

Research Article

Music Distraction among Young Drivers: Analysis by Gender and Experience

Carlos A. Catalina ^{1,2} **Susana García-Herrero** ¹ **Elvira Cabrerizo** ¹ **Sixto Herrera** ³
Santiago García-Pineda ¹ **Fatemeh Mohamadi** ⁴ and **M. A. Mariscal** ¹

¹Escuela Politécnica Superior, Universidad de Burgos, Burgos, Spain

²Instituto Tecnológico de Castilla y León, Burgos, Spain

³Department of Applied Mathematics and Computer Science, Universidad de Cantabria, Santander, Spain

⁴School of Architecture and Cities, University of Westminster, London, UK

Correspondence should be addressed to Susana García-Herrero; susanagh@ubu.es

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The aim of this study was to quantify the probability of committing a speed infraction by young drivers and to investigate to what extent listening music could affect young drivers' emotions as well as their driving performances at the wheel. To achieve this aim, employing Bayesian networks, the study analysed different music styles, in which they resulted in sample drivers' speed infractions. Gender and drivers' experiences at the wheel were the other factors, which were taken into account when interpreting the study results. Variables taken into account in this study included type of music whilst driving, gender of drivers, and drivers' driving experiences. These variables further incorporated into the study of other telemetric variables including acceleration, number of revolutions per minute (RPM) of the engine, brake, traffic, and other types of infractions other than speed, which were considered as dependent variables. A driving simulator was used, and different driving simulation studies were carried out with young people aged between 20 and 28 years. Each participant carried out three simulations by listening to different type of music in each journey. The study defined a conceptual model in which the data were analysed and evaluated mathematically through Bayesian networks. A sensitivity analysis was performed to evaluate the influence of music on driving speed. Based on the different variables, the study further analysed the probability of speed infractions committed by drivers and their adequate speed. The range of frequency probabilities varied between 96.32% (which corresponds to experienced male drivers who do not listen to music) and 79.38% (which corresponds to less-experienced female drivers who listen to music), which resulted in their happiness or aggression.

1. Introduction

The number of fatalities related to traffic accidents continues to grow globally and already have reached the figure of 1.35 million deaths annually [1]. Consequently, different measures of actions have been taken to reduce the number of traffic accidents. In Spain, at the national level, the "Objective Zero" plan, developed by the Government of Spain, was formulated through the so-called "Strategic Road Safety Plan 2011–2020" in order to target zero victims in traffic accidents in Spain [2]. According to the Directorate General

of Traffic of Spain [3], in 2016, the human factor was the cause of 70% of traffic accidents in Spain.

Several researchers have reported the behavior of drivers as the most influential factor in road traffic accidents [4, 5]. Such studies have argued the behavior of drivers as one of the most influential factors in fatal accidents since it contributes to speed violation and, as a result, an increment of the risk of suffering an accident and the severity of the injury [6–8].

Moreover, Blanco [9] identified two types of risk from the drivers' point of view: perceived risk and assumed risk.

According to Blanco, there is currently an underestimation of perceived risk and overvaluation of the risk assumed, for example, using drugs, reversing, or exceeding the speed limit can closely contribute to high risk of accidents caused by drivers. Whilst such behavior of drivers often causes accidents, the drivers tend to not consider or assume those behaviours as risky, for example, Choudhary and Velaga stated that “drivers are exposed to a greater risk while operating a music player because this is not perceived as a risky behavior [10].” Additionally, as found by Oviedo-Trespalacios [11], around 83% of the young people will allow the use of music player in an application designed to avoid the use of smartphones while driving. As a result, drivers do not consider listening to music as a risk factor.

The impact of listening to music while driving is an important field that has been studied by several researchers. However, different results have been reported, for example, Brodsky documented harmful effects of music on drivers in three categories: the excitement, aggressiveness, and distraction of the drivers themselves whilst driving [12]. In contrast, Ünal et al. [13] concluded that listening to music while driving can be considered as a good strategy to counteract boredom and to satisfy demands at the wheel. Others studies reported the effect of music as a counter measure against drivers’ fatigue [14, 15]. Dalton et al. analysed the sound types and volumes that mostly affect the driving style [16]. Other studies have narrowed down their focus on how the change of abrupt music to quiet music is more effective than gradual change to music in terms of calming drivers in stressful situations [13]. The study of Qi et al. [17] determined that changes in ambient music have significant effects on drivers’ behaviours. Zhu et al. [18] concluded that music with a specific rhythm mitigates the emotion of anger and improves driving quality.

The meta-analysis performed by Millet et al. [19] includes several variables to measure driving performance, with a categorization on “operational definitions,” as recommended by Caird et al. [20, 21]. The categories comprised of vehicular longitudinal control (e.g., speed and speed variance), vehicular lateral control, driver reaction time, traffic signal violation, and collisions. The metasurvey resulted in interesting findings in two categories including “group who listened to music while driving showed significantly more collisions and poorer longitudinal control when compared to subjects in the control group.”

Wen et al. [22] analysed the impact of music on young individuals, while taking into account the user’s personality, their driving speed, and the frequency of their lane crossing. They found that rock music increases the standard deviation of speed and frequency of lane crossing more than light music or no music. However, Navarro [23] did not find a direct relation between driving with music and the car-following distance. Finally, Zimasa et al. [24] found that negative moods as a result of listening to music lead to aggressive driving.

In recent years, the use of driving simulators for the training purposes has become trendy aiming for improving knowledge associated with driving. Moreover, as driving simulators are risk-free and time and cost-effective [25, 26],

they can be used to simulate the real situation and investigate the impact of drug consumption [26], drowsiness [27], mobile phone [28], adjusting the radio, and searching music on portable devices such as an MP3 [29–32] on driving style. Observing the behavior of the driver, designing/controlling the vehicle and testing drive systems for driving are amongst the most important investigations performed through employing driving simulators.

In addition, driving simulators are being used for observing how drivers behave in the face of conflicting situations or dilemmas [33, 34]. They also allow the study of high-risk situations, such as pedestrian crossings [35] or curves [36] and even for cycling [37]. In this way, employing simulators help researchers to look for effective strategies in order to spot-on the risk factors, measure them, and finally come up with solutions to lower the risk probabilities down.

To this end, as highlighted above, the aim of the present study is to carry out a driving simulation experiment in order to quantify the extent to which listening (or not listening) to music affects the probability of committing a speed violation. Different emotions induced by different kinds of music and their impacts on drivers’ behaviours are also considered in the current study. Furthermore to this, the sex of drivers and the level of their driving experience have been taken into account.

2. Data and Methodology

2.1. Database

2.1.1. Simulator. To conduct the current study, the DriveSIM driving simulator alongside with all other necessary hardware including the pedals, the parking brake, the steering wheel, the panel controls, the seat, and the other necessary supports of the vehicle were used. The installation had three television screens to get a peripheral vision during the driving simulation. The simulator included all kinds of situations as well as ultrarealistic contexts that allowed users to practice as if they were in command of a real vehicle. Experiencing very different situations such as driving with adverse weather, aggressive behavior of other drivers, and/or driving in various types of roads were also included in a simulator study. The vehicle chosen to carry out the simulations embodied the dynamic characteristics of a vehicle with 4×4 traction including 151 HP, diesel, an average consumption of 5.7 L, a weight of 1550 kg, and a manual gear control. The chosen routes were via high performance with high traffic of other users.

The selected simulator recorded the telemetry of the vehicle every 15 frames into the internal database, and the computer used run the programme between 30 and 45 FPS (frames per second). FPS is a commonly used measurement tool in the computer graphic field. It measures the number of times that the PC is able to calculate everything needed in terms of input of the user, calculated dynamics, and AI traffic and is able to render the 3D environment in the different cameras operating in the simulator. It can save two/three records per second simulated.

The information provided by the simulator included the following parameters: the position of the vehicle, speed, angular and linear acceleration, rotation, pressure, vertical force and side, wheel temperature, suspension, brake temperature, address, the position of the pedals, gears, parking brake, lights, turn signals, revolutions, the maximum speed allowed, and so on. The simulator also saved a record with the infractions committed by the driver during the simulation. The simulator had a total of 93 possible infractions, which were grouped into the following categories: traffic lights, vertical traffic signs, road markings, and other infractions of speed infractions. The following sections demonstrate discussions of each category separately.

2.1.2. Study Population. A total number of 19 young Spanish drivers aged between 20 and 28 years old participated in this study. Prior to the testing, participants were asked to fill out a form in which they provided researchers with the information in terms of their age, sex, driving experience (for example: how often they drive on a per week basis). In this way, the study population was divided into demographic groups depending on their gender and their driving experience.

2.1.3. Music. The current study is based on the classification of moods induced by music. Moods are grouped into four basic emotional situations based on the study carried out by the University Pompeu Fabra [38]. These emotional situations are aggression, sadness, relaxation, and happiness. A general narrative of a natural driving while using the simulator was provided. Specific trip purposes such as urgent or nonurgent were excluded from this study as they could result in skewed answers to the main research question of the study.

Table 1 shows different moods and their relation with different musical genres.

Referring to the first column in Table 1, different musical genres are listed. The headings for the following columns are based on different states of mood including aggression, sadness, relaxation, and happiness. Moods are valued in the table above with a “+” and “-” symbols. Symbol “+” represents when the state of mind to which it refers is more present than in the rest of genres. Symbol “-” represents when the status of mood is less present than in the rest of genres.

In present study, the four states of moods were regrouped into two groups including aggression/happiness and sadness/relaxation. A total number of 20 songs including new and old songs were listed for each of the two groups.

The songs were selected from the main platforms of the moment including AllMusic, iTunes, and Spotify, which allow to identify and select musical genres. Considering that different music style can result in different emotional moods; before their selection, they were listened in order to ensure that they belong to the emotion sought in each case. They are selected and classified according to the corresponding group of emotions, as indicated in Table 2.

TABLE 1: Musical genres and moods that produce.

Genre	Aggression	Sadness	Relaxation	Happiness
Rock	+	-	-	+
Alternative	+	-	-	+
Rap	+	-	-	-
Electronic	+	-	-	-
Blues	-	+	+	-
Folk	-	+	+	-
Jazz	-	+	+	-
Classical	-	+	+	-
Soundtrack	-	+	+	-
Vocal	-	+	+	-
Country	-	+	+	+
Reggae	-	-	-	+
Pop	-	-	-	+
RBSoul	-	-	-	+
Latino	-	-	-	+

It has long been argued that music is something very personal. In his study “Book of Music and Emotion,” Juslin [39] analysed different perspectives such as philosophy, musicology, and psychology in relation to the impact that music can have on emotion. In this book, factors of development and personality as well as the social factors are covered.

In this study, each participant had their personalised list of songs from Table 1. Prior to carrying out the simulations, all participants had filled out a survey, in which they evaluated the songs in terms of their association with happiness/aggressions and their association with sadness/relaxation. In this way, a custom list of songs for each participant, with the 3 songs of happy/aggressive that were most valued in terms of their contribution to activation, and the 3 songs of sadness/relaxation were valued in terms of their contribution to relaxation.

2.1.4. Realisation of the Simulations. In the first place and prior to taking records of the results generated by the simulation, the participants were subjected to a first contact with the simulator. Each simulation test allowed participants to adapt themselves to the characteristics and the sensitivity of the stimulator, becoming familiar with the driving simulators varied between participants, demonstrating a difference between 10 and 20 minutes. Once the drivers felt comfortable, they proceeded to perform two driving experiments.

In the first place, a simulation was carried out without music. This served as a reference for later analysis to monitor the differences between driving with or without music. The duration of this simulation was 10 minutes, and it was carried out for all participants on the same route.

The second round of the simulation was carried out with music. In this simulation, each participant listened to the custom music tracks. The driving route (vias de high performance) in the second round was similar to the driving route in the first round (driving without music). The tour began with listening to songs that resulted in sadness/relaxing emotions and then continued with the songs that provoked aggression/happiness in drivers.

TABLE 2: Final song selection.

Aggression/Happiness	Sadness/Relaxation
Single Ladies (Put a Ring on It)—Beyoncé	Only Time—Enya
(I Cannot Get No) Satisfaction—The Rolling Stones	Riptide—Vance Joy
Uptown Funk—Mark Ronson y Bruno Mars	Bow and Arrow genre—Reuben and the Dark
Happy—Pharrell Williams	No Shade in the Shadow of the Cross—Sufjan Stevens
One More Time—Daft Punk	Should Have Known Better—Sufjan Stevens
We Will Rock You—Queen	The Last Goodbye—Billy Boyd
La Gozadera—Gente de Zona	Hurt—Johnny Cash
Girls Just Want To Have Fun—Cyndi Lauper	Underwood See You Again—Wiz Khalifa/Cover Flute, Violin, Piano
I love Rock n roll—Joan Jett The Blackhearts	River Flows in You—Yiruma
Shake It Off—Taylor Swift	If I Die Young—The Band Perry
So What Alcohol—Pink	Melodía Desencadenada—Ghost
Bang Bang—Jessie J, Ariana Grande, Nicki Minaj	Elysium—Gladiator
Sax—Fleur East	Hallelujah—Pentatonix
All Star—Smash Mouth	True Love Waits—Radiohead
Party Rock—LMFAO	I Will Always Love You—Whitney Houston
Pump It—The Black Eyed Peas	Clown—Emeli Sandé
El Vals del Obrero. Resistencia—Ska-P	Let It Be—The Beatles
El lado de los Rebeldes—LA RAÍZ	Hallelujah—Lindsey Stirling
Highway to Hell—AC/DC	Kings of the Past—Lion King
Moves Like Jagger—Maroon 5-ft. Christina Aguilera	My Heart Will Go On—Whitney Houston

Overall, each participant spent a minimum of 30 minutes with the driving simulator (10 minutes for training, 10 minutes on driving without music, and 10 minutes on driving with music).

2.1.5. Data to Analyse. The simulator employed in this study recorded all telemetry data in a database. Of all the data collected for this study, the following variables were selected for further analysis: speed, revolutions, infractions, acceleration, brake, and the maximum speed allowed. All these variables are explained in detail in Section 3 (Figure 1. Conceptual model).

All these records were synchronised with the personalised list of music for each participant. This was performed to obtain the telemetry data, correlated with the type of songs, which were listened to at every moment. After the realisation of the 57 simulations (19 participants and 3 scenarios: without music, with music type which relaxed, and music which activated), the results demonstrated a total number of 107,395 records (an average of 5,650 records for each participant).

2.2. Bayesian Network. As pointed out earlier in the Introduction section, the aim of this study was to appraise the probability of committing a speed infraction based on the drivers' behavior. To achieve this aim, discrete Bayesian networks (BNs) were employed since they are highly regarded as machine learning technique, in which they efficiently learn the joint probability distribution (JPD) of multivariate problem involving discrete variables $X = \{X_1, \dots, X_n\}$ [40], where X_i is the each variable considered in the model. The created model enabled us to estimate the probability of each variable (inference) based on the knowledge of the state of some of the variables

(evidence). In particular, we were able to gain knowledge on how the probability of committing a speed infraction changes depending on the driver's behavior (sensitivity analysis). This was in keeping with previously performed research, in which they have used Bayesian networks in their studies of traffic accidents to raise that various relationships exist between several factors [7, 41–44].

Bayesian networks (BNs) are models combining probability and graph theory to efficiently learn the joint probability distribution (JPD) of the considered aleatory variables (X_i):

$$p(X_1, \dots, X_n). \quad (1)$$

In particular, BNs are based on directed acyclic graphs (DAG) representing the probabilistic dependence, direct or conditional, among the variables and, using the Bayes rule, enabling the factorization of the JPD (joint probability function)

$$p(x_1, x_2, \dots, x_n) = \prod_{i=1}^n p(\pi_i), \quad (2)$$

where x_i corresponds to a realisation of the aleatory variable X_i , and π_i is the set of parents of node X_i in the graph, namely the set of nodes linked with X_i by an arrow pointing to this node. As a consequence, first, the DAG was obtained (structural learning) by applying the score-based greedy learning algorithm proposed by Buntine [45], and then, the parameters associated to the factorization are estimated by maximum likelihood as these are the ones that better explain the observed data.

Currently, there are a lot of packages, libraries, and programs to learn Bayesian networks implemented in different programming languages (e.g., R: <http://www.bnlearn.com/>, Python: <https://pomegranate.readthedocs.io/en/latest/BayesianNetwork.html>, or Matlab: <https://github.com/bayesnet/bnt>). Based on previous experiences [44, 46–51],

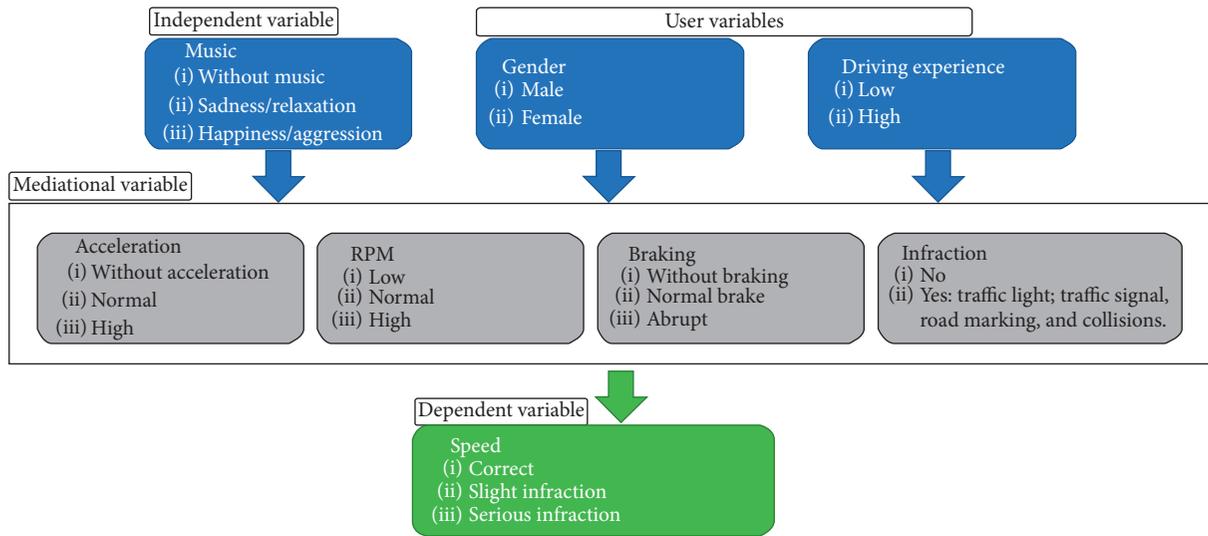


FIGURE 1: Conceptual model.

the Matlab Toolbox Bayes Net [52] (<https://github.com/bayesnet/bnt>) was the package finally considered.

Once the model has been obtained, the probability of any event can be estimated. In particular, for the target variable, the Bayesian network assigns a probability for each state, and then, it can be interpreted as a Bayesian classifier. In order to know the skill of our model, a 10-fold cross-validation was developed creating a random partition of the database in ten subsamples, so using the 90% to train and the remaining 10% to evaluate and repeating this process, it has been evaluated in order to know the skill of our model and avoid overfitting. To this aim, perform this procedure ten times, one for each subsample. As a result, 11 test samples were obtained, one per fold and the latest one considering the prediction of the complete sample obtained by joining the 10 folds.

The evaluation of each model was performed using the area under the ROC (receiver operating characteristic) curve (AUC) [53], which is a standard score for probabilistic and binary classifiers that varies from 0.5 (random guess) to 1 (perfect performance) and was considered as a measure of the overall accuracy of the model [54].

Finally, once the model has been evaluated and its predictability tested, the 100% of the database has been considered to train the model used for the sensitivity analysis.

3. Conceptual Model

The conceptual model (Figure 1) used in this study contains the following groups of variables:

The music variable has been divided into three states. The first one refers to driving without background music, the second refers to when driving while listening to either a sad or a relaxing music, and finally, the third state refers to driving while listening to a background music that is classified as a music that can result in cheerfulness or aggression.

Demographic and driving experience variables as user variables have also been considered in this study. For the driving experience variable, two states are defined. One in

which it refers to drivers with little experience at the wheel, and the other in which it refers to those who have an extensive experience at the wheel. The data for the driving experience was obtained from the forms filled out by the participants prior to analysis. Both the years their driving license was issued, and the frequency of driving car was taken into account. The questions related this issue were “How often do you drive a car?” and “when driving license was issued?” If the driver had the driving license for more than 1 year and a half and, at the same time, he/she drives more than once a week, then the variable “experience steering a wheel” is classified as experienced; otherwise, the driver is classified as little experience.”

The telemetry variables that have been taken into consideration to develop the mathematical model are as follows: acceleration, revolutions, infractions, brake, and finally, the speed that is the variable object of study.

As regards the “acceleration” variable, three states have been considered. The first state indicates that there is no acceleration; all the cases in which the vehicle carries a constant speed is stopped or carries a negative acceleration (braking) is included in this section. The second state indicates that the acceleration is normal. The third state indicates that the acceleration is high.

The variable “revolutions” also have three different states. The first state refers to the time and situation when revolutions are lower than 2250 rpm. The second state refers to the situation and time if revolutions are between 2250 and 3000 rpm. Finally, the third state refers to situation and time if the level of revolutions is higher than 3000 rpm.

The variable “infractions” is divided into two states. The first state indicates that an infringement is being committed, and the second state indicates that not any infringement is being committed. The infractions do not take into account the speed infraction since a specific variable has been defined for studying it.

The grouping of the infractions are as follows: traffic lights (skipping a red light), traffic signs (failure to comply

with traffic signs), road markings (failure to comply with the different road markings), safety distances (failure to maintain the safety distance), lights (incorrect use of lights), collisions (collisions with other vehicles or objects on the road), abuses (pedestrian or animal abuse), and other infractions.

The “brake” variable contains three states. The first state is the one obtained when the driver is not pushing the brake. In addition, we distinguish the other two states: if the braking is normal or if it is done abruptly.

With regards to “speed” considered as the target variable, this variable has been divided into three states according to the speeds states established by the DGT as suitable for driving (Table 3). Driving speed below legal speed limit, driving speed more than legal limit but less than the radar limit (driving speed is between the speed limit and the speed of activation of the cinemometer), and driving speed higher than the radar limit.

Table 4 below shows the registered cases and their percentage for each state of the variables that are part of the model.

In this case, the number of records shown in (Table 4) is important since they display the status of the vehicle in each “instant.” In this table, the vehicle data of each simulation are collected. The data are stored keeping in mind the FLOPS.

This model has been validated since all AUCs exceed 0.7, meaning that they are data reliable (Table 5).

4. Results

4.1. Sensitivity Analysis. Different sensitivity analysis performed in this study is shown below. Figure 2 represents the results generated from the Bayesian network. As the graph illustrates, speed as the core variable located in the centre of the graph has direct links with all the variables considered in the model and introduces conditional dependencies between its parents (gender, driver experience, and braking) and children variables (infraction, acceleration, RPM, and music) given by the V-structures of the Bayesian network (e.g., speed \rightarrow infraction \leftarrow driving experience). In this sense, given any children variables involved, a statistical dependency grows between infraction and its parents. As a result, several sets of flow generated by the model reflect the sequence pointed out in the conceptual model. The model, however, includes relations which could be less obvious in obtaining a more useful model.

4.1.1. Influence of Music on the Probability of Speed Infraction. Table 6 shows the probability of driving based on different driving speed states. From the results, the probability of driving below legal speed limit while not listening to music is 95.34%. Looking at the first column, it is evident that most of the time that drivers were behind the wheel and respected the speed limits. However, the corresponding probability varies depending on the type of music. That is listening to sad and happy music reduces the probability of driving at an adequate speed to 89.9% and 86.59%, respectively.

TABLE 3: DGT speed.

Speed limitation (km/h)	30	40	50	60	70	80	90	100	110	120
Cinometer activation speed	38	48	58	68	78	88	98	109	120	131

Such a solid evidence indicates that when drivers do not listen to any music, the probability of committing a slight infringement (above the legal speed but below the threshold of the radars) is 4.18%. However, when drivers listen to any kind of music, the probability of their committing infraction increases to 7.35%. Similarly, if the drivers do not listen to any type of music, the probability of committing a serious infraction (detected by the radars), therefore, stands at 0.48%. Yet, if the drivers listen to a sad and happy music, the probability of exceeding the speed accounts for 2.74% and 6.06%, respectively.

Referring to Table 4, it can be argued that the reference data (a priori) indicates that, without analysing the type of music, the percentage of time driving at an appropriate speed, committing a slight infraction, and or a serious infraction account for 90.68%, 6.24%, and 3.08% of cases, respectively. Therefore, the probability of committing a serious infraction is almost half in comparison to the probability of committing a slight infraction. When making a comparison between the data presented in Table 6 with the data obtained in Table 4 “a priori,” it can be concluded that the probability of driving at an adequate speed is higher if drivers do not listen to music. The probability of committing a serious speed violation then is bigger if drivers listen to music that generates happiness/aggression.

4.1.2. Influence of Music and Gender on the Probability of Infringement of Speed. In the second round of analysis, the probability of driving at an adequate speed, at minor infraction speed, and at a serious infraction speed were examined in their relation to the type of music variables including no music, sadness/relaxation, and happiness/aggression while taking into account the gender variable (male/female). The results of such a cross-tabulation tests are shown in Table 7.

The performed cross-tabulation tests revealed that, in the absence of music, the probability of driving at an adequate speed in women (95.94%) is slightly higher than that in men (94.38%). Further analysis revealed the data for the probability of driving at an adequate speed, at minor infraction speed, and at a serious infraction speed in relation to different type of music listened by male and female drivers. What becomes apparent from the analysis is that when it comes to listening to whether a sad or relaxing music, men are those who have a greater chance of driving at an adequate speed, 92.19%. The figure for female drivers is 88.65%. Concerning the type of music that transmits whether happiness/aggression emotions, the same tendency repeats. Men drivers have a greater chance of driving at an adequate speed of 87.92% in comparison to female drivers 85.88%. Nevertheless, the probability of driving at an adequate speed

TABLE 4: Table of records.

Variable	State	No of records	Percentage (%)
Speed	Correct	97,879	90.68
	Minor infraction	6,736	6.24
	Serious infraction	3,320	3.08
Music	Without music	37,744	34.97
	Music sadness/relaxation	33,620	31.15
	Music happiness/anger	36,571	33.88
Acceleration	No acceleration	49,202	45.58
	Normal acceleration	29,366	27.21
	High acceleration	29,366	27.21
RPMs	<2250	64,522	59.76
	2250 < x < 3000	32,912	30.49
	>3000	10,501	9.75
Brake	No brake	98,453	91.22
	Normal brake	4,742	4.39
	Abrupt brake	4,740	4.39
Infractions	No infraction	103,999	96.33
	Infraction	3,936	3.67
Sex	Women	63,840	63.78
	Men	39,095	36.22
Driving experience	Low	49,306	45.68
	High	58,629	54.32

for both male and female drivers is lower than in the case of listening to a sad/relaxing music, even less at the time both gender drive without listening to any music.

In light of above, it can be concluded that women drive at a more appropriate speed than men when music does not play any role as a factor of distraction. However, in the presence of music (either a sad or a relaxing type of music), women have a greater chance of committing either a minor or a major speed violation. Column 4 (minor infraction speed) and column 5 (serious infraction speed) present this data. In any case, either men or women, both have greater chances of committing infraction in comparison to driving without music.

Discussing the data in details, it can be argued that in the case of female drivers, when they listen to a relaxing or sad music, the level of their committing to a minor infraction is higher than when they listen to happy/aggression type music. However, this is not a case when it comes to committing serious speed violations. This means that the probability of committing an infraction by female drivers is greater if the type of music heard transmits to cheerful/aggression emotions of drivers.

When it comes to male drivers, it can be appreciated that in all music states, there is a reduction in the probability of exceeding the speed. However, this reduction is not the same in all cases. When they listen to sad music or they do not listen to music, we have reductions in odds of more than 4.5 points in both cases, compared to a reduction of 3 points when it comes to happy music.

To this end, it could be concluded that both men and women whether listen to music or not, the likelihood of their committing a serious excess in speed are decreased for all cases. When listening to sad/relaxing music, it is women who have a higher probability of committing either minor or major speed infractions. However, when

TABLE 5: Area under the ROC curve.

Estate 1	Estate 2	Estate 3
0.76383	0.72272	0.81235
0.76108	0.7122	0.8102
0.75167	0.72043	0.80972
0.73589	0.7036	0.81726
0.74621	0.70979	0.79946
0.74307	0.70411	0.80594
0.75507	0.71723	0.80274
0.73844	0.70965	0.78705
0.75963	0.7204	0.7874
0.75929	0.71533	0.82535
0.75131	0.71337	0.80597

listening to a music that transmits to their happiness/anger emotions, men have higher probability of committing a minor speed infraction (7.61%) compared to women (7.20%). This reverses in terms of committing a serious speed infringement. The figure for female drivers is higher than for male drivers. 6.91% for female drivers and 4.47% for male drivers.

When listening to happy music, women keep the percentage of speed violation almost constant in the environment of 7%. Men reduce the percentage of infringement serious compared to the mild but to a lesser extent than when they listen to sad music or do not listen to music.

4.1.3. Influence of Music and Driving Experience on the Probability of Speed Violation. The aim of third round of analysis is to examine whether the driving experience could play any role on the speed violation depending on no music or the music type that was listened. If so, to what extent

TABLE 6: Probability of speed violation in relation to the music.

Music	Adequate speed (%)	Minor speed infraction (%)	Serious speed infraction (%)
No music	95.34	4.18	0.48
Sadness/relaxation	89.90	7.36	2.74
Happiness/aggression	86.59	7.34	6.06

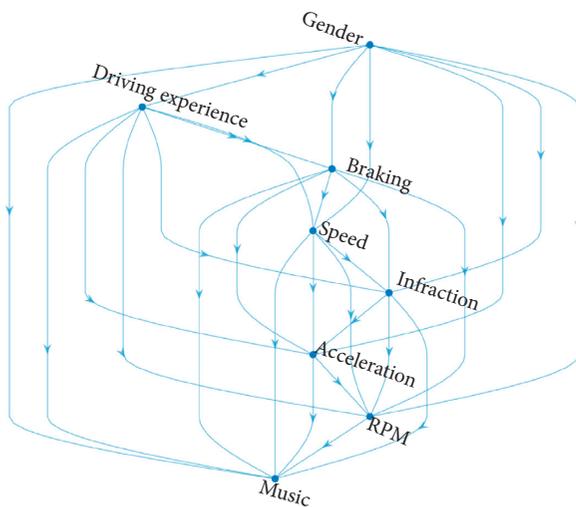


FIGURE 2: Bayesian network graph.

driving experience could result in any infringements on speed. The results are presented in Table 8.

As Table 8 indicates, under the “No music” variable, the drivers with less driving experience have a higher probability of driving at an adequate speed of 96.26%. 1.5 points higher probability compared to expert drivers. However, when music is played, probabilities change. Listening to songs that convey sadness or relaxation, in less-experienced drivers, reduces their chance of driving at an adequate level. The probability reaches 86.89% compared to highly experienced drivers, in which their probability to drive at an adequate speed reaches 92.54%. Slightly similar results become evident when less expert drivers listen to songs that convey to their either joy or aggression emotions. Only 80.26% of less-experienced drivers drive at an adequate speed. This is while, 92.89% of highly experienced drivers drive at an adequate speed.

When the effect of music on drivers with little experience is analysed, it becomes apparent that driving without music entails performing a lower percentage of minor infractions as well as serious infractions: 2.92% and 0.84%, respectively. In the case of driving while listening to music that causes happiness or anger in the less-experienced drivers, the percentage of infractions in both minor and major cases is around 10% (9.95% and 9.80%). This means that, when driving with cheerful music on, the less-experienced drivers do not perceive the increase in speed and commit minor and/or serious infractions with almost the same probability that approaches 10% in both cases.

These findings suggest that less-experienced drivers are highly affected by the songs they listen to. This is while highly experienced drivers have greater control over their emotions

when they simultaneously listen to any kind of music and drive. Further to this, it can be argued that, although in the case of driving without listening to music, less-experienced drivers are those who have a higher probability of driving at an appropriate speed; less-experienced drivers are also those who are mostly affected by music, and thus have less probability of driving at an adequate speed.

Referring to the expert drivers, not listening to music follows the same pattern as with less expert drivers. 94.71% of expert drivers drive at an adequate level of speed in comparison to the time they listen to any type of music. Similar to less-experienced drivers, driving without listening to music makes highly experienced drivers aware of their infractions and prevents them from driving at a speed above the threshold of the radars. Listening to either cheerful or sad music, however, changes the pattern for experienced drivers too. It goes from producing a reduction in the probability of serious infringement when listening to sad music from 1.32% to a minor infringement of 6.14%. Same pattern happens with happy music. The figure for serious speed infraction is 2.35% when compared to minor infraction speed which is 4.76%.

Taking the spectrum of the above analysis, it can be asserted that expert drivers suffer to a lesser extent of effects of listening to music while driving, and this is while less-experienced drivers are highly affected by listening to music. In all cases, driving without listening to music makes both categories of drivers to be aware of their actions and the surrounding driving environment and avoid exceeding the speed above the limit of the radars.

4.1.4. Influence of the Music of the Driving Experience and the Gender in the Probability of Speed Violation. Through conducting a multidimensional cross-tabulation procedure, the probability of driving at an adequate speed or at an inadequate speed depending on the music type, gender, and driving experience was examined. Table 9 represents the data for this analysis.

“No music” variable was the first variable to be considered for the first round of analysis. “No music” played while driving and how experienced both male and female drivers were at the wheel were examined and compared. Highly experienced women drivers tend to respect speed limit most of the time when they were not listening to music while driving. 95.76% was the figure that appeared during the analysis in contrast to the figure of 92.99% that appeared for highly experienced male drivers. Few differences, however, were presented in the findings for less-experienced female and male drivers when they were not listening to music. 96.32% of less-experienced male drivers were driving at an adequate speed level in comparison to female drivers,

TABLE 7: Probability of speed infraction depending on music type and gender.

Music	Gender	Adequate speed (%)	Minor speed infraction (%)	Serious speed infraction (%)
No music	Women	95.94	3.55	0.51
	Men	94.38	5.17	0.44
Sadness/relaxation	Women	88.65	7.92	3.42
	Men	92.19	6.33	1.48
Happiness/aggression	Women	85.88	7.20	6.91
	Men	87.92	7.61	4.47

TABLE 8: Probability of speed infraction depending on the music type and experience steering wheel.

Music	Experience	Adequate speed (%)	Minor speed infraction (%)	Serious speed infraction (%)
No music	Low	96.26	2.92	0.82
	High	94.71	5.04	0.25
Sadness/relaxation	Low	86.89	8.75	4.36
	High	92.54	6.14	1.32
Happiness/anger	Low	80.26	9.95	9.80
	High	92.89	4.76	2.35

TABLE 9: Probability of speed violation based on music, gender, and experience at the wheel.

Music	Gender	Experience	Adequate speed (%)	Minor speed infraction (%)	Serious speed infraction (%)
No music	Women	Low	96.22	3.07	0.71
		High	95.76	3.87	0.37
	Men	Low	96.32	2.70	0.99
		High	92.99	6.97	0.05
Sadness/relaxation	Women	Low	84.17	10.43	5.40
		High	93.02	5.48	1.50
	Men	Low	92.77	5.13	2.09
		High	91.77	7.19	1.04
Happiness/anger	Women	Low	79.38	10.00	10.62
		High	93.45	3.95	2.60
	Men	Low	82.34	9.82	7.84
		High	92.05	5.97	1.97

in which 96.22% of them were driving at an adequate speed level.

As predicted, the data for listening any type of music (either sad/relaxing or cheerful/irritating) amongst both experienced and less-experienced male and female drivers changed. Less-experienced male drivers appeared to have a higher probability of driving at an adequate level of speed in comparison to less-experienced female drivers. In contrast, the highly experienced female drivers appeared to drive at an adequate speed level in comparison to highly experienced male drivers.

Comparison of less-experienced or highly experienced male drivers indicate that with sad music, less-experienced men drivers have a higher probability of driving at an adequate speed level (one-point percentage above the expert men). With the happy type of music, this situation gives a total turn. The expert men keep their probability of constant driving at an adequate speed of 92.05%, while this probability reduces drastically, reaching 82.34% for less-experienced drivers.

It can be concluded that both highly experienced male and female drivers are less likely to be affected by music or with no music while driving. This is because the probability

of exceeding the speed limit remains constant in both. However, the effect of listening to music is accentuated when the male drivers are less experienced. The probabilities of driving at an adequate speed in women are in the range of 96–79% and in men 96–82%. When the speed is analysed in greater depth, it is observed that the most situations to commit a serious infraction on speed happen by listening to music that convey happy/angry emotions. In both men and women, probability is much higher if the driver is less experienced than is an expert driver. Therefore, the less-experienced men drivers are those who are to a greater extent affected by the music, especially when it transmits to their joy/aggressive emotions.

Serious speed infraction for less-experienced drivers is discussed in more details. In the case of less-experienced female drivers who listen to the type of music that convey happiness/aggression emotions to them, the probability is more than 10%. This is almost duplicated when compared with the music type that conveys sadness/relaxing emotions to them (5%). When this situation is compared with the “ideal” situation of driving without music (0.71%), the probability of committing a serious infraction on the speed has been multiplied by 15%. Nevertheless, the probability to

commit serious speed infraction in the second worst situation (listening to the music that convey sad/relaxing emotions) in less-experienced men, the figure, reaches 2%, almost quadrupling the probability by placing it near 8%. When this situation is compared with the “ideal” of driving without music (0.99%), the probability of committing a serious infringement on speed has been multiplied almost by 7 times. This suggests that men in contrast to women present a greater increase in their probability of committing any speed infractions in the case of listening sad/relaxing music compared with cheerful/irritating music. However, overall, women are those who present a greater increase in the likelihood of committing a serious speed infraction, from the case of more satisfying to the irritating music that causes joy/aggression in them.

The data presented in Tables 4 and 9 bare comparison for their results in which they make it evident that less-experienced drivers (both men and women) are more influenced by the music type that generates happiness/anger emotions in them. Thus, the probabilities of their committing either a serious and/or minor infractions are far greater to “a priori” data (around 5 percentage points).

5. Conclusions

Throughout this work, we have sought to find an answer to the question of to what extent listening to music can influence the mood and the performance of drivers while driving. To find an answer to this question, several simulation tests were carried out with the total number of 19 young drivers aged between 20 and 28 years old, taking into account both their gender and their driving experience. Through conducting simulation-based research and employing Bayesian networks as the analysis platform to analyse the data, we were able to come up with several conclusions as follows:

The first round of analysis made it apparent to us that, regardless of the type of music that is listened while driving, the probability of committing a slight infraction on speed is 3% higher than driving without music. However, when it comes to a serious infringement of the speed, the fact of listening to sad music while driving results in an increased level of 2% compared to driving without music and listening to happy music that results in an increased percentage of 5.5%. It can, therefore, be concluded that driving with music increases the tendency to increase in speed level. Especially, if happy music is played, drivers commit more serious infractions (their speed reaches above the radar limit).

Nevertheless, the aim of the present study was to go beyond the surface and deepen more in research through conducting a further analysis, in which we examined the relationship between listening to music and its effects on driving mood and performance on both male and female drivers. This was performed as we believed not all drivers are the same. Some observations can be made from the analysis. First, either listening to relaxing music or not listening to music reduces the probability of committing a serious excess in speed for both genders. However, women have a lower chance of driving to an adequate speed when they listen to music.

Concerning the type of music, it can be concluded that both driving while listening sad music or driving without listening to music, makes drivers aware of their infractions and prevents them from driving over the threshold of the radars.

As already highlighted, when defining a driver, an important aspect to be considered is how experienced a driver (she/he) is at the wheel. We argue that although in the case of driving without music, less-experienced drivers have a higher probability of driving at an adequate speed, and less-experienced drivers are also those who are mostly affected by music when it makes an appearance in the driving.

On the other hand, when less-experienced drivers are behind the wheel and listen to a happy music, they are unable to notice the increase in their speed, and thus commit either serious or minor infractions with almost same probability. In the case of expert drivers, listening to a sad music and not listening to any music follows the same pattern as with less-experienced drivers. In terms of listening to cheerful music, the pattern, however, changes. It goes from being stable to producing a reduction of the likelihood of serious infringement against a minor infraction. Therefore, it can be argued that expert drivers suffer to a lesser extent of the effect of music. This is in contrast to less-experienced drivers who can be highly affected by listening to music. In all cases, driving without listening to any music makes drivers aware of the road and the surrounding environment; as a result, they avoid exceeding the speed above the limit of the radars.

Concerning the relaxing music, its effect is more evident on less-experienced drivers. The reduction in the probability of exceeding the speed is from serious infraction versus the likelihood of a minor infraction, which is greater than driving without music. However, when it comes to happy music, the results change. The less-experienced drivers do not realize and commit any infractions for speeding, either mild or severe, with the same probability.

Concerning the cross-tabulation analysis of the role of driving experience and gender together, it can be concluded that in both cases for male and female experts, the driving performance is less affected by music or without listening to music since the probability of exceeding speed is constant in both serious and minor speed infractions. However, it should be noted that when drivers are less experienced, the effect of music on their driving performance is more noticeable. Analysing speed in greater depth, it is observed that the greater probabilities of committing a serious violation of speed occur when happy/angry music is listened.

In both men and women cases, the probability of being affected by music is much greater if the driver is less experienced compared to an expert driver. Conclusion would be that less-experienced drivers are those who are to a greater extent affected by music.

Analysing less-experienced drivers in terms of committing a serious speed violation, it becomes apparent that men in contrast to women present a greater increase in probability in the case of listening sad/relaxing music compared to happy/aggressive type music. However, women are those who show the greatest increase in probability of

committing a serious speed infraction from driving without background music or the most favourable types of music, even to the most aggressive type of music that causes either joy/aggressive emotions in them.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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