

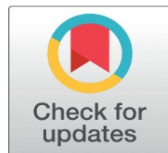
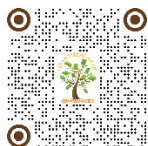
DEVELOPMENT OF AN ACCIDENT PREDICTOR INTERFACE FOR PREDICTING ACCIDENT POTENTIALS OF TRANSPORT VEHICLES IN NIGERIA

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Received 20 July 2024
Accepted 28 August 2024
Published 05 October 2024

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DOI [10.29121/ShodhAI.v1.i1.2024.15](https://doi.org/10.29121/ShodhAI.v1.i1.2024.15)

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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ABSTRACT

In this work, an accident prediction model was developed for determining the accident potential of a vehicle while on transit. The developed model identifies Human factors (HF), Mechanical factors (MF) and Environmental factors (EF) as the main factors responsible for vehicle crashes. The accident data used for this research was obtained from the Nigerian Federal Road Safety Corps (FRSC). Analysis of the accident data showed that HF contributes 0.846 accident probability, MF contributes 0.138 accident probability while EF contributes 0.016 accident probability. Also, driver's age, distance of travel and maintenance frequency of the vehicle were considered in the development of the model, since they also play significant roles in determining accident probabilities. The model gives results ranging from 0-1. When the value is close to 0, it signifies low accident probability while values close to 1 signify high accident probability. An accident predictor interface was developed by combining all the possible accident cause factors. The accident predictor interface gave the least accident probability value of 0.2892 for the following combination: driver age of 60+ years, regular maintenance frequency and travel distance of $C \leq 250$ Km. Application of the results of this model will significantly reduce the rate of road accident occurrences. Finally, transport companies and fleet owners are encouraged to embrace and use this innovation for safer operations.

Keywords: Accident, Accident Potential, Accident Data, Vehicle Crash, Accident Prediction

1. 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 [Gupta et al. \(2009\)](#) 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 [Oyedepo, O. J. \(2010\)](#) 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 [Oyedepo, O. J. \(2010\)](#) 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 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 [FRSC et al. \(2006\)](#) 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 [FRSC, \(2016\)](#) 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. Furthermore, the disability load for this age group records about 60.0 percent of all disability-life years [Beirness et al. \(2011\)](#). 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 [Beirness et al. \(2011\)](#). 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 [World bank \(2015\)](#). 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 [World bank \(2015\)](#).

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. 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. About 35,092 road traffic fatalities were documented in the US in 2015, an increase of 7.2% compared to the preceding year. It is in consideration of these trend 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.

2. 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 [Table 1](#). The accident data was analysed 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 the accident-cause factors.

Table 1

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

Source FRSC, 2016

Road Traffic Accident Causes in Nigeria from 2012 to 2016

The twenty accident-cause-factors presented in [Table 1](#) were 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 flow-diagram is developed and presented in [Figure 1](#).

Figure 1

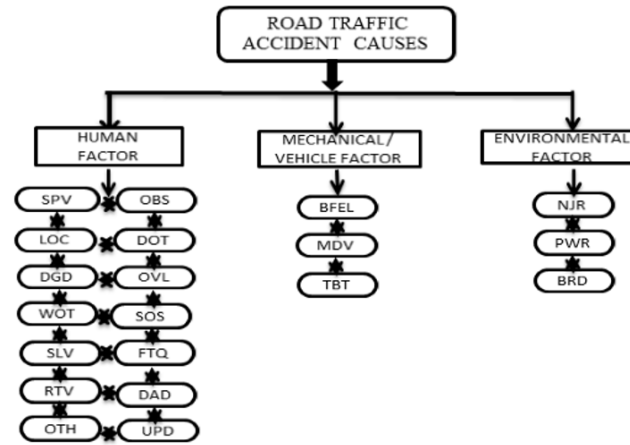


Figure 1 Flow-Diagram Showing the Causes of Road Transport Accident

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 Abdulhafedh, A. (2017), Kalyoncuoğlu et al. (2014), Hermitte, T. (2012), Oyetunji et al. (2017), 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

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
$X_i = (score A_i \div \sum score A_i) * 0.846$			
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
$X_j = (score B_j \div \sum score B_j) * 0.138$			

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, 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

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

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 [Figure 1](#) was also computed from [Table 3](#) and the results shown in [Table 4](#).

Table 4

Table 4 RTA-Causes and Probabilities by three Main Accident Factors							
	2012	2013	2014	2015	2016	Total	Pr.
HF	5462	13838	9795	10237	9640	48972	0.846
MF	1125	2305	1517	1489	1572	8008	0.138
EF	156	350	149	97	162	914	0.016
TOTAL	6743	16493	11461	11823	11374	57894	1

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):

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

Therefore, it follows from Equation (1) that:

$$\text{HFpr}(i) + \text{MFpr}(j) + \text{EFpr}(k) = 1 \quad (2)$$

Where $\text{pr}(i)$, $\text{pr}(j)$ and $\text{pr}(k)$ 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,

The base model (Equation 1) is predicated on the assumption of 100% accident certainty. But in reality, this is not perfectly true; there exist as an equal likelihood of no accident as there is likelihood of accident occurrence as transport vehicles are in transit. To compensate for this scenario, therefore, the parameter, β , a summation of the interacting accident predictive factors, must be subtracted from the model output response (in this case, 1).

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 $\beta_{i,j,k,\dots,n}$, 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 $\beta_{i,j,k}$.

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

Therefore,

$$\beta_{i,j,k} = X_i + X_j + X_k \quad (3)$$

Hence, Equation (2) becomes,

$$\text{HFpr}(i) + \text{MFpr}(j) + \text{EFpr}(k) = 1 - \beta \quad (4)$$

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

Then,

$$pr(i)X_i + pr(j)X_j + pr(k)X_k + \beta = 1 \tag{5}$$

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

$$\mu (X_i, X_j, X_k) = pr(i)X_i + pr(j)X_j + pr(k)X_k + \beta_{ijk} \tag{6}$$

Equation (6) is the required accident prediction model for transport vehicles.

Where:

μ = Probability of Accident occurring

(X_i, X_j, X_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 predictive factors interplay;

$\mu (X_i, X_j, X_k)$ = accident probability when the i th, j th and k th predictive factors are combined.

2.1. ACCIDENT PREDICTIVE-FACTORS COMBINATIONS

There are three sets of accident-predictive factors A_i , B_j and C_k , respectively. Each set of predictive factors contains three distinct elements. The combination design is such that each element of a set combines with one element of each of the remaining two sets to form another set $\{a_i, b_j, c_k\}$. The combination that yields the probability of accident occurring (μ) most approximately equal to zero is the safest combination.

2.1.1. NUMBER OF POSSIBLE PREDICTIVE-FACTOR COMBINATIONS

To determine the number of possible predictive factor combination sets:

Let n be the total number of elements in A_i , B_j and C_k ; r the number of elements in a set of the expected combination $\{a_i, b_j, c_k\}$; k the number of elements that must be repeated in the resultant combination [Brualdi et al. \(2010\)](#).

In general, the number of combinations of n items taking r at a time is given as (Brualdi, 2010):

$$\binom{n}{r} = nCr = \frac{n!}{r!(n-r)!} \tag{7}$$

For repeated combination, the number of ways to obtain the expected set of elements is given as (Brualdi, 2010):

$$\binom{n-k}{r-k} = (n-k)C(r-k) = \frac{(n-k)!}{(r-k)!((n-k)-(r-k))!} \tag{8}$$

But in the case of this conditioned combination, k elements must not be repeated in the set $\{a_i, b_j, c_k\}$. k is therefore, subtracted from the result of the

repeated combination to obtain the required conditioned combination (Brualdi, 2010). The number of ways to obtain the conditioned elements $\{a_i, b_j, c_k\}$ is given as:

$$\binom{n-k}{r-k} = (n-k)C(r-k) = \frac{(n-k)!}{(r-k)!((n-k)-(r-k))!} - k \quad (9)$$

Since any element of a set must not be repeated in the combination, k is therefore assigned a value of 1. To determine the number of combinations of the set $\{a_i, b_j, c_k\}$, Equation (9) is solved by substituting n , r and k values into the equation.

2.2. ACCIDENT PREDICTOR PROGRAMMING

The accident predictor interface runs on the Excel spreadsheet. The software uses Excel command programming and is based on the characteristics of the accident predictive factors associated with the model. In the programming, the following parameters are considered: X_i , on column 'F' row 'i' [F_i], X_j , on column 'F' row 'j' [F_j], X_k , on column 'F' row 'k' [F_k], X_iPrion column 'L' row 'i' [L_i], X_jPrjon column 'M' row 'j' [M_j], $XKPrKon$ column 'N' row 'K' [NK], $\beta_{i,j,k}$ on column 'O' row 'i,j,k' [$O_{i,j,k}$] and $\mu(i,j,k)$ on column 'P' row 'i,j,k' [$P_{i,j,k}$]. The parameter $\mu(i,j,k)$ is the final output response of the accident calculator; the likelihood of accident occurrence as predicted by the model.

2.2.1. ACCIDENT PREDICTOR INTERFACE

An Accident Predictor interface was programmed to eliminate the complexity involved in computing the accident occurrence probability indices. The software is user-friendly as it requires no special expertise. To use the calculator, one only needs to determine the accident predictive-factor scores and insert them into the appropriate fields, then press the 'enter' key and the calculator displays the accident occurrence probabilities in a yellow-coloured column at the extreme right-hand side.

To adjust or edit any of the predictive-factor scores, double click the 'entry' to edit, then press the 'esc' key to return. The calculator is also colour coded to enhance clarity of computed results. The different colours used on the calculator are interpreted by the 'colour key' located at the bottom left of the calculator. The shaded arrow near the colour keys indicates that the entries below it is adjustable.

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

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					

3. 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.

There are three sets of accident-predictive factors A_i , B_j and C_k , respectively. Each set of predictive factors contains three distinct elements: $A_i = \{A1, A2, A3\}$; $B_j = \{B1, B2, B3\}$; $C_j = \{C1, C2, C3\}$. The combination design is such that each element of a set combines with one element of each of the remaining two sets to form another set $\{a_i, b_j, c_k\}$.

To determine the number combinations of the set $\{a_i, b_j, c_k\}$, we then solve equation 9 by substituting $n = 9$, $r = 3$ and $k = 1$ into the equation.

Hence, the total number of required combinations for the set $\{a_i, b_j, c_k\}$ is 27 ways or combinations. The 27 possible combinations of the predictive factors (age of the driver, maintenance frequency and distance of travel) are considered and summarized in Table 6.

Table 6

Table 6 Accident Probability (μ_i, J, K) of the Various Possible Combinations					
Combination i, j, k	$\mu_{i,j,k}$	Combination $i, j, k2$	$\mu_{i, j, k3}$	Combination $i, j, k4$	$\mu_{i,j,k}$
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	0.318
A1, B2, C3	0.8413	A2, B2, C3	0.581	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

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	A2, B3, C2	Combination of driver age (39-59), maintenance frequency (Reactive) and	A3, B3, C2	Combination of driver age (60+), maintenance frequency (Reactive) and

	distance of travel ($250 \leq C \leq 500$ KM)		distance of travel ($250 \leq C \leq 500$ KM)		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 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 could be deduced that accident probability of a vehicle increases as the distance of travel increases and/or maintenance frequency of the vehicle reduces. More so, transport companies are advised against employing drivers between the ages of 18-38 as accident probability is very high within this age.

4. CONCLUSION

In an attempt to tackle the problems posed by road accidents in our clime, particularly the transport vehicles accidents, an accident prediction model has been developed in this paper for transport vehicles. This model will help in reducing accidents involving transport vehicles and their drivers if strictly adhered to. The results of the predictions suggest the probabilities of accident occurrence and as well offer informed guide for fleet operators' decision making.

The focus was on transport vehicles because study has shown the group to be involved in road accident more often than the private vehicles drivers. More so any accident occurrence involving this target group would have a chain effect as several families and their livelihood may be drastically affected.

The study has shown, among other things, that of the various accident-occurrence Probabilities, μ (i, j, k) for the various accident predictive-factor combinations, about 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. Generally, [A1, B3, C3] combination gave the highest probability value of 0.8675 while combination [A3, B1, C1] gave the least probability value of 0.2892. Hence, vehicles are considered safer under these combinations of these low accident-occurrence probability and the safest among all being combination [A3, B1, C1] with a value of 0.2892.

The results also show that accident probability of a vehicle increases as the distance of travel increases and/or maintenance frequency of the vehicle reduces. The transport companies are therefore advised against employing drivers of the age range of 18-38 as accident probability is very high within this age range. However, they are advised to embrace combination [A3, B1, C1] for minimum accident vehicular accident involvement.

For effective accident prediction, the accident predictive factors are of chief importance. The transport vehicle owners or fleet managers have to consider critically the predictive factors, score them and then integrate them into the model for the accident prediction. Furthermore, to enhance speedy and accurate accident calculations for accident predictions, an excel-based accident prediction software interface has been developed for the model.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

Authors are grateful to the entire staff of Mechanical Engineering of Michael Okpara University of Agriculture, Umudike and the entire staff of the Federal Road Safety Corpse, Abia State, for providing all necessary data that made this research work a success.

REFERENCES

- Abdulhafedh, A., (2017). Road Crash Prediction Models: Different Statistical Modeling Approaches. *Journal of Transportation Technologies*, 2017, 7:190-205
- Beirness, D. J. and Beasley, E., (2011). A Comparison of Drug- and Alcohol-Involved Motor Vehicle Driver Fatalities. Canadian Centre on Substance Abuse, Ottawa, 2011
- Brualdi, Richard A., (2010). *Introductory Combinatorics (5th Ed.)*, Pearson Prentice Hall, 2010, ISBN 978-0-13-602040-0.
- FRSC and Balogun Y. (2006). Research and Development Opinions, Federal Road Maintenance Agency January/February 2006 Pg. 13-16
- FRSC, (2016). FRSC Annual Report 2016 ; www.frsc.gov.ng/publications, Retrieved on April 8, 2018
- Gupta, B.L. and Gupta A., (2009). Different Modes of Transportation : Roads, Railways, Bridges, Tunnels & Harbour. *Dock Engineering*, 2009. Chapter 1; pp 1.2-1.4.
- Hermitte, T., (2012). Review of Accident Causation Models used in Road Accident Research of the EC FP7 project DaCoTA, 2012
- Kalyoncuoğlu, F.S, & Tığdemir, M., (2014). The Effects of Daily Driven Distance and Age Factor on the Traffic Accidents. *Transportation Department, Engineering Faculty, Civil Engineering*, 2014 <https://doi.org/10.7307/ptt.v26i3.1306>
- Oyedepo, O. J., (2010). Accident Prediction Models for Akure - Ondo Carriageway, Ondo State Southwest Nigeria : Using Multiple Linear Regressions. *An International Multi-Disciplinary Journal, Ethiopia* Vol. 4 April, 2010, ISSN 2070-0083. <https://doi.org/10.4314/afrev.v4i2.58286>
- Oyetunji, M.O., Oladeji, F.A., Falana, P.A., & Idowu, P.A., (2017). Prediction of Road Traffic Accident in Nigeria Using Naïve Baye's Approach. *Advances in Multidisciplinary & Scientific Research Journal*, volume 3(1), 2017, Pp 23-30 <https://doi.org/10.4236/jtts.2017.72014>