

## Impacts of real-time feedback on driving behaviour: a case-study of bus passenger drivers

**Catarina Rolim<sup>1</sup>, Patrícia Baptista<sup>2</sup>, Gonçalo Duarte<sup>3</sup>**

LAETA, IDMEC, Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal  
IN+, Center for Innovation, Technology and Policy Research - Instituto Superior Técnico,  
Universidade de Lisboa, Lisboa, Portugal

**Tiago Farias<sup>4</sup>**

LAETA, IDMEC, Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal

**João Pereira<sup>5</sup>**

Laboratory of Biostatistics and Medical Informatics, IBILI – Faculty of Medicine, University of  
Coimbra, Coimbra, Portugal

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Over the years, there has been an increase in the focus on driving behaviour as a solution to minimize the road transportation high levels of energy consumption, as well as the emission of pollutants.

The aim of this study was to analyse the impacts of real-time feedback on the driving behaviour of bus drivers, and to assess the potential impact of the characteristics of these subjects (age and time working at the company) on such behaviour. Data was collected with an on-board device installed in buses of a Portuguese urban transport operator. Three monitoring periods were considered: an initial phase, in which real-time feedback was given to drivers (phase 1), followed by a period of no feedback (phase 2), and then a final stage in which feedback was resumed (phase 3). A repeated measures analysis of variance was performed to assess the impacts of feedback in several driving indicators across the aforementioned phases. The results revealed that bus drivers accrue benefits from the feedback received, with significant differences between the three monitoring periods for all driving indicators analysed. After suspending the feedback, increases between 6% and 55% of the incidence of undesired driving indicators were observed, mainly in extreme brakes, extreme accelerations, excess RPM, and hard stops. Such insights can provide bus operators with new tools to develop programs promoting efficient driving behaviours.

*Keywords: driving behaviour, real-time feedback, eco-driving training, bus passenger driver.*

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### 1 Introduction

The transportation sector plays a crucial role in the quality of life of the general population. It provides access to people, places and goods, presenting several choices of transportation that enable our capacity to move about. It allows us to become independent but also close

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<sup>1</sup> A: Av. Rovisco Pais, 1, Lisbon, Portugal E: [catarina.rolim@tecnico.ulisboa.pt](mailto:catarina.rolim@tecnico.ulisboa.pt)

<sup>2</sup> A: Av. Rovisco Pais, 1, Lisbon, Portugal E: [patricia.baptista@tecnico.ulisboa.pt](mailto:patricia.baptista@tecnico.ulisboa.pt)

<sup>3</sup> A: Av. Rovisco Pais, 1, Lisbon, Portugal E: [goncalo.duarte@tecnico.ulisboa.pt](mailto:goncalo.duarte@tecnico.ulisboa.pt)

<sup>4</sup> A: Av. Rovisco Pais, 1, Lisbon, Portugal E: [tiago.farias@tecnico.ulisboa.pt](mailto:tiago.farias@tecnico.ulisboa.pt)

<sup>5</sup> A: Azinhaga Santa Comba, Celas, 3000-548 Coimbra E: [joao.mspereira@gmail.com](mailto:joao.mspereira@gmail.com)

to each other. This sector, however, also faces harsh criticisms due to its fossil fuel dependency, increasing energy consumption, pollutants emissions, congestion levels, and noise pollution. In 2013, the transportation sector was responsible for 32% of the sector final energy consumption in Europe (EUROSTAT, 2014). Solutions to overcome these trends in the transportation sector have focused essentially on the development of alternative vehicle technologies and energy sources, not only leading to improvements in fuel efficiency (Saboohi & Farzaneh, 2009), but also in information and communication technologies (ICT). The latter can reduce traffic congestion, improve navigational performance, decrease the likelihood of accidents, reduce fuel costs, air pollution, and increase driver efficiency (Mannering, Kim, Ng & Barfield, 1995). Besides these, growing attention has been given to behaviour, in particular to the effects of education, training and feedback on driving performance, vehicle purchase decisions and mobility patterns. ICT solutions, such as on-board monitoring devices, can collect information on driving patterns (e.g. speed, idling time, mileage, number of accelerations and decelerations, etc.) allowing the drivers to (i) understand their driving behaviour and, consequently, (ii) educate them towards more efficient driving habits (Larsson & Ericsson, 2009; Rolim, Baptista, Duarte & Farias, 2014) and safer driving patterns, while also leading to (iii) improvements in road safety, as well as (iv) decreases in fuel consumption and consequent pollutants emissions (Wälberg, 2007). The deployment of these technologies, associated with educational programs, can be used as a tool in different contexts and services to promote behavioural change.

Several studies have been developed to assess the impact of education, training and feedback on driving behaviour (Barth & Boriboonsomsin, 2009; Beusen et al, 2009; Dijksterhuis et al, 2015; Jamson, Hibberd & Jamson, 2015; Pampel, Jamson, Hibberd & Barnard, 2015; Rolim et al, 2016, Tulusan, Stegger, Staake & Fleisch, 2012) but these target mainly drivers of light-duty vehicles. While some studies have been performed focusing on heavy-duty vehicles (e.g. buses), these are essentially short-term studies addressing fuel consumption improvements based on efficient driving training (Rohani, 2012; Rohani, Wijeyesekera & Karim, 2013; Strömberg & Karlsson, 2013; Wälberg, 2007; Zarkadoula, Zoidis & Tritopoulou, 2007;), with little focus on the impacts of feedback, particularly, real-time feedback on behaviour changes. As such, the main contributions of this paper will be to quantify the long-term impacts of real-time feedback on the adoption of efficient driving behaviours in a fleet of passenger urban buses. Additionally, this study will assess the potential impact of drivers' characteristics (age and time working at the bus company) on behaviour changes. Driving behaviour was evaluated with data collected from an on-board device installed in 385 passenger urban buses from a Portuguese urban transport operator. Results can provide fleet managers, large fleet companies or public transport providers with innovative tools to develop and implement programs to supervise, evaluate and reward the performance of the drivers based on real-driving data and drivers' performance to achieve targets for fuel consumption, emissions, and overall cost reductions.

### *1.1 Driving behaviour characterization*

Changing behaviour to achieve more sustainability is difficult, since the measures applied will face limitations and acceptance resistance from the users (Prillwitz & Barr, 2011). According to Goldenbeld, Leveit & Heidstra (2000), these measures ultimately give order, stability, and, to a certain extent, security, contributing to the efficiency of several behaviour routines. Ouellete & Wood (1998) found evidence that a repetitive practice of behaviour in constant contexts will lead to automatic behaviour patterns without conscious deliberation. A high percentage of driving behaviours are habits, which explains why it is so difficult to change them. In order to change habitual behaviour, it is necessary to make people more aware of the original choice process that preceded the actual behaviour.

Driving activity is broadly composed of two variables: i) performance (skills of the driver) and ii) behaviour (drivers driving style). The former can improve with practice and

training since it is related to information processing and motor skills. The latter is linked to drivers' choices and habits, e.g. speeding or aggressiveness. Driving style is shaped by drivers' characteristics, which include intrinsic factors such as gender and age, as well as extrinsic variables such as social context (Özkan, Lajunen, Chliaoutakis, Parker & Summala, 2006). Driving behaviour will echo not only the drivers psychological profile, but also the context in which the driving occurs, leading e.g. to rises in alertness and aggressiveness (Murcotts Driving Excellence, 2015).

Intention, habit, and perceived behaviour are among the variables with a considerable impact on behaviour. Since they are intrinsically correlated, they must be the target when designing and implementing behaviour change measures and strategies (Gardner & Abraham, 2008). Changing behaviour can be achieved through learning; it is essential, however, to provide people with the necessary tools to enable the practice of new strategies until these become definitive (Murcotts Driving Excellence, 2015). Positive feedback and reinforcement are probably the most powerful educational elements in driving behaviour change. It has been shown that, when people have access to the results of their actions, they are more likely to change their behaviour over time (Barkenbus, 2010).

Another aspect to take into consideration is that people are different. Therefore, changing behaviour measures and policies should not be developed addressing only the average driver (Goodwin, 1995). Any strategy must consider cohort differences and should be outlined to address the different motivations and reservations of several cohorts (Raney, Mokhtarian & Salomon, 2000).

### *1.2 Public bus operator service – driving behaviour*

When developing programs for the adoption of more efficient driving techniques, a distinction between professional and private drivers must be taken into consideration. Bus drivers are among the groups of professionals that are most stressed and negatively affected by their work demands and environment. A bus fleet must maintain the quality of service and performance in order to incentivise people to keep using it, considering both local and passenger needs. Nowadays, consumers are more worried with fast and reliable services, short walking distance to stops, accessible buses, cheap services and friendly and safe drivers (Rohani; Wijeyesekera & Karim, 2013). The management department of bus operators is responsible for the improvement and preservation of the quality of service. Bus drivers, however, play a determinant role, since they are closer to the customer: they must be perceived as safe, knowledgeable and personable, not an easy task when considering the demands of the job (Rohani; Wijeyesekera & Karim, 2013; Dorn, Stephen, Wählberg & Gandolfi, 2010). In fact, a review of the well-being of bus drivers revealed that they are likely to suffer from ill health due to stress (Tse, Flin & Mearns, 2006).

Public bus operation services depend on external (e.g. economic factors) and internal (e.g. service quality) factors. The latter must be taken into account by the agencies when defining operational goals (Rohani, 2012). Several solutions can be deployed to maintain the quality of service while reducing fuel consumption and operational costs. These measures can be applied at a vehicle, driver and traffic management level. The adoption of traffic management solutions and programs designed to educate the driver towards sustainable behaviours are mainly directed towards behaviour changes in terms of e.g. accelerations, braking, and excess speeding, while always taking into consideration the service level (WSP, 2012).

Significant improvements on fuel efficiency can be achieved with driving behavioural changes, imposing minimum costs to the operators (Rohani, 2012). Educational tools based on eco-driving are simple and easy to communicate to the drivers; the challenge, however, lies in incentivizing them. On-board monitoring devices can be used to provide feedback to the bus drivers regarding fuel consumption and other driving indicators (Wählberg, 2007).

Several studies have been performed to analyse the use of feedback and training on driving behaviour. Fleet safety managers have indicated that the effectiveness of training and educational tools on driving behaviour decreases as they become less frequent (Hickman, Hanowski & Ajayi, 2009).

Several studies have proven that training has a short-term effect on behaviour, though no long-term effect was observed, mainly on fuel consumption, accident rate and acceleration (Wålberg, 2007; Zarkadoula, Zoidis & Tritopoulou, 2007). Acceleration levels have been linked with fuel consumption rates, with more than 50 mL of fuel saved per acceleration if the bus driver decreases the rate of acceleration when leaving a stop (Rohani, Wijeyesekera & Karim, 2013). Results from a research study performed in Sweden with two groups of drivers (one received real-time feedback while the other also participated in training sessions) revealed that both groups responded similarly, with reduced fuel consumption and frequency of undesired behaviour, a strong indicator of the efficacy of the feedback (Strömberg & Karlsson, 2013). Studies analysing the impacts of individual factors on driving behaviour have identified characteristics such as age, gender, driving experience, socio-economic and educational status, and personality traits, among others, as correlated with riskier behaviours (Lancaster & Ward, 2002). Mather (2007) found that there are age differences in driving, with older drivers being more prone to present undesired behaviours in certain situations. Nonetheless, it remains to be assessed if these differences are caused by aging, or rather by the learning context. Older drivers (more than 46 years) were found to present a more positive reaction to enforcement penalties, presenting a less aggressive driving behaviour when compared to younger drivers (Andy, 2006).

## 2 Methodology

### 2.1 Bus passenger transport company – Rodoviária de Lisboa

This study was performed with the collaboration of Rodoviária de Lisboa S.A., a Portuguese urban transport operator, with a total of 385 mini, standard and articulated buses. In 2011, a total of 20 million km were travelled, serving approximately 61 million passengers. The almost 600 drivers of the company are divided between three Activity Centres within Lisbon's metropolitan area (Odivelas with 216 drivers; Vila Franca de Xira with 122 drivers; and Loures with 249 drivers).

Since 2004, the company has invested on increasing the quality of service, taking into consideration both the employee and passenger needs, as well as the reduction of the environmental impact, as measured by fuel consumption and pollutant emissions. This program combines vehicle monitoring during regular operation to collect driving data, as well as in-class training. Drivers are subjected to annual in-class training sessions, based on their driving performance indicators obtained with a data logger. In these sessions, eco-driving techniques are presented.

### 2.2 Experimental tool - GISFROT/VDO-FM2000 Plus

Since 2008, Rodoviária de Lisboa uses a data logger (VDO-FM2000 Plus) and a managing software platform, named GISFROT, developed by the company. This device collects data from vehicle and engine speed directly from the tachograph and a maximum of 8 digital/analogue inputs at a 1 Hz frequency (Kienzle-VDO, 2011). Collected data includes excess speeding, extreme brakes and accelerations, excess rotations per minute (RPM) and speed, among other indicators. The device is used to identify undesirable behaviours and to indicate them as they occur to the driver through a sound signal. At the end of a working day, all trips are imported through a software, also developed by Rodoviária de Lisboa. This software combines the information of the vehicle with the driver and route scheduling, creating a database where drivers can be compared and ranked, based on a

weighted average of the most important events. The device is currently installed in 100 buses. Approximately 600 drivers use these vehicles across the company's three activity centres, in the Lisbon metropolitan area.

### 2.3 Procedure

A case-study, with a sample of drivers, belonging to one of the company's operating centre (Caneças) was selected. The impacts of real-time feedback (sound signals) on driving behaviour were assessed considering three monitoring periods, as described in Table 1:

**Table 1. Description of three monitoring periods.**

	Type of feedback	Time period
Phase 1	Real-time feedback	October 2010 – September 2011
Phase 2	No feedback	October 2011 – September 2012
Phase 3	Real-time feedback	October 2012 – June 2013

The results present the comparison between the three monitoring periods, considering the impacts of real-time feedback on the performance of driving indicators, as well as the effect of demographic characteristics (e.g. age and time working at the company). The main driving indicators analysed were: hard stops and starts, extreme acceleration and braking, idling, excess RPM and speed. Data in each of these indicators refer to the percentage of time each driver spent in each of these "undesirable events". The sound signals providing real-time feedback to the drivers were the same for all driving indicators in the analysis.

### 2.4 Drivers characterization

A sample of 204 drivers participated in this study. As seen in Table 2, drivers had an average age of approximately 42 years, and an experience (defined as time working at the company) of approximately 10 years. Drivers have participated in training sessions developed by the company to promote eco-driving behaviours. These sessions occurred mainly in Phase 1 of this experiment, with a total of 220 hours of sessions, with an average of 1 monitoring hour per driver (Table 3.). No sessions were promoted during phases 2 and 3. As for the drivers' logging to the online platform to check their driving performance (though data was only available for the year 2012), in Phase 2 a total of 767 logs were recorded, with an average of approximately 4 logs per driver. A decrease of 60% on the number of accesses was observed in Phase 3, with a total of 300 logs and an average of 1.5 logs per driver (see Table 3.). A total of 93 397 hours of driving under regular operation were monitored throughout the three phases. Phase 1 presented the higher number of monitored hours, with an average of 210 hours per driver. A decrease of 59% in the number of monitoring hours occurred between Phase 1 and Phase 3, as seen in Table 3.

**Table 2. Age and time work at the company descriptive statistics**

	N	Mean	Std. Deviation
Age (years)	204	41.8	9.6
Time working at the company (years)	204	9.8	9.1

**Table 3. Drivers' monitoring hours, participation in training sessions, and access to platform according to the three monitoring phases**

	Monitoring hours		Training sessions		Online platform access	
	Sum	Mean	Sum	Mean	Sum	Mean
Phase 1	42635	210.0	220.0	1.08	n/a	n/a
Phase 2	33360	163.5	2.0	0.01	767	3.8
Phase 3	17402	85.3	-	-	300	1.5
Total	93397	457.8	222.0	1.08	1067	5.2

### 2.5 Data analysis

A behavioural experimental study with 204 drivers was conducted. All statistical analyses were performed using the SPSS statistical package version 22 (IBM SPSS Statistics for Windows, Version 22.0. Armonk, NY: IBM Corp.). Descriptive statistics were calculated for all variables. Taking into account the longitudinal structure of the study in which the same group of individuals was measured in different conditions (three monitoring periods), a repeated measures analysis of variance (ANOVA) was performed to assess changes in the mean scores over the three conditions. While the paired sample t-test is usually used to assess mean differences in pre and post conditions, it is not applicable when more than two stages are considered, since it increases the probability of making a Type I error, hence the choice of a repeated measures ANOVA.

For the repeated measures ANOVA, feedback time was considered a within-subject variable with three conditions: real-time feedback (Phase 1), no feedback (Phase 2) and real-time feedback (Phase 3). Driving behaviour variables were introduced as dependent variables. When using repeated measures ANOVA, the assumption of sphericity must be tested to ascertain if the variances of differences between groups are equal: the Mauchly's Test of Sphericity is computed by SPSS for this purpose (perfect sphericity leads to an indicator  $\epsilon = 1$ ). When this assumption of equality/sphericity is violated, the degrees of freedom linked to the F-ratios should be corrected. As such, whenever sphericity was not assumed, a Huynh-Feldt correction was applied. This correction can be used when presents a value higher than 0.75. With results lower than 0.75, the Greenhouse-Geisser correction should be used instead (Field, 2014). Significant findings were followed up with post-hoc tests, corrected for multiple comparisons with Sidak's method, in order to compare differences over the three monitoring periods. This correction is applied when several significant tests have to be performed controlling for Type I error (Field, 2014). All effects were considered statistically significant based on a corrected alpha level of 0.05.

Spearman correlation analysis for the data revealed that age and time working at company were significantly related ( $r = 0.756$ ,  $n=204$ ,  $p<0.001$ ). Higher working time at the company was associated with higher drivers' age. As such, age was not considered when performing the repeated measures ANOVA. Time working at the company was entered as covariate in the analysis of variance. While the bus drivers were given training sessions, these occurred mainly during the first phase, and therefore the analysis of their effect on the driving behaviour was not performed. Regarding access to online information on driving performance, drivers did not access it in a consistent way over the three monitoring periods, leading to its exclusion from the analysis performed in this study.

## 3 Results

The following section presents the results obtained from the repeated measures ANOVA for the driving behaviour variables studied: hard starts, hard stops, extreme brakes, extreme accelerations, idling, excess RPM and excess speed. Table 4 presents results from the repeated measures ANOVA regarding the within-subject effects tests. Corrected post-

hoc results are presented in Table 5. The statistical analysis results are discussed on a single indicator basis in the next sections.

**Table 4. Tests of Within-subject effects for the driving indicators analysed with Sidak's method**

Driving indicator		Source <sup>1</sup>	Mean Square <sup>2</sup>	F <sup>3</sup>	Sig. <sup>4</sup>
Hard starts	Phase	Huynh-Feldt	0.026	17.769	0.000
	Phase * Time working	Huynh-Feldt	0.002	1.370	0.255
Hard stops	Phase	Sphericity assumed	0.124	33.248	0.000
	Phase * Time working	Sphericity assumed	0.011	2.868	0.058
Extreme braking	Phase	Sphericity assumed	0.230	41.723	0.000
	Phase * Time working	Sphericity assumed	0.038	6.829	0.001
Extreme accelerations	Phase	Sphericity assumed	0.450	38.115	0.000
	Phase * Time working	Sphericity assumed	0.013	1.106	0.332
Idle	Phase	Sphericity assumed	48.938	12.718	0.000
	Phase * Time working	Sphericity assumed	17.747	4.612	0.011
Excess RPM	Phase	Huynh-Feldt	5.690	17.564	0.000
	Phase * Time working	Huynh-Feldt	0.759	2.344	0.107
Excess speed	Phase	Huynh-Feldt	41.678	91.255	0.000
	Phase * Time working	Huynh-Feldt	0.220	0.483	0.599

1 - Test assumed considering variances of differences between conditions

3 - Ratio of the model to its error

2 - Average of sum of squares

4 - Level of significance

**Table 5. Pairwise comparisons for the driving indicators analysed**

Driving indicator	Pairwise comparison <sup>1</sup>	Sig. <sup>2</sup>	Mean difference (i-j) <sup>3</sup>	(95% CI) <sup>4</sup>
Hard starts	Phase 1(i) vs Phase 2 (j)	0.182	-0.007	(-0.015,0.0002)
	Phase 2(i) vs Phase 3 (j)	0.000	0.031	(0.022,0.040)
	Phase 1(i) vs Phase 3 (j)	0.000	0.024	(0.014,0.034)
Hard stops	Phase 1(i) vs Phase 2 (j)	0.000	-0.051	(-0.064,-0.037)
	Phase 2(i) vs Phase 3 (j)	0.000	0.063	(0.048,0.079)
	Phase 1(i) vs Phase 3 (j)	0.131	0.013	(-0.003,0.028)
Extreme braking	Phase 1(i) vs Phase 2 (j)	0.000	-0.063	(-0.080,-0.045)
	Phase 2(i) vs Phase 3 (j)	0.000	0.076	(0.057,0.095)
	Phase 1(i) vs Phase 3 (j)	0.181	0.014	(-0.004,0.031)
Extreme accelerations	Phase 1(i) vs Phase 2 (j)	0.000	-0.120	(-0.146,-0.095)
	Phase 2(i) vs Phase 3 (j)	0.000	0.119	(0.092,0.147)
	Phase 1(i) vs Phase 3 (j)	1.000	-0.001	(-0.027,0.025)
Idle	Phase 1(i) vs Phase 2 (j)	0.000	1.190	(0.750,1.631)
	Phase 2(i) vs Phase 3 (j)	0.000	-1.684	(-2.193,-1.175)
	Phase 1(i) vs Phase 3 (j)	0.056	-0.494	(-0.996,0.009)
Excess RPM	Phase 1(i) vs Phase 2 (j)	0.000	-0.279	(-0.391,-0.167)
	Phase 2(i) vs Phase 3 (j)	0.944	-0.032	(-0.188,0.123)
	Phase 1(i) vs Phase 3 (j)	0.000	-.312	(-0.428,-0.195)
Excess speed	Phase 1(i) vs Phase 2 (j)	0.012	-0.163	(-0.298,-0.028)
	Phase 2(i) vs Phase 3 (j)	0.000	1.209	(1.029,1.390)
	Phase 1(i) vs Phase 3 (j)	0.000	1.046	(0.896,1.197)

1 - Comparison of all combinations of the treatment groups

3 - Difference between the means of the combined treatment groups

2 - Level of significance with Sidak's method

4 - 95% Confidence interval (lower and upper bound)

### 3.1 Hard Starts

Regarding the driving indicator "hard starts", the Mauchly's sphericity test concluded that the assumption of sphericity had been violated ( $\chi^2(2)=6.606$ ,  $p=0.037$ ) for the main effect. As such, the degrees of freedom were corrected using the Huynh-Feldt estimate of sphericity ( $\epsilon=.982$ ). A significant main effect of feedback on hard starts was observed ( $F(1.964, 381.04)=17.769$ ,  $p<0.001$ ), as can be seen in Table 4. No significant effect of the covariate time working at the company was found. Pairwise comparisons revealed

significant differences ( $p < .001$ ) between Phase 2 and 3, and Phase 1 and 3 (Table 5). Even though drivers increased the percentage of time in hard starts, when they stopped receiving feedback (Phase 2), this change was not statistically significant. After a period of no feedback, however, drivers significantly decreased incidence of hard starts (Phase 3), with a decrease of 21%, as can be seen in Figure 1. The pairwise comparison between the two phases with feedback (Phase 1 and 3), indicates that receiving feedback after a period of absent information led to larger decreases (17%) in the performance as measured by the number of hard starts.

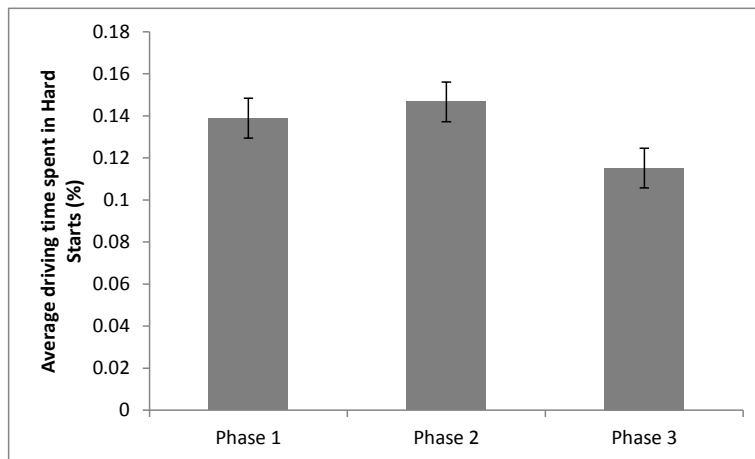


Figure 1. Average percentage of driving time in Hard Starts

### 3.2 Hard Stops

The mean scores for the 3 phases were significantly different when using ANOVA with repeated measures and assuming sphericity ( $F(2,388)=33.248$ ,  $p < .001$ ), indicating that the feedback had an impact on the performance of hard stops, as it can be seen in Table 4. No statistical significant interaction was found between the Phases and the drivers time working at the company. The post hoc analysis revealed significant differences ( $p < .001$ ) between Phase 1 and Phase 2 (Table 5), with a 25% increase on the incidence of this behaviour. Phase 3 was also significantly different than Phase 2, showing that feedback led to a decrease of 26% in hard stops.

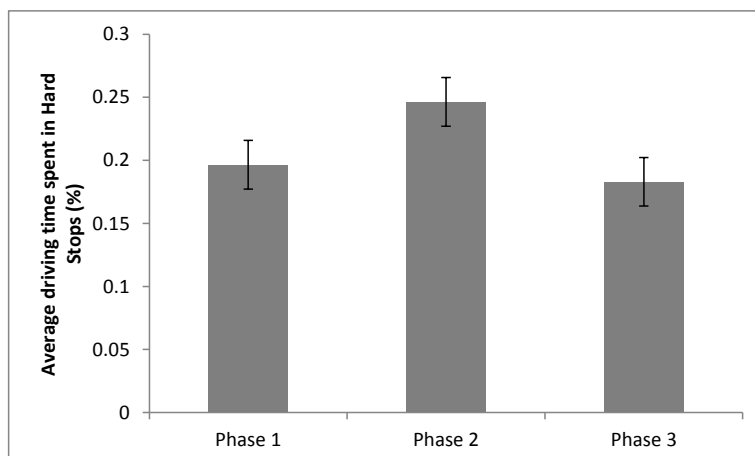


Figure 2. Average percentage of driving time in Hard Stops

### 3.3 Extreme braking

Regarding the percentage of time performing extreme braking, sphericity was not violated. Table 4 shows a significant feedback main effect on extreme brakes ( $F(2, 388)=41.723$ ,



$p < .001$ ). A significant interaction between feedback (i.e. Phases) and time working at the company was shown within this indicator ( $F(2,388)=6.829$ ,  $p < .001$ ). The covariate “years working at the company” had some impact on the changes in the behaviour over the three phases. Follow-up tests, presented in Table 5, indicated that from Phase 1 (real-time feedback) to Phase 2 (no feedback), drivers significantly changed performance of extreme brakes ( $p < .001$ ), with a 26% increase of the occurrence of the behaviour, as seen in Figure 3. Table 5 also reveals that, from Phase 2 to Phase 3 (real-time feedback), drivers significantly decreased the incidence of this behaviour ( $p < .001$ ). This decrease was of 25%, as seen in Figure 3. The comparison analysis between both phases with real-time feedback, revealed no significant differences ( $p=0.181$ ), as seen in Table 5.

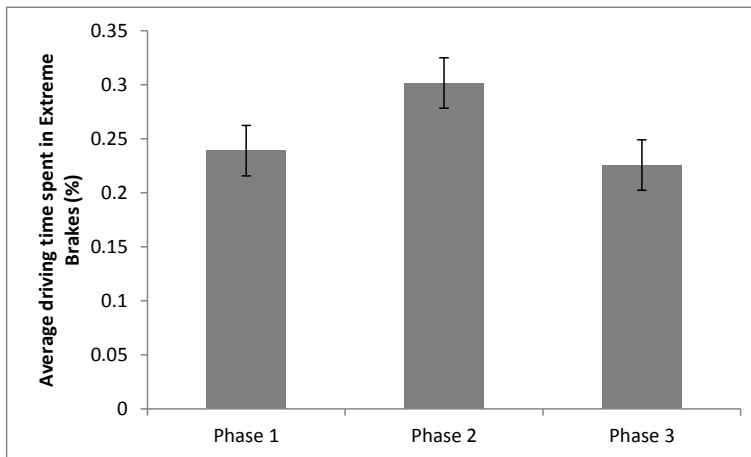


Figure 3. Average percentage of driving time in Extreme Brakes.

#### 3.4 Extreme accelerations

The repeated measures ANOVA revealed a main effect of feedback on the driving time spent performing extreme accelerations, assuming sphericity ( $F(2, 388)=38.115$ ,  $p < .001$ ) (Table 4.). No significant effect of the covariate “time working at the company” was found, as seen in Table 4.. The significant main effect of feedback reflects a significant difference ( $p < .001$ ) between Phase 1 and 2, as well as between Phase 2 and 3, indicating a significant increase of time spent in extreme accelerations when drivers stopped receiving feedback (Phase 2), contrasting with a significant decrease when feedback was resumed (Phase 3), as seen in Table 5. An increase of 44% and a decrease of 30% were observed between phase 1 and 2, and Phase 2 and 3, respectively. No statistical significant difference was found between Phase 1 and 3.

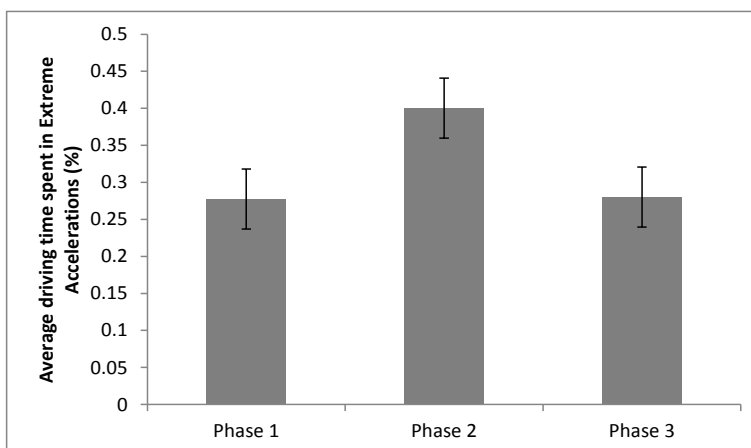


Figure 4. Average percentage of driving time in Extreme Accelerations.

### 3.5 Idle

Significant main effects of feedback were found (assuming sphericity) on percentage of driving time spent idling ( $F(2,376)=12.718$ ,  $p<.001$ ). A significant interaction between the effect of the feedback and the time working at the company was also observed ( $F(2,376)=4.612$ ,  $p=0.011$ ), suggesting that, besides the feedback, this latter covariate had some influence in the evolution of driving behaviour, as seen in Table 4. Once again, the pairwise comparisons showed significant differences ( $p<.001$ ) between Phase 1 and 2, and Phase 2 and 3, as shown in Table 5. When drivers stopped receiving real-time feedback, however, a decrease of 25% in the percentage of time spent idling occurred, while an increase of 46% was observed when feedback was reinstated, as seen in Figure 5.

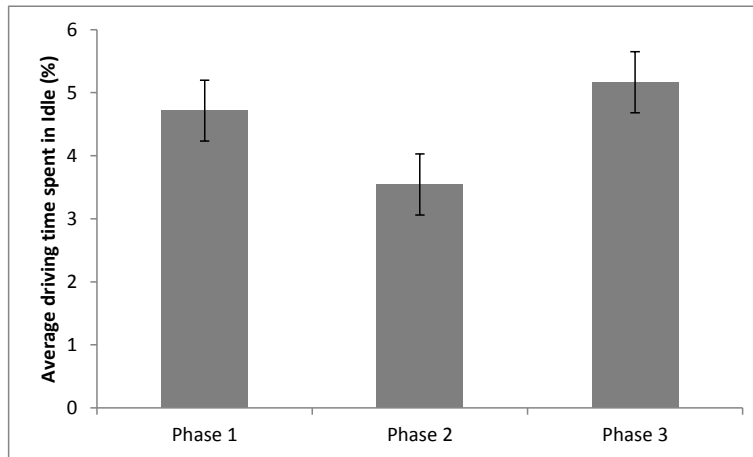


Figure 5. Average percentage of driving time in Idle.

### 3.6 Excess RPM

When using repeated measures ANOVA with a Huynh-Feldt correction of sphericity ( $\epsilon =.845$ ), the mean feedback impact scores were significantly different ( $F(1.690, 317.678)=17.564$ ,  $p<.001$ ) (Table 4). No significant effect of the covariate time working at the company was found. The main effects of feedback revealed significant differences between Phases, as presented in Table 5. These differences were observed between Phase 1 and 2 ( $p<.001$ ), with an increase of 55% in time spent in excess RPM with no feedback (Phase2), and a further increase of 4% in Phase 3.

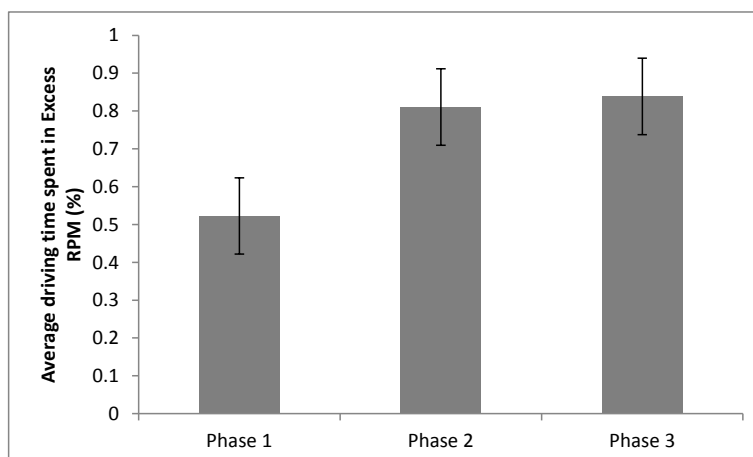


Figure 6. Average percentage of driving time in Excess RPM.

### 3.7 Excess Speed

Regarding percentage of time spent in excess speed, Mauchly's sphericity test indicated that sphericity could not be assumed ( $\chi^2(2)=24.915$ ,  $p<.001$ ). The Huynh-Feldt correction was used ( $\epsilon =.904$ ), indicating that a main effect of feedback was found ( $F(1.809, 350.881)=41.678$ ,  $p<.001$ ). No significant effect, however, was found for time working at the company (see Table 4). Follow-up tests revealed that all Phases were statistically different, as seen in Table 5. Between Phase 1 and 2 ( $p<.012$ ), an increase of 7% was observed in terms of time spent in excess speed (as can be seen in Figure 7). A significant ( $p<.001$ ) decrease was found between Phase 2 and 3, with drivers reducing 49% of this indicator. A significant difference ( $p<.001$ ) was also revealed between Phase 1 and 3 (Figure 7).

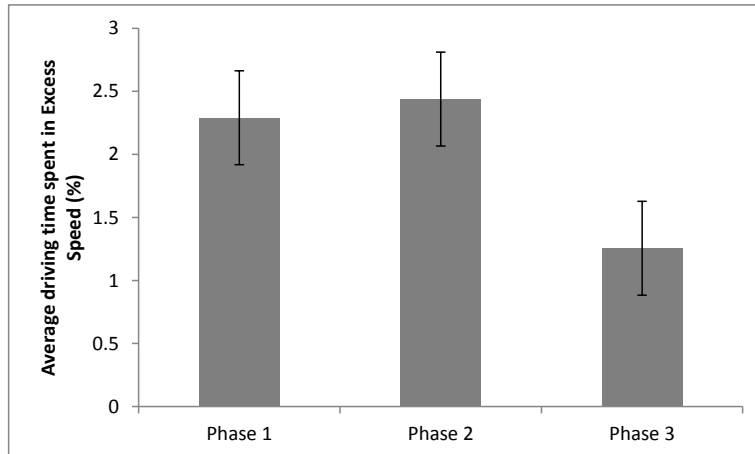


Figure 7. Average percentage of driving time in Excess Speed.

## 4 Discussion and Conclusions

This study found that bus drivers gain great benefits from receiving real-time feedback. When drivers stopped receiving real-time feedback, they increased their incidence of undesired behaviours, only for it to be reduced when real-time feedback was resumed. This can be observed in driving indicators such as hard starts, hard stops, extreme braking and acceleration and excess speed. With the exception of idling and extreme braking, the influence of the variable "time working at the company" was not observable in the evolution of driving performance. These results follow the same trend found by Strömberg and Karlsson (2013), whose study revealed that feedback provided the drivers with the necessary information to adopt more efficient driving behaviours. Thus, it is possible to stress that the manipulation of feedback was sufficient to originate changes in bus drivers driving behaviour. This is of particular importance to bus operators when developing goals and strategies to promote more efficient driving performance and, consequently, reduce fuel consumption. Also, the impact of demographic variables was only present in two driving indicators - idle and extreme brakes -, indicating that the adoption of some behaviours can be differently perceived and accepted by drivers, in accordance with Lancaster & Ward (2002), which showed that some demographic variables are correlated with aggressive driving, and with Strömberg, Karlsson & Rexfelt (2015), which found differences between experienced and new drivers in what concerns the concept of eco-driving (new drivers perceived eco-driving as a technique shaped by driving education, while experienced drivers perceived eco-driving as a strategic and tactical decision).

The bus drivers participated only in training sessions during the first monitoring period (with real-time feedback). When receiving no feedback, as well as no training, drivers increased the incidence of undesired behaviours in all indicators, with the exception of idle

time. Therefore, bus operators should take into consideration the potential importance of training when promoting more sustainable behaviours, while also taking into consideration the time each driver needs to accept and start adopting these behaviours. Several studies have also found that the ability to maintain new behaviours tends to deteriorate over time (Wälberg, 2007; Hickman, Hanowski & Ajayi, 2009; Beusen et al, 2009; Barth & Boriboonsomsin, 2009). Furthermore, the same pattern was not observed in all driving indicators, with higher or lower increases/decreases observed over the three phases of the study. Such results can be the combination of several factors, such as the perception that drivers do not have the same reactions in response to real-time feedback for all driving indicators. As such, some behaviours associated with a particular indicator might be easily changed or adopted in comparison to others. The same can be said about going back to old patterns when no real-time feedback is provided, observing more permanent changes in some indicators than others. Additionally, the impact of external factors can also be taken into account when analysing such differences, notably the effect of bus route, bus type, passenger load, weather and traffic conditions, since these can also influence the indicators performance differently. Results also seem to indicate that drivers focus more on indicators related with safety than with environmental issues. Decreases were observed in phase 3, during which real-time feedback was resumed after a period of feedback not being available to drivers, in indicators such as hard starts and stops, extreme braking, acceleration, and excess speed. The opposite was observed for idling and excess rpm, suggesting not only a higher concern with safety driving performance, but also that safety related indicators might be more easily grasped and controlled by the drivers in terms of adopting and changing their driving performance.

Finally, insights on the impact of type of bus driven, which can have different sizes and age, on driving behaviour is of particular interest, mainly on fuel consumption, and should be pursued in the future. The use of statistical models to estimate driving indicators impact on fuel consumption and pollutant emissions over time must also be addressed, taking into consideration the feedback type and drivers characteristics, providing bus operators with the necessary tools to develop specifically designed programs according to the goals of the company.

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## References

Andy, W. C. W., 2006. *A Study of road traffic accidents in relation to public light bus driving behaviour in Hong Kong*. s.l.:Master of Arts in Transport Policy and Planning, University of Hong Kong.

Anon., 2015. *Murcotts Driving Excellence*. [Online] Available at: <http://www.murcotts.edu.au/resources/driver-behaviour-training/> [Accessed 11 May 2015].

Barkenbus, J. N., 2010. Eco-driving: an overlooked climate change initiative. *Energy Policy*, 38(2), pp. 762-769.

Barth, M.; Boriboonsomsin, K., 2009. Energy and emissions impacts of a freeway-based dynamic eco-driving systems. *Transportation Research Part D: Transport and Environment*, 14(6), pp. 400-410.

Beusen, B.; Broekx, S.; Denys, T.; Becks, C.; Degraeuwe, B.; Gijssbers, M.; Scheepers, K.; Govaerts, L.; Torfs, R.; Panis, L. I., 2009. Using on-board logging devices to study the longer-term impact of an eco-driving course. *Transportation Research Part D*, 14(7), pp. 514-520.

Catarina Rolim, Patrícia Baptista, Gonçalo Duarte, Tiago Farias, João Pereira, November 2016. Impacts of delayed feedback on eco-driving behavior and resulting environmental performance changes. *Transportation Research Part F: Traffic Psychology and Behaviour*, Volume 43, pp. 366-378.

Dijksterhuis, C., Lewis-Evans, B., Jelijs, B., de Waard, D., Brookhuis, K. & Tucha, O., 2015. The impact of immediate or delayed feedback on driving behaviour in a simulated Pay-As-You-Drive system. *Accident Analysis & Prevention*, Volume 75, pp. 93-104.

Dorn, L., Stephen, L., Wählberg, A., Gandolfi, J., 2010. Development and validation of a self-report measure of bus driver behaviour. *Ergonomics*, 53(12), pp. 1420-1433.

EUROSTAT, 2014. *Energy, transport and environment indicators*. [Online].

Field, A., 2009. *Discovering Statistics Using SPSS*. s.l.:Sage.

Gardner, B.; Abraham, C., 2008. Psychological correlates of car use: A meta-analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, 11(4), pp. 300-11.

Goldenbeld, C., Leveit, P. B. M. & Heidstra, J., 2000. Psychological perspectives on changing driver attitude and behaviour. *Recherche Transports Sécurité*, Volume 67, pp. 65-81.

Goodwin, P. B., 1995. Car dependence. *Transportation*, Volume 2 (3), pp. 151-152.

Hickman, J. S.; Hanowski, R. J.; Ajayi, O., 2009. *Evaluation of an onboard safety monitoring device in commercial vehicle operations*. Iowa City, s.n.

IBM Corp, Released 2013. *IBM SPSS Statistics for Windows, Version 22.0*. Armonk, NY: IBM Corp.

Jamson, S. L., Hibberd, D. L. & Jamson, A. H., 2015. Drivers' ability to learn eco-driving skills; effects on fuel efficient and safe driving behaviour. *Transportation Research Part C: Emerging Technologies*, Volume 58, pp. 657-668.

Kienzle-VDO, 2011. *Kienzle-VDO*. [Online]  
Available at: [http://www.kienzle.de/index.php?406&backPID=406&tt\\_products=160](http://www.kienzle.de/index.php?406&backPID=406&tt_products=160)  
[Accessed 29 08 2011].

Lancaster, H.; Ward, R., 2002. *The contribution of individual factors to driving behaviour: implications for managing work related safety*, s.l.: Entec UK Limited.

Larsson, H.; Ericsson, E., 2009. The effects of an acceleration advisory tool in vehicles for reduced fuel consumption and emissions. *Transportation Research Part D*, 14(141-146).

Mannering, F.; Kim, S-G.; Ng, L.; Barfield, W., 1995. Traveler's preferences for in-vehicle information systems: An exploratory analysis. *Transportation Research Part C: Emerging Technologies*, 3(6), pp. 339-351.

Mather, R. D., 2007. Age and driving behaviour: contributions from human factors.. *Journal of Scientific Psychology*, pp. 24-31.

Ouellette, J. A.; Wood, W., 1998. Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin*, 124(1), pp. 54-74.

Özkan, T.; Lajunen, T.; Chliaoutakis, J. E.; Parker, D.; Summala, H., 2006. Cross-cultural differences in driving behaviours: a comparison of six countries. *Journal of Transportation Research Part F*, Volume 9, pp. 227-242.

Pampel, S. M., Jamson, S. L., Hibberd, D. L. & Barnard, Y., 2015. How I reduce fuel consumption: An experimental study on mental models of eco-driving. *Transportation Research Part C: Emerging Technologies*, Volume 58, pp. 669-680.

Prillwitz, J.; Barr, S., 2011. Moving towards sustainability? Mobility styles, attitudes and individual travel behaviour. *Journal of Transport Geography*, 19(6), pp. 1560-1600.

Raney, E. A.; Mokhtarian, P. L.; Salomon, I., 2000. Modeling individuals' consideration of strategies to cope with congestion. *Transportation Research Part F*, Volume 3, pp. 141-165.

Rohani, M.; Wijeyesekera, D. V.; Karim, A. T. Abd., 2013. Bus Operation, Quality Service and The Role of Bus Provider and Driver. *Procedia - Engineering*, Volume 53, pp. 167-178.

Rohani, M., 2012. *Bus driving behaviour and fuel consumption*, s.l.: University of Southampton, Faculty of Engineering, Science & Mathematics, School of Civil Engineering & the Environment, PhD Thesis.

Rolim, C. C., Baptista P. C., Duarte, G. O., Farias, T. L., 2014. Impacts of on-board devices and training on light duty vehicle driving behavior.. *Procedia - Social and Behavioral Sciences*, Volume 111, pp. 711-720.

Saboochi, Y.; Farzaneh, H., 2009. Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption. *Applied Energy*, 86(10), pp. 1925-1932.

Strömberg, H. K.; Karlsson, I. C. M., 2013. Comparative effects of eco-driving initiatives aimed at urban bus drivers - Results from a field study. *Transportation Research Part D*, Volume 22, pp. 28-33.

Strömberg, H., Karlsson, I. C. & Rexfelt, O., 2015. Eco-driving: drivers' understanding of the concept and implication for future interventions.. *Transportation Policy*, Volume 39, pp. 48-54.

Tse, J. L. M.; Flin, R.; Mearns, K., 2006. Bus driver well-being review: 50 years of research.. *Journal of Transportation Research Part F*, Volume 9, pp. 89-114.

Tulusan, J., Steggers, H., Staake, T. & Fleisch, E., , 2012. Supporting eco-driving with ecofeedback technologies: recommendations targeted at improving corporate car drivers' intrinsic motivation to drive more sustainable. *All Sprouts Content*, 12(3).

Wälberg, A. E., 2007. Long-term effects of training in economical driving: Fuel consumption, accidents, driver acceleration behavior and technical feedback.. *International Journal of Industrial Ergonomics*, Issue 37, pp. 333-343.

WSP, 2012. *Energy Efficiency Measures for Buses and Bus Transport - Possibilities and Experiences from Other Actors*, s.l.: s.n.

Zarkadoula, M.; Zoidis, G.; Tritopoulou, E., 2007. Training urban bus driver to promote smart driving: a note on a Greek eco-driving pilot program. *Transportation Research Part D*, Volume 12, pp. 449-541.