International Journal of Occupational Safety and Ergonomics (*JOSE*) 2006, Vol. 12, No. 3, 281–296

Driver Celeration Behavior and the Prediction of Traffic Accidents

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A study was undertaken to investigate whether driver celeration (overall mean speed change) behavior can predict traffic accident involvement. Also, to test whether acceleration, deceleration or the combined celeration measure was the better predictor. Bus driver celeration behavior was measured repeatedly in real traffic, driving en route, and correlated with accidents for which the drivers were deemed at least partly responsible. Correlations around .20 were found in several samples between celeration behavior and culpable accidents for a 2-year period. The results show that although celeration behavior is only semi-stable over time, it predicts with some accuracy individual accident involvement over 2 years. The predictive power of acceleration and deceleration was slightly lower than the combined measure, in accordance with theory. The correlations found were strong enough to warrant the use of celeration behavior as a predictive variable for transportation companies in their safety work.

bus driver   traffic accident   crash   acceleration   celeration   driver behavior

1. INTRODUCTION

The search for individual differences in psychological traits that can predict traffic accident liability has not been very successful. At least, no single individual variable has been found to be strongly related to accident record. Although this may partly be an effect of weak methodology in such research [1], it is probably also an effect of any one predictor being rather specific (e.g., speed or short headways), and therefore not being able to predict accidents in general, but only a sub-sample of them. This statement rests on the assumptions that accidents have a wide variety of causes, and that most predictors used are related only to one or a few of these (for reviews see af Wåhlberg [1] and Lester [2]).

On the other hand, a specific predictor could predict several types of accidents, due to one type of behavior being correlated with others (e.g., those who drive fast also keep short headways). This would increase the predictive power, but it would seem improbable that any one such syndrome could be very broad. The solution to this problem (apart from better methods) could be to use multiple predictors, like Harano, Peck and McBride [3], Asher and Dodson [4] and Häkkinen [5] did. However, such studies are very uncommon, because the downside is of course the large expenses and low practical applicability.

Another approach would be to use a general predictor, like age. The problem with such a predictor, however, is that it is too general, and neglects all the individual differences within any age group, thus being rather uninteresting from

The driver celeration behavior data used in this study was gathered as part of a project on fuel efficient driving funded by the Swedish Road Administration, grant AL90AB 2001:7758. Hanna Skagerström did all the basic data editing and transformations, and in general kept things in order. As usual, the personnel at Gamla Uppsalabuss helped out in various ways. Thanks to Mats Hammarström at Uppsalabuss for providing data of crucial importance. Professor Lennart Melin (Deptartment of Psychology, Uppsala University) supplied useful input for the whole endeavor, especially the analysis of data and writing of this paper, and was also a valuable support and discussion partner in general. Finally, an anonymous reviewer gave useful suggestions.

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a scientific, especially psychological, point of view. What is needed is therefore a predictor that is related to many risky individual behaviors, a predictor that is general but does not smear out the individual differences. Such a general-individual predictor has been proposed, discussed and tested in various ways in previous papers [6, 7, 8, 9, 10]. It has been named driver celeration behavior[1], is conceptualized as the variability of driving behavior, and measured as the mean of speed changes during movement of a vehicle.

The driver celeration behavior theory [10] states that most driver behaviors are control actions relating to the vehicle and the driving environment, and that these behaviors cause changes in speed (lateral and longitudinal), which can be called celerations. A high mean level of celeration indicates an uneven driving style, which is predictive of accidents, because such behaviors are dangerous, due to low safety limits and unpredictability of the behavior of the driver for other road users. These behaviors are supposed[2] to be habitual (i.e., have some stability over time and environment), and some proof of this has been reported [7, 8]. However, the correlations between periods are not really satisfactory, and the problem of predicting anything from a semi-stable variable will thus be further discussed in the closing of this paper.

The data so far on driver celeration behavior and accidents is scarce and weak [6, 8, 9, 11, 12[3]; 13], but given the methodological shortcomings of these studies (see af Wåhlberg [1]), the results are not disappointing. What has been needed is mainly a large set of celeration data, which has been collected under "ecological" circumstances, good accident data, and control of confounding factors. In the present study, the first three factors are probably present, while there are many confounders that will be treated separately in other papers.

The method for obtaining data was somewhat different in the present study as compared to the previous ones [6, 8]. Earlier, data was gathered manually, by riding on the buses with a measuring device. This was now upgraded to equipping five buses with logging devices[4] that were hidden under the dashboard. These buses were continually in service on one particular route (the same as in previous studies). Thus, the potential sample was very much larger than before, as was the time for sampling of driving for each driver. The measuring equipment used the signal from the bus speedometer, and calculated accelerations as the changes in speed over time, i.e., only longitudinal accelerations and decelerations were measured. This is in contrast to the driver celeration behavior theory and previous studies where the resultant of lateral and longitudinal was included. However, in the second driver celeration behavior study [8], it was found that lateral movements added very little variation to the resultant, and the use of longitudinal accelerations only was therefore judged to be sufficient as an approximation, especially as the data set would be very large.

Also, an argument was forwarded by a reviewer of a previous study that acceleration and deceleration are not equally under volitional control, as the strength of accelerations are limited by the power of the engine, while deceleration is only physically limited by the braking power of the vehicle, which is usually considerably higher, creating an uneven space of behavioral choice. There might therefore exist a ceiling effect regarding acceleration, which could have a detrimental effect on predictive power. Therefore, in the present study, accelerations and decelerations were tested separately, alongside with the absolute celeration variable (which equals the gas/brake variable in the two previous studies). However, the driver celeration behavior theory predicts that the overall celeration variable is a better predictor of accidents, because more speed change data is included, and all changes contain some risk.

[1] Actually, the terminology has changed somewhat over time, but this is hopefully the final version. The word celeration is not a new construction but is used, e.g., within statistics. In the present work, it is only used in the sense stated in af Wåhlberg [10].
[2] This is not a necessary assumption of the theory, but is an advantage when it comes to practical use.
[3] The two studies by Lajunen [11, 12] seem to use the same set of data.
[4] The logging device was a variant of a vehicle microcomputer developed by the Swedish company Drivec AB (www.drivec.se), with software adapted for the project that generated the data used in the present study.

It should be noted that the division of celeration into positive and negative leaves another component unaccounted for: even speed or zero acceleration. This is included in the (absolute) celeration variable, but must be left out of acceleration and deceleration. This, however, is partly a measurement problem; if the measurement system is very finely graded, it will hardly register any even speed. The exact cut-off values and calculation methods used here are stated in the Appendix.

To sum up, the aims of the present work were to

- replicate the results of the former studies, which found some positive correlations between driver celeration behavior and accidents, in a larger sample;
- compare the relative predictive power of (mean) acceleration, deceleration, and celeration.

2. METHOD

2.1. Subjects and Driver Celeration Behavior Measurement Method

The subjects were all bus drivers working at the Gamla Uppsalabuss bus company in Uppsala, Sweden. Measuring was done on one bus route during normal driving. Drivers were not aware of the study.

Although the samples used included a large part of the population of drivers (about 350 at any one time), it may be suspected that a sample gathered in the present way is not quite random. This is due to two factors; people working more hours will be over-represented, as they are more probable to turn up and be measured. Also, duty rotation is not random for the majority of drivers, but restricted within certain parts of all possible duties (e.g., early shifts). As the buses equipped with the measuring devices were always on the same departure scheme, the same duties would always apply, and drivers who did not work on these shifts were therefore not measured. However, the system is not watertight; shifts may be vacant and worked by anyone who is free. On the other hand, the repeated appearance of a smaller number of drivers also means that several samples could be gathered, simply by using the first time a driver appeared for the first sample and so on (see Appendix).

The buses used for measurements were all of the same type, Volvo B10L, (grand total weight 18.9 tonnes, 12 m long) with a low floor. This type of bus was not exactly representative for the general population of buses at the company[5], but probably not so different as to make a real difference. The route used for measurements was 12.4 km long (single journey), running from one side of the city to the other and back, passing the center of town. It was a very busy route, which might have something like 2,000 passengers on a normal day. Five buses were equipped with logging devices, described in section 2.2. These buses were in traffic for about 12 hrs a day on weekdays and 7 hrs on Saturdays (the latter data not used in the present study). The route used was not in service on Sundays. Summer data was not used in the present paper, as traffic was very different during this period, compared to the rest of the year.

Measurements started on August 20, 2001, the day of the shift from summer to winter timetable, as part of a project on fuel-efficient driving [14, 15]. The last data used was gathered in February 2004. A total of 28 samples was gathered, mainly repeated measurements of the same drivers (see Appendix).

It might be noted that the quality of exposure of the subjects in the present study (as in the previous two) was very homogenous; duty rotation ensured this state of being. This means that some problems, like avoidance of difficult driving [16], were not present.

2.2. Measurement Equipment

Microcomputers were installed under the dashboard of five buses and connected to the

[5] There is a variety of buses used by the company from four makers (Scania, Volvo, Neoplan, Ontario), mainly of two types: two axles, about 12 m, 15+ tonnes taking 70–80 passengers, and three axles, 18+ m, about 25 tonnes with up to 120 passengers. The high floor type still dominates, although low floors are becoming more common.

speedometer. The bus speedometers worked by receiving discrete pulses (not a continuous signal) that originated from magnets located on an axle in the transmission system. Whenever a magnet passed a fixed point, an electrical pulse was originated. The logging device that gathered the data on the measurement buses sampled the speedometer signal with 10 Hz and calculated positive and negative acceleration with 2.5 Hz using the differences in speed between discrete speed data points. A simple smoothing function[6] was used: the mean of the four previous values (see Appendix for details). The data was stored in a memory, which was collected and tapped every 2 days.

For purposes of other research, zero acceleration (even speed) was defined as values closer to zero than 0.045 m/s^2. In the present study, acceleration was therefore the mean of all values above 0.045 m/s^2 for a driver, and deceleration all values lower than –0.045 m/s^2. Celeration, on the other hand, included all values (when $v > 0$) for the calculation of the mean, resulting in a lower absolute value on this variable as compared to the other two.

2.3. Demographical Data and Confounding Variables

Available from the bus company was data on the drivers' age, gender, ethnicity and hours worked, the last being a good measure of the amount of exposure to risk of accident in this type of population, although the correlation with accidents is not strong. These data were used to check how representative the samples were of the population. The descriptive statistics for some samples and the total number of drivers for each of the years 2001–2003 are shown in Table 1. These samples were of course very representative of the population, sometimes being close to 50% of all drivers working for the company. Some small differences can be seen, however. The probable reasons for this have been discussed in section 2.1., and the samples indeed had an over-representation of drivers who worked full time (this was ascertained from their employment numbers), as compared to their percentage in the population. This means that the driver samples also had more accidents in absolute numbers, but fewer per hour worked, compared to the population.

TABLE 1. The Percentage of Men, Percentage of People With Swedish Names, Mean Age, Mean Number of Hours Worked, and Mean Number of Responsible Accidents (per 1,000 Hours Worked and per Year) for Some Samples and for the Total Number of Active Drivers at Gamla Uppsalabuss (Uppsala, Sweden) for Each of the Years 2001–2003. Age Calculated for December 30 of Each Year

Sample/Population (Year)	*N*	Gender (%)	Ethnicity (%)	Age (%)	Hours Worked per Year	Crashes per Year	Crashes per Hour per Year
Sample 1 (2001)	203	90.6	43.3	44.7	1396.4	0.325	0.233
Sample 4 (2001)	169	88.2	43.8	45.4	1385.9	0.296	0.214
Population (2001)	414	89.4	57.0	45.4	1214.9	0.222	0.183
Sample 11 (2002)	145	90.3	48.3	46.3	1649.6	0.269	0.163
Sample 16 (2002)	149	90.6	45.6	46.2	1553.2	0.248	0.160
Population (2002)	397	88.9	53.7	46.6	1306.7	0.176	0.135
Sample 22 (2003)	181	89.0	45.3	46.9	1515.7	0.276	0.182
Sample 27 (2003)	80	88.7	43.8	45.9	1551.2	0.262	0.169
Population (2003)	419	89.0	52.5	46.1	1260.4	0.208	0.165

[6] Smoothing functions are similar to moving averages; in this case, the goal was to counter the unevenness introduced by the digital signal and make the result more like an analog signal.

2.4. Accident Data

Accident data gathering and treatment has its own problems, which has been a recurrent theme in the driver celeration behavior studies and other work [1, 6, 8, 17, 18]. To the previous arguments and references concerning why only responsible accidents should be used in studies on individual psychological predictors of accidents may now be added that Garretson and Peck [19] found at fault and not-at-fault accidents to have different predictors, (see also Ball, Owsley, Sloane, Roenker and Bruni [16]). Similarly, Cation, Mount and Brenner [20] found only "avoidable" accidents to be associated with their predictor. On the other hand, McBain [21] found only non-preventable accidents to be correlated (and strongly so) with some of his predictors. Still, the majority of the evidence would seem to suggest that culpable accidents should be used as criterion for behavior variables.

It might also be pointed out that the accident criterion source (bus company records) used in the present study has a validity that is probably much higher than other sources; self-reports are notoriously unreliable, as shown for traffic crashes ([18, 22, 23, 24, 25, 26], but see also Dalziel and Job[7] [27]), as well as accidents in general [28], while state, hospital, and insurance company records mainly cover serious crashes [29] and also reflect regional habits of reporting [30]. There are also strange discrepancies between self-reported and police data (see, e.g., Várhelyi, Hjälmdahl, Hydén and Draskóczy [31]). Anyway, the database used in the present study contains more accidents than the drivers themselves could report retrospectively for a 3-year period [18]. The number of accidents per driver and year is higher for this population as compared to Swedish car drivers, but considerably lower than, e.g., the bus drivers studied by Blasco, Prieto and Cornejo [32].

The accident data used as dependent variable had been gathered through the years and is described and analyzed in detail in af Wåhlberg [17, 33, 34]. Driver reports about all kinds of incidents had been coded for, amongst other variables, responsibility of driver, and entered into a database. All happenings, which resulted in physical damage (more severe than scratches in paint) and/or injuries (bloodshed, or medical treatment necessary), due to traffic events (not intentional destructive behavior) were included. For the present study, the inclusion criteria were widened to include accidents at high speed (>50 km/hr), hitting animals, and incidents happening within the enclosed bus garage area. These had previously been excluded due to the aims of previous studies [17, 33] (low speed/urban settings accidents). However, none of these added categories was large, so the difference was probably slight. The meaning of this broadening of the dependent variable is that not only traffic accidents in the sense of the public road system and its human users are included, but all types of mishaps which are at least partly due to the vehicle control behavior of the bus driver and result in some kind of damage were included. This is probably preferable both from the view of the bus company and society (not to mention statistically), and is fully compatible with the driver celeration behavior theory [10], although not necessary.

Only incidents for which the driver was in some way held responsible were included, meaning about 70% of the total. Responsibility was determined by the use of a rather harsh criterion; only happenings that could only have been avoided by being somewhere else (e.g., being hit from behind while stationary at a bus stop) were deemed as being the sole fault of some other road user. This criterion and the coding process are further described in af Wåhlberg [17]. The inter-rater reliability was not very satisfactory (70%) for this variable, and it is therefore expected that a large degree of error has been included with this parameter.

2.5. Grouping of Data and Statistical Treatment

The data used in the present work was actually gathered continuously, but, due to many repeated measurements of drivers, they were sorted into

[7] The high agreement between self-reports and archival material found by these authors was probably due to methodological peculiarities that are usually not present in other studies.

periods (seasons) with no overlap, and in samples with some overlap in time (see Appendix), meaning that the first measurement of one driver could have been collected after the second or even third of another driver.

As before, correlations were calculated on different periods, as the optimal period for prediction is not known (for a discussion of this type of problem, see af Wåhlberg [1] and McKenna [35]). In the second celeration behavior study [8], it was found that 6 years tended to give the best result, much in agreement with Ball, Owsley, Sloane, Roenker and Bruni [16]. However, the optimal prediction time span should be individual for each variable used, due to its stability over time.

As accident data tend to be Poisson-distributed for short periods (while celeration values are normally distributed [7]), the choice of statistical method was not quite straightforward. However, in this study, as in the previous two, mainly Pearson correlations were used. This choice was made for two reasons; firstly, when longer periods are used for accident frequency calculations, the distribution will necessarily go from Poisson towards normality, and in this population the naughts will be fewer than the ones after about 5 years calculated on responsible crashes only (which are about 70% of total, see af Wåhlberg [17]). Secondly, during the work on the first driver celeration behavior study, a Poisson regression was tested and yielded very similar results to the Pearson calculations. Also, Arthur and Doverspike [36] tested a log-linear transformation of accident data without getting any difference in correlations with their predictors. In the present study, correlations were supplemented by an ANOVA analysis of the celeration data, and regression analyses with age, gender and ethnic origin as added predictors.

The driver celeration behavior theory states that it is the behavior of the driver when the vehicle is moving that is of interest (because that is when the driver is actually in active control). Therefore, celeration values were calculated only for the periods when the bus was actually moving ($v > 0$). Furthermore, it is the mean absolute value of speed changes during movement that should be calculated, as a measure of vehicle control behavior.

The raw data is a string of values in meters/seconds^2 over time, each denoting how much speed has changed within this period (see Appendix). For each measurement occasion (where a number of individual's occasions make up one sample), one single value is calculated which is the mean of all the raw data values when $v > 0$. These values can also be added to each other over measurement occasions for a driver, and a new mean created, presumably with better predictive properties. This is the empirical approximation of the overall celeration value, which is a sum of all celeration values [10].

Now a note on the somewhat difficult terminology within this work. The main source of possible confusion rests with the word *mean*. As this is a mathematical term, it cannot easily be replaced. Therefore, be certain to differentiate between the following uses;

(a) the mean of celeration behavior for an individual on one measurement occasion;
(b) the mean of celeration behavior for a sample, i.e., a group mean;
(c) the mean celeration behavior for an individual over samples, i.e., several cases of (a).

All correlations with accidents were computed for (a) or (c), while values of (b) can be seen in Table 2.

As the variation within subjects seems to be large in these data (the correlations between celeration behavior measurements in the first four samples used here were found to be around .40–.50 in af Wåhlberg [7], and aggregation of data generally yield a more stable estimate of the true value (in this case mean celeration behavior of a driver), it is of interest to try to increase the stability of the celeration variable, and therefore its predictive power, by using the mean celeration behavior over several samples, or taking the mean accident correlation from several samples.

TABLE 2. The Means, Standard Deviations, Maximums and Minimums of the Celeration Variables in meters/second^2, and These Statistics for the Distance That the Celeration Values are Calculated Over (km), for Samples 1–9

Sample 1 (*N* = 208)

Variable	*M*	*SD*	Max	Min
Acceleration	0.579	0.070	0.806	0.337
Deceleration	–0.557	0.074	–0.821	–0.360
Celeration	0.530	0.066	0.766	0.321
Distance	36.4	13.7	62.3	12.2

Sample 2 (*N* = 144)

Variable	*M*	*SD*	Max	Min
Acceleration	0.582	0.069	0.762	0.338
Deceleration	–0.557	0.063	–0.706	–0.383
Celeration	0.531	0.061	0.675	0.324
Distance	36.2	14.3	62.3	12.3

Sample 3 (*N* = 81)

Variable	*M*	*SD*	Max	Min
Acceleration	0.582	0.066	0.740	0.435
Deceleration	–0.558	0.072	–0.735	–0.387
Celeration	0.531	0.064	0.683	0.393
Distance	36.7	15.5	63.8	11.8

Sample 4 (*N* = 171)

Variable	*M*	*SD*	Max	Min
Acceleration	0.568	0.081	0.808	0.331
Deceleration	–0.543	0.080	–0.798	–0.357
Celeration	0.519	0.074	0.754	0.319
Distance	37.0	15.0	63.0	12.1

Sample 5 (*N* = 82)

Variable	*M*	*SD*	Max	Min
Acceleration	0.571	0.071	0.729	0.434
Deceleration	–0.540	0.070	–0.738	–0.406
Celeration	0.519	0.064	0.679	0.383
Distance	38.4	14.9	62.5	12.4

Sample 6 (*N* = 55)

Variable	*M*	*SD*	Max	Min
Acceleration	0.593	0.074	0.814	0.451
Deceleration	–0.548	0.074	–0.801	–0.383
Celeration	0.532	0.066	0.756	0.388
Distance	33.9	14.6	61.7	12.4

Sample 7 (*N* = 166)

Variable	*M*	*SD*	Max	Min
Acceleration	0.592	0.066	0.795	0.413
Deceleration	–0.549	0.072	–0.794	–0.370
Celeration	0.533	0.062	0.746	0.361
Distance	39.2	13.3	62.6	12.3

Sample 8 (*N* = 108)

Variable	*M*	*SD*	Max	Min
Acceleration	0.576	0.062	0.720	0.407
Deceleration	–0.536	0.065	–0.704	–0.419
Celeration	0.519	0.059	0.665	0.400
Distance	38.6	13.0	62.6	12.4

Sample 9 (*N* = 70)

Variable	*M*	*SD*	Max	Min
Acceleration	0.577	0.064	0.726	0.477
Deceleration	–0.538	0.070	–0.731	–0.412
Celeration	0.521	0.062	0.698	0.398
Distance	37.6	15.3	62.6	12.3

Notes. Mean values differ very little between samples. These data are therefore not shown for the other samples. The minimum and maximum values of deceleration have been switched, as strength goes up with lower (negative) values, and the values for celeration are lower than those for acceleration and (absolute) deceleration, as it is calculated including the zero celeration values (even speed), thus “diluting” the mean with zeroes.

3. RESULTS

Differing *N*s will be reported in the various calculations, as the number of subjects available for each calculation was due to factors like replacement of drivers by the company over time, unreliable data, and how many times a driver had been measured.

It can be seen in Table 2 from the group means and standard deviations of the celeration variables that the drivers tended to drive in a slightly less forceful way during the winter, at least when the first snow had fallen (sample 4). Otherwise, the differences were slight between samples, i.e., over time and to some degree among subjects. The distance reported is that used for calculating the celeration variable. As it differs somewhat (or even rather much in some cases), this aspect of the methodology might actually insert some error variance.

TABLE 3. The Pearson Correlations Between the Celeration Variables and the Number of Responsible Accidents for All Samples. In the Next to Last Column, the Mean of These Correlations, Calculated as the Square Root of the Mean of the Squared Correlations, Unweighted for *N*. Finally, to the Utmost Right, the Correlations of Accidents With the Mean of All Available Measurements From Each Set for Each Driver on the Three Predictor Variables.

Sample	1	2	3	4	5	6	7	8	9	*M* of 1–9	1–9 Aggregated
N	203	142	80	169	81	54	163	107	70	118.8	243
Celeration	.125	.203*	.311**	.232**	.106	.197	.175*	.193*	.332**	.220	.220***
Acceleration	.112	.152	.310**	.223**	.094	.181	.179*	.206*	.355**	.217	.185**
Deceleration	–.094	–.226**	–.247*	–.227**	–.085	–.217	–.139	–.163	–.235	–.191	–.198**

Notes. The first set (samples 1–9) was measured in 2001–2002 (1–9 measurements per driver, *M* 4.4) and used accidents 2001–2002 as dependent variable. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Sample	11	12	13	14	15	16	17	19	20	21	*M* of 11–21	11–21 Aggregated
N	145	71	174	143	108	149	93	130	73	40	112.6	224
Celeration	.290***	.146	.139	.294***	.231*	.250**	.185	.225**	.151	.266	.225	.223***
Acceleration	.274***	.079	.161*	.252**	.203*	.246**	.193	.200*	.119	.207	.216	.226***
Deceleration	–.280***	–.226	–.102	–.240**	–.236*	–.232**	–.140	–.189*	.009	–.211	–.197	–.187**

Notes. The second set (samples 11–21) was measured in 2002–2003 (1–10 measurements per driver, *M* 5.1) and used accidents 2002–2003 as dependent variable. Samples 10 and 18 excluded due to too few cases. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Sample	22	23	24	25	26	27	*M* of 22–27	22–27 Aggregated
N	181	149	123	100	78	80	118.5	189
Celeration	.193**	.246**	.261**	.129	.150	.173	.198	.214**
Acceleration	.187*	.247**	.214*	.146	.067	.120	.174	.183*
Deceleration	–.154*	–.192*	–.247**	–.078	–.177	–.222*	–.186	–.181*

Notes. The third set (samples 22–27) was measured in 2003–2004 (1–7 measurements per driver, *M* 3.8) and used accidents 2002–2003 as dependent variable. Sample 28 excluded due to too few cases. $^{*}p < .05$, $^{**}p < .01$.

As data had been gathered for several years, different periods were used to form the dependent variable. Therefore, the data was split into three sets, which also served the purpose of covering about a year each (fall–winter–spring). Summer data was not used, due to very little traffic and in general a very different traffic environment. Table 3 illustrates the correlations computed between the celeration variables in each sample and the number of accidents over two different 2-year periods (the period closest in time to when the sample correlated with it was gathered). The mean of these correlations in each set of samples was also calculated.

Also, the measurements were aggregated over samples, i.e., a mean celeration behavior (in the sense of (c) was calculated for each driver for three different periods. These aggregates were then used as correlates, and the results are shown in the most right-hand column in Table 3. It can be seen that the aggregation of celeration data over samples has pretty much the same effect as computing the mean correlation over samples. The differences between the correlations of celeration versus acceleration/deceleration all had alpha levels below .10 but above .05 (significance test for difference between dependent correlations) for the aggregated data, apart from acceleration in the second set, where the difference was contrary to prediction.

Concerning the period chosen for correlation with the predictors, it should be pointed out that several periods of differing length were tested. One-year periods yielded similar but worse results than 2 years, and longer periods yielded mainly non-significant correlations.

Thereafter, a multiple regression analysis was undertaken with the confounding variables that were available (gender, age, ethnic origin and

TABLE 4. The Difference in Mean Celeration (m/s^2) Levels (Aggregated Over Samples) Among Groups of Drivers With Differing Numbers of Accidents During 2001–2002 (1–9) and 2002–2003. Analysis of Variance Calculated. Tukey Post-Hoc Tests Indicated That in All Cases the Effect Was Carried by the Last Group (3–4)

No. of Accidents	0	1	2	3–4	*F*	*dt* Error	*p*
N	159	53	23	8			
M celeration 1–9	0.526	0.531	0.553	0.575	4.05	239	< .01
N	143	57	16	8			
M celeration 11–21	0.491	0.500	0.518	0.548	3.41	220	< .01
N	121	48	12	8			
M celeration 22–27	0.475	0.483	0.494	0.529	3.62	185	< .05

Notes. dt—delta time.

experience) as predictors along with each of the acceleration variables in the aggregated form (as seen in Table 3, right-hand column). The results were that, out of nine regressions run, only in one instance did one of the other variables (ethnic origin) add significantly to the model. Therefore, in accordance with theory [10], these variables do not seem to add any predictive power beyond what celeration yields.

The effect of celeration on accidents can also be expressed as the difference in celeration level between those with different numbers of incidents (see Table 4 for aggregated samples). As might be noted, all samples proceed in the same order of magnitude; a higher celeration group mean indicates a higher accident group mean.

Thereafter, the regression equation for the correlation between the mean celeration of samples 1–9 and accidents 2001–2002 (right-hand column in Table 3) was used to predict the accidents of 2002–2003 for the drivers in samples 22–27. Using only a dichotomized grouping (no accidents versus accidents), a cut-off point at 0.5 predicted accidents correctly identified 63% of drivers, as compared to the random allotment result of 50%. Overlap between predicted and original sample was 151 drivers.

As for the stability of celeration behavior, the correlation between mean values in samples 1–9 and 22–28 was .64 (p < .001) for drivers with at least four measurements in each period (N = 60). The time elapsed between measurements in the two periods was at least 14 months, and a maximum of more than 3 years. This result indicates an increase in stability with aggregation of data, as expected.

Finally, celeration behavior correlated above .90 with acceleration and deceleration in the first nine samples, and .20–.60 with mean speed of driving. It should, however, be remembered that the celeration variable partly includes speed [10] if conceptualized as the mean of movement (not the time to get from point A to point B). If mean speed on the other hand is calculated including standstills along the route, there is no association with celeration behavior [7, 9].

4. DISCUSSION

Despite the shifting results in the un-aggregated data, the present work lends some support to the basic prediction of the driver celeration behavior theory; that there is a positive association between celeration behavior and traffic accidents. However, it would also seem to be clear that the predictive power over time is rather limited, given the present amount of data and method, 2 years yielding the only useful correlations. Given the not very high stability of the celeration variables (see below), and even lower intercorrelations of accidents between years (preliminary, unpublished analyses) in the population studied, this was expected (for examples of calculations on the stability of accident record over time on similar populations, see Häkkinen [5], Cresswell and Froggatt [37], Milosevic and Vucinic [38]).

Concerning the interpretation of the differences in correlation values between celeration and acceleration/deceleration, none of these were significant at the $p < .05$ level. However, five out of six differences were as predicted and significant at $p < .10$. This would seem to lend some weak support to the prediction of celeration as the best correlate, although the difference is probably so slight as to have little practical impact.

Turning to the aggregation of data, the differences between aggregating over correlations (taking the mean over samples) or aggregating celeration data and correlating with accidents would seem to be slight. This was not quite as expected, but was probably due to the drivers with few measurements still inserting a high degree of error into the aggregation over measurements. However, the question about the effects of aggregation will need to be studied further.

There are also several other methodological points concerning the celeration variable that so far have not been adequately addressed. First, the stability over time did not increase as expected with increased amounts of data per measurement day (compare the results in af Wåhlberg [7, 8]), where the correlations between measurements were similar, despite large differences in the amount of data from each day). Several reasons may be suspected, such as differences in weather, number of passengers and traffic. However, several of these have been investigated and not found to be very strong. Instead, it would seem that it is the amount of time between measurements that add error variance [7]. But then the question arises why this is so. Why does a driver change his style over time in a so far unpredictable manner? Apart from random happenings such as a row at home, or a particularly nasty passenger, there is one possible, and testable, confounder; accidents. How people react to accidents in terms of their own driving is hardly researched at all, but some researchers claim that avoidance and other reactions are at hand after accidents [39, 40, 41, 42, 43, 44], outcomes that would make us expect that the occurrence of an accident would decrease the probability of having another one. However, Blasco, Prieto and Cornejo [32] found just the opposite, namely that accidents tend to cluster in time. Their conclusion was that having an accident changes in some way people's driving—towards a more negative emotional state, which in turn predisposes them to having another crash. This hypothesis has two weak points; why would a person become more risky instead of more careful in his/her driving after an adverse event, and especially, how can the trend be broken, i.e., why is there not an infinite regression towards an infinite number of accidents? Despite these problems, the data presented by Blasco et al. agrees with their hypothesis. However, you might as well assume that the clustering is caused by another semi-stable factor, like a stressor. That stressing life events may cause a temporary increase in accident proneness has been found by Selzer and Vinokur [45], Selzer, Rogers and Kern [46], McMurray [47] and Holt[8] [48], while Isherwood, Adam and Hornblower [49] did not find anything of the kind.

Another possible confounder was found during an analysis of data for another part of the project that provided the celeration data; daylight. In some calculations it was found that mean level of celerations changed with temperature. However, this was suspected to be an artifact of temperature correlating with the amount of daylight; the real association being drivers accelerating less during dark hours. This suspicion is in accordance with the finding of Fuller [50] that truck drivers kept longer headways during late shifts, which occurred mainly during darkness, and will be tested on the present data in the future.

The present results have been found for bus drivers in a Swedish town of some size, putting strong limits on the generalization of results. However, the theory behind the study predicts that the same kind of association would exist in all populations, with the only limitation being that raw values may not be comparable between environments and vehicles, a problem that a weighting factor calculated from the means of the populations ought to be able to handle, or a standardization of values.

The use of several different periods for calculating accident frequency is a fairly novel methodological tool (previously used by Quimby

[8] The methodology of those four studies was of low quality.

and Watts [51], who found 2 years to be better than 3; and Ball, et al. [16], where 5 years was superior to shorter periods). Most studies of accident prediction would seem to pick a period without any justification at all (see af Wåhlberg [1], for a review and discussion). Given the present results and those of previous studies, it would seem justified to repeat the advice that researchers study their predictors from the viewpoint of the prediction time range.

Returning to the level of predictive power of celeration found in this study, it should be emphasized that the method used was rather basic. In fact there are a number of methodological and theoretical tools that may be applied to data of this type and which are expected to increase the predictive power. These include further aggregation of celeration data, and holding constant the influence of traffic density, amount and type of exposure. When these methods have been developed, it is expected that correlations with accidents will increase substantially. It should also be borne in mind that the presently used measurement method is only an approximation for the theoretical variable, both in terms of amount and type of data.

The findings in the present study, as well as the general approach to the causes and predictions of crashes, would seem to be at odds with the view recently forwarded that human error is "...not an explanation of failure..." and that "...effective countermeasures start not with individual human beings...but rather with the error-producing conditions present in their working environment" (p. 371) [52]. Incidentally, the author also claims that "most of those involved in accident research and analyses are proponents of the new view" (p. 372). Despite the possibility that the criticism of the habit of accident researchers of simply blaming human error for any mishap is valid, this would seem to be expanded into a sort of system view where humans have no individual influence, as all blame is instead on the system, and anyone in the same situation would seem to be expected to have done the same acts (which lead to an accident). This reasoning overlooks two or three very basic findings about humans and accidents; behavior varies between people, even when the situation is exactly the same, while some stability of behavior is present for the individual, even when circumstances change, and there is some stability in accident liability [5, 32, 37, 38]. None of these findings fit into "the new view". The present work (and of course a large number of other psychological studies) instead indicates that traffic accident involvement can be predicted from the behavior of those involved over long periods of time. While this does not exclude that the system has detrimental influences on the behavior of the drivers, it does invalidate the extreme view that "human error is a symptom of trouble deeper inside the system" (p. 372) [52] and nothing much else (see also McKenna [53] for similar though less extreme views).

The theory of driver celeration behavior describes the relationship between individual celeration behavior and traffic accident record, and make predictions about the relations between various predictors of accidents. However, the theory does not state how or why celeration behavior originates, why it differs between drivers and so forth. In essence, all the favorite subjects of psychologists are missing. This is due to the main goal of this research being finding a strong predictor of traffic accidents which could be practically useful. This goal excluded, on theoretical grounds, the use of variables not directly related to driving, like personality and intelligence. Also, many such variables have been tested, and not fared well as predictors of accidents (see reviews [54, 55, 56, 57, 2, 58, 59] and the meta-analysis by Arthur, Barrett and Alexander [60]). However, when celeration behavior has been thoroughly tested and found to be predictive of accidents and its related phenomena, in accordance with theory, the time will have come to turn to the these distal variables and try to ascertain why celeration behavior differ between and within individuals as it does [7]. For methodological and practical reasons it would seem to be most important to start with the within-subject variation, as it makes single measurements fairly unreliable, and determinants of sudden high peaks in a driver's behavior could be useful for safety work.

It has been suggested that the celeration variable might be due to differences in impulsivity, a part of neuroticism in the Big Five personality inventory. Such a proposition is compatible with the celeration theory, as there is no theoretical connection between them, and a lack of data on this possible association. It should also be noted that all the Big Five dimensions seem to be modestly related to accident involvement [61].

The time would seem to be ripe to suggest that the driver celeration measure should be introduced into research and practical settings on a larger scale than hitherto. In the present paper and others it has been shown to be associated with traffic accidents, but other work has also found correlations with fuel consumption [14] and passenger comfort [15]. Furthermore, its psychometric and statistical qualities are acceptable [7], and should be possible to increase further with more aggregation of data [62]. This would seem to argue strongly in favor of using this variable for all types of driver studies, but also as an objective measure in training and testing situations, and above all for continuous surveillance and feedback. There is of course a need for further validation in different settings, but the evidence so far seems to indicate that the properties of this measure compare rather favorably to most other variables and concepts used when it comes to measuring and predicting driver behavior.

REFERENCES

1. af Wåhlberg AE. Some methodological deficiencies in studies on traffic accident predictors. Acci Anal Prev. 2003;35:473–86.
2. Lester J. Individual differences in accident liability: review of the literature (RR306). Crowthorne, UK: Transport and Road Research Laboratory; 1991.
3. Harano RM, Peck RC, McBride RS. The prediction of accident liability through biographical data and psychometric tests. J Saf Res. 1975;7:16–52.
4. Asher W, Dodson B. Automobile accidents in the year following high school: the predictive value of 377 unobtrusive variables. Beh Res Highway Saf. 1971;2:107–22.
5. Häkkinen S. Traffic accidents and driver characteristics [doctoral dissertation]. Helsinki, Finland: Finland's Institute of Technology; 1958.
6. af Wåhlberg AE. The relation of acceleration force to traffic accident frequency: a pilot study. Transportation Research Part F: Traffic Psychology and Behaviour. 2000;3:29–38.
7. af Wåhlberg AE. Stability and correlates of driver acceleration behaviour. In: Dorn L, editor. Driver Behaviour and Training, Proceedings of the First International Conference on Driver Behaviour and Training. Aldershot, UK: Ashgate; 2003. p. 45–54.
8. af Wåhlberg AE. The stability of driver acceleration behavior, and a replication of its relation to bus accidents. Acci Anal Prev. 2004;36:83–92.
9. af Wåhlberg AE. Speed choice versus celeration behavior as traffic accident predictor. J Saf Res. 2006;37:43–51.
10. af Wåhlberg AE. Driver acceleration behavior and accidents—an analysis [manuscript submitted for publication]. Available from: http://www.psyk.uu.se/hemsidor/busdriver/af%20Wahlberg%20Driver%20celeration%20behavior-2005.pdf
11. Lajunen T, Summala H. Effects of driving experience, personality, driver's skill and safety orientation on speed regulation and accidents. In: Rothengatter T, Carbonell Vaya E, editors. Traffic and transport psychology, theory and application. Amsterdam, The Netherlands: Pergamon; 1997. p. 283–94.
12. Lajunen T, Karola J, Summala H. Speed and acceleration as measures of driving style in young male drivers. Perc Mot Skills. 1997;85:3–16.
13. Quimby A, Maycock G, Palmer C, Grayson GB. Drivers' speed choice: an in-depth study (TRL326). Crowthorne, UK: Transport Research Laboratory; 1999.
14. af Wåhlberg AE. Fuel efficient driving training—state of the art and quantification of effects. In: Proceedings of Soric'02. Manama, Bahrain; 2002. Available from: http://www.psyk.uu.se/hemsidor/busdriver/af_Wahlberg_Fuel_efficient_driving_training.pdf

15. af Wåhlberg AE. Short-term effects of training in economical driving; passenger comfort and driver acceleration behavior. Int J Indust Ergo. 2006;36:151–63.
16. Ball K, Owsley C, Sloane ME, Roenker DL, Bruni J. Visual attention problems as predictor of vehicle crashes in older drivers. Invest Ophthal Visual Sci. 1993;34: 3110–23.
17. af Wåhlberg AE. Characteristics of low speed accidents with buses in public transport. Acci Anal Prev. 2002;34:637–47.
18. af Wåhlberg AE. On the validity of self-reported traffic accident data. In: Proceedings of Soric'02. Manama, Bahrain; 2002. Available from: http://www.psyk.uu.se/ hemsidor/ busdriver/af_Wahlberg_On_the_validity_of_self-reported_accident_data.pdf
19. Garretson M, Peck RC. Factors associated with fatal accident involvement among California drivers. J Saf Res. 1982;13: 141–56.
20. Cation WL, Mount GE, Brenner R. Variability of reaction time and susceptibility to automobile accidents. J Appl Psy. 1951;35:101–7.
21. McBain WN. Arousal, monotony, and accidents in line driving. J Appl Psych. 1970;54:509–19.
22. Chapman P, Underwood G. Forgetting near-accidents: The roles of severity, culpability and experience in the poor recall of dangerous driving situations. Appl Cogn Psy. 2000;14:31–44.
23. Maycock J, Lockwood C, Lester JF. The accident liability of car drivers (RR315). Crowthorne, UK: Transport and Road Research Laboratory; 1991.
24. Maycock G, Lester J. Accident liability of car drivers: follow-up study. In: Grayson GB, editor. Behavioural research in road safety V. Crowthorne, UK: Transport Research Laboratory; 1995. p. 106–20.
25. Pelz DC, Schuman SH. Dangerous young drivers. Highway Res News. 1968;33: 31–41.
26. Burns PC, Wilde GJ. Risk taking in male taxi drivers: relationships among personality, observational data and driver records. Pers Ind Diff. 1995;18:267–78.
27. Dalziel JR, Job RF. Motor vehicle accidents, fatigue and optimism bias in taxi drivers. Acc Anal Prev. 1997;29:489–94.
28. Gordon JE, Gulati PV, Wyon JB. Reliability of recall data in traumatic accidents. Arch Environ Heal. 1962;4:575–8.
29. Smith RN. The reporting level of California State Highway accidents. Traffic Eng. 1966;29:20–5.
30. Fife D, Cadigan R. Regional variation in motor vehicle accident reporting: findings from Massachusetts. Acc Anal Prev. 1989;21:193–6.
31. Várhelyi A, Hjälmdahl M, Hydén C, Draskóczy M. Effects of an active accelerator pedal on driver behaviour and traffic safety after long-term use in urban areas. Acci Anal Prev. 2004;36:729–37.
32. Blasco RD, Prieto JM, Cornejo JM. Accident probability after accident occurrence. Saf Sci. 2003;41:481–501.
33. af Wåhlberg AE. Characteristics of low speed accidents with buses in public transport. Part II. Acci Anal Prev. 2004;36:63–71.
34. af Wåhlberg AE. Differential accident involvement of bus drivers. In: Dorn L, editor. Driver behaviour and training. Volume II, Proceedings of the Second International Conference on Driver Behaviour and Training. Ashgate: Aldershot, Hants., UK; 2005. p. 383–91.
35. McKenna FP. Accident proneness: a conceptual analysis. Acci Anal Prev. 1983;15:65–71.
36. Arthur W Jr, Doverspike D. Locus of control and auditory selective attention as predictors of driving accident involvement: a comparative longitudinal investigation. J Saf Res. 1992;23:73–80.
37. Cresswell WL, Froggatt P. The causation of bus driver accidents: an epidemiological study. London, UK: Oxford University Press; 1963.
38. Milosevic S, Vucinic S. Statistical study of tram drivers' accidents. Acci Anal Prev. 1975;7:1–7.
39. Foeckler M, Hutcheson F, Williams C, Thomas A, Jones T. Vehicle drivers and fatal accidents. Sui Life Threat Beh. 1978;8: 174–82.

40. Mayou RA, Bryant B, Duthie R. Psychiatric consequences of road traffic accidents. Brit Med J. 1993;307:647–51.
41. Mayou RA, Simkin S, Threlfall J. The effects of road traffic accidents on driving behaviour. Injury. 1991;22:365–8.
42. Maag U, Vanasse C, Dionne G, Laberge-Nadeau C. Taxi drivers' accidents: how binocular vision problems are related to their rate and severity in terms of the number of victims. Acci Anal Prev. 1997;29:217–24.
43. Rajalin S, Summala H. What surviving drivers learn from a fatal accident. Acci Anal Prev. 1997;29:277–83.
44. Stewart AE, St Peter CC. Driving and riding avoidance following motor vehicle crashes in a non-clinical sample: psychometric properties of a new measure. Beh Res Ther. 2004;42:859–79.
45. Selzer ML, Vinokur A. Role of life events in accident causation. Ment Health. 1975;2: 36–54.
46. Selzer ML, Rogers JE, Kern S. Fatal accidents: The role of psychopathology, social stress, and acute disturbance. J Psychi. 1968;124:1028–36.
47. McMurray L. Emotional stress and driving performance: The effect of divorce. Behav Res Highway Saf. 1970;1:100–14.
48. Holt PC. Stressful life events preceding road traffic accidents. Injury: Brit J Acci Surg. 1982;13:111–5.
49. Isherwood J. Adam KS, Hornblower AR. Life event stress, psychosocial factors, suicide attempts and auto-accident proclivity. J Psychoso Res. 1982;26:371–83.
50. Fuller RG. Determinants of time headway adopted by truck drivers. Ergonomics. 1981;24:463–74.
51. Quimby AR, Watts GR. Human factors and driving performance (TRRL1004). Crowthorne, UK: Transport and Road Research Laboratory; 1981.
52. Dekker SW. Reconstructing human contributions to accidents: the new view on error and performance. J Saf Res. 2002;33:371–85.
53. McKenna FP. The human factor in driving accidents: An overview of approaches and problems. Ergonomics. 1982;25:867–77.
54. Signori EI, Bowman RG. On the study of personality factors in research on driving behavior. Perc Mot Skills. 1974;38: 1067–76.
55. McGuire FL. Personality factors in highway accidents. Hum Fact. 1976;18:433–42.
56. Golding AP. Differential accident involvement: a literature survey (Report PERS 356). Johannesburg, South Africa: National Institute for Personnel Research, Council for Scientific and Industrial Research; 1983.
57. Hansen CP. Personality characteristics of the accident involved employee. J Bus Psyc. 1988;2:346–65.
58. Elander J, West RJ, French DJ. Behavioral correlates of individual differences in road-traffic crash risk: an examination of methods and findings. Psy Bull. 1993;113:279–94.
59. Peck RC. The identification of multiple accident correlates in high risk drivers with specific emphasis on the role of age, experience and prior traffic violation frequency. Alco Dr Dri. 1993;9:145–66.
60. Arthur W Jr, Barrett GV, Alexander RA. Prediction of vehicular accident involvement: a meta-analysis. Hum Perf. 1991;4:89–105.
61. Clarke S. Robertson IT. A meta-analytic review of the Big Five personality factors and accident involvement in occupational and non-occupational settings. J Occup Organiz Psychol. 2005;78:355–76.
62. Rushton JP, Brainerd CJ, Pressley M. Behavioral development and construct validity: the principle of aggregation. Psych Bull. 1983;94:18–38.

APPENDIX

Calculation of Predictor Variables and Ordering of Measurements

All predictor variables come from the same data; measurement of pulses from the speedometer system of the buses. These pulses signify that a certain length of road has been traveled (for the buses in the present study 1/6900 of a kilometer). By counting the number of pulses for a period (given by the internal clock of the measurement system), it is possible to calculate mean speed during this period.

The speed signal is tapped from the vehicle's speedometer with a frequency of 10 Hz, an interval of 100 ms. During this interval, the number of complete pulse-cycles is counted, and speed and acceleration calculated with the following formulas.

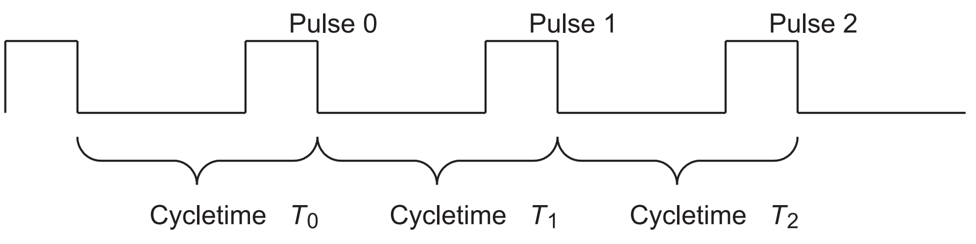

Figure 1. Example.

Example

$t = T_0 + T_1 + T_2$,
$n = 3$.

Speed calculation formula:

$v = ((n/t)/w) \bullet 1000$,

where v—speed (m/s), n—number of pulses from the speedometer, t—time for n pulses to accumulate (s), w—pulses per kilometer.

Acceleration calculation formula:

$$a_{(4\,n)} = ((v_{(4\,n)} + v_{(4\,n+1)} + v_{(4\,n+2)} + v_{(4\,n+3)})/4 - (v_{(4\,n)} + v_{(4\,n-1)} + v_{(4\,n-2)} + v_{(4\,n-3)})/4)/2.5,$$

where a—acceleration (m/s^2), v—speed (m/s), n—number of acceleration measurement points.

Calculation of Predictors

The data from the measurement system was given as several columns of values (of which only speed change is of importance here), with each case representing a time frame (0.4 s for speed changes). From such a file the values of the predictors were computed as a mean for a time segment (cases 1 to n), which had been identified as having been driven by a certain driver.

Celeration was calculated as the absolute mean of all speed changes when $v > 0$. Deceleration and acceleration were similarly calculated as means from all values below –0.045 m/s^2 and above 0.045 m/s^2, respectively.

Ordering of Measurements

As measuring was operative continuously for several years, drivers who worked a lot, and on certain duty rotation lists, tended to be measured several times, while others were rarely so. To utilize as much data as possible, but still retain a data arrangement that was ordered in time, these repeated measurements were ordered into samples within periods. One such period can be seen in Table A1 (where numbers designate measurement order, i.e., 1 is the first measurement of this driver). It shows that driver Nilsson was measured three times during the fall season. These three measurements were easily ordered into the three samples of this period. Driver Jonsson, on the other hand, was only measured twice, and would therefore be absent from the third sample. Note also that despite the first measurements of Nilsson and Jonsson being a month apart, these would still both be ordered into the first sample. Finally, although Andersson was among the last to be measured, his single value would still be put with other first measurements in sample 1 (Table A2).

TABLE A1. The Order of Measurements

Driver	August	September	October	November	December
Nilsson	1		2		3
Jonsson		1	2		
Pettersson			1	2	3
Andersson					1

TABLE A2. Measurements in Samples

Driver	Sample 1	Sample 2	Sample 3
Nilsson	1	2	3
Jonsson	1	2	
Pettersson	1	2	3
Andersson	1		

When the season was finished (decided by the weather), a new grouping would start, in this case winter, with three new samples (4–6), where the first measurement of each driver this season was ordered into sample 4, and so on.