

A Mechanistic Model for Predicting Accident Potential of Vehicles Transiting in Nigerian Roads

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 [10, 11]. As reported by 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 the 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 vehicle owners and the unwholesome attitude 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, 12]. 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 loved 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]. The 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 spot, and put enormous efforts into protective measures, the yearly traffic crash toll has not hitherto been 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 crash[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

57 planning; upgrading of vehicle safety attributes; advancement of post-crash care for victims of road traffic
 58 crashes; and enhancement of driver behavior as well as raising public consciousness[7]. About 35,092 road
 59 traffic fatalities were documented in the US in 2015, an increase of 7.2% compared to the preceding year [7]. It
 60 is in consideration of these trend that the research is targeted at developing a model that could predict the
 61 probability of a transport vehicle to have accident while on transit. This prediction model would be used by
 62 transport agencies/fleet owners to increase knowledge of the safety of their vehicles [7].

64 2.0 Methodology

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

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

73 S/N	Road Traffic Accident (RTA) CAUSES	2012	2013	2014	2015	2016
1.	Speed violation (SPV)	2374	5495	3496	3195	3848
2.	Loss of control (LOC)	1183	2928	2445	2770	1753
3.	Dangerous Driving (DGD)	1096	2082	1324	1137	969
4.	Wrong Overtaking (WOT)	270	623	147	546	832
5.	Sign/Light Violation (SLV)	3	333	905	1097	736
6.	Tyre Burst (TBT)	623	1271	873	813	689
7.	Route Violation (RTV)	165	582	513	524	591
8.	Brake Failure (BFL)	344	584	418	479	567
9.	Mechanically Deficient Vehicle (MDV)	158	450	226	197	316
10.	Others, Unidentified causes (OTH)	0	228	175	262	246
11.	Road Obstruction Violation (OBS)	116	85	181	167	182
12.	Dangerous Overtaking (DOT)	106	591	261	216	144
13.	Overloading (OVL)	46	165	114	82	99
14.	Sleeping on Steering (SOS)	36	207	48	55	78
15.	Fatigue (FTQ)	5	263	61	85	73
16.	Driving Under Alcohol/Drug (DAD)	36	179	93	63	57
17.	Use of Phone While Driving (UPD)	26	77	32	38	32
18.	Night Journey (NJR)	13	15	20	14	11
19.	Poor Weather, (PWR)	4	40	28	16	27
20.	Bad Road (BRD)	139	295	101	67	124

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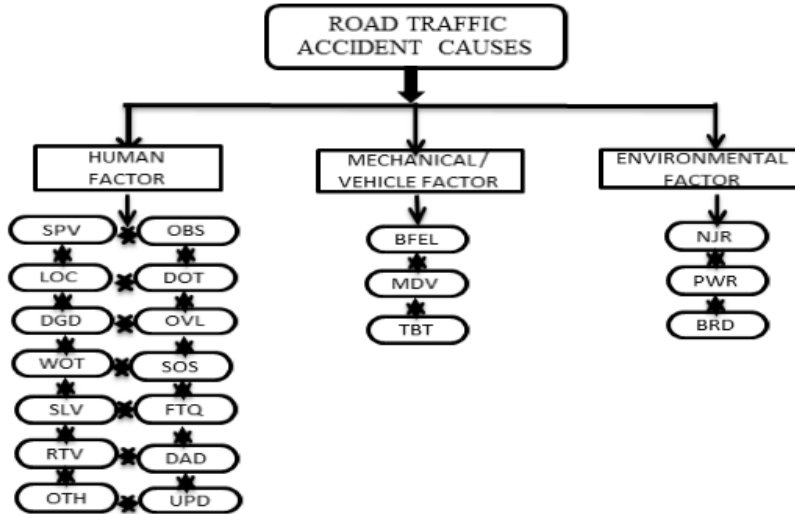


Fig. 1: Flowchart showing the causes of Road Transport Accident

Figure 1 shows 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 with 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
$X_i = (\text{score } A_i \div \sum \text{score } A_i) * 0.846$			
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
$X_j = (\text{score } B_j \div \sum \text{score } B_j) * 0.138$			
Distance of Travel (C_k)			
	Class	Score	Fractional Score, X_k
Group C1	$C \leq 250$ KM	1	0.0027
Group C2	$250 \leq C \leq 500$ KM	2	0.0053
Group C3	$C \geq 500$ KM	3	0.008
$X_k = (\text{score } C_k \div \sum \text{score } C_k) * 0.016$			

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, P_r) 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

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The accident occurrence probability (Pr) for each accident-cause factor, is the ratio of the total accident 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. Pr for the three main accident cause factors as classified in Fig.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

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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:

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

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

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

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

Hence,

$$HFpr_i + MFpr_j + EFpr_k = 1 \quad (3)$$

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

126 That is, $HF = MF = EF = 1$

127 Where:
 128 $pr_i = 0.846, pr_j = 0.138$ and $pr_k = 0.016$ (Table 2)

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

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

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

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

139 Hence, Equation 3 becomes,
 140 $0.846HF + 0.138MF + 0.016EF = 1 - \beta$

141 Therefore:
 142 $0.846HF + 0.138MF + 0.016EF + \beta = 1$ (4)

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

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

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

148 $X_j = (\text{score } B_j \div \sum \text{score } B_j) * 0.138$

149 $X_k = (\text{score } C_k \div \sum \text{score } C_k) * 0.016$

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

151 Then,
 152 $0.846A_i + 0.138B_j + 0.016C_k + \beta = 1$ (5)

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 154 Since X_i, X_j and X_k are respectively proportional to A_i, B_j and C_k ; It therefore implies that:

155 $\mu_{(A_i, B_j, C_k)} = 0.846X_i + 0.138X_j + 0.016X_k + \beta_{ijk}$ (6)

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 158 Where:
 159 μ = Accident probability (the dependent variable as a result of the interactions of the independent variables — X_i
 160 $, X_j, X_k$ and $\beta_{i,j,k}$;

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

162 $\beta_{i,j,k}$ = the uncertainty of accident occurring when the $i^{\text{th}}, j^{\text{th}}$ and k^{th} certainty factors interplay;

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

164 $\mu_{(A_i, B_j, C_k)}$ = accident probability when the $i^{\text{th}}, j^{\text{th}}$ and k^{th} predictive factors are combined.

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

166 $\mu_{(A_i, B_j, C_k)} = 0.846X_i + 0.138X_j + 0.016X_k + \beta_{ijk}$ (7)

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 169 In order to validate the developed accident prediction model, the various possible combinations of the predictive
 170 factors (age of the driver, maintenance frequency and distance of travel) are considered and then integrated into
 171 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					

176 Incorporating the different combinations into the accident model yields:
 177 Combination 1: $\mu (A1, B1, C1) = 0.846A1 + 0.138B1 + 0.016C1 + \beta_{i,j,k}$
 178 Combination 2: $\mu (A1, B1, C2) = 0.846A1 + 0.138B1 + 0.016C2 + \beta_{i,j,k}$
 179 Combination 3: $\mu (A1, B1, C3) = 0.846A1 + 0.138B1 + 0.016C3 + \beta_{i,j,k}$
 180 Combination 4: $\mu (A1, B2, C1) = 0.846A1 + 0.138B2 + 0.016C1 + \beta_{i,j,k}$
 181 Combination 5: $\mu (A1, B2, C2) = 0.846A1 + 0.138B2 + 0.016C2 + \beta_{i,j,k}$
 182 Combination 6: $\mu (A1, B2, C3) = 0.846A1 + 0.138B2 + 0.016C3 + \beta_{i,j,k}$
 183 Combination 7: $\mu (A1, B3, C1) = 0.846A1 + 0.138B3 + 0.016C1 + \beta_{i,j,k}$
 184 Combination 8: $\mu (A1, B3, C2) = 0.846A1 + 0.138B3 + 0.016C2 + \beta_{i,j,k}$
 185 Combination 9: $\mu (A1, B3, C3) = 0.846A1 + 0.138B3 + 0.016C3 + \beta_{i,j,k}$
 186 Combination 10: $\mu (A2, B1, C1) = 0.846A2 + 0.138B1 + 0.016C1 + \beta_{i,j,k}$
 187 Combination 11: $\mu (A2, B1, C2) = 0.846A2 + 0.138B1 + 0.016C2 + \beta_{i,j,k}$
 188 Combination 12: $\mu (A2, B1, C3) = 0.846A2 + 0.138B1 + 0.016C3 + \beta_{i,j,k}$
 189 Combination 13: $\mu (A2, B2, C1) = 0.846A2 + 0.138B2 + 0.016C1 + \beta_{i,j,k}$
 190 Combination 14: $\mu (A2, B2, C2) = 0.846A2 + 0.138B2 + 0.016C2 + \beta_{i,j,k}$
 191 Combination 15: $\mu (A2, B2, C3) = 0.846A2 + 0.138B2 + 0.016C3 + \beta_{i,j,k}$
 192 Combination 16: $\mu (A2, B3, C1) = 0.846A2 + 0.138B3 + 0.016C1 + \beta_{i,j,k}$
 193 Combination 17: $\mu (A2, B3, C2) = 0.846A2 + 0.138B3 + 0.016C2 + \beta_{i,j,k}$
 194 Combination 18: $\mu (A2, B3, C3) = 0.846A2 + 0.138B3 + 0.016C3 + \beta_{i,j,k}$
 195 Combination 19: $\mu (A3, B1, C1) = 0.846A3 + 0.138B1 + 0.016C1 + \beta_{i,j,k}$
 196 Combination 20: $\mu (A3, B1, C2) = 0.846A3 + 0.138B1 + 0.016C2 + \beta_{i,j,k}$
 197 Combination 21: $\mu (A3, B1, C3) = 0.846A3 + 0.138B1 + 0.016C3 + \beta_{i,j,k}$
 198 Combination 22: $\mu (A3, B2, C1) = 0.846A3 + 0.138B2 + 0.016C1 + \beta_{i,j,k}$
 199 Combination 23: $\mu (A3, B2, C2) = 0.846A3 + 0.138B2 + 0.016C2 + \beta_{i,j,k}$
 200 Combination 24: $\mu (A3, B2, C3) = 0.846A3 + 0.138B2 + 0.016C3 + \beta_{i,j,k}$
 201 Combination 25: $\mu (A3, B3, C1) = 0.846A3 + 0.138B3 + 0.016C1 + \beta_{i,j,k}$
 202 Combination 26: $\mu (A3, B3, C2) = 0.846A3 + 0.138B3 + 0.016C2 + \beta_{i,j,k}$
 203 Combination 27: $\mu (A3, B3, C3) = 0.846A3 + 0.138B3 + 0.016C3 + \beta_{i,j,k}$

204 3.0 Results and Discussion

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

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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>i,j,k</i>	Explanation	Combination <i>i,j,k</i>	Explanation	Combination <i>i,j,k</i>	Explanation
A1, B1, C1	Combination of driver age (18-38), maintenance frequency (Regular) and distance of travel ($C \leq 250$ KM)	A2, B1, C1	Combination of driver age (39-59), maintenance frequency (Regular) and distance of travel ($C \leq 250$ KM)	A3, B1, C1	Combination of driver age (60+), maintenance frequency (Regular) and distance of travel ($C \leq 250$ KM)
A1, B1, C2	Combination of driver age (18-38), maintenance frequency (Regular) and distance of travel ($250 \leq C \leq 500$ KM)	A2, B1, C2	Combination of driver age (39-59), maintenance frequency (Regular) and distance of travel ($250 \leq C \leq 500$ KM)	A3, B1, C2	Combination of driver age (60+), maintenance frequency (Regular) and distance of travel ($250 \leq C \leq 500$ KM)
A1, B1, C3	Combination of driver age (18-38), maintenance frequency (Regular) and distance of travel ($C \geq 250$ KM)	A2, B1, C3	Combination of driver age (39-59), maintenance frequency (Regular) and distance of travel ($C \geq 250$ KM)	A3, B1, C3	Combination of driver age (60+), maintenance frequency (Regular) and distance of travel ($C \geq 250$ KM)
A1, B2, C1	Combination of driver age (18-38), maintenance frequency (Irregular) and distance of travel ($C \leq 250$ KM)	A2, B2, C1	Combination of driver age (39-59), maintenance frequency (Irregular) and distance of travel ($C \leq 250$ KM)	A3, B2, C1	Combination of driver age (60+), maintenance frequency (Irregular) and distance of travel ($C \leq 250$ KM)
A1, B2, C2	Combination of driver age (18-38), maintenance frequency (Irregular) and distance of travel ($250 \leq C \leq 500$ KM)	A2, B2, C2	Combination of driver age (39-59), maintenance frequency (Irregular) and distance of travel ($250 \leq C \leq 500$ KM)	A3, B2, C2	Combination of driver age (60+), maintenance frequency (Irregular) and distance of travel ($250 \leq C \leq 500$ KM)
A1, B2, C3	Combination of driver age (18-38), maintenance frequency (Irregular) and distance of travel ($C \geq 250$ KM)	A2, B2, C3	Combination of driver age (39-59), maintenance frequency (Irregular) and distance of travel ($C \geq 250$ KM)	A3, B2, C3	Combination of driver age (60+), maintenance frequency (Irregular) and distance of travel ($C \geq 250$ KM)
A1, B3, C1	Combination of driver age (18-38), maintenance frequency (Reactive) and distance of travel ($C \leq 250$ KM)	A2, B3, C1	Combination of driver age (39-59), maintenance frequency (Reactive) and distance of travel ($C \leq 250$ KM)	A3, B3, C1	Combination of driver age (60+), maintenance frequency (Reactive) and distance of travel ($C \leq 250$ KM)
A1, B3, C2	Combination of driver age (18-38), maintenance frequency (Reactive) and distance of travel ($250 \leq C \leq 500$ KM)	A2, B3, C2	Combination of driver age (39-59), maintenance frequency (Reactive) and distance of travel ($250 \leq C \leq 500$ KM)	A3, B3, C2	Combination of driver age (60+), maintenance frequency (Reactive) and distance of travel ($250 \leq C \leq 500$ KM)
A1, B3, C3	Combination of driver age (18-38), maintenance frequency (Reactive) and distance of travel ($C \leq 250$ KM)	A2, B3, C3	Combination of driver age (39-59), maintenance frequency (Reactive) and distance of travel ($C \leq 250$ KM)	A3, B3, C3	Combination of driver age (60+), maintenance frequency (Reactive) and distance of travel ($C \leq 250$ KM)

A_i = Age of driver B_j = Maintenance frequency C_k = Distance of travel
 $i = 1,2,3$ $j = 1,2,3$ $k = 1,2,3$

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From Tables 6 and 7, it could be 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 climate, 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

236 on transport vehicles because the group is more prone to road accident than other categories of vehicles and
237 drivers.

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Declaration of interest: NONE

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