accident occurrence as transport vehicles are on transit. To compensate for this therefore, the parameter **β**, a summation of the interacting accident predictive factors, must be subtracted from the model output response.

Where: **β**= the uncertainty of accident occurring (i.e. the error term associated with the assumption that accident occurred when it actually did not occur). For *n* number of predictive factors, the parameter, **β** becomes $\boldsymbol{\beta}_{\mathbf{i,j,k},\ldots n}$, where *i,j,k* and *n* are the respective predictive factors. For purpose of convenience and clearer illustration, the number of predictive factors *n* has been limited to 3(i.e. *n* = 3); hence $\boldsymbol{\beta}_{\mathbf{,i,j,k}}$.

By definition, $\boldsymbol{\beta}_{\mathbf{i,j,k}}$ is the probability of either $\boldsymbol{X_i}$ occurring or $\boldsymbol{X_j}$ occurring or $\boldsymbol{X_k}$ occurring ($\boldsymbol{X_i + X_j + X_k}$).

Therefore, $\boldsymbol{\beta_{i,j,k} = X_i + X_j + X_k}$

Hence, Equation 3 becomes,

$$0.846HF + 0.138MF + 0.016EF = 1 - \beta$$

Therefore:

$$0.846HF + 0.138MF + 0.016EF + \beta = 1 \qquad (4)$$

The interplay of the accident predictive factors influences the probability of accident occurring or not as the transport vehicles transit from one point to the other. This is shown in equations 5-7.

Let x_i, x_j and x_k be the fractional score of A_i, B_j and C_k, respectively (Table 2).

Where $\boldsymbol{X_i}$= *(score* $A_i \div \sum$*score* A_i*) *0.846*

$\boldsymbol{X_j}$= *(score* $B_j \div \sum$*score* B_j*) *0.138*

$\boldsymbol{X_k}$= *(score* $C_k \div \sum$*score* C_k*) *0.016*

Similarly, if we assume $A_i = B_j = C_k = 1$

Then,

$$0.846A_i + 0.138B_j + 0.016C_k + \beta = 1 \qquad (5)$$

Since $\boldsymbol{X_i}$, $\boldsymbol{X_j}$ and $\boldsymbol{X_k}$ are respectively proportional to A_i, B_j and C_k; It therefore implies that:

$$\mu_{(Ai,\,Bj,\,Ck)} = 0.846X_i + 0.138X_j + 0.016X_k + \beta_{ijk} \ (6)$$

Where:

μ = Accident probability (the dependent variable as a result of the interactions of the independent variables $-\boldsymbol{X_i}$,$\boldsymbol{X_j}$, $\boldsymbol{X_k}$ and $\beta_{i,j,k}$;

(A_i, B_j, C_k) = a combination of the i^{th}, j^{th} and k^{th} predictive factors

$\beta_{i,j,k}$ = the uncertainty of accident occurring when the i^{th}, j^{th} and k^{th} certainty factors interplay;

Also, $\beta_{i,j,k} = \boldsymbol{X_i + X_j + X_k}$

$\mu_{(Ai,\,Bj,\,Ck)}$ = accident probability when the i^{th}, j^{th} *and* k^{th} predictive factors are combined.

Equation 6 therefore yields Equation 7, which is the required accident prediction model for transport vehicles:

$$\mu_{(Ai,\,Bj,\,Ck)} = 0.846X_i + 0.138X_j + 0.016X_k + \beta_{ijk}(7)$$

In order to validate the developed accident prediction model, the various possible combinations of the predictive factors (age of the driver, maintenance frequency and distance of travel) are considered and then integrated into the model. The possible accident predictive factor combinations are obtained and presented in table 5.

Table 5: Possible Combinations of Predictive Factors

Combination *i,j,k*					
1	A1, B1, C1	10	A2, B1, C1	19	A3, B1, C1
2	A1, B1, C2	11	A2, B1, C2	20	A3, B1, C2
3	A1, B1, C3	12	A2, B1, C3	21	A3, B1, C3
4	A1, B2, C1	13	A2, B2, C1	22	A3, B2, C1
5	A1, B2, C2	14	A2, B2, C2	23	A3, B2, C2
6	A1, B2, C3	15	A2, B2, C3	24	A3, B2, C3
7	A1, B3, C1	16	A2, B3, C1	25	A3, B3, C1
8	A1, B3, C2	17	A2, B3, C2	26	A3, B3, C2
9	A1, B3, C3	18	A2, B3, C3	27	A3, B3, C3
Total Combinations = 27					

Incorporating the different combinations into the accident model yields:

Combination 1: $\mu\ (A1, B1, C1) = 0.846A1 + 0.138B1 + 0.016C1 + \beta i, j, k$

Combination 2: $\mu\ (A1, B1, C2) = 0.846A1 + 0.138B1 + 0.016C2 + \beta i, j, k$

Combination 3: $\mu\ (A1, B1, C3) = 0.846A1 + 0.138B1 + 0.016C3 + \beta i, j, k$

Combination 4: $\mu\ (A1, B2, C1) = 0.846A1 + 0.138B2 + 0.016C1 + \beta i, j, k$

Combination 5: $\mu\ (A1, B2, C2) = 0.846A1 + 0.138B2 + 0.016C2 + \beta i, j, k$

Combination 6: $\mu\ (A1, B2, C3) = 0.846A1 + 0.138B2 + 0.016C3 + \beta i, j, k$

Combination 7: $\mu\ (A1, B3, C1) = 0.846A1 + 0.138B3 + 0.016C1 + \beta i, j, k$

Combination 8: $\mu\ (A1, B3, C2) = 0.846A1 + 0.138B3 + 0.016C2 + \beta i, j, k$

Combination 9: $\mu\ (A1, B3, C3) = 0.846A1 + 0.138B3 + 0.016C3 + \beta i, j, k$

Combination 10: $\mu\ (A2, B1, C1) = 0.846A2 + 0.138B1 + 0.016C1 + \beta i, j, k$

Combination 11: $\mu\ (A2, B1, C2) = 0.846A2 + 0.138B1 + 0.016C2 + \beta i, j, k$

Combination 12: $\mu\ (A2, B1, C3) = 0.846A2 + 0.138B1 + 0.016C3 + \beta i, j, k$

Combination 13: $\mu\ (A2, B2, C1) = 0.846A2 + 0.138B2 + 0.016C1 + \beta i, j, k$

Combination 14: $\mu\ (A2, B2, C2) = 0.846A2 + 0.138B2 + 0.016C2 + \beta i, j, k$

Combination 15: $\mu\ (A2, B2, C3) = 0.846A2 + 0.138B2 + 0.016C3 + \beta i, j, k$

Combination 16: $\mu\ (A2, B3, C1) = 0.846A2 + 0.138B3 + 0.016C1 + \beta i, j, k$

Combination 17: $\mu\ (A2, B3, C2) = 0.846A2 + 0.138B3 + 0.016C2 + \beta i, j, k$

Combination 18: $\mu\ (A2, B3, C3) = 0.846A2 + 0.138B3 + 0.016C3 + \beta i, j, k$

Combination 19: $\mu\ (A3, B1, C1) = 0.846A3 + 0.138B1 + 0.016C1 + \beta i, j, k$

Combination 20: $\mu\ (A3, B1, C2) = 0.846A3 + 0.138B1 + 0.016C2 + \beta i, j, k$

Combination 21: $\mu\ (A3, B1, C3) = 0.846A3 + 0.138B1 + 0.016C3 + \beta i, j, k$

Combination 22: $\mu\ (A3, B2, C1) = 0.846A3 + 0.138B2 + 0.016C1 + \beta i, j, k$

Combination 23: $\mu\ (A3, B2, C2) = 0.846A3 + 0.138B2 + 0.016C2 + \beta i, j, k$

Combination 24 $\mu\ (A3, B2, C3) = 0.846A3 + 0.138B2 + 0.016C3 + \beta i, j, k$

Combination 25: $\mu\ (A3, B3, C1) = 0.846A3 + 0.138B3 + 0.016C1 + \beta i, j, k$

Combination 26: $\mu\ (A3, B3, C2) = 0.846A3 + 0.138B3 + 0.016C2 + \beta i, j, k$

Combination 27: $\mu\ (A3, B3, C3) = 0.846A3 + 0.138B3 + 0.016C3 + \beta i, j, k$

3.0 Results and Discussion

The developed accident prediction model was tested by integrating the various possible combinations of the concurrent predictive factors, as determined, into the model to predict the likelihood of accident occurrence. The model gave an output that ranged from 0 – 1; values close to 0 mean low accident probability while values close to 1 depicted high accident occurrence probability. Table 6 shows the various possible predictive factor combinations as well as their accident probabilities (**$\mu_{i,j,k}$**).

Table 6: Accident Probability ($\mu_{i,j,k}$) of the various possible combinations

Combination *i,j,k*	$\mu_{i,j,k}$	Combination *i,j,k*	$\mu_{i,j,k}$	Combination *i,j,k*	$\mu_{i,j,k}$
A1, B1, C1	**0.8098**	A2, B1, C1	**0.5495**	A3, B1, C1	**0.2892**
A1, B1, C2	**0.8124**	A2, B1, C2	**0.5521**	A3, B1, C2	**0.2918**
A1, B1, C3	**0.8252**	A2, B1, C3	**0.5549**	A3, B1, C3	**0.2946**
A1, B2, C1	**0.8359**	A2, B2, C1	**0.5757**	A3, B2, C1	**0.3154**
A1, B2, C2	**0.8386**	A2, B2, C2	**0.5783**	A3, B2, C2	**0.3180**
A1, B2, C3	**0.8413**	A2, B2, C3	**0.5810**	A3, B2, C3	**0.3208**
A1, B3, C1	**0.8621**	A2, B3, C1	**0.6018**	A3, B3, C1	**0.3416**
A1, B3, C2	**0.8648**	A2, B3, C2	**0.6045**	A3, B3, C2	**0.3442**
A1, B3, C3	**0.8675**	A2, B3, C3	**0.6072**	A3, B3, C3	**0.3469**

μ_i= Accident Probability of the i^{th} combination

Table 6 shows all the possible combinations considered. 66.67% of the total combinations have accident occurrence probabilities greater than 0.5. This implies a high accident potential. The remaining 33.33% has accident probability less than 0.5. Hence, vehicles are considered safer under these conditions. Generally, A1, B3, C3 combination gave the highest probability value of 0.8675 while A3, B1, C1 combination gave the least probability value of 0.2892. A more robust table showing the explanation of the various combinations is presented in Table 7.

Table 7: Predictive factor combination with explanation

Combination *i,j,k*	Explanation	Combination *i,j,k*	Explanation	Combination *i,j,k*	Explanation
A1, B1, C1	Combination of driver age (18-38), maintenance frequency (Regular) and distance of travel (**C** ≤ 250 KM)	A2, B1, C1	Combination of driver age (39-59), maintenance frequency (Regular) and distance of travel (**C** ≤ 250 KM)	A3, B1, C1	Combination of driver age (60+), maintenance frequency (Regular) and distance of travel (**C** ≤ 250 KM)
A1, B1, C2	Combination of driver age (18-38), maintenance frequency (Regular) and distance of travel (250≤C≤ 500 KM)	A2, B1, C2	Combination of driver age (39-59), maintenance frequency (Regular) and distance of travel (250≤C≤ 500 KM)	A3, B1, C2	Combination of driver age (60+), maintenance frequency (Regular) and distance of travel (250≤C≤ 500 KM)
A1, B1, C3	Combination of driver age (18-38), maintenance frequency (Regular) and distance of travel (C ≥ 250 KM)	A2, B1, C3	Combination of driver age (39-59), maintenance frequency (Regular) and distance of travel (C ≥ 250 KM)	A3, B1, C3	Combination of driver age (60+), maintenance frequency (Regular) and distance of travel (C ≥ 250 KM)
A1, B2, C1	Combination of driver age (18-38), maintenance frequency (Irregular) and distance of travel (C ≤ 250 KM)	A2, B2, C1	Combination of driver age (39-59), maintenance frequency (Irregular) and distance of travel (C ≤ 250 KM)	A3, B2, C1	Combination of driver age (60+), maintenance frequency (Irregular) and distance of travel (C ≤ 250 KM)
A1, B2, C2	Combination of driver age (18-38), maintenance frequency (Irregular) and distance of travel (250≤C≤ 500 KM)	A2, B2, C2	Combination of driver age (39-59), maintenance frequency (Irregular) and distance of travel (250≤C≤ 500 KM)	A3, B2, C2	Combination of driver age (60+), maintenance frequency (Irregular) and distance of travel (250≤C≤ 500 KM)
A1, B2, C3	Combination of driver age (18-38), maintenance frequency (Irregular) and distance of travel (C ≥ 250 KM)	A2, B2, C3	Combination of driver age (39-59), maintenance frequency (Irregular) and distance of travel (C ≥ 250 KM)	A3, B2, C3	Combination of driver age (60+), maintenance frequency (Irregular) and distance of travel (C ≥ 250 KM)
A1, B3, C1	Combination of driver age (18-38), maintenance frequency (Reactive) and distance of travel (C≤ 250 KM)	A2, B3, C1	Combination of driver age (39-59), maintenance frequency (Reactive) and distance of travel (C≤ 250 KM)	A3, B3, C1	Combination of driver age (60+), maintenance frequency (Reactive) and distance of travel (C≤ 250 KM)
A1, B3, C2	Combination of driver age (18-38), maintenance frequency (Reactive) and distance of travel (250≤C≤ 500 KM)	A2, B3, C2	Combination of driver age (39-59), maintenance frequency (Reactive) and distance of travel (250≤C≤ 500 KM)	A3, B3, C2	Combination of driver age (60+, maintenance frequency (Reactive) and distance of travel (250≤C≤ 500 KM)
A1, B3, C3	Combination of driver age (18-38), maintenance frequency (Reactive) and distance of travel (C≤ 250 KM)	A2, B3, C3	Combination of driver age (39-59), maintenance frequency (Reactive) and distance of travel (C≤ 250 KM)	A3, B3, C3	Combination of driver age (60+), maintenance frequency (Reactive) and distance of travel (C≤ 250 KM)

A*i*= Age of driver *i* = 1,2,3 **B*j*** = Maintenance frequency *j* = 1,2,3 **C*k*** = Distance of travel *k* = 1,2,3

From Tables 6 and 7, it be could deduced that accident probability of a vehicle increases as the distance of travel increases and/or maintenance frequency of the vehicle reduces. Finally, transport companies are advised against employing drivers between the ages of 18-38 as accident probability is very high within this age.

4.0 Conclusion

In an attempt to tackle the problems posed by road accidents in our clime, particularly the transport vehicles, an accident prediction model has been developed in this paper for transport vehicles. The model integrated the interplay of the various accident-predictive factors for efficient prediction.

This model will help in reducing accidents involving transport vehicles and their drivers if strictly adhered to. As the results of the predictions suggest the probabilities of accident occurrence as well as offer informed guide for fleet operators' decision making, road accident occurrence will be effectively reduced. The focus is mostly on transport vehicles because the group is more prone to road accident than other categories of vehicles and drivers.

Declaration of interest: NONE

References

[1] Gupta, B.L. and Gupta A., (2009): Different Modes of Transportation: Roads, Railways, Bridges, Tunnels &Harbour Dock Engineering, Chapter 1; pp 1.2-1.4.

[2] Oyedepo, O. J.,(2010):Accident Prediction Models for Akure – Ondo Carriageway, Ondo State Southwest Nigeria; Using Multiple Linear Regressions (Pp. 30-49): *An International Multi-Disciplinary Journal , Ethiopia Vol. 4 (2) April, 2010* ,ISSN 2070-0083 (Online)

[3] FRSC and Balogun Y (2006): Research and Development Opinions, Federal Road Maintenance Agency; January/Febuary 2006 Pg. 13-16

[4] FRSC (2016): FRSC Annual Report 2016; www.frsc.gov.ng/publications

[5] Beirness, D.J. and Beasley, E. (2011): A Comparison of Drug- and Alcohol-Involved Motor Vehicle Driver Fatalities. Canadian Centre on Substance Abuse, Ottawa

[6] World Bank (2015): The World Bank-Transport for Development. http://blogs.worldbank.org/transport/why-vehicle-safety-matters-crash-related-deat hs?cid=EXT_WBBlogSocialShare_D_EXT

[7] Abdulhafedh, A. (2017). Road Crash Prediction Models: Different Statistical Modeling Approaches. *Journal of Transportation Technologies*, 7,190-205

[8] Kalyoncuoğlu, F.S, and Tığdemir, M. (2014): *The Effects of Daily Driven Distance and Age Factor on the Traffic Accidents*. Transportation Department, Engineering Faculty, Civil Engineering

[9] Hermitte, T (2012) Title, D5.9 Review of Accident causation models used in Road Accident Research of the EC FP7 project DaCoTA