

# Assessability of Road Accidents – a Methodology for Exploring the Effect of Accident Type and Data Recording Technology

Vida Gábor<sup>1</sup>, Wenzsky Nóra<sup>2</sup>, Török Árpád<sup>1</sup>

<sup>1</sup> Department of Automotive Technologies, Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics  
Stoczek utca 6, 1111 Budapest, Hungary  
e-mail: vida.gabor@kjk.bme.hu, torok.arpad@kjk.bme.hu

<sup>2</sup> Centre of Modern Languages, Faculty of Economic and Social Sciences, Budapest University of Technology and Economics  
Egry József utca 1, 1111 Budapest, Hungary  
e-mail: wenzsky.nora@gtk.bme.hu

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*Abstract: Road accidents are reconstructed by forensic experts to reveal the causes of accidents and help authorities determine liability. However, how well an accident is assessable depends on various factors. The database-independent methodology proposed here makes it possible to explore the relationship between assessability, accident type and data recording technology. A combination of statistical tests (Mann–Whitney U Test, Wilcoxon Signed-rank Test, Kruskal–Wallis Test with Bonferroni Correction) are to be applied to a database of road accidents. As a result of these tests, it can be determined how the assessability of various accident types can be improved by the development in data recording technologies. This widely applicable, novel tool of the Cognitive Mobility realm is in practice a methodology for exploring the assessability of various types of road accidents. It can help decision-makers determine the development directions of new technologies.*

*Keywords: accident reconstruction; assessability; statistical methods; data recording technology; forensic expert*

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## 1 Introduction

Road accident reconstruction, as its name implies, is a process that goes in the opposite direction as designing and construction. While designers calculate what could happen if forces are exerted on a structure built from the given materials, forensic experts determine what processes may have taken place, what forces may have been exerted if the given accident happened. In order to be able to reconstruct an accident, and thus determine causes and liability, basically as much data should be obtained about the case as possible. The range of data used for the reconstruction

process is wide. Being static, some data are easy to obtain, such as information on the terrain of the accident site, the make of the vehicles included or the traffic rules valid at the given section of the road. Other data must be recorded after the whole process, e.g. the position of the vehicles, skid marks, injuries and the damage caused.

However, the success of accident reconstruction does not solely depend on the amount of data collected. The assessability of an accident, i.e. how well the process can be reconstructed and how much liability can be determined, depends on various other factors as well, including accident type (e.g. head-on collision vs. leaving the track), data quality (e.g. accuracy) and data recording technology (e.g. yaw marks photographed vs. speed data recorded by the vehicle's tachograph). If it is known how these different factors affect level of assessability, data recording technologies can be developed in a way that could make accident reconstruction more precise not only for all accident types, but for a specific accident type if necessary. Moreover, based on such a quantification methodology, it may be determined what data recording technology is required for a certain accident type to be assessed at the highest possible level. Conversely, if we know the applied data recording technology, we can predict the level of assessability for each accident type.

With the emergence of highly or fully automated vehicles, i.e. a cognitive multimodal transport system [1], new types of accidents are expected to occur. In order to be able to reconstruct and assess these yet unknown accident types, probably new data recording technologies need to be developed. The model presented here is freely expandable, i.e. emerging accident recording technologies and accident types can also be added to it. This way, the effectiveness of the new technologies can also be measured. Also, the methodology can be customized to the needs of users – maybe for a certain database, more accident categories should be established or more levels of data recording technologies are to be explored.

In order to be able to develop and operate efficient, safe and environmentally friendly mobility systems and vehicle networks, it is indispensable to identify the factors that influence the operation of the various networks. As a result, the role of unconscious, irrational factors in the decision making process about mobility networks may be minimized. The aim of this article is to show how it is possible to identify the data that should be collected to help identify the causal links that lead to accidents in the best way.

This study presents a novel methodology based on various statistical methods for quantifying how accident type and data recording technology affect the assessability of road accidents. Section 2 clarifies basic concepts and reviews the relevant literature. In Section 3, the methodological steps are described in detail: the statistical methods to explore the possible differences between accident types and data recording technologies are presented. Section 4 concludes the article. The methodology presented here was developed based on a database of real road accidents [2].

## 2 Background

The basic concepts used in this study are defined as follows.

- The **assessability of an accident** is the degree to which the causes of the accident and liability can be determined based on the available data. Four categories of assessability are set up here (Table 1).

Table 1  
Accident assessability levels

<i>Accident process</i> \ <i>Accident cause Liability</i>	<i>Not determinable</i>	<i>Determinable</i>
<i>Not or partly determinable</i>	<i>Level 1</i>	<i>Level 3</i>
<i>Fully determinable</i>	<i>Level 2</i>	<i>Level 4</i>

- **Traditional data recording technology** ( $T_0$ ) is the technology to be applied by the police in the case of a road accident or a traffic crime. For example, in Hungary the technology is defined by the relevant Police Decree [3].
- **EDR data recording technology** ( $T_1$ ) is defined as traditional data recording technology complemented by accident data recorded in the Event Data Recorder modules of the vehicles participating in the given accident, as defined by the regulatory framework [4].
- **EDR+ data recording technology** ( $T_2$ ) is defined as EDR data recording technology complemented by data recorded in highly automated or fully automated vehicles. These extra data may include GPS coordinates, GPS time, video recordings of the accident environment, elements/objects in the traffic environment and their distance from the ego vehicle (Figure 1).
- **Accident type** is the category of a given accident process, determined by the most prominent property of the accident with regard to accident causes and liability. The seven categories (denoted  $A_1$ – $A_7$ ) used in this study were set up based on the following properties: relative position of the collided vehicles (e.g., rear-end) or the conflict type (e.g., lane changing) or the traffic environment (e.g., at traffic lights) [2].



Figure 1  
Data recording technologies applied in this study

In order to be able to explore relationships between data recording technologies, accident type and assessability, a database must be compiled. The statistical calculations are to be carried out on this database, which is illustrated in Table 2. Column 1 is the registry number of the accident; Column 1 encodes the accident type. Columns 3-5 show assessability levels according to Table 1 above. The methodology presented below was tested against a public database of real-life road accidents [2]. As the overwhelming majority of these accidents were recorded by traditional methods, and EDR data were only available in a low number of cases, Columns 4 and 5 give the assessability for the case if data provided by the relevant modern data recording technology were present.

Table 2  
Database structure

No.	Accident type [A <sub>1-i</sub> ]	Data recording technology		
		T <sub>0</sub>	T <sub>1</sub>	T <sub>2</sub>
		Assessability [1–4]		
1	1	1	1	4
2	3	3	4	4
3	2	2	4	4
...				
n	6	3	3	4

Statistical methods have been applied successfully to analyze objectively measurable characteristics of road accidents or of accident participants. For example, Shaadan et al. [5] used the Mann–Whitney Test to reveal the correlations between the gender of accident participants and the number of serious or fatal accidents, and also between the age of participants and the severity of accidents.

The topic of the present study is closer to those research projects that examine the physical parameters of road accidents. The Mann–Whitney Test and the Chi-square Test was applied by Baker [6] in an analysis of correlations between the dynamics of the crash and the severity of brain damage caused by the accident. Ayazi et al.

[7] applied the Chi-square Test to reveal the correlations between accident causes and types, environmental factors (e.g., road and visibility conditions) and accident severity.

Concerning the latest technology, accidents by self-driving cars were simulated by [8]. The collision reconfiguration system applying three different decision-making strategies was tested: the degree of seriousness of accidents was analyzed using the Kruskal–Wallis Test.

However, to the best of our knowledge, assessability of road accidents has not been analyzed with the help of statistical methods. It is self-evident that assessability, thus the success of reconstruction basically depends on the amount of accident data. In general, the higher the amount of available data is, the higher level of assessability can be reached. However, according to our hypothesis, assessability levels also depend on accident type and the applied data recording technology. In order to reveal the differences between these categories, statistical methods are to be utilized. The methodology and the various statistical tests used here are described in detail in Section 3.

### 3 Methodology

The system presented here is a step-by-step method for revealing, by means of statistical analyses, how factors, namely accident type and data recording technology, affect the assessability of road accidents. In general, the type of statistical tests that can be applied to a given dataset depends on the characteristics of the sets, primarily on the distribution of data. It must be checked whether the data in the samples are distributed according to normal distribution (e.g., using the Saphiro–Wilk Test [9]).

If the examined sample has a normal distribution, the means of the examined groups can be compared using the analysis of variance (ANOVA) [10]. This method can actually be defined as a generalization of the t-test for comparing more than two samples. It is important to emphasize that the application of ANOVA requires the distribution of the analyzed samples to be normal regarding the investigated variable. When applying the ANOVA method, the variance of the sample is given by the following formula:

$$s^2 = \frac{1}{n-1} \sum_i (x_i - \bar{x})^2 \quad (1)$$

where

$s^2$  – mean square;

$n$  – number of elements in the sample;

$x_i$  – variable value of the  $i^{\text{th}}$  element;

$\bar{x}$  – mean value of the investigated variable.

Based on the introduced formula, the analysis of variance identifies three different variance metrics:

- (1) a total variance which can be derived from the deviations between the grand mean and the variable values of the elements;
- (2) an error variance, which can be derived from the deviations between the variable values of the elements and their appropriate treatment means, and
- (3) a treatment variance.

Table 3  
Comprehensive overview of the methodology

No.	Data recording technology	Samples		Tested entities	Samples Independent (I) Connected (C)	Comparison	Statistical test
		1	2				
1.	$T_0$	$A_i$	a) comp. set ( $UA_i$ ) b) total set (U)	Assessability of accident types according to data recording technology	I	pairwise	Mann-Whitney U Test
2.	$T_1$	$A_i$	a) comp. set ( $UA_i$ ) b) total set (U)				
3.	$T_2$	$A_i$	a) comp. set ( $UA_i$ ) b) total set (U)				
4.	$T_0 - T_1$	$A_i T_0$	$A_i T_1$	Change in assessability according to type of change	C	pairwise	Wilcoxon Signed Rank Test
5.	$T_0 - T_2$	$A_i T_0$	$A_i T_2$				
6.	$T_0$ $T_1$ $T_2$	a) $A_i T_0$ b) $A_i T_1$ c) $A_i T_2$	a) $A_j T_0$ b) $A_j T_1$ c) $A_j T_2$	Assessability ranks within data recording technology	I	groupwise	Kruskal-Wallis Test Bonferroni Correction
7.	$T_0$ $T_1$ $T_2$	a) $A_i T_0$ b) $A_i T_1$ c) $A_i T_2$	a) $A_j T_0$ b) $A_j T_1$ c) $A_j T_2$				
8.	$T_0$ $T_1$ $T_2$	a) $A_i T_0 - T_1 \Delta$ b) $A_i T_0 - T_2 \Delta$ c) $A_i T_1 - T_2 \Delta$	a) $A_j T_0 - T_1 \Delta$ b) $A_j T_0 - T_2 \Delta$ c) $A_j T_1 - T_2 \Delta$	I	pairwise	Mann-Whitney U Test	
9.	$T_0$ $T_1$ $T_2$	a) $A_i T_0 - T_1 \Delta$ b) $A_i T_0 - T_2 \Delta$ c) $A_i T_1 - T_2 \Delta$	a) $A_j T_0 - T_2 \Delta$ b) $A_j T_0 - T_2 \Delta$ c) $A_j T_1 - T_2 \Delta$				
<p><math>T_0, T_1, T_2</math> – data recording technologies      <math>A_i, A_j</math> – assessability of accidents in a given accident type  <math>\Delta</math> – change in assessability of accidents for a given accident type</p>							

However, it must be emphasized that in the case of non-normally distributed variables, non-parametric statistical methods must be applied.

Based on our experiences and the performed investigations, the distributions of the variables characterizing road accidents are not normal. Therefore, non-parametric statistical methods are applied in further research phases. Accordingly, the methods presented here were selected because the example dataset did not have a normal distribution. Furthermore, the assessability values examined here are independent of each other, as the assessability of a given accident does not depend on the assessability of another accident.

In this analysis,  $T_0$ ,  $T_1$  and  $T_2$  denote the data recording technologies.  $T_0$  is the baseline technology (in our database, traditional).  $T_1$  marks a higher level of development: it includes all techniques in  $T_0$ , and some more advanced ones (in our database, this category corresponds to EDR).  $T_2$  denotes the highest level (in our case, EDR+), which means that in addition to all previous techniques ( $T_0$  and  $T_1$ ), further data recording techniques are available. Accidents were put into 7 categories (denoted  $A_1$ – $A_7$ ), and assessability had four levels (marked 1–4, 4 being the highest level).

### 3.1 Comparison of Accident Types

In the first round of analyses, pairwise comparisons are to be made in order to explore whether there are any accident types whose assessability is significantly different from that of other accident types. For this analysis, the Mann–Whitney U Test was applied [11, 12], which compares two samples (Sample 1 and Sample 2), which are the values of the same parameter – in this case, assessability. The test calculates the probability of a randomly selected value  $X$  from Sample 1 being greater than value  $Y$  randomly selected from Sample 2. The calculation is based on Equations (2-4).

$$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - R_1 \quad (2)$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - R_2 \quad (3)$$

$$Z = \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} \quad (4)$$

where,

$n_1$  – number of elements in Sample 1;

$n_2$  – number of elements in Sample 2;

$R_1$  – sum of the ranks in Sample 1;

$R_2$  – sum of the ranks in Sample 2;

$U_1$  – test function value for Sample 1;

$U_2$  – test function value for Sample 2;

$Z$  – value of function approaching the normal distribution.

For our database, for each test in this group, the significance level of the Mann–Whitney U Test was set to  $\alpha = 0.05$ . Our hypotheses were identified according to the following consideration. In the case of randomly selected values  $X_{\text{Sample1}}$  and  $X_{\text{Sample2}}$  from two different populations, the probability of  $X_{\text{Sample1}}$  being larger or equal to  $X_{\text{Sample2}}$  is larger than the probability of  $X_{\text{Sample2}}$  being larger than  $X_{\text{Sample1}}$ :

H0:  $X_{\text{Sample1}} \geq X_{\text{Sample2}}$

H1:  $X_{\text{Sample1}} < X_{\text{Sample2}}$

This means the test investigates the probability of Type I error (i.e., of rejecting a correct H0) related to the compared assessability values. If the chance of rejecting a correct null hypothesis is too high, we cannot accept H1. Accordingly, if  $p$  is lower than  $\alpha = 0.05$ , the probability of Type I error is tolerably low, so the null hypothesis (H0) can be rejected, and H1 is accepted, i.e., the assessability of accidents in the examined type is significantly worse than that of the bigger set (Sample 2). Such a result entails that with the given data recording technology, the examined accident type cannot be assessed as well as the other accidents.

There are two runs within each test type: in the first run, assessability values of a given accident type (Sample 1) are compared to such values of the complementary set. The aim of this is to see whether the level of assessability of the tested accident type is different from that of the other types. In the second run, Sample 1 is compared to the total set.

### 3.1.1 Test 1 – Baseline

The aim of the first test is to see for each accident category whether there is a significant difference in assessability levels compared to all other accident categories and to the average of the total sample, with data recording  $T_0$ .

In this test, Sample 1 is composed of the assessability values for a given accident type (Figure 2), for example  $A_1$ . In the first run, the assessability values of the given accident type are compared to the assessability values of the complementary set (Sample 2), i.e., those of all the other accident types (in our case,  $A_2$ – $A_7$ ). In the next run, Sample 2 is larger than in the first run: it is the total, unified set, i.e., in our case assessability values for all accident types ( $A_1$ – $A_7$ ).

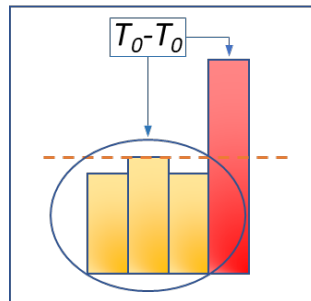


Figure 2

Test 1 – assessability of Sample 1 (red) compared to that of Sample 2 (yellow), data recorded by  $T_0$

### 3.1.2 Test 2 – Higher Level Data Recording ( $T_1$ )

Test 2 aims to reveal whether there is a significant difference in assessability for a given accident category with data recorded by a higher-level technology, namely  $T_1$  compared to other accident types (Figure 3). Therefore, Sample 1 is the assessability of a given accident type with  $T_1$  data recording. Results are calculated for a comparison with the baseline category and also for the same data recording category.

Consequently, in Test 2a, assessability values in Sample 1 are compared to the average assessability of the complementary set and the total set with the baseline level data recording technology  $T_0$ . In Test 2b, however, values in Sample 1 are compared to values in the complementary and the total set if data are recorded by  $T_1$ .

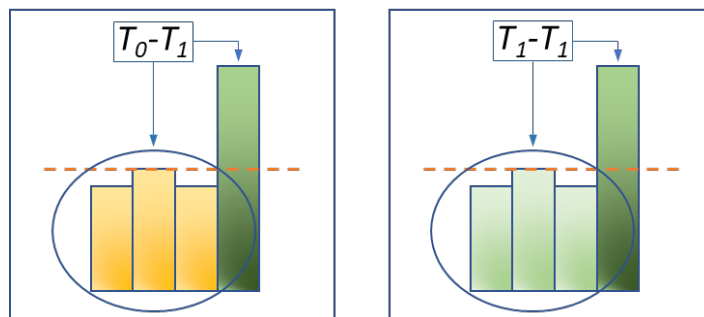


Figure 3

Test 2 – assessability of Sample 1 (dark green,  $T_1$ ) compared to that of Sample 2 (yellow) – data recorded by  $T_0$  (Test 2a, left); and to Sample 2 (light green) data recorded by  $T_1$  (Test 2b, right)

### 3.1.3 Test 3 – Highest Level Data Recording ( $T_2$ )

Similarly, to Test 2, the aim of Test 3 is to reveal whether there is a significant difference in assessability for a given accident category with data recorded by the highest-level technology, namely  $T_2$ , compared to other accident types (Figure 4). Therefore, Sample 1 is the assessability of a given accident type with  $T_2$  data recording. Results are calculated for a comparison with the baseline category  $T_0$  and also for the same data recording category,  $T_2$ .

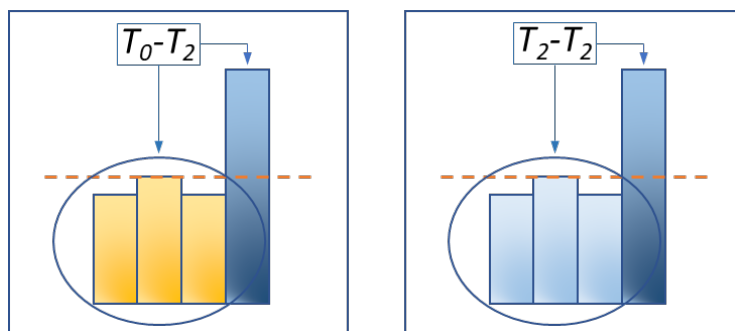


Figure 4

Test 3 – assessability of Sample 1 (dark blue,  $T_2$ ) compared to that of Sample 2 (yellow) – data recorded by  $T_0$  (Test 3a, left); and to Sample 2 (light blue) data recorded by  $T_2$  (Test 3b, right)

As a result of, Tests 1-3, it can be seen which accident types have a significantly lower assessability than the others for each data recording category.

## 3.2 Comparison of Data Recording Technologies

The second round of analyses focuses on data recording technologies. The aim is to test whether the development of data recording technologies (from  $T_0$  to  $T_2$ ) can actually improve the assessability of the different accident groups. To see this, the assessability levels according to data recording technology within an accident type were compared (Figure 5).

The Wilcoxon Signed-rank Test [13] was applied to compare the connected groups which had a non-normal distribution. In each group, the accidents were the same, and an assessability value was assigned to each accident according to data recording technology. The tested hypotheses are as follows.

$H_0$ : The median difference is zero.

$H_1$ : The median difference is not zero,  $\alpha = 0.05$ .

Pairwise differences in assessability are ranked according to their absolute value, and ranks are assigned. In the next step, positive or negative signs are assigned to these ranks, depending on whether the original difference was positive or negative.

Then, test ranks ( $R_i$ ) of corresponding pairs ( $Y_i - X_i$ ) are summed separately, i.e. positive values ( $W^+$ ) (5) and negative values ( $W^-$ ) (6), and the negative sum is subtracted from the positive sum (7).

$$W^+ = \sum_{Y_i - X_i > 0} R_i \quad (5)$$

$$W^- = \sum_{Y_i - X_i < 0} R_i \quad (6)$$

$$W = W^+ - W^- \quad (7)$$

After identifying test statistics ( $W$ ), we have to compare it to the critical value depending on sample size and significance level.

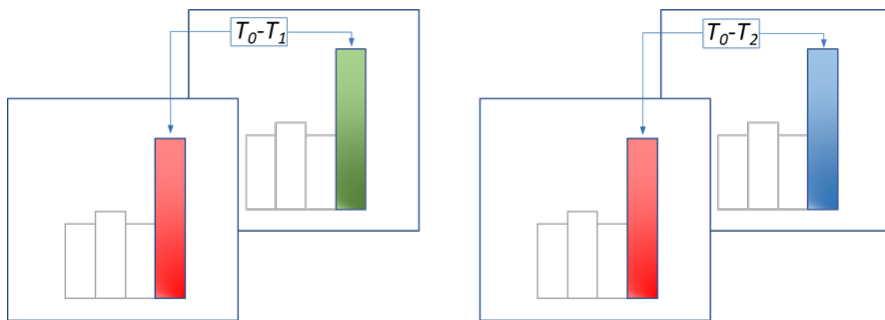


Figure 5

Assessability of a given accident group (Sample 1: red,  $T_0$ ) according to data recording technology.

Test 4 (left) – data recording technology  $T_1$  (green); Test 5 (right) – data recording technology  $T_2$  (blue)

### 3.2.1 Test 4 – Baseline ( $T_0$ ) vs. $T_1$

In this test, for each data recording technology, assessability values for each accident are compared: Sample 1 corresponds to values assigned for  $T_0$  and Sample 2 to  $T_1$  data recording technology. The test reveals whether there is a significant change in assessability with the introduction of  $T_1$  technology for the given accident type.

### 3.2.2 Test 5 – Baseline ( $T_0$ ) vs. $T_2$

The aim of this test is to reveal how the introduction of the highest level of data recording technologies affect assessability compared to the baseline. Thus, for each data recording technology, assessability values for each accident are compared:

Sample 1 corresponds to values assigned for  $T_0$  and Sample 2 to  $T_2$  data recording technology.

### 3.3 Ranking by Assessability

The previous tests can prove whether there is a difference in assessability levels for different accident types with different data recording technologies. However, the above tests cannot rank the accident types according to assessability. To reveal the ranking between accident types, assessability levels for different accident types were compared within each data recording technology. For this, a 2-step analysis was carried out. In Test 6, the Kruskal–Wallis Test with Bonferroni Correction was applied to compare multiple independent groups (i.e., assessability levels for accident types  $A_1$ – $A_7$  within categories  $T_0$ ,  $T_1$  and  $T_2$ ). In Test 7, those pairs in which stochastic dominance is proven by Test 6 were compared with the Mann–Whitney Test.

#### 3.3.1 Test 6 – Comparison of All Possible Pairs

In this test, Sample 1 is made up of the values for assessability for a given accident type, for a certain data recording technology (e.g.,  $A_2$ ,  $T_1$ ). Sample 2 is composed of values for assessability for another accident type, for the same data recording technology (e.g.,  $A_3$ ,  $T_1$ ). All possible pairs are tested for each data recording technology (for  $T_0$ ,  $T_1$ , and  $T_2$ , respectively, see Figure 6). Thus, non-normally distributed independent group samples are compared using the Kruskal–Wallis Test [14].

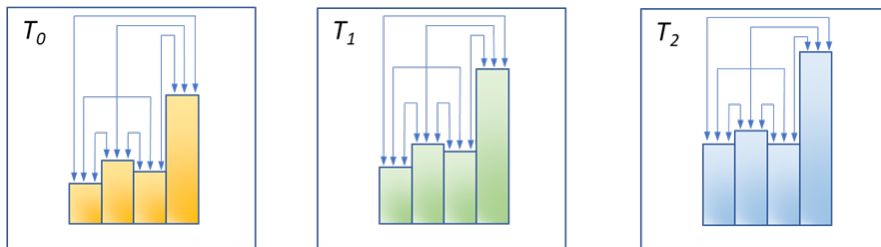


Figure 6

Test 6: assessability of accident groups according to data recording technology: Test 6a:  $T_0$  (yellow); Test 6b:  $T_1$  (green); Test 6c:  $T_2$  (blue)

For this test, the following hypotheses are formed.

$H_0$ : the medians of Samples are equal

$H_1$ : some of the medians of the Samples are not equal

The following formula is used for calculating the statistical test results.

$$H = (N - 1) \frac{\sum_{i=1}^g n_i (\bar{r}_i - \bar{r})^2}{\sum_{i=1}^g \sum_{j=1}^{n_i} (r_{ij} - \bar{r})^2} \quad (8)$$

where

$n_i$  – is the number of elements in the  $i^{\text{th}}$  sample;

$r_{ij}$  – is the rank (among all elements) of the  $j^{\text{th}}$  element in the  $i^{\text{th}}$  sample;

$N$  – is the number of elements across all groups;

$\bar{r}_i$  – is the average rank of the  $i^{\text{th}}$  sample;

$\bar{r}$  – is the average rank of all samples in the unified sample;

$g$  – is the number of samples.

In order to minimize Type I Error, i.e. rejecting the null hypothesis although it is actually true, the Bonferroni Correction was applied. The aim of this correction is to diminish the unfavorable effect of the Type I Error, which increases when comparing groups [15]. The basic principle is that the significance level ( $\alpha$ ) is lowered proportionally to the number of hypothesis tests ( $m$ ). Consequently, the null hypothesis is dropped if for the value  $p_i$  of the  $i^{\text{th}}$  hypothesis test proves to be true.

The following inequity (9) supports the applicability of the Bonferroni correction [16]. In this formula,  $m_0$  marks the number of true null hypotheses.

$$EF = P \left\{ \bigcup_{i=1}^{m_0} \left( p_i \leq \frac{\alpha}{m} \right) \right\} \leq \sum_{i=1}^{m_0} \left\{ P \left( p_i \leq \frac{\alpha}{m} \right) \right\} = m_0 \frac{\alpha}{m} \leq \alpha \quad (9)$$

Test 6 shows for which pairs the assessability difference can be regarded as stochastically dominant within a given data recording technology group. For example, if for the accident type pair  $A_3$ – $A_5$  the Kruskal–Wallis Test has a significant  $p$ -value for the  $T_1$  data recording technology, it means that the level of assessability for either  $A_3$  or  $A_5$  is significantly higher than for the other member of the pair. However, this test does not determine for which group the values are higher.

### 3.3.2 Test 7 – Pairwise Comparison

To determine for which member of the pair the assessability change is more significant, a pairwise comparison is required. The comparison is to be made by the Mann–Whitney U Test for each pair (c.f. Section 3.1, Tests 1-3). Only those pairs are to be tested, in which the Test 6 indicated stochastic dominance (Figure 7).

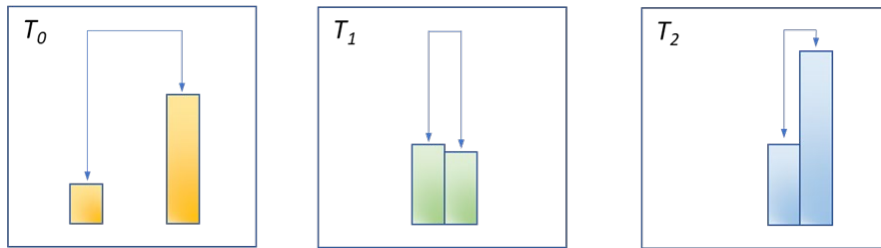


Figure 7

Comparison of accident groups with stochastic dominance from Test 6: Test 7a:  $T_0$  (yellow); Test 7b:  $T_1$  (green); Test 7c:  $T_2$  (blue)

In this test, Sample 1 is composed of the assessability values for a given accident type for a given data recording technology, for example  $A_1$  ( $T_1$ ). Sample 2 is the set of assessability values for another accident type for the same data recording technology, for example  $A_3$  ( $T_1$ ).

As a result of, Tests 6 and 7, it can be determined for the significantly differing pairs which one has a significantly higher assessability value than the other member of the pair. Thus, a partial ordering can be set up.

### 3.4 Change in Assessability

In order to see to what extent assessability changes with the introduction of more and more developed data recording technologies, the values for assessability change for each accident type ( $A_1$ – $A_7$ ) are to be compared to those of each other group with the same method that is followed by Tests 6 and 7. The only difference is that the dependent variable is the change in assessability for a given accident type between two data recording technologies.

#### 3.4.1 Test 8 – Comparison of All Possible Pairs

In this test, Sample 1 is made up of the values for assessability change for a given accident type, for a certain development in data recording technology (e.g.  $A_2$ , development  $T_0$ – $T_1$ ). Sample 2 is composed of values for assessability change for another accident type, for the same development in data recording technology (e.g.,  $A_3$ , development  $T_0$ – $T_1$ ). All possible pairs are tested for each type of development (i.e.,  $T_0 - T_1$ ,  $T_0 - T_2$ ,  $T_1 - T_2$ , see Figure 8). As there are four assessability levels (1-4), the values examined here range from 0 (no change) to 3 (maximum change from 1 to 4).

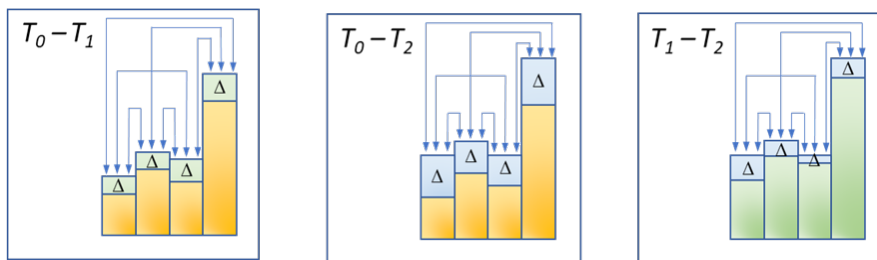


Figure 8

Test 8: comparison of assessability change ( $\Delta$ ): Test 8a:  $T_0-T_1$  (yellow–green); Test 8b:  $T_0-T_1$  (yellow–blue); Test 8c:  $T_1-T_2$  (green–blue)

Test 8 shows for which pairs the assessability change can be regarded as stochastically dominant for a certain type of change in data recording technology (i.e., a)  $T_0 - T_1$ , b)  $T_0 - T_2$  or c)  $T_1 - T_2$ ). For example, if for the accident type pair A3–A5 the Test 8 has a significant  $p$ -value for the  $T_1 - T_2$  development in data recording, it implies that the assessability change for either A3 or A5 is significantly higher than for the other member of the pair. However, this test does not determine for which group the values are higher.

### 3.4.2 Test 9 – Pairwise Comparison

To determine for which member of the pair the assessability change is more significant, a pairwise comparison is required. The comparison is to be made by the Mann–Whitney U Test for each pair (c.f. Section 3.1, Tests 1-3). Only those pairs are to be tested, in which the Test 8 indicated stochastic dominance (Figure 9).

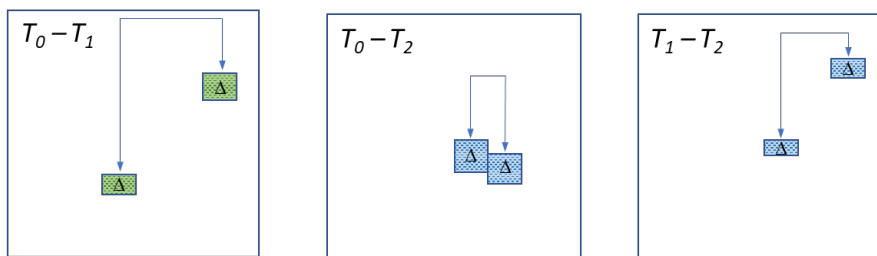


Figure 9

Test 9: comparison of significant assessability change ( $\Delta$ ): Test 9a:  $T_0-T_1$ ; Test 9b:  $T_0-T_1$ ; Test 9c:  $T_1-T_2$

In this test, Sample 1 is composed of the assessability change values for a given accident type for a given data recording technology change, for example  $A_1+T_1-T_2$ . Sample 2 is made up of assessability change values for another accident type for the same data recording technology change, for example  $A_3+T_1-T_2$ .

The result of the test shows for which accident type which development of data recording technology resulted in a significant improvement in assessability.

## Conclusions

This study presented a detailed methodology composed of various statistical tests for exploring how the development of data recording technologies and accident type influence the assessability of road accidents. The series of tests can be run on any database composed of real or simulated road accidents, in which the independent variables are accident type and data recording technology, and the dependent variable is the level of assessability for each accident.

The analysis described here is a combination of statistical methods that can be applied to samples with non-normal distribution: the Mann–Whitney U Test, the Wilcoxon Signed-rank Test and the Kruskal–Wallis Test with Bonferroni Correction. As a result of, these tests, it can be determined which data recording technologies improve the assessability of accidents the best and to what extent the assessability of which accident types improves due to a change in assessability. Such results can be utilized by the automotive industry to set the direction of development for data recording technology.

This methodology was tested against a database of real road accidents in Hungary [2]. However, the list of accident types and data recording technologies can be extended without a modification of the model. Thus, the methodology proposed here can be applied to databases other than the test database. Consequently, the effects of future developments in data recording and the emergence of new or different accident types can also be tested by this methodology.

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