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**COMBINING DRIVING PERFORMANCE INFORMATION IN AN INDEX SCORE: A  
SIMULATED CURVE-TAKING EXPERIMENT**

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## ABSTRACT

This study investigated the relative performance of (car) drivers at the individual level, using data from a driving simulator, in order to identify the best drivers within the sample and to gain insight into the most problematic behavior of each driver. To this end, 38 participants varying in age and gender were enrolled to take part in a particular simulator scenario (i.e., curve taking) and their speed, acceleration and lateral position – the three most important driving performance indicators based on literature review – were monitored at various points (before, during and after the curve). As a widely accepted tool for performance monitoring, benchmarking and policy analysis, the concept of composite indicators (CIs), which combines single indicators into one index score, was employed, and the technique of data envelopment analysis – an optimization model for measuring the relative performance of a set of decision making units, or drivers in this study – was used for the index construction. Based on the results, best-performers were distinguished from underperforming drivers. Moreover, by analyzing the weights allocated to each indicator from the model, the most problematic parameter (e.g., lateral position) and point along the curve (e.g., at curve end) were identified for each driver, leading to specific driver improvement recommendations (e.g., training programs).

**Keywords:** Driver's relative performance; Driving simulator data; Composite indicators; Index score; Data envelopment analysis.

## 1 INTRODUCTION

About 1.24 million people die each year on the world's roads and between 20 and 50 million sustain non-fatal injuries (1). According to the share of road fatalities by road user type, drivers represent the largest share (2,3). As a result, better understanding the behavior of different drivers is an essential component for future safety improvements on the roadways of the world.

Driving simulator studies provide a safe and controllable environment to perform research on traffic safety, e.g., evaluating vehicle designs, testing traffic control devices, developing and evaluating new in-vehicle and co-operative infrastructure technologies, and analyzing drivers' behavior (4). Over the last decades, a lot of research efforts have already been paid to the application of driving simulators for safety issues (e.g. 5,6,7). However, most of them relied on statistical methods in which the focus was usually on the averages (such as to calculate the mean value and the standard deviation of a particular parameter for the sample), whereas limited research has been carried out based on individual driver risk, which is particularly important in the development of proactive driver education programs and safety countermeasures.

In this study, we aim to investigate the driving behavior of different drivers in and nearby a curve using data from a fixed-based driving simulator. Horizontal curves, particularly on two-lane rural roads, have been recognized as a significant safety issue for many years: crash rates are 1.5 to 4 times higher on horizontal curves than on straight road sections, and 25-30% of all fatal accidents occur in curves (8). In doing so, the concept of composite indicators (CIs), in which various relevant information is combined in one figure, is employed, and the technique of data envelopment analysis (DEA) in general, and the multiple layer DEA in particular, is used for the index construction. To our knowledge, it is the first time that this model is used for the evaluation of individual drivers' performance. The results will enable us to distinguish the best drivers from underperforming ones and to advise drivers with detailed suggestions for improving their driving performance with respect to curve-taking.

We start in Section 2 with the presentation of appropriate indicators of driving behavior and the data collection and processing. The methodology is discussed in Section 3. Section 4 deals with the corresponding results in terms of a ranking of the drivers based on their index score, an illustration of the most problematic driving parameter for a particular driver, and a comparison between the best and the worst driver in the sample. Section 5 concludes the paper and offers some final remarks. Finally, Section 6 discusses about limitations and further research.

## 2 DATA

### 2.1 Driving Parameters

In general, driving behavior comprises the vehicle control in longitudinal and lateral direction. According to the European "Safety Handbook in Secondary Roads" (9), the speed, acceleration, and lateral position are the three most common parameters to describe and analyze the behavior of a driver. Amongst other parameters, these three measures were recorded by the simulator.

#### *Speed [km/h]*

Speed is at the core of the road safety problem. Very strong relationships have been established between speed on the one hand and crash risk and severity on the other hand. In fact, speed is involved in all accidents: no speed, no accident. In around 30% of the fatal accidents, speed is an essential contributory factor (29). At a higher speed, it is more difficult to react in time and

prevent an accident. Basically, there are two different speeds: the speed which is only influenced by the traffic facility and the environment and the speed which is additionally influenced by traffic. To investigate the impacts of road geometry and environment a speed which is not influenced by traffic should be considered. For this purpose, the spot speed should be used which is the speed in a defined spot at a defined time (9).

#### *Acceleration [m/s<sup>2</sup>]*

The acceleration is defined as the speed change within a time interval. Regarding the direction of acceleration, there is a longitudinal and lateral acceleration. The longitudinal acceleration is a value of speed change that can be used, as well as the lateral acceleration, as comfort criterion which gives information about how fast a driver changes his/her direction (9). For this study, we use the resultant of longitudinal and lateral acceleration.

#### *Lateral Position [m]*

The lateral position is the position of the vehicle within a lane. It is a geometrical value which is e.g., the distance between the center of the road and the vehicle's longitudinal axis. This indicator offers the possibility to analyze the driven track. Especially in curves the lateral position of cars is a perfect indicator to investigate corner cutting (9).

## **2.2 Participants**

Thirty-eight volunteers participated in this study. Four participants were excluded. Two did not finish the experiment due to simulator sickness and two had missing data and were ignored. Thus, 34 participants (of which 23 men) between 18 and 54 years old (mean age = 26.32; SD = 10.47) remained in the sample.

## **2.3 Driving Simulator**

The experiment was conducted on a medium-fidelity driving simulator (STISIM M400; Systems Technology Incorporated). It is a fixed-based (drivers do not get kinesthetic feedback) driving simulator with a force-feedback steering wheel, brake pedal, and accelerator. The simulation includes vehicle dynamics, visual/auditory (e.g. sound of traffic in the environment and of the participant's car) feedback and a performance measurement system. The visual virtual environment was presented on a large 180° field of view seamless curved screen, with rear view and side-view mirror images. Three projectors offer a resolution of 1024 × 768 pixels and a 60 Hz frame rate. Data were collected at frame rate.

## **2.4 Data Processing**

A real-world curve was replicated as realistically as possible in the driving simulator and all participants completed a drive of 16.2 kilometers.

Data analysis for the three indicators is based on values obtained at eight different measurement points along the driving scenario, i.e., P1=500m, P2=166m and P3=50m before curve, P4=curve entry, P5=middle of the curve, P6=curve end, and P7=50m, P8=100m after curve, for each driver (see FIGURE 1). Therefore, driving performance of each driver is to be evaluated based on these 24 indicators.

< Please insert FIGURE 1 here >

Instead of using the raw data in the model, the following process was conducted for each point, separately.

### *Speed*

Apart from the emergency services, nobody should drive faster than the legal speed limit. As a result, given the posted speed limit of the road in the simulated and real environment of 70 km/h, all drivers are first divided into two groups based on their driven speed, i.e., below or equal to 70 km/h on the one hand and above 70 km/h on the other. Next, by using hierarchical cluster analysis in SPSS, each group is further divided into several sub-groups. Finally, all the sub-groups were assigned descending grades starting from 6 (a maximum of 6 sub-groups), illustrating the degree of each driver's performance, so that the higher the grade, the better the performance. This process is carried out in each of the eight points, respectively. TABLE 1 shows the results of clusters at 500m before the curve (point 1).

< Please insert TABLE 1 here >

### *Acceleration (Acc)*

Next, the hierarchical cluster analysis is applied on the acceleration data at different points. As a result, each group is allocated a grade indicating its performance. Again the higher the grade, the better the performance. TABLE 2 shows an example of grading at curve entry (point 4).

< Please insert TABLE 2 here >

### *Lateral Position (LP)*

According to the PIARC Road Safety Manual (10), the ideal position on a curve is where the center of the vehicle is located on the center of the lane. Since the road width in the simulator scenario is 2.8m, based on the average passenger car dimension, drivers are assigned a grade according to TABLE 3. A score of 6 indicates best performance because he/she drives in almost the middle of the lane (within a range of  $\pm 0.1$  m from the center-line), while a score of 4 is given to the worst-performers because they pass either the center-line or edge-line of the road. Finally, drivers not belonging to these two groups are assigned a score of 5.

< Please insert TABLE 3 here >

## **3 METHODOLOGY**

### **3.1 Index Score**

Indicators enhance our understanding of situations and issues by transforming raw data into meaningful information. Indicators are helpful tools for monitoring, benchmarking, visualization, etc. (11,12,13,14). Recently, various indicators have been combined in so-called composite indicators (CIs) or index (e.g., 15,16). Simplistically, a composite indicator synthesizes the information included in a selected set of indicators in one figure (17). In this study, a composite indicator is created with respect to driving performance. Based on the driving performance index scores, drivers can be ranked in terms of relative overall driving performance tested by means of a simulator, and useful insight in the area of underperformance of each driver can be gained by analyzing the allocated indicator weights.

In recent years, there has been an increasing interest in the methodology for creating a composite indicator, in which the assignment of weights to each indicator is an essential step (18). One of the promising weighting methods is data envelopment analysis (DEA), based on

which the best possible indicator weights are determined for each Decision Making Unit (DMU) or driver in our case (19,20). In other words, the most optimal index score is obtained for each driver. During the past years, various indexes have been developed by using the DEA technique. The environmental performance index (21), the human development index (22), the macro-economic performance index (23), the sustainable energy index (24), the technology achievement index (25), and the road safety performance index (26), are examples among others.

In literature, countries or organizations are often compared against each other using observed indicator values. The research presented in this study will make use of a particular type of data, namely driving simulator data. Within the field of driving simulator research, this study distinguished itself by focusing on the individual level, and determining the optimal driving performance index score for each individual, resulting in new insights and valuable recommendations.

### 3.2 MLDEA-CI Model

In the basic DEA-based CI model, by solving a linear programming problem, the best possible indicator weights are determined, and an index score between zero and one is obtained for each unit, with a higher value indicating a better relative performance. The model used in this study is the multiple layer DEA based CI model (MLDEA-CI). In addition to the DEA-based CI studies mentioned above, a valuable extension occurred in Shen et al. (27,28) by developing a model which is able to take into account the layered hierarchy of indicators that often exists in reality (see FIGURE 1).

More specifically, suppose that a set of  $n$  DMUs is to be evaluated in terms of  $s$  indicators (y) with a  $K$  layered hierarchy, the MLDEA-CI model can be formulated as follows (28):

$$\begin{aligned}
 CI_0 &= \max \sum_{f_1=1}^s \hat{u}_{f_1} y_{f_1 0} \\
 s.t. \quad & \sum_{f_1=1}^s \hat{u}_{f_1} y_{f_1 j} \leq 1, \quad j = 1, \dots, n \\
 & \sum_{f_1 \in A_{f_k}^{(k)}} \hat{u}_{f_1} / \sum_{f_1 \in A_{f_{k+1}}^{(k+1)}} \hat{u}_{f_1} = w_{f_k}^{(k)} \in \Theta, \quad f_k = 1, \dots, s^{(k)}, \quad k = 1, \dots, K-1 \\
 & \hat{u}_{f_1} \geq 0, \quad f_1 = 1, \dots, s
 \end{aligned} \tag{1}$$

where

$\hat{u}_{f_1}$  is the set of most favorable optimal weights for DMU<sub>0</sub>, which are obtained by solving the model.

$s^{(k)}$  is the number of categories in the  $k^{\text{th}}$  layer ( $k=1, 2, \dots, K$ ).  $s^{(1)}=s$ .

$A_{f_k}^{(k)}$  denotes the set of indicators of the  $f^{\text{th}}$  category in the  $k^{\text{th}}$  layer.

$w_{f_k}^{(k)}$  denotes the internal weights associated with the indicators of the  $f^{\text{th}}$  category in the  $k^{\text{th}}$  layer, which sum up to one within a particular category.

$\Theta$  denotes the restrictions imposed to the corresponding internal weights.

In general, the model (1) reflects the layered hierarchy of the indicators by specifying the weights in each category of each layer. Meanwhile, by restricting the flexibility of these weights, denoted as  $\Theta$ , consistency with prior knowledge and the obtainment of acceptable layer-specific weights are guaranteed, which cannot be realized in the one layer model. The main idea of the

model is to first aggregate the values of the indicators within a particular category of a particular layer by the weighted sum approach in which the sum of the internal weights equals to one. Then, for the first layer, the weights for all the sub-indexes are determined using the basic DEA approach.

In our case, 34 drivers are to be evaluated based on 24 aforementioned driving indicators, structured in a 3 layered hierarchy (see FIGURE 1). The subscript,  $o$ , refers to the driver whose index score is to be obtained by solving the constrained optimization problem, which maximizes the index value of the driver and satisfies the imposed restrictions. The first restriction guarantees an intuitive interpretation of the composite indicator and implies that no driver in the data set can be assigned an index value larger than one under these weights. With respect to the second restriction, the layered hierarchy of the indicators is reflected by specifying the weights in each category of each layer and further restricting their flexibility. In doing so, obtainment of realistic and acceptable weights is guaranteed. In addition, by the third restriction, all weights are constrained to be non-negative.

### 3.3 Model Preparation

In this study, the MLDEA-CI model is applied to evaluate the driving performance of each of the 34 drivers by combining all the 24 hierarchically structured indicators in one index score. The method assigns the best possible weights to each indicator thereby maximizing the index score for a particular driver while at the same time respecting the following restrictions imposed by the model: (1) The set of weights suggested for each driver must also be feasible for all the other drivers included in the data set; (2) the driving performance during the curve is considered to be more important than before or after the curve. Therefore, a relative weight restriction is given ensuring that the indicators in and along the curve, i.e., at curve entry (P4), middle of the curve (P5) and curve end (P6), receive a higher weight than the other points; (3) to guarantee that all the three aspects of driving performance - speed, acceleration and lateral position - will be represented to some extent in the index score, the share of each of these three factors in the final index score is restricted to be equal with 30% variability to still allow a high level of flexibility.

## 4 RESULTS

Using simulator data – values of 24 driving performance indicators for each of the 34 drivers – and applying the MLDEA-CI model, we obtain the following results: best-performing drivers are distinguished from underperforming ones, based on their optimal index scores a drivers ranking (4.1), an illustration of the required improvement priorities for a particular driver based on weight allocation (4.2), and a visualization of the performance of the best and worst driver. Each aspect is subsequently discussed.

### 4.1 Index Scores and Drivers Performance

By applying the model, 24 driving performance indicators are now combined in an index score for each driver by selecting the best possible indicator weights under the imposed restrictions. As a result, the index score of each driver is calculated in relation to all the other drivers who took part in the experiment. Index values lie between zero and one with an index value equal to one identifying a best-performer, whereas a score less than one implies underperforming drivers (see TABLE 4).

< Please insert TABLE 4 here >



## 4.2 Weight Allocation and Required Improvement Priorities

In addition to the overall index score of the drivers, more detailed insight can be gained from the assigned weights which can be interpreted as indications of the importance shares of the corresponding indicator.

< Please insert FIGURE 2 here >

The model not only pursues the optimal index score for each individual, but also guarantees acceptable weights through the imposed restrictions. FIGURE 2 shows the assigned weights and shares (the values in brackets) for the case of the driver with the lowest index score in the data set (i.e., driver No. 21). As can be seen, the performance with respect to all three driving parameters is taken into account in the overall index score with the share of speed equal to 32.48%, that of acceleration 25.62% and that of lateral position 41.90%. Moreover, the index score is influenced most by the driver's performance at the curve (to which a weight of 0.5 or 0.6 is given).

More importantly, based on the principle of the MLDEA-CI model, an indicator is assigned a high weight if the driver performs relatively well on that aspect. On the contrary, low weights provide us with valuable information about the aspects requiring more attention for improvement. Therefore, areas of underperformance can be detected for each driver, and required improvement priorities can be formulated.

Taking the indicators of speed, acceleration and lateral position related to the worst-performer as an example, it can be seen that this person is doing relatively well with respect to the lateral position aspect (with the highest share of 41.90%) whereas more attention should be paid to the acceleration parameter (with the lowest share of 25.62%), especially at positions P3 before curve, P6 at curve, and P7 after curve.

## 4.3 Comparison of Drivers in Terms of Driving Performance Parameters

In order to make a comparison between best-performing and underperforming drivers, their performance in each aspect is depicted in the following sections.

### *Speed*

FIGURE 3 shows the speed of the best-performer versus the worst-performer. The best-performer drives smoothly and respects the posted speed limit. The underperforming driver, on the contrary, can be labeled as worst-performer either because of the high speed or evasive changes along the curve. As can be seen from the graph, the driver needs to correct his/her performance while approaching and departing the curve.

< Please insert FIGURE 3 here >

### *Acceleration*

The total acceleration can be decomposed into longitudinal acceleration and lateral acceleration. The longitudinal acceleration, indicating how fast a driver changes his/her speed, is shown in FIGURE 4a. According to Lamm and Chouriri (30), the observed deceleration rates when approaching horizontal curves should not be significantly different from  $-0.85 \text{ m/s}^2$ . Others proposed higher acceptable values up to  $-1.34 \text{ m/s}^2$  and  $-1.8 \text{ m/s}^2$  (31). It can be seen that the worst-performer exceeded dramatically the maximum threshold when approaching and leaving the curve. The result is consistent with the priorities we gave in Section 4.2. In addition, the

lateral acceleration - indicative of how fast a driver changes its direction- shown in FIGURE 4b confirms inappropriate driving behavior of the worst-performer.

< Please insert FIGURE 4 here >

#### *Lateral Position*

When driving, it is commonly accepted that the higher the variability in the lateral position of a vehicle, the less safe of a driver (32). By comparing the performance of the best-performer and the worst-performer with respect to their lateral positions in this experiment, as shown in FIGURE 5, it is easy to see that the worst-performer was involved in more dangerous situations. However, according to the threshold of lateral position indicated in TABLE 3, it should be noted that although the best-performer in this experiment was doing better than the worst one, he was still not doing perfect, especially at the middle of the curve.

< Please insert FIGURE 5 here >

## **5 CONCLUSION**

In order to measure the multi-dimensional concept of driving performance which cannot be captured by a single indicator at one point in time, we investigated in this study the construction of an overall driving performance index for drivers evaluation. In doing so, a multiple layer DEA-based composite indicator model was applied on a hierarchy of driving performance indicators. Based on this model, the most optimal driving performance index score between zero and one for each of the 34 drivers was determined by combining all the 24 hierarchical indicators, with higher values indicating better relative performance. From the index scores, the best-performing drivers – having an index score of one – were deduced. At the same time, underperforming drivers were revealed.

Apart from identifying the best-performing and underperforming drivers, their relative performance with respect to speed, acceleration, and lateral position was compared.

In addition, based on the principle of the MLDEA-CI model, an indicator is assigned a high weight if the driver performs relatively well on that aspect. On the contrary, low weights provide valuable information about the aspects requiring most attention for improvement. Therefore, areas of underperformance were detected, and required improvement priorities formulated.

To conclude, this study suggests that the MLDEA-CI methodology is appropriate for driver's evaluation and for the identification of the most problematic aspects of driving. Next, drivers can be trained in different tasks in the simulator, according to each driver's weakness, thereby improving driver's abilities and the level of road safety. Moreover, regarding the future usefulness of the results from this methodology, there are opportunities in terms of selecting candidates for driving jobs, identifying high risk drivers, improving the rating process and rewarding low risk drivers.

## **6 LIMITATIONS AND FUTURE RESEARCH**

The issue of external validity is often raised when discussing the results of research employing driving simulations. Although moving base simulators provide a more correct rendering of real driving behavior and a greater degree of realism (33), there are strong indications that geometric design issues are examinable in a fixed-base driving simulators in a perfectly adequate way (*e.g.*, 34,35). In addition, Bella (34) and Godley et al. (36) concluded that speed parameters can be validated as dependent measures for research using a driving simulator. Moreover, the simulator

used in this study is equipped with a 180° field of view, which satisfies the prescribed minimum of 120° field of view for the correct estimation of longitudinal speed (37).

Future research on the composite driving performance indicator can be done concerning the data, i.e., adjusting the model in order to allow the use of raw data instead of assigned grades to different indicator clusters. In addition, other road types or other sections of road (e.g., intersections) as well as roads with different speed limits may be considered. Moreover, in the future, besides the data of driving simulator performance, personality and psychometric tests and driver's crash records, could also be taken into account in the index construction. Finally, since the result obtained from the MLDEA-CI can be largely influenced by the selection of indicators, hierarchical structure, data quality and chosen weight restrictions, it is important to rigorously investigate the robustness of the indexes by sensitivity analysis in the future. In addition, it would also be valuable to incorporate an artificially created, ideal driver in the analysis, so that instead of a relative evaluation within a specific group, a comparison of drivers with an optimal driver would be possible.

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## List of TABLES

**TABLE 1 The Threshold of Speed Clusters at 500 m Before The Curve (point 1)**

**TABLE 2 The Threshold of Acceleration Clusters at Curve Entry (point 4)**

**TABLE 3 The Threshold of Lateral Position at Each Point**

**TABLE 4 Drivers' Performance Based on Their Driving Index Score**

List of FIGURES

**FIGURE 1 Hierarchically structured driving performance indicators.**

**FIGURE 2 Assigned weights and shares from the model for the case of the worst-performer.**

**FIGURE 3 The speed of the best-performer versus the worst-performer.**

**FIGURE 4 The acceleration of the best-performer versus the worst-performer.**

**FIGURE 5 The lateral position of the best-performer versus the worst-performer.**

**TABLE 2 The Threshold of Speed Clusters at 500 m Before The Curve (point 1)**

Drivers driving with a speed $\leq 70$ Km/h			Drivers driving with a speed $> 70$ Km/h		
Speed range	Nr. of drivers (%)	Grade	Speed range	Nr. of drivers (%)	Grade
[67.61 , 69.53]	9 (26.47)	6	[70.49 , 74.48]	10 (29.41)	3
[61.88 , 66.50]	6 (17.65)	5	[78.34 , 99.07]	7 (20.59)	2
52.71	1 (2.94)	4	126.42	1 (2.94)	1



**TABLE 2 The Threshold of Acceleration Clusters at Curve Entry (point 4)**

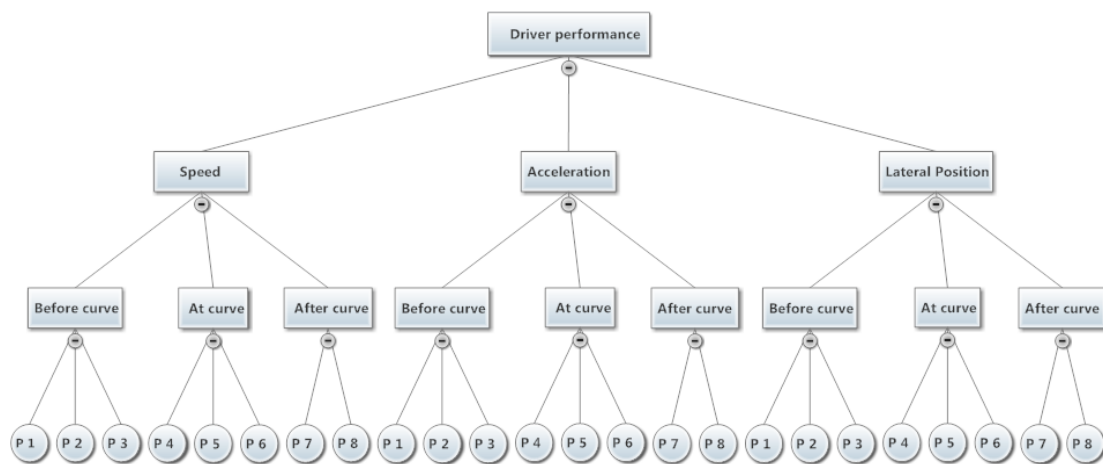
Acceleration range	Nr. of drivers (%)	Grades
[0.273 , 0.691]	17 (50)	6
[0.763 , 1.097]	14 (41.18)	5
[1.410 , 1.918]	3 (8.82)	4

**TABLE 3 The Threshold of Lateral Position at Each Point**

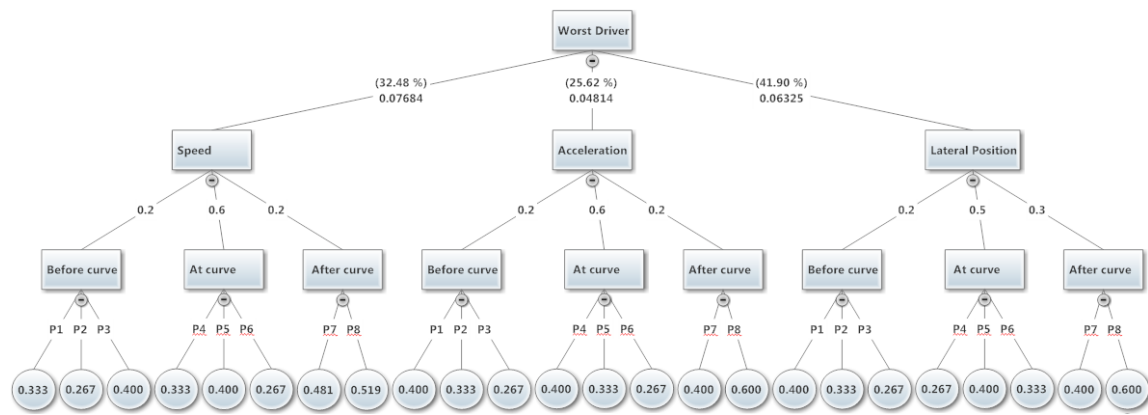
Threshold for “Lateral Position”	Grades
$1.3 \leq LP \leq 1.5$	6
$0.95 < LP < 1.3$ or $1.5 < LP < 1.85$	5
$LP \leq 0.95$ or $LP \geq 1.85$	4

**TABLE 4 Drivers' Performance Based on Their Driving Index Score**

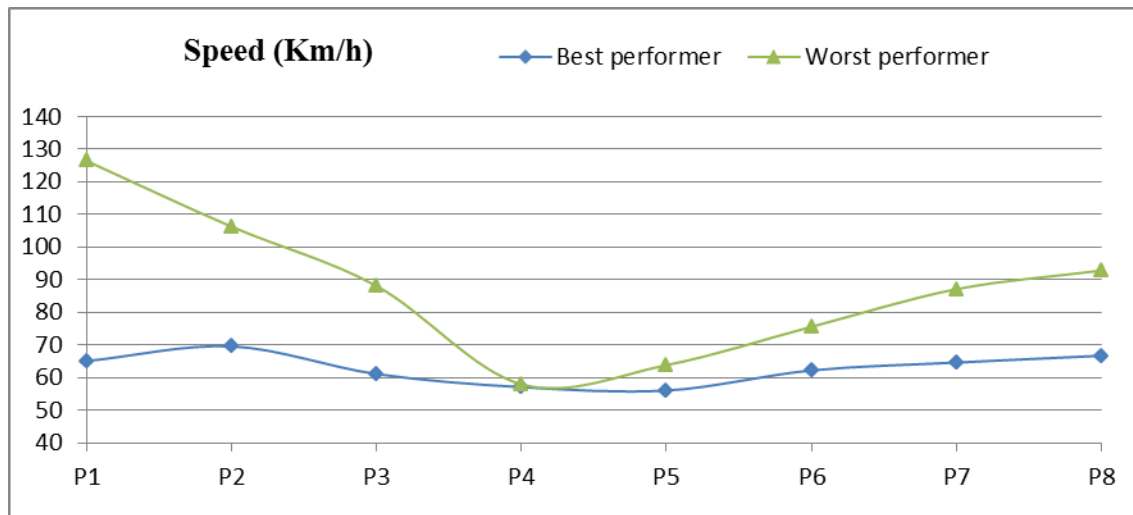
Drivers' Status	Best-performing drivers				Underperforming drivers						
Driver's Number	1	13	14	33	6	34	...	18	28	29	21
Index Score	1	1	1	1	0.9969	0.9932	...	0.8217	0.8042	0.7932	0.7398



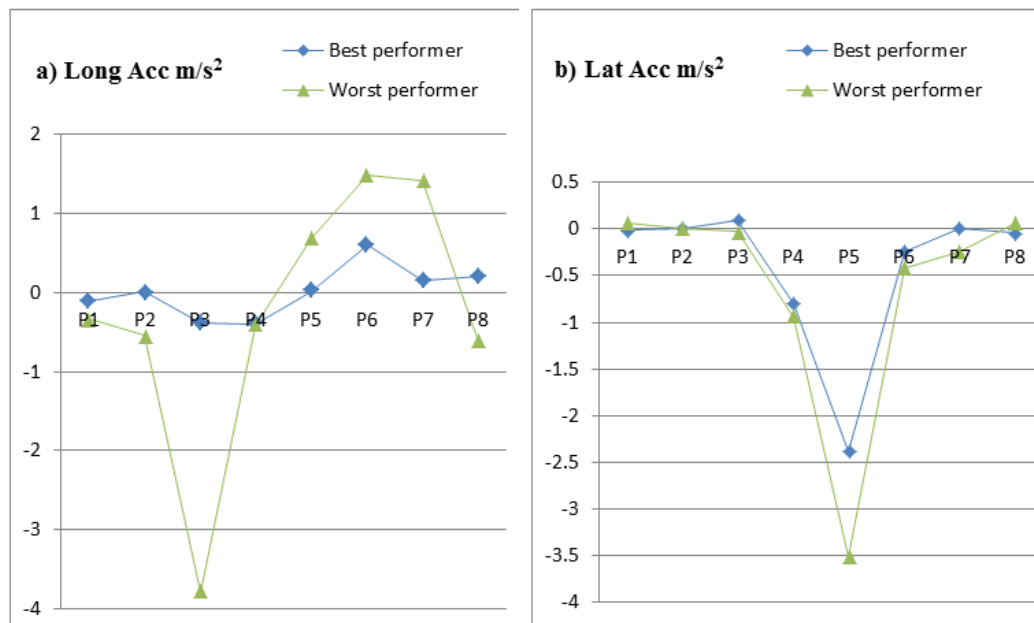
**FIGURE 1** Hierarchically structured driving performance indicators.



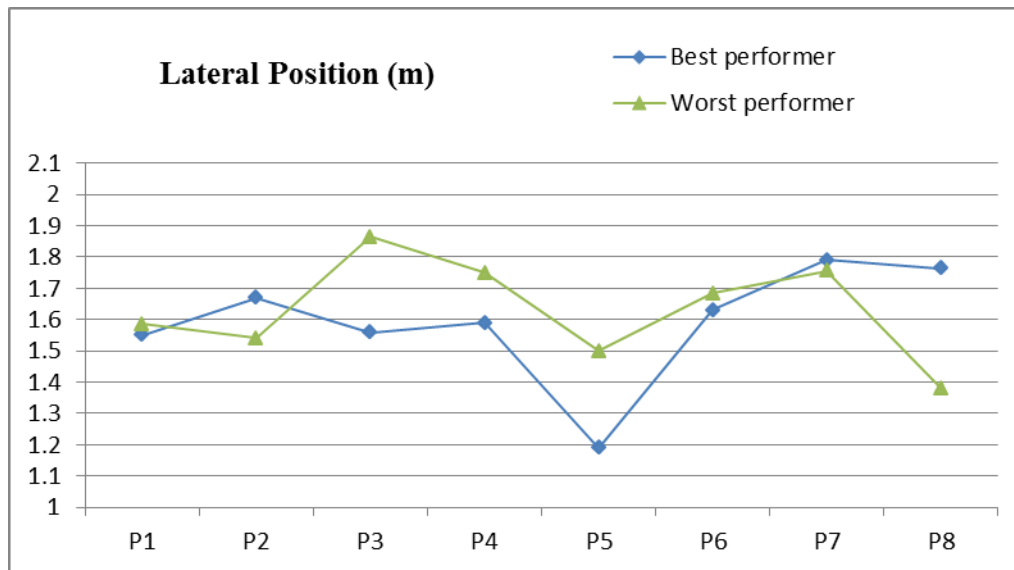
**FIGURE 2** Assigned weights and shares from the model for the case of the worst-performer.



**FIGURE 3** The speed of the best-performer versus the worst-performer.



**FIGURE 4** The acceleration of the best-performer versus the worst-performer.



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