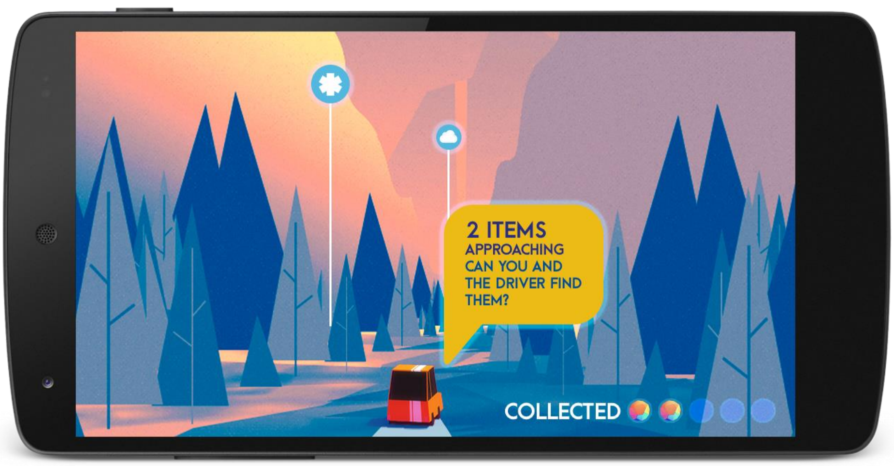
Smart Mobility Project

End of Project Report

The University of Nottingham

October 2016



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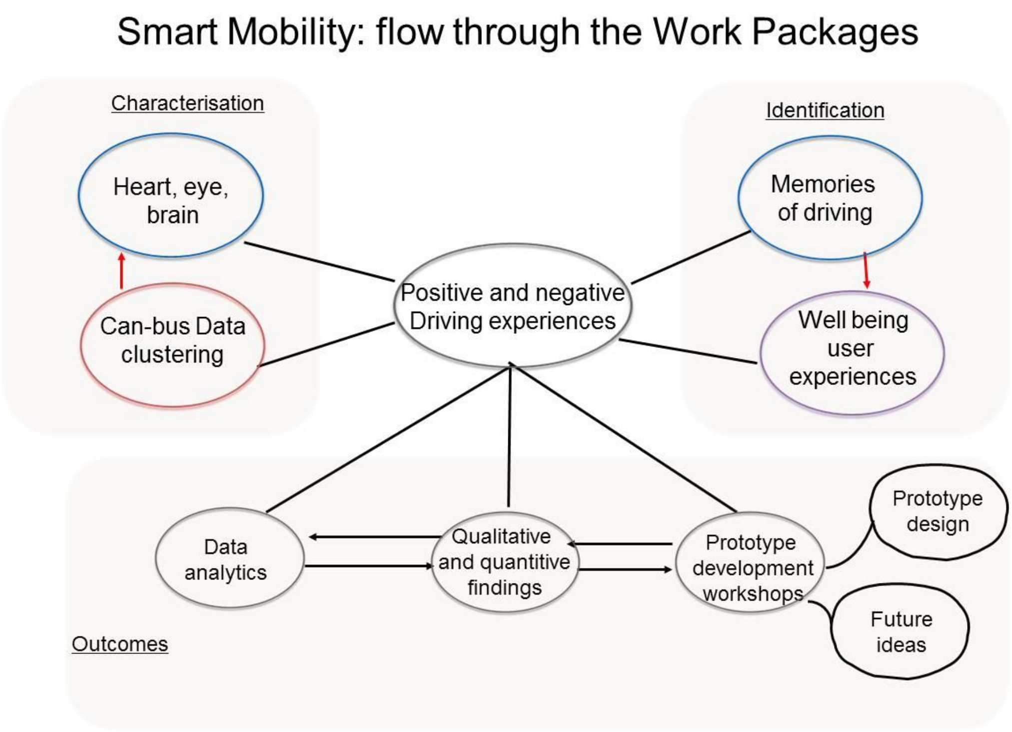
Executive Summary

This report presents a preliminary investigation into the "Smart Mobility" challenge. The end vision:

To use the richer data set available from Ford vehicles, plus external data, to generate consumer "insights" that encourage safer, more aware, and more efficient drivers within urban and non-urban environments.

The initial study has focussed on four key elements within separate work packages to enable this vision:

1. Data analytic techniques aiming to produce algorithms for real time in vehicle data processing to classify journeys;
2. Driver experience feedback and engagement around journeys by the study of language use within regularly kept driving diaries;
3. Relationship of vehicle measures to cognitive state investigated through a simulated drive with eye tracking and brain activity recording;
4. User experience design exploration.



Summary results

1. The offline data analysis of the Ford supplied data clearly demonstrated that clustering techniques could identify categories of journey that have straightforward human comprehensible interpretations of urban, motorway and mixed journeys. Furthermore, there was clear segmentation of the journey via change points into the relevant component elements. Importantly, having been learnt, these algorithms can then be deployed in-vehicle to allow real time classification for future journeys as they proceed

2. The driver experience feedback via the diary studies provided rich data, indicating many factors that can influence the experience, both contextual and personal. Quantitative studies of the languages indicated strong correlations of positive driving experiences with words related to achievements, power and reward, while negative driving experiences featured words associated with risk and lack of control

3. The simulated hazardous and normal driving experience did effectively produce different driving 'styles'. The brain and eye activities in these two scenarios strongly correlated to the vehicle measures of steering and braking indicating the possibility that in-vehicle sensors can be used to infer driver cognitive state. Noting the same participants took part in work package 2 and 3, there was a noticeable change in language in the diaries after the simulator experience, which could be related to changes in behaviour

4. The Horizon-funded user experience design has undertaken scoping work based on the results from the previous work packages and will shortly deliver the design workshops.

Where next

The results so far are extremely promising. **These indicate that in-vehicle journey and driver analytics, even using only existing sensors, have the ability to indicate driver cognitive state and experience**. As is common in research, the answers obtained introduce new questions, but with the insights gained already, we can produce some recommendations for next steps.

A future large scale data capture of journeys should include both a greater variety of journeys and more repetitions of the same journey. This would provide data to ensure that the clustering techniques remain robust across the complete parameter space, as well as provide a data set that could be investigated for "good" and "bad" experiences.

Some of the participants, perhaps especially those with repetitive journey behaviours, should be selected for a larger scale diary study. This would provide the journey data captured with rich experiential data to train and check the classification algorithms.

There is also a place for many more experiments using the human sensing technologies both in the simulator and "in the wild". There is scope for more highly controlled experiments in the laboratory but also looking to repeat these on the actual roads to validate the robustness of the simulated experience. Furthermore, labelling a significant sample of the overall journeys recorded with the highly detailed cognitive insights from these human sensing technologies by in-vehicle deployments would greatly enhance the datasets and the robustness of the results.

Update on Horizon-funded User Experience Design

Based on the research from this and the other work packages, the design of three concepts are being developed:

- 'The World Outside my Window' - an iSpy/treasure hunt driving game for passengers and the driver to play together
- 'The Car that Talks' - a driving app that allows the driver and the car to playfully communicate with each other
- 'The Driver Not the Car' - designing a service that looks at the future of transportation and driver experience

The key themes that are being looked at across each of these concepts is firstly the importance of 'courtesy' as a positive experience of driving and how we can encourage 'driving courtesy' through playful and mindful interactions between the driver, the passengers and data from the car (braking, acceleration, flashing lights etc.) and the outside world (weather, pollution levels, traffic etc.).

The second theme of interest is the impact of weather as both positive and negative experiences of driving, particularly how extreme weather impacts on driver experience.

Finally the most obvious positive/negative impact appeared to be the perceived behaviour of risk and uncertainty creating hazardous driving scenarios by other drivers, cyclists and pedestrians as well as road works and traffic.

We are interested in how these themes will evolve and change in the future as different cars and transportation becomes available (such as driverless cars).

Two public workshops are booked to be run in November - one in London at the Digital Catapult Centre and one in Nottingham at the National Video Game Arcade.

These workshops will involve:

- presentations of the three design concepts
- running paper tests of the concepts (short activities to try out some of the key elements of the concepts using paper and pens)
- an activity for the participants to extend and adapt these concepts
- an activity for the participants to feedback their own ideas and concerns

These user experience workshops will provide indicators of prospective engaging uses of the cognitive state information that the data analytics and psychology work has demonstrated can be derived from the in-vehicle sensors. Whether these point to specific interventions like in-car assist for drivers, smartphone apps for passengers, or long term reporting for driver reflection, small scale trials of some of these experiences "in-the-wild" would be the next step to link together all elements of the work into delivering the vision of "Smart Mobility".

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Data Analytics

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Objective

The objective set for this work package was to analyse and investigate a real world dataset provided by Ford Smart Mobility consisting of telematics data acquired from a fleet of Ford vehicles over the course of 6 months. Research was to be conducted to develop a new approach for exploring and investigating big data for extracting valuable insights regarding driving behaviours and journey characteristics. The analysis was to result in the groundwork for developing a framework for an adaptive and expandable intelligence system to be implemented in cars for automatically identifying the type of journeys undertaken by the driver and discovering patterns within the driver's behaviour.

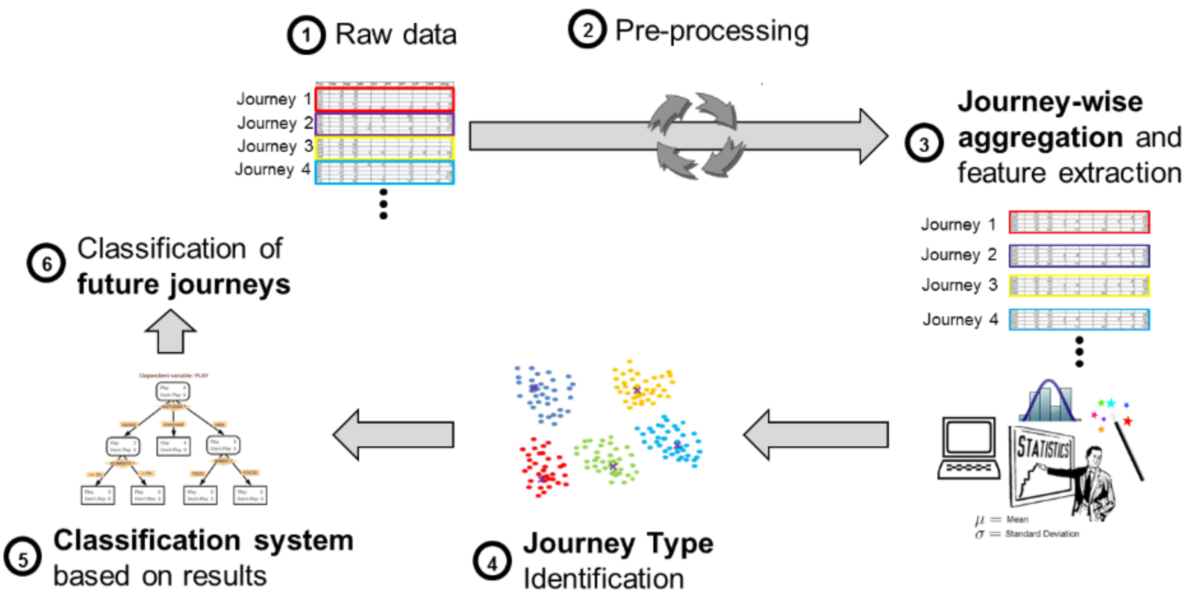
Methodology

Over the course of the project, a two-phase methodology was developed which is capable of classifying journeys according to their route characteristics (i.e. an urban journey vs. a motorway journey) and also the analysis of driving behaviour related patterns within those journey types. A more detailed description of all the elements can be found in Appendix A.

Phase 1 - Journey Type Classification

Phase 1 is carried out over 6 steps as illustrated in Figure 1. First, the raw data set containing all recorded journeys in form of multivariate time series is retrieved (1) and then pre-processed to fit the needs of the following steps (2). Next, the pre-processed data is aggregated into a range of summary statistics (see Appendix A 3) and a set of features is extracted (3). These features are used for the process of journey type identification through the use of clustering techniques (4). Based on the resulting journey types found, a classification model (e.g. decision tree, support vector machine, neural network) can be trained (5) and can be used to classify future journeys where the journey type is unknown (6).

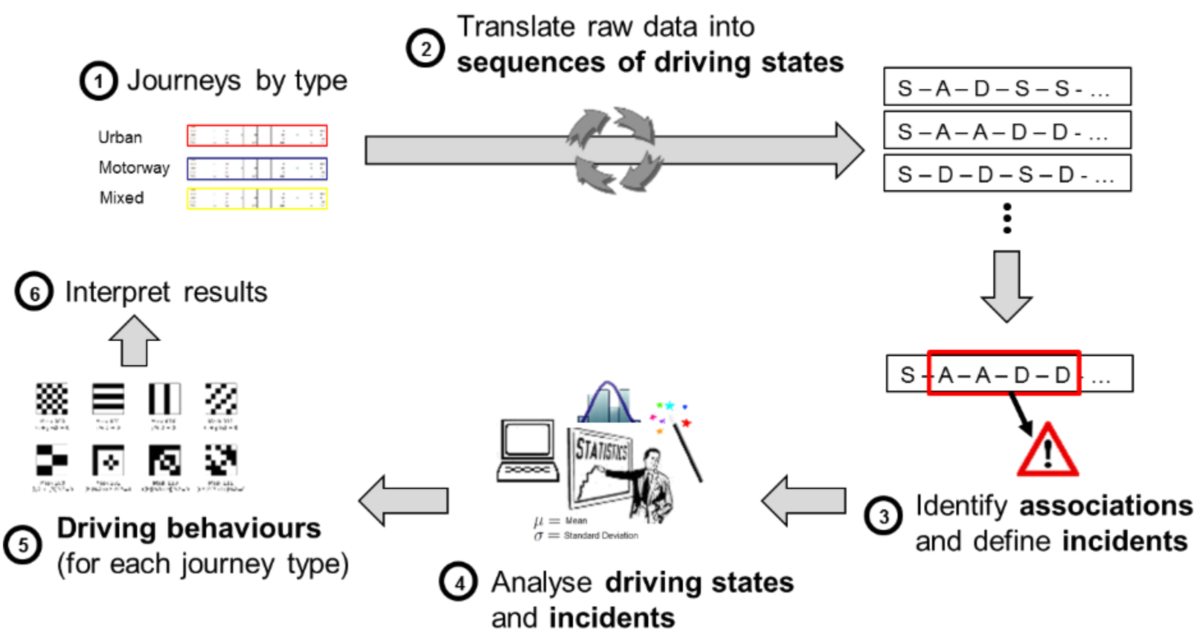
Figure 1: Journey Type Classification



Phase 2 – Driving Behaviour Analysis

Phase 2 (see Fig. 2) analyses and extracts driving behaviour patterns within each of the previously detected journey types (1). To achieve this, the numerical data records are transformed into *driving states* (2), which are a nominal representation of a set of recorded attributes (e.g. "high speed + high acceleration + no steering"). Based on these driving states, common co-occurrences or sequences of driving states can be identified and enable the definition of *incidents*, such as "harsh braking", "harsh cornering" or "harsh acceleration" (3). The subsequent study and analysis of incidents (4) detects patterns of driving behaviours or common behaviours in specific situations such as speeding, turning, gear shifting etc. (5). The combined interpretation (6) of these insights result in journey-type specific driving traits and possibly driver profiles.

Figure 2: Driving Behaviour Analysis

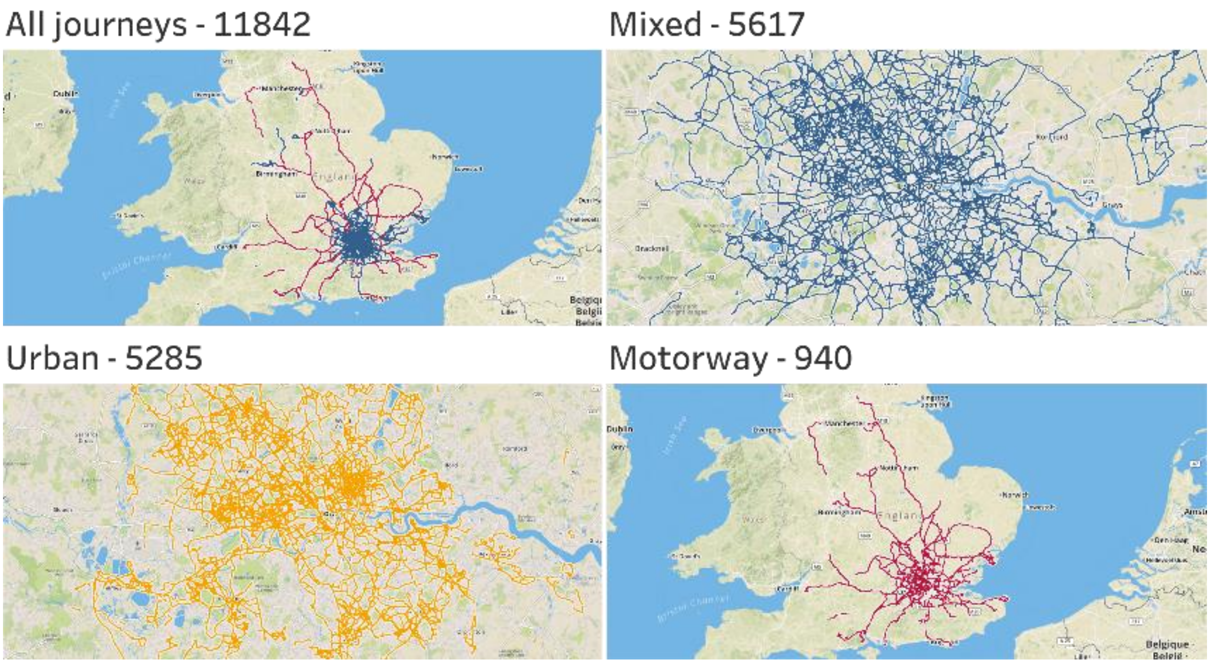


Key Results

Clustering

Through the use of clustering techniques, the developed methodology is able to successfully distinguish journeys based on their characteristics. Figure 3 shows the three main clusters that could be identified in this initial study, separating the journeys into the 3 clusters *predominantly urban*, *predominantly motorway*, and *mixed*. A more detailed description of the clustering procedure can be found in Appendix A 3.2.

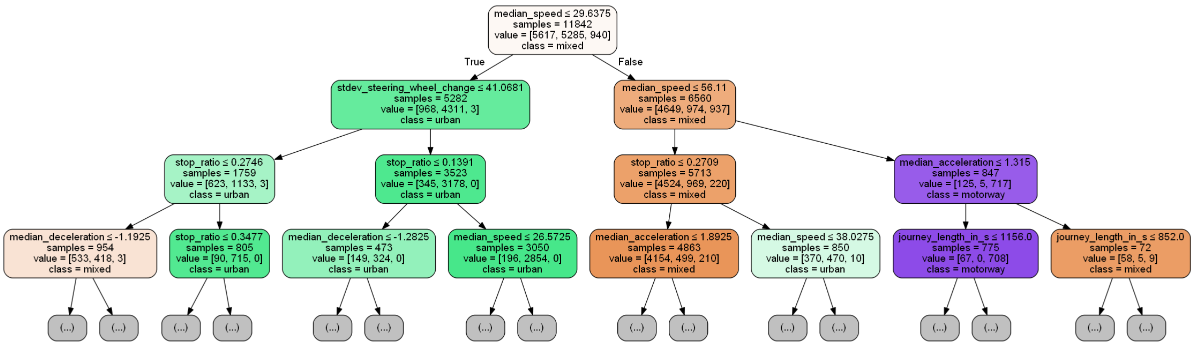
Figure 3: Journey type clusters



Classification System

Based on the clustering results shown in Fig. 3, a classification model could be trained that is capable of classifying future journeys that were not included in the data set used for detecting the clusters shown above. Figure 4 depicts a possible decision tree that was trained on the journey records using the cluster information. The illustration shown here is described in more detail in Appendix A 3.3.

Figure 4: Example decision tree trained using the cluster information illustrated in Fig. 3

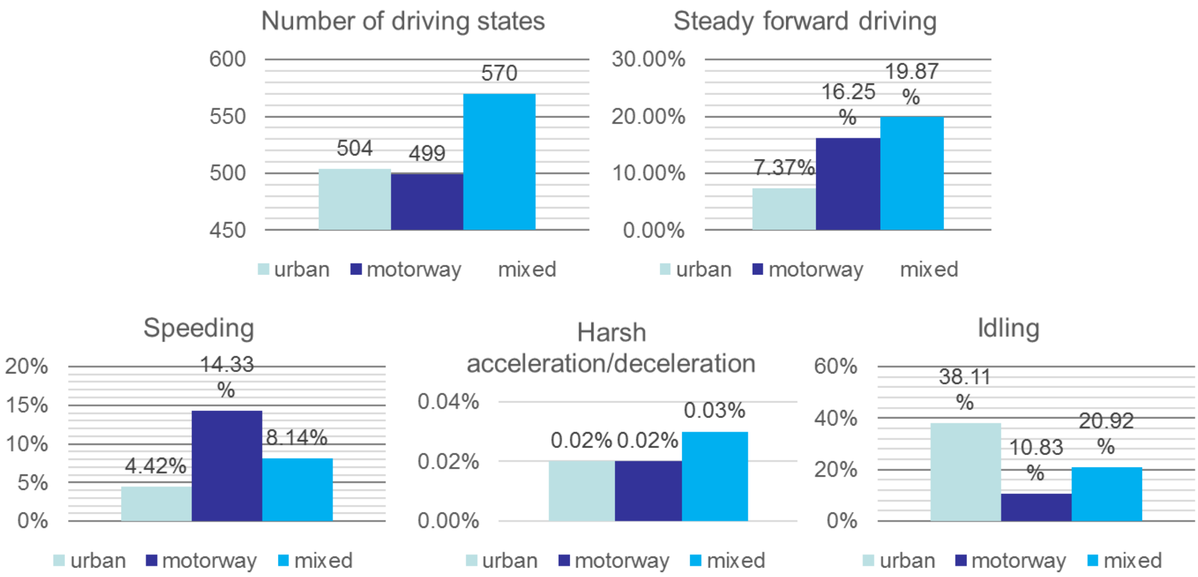


The learning algorithm used for training such a classification model can be varied and further optimised to ensure higher prediction quality for future data, for example the usage of support vector machines or neural networks would be possible. Furthermore, the classification model can be retrained every time the data base of journeys is updated, making the model even more robust and reliable over time. Ultimately, a classification system using trained model could be implemented directly into the car's software to identify the type of new journeys directly on-board while the driver is underway.

Driving states and situation-specific driving behaviours

The translation of numerical journey records into *driving states* as a nominal representation of a set of attributes facilitates the analysis of driving patterns and yields insights regarding where and how frequently certain driving situations occur (see Appendix A 4 for more details). Figure 5 shows a few examples of statistics obtained through data transformation.

Figure 5: Excerpt of results obtained through analysis of driving states



The top left chart describes the number of individual driving states that have been identified within each of the journey types. The top right chart and the bottom right chart shows percentages of very common states. *Steady forward driving* refers to a state where the car is driving at a stable speed with no steering, whereas *idling* refers to a state where the car is standing still or moving very little without any no steering activity. The charts on the bottom left and middle show the percentages of data points for each journey type where speeding or harsh accelerations/decelerations occur, respectively. This analysis can be extended by looking at sequences of driving states to identify patterns of driving states (driving traits) that can ultimately lead to the definition of driving profiles.

Change Point Detection

Points in a data record (time series) where a variable or a combination of variables undergoes a sudden and significant change are called *Change Points*. Their detection makes it possible to identify locations where the characteristics of a journey abruptly change in some way, allowing to analyse the characteristics of the road itself. These changes can be caused by the behaviour of the driver (harsh brakes, harsh turning, etc.), factors of the road (traffic lights, narrow turns) or factors of the environment (e.g. traffic jams).

Figure 6: Change Point Detection for a single journey (Change Points are marked red)

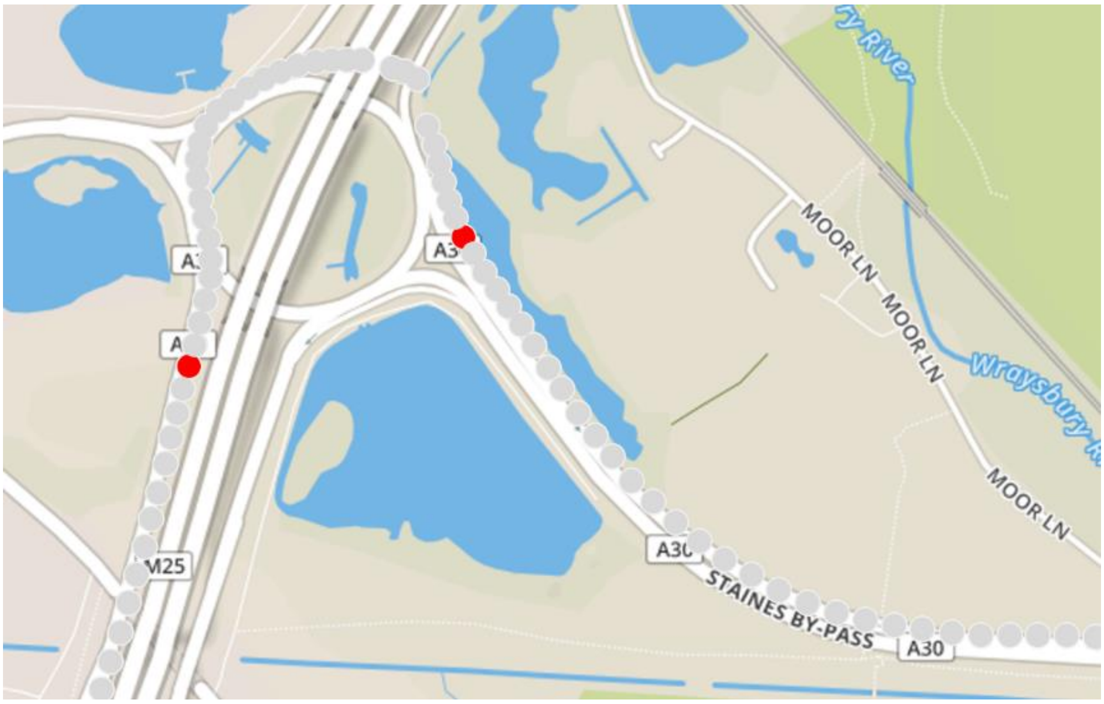
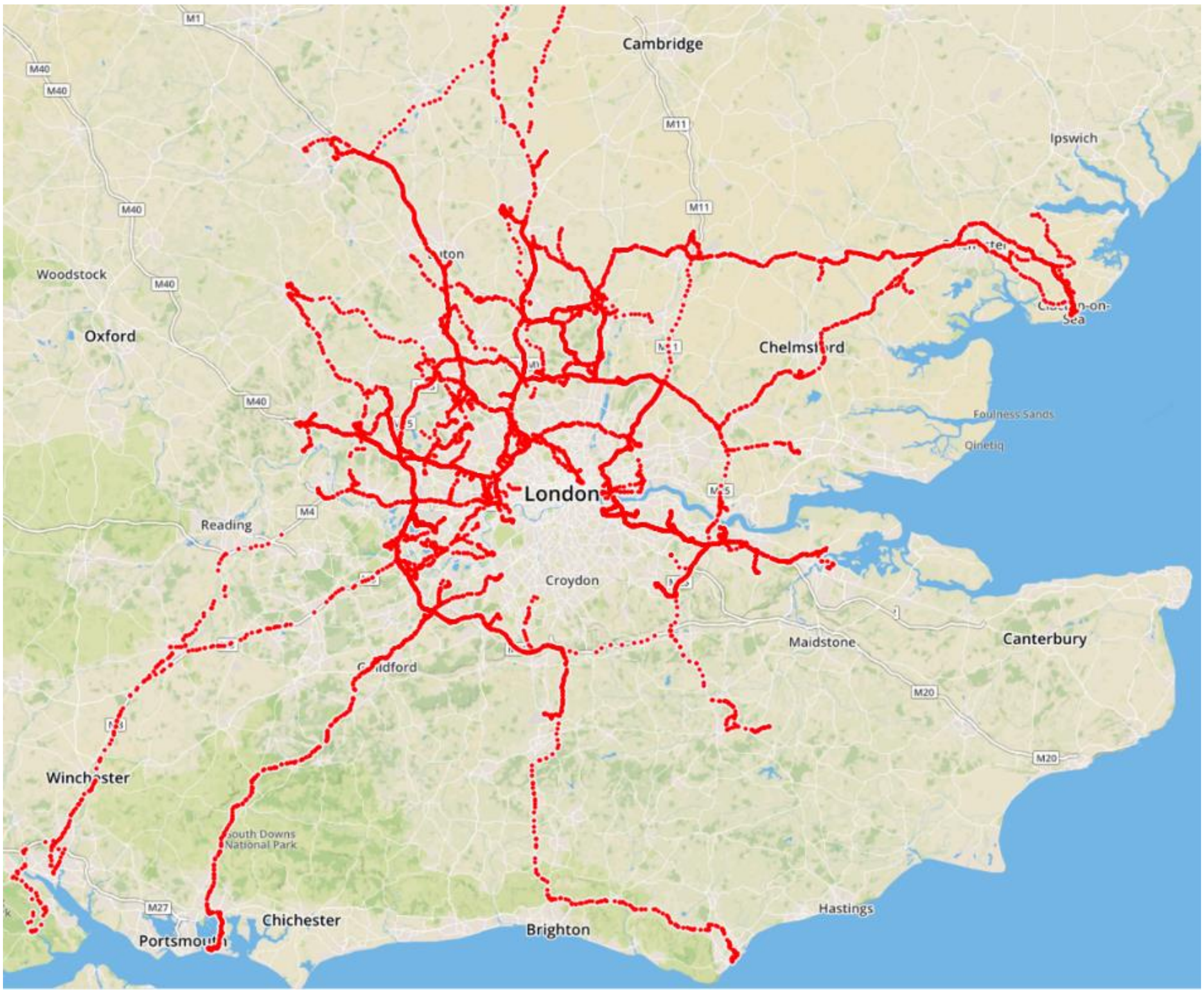


Figure 6 shows records of a car entering and leaving a roundabout, change points are marked in red. Change Points occur upon entering and leaving the roundabout, most likely caused through a combination of changes in acceleration/deceleration and steering behaviour. By not only looking at Change Points for individual journeys, but rather combining information about Change Points for a group of journeys, insights can be gained about locations where Change Points occur frequently, marking potential *Hot Spots*, where the drivers tend to undergo some changes in their behaviour, for example due to characteristics of the road. Information about such Hot Spots could be useful if communicated to the car using location-based information, for example to warn the driver about potential upcoming Hot Spots. Figure 7 is a visualisation of Change points identified in 238 predominantly motorway journeys, areas where the red markings are denser are areas where Change Points happen particularly frequently (See Appendix A 4.3 for more details about Change Point Detection).

Figure 7: Visualisation of Change points for predominantly motorway journeys



Discussion and Future Work

The proposed methodology poses the base for a framework of an in-car intelligence system capable of analysing a driver's journey and extracting driving traits and characteristics of the route for a combined assessment of the drive. Over time, the car could utilise the insights gained from its driver and would adapt its functions or the way it communicates with the driver, giving more precise and individual feedback. The approach offers enough flexibility in both phases and many of the parameters such as the depth of the clustering procedure, the choice of learning algorithm for the classification system, the definition of incidents and their interpretation can be optimised and adjusted very much to depending on the intended use case and its specific requirements.

Possible applications can be the identification of Hot Spots, either caused through the characteristics of the road or through common (bad) driving behaviours. Based on the Hot Spot information, the car could issue warnings to the driver whenever such a Hot Spot is approached. By linking Hot Spot information from other cars that run the same framework, a *Hot Spot Map* could be created, benefiting not only the individual driver, but the entire fleet of smart, connected cars. Such a connected, intelligent fleet of cars would not only make an individual journey safer, but would benefit the entire fleet as it keeps learning and evolving from all fleet drivers.

Ultimately, this could lead to an overall assessment of the journey in terms of driving risks caused by said Hot Spots or an individual rating mechanic to provide detailed feedback to the driver about his driving performance and the safety of his driving traits.

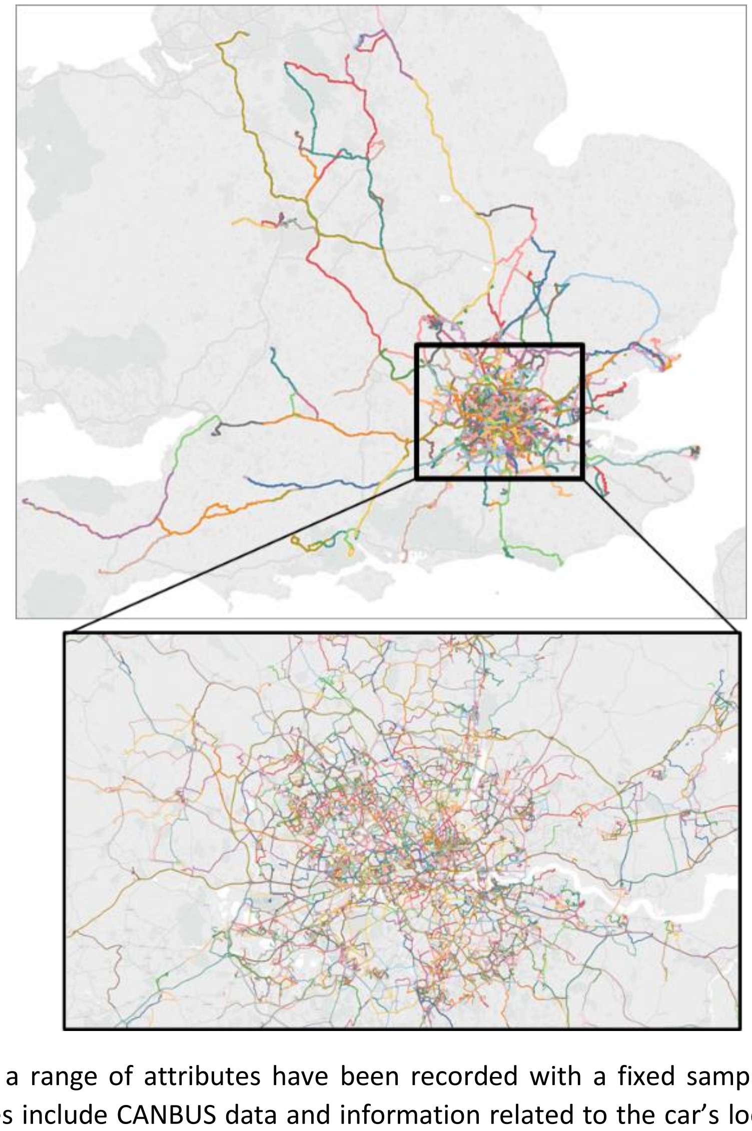
In order to achieve this, the methodology proposed in this work has to be refined and validated in order to develop a full, solid and reliable framework. While the current dataset features a high number of journeys from all parts of the UK, a few areas of improvement were identified that if addressed would greatly benefit the framework development. The large amount of variation in the dataset featuring a very diverse spectrum of journeys limits the accuracy of particularly distinguishing variation that is caused by driving behaviour from variation that is caused by characteristics of the journey/the road the car is travelling on. For further research, we propose a new, refined data collection with precisely defined boundary conditions to ease the development of the proposed framework and to revisit the current dataset once the framework has been successfully established, evaluated and validated.

Appendix A

A 1 - Raw Data

A raw data set consisting of 17,722,841 data points was received for analysis. This data set represents records of CANBUS car data from 47 different Ford Fiesta vehicles that have completed a total of 16,033 individual journeys over a period of 6 months. A visualization of all the journeys contained in the data set is shown in Figure A.1. Each individual journey is represented by a different colour. Most of the journeys were recorded in the Greater London area, leading to a particularly dense set of journeys as can be seen in the zoomed in view in Figure A.1. Yet, the data set features a very diverse range of journeys regarding journey length, journey location and the predominant type of roads that have been travelled.

Figure A.1: Visualisation of all journeys contained in the raw data set



For each journey, a range of attributes have been recorded with a fixed sample rate of 1Hz. The recorded attributes include CANBUS data and information related to the car's location, such as GPS coordinates or OpenStreetMaps information. The full set of 18 variables that are contained in the raw data set are shown in Table A.1. The left column lists the attribute names as they are included in the raw dataset, the right column gives a short description for each attribute.

Table A.1: Attributes contained in the raw data set

Attribute	Description
id	Unique ID for each recorded data point in the entire dataset
journey_id	unique id for each journey that was
asset_id	unique vehicle id
time	Date and Time (HH:MM:SS format)
custom_steering_wheel_angle	steering wheel angle in degrees
custom_shift_indicator_light	attribute indicating whether the shift indicator light is on or off
custom_clutch_pedal_switch	attribute indicating whether the clutch pedal has been pressed
custom_accelerator_pedal_position	pedal position in percent
custom_engine_speed	engine speed in RPM
custom_vehicle_speed	vehicle speed in km/h
custom_engine_torque	engine torque in Nm
custom_brake_pressure	brake pressure in bar
custom_gear	the gear the vehicle is currently driving in
custom_direction_indicator_light	attribute specifying the state of the turn signal (off/left/right)
custom_fuel_level	fuel level in percent
longitude	GPS coordinate
latitude	GPS coordinate
osm_id	unique OpenStreetMaps (OSM) ID of the road (or similar, e.g. parking lot, junction) that is closest to the car's current location

A 2 - Project Outline

Given the size and diversity of the journeys in the raw data set (see Fig. A.1), it seemed likely that trying to analyse driving behaviour straight away seemed infeasible, since for example a short, urban journey in London is very likely to be inherently different form a long journey from London to Manchester with a lot of motorway driving.

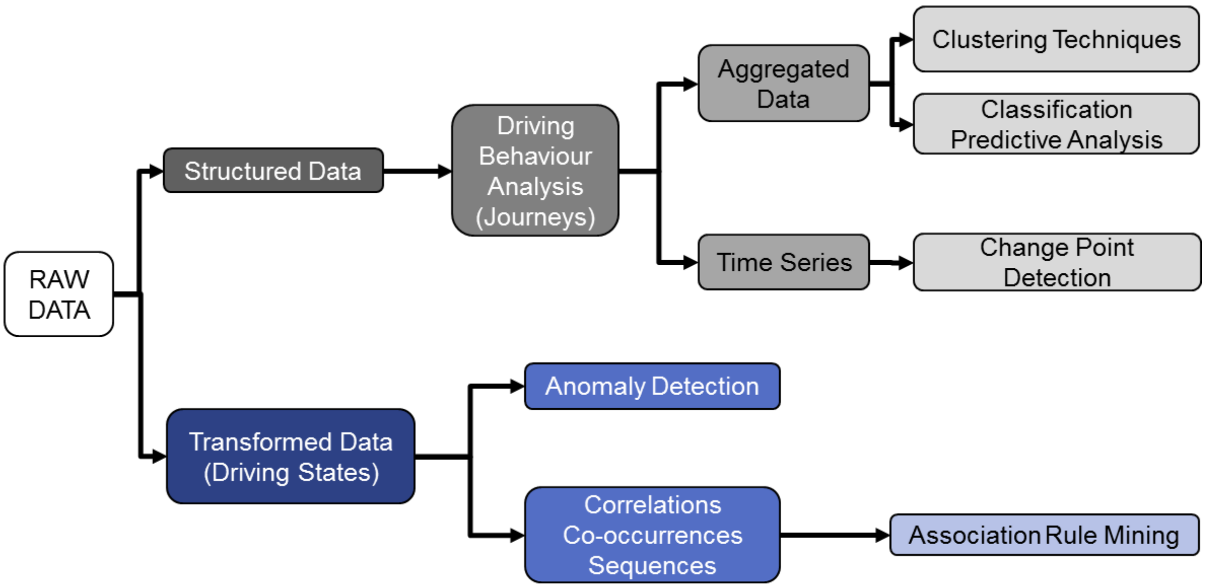
Therefore, the first phase of the project focused on identifying groups of journeys that are similar to each other and distinguish between types of journeys using clustering techniques. Once the groups of journeys have been identified, it is possible to train a classification model based on those clustering results, so that future journeys can be quickly classified and assigned to one of the clusters that have been discovered.

The second phase of the developed methodology then focuses on analysing driving behaviour within each identified type. The assumption was made that while for example all driving behaviour on motorway is likely to be different compared to all urban driving behaviours, there still will be differences within the motorway driving behaviours to distinguish between several driving behaviour patterns.

The actual analysis is performed using a range of techniques and algorithms. Figure A.2 gives an overview over the range of techniques that had initially been considered for analysis. Over the course of the project, some of them turned out to be less promising or not applicable to the actual data set. The ones that have been carried out successfully are marked by green check marks.

The top half of the tree structure groups approaches that use structured data in its numerical form, whereas the bottom half lists approaches where the raw data is transformed from a numerical format to a nominal one, translating to so-called *driving states*, which will be explained later in more detail.

Figure A.2: Project Overview



Structured Data Approaches

The structured data is seen from a journey perspective, which focuses on differences between journeys that are independent from differences in drivers. As mentioned before, given the variation of the dataset regarding the journeys, we decided to analyse the dataset from the journey perspective first, rather than looking at the data from a perspective focused on the drivers.

Each journey in the raw dataset is represented as a multivariate time series and can either be analysed as such using time series analysis techniques, or alternatively, the information contained in the time series can be compressed and aggregated by calculating summary statistics such as mean or median values. Using aggregated data, conventional clustering and classification techniques can be applied. The direct use of the raw data as multivariate time series enables the use of change point detection.

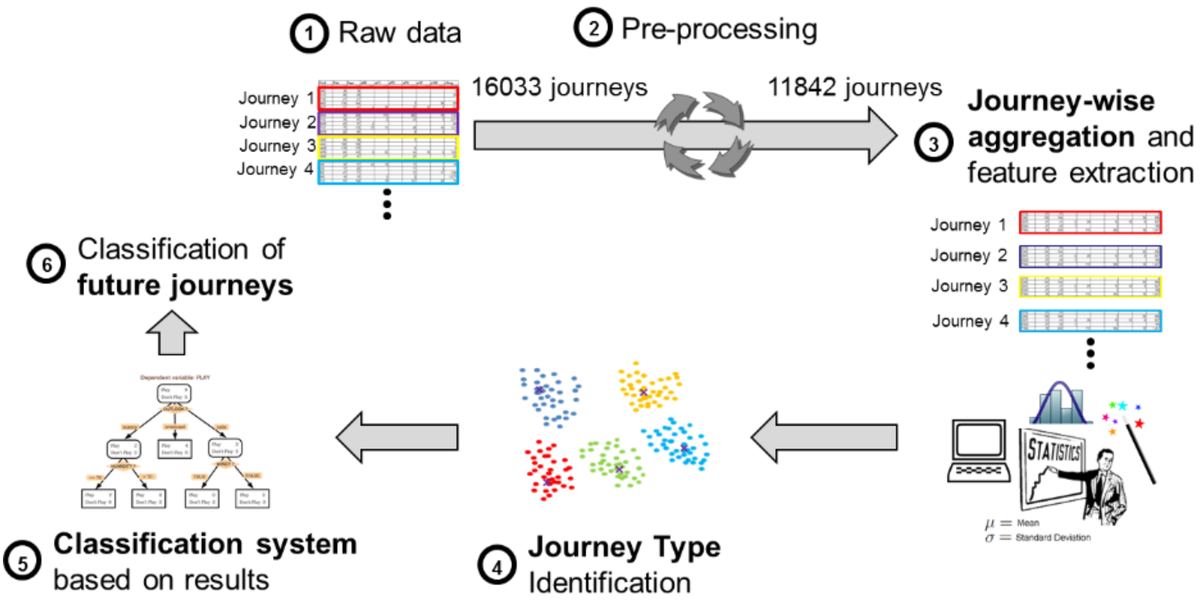
Transformed Data Approaches

Transforming the raw data from a numerical format into a nominal one can be utilized for anomaly detection and association rule mining. The raw data is transformed into nominal data by translating the numerical values into nominal value ranges, (e.g. *low speed*, *medium speed* and *high speed*). While a certain degree of information and granularity is lost in the process, the possibility of applying methods usually found in market basket analysis can reveal patterns of driving states that often occur together or occur after another, leading to the identification of driving traits and driving behaviours.

A 3 - Phase 1 - Journey Type Classification

Phase 1 is carried out over 6 steps as illustrated in Figure A.3. First, the raw data set containing all recorded journeys in form of multivariate time series is retrieved. The raw data containing 16033 journeys is pre-processed, filtering missing and/or erroneous data which can be caused for example by errors that occurred during data recording. After pre-processing, a total of 11842 journeys remain and each of those multivariate time series is aggregated into a range of summary statistics. A set of features is extracted from the resulting aggregated data set and is used for clustering in step 4. Using the clustering results, a classification model can be trained (e.g. decision tree, support vector machine, neural network). Once a robust and reliable classification model is obtained, it can be reused to classify future journeys where the journey type is unknown.

Figure A.3: Journey Type Classification



A 3.1 - Pre-Processing and Raw Data Aggregation

The raw data comprising of records of 16033 journeys is pre-processed to remove erroneous or missing entries in preparation for the clustering procedure that is to follow.

STEP 0: Merge raw dataset with OSM data and information about time of day (no journeys removed)

Data retrieved from OpenStreetMaps using the 'osm_id' value in the raw data is added. This includes (where available): speed limits, road names and types (as categorized in OSM), binary attributes about the existence of bridges, tunnels. Furthermore, using the timestamps provided in the raw data, the time of day (dawn, day, dusk, night) was determined for each data point and added to the dataset. The full list of added attributes is shown in Table A.2. 16033 journeys remain.

Table A.2: Attributes that have been added to the raw data

Attribute	Description
time of day	Time of day calculated using GPS coordinates and the timestamp (Dawn, Day, Dusk, Night).
name	information retrieved from OSM, both name and ref give information about names of streets, roads, junctions etc. if available
ref	
type	information retrieved from OSM, type needs explanation
oneway	binary attribute indicating if osm id points to a one-way street
bridge	binary attribute indicating if osm id points to a bridge
tunnel	binary attribute indicating if osm id points to a tunnel
maxspeed	speed limit in km/h for a specific osm id (if available)

STEP 1: Handle missing OSM data points and determine speeding (no journeys removed)

N/A values in the data retrieved from OSM is replaced by strings 'missing' or by the value 0. Through OSM, speed limits could be retrieved for about 56% of all the data points, the remaining 44% of unknown speed limits is replaced by the national speed limit of 70 mph which is 112.654 $\frac{km}{h}$. A binary attribute is created to determine for each data point whether the car was driving above the speed limit or not. 16033 journeys remain. The national speed limit was chosen as a global upper limit, since the type of each journey was unknown at this stage of the process and attempting to reconstruct or interpolate speed limits for every data point was not feasible. Gathering accurate information about speed limits will be a very important point to consider in future research, but in this project the national speed was chosen as a guaranteed upper limit regardless of the type of road.

STEP2: Filter N/A values in the car data (81 journeys removed)

According to the data dictionary provided, data points where the value for accelerator pedal position is 255 (which indicates an error) are removed. Data points, where both engine speed and vehicle speed are N/A are also removed. Explain why? Finally, data points where steering wheel angle is N/A and engine speed<1500 and vehicle speed<1 are also removed from the dataset. 15952 journeys remain.

STEP 3: Handle further error values in the car data (no journeys removed)

Further erroneous values as described in the data dictionary are removed for:

- car gear: data points with erroneous values 7 and 15 removed
- shift indicator light: data points with erroneous value 3 removed
- brake pressure: data points with erroneous value 355.35 removed
- direction indicators: data points with erroneous value 3 removed

15952 journeys remain.

STEP 4: Compute acceleration and steering wheel angle changes (no journeys removed)

As a measure of acceleration, the difference in vehicle speed between two consecutive data points is calculated. Given the sample rate of 1 Hz, the resulting unit of acceleration is $\frac{km}{h \cdot s}$. The change in steering wheel angles is calculated in a similar way as the difference in steering wheel angle between two consecutive data points. 15952 journeys remain.

STEP 5: Calculate initial core journey statistics and filter journeys (982 journeys removed)

For filtering purposes, core statistics such as the journey length, median vehicle speed and average vehicle speed are calculated for each journey in the dataset. Journeys that are either very short (<30s) or very long (>10800s = 3 hours) are removed. Furthermore, journeys that show abnormally large acceleration or deceleration values (>+30 $\frac{km}{h \cdot s}$ or <-40 $\frac{km}{h \cdot s}$) are removed from the data set. Journeys that show abnormally large changes in steering wheel angle ($|steering\ wheel\ change| > 900\ \frac{degrees}{second}$) are removed. Lastly, journeys that yielded an average speed of 0, implying that the car did not move at all were also removed. 14970 journeys remain.

STEP 6: Brake pressure value adjustments (no journeys removed)

In accordance to a discussion that took place during a conference call with Ford, brake pressure records showing a value below 1 bar are adjusted and raised to 1 bar, which is interpreted as the base pressure when the driver is not actively braking. 14970 journeys remain.

STEP 7: Calculate full journey statistics (no journeys removed)

Similar to the calculation of the core statistics in step 5, summary statistics for each journey are calculated. Table A.3 lists all attributes that are calculated for each individual journey record and will be used for clustering techniques later on.

Table A.3: Aggregated attributes extracted for each journey in the dataset

attribute name	description
journey length	journey length in seconds, equals the number of data points due to the sample rate at 1Hz
median vehicle speed	median vehicle speed ignoring data points where the car was not moving (vehicle speed = 0)
median engine speed	median engine speed ignoring data points where the car was not moving (vehicle speed = 0)
median brake pressure	median brake pressure ignoring data points where the driver was not actively braking
median acceleration	median of all points where the car was accelerating (vehicle speed change > 0)
acceleration standard deviation	standard deviation of all points where the car was accelerating (vehicle speed change > 0)
median deceleration	median of all points where the car was decelerating (vehicle speed change < 0)
deceleration standard deviation	standard deviation of all points where the car was decelerating (vehicle speed change < 0)
average steering wheel change	median of all steering wheel changes
steering wheel change standard dev.	standard deviation of all steering wheel changes
median gear	median gear of data points where the car was not in neutral gear
number of stops	number of times the vehicle stopped (vehicle speed = 0)
average length of stops	average length of stops in seconds
stop ratio	percentage of points in each journey where the car was not moving
speeding ratio	percentage of points in each journey where the car was speeding

motorway ratio	percentage of points in each journey where the car was driving on a motorway as indicated by OSM ‘type’
shifting indicator ratio	percentage of points in each journey where the shifting indicator light was on
turn signal ratio	percentage of points in each journey where turn signal was switched on
harsh steering ratio	percentage of points in each journey harsh steering occurred while the car was moving (vehicle speed >0 & steering wheel change > 90 degrees)
daytime ratio	percentage of points in each journey that were recorded during daytime
ratio of acceleration and deceleration threshold violations	percentage of points in each journey where acceleration or deceleration thresholds were exceeded. (Threshold taken from Verizon telematics)

STEP 8: Filter journeys and normalise journey statistics (2704 journeys removed)

Once the full statistics have been calculated, journeys that show abnormally long average lengths of stops (>600 seconds) and journeys that show the reverse gear as the median gear are removed. Afterwards, the calculated journey statistics are normalized to a scale [0;1] to avoid attributes being favoured during clustering solely due to their value being on a greater scale compared to other attributes. 12266 journeys remain.

STEP 9: remove journeys where any statistics show N/A values (424 journeys removed)

Despite removing most of the N/A values in the dataset in previous steps, the few that remain cause some statistics that are calculated to be N/A as well. To prevent issues when applying clustering algorithms later on, journeys that show any N/A attributes are removed. 11842 journeys remain.

A 3.2 - Journey Clustering

The aggregated journey statistics are used to cluster the journeys using k-means clustering. In order to distinguish between journey types in a way that is independent from driver-specific behaviours, ultimately the attributes shown in Table A.4 are used for clustering.

Table A.4: Attributes used for journey clustering

attribute name
journey length
median vehicle speed
median engine speed
median brake pressure
median acceleration
acceleration standard deviation
median deceleration
deceleration standard deviation
average steering wheel change
steering wheel change standard dev.
median gear

average length of stops
stop ratio
speeding ratio
motorway ratio
turn signal ratio
harsh steering ratio

The number of clusters *k* is determined by calculating a set of clustering validity indexes for a range of values *k* between 2 and 20. If the number of clusters is not known before starting the analysis it is often convenient to resort to some external validation criteria. According to specific rules, they indicate the appropriate number of groups to consider in the analysis. The results are shown in Fig. A.4. The orange points in the graph indicate the suggested best number of clusters for each validity index. The majority of validity indexes suggest 3 clusters, therefore *k=3* is chosen for the k-means clustering approach.

Figure A.4: Validity indexes for k-means clustering

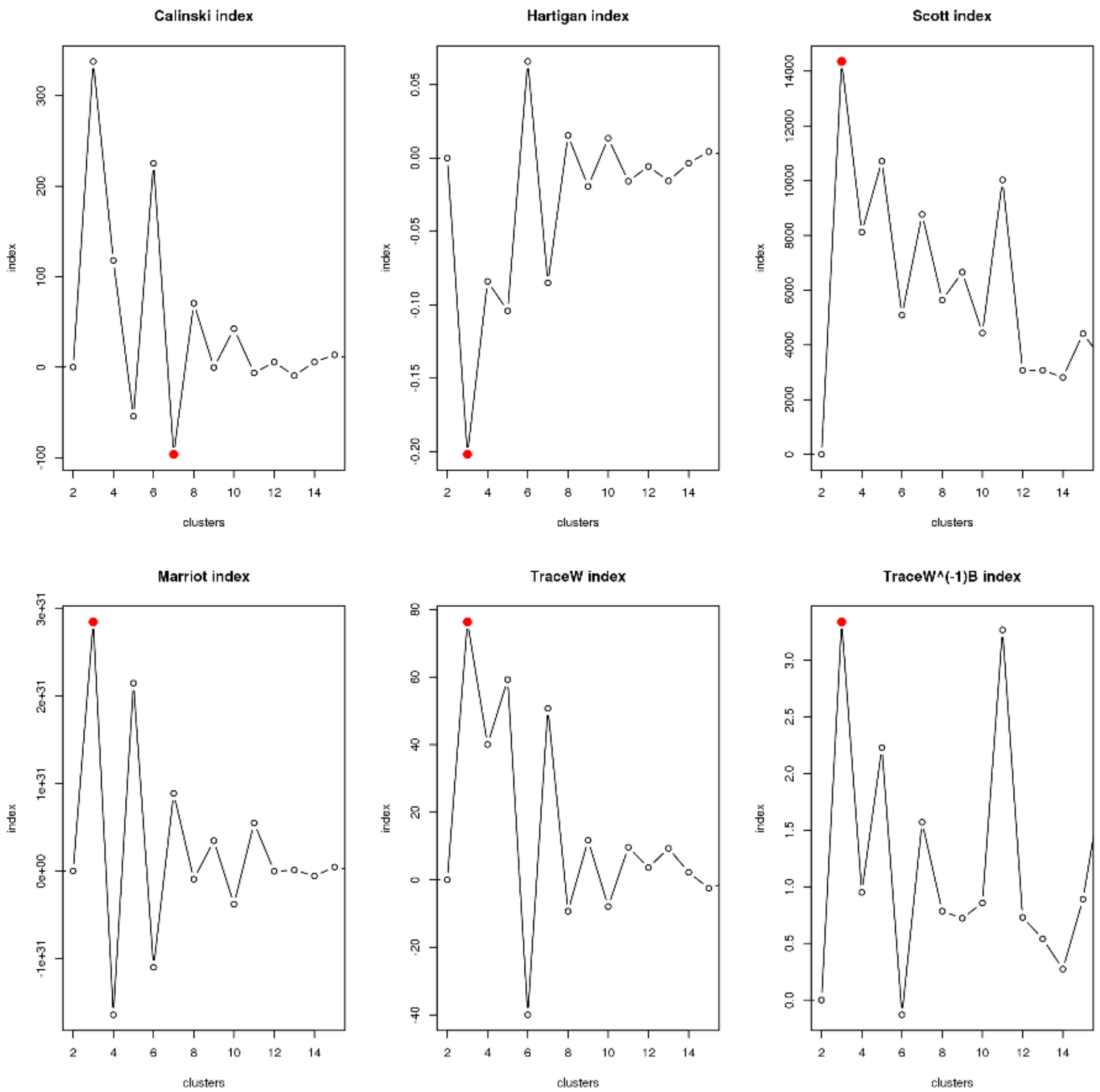
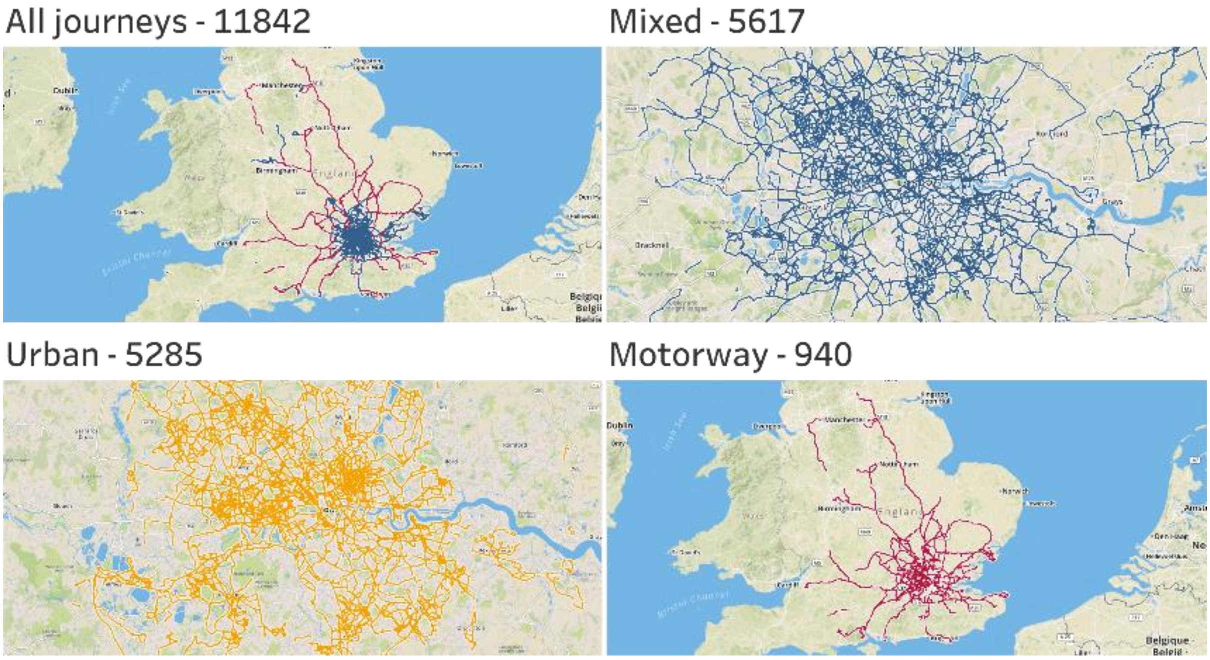


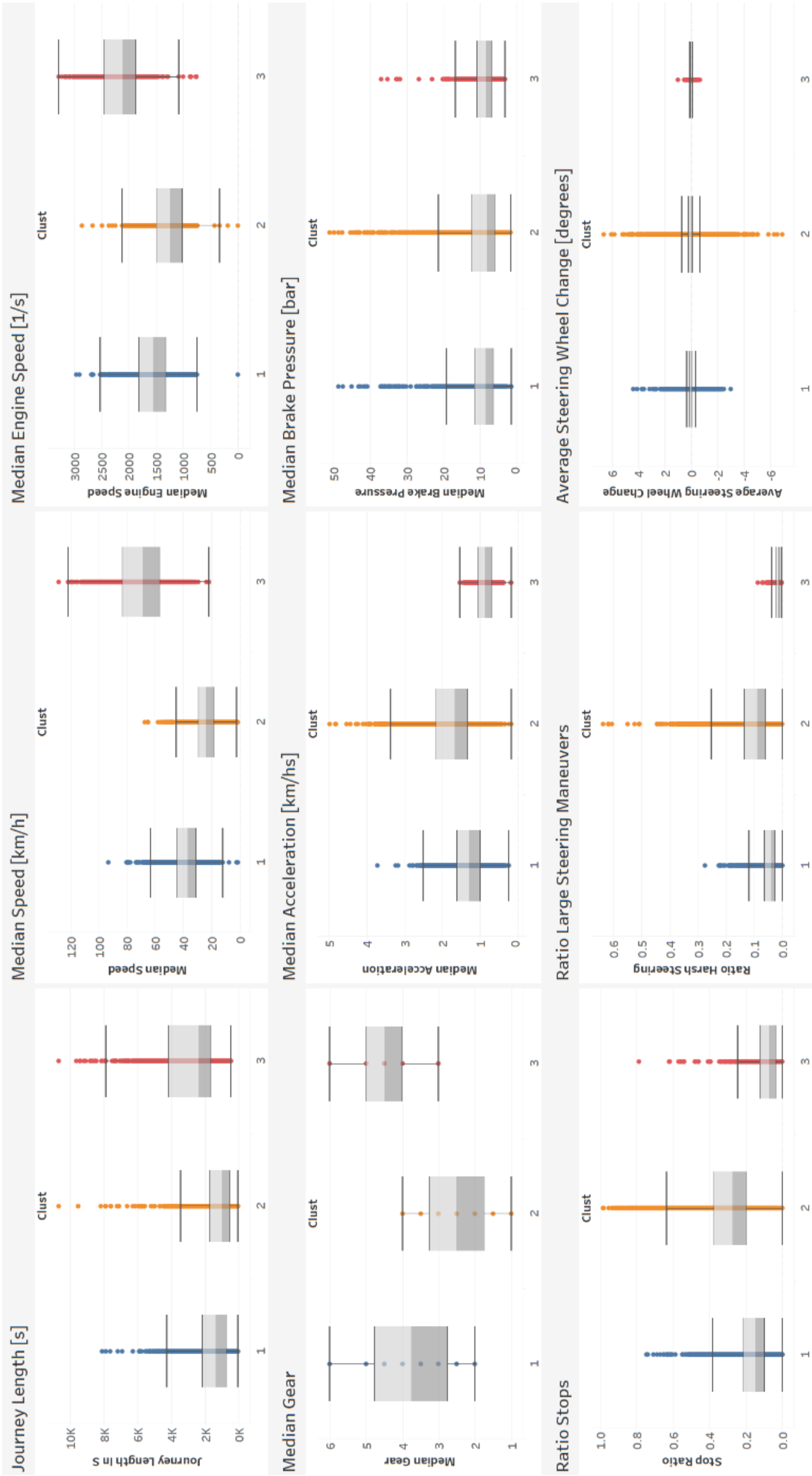
Figure A.5 shows the resulting clusters of journeys visualised on a map. This facilitates the interpretation of the clusters and made it possible to identify one cluster with *predominantly motorway journeys* (red), one with *predominantly urban journeys* (orange) and a third *mixed journeys* cluster (blue), which seems to share characteristics of the other two. Since the majority of journeys were recorded in the Greater London Area, it is not surprising that the vast majority of journeys fall either into the *urban* or the *mixed* cluster, whereas the *motorway* cluster consists of only about 8% of all journeys. The clustering procedure could be extended and refined to identify sub-groups within those shown in the Figure below, potentially achieving a more detailed distinction between journey types.

Figure A.5: Visualisation of the 3 journey clusters *motorway*, *urban* and *mixed*



Comparing boxplot visualisations of the attributes for each of the three clusters reveal a handful of attributes that seem to contribute the most to the distinction of the clusters. Among them are vehicle speed and engine speed, also median gear and the ratio of harsh steering manoeuvers. Figure 6 shows boxplot visualisations for 9 of the 17 attributes that have been used for clustering (see Table A.4).

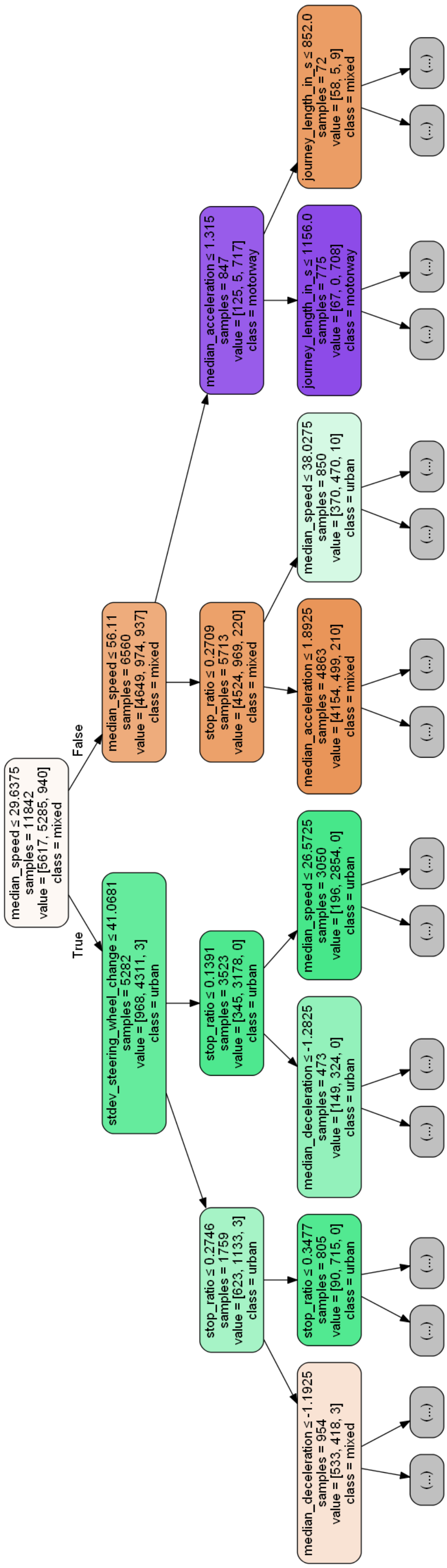
Figure 6: Box plot visualisations of the attributes that show the most significant differences between



A 3.3 Classification System

Based on the clustering results shown in Fig. A.5, a classification model could be trained, capable of classifying future journeys that were not included in the data set used for detecting the clusters illustrated before. Figure A.6 – A.8 depict a possible decision tree that was trained on the journey records using the cluster information as shown in Figure A.5. The full tree shown here has a maximum depth of 10, although only the first 3 levels are shown in the illustrations below.

Figure A.6: Example decision tree trained using the cluster information illustrated in Fig. 3



Looking at the decision tree in more detail helps identifying the most significant attributes that split the journeys into the three classes. In the first few levels of the decision tree, the median vehicle speed of a journey is the key attribute for separating the three main sub-branches of the decision tree. The left half of the tree (Figure A.7) is very much dominated by the *predominantly urban* class (green), whereas the right half of the tree (Figure A.8) is further split depending on the median speed value into sub-trees that belong for the most part to either the *mixed* class (brown) or the *predominantly motorway* class (purple).

Figure A.7: Detailed view of the left half of the decision tree

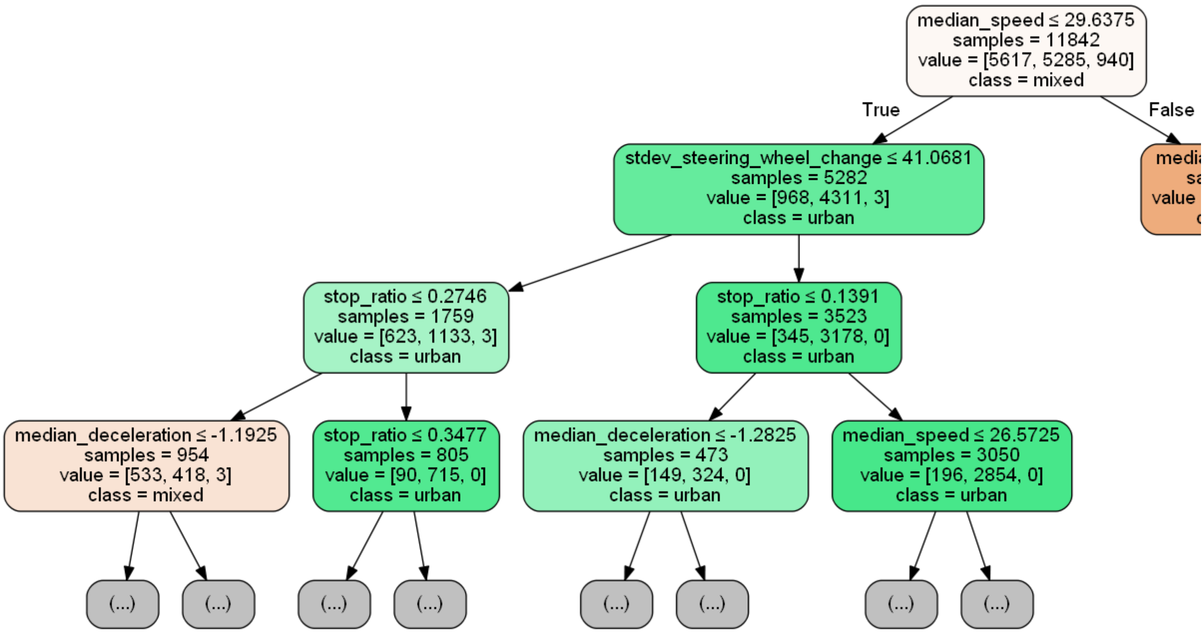
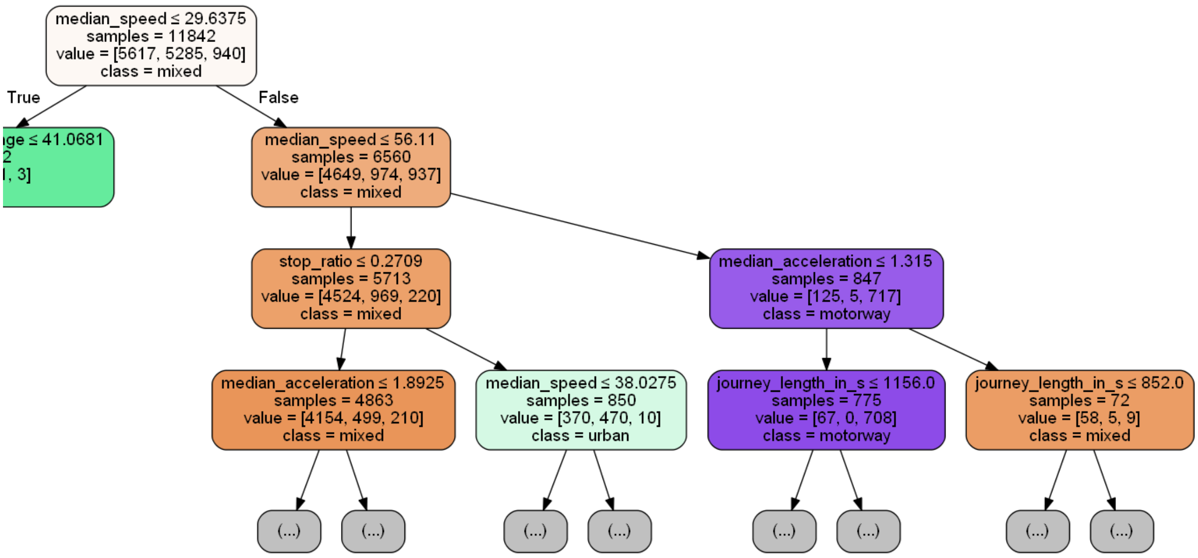


Figure A.8: Detailed view of the right half of the decision tree



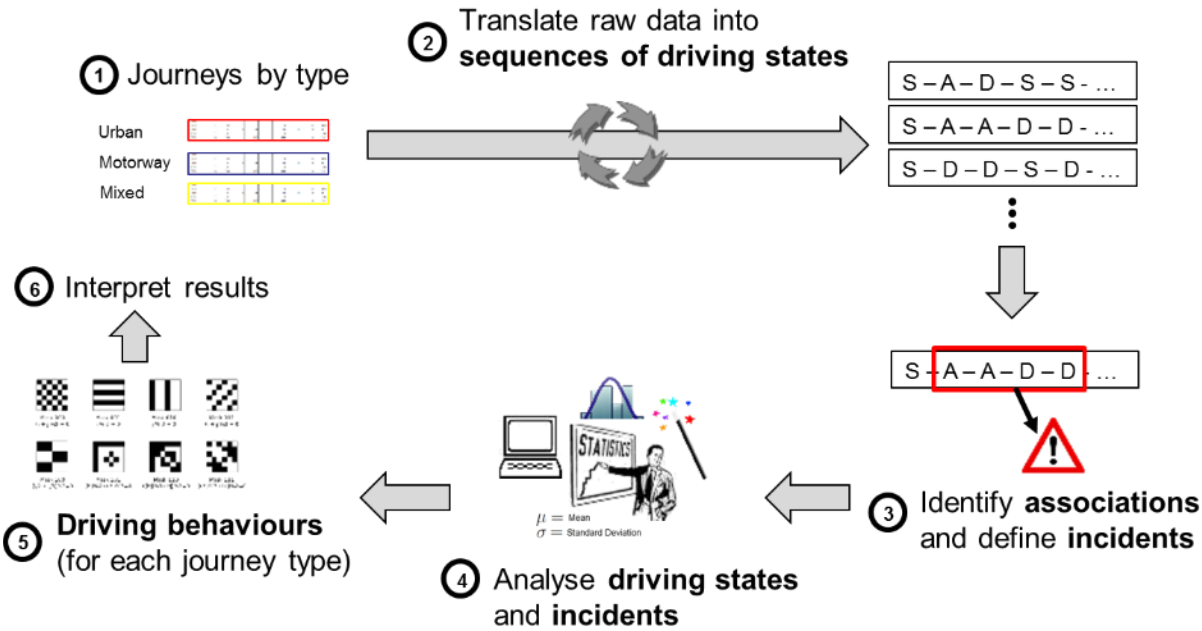
The decision tree illustrated here is a mere example of how a classification model could be constructed, the learning algorithm used to obtain such a classification model can be varied. Decision trees were chosen for this project because of their relatively intuitive nature and the ease of visualisation while yielding reliable classification performances. The decision tree shown here achieves a classification accuracy of 87%, with only minor parameter optimisation applied and using a stratified

10-fold cross validation procedure for performance evaluation. Other, more sophisticated learning algorithms such as Support Vector Machines, Neural Networks or Ensemble Classifiers can be used to achieve higher classification performance, each requiring slightly different measures for parameter optimisation and performance evaluation.

A 4 - Phase 2 – Driving Behaviour Analysis

Phase 2 (see Fig. A.9) analyses and extracts driving behaviour patterns within each of the previously detected journey types (1). To achieve this, the numerical data records are transformed into *driving states* (2), which are a nominal representation of a set of recorded attributes (e.g. "high speed + high acceleration + no steering"). Based on these driving states, common co-occurrences or sequences of driving states can be identified and enable the definition of *incidents*, such as "harsh braking", "harsh cornering" or "harsh acceleration" (3). The subsequent study and analysis of incidents (4) detects patterns of driving behaviours or common behaviours in specific situations such as speeding, turning, gear shifting etc. (5). The combined interpretation (6) of these insights result in journey-type specific driver traits that ultimately lead to the creation of driver profiles.

Figure A.9: Driving Behaviour Analysis



A 4.1 - Data Transformation

The transformation of numerical data into nominal *driving states* is a key part of the second phase of the proposed approach for driving behaviour analysis. Each numerical attribute present in the raw data has to be converted into nominal categories by defining numerical value ranges to split the numerical raw data (e.g. $0\frac{km}{h} < x \leq 30\frac{km}{h}$: low vehicle speed, $30\frac{km}{h} < x \leq 60\frac{km}{h}$: medium vehicle speed, $x > 60\frac{km}{h}$: high vehicle speed). The definition of these value ranges requires the input from experts to supply domain knowledge to ensure that the threshold values are chosen in a reasonable and meaningful way. At the same time, the granularity of the data nominalisation has to be chosen carefully. A high granularity resulting in very detailed and narrowly defined nominal categories might cause too much variation in the nominalised dataset, making the identification of driving patterns very difficult due to the amount of noise in the data. On the other hand, a very low level of detail is likely to yield equally dissatisfying results due to a worse distinction between different driving patterns, leaving potential sub-groups undetected. Table A.4 lists all data transformations used in this project. The threshold values were chosen using information provided from Ford and Transport API, as well as sources found in the literature.

Table A.4: Data nominalisation

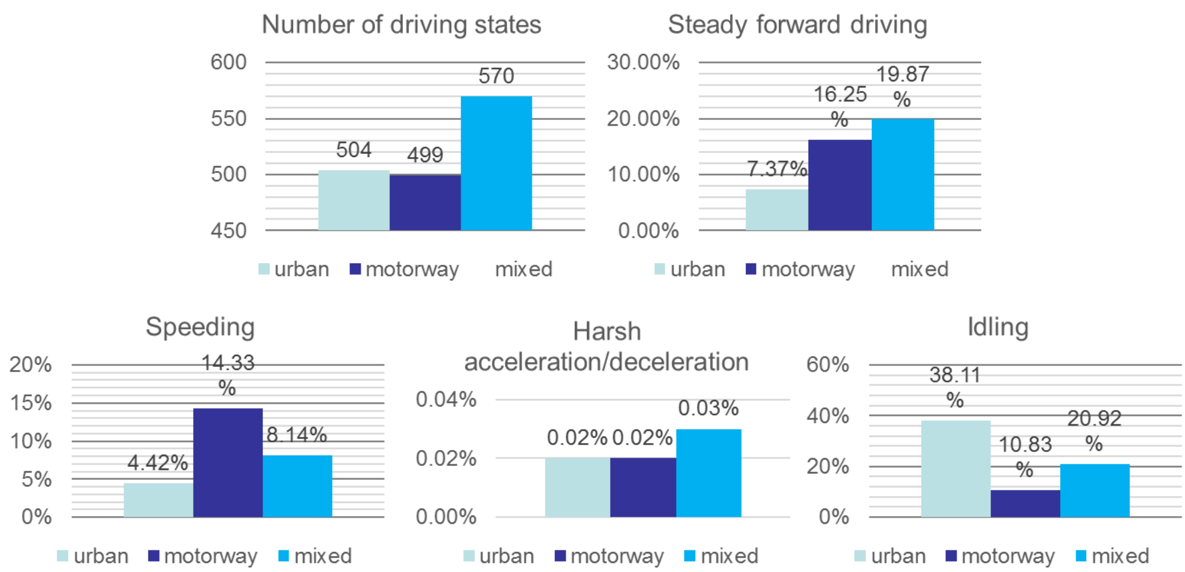
attribute	nominalisation	
vehicle speed	0 <x <= 5	very low speed
	5 < x <= 20	low speed
	20 < x <= 30	medium low speed
	30 < x <= 50	medium speed
	50 < x <= 60	medium high speed
	60 < x <= 70	high speed
	x > 70	very high speed
speeding	yes	
	no	
acceleration	x < -2	deceleration
	-2 <= x <=2	steady
	x > 2	acceleration
acceleration threshold violation	x > threshold	harsh acceleration
	x < threshold	harsh deceleration
turn signal	on	
	off	
steering wheel angle change	|x| < 10	no steering
	10 < |x| <= 30	low steering
	30 < |x| <= 90	medium steering
	x > |90|	high steering
gear	x = 0	neutral gear
	x ϵ [1,2]	low gear
	x ϵ [3,4]	medium gear
	x ϵ [5,6]	high gear
time of day	dawn	
	day	
	dusk	
	night	
cluster	urban	
	motorway	
	mixed	

An important thing to note here is that the thresholds used in this study for the nominalisation are to be seen as initial assumptions for developing the methodology proposed in this report and are very much flexible and subject to adjustment and refinement in future projects. The integration of more detailed domain knowledge can be very valuable for this process, while a refined data collection process might also help optimising the degree and detail of the nominalisation for the given task.

A 4.2 - Driving Behaviours – Speeding, Gear Shifting

The top left chart in Figure A.10 describes the number of individual driving states that have been identified within each of the journey types. The top right chart and the bottom right chart shows percentages of very common states. *Steady forward driving* refers to a state where the car is driving at a stable speed with no steering, whereas *idling* refers to a state where the car is standing still or moving very little without any no steering activity. The charts on the bottom left and middle show the percentages of data points for each journey type where speeding or harsh accelerations/decelerations occur, respectively. This analysis can be extended by looking at sequences of driving states to identify patterns of driving states (driving traits) that can ultimately lead to the definition of driving profiles.

Figure A.10: Excerpt of results obtained through analysis of driving states



Analysis for Speeding behaviour using association rule mining shows that speeding is more likely to happen on motorways and driving states involving speeding indicate many of them occur in combination with light steering movement, such as changing lanes when overtaking or coming onto a motorway from a junction. Figure A.11 shows all data points where speeding occurred. The higher number of journeys recorded in the Greater London area explains the higher density of speeding events there.

Figure A.11 Visualisation of data points where speeding was detected in the raw dataset

Apart from speeding, shifting behaviour was also analysed to see how much time would pass between the built-in shifting indicator recommending to shift gears (either up or down) and the driver to actually starting to initiate a gear shift (pressing the clutch pedal). In the raw data, a total of 386726 instances of gear shifts that followed a shifting recommendation occurred, whereas 356020 occurrences of shift indications were not followed by a gear shift. There is no information about whether the driver's act of changing gears was originally initiated because of the shifting indicator light, but analysis show that the majority of gear shifts were executed between 1 and 2 seconds after the light lit up. Figure A.12 shows a histogram plot for shifting response times of up to 10 seconds, Table A.5 lists the most frequent response times.

Figure A.12: Histogram plot of shifting response times between 0 and 10 seconds

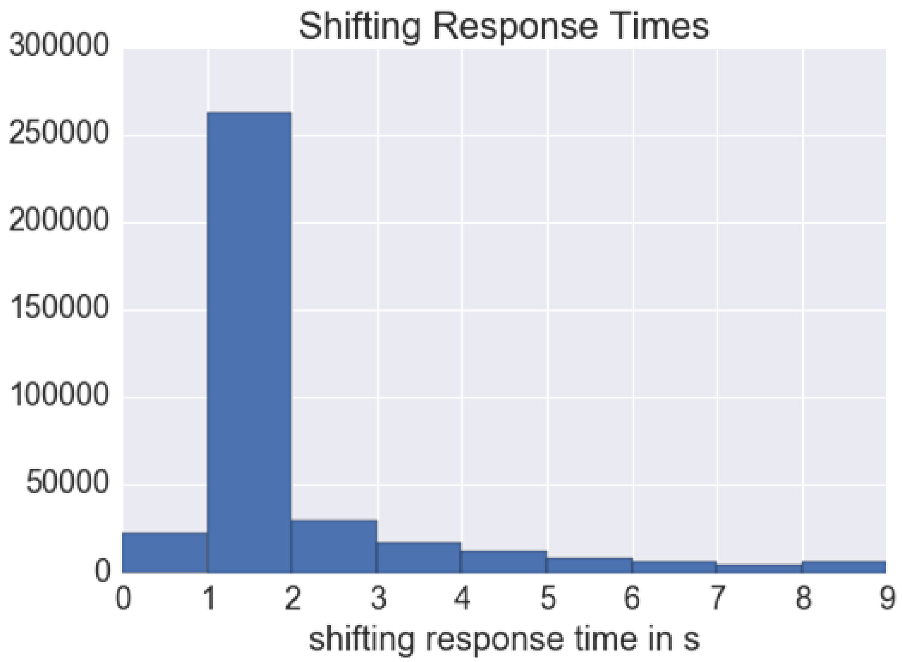


Table A.5: Most frequent gear shift response times

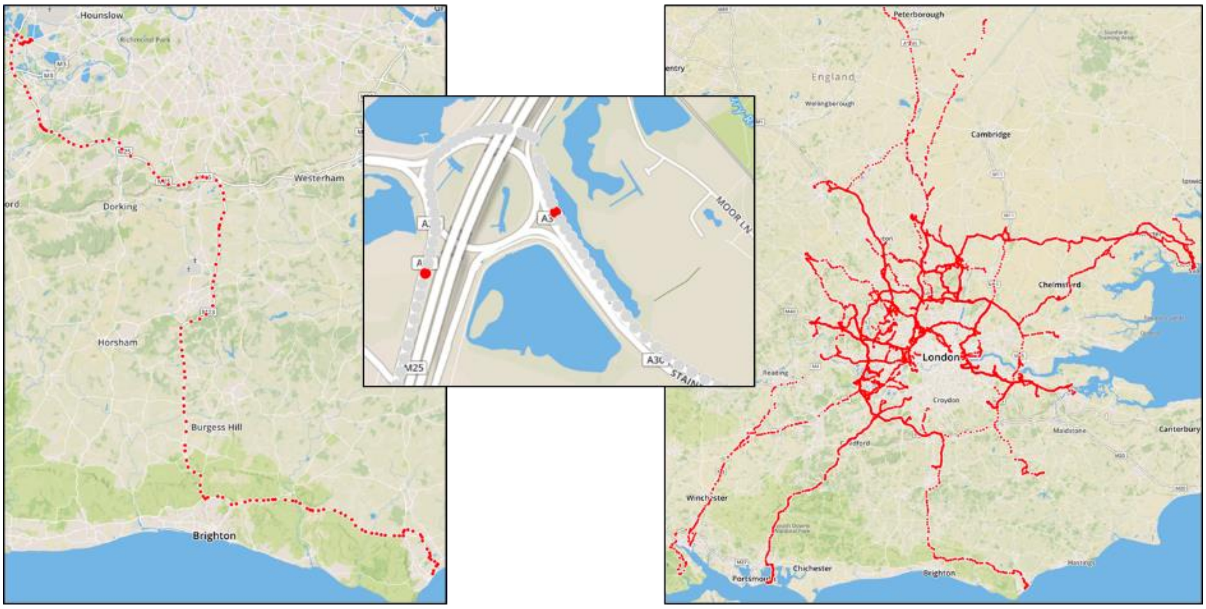
shifting response time	**% of instances**
1 second or less	5.9 %
between 1 and 2 seconds	67.7%
between 2 and 3 seconds	7.7%
between 3 and 4 seconds	4.4%
more than 4 seconds	15.2%

A 4.3 - Change Point Detection

Change Point Detection (CPD) is the process of detecting distributional changes within time-ordered observations. The R package *ecp* for multiple change point analysis of multivariate time series (Matteson and James, 2013) provides methods for CPD that are able to detect any type of distributional change within a time series. The method is robust and non-parametric in nature, the only assumption being the existence of an α^{th} moment of the time series data. CPD is capable of simultaneously estimating both the number of change points in a time series and their locations.

Change points occur due to changes in any of the variables contained in the multivariate time series. Applied to the present dataset, change points can be caused by factors related to driving behaviour, (e.g. harsh braking, harsh steering manoeuvres), factors related to the road the car is driving on (e.g. narrow turns, traffic signs) or factors related to the environment (e.g. traffic jams). Figure A.14 illustrates change points for a single journey (left), a journey segment (middle) and for a group of journeys from the predominantly motorway class (right).

Figure A.14: Change Points for a single journey (left), a journey segment (middle) and a group of journeys (right)



Change Points and their occurrence describe the characteristics of the road itself, making it possible to distinguish between journey types based on Change Point Analysis. For example, a relatively "smooth" journey on a motorway is likely to have less change points compared to a busy urban journey with a lot of traffic. The number of change points can also be seen as an indirect measure for the "riskiness" of a certain journey. For example, a journey along a very narrow, windy road with many turns is likely to prompt more changes in driving behaviour, resulting in a higher number of change points compared to a journey on a broad, straight road.

The detailed analysis whether a change point is caused by the characteristics of the road or the behaviour of the driver (or a combination of both) has to be conducted by looking at the change points in more detail in order to find out which attributes are causing the change.

Applying CPD to a large number of journey records in combination with the aforementioned incidents also makes it possible to identify *Hot Spots*, i.e. locations where incidents are likely to occur more frequently. This could be used to issue warnings to the driver before the car reaches such a location in order to make the driver more aware of possible dangers or risks. Distinguishing Hot Spots that are caused by the road from those that are primarily caused through (bad) driving behaviour can also help the car to adjust its warning messages to the current driver's profile, allowing to integrate a machine learning system into the car that is capable of learning its driver's profiles and adapting the car's reactions accordingly.

Smart Mobility Project

A combined Real-World and Driving Simulator Investigation into the Car, the Heart, the Eye and the Brain (CHEB)

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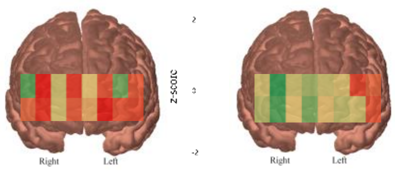

Summary

A combined real-world and simulator study was conducted which aimed to investigate the links between in-car vehicle based data, behavioural and physiological measures of the driver, and the drivers' self-reported memories of their own driving experiences. This report combines the final reports from two workpackages 'From Car to Heart, Eye and Brain' and 'Remembering Driving'.

The study was conducted both in the field, using audio diaries carried by the participants and in the University of Nottingham high-fidelity 'NITES 1' driving simulator. Participants carried their audio diaries for 2 weeks, in the weeks preceding and following a visit to the NITES simulator. They were asked to complete an audio diary reporting their positive and negative driving experiences after every drive they did during the study. During the visit to the simulator, participants drove a route through simulated Nottingham. Half of the route was seeded with additional hazards, making a high demand driving experience. The other half was on similar roads but was without the additional hazards.

The results showed that vehicle based measures correlated with driver based measures such as eye movements and brain activity. Distinctly different patterns of behaviour were associated with hazardous and comparable control drives. Drivers could be in a state where they were highly focused on the road ahead, showed more brain workload and were less likely to check the sides of the roads.

We also showed that we could generate rich accounts of both positive and negative experiences of driving. When people talk about their best driving experience, they talk about achievement, power and reward. When people talk about their worst experiences, they talk about risk and lack of control. Finally, the differences in how often people talk about positive or negative experiences also appears to be linked with their driving styles in the simulator.

Introduction

Ford is interested in improving the experience of its drivers using data recorded by the vehicle. One aim of the current study is to provide detailed subjective information about how drivers feel when driving and what they remember from their journeys. Understanding the driver and relating their behaviour to vehicle-based measures would improve the capacity of vehicle manufacturers to understand and improve the driving experience. Before this is possible it is necessary to measure and compare driver behaviour and physiology as well as drivers' experiences and memories of driving. Collecting these data in a systematic way allows greater insights than from the vehicle data alone. Furthermore, collecting self-reports from participants whose driving and physiology is also recorded allows us to relate that to their objective driving behaviour.

Remembering Driving:

If we want to understand how people feel about their driving experiences, it seems obvious to simply ask them. Getting drivers to accurately reflect on their own driving is, however, difficult. One reason for this is that drivers' memories are notoriously inaccurate (e.g. Chapman et al., 1999) and sometimes systematically distorted (e.g. Chapman & Groeger, 2004). The accuracy and richness of drivers' reports of their own driving can be dramatically improved by having them report details immediately after each journey is complete (Chapman & Underwood, 2000). In the current study drivers recorded electronic diaries for two specific weeks of driving – one week before a visit to the university's driving simulator, and one week after the visit.

Analysing the reported memories quantitatively, rather than the typical qualitative approach, can enhance the value and insights available from the data. Here verbal descriptions of events were transcribed and automatically scored to provide details of the memories. Words used are categorised according to pre-specified hypotheses and word frequency compared between categories.

Role of Feedback: One of the main opportunities that automatic measurement of driving behaviour by the vehicle provides is the chance to give feedback to the driver on their performance. In the current study we provided all participants with personalised feedback on their simulated driving, but for half of them this feedback was provided before their second week of audio diaries. This allowed us to explore the way that feedback on a specific simulated drive impacts the way they think about their subsequent everyday driving.

From Car, Heart, Eye and Brain

The advanced driving simulators at the University of Nottingham give us the opportunity to measure driving behaviour in a standardised route, while recording details of the car controls and simultaneously recording the driver's visual search patterns, physiological arousal, and frontal lobe activation.

We compare driving between hazardous and control (not so hazardous) driving experiences. There is considerable evidence that eye movements vary between different driving situations and this reflects different levels of cognitive processes such as workload, inhibition, attention and stress depending on the situation and driver characteristics (e.g. Chapman & Underwood, 1998). What is less well known is how this relates to data collected from the vehicle. By combining these two data sources we will be able to relate driving behaviour to cognitive states of the driver.

Similarly to eye movements, there is an emerging ability to measure brain activity during driving. Near Infra Red Spectroscopy offers the ability to measure blood flow to parts of the brain. Blood flow is determined by neural activity, so this allows us to measure that parts of the brain are working at any particular time. Measures taken over the drivers' frontal lobes are particularly interesting as they are known to relate directly to the workload of the driver as well as being involved in the inhibition of risky behaviour (Foy, Runham & Chapman, 2016).

The measures taken from the driving simulator, heart rate monitor, eye tracker as well as fNIRS were expected to capture more, and less, stressful driving situations as well as periods of higher and lower arousal. This means that these measures could represent and therefore correlate with, workload. Mental workload is defined as "*the specification of the amount of information processing capacity that is used for task performance*" (p. 15, de Waard, 1996). Hence, workload is directly related to the mental resources employed, but does not necessarily affect driving performance (de Waard, 1996). It may however affect physical measures. We expect that workload, in terms of eye movements and brain activity will be correlated with driving behaviour (in terms of speed, acceleration etc) (Birrell and Young, 2011, de Waard, 1996, Engström et al., 2005, Haigney et al., 2000, Horberry et al., 2006, Kircher et al., 2004, Hibberd et al., 2013, Fairclough et al., 1993, Iqbal et al., 2004).

The following sections outline the method that was used in the study, the key results and implications (driver performance measures, brain, heart and eye data, as well as driving diaries). Detailed methods and results are presented in the appendices.

Methodology

A diagrammatic depiction of the study protocol is shown in Figure 1. Full methodological details can be found in Appendix A. There were five phases to the study. In the first phase participants were familiarised with the simulator, diaries and the nature of the study. In the second phase they carried the audio recorder and recorded audio diaries after each of their drives (including best and worst situations).

In phase 3 (after a week), the driver came back to the NITES facility to complete two drives in the simulator, lasting approximately 10 minutes each. In one of the simulator drives six additional hazards were added to the normal route. A hazard is defined as an event that required the driver to brake or take evasive action. In the other scenario there were no additional hazards, making it more representative of 'everyday' driving. Whilst drivers were completing these two routes, a series of measurements were taken regarding the driver's behaviour, eye movements, brain activity and heart rate. The key measures recorded and used in the analysis are listed and defined in Table 1

In phase 4, the driver was then posted a second audio recorder and asked to provide another seven days' worth of driving diaries, using the same procedure as before. Half of the participants in the study also received an additional A3 feedback sheet (see Appendix A). This sheet contained, across time, details of the driver's behaviour, eye movements, brain activity and heart rate changes. In phase 5, the driver was debriefed and reimbursed.

Figure 1: Timeline of participation in the study

Table 1: list of measures

	Unit	Sampling rate	Description
Speed	mph	100 Hz	Speed of participant vehicle, provided by XPI Sim software
Acceleration	m/s^2	100 Hz	Rate of longitudinal acceleration, computed by determining the change in speed over each sampling period
Absolute acceleration	m/s^2	100 Hz	The distance of each acceleration value from 0, computed by multiplying negative values by (-1)
Steering reversal rate	number per minute	100 Hz	Steering reversals were defined as a change in the steering angle from clockwise to anticlockwise or vice versa, provided that the rotational speed (the change in steering wheel angle) during the previous 2 seconds had been larger than 3 ˚/s at least once (de Groot et al., 2011, Theeuwes et al., 2002). The reversal rate was calculated using the time period ranging from the previous 30 seconds to the future 30 seconds (cf. Society of Automotive Engineers, 2013).
Mean fixation duration	s	60 Hz	Mean duration of eye fixations during driving: An ongoing fixation is defined as a gaze concentration of the current and 5 previous samples (total time period of 100 ms), without the distance between two subsequent samples being more than 3 ˚. A fixation is the entirety of subsequent samples for which these fixation conditions are valid. The mean was computed using the durations of the fixations in the time period ranging from the previous 10 seconds to the future 10 seconds.
Spread of search	°	60 Hz	Horizontal spread of eye movements during driving, defined as the standard deviation of the mean horizontal positions (in ˚) of the fixations within the time period ranging from the previous 10 seconds to the future 10 seconds
Percent road centre	%	60 Hz	A fixation in the road centre was defined as a fixation limited to 20˚ horizontally and 15˚ vertically around the mean fixation point (mean coordinates for all fixations in a drive). The percentage refers to all fixations in the time period ranging from the previous 10 seconds to the future 10 seconds (cf. Victor et al., 2005).
Heart rate	beats per min	62.5Hz	Heart rate data provided by Acqknowledge 4.0 software.
Brain Activity Total Hb	Concentration in µM	2 Hz	fNIRS data was pre-processed using HomER2 v.2.2., running on Matlab R2012A, Measure used is total DeOxygenated and Oxygenated Haemoglobin, which varies with neural activity.

Results

Comparison of hazardous and control routes

We compared the averaged measures for the two drives. For this part of the analysis mean values were computed for the entire drives. For each of these measures a comparison was performed using paired-samples t-tests. These were one-tailed, because the direction of the effect had been hypothesised.

Table 2 shows the mean and standard deviation of each measure, along with the results of the significance testing. As expected there were differences in measures of driving between the hazardous and control drives. The mean speed increased from the hazardous to the control drive by 2.2 mph, and the acceleration variation decreased by 43%. The number of steering reversals rose from 15.5 to 18.7 per minute. The brain activity measures for the right and left hemispheres did not change significantly, but the variation of each lowered substantially from the hazardous to the control drive.

> *Key finding: Our two types of drive successfully elicited different driving behaviour as measured in the car*

Table 2: Comparison of the hazardous and control routes (* denotes significantly different from 0, p < 0.05). Behavioural and physiological measures are in the lower part of the table.

		Hazardous route		Control route	
	Unit	Mean	StDev (group)	Mean	StDev(group)
Speed	mph	21.3*	1.8	23.5*	2.3
Accel'ration	m/s^2	0.021	0.020	0.028	0.015
Standard deviation of acceleration	m/s^2	3.0*	3.4	1.7*	1.7
Steering reversal rate	no/ minute	15.5*	3.7	18.7*	4.1
Mean fixation duration	seconds	0.33	0.18	0.32	0.16
Spread of search	°	12.0	3.8	11.6	3.3
Percent road centre	%	0.30	0.11	0.30	0.11
Heart rate	beats per minute	80.2	13.8	76.8	12.0
Total Hb left	concentration in µM	3.4×10^{-6}	13.0×10^{-6}	4.0×10^{-6}	20.9×10^{-6}
Standard deviation of Total Hb left	concentration in µM	18.3×10^{-6}*	15.7`x10^{-6}	11.6×10^{-6}*	9.4×10^{-6}
Total Hb right	concentration in µM	4.4×10^{-6}	24.5×10^{-6}	13.2×10^{-6}	78.3×10^{-6}
Standard deviation of Total Hb right	concentration in µM	24.2×10^{-6}*	25.4×10^{-6}	16.3×10^{-6}*	16.5×10^{-6}

Correlations over time between vehicle and physiological measures

For this part of the analysis each drive was divided into sections of 10 seconds each. Correlations between the measures were conducted for each driver individually and then averaged. These are reported for each drive separately (Appendix B) and then compared between the hazardous and control drives (Table 3 and Figures 2 and 3). This section and Appendix B report correlations over time. For completeness, correlations averaged over the drives are also reported in Appendix C

Summary of separate correlations for driving based measures:

As expected, the vehicle-based measures were correlated in both the hazardous and control drives, reflecting the drivers' responses to the hazards (See Appendix B). Furthermore, these correlations were different in the two drives (Table 3, top part). In the hazardous route, the correlations were stronger between speed and absolute acceleration compared to the control drive (-0.30 vs. -0.23). Interestingly, the correlation between acceleration and absolute acceleration was negative (-0.10) in the hazardous, but positive (0.08) in the control drive. In addition, there was a negative relationship between absolute acceleration and steering reversals (-0.10), was which positive in the control drive (0.07).

Key Finding: Our two drives (hazardous and control) effectively produced different driving 'styles'.

Summary of correlations with vehicle measures and behavioural and physiological measures

A number of significant correlations between car and eye tracking measures could be found. These are presented separately for each drive in Appendix B. Correlations between driver based measures and vehicle measures differed between the hazardous and control drives and these differences are shown in Table 3, and illustrated for selected comparisons, in Figure 2.

In the hazardous route, speed was slightly positively correlated with mean fixation duration (0.07), negatively with spread of search (-0.22) and positively with percent road centre (0.23). Correlations between eye movements and speed were reduced overall in the control drive.

When acceleration measures were analysed, in the hazardous drive, more acceleration was correlated with greater spread of search (0.10) and less time with eyes at road centre (-0.10). It appears that negative accelerations accounted for more front-focussed eye movements. As with speed, correlations were reduced in the control drive such that only the correlations with the absolute value of acceleration remain, with 0.14 (spread of search) and -0.11 (percent road centre).

The steering reversal rate positively correlates with the percent eyes road centre measure and slightly negatively with the spread of search (-0.09). The relationship between steering corrections and search behaviour can be found in the control route as well, but here it is much more pronounced. The negative relationship between spread of search and the steering reversal rate appears to be stronger in the control drive with -0.28, as opposed to only -0.09 in the hazardous route.

Correlations with the frontal brain activity measure (FNIRS) also differentiated between the hazardous and control drives. Brain activity was higher for lower speeds and when drivers had greater acceleration. Brain activity was also correlated with the eye movement measures, and this differed between the two drive types. Correlations with brain activity are shown in Appendix B, Table 3 and illustrated in Figure 4.

Key findings: When drivers drove faster, or were braking, they performed more steering corrections, concentrated their gaze towards the road centre and searched less in the horizontal plane. Eye movement patterns correlated with our brain activity measure. This pattern of eye movements is typical of high demand situations (Chapman & Underwood, 1998) and is consistent with the findings from the brain activity measure. These measures were also able to differentiate between the hazardous and non-hazardous drives. This could suggest that when drivers are coping with hazards they have fewer resources available to detect peripheral information.

Table 3: Differences between hazardous and control correlations (hazardous minus control (* denotes significantly different from 0, p < 0.05) Behavioural and physiological measures are highlighted

	Speed	Acceleration	Absolute acceleration	Steering reversal rate	Mean fixation duration	Spread of search	Percent road centre	Total Hb left
Speed								
Acceleration	-0.06							
Absolute acceleration	-0.07*	-0.17*						
Steering reversal rate	-0.07*	-0.02	-0.16*					
Mean fixation duration	0.10*	-0.03	0.02	-0.02				
Spread of search	0.15*	0.11*	-0.06	0.19*	-0.04			
Percent road centre	-0.04	-0.07	0.03	-0.03	0.04	0.06*		
Total Hb left	-0.02	-0.04	0.11*	0.10*	0.05	-0.20*	0.14*	
Total Hb right	-0.11*	0.00	0.10*	0.06	-0.01	-0.13*	0.06*	0.10*

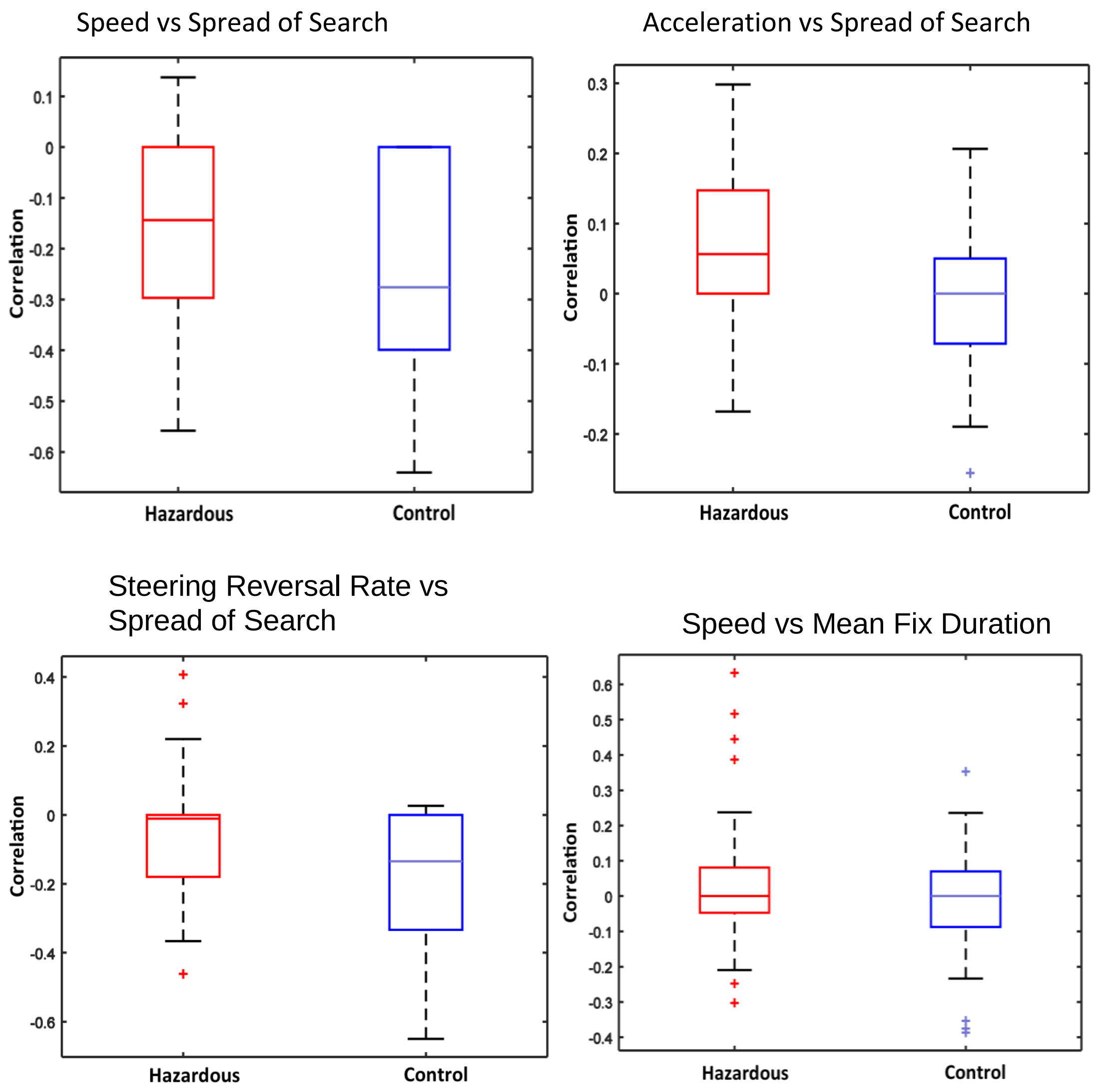

Figure 2: Examples of differences in correlations between Hazardous and Control Drives; Acceleration (right) and Speed (Left) and Spread of Search eye movement in Hazardous drive and control drive

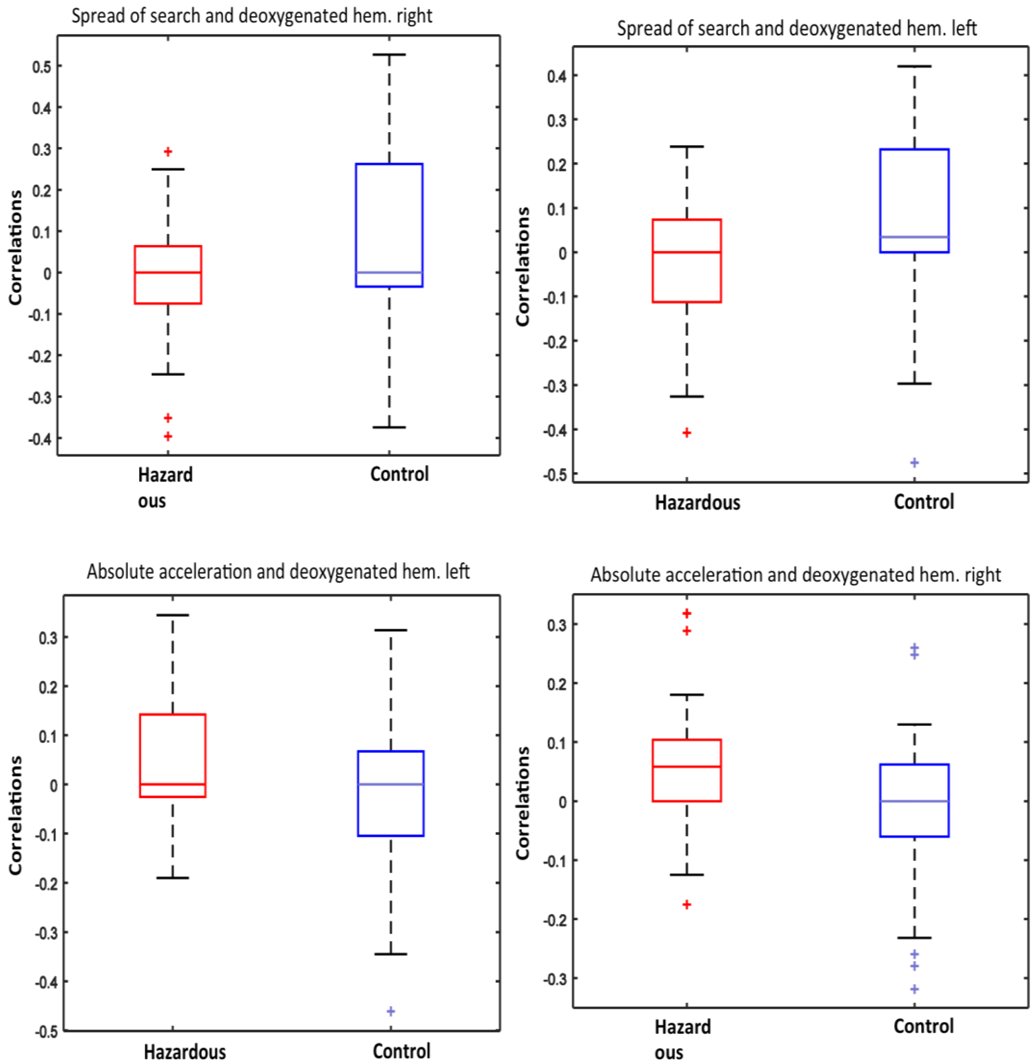

Figure 3: Correlations in hazardous and control drive between Brain activity (Total Hb) in the left (left) and right (right) hemisphere and spread of search.

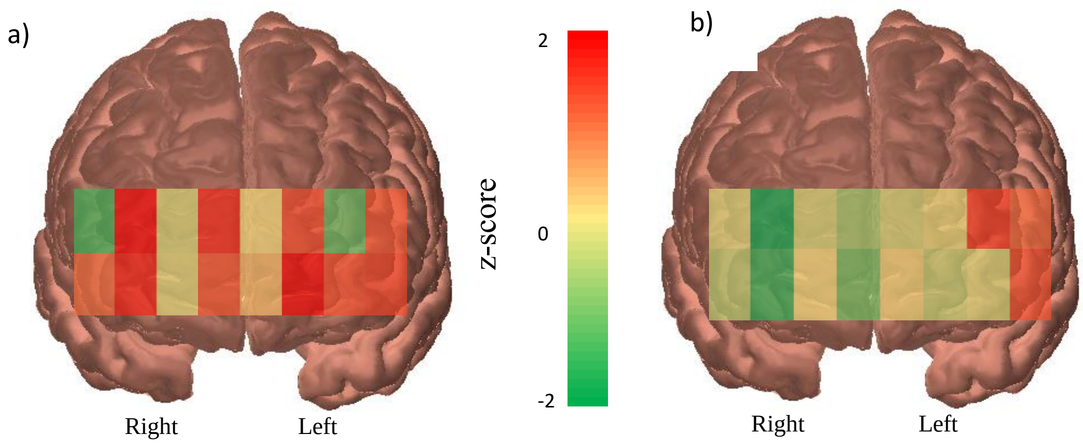

Figure 4: Levels of prefrontal cortex activation channel-by channel during a) hazardous driving, and b) control driving, for a sample participant. Z-scores represent a change from a resting baseline.

Driving diaries

After the audio diaries had been transcribed and anonymised, each diary entry was separated into its best and worst parts of journeys. These best and worst journey entries were then analysed using Linguistic Inquiry and Word Count (LIWC) software, to extract the frequency at which types of words were used. For example, the software extracted the levels of positive and negative language used. This was combined with the reported ratings of positivity and ratings of control for the purposes of analysis.

As can be seen in Figure 5, diary entries describing the 'best' parts of journeys included a greater use of positive words. These entries were also related to a greater use of words related to drive, achievement, power and reward, as well as a greater rating of overall positivity. This indicates that the

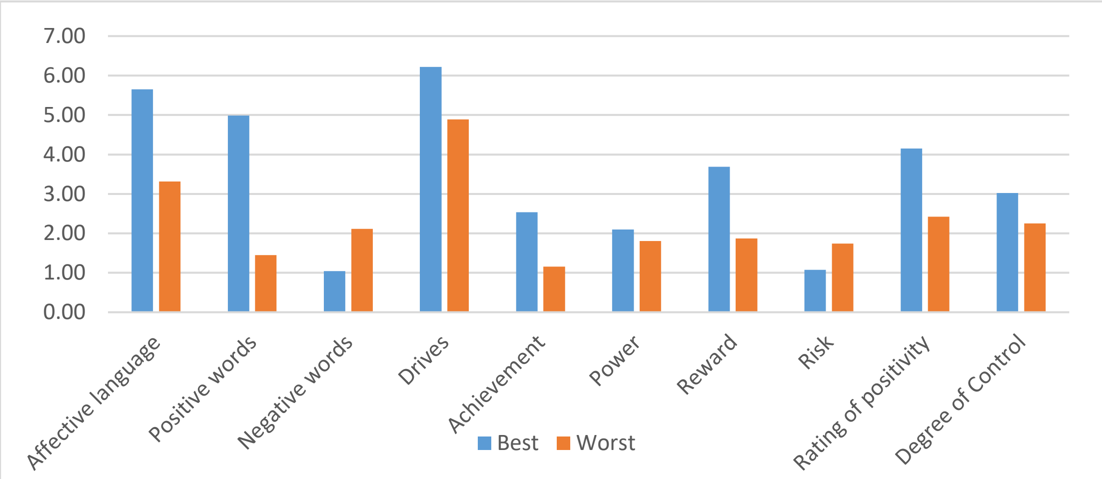

Figure 5: Rating of the amount of affective language, positive words, negative words, words relating to drive achievement, power, reward and risk used, along with ratings of positivity and ratings of control.

overall events of 'best' journey events reflect an aspiration to complete a specific task whilst driving, whether that be for the purposes of achieving something, or to feel a sense of power or reward, the successful completion of which results in an overall positive feeling for the driver. For example, drivers made comments such as:

> *"The best driving event was the fact that drivers seemed to be courteous towards me and said thank you if I let them go first… I feel that I created the driving sort of environment that enabled people to be react positively to me by thanking me."*

In this example, it is the act of being considerate to other drivers that makes the driver feel that they have been successful in creating a positive driving environment for others, which in turn may make them feel a sense of power, which in turn creates a sense of positivity.

In contrast, diary entries describing the 'worst' aspects of the journey are associated with a greater use of negative language, as well as a greater use of language related to risk, and a lower degree of overall control. This suggests that worst driving events are related to more risky situations that place the driver in danger; moreover, these events may not necessarily be in the control of the driver in question. For example, many reported that bad weather was the worst part of journeys. Other drivers were also seen as responsible for a significant proportion of worst driving events, for example one driver stated:

"Worst thing was driving along and a bus under cut me from the inside, causing me to brake harshly. And then drove off in front of me, as if he owned the road. Quite angry."

In this example, the driver of the bus is responsible for the event's occurrence, and the act of undertaking the car results in a situation that could have potentially led to an accident. This indicates the higher level of risk associated with this situation, which in turn leads to more negative language, such as the driver stating that the situation made them feel "Quite angry".

What can the language in initial driving diaries tell us about subsequent variables taken from the simulated drives?

After analysing the diary data, we assessed the relationship between these and the data obtained from the hazardous and control drives completed in the simulator. In order to answer this, correlations were taken between the variables taken from the best and worst driving events from the first week of diaries, and behavioural and biological variables taken during the hazardous and control drives. More detail of this can be seen in Appendix E.

Higher levels of reported control in best driving events are positively associated with behaviours such as steering reversal rate (Table 9). This is applicable for both hazardous (0.516) and control (0.429) drives. Higher use of affective language in best driving events was also positively correlated with levels of acceleration (0.438), suggesting that those with greater levels of emotionally-laden language related to driving were those that drove faster in the simulator. From a biological perspective, those that reported more 'best' driving events were also associated with greater modulation of brain activity with driving. For example, higher ratings of positivity were associated with greater levels of activation in the frontal right side of the brain (0.399). The type of drive-related language was also associated with activation in the frontal right side of the brain, but this differed according to the type of language. For example, whilst a greater use of power-related language was associated with increased activation (0.628), a greater use of language related to achievement was associated with decreased activation (-0.839).

The language used in worst driving events is associated with simulator variables, however this differs slightly from the best driving events (Table 11). For example, those who use less achievement-related language used are those who also had more steering wheel reversals (-0.848), and lower levels of negative emotion in worst driving events were associated with an increase in steering reversal rate (-0.8). In terms of attention levels, the use of drive-related language was negatively associated with fixation duration. In other words, a lower use of language associated with drives was associated with an increase in mean fixation duration, which was consistent across both hazardous (-0.416) and normal (-0.475) drives. Biological relationships are also shown in Table 12. Difference in brain activity are also evident, however this is dependent on hemisphere. Increases in language related to overall affect (0.53), drives (0.465), and specifically achievement (0.892) are associated with increases in activity in the frontal left hemisphere. In the frontal right hemisphere, an increase in affect language (0.528), particularly negative language (0.719), is associate with increase in activation in this area.

What can the experience of driving in a simulator tell us about the language produced in later driving diaries?

To answer this question, correlations were measured between the variables extracted from the simulator for both hazardous and control drives, and the variables taken from the best and worst driving events from the second week of driving diaries. These diaries are after drivers have experienced the simulator and are likely to have reflected more on their driving. We did not see any overall difference between those that received feedback on their driving and those that did not (using a 2x2x2 mixed ANOVA with factors of time x memory type x feedback condition) so we combined all drivers into one group. These variables can be seen in Appendix E.

It seems to be driving behaviours, rather than biological variables, that are associated with the language produced In the best driving events (Tables 13 and 14). For example, increased steering reversal rates are positively correlated with levels of perceived control (0.633 for hazardous and 0.642 for normal drives), increased speed is associated with an increase in language related to achievement (0.966), and increased speed variability is also associated with an increase in the levels of power-related language produced during best driving events (0.691). However, higher levels of speed variability and acceleration were associated with lower levels of drive-related (-0.545) and reward-related language respectively (-0.513). A negative correlation was also found between left frontal brain activity and the use of negative emotion, in that increased activation in this area of the brain was associated with a reduction in later use of negative emotion in best driving events (-0.909).

In contrast to the best driving events, a mixture of behavioural and attentional measures is associated with the type of language produced in worst driving events (Tables 15, 16). Correlations between driving behaviours in the simulator and language parameters are positive; increases in acceleration are associated with increases in drive-related language (0.4), increases in speed and acceleration are associated with increases in affect language (0.438 and 0.457 respectively), particularly language related to positive emotion (0.495), and increases in steering reversal rate are associated with increases in ratings of positivity (0.425) and control (0.404). This suggests that feelings about driving are more positive after driving in the simulator, even when describing the worst events of a journey. In terms of eye movements, an increase in spread of search is associated with an increase in achievement-related language (0.99), increases in fixation duration are associated with increases in power-related language (0.654) and increases in the percentage of time looking at the centre of the road is associated with decreases in reward-related language (-0.599).

> *Key Findings: What is recalled about everyday driving journeys can be associated with drivers driving behaviour. For instance: those that used more emotional language drove faster in the simulator. Those that reported positive experiences also had more variation in brain activity related to workload that might suggest that variations in workload and effort are pleasurable to these people.*

Summary of Key Findings and Implications

Our driver participants showed two different driving behaviours depending on the type of drive they were conducting.

When drivers performed more steering corrections, or drove faster, or were braking, they concentrated their gaze towards the road centre and searched less in the horizontal plane. Eye movement patterns correlated with our brain activity measure. This pattern of eye movements is typical of high workload situations and this was also shown in their brain activity. These measures were also able to differentiate between the hazardous and non-hazardous drives. This could suggest that when drivers are coping with hazards they have fewer resources available to detect peripheral information. **It may, therefore be possible to infer driver cognitive state from the vehicle based measures and optimise driver support towards that state. Before considering this it would be necessary to test specific hypotheses regarding the relationships.**

We used a quantitative measure of recalled memories. When people talk about their best driving experience, they talk about achievement, power and reward. For example, when people talk about their worst experiences, they talk about risk and control. **Systematic and quantitative analysis of driver memories and recall can enhance insights from driver memories.**

One goal of this research was to investigate whether feedback about drivers' physiological or driving states would change their attitude to driving. We did not see any clear change in driver memories or emotion between the group of participants who received our feedback sheet and those that did not. On the other hand the patterns of recalled driving and the relationships between simulator driving and driving recall were not the same before and after the simulator experience. **Thus, it is possible that increased insight into driving can change attitudes or behaviour (and this would be consistent with other literature). As our study was not designed to ask or answer this question this supposition must remain tentative at this stage.**

What is recalled about everyday driving journeys can be associated with drivers' actual driving behaviour. For instance: those that used more emotional language drove faster in the simulator. Those that reported positive experiences also had more variation in brain activity related to workload that might suggest that variations in workload and effort are pleasurable to these people**.** **It remains to be seen whether differences between drivers are 'traits' or 'states' i.e. whether a drivers' emotive or cognitive response to a situation is specific to the person, or more dependent on the situation.**

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Appendix A: Detailed Methodology

1.1.1 *Participants*

A total of 66 regular drivers were initially contacted to take part in the study. 26 drivers completed the entire study, criteria for exclusion were availability for the multipart study and comfort within the driving simulator, which was assessed with a practise simulator drive at a first session. Fifteen of these drivers were male and 11 were female. Drivers were aged, on average, 36.3 years old (*sd*=13.87). They had been in possession of a full drivers licence for an average of 16 years and 5 months (*sd*=13 years 8 months), and drove approximately 155 miles per week (*sd*= 137.27 miles).

1.1.2 *Design*

Overall, the study used a mixed design, with two within-subjects factors and one between subjects factor. Audio diaries were analysed before and after drivers completed the second phase of simulated driving making this the first within-subjects factor. The presences of Feedback was the between participants factor: Half of the drivers received feedback based on their performance in the simulator prior to completing the second set of driving diaries (see details below).

The second within-subjects variable concerned the type of scenario participants were required to navigate through during their second simulator session. All drivers completed two ten minute drives while measures of driving behaviour, brain activity, and heart rate, were also recorded. The first of these drives was described as a more hazardous, more unfamiliar drive. The second drive was the same route back, and therefore described as a more familiar, ‘everyday’ driving. The hazardous drive was always completed first, in order to present the second drive as the more familiar drive. Additionally, the researchers did not include any hazards within this scenario.

The dependent variables were the measures taken from the analysis of the diary transcripts and from the physiological, behavioural and simulator based measures. For the audio diaries, this included levels of affective language, the amount of positive and negative words used, and the level of ambitions, or drives, specifically achievement, power, reward and risk. Ratings of positivity and control were also recorded for best and worst journey events. With regards to the data collected during the second simulator session, this included measures of speed (in mph), acceleration rates (in m/s^2), average heart rate (in BPM), levels of frontal lobe activity (in µM), spread of search (in degrees) and mean fixation duration.

1.1.3 *Materials/Stimuli*

1.1.3.1 Questionnaires

Drivers were given two questionnaires to complete prior to completing their first simulated drive. The first questionnaire was split into two halves; the first half asked a series of questions regarding the driver’s general behaviour on the road, whilst the second half asked a series of questions regarding the driver’s perception of their own skills. The first three of these questions asked the individual how skilful and safe they were, and likely they would be to be involved in a crash compared to the average driver. The driver could say that they were ‘More skilful’, ‘The same’, or ‘Less skilful’. The remaining 29 skills questions listed a series of specific driving skills, and asked the driver to rate how good they thought they were on each skill, compared to the average British driver. These questioned were asked on a 7-point Likert scale, with responses ranging from ‘Much worse’ to ‘Much better’ than the average British driver (See Appendix D).

The second questionnaire administered to drivers was an extended version of the Driver Behaviour Questionnaire (DBQ; Reason et al., 1990). The DBQ used in this study is a 27-item questionnaire asking the driver how often they commit a series of aberrant behaviours. These behaviours are separated into errors and violations, Drivers answered the questions on a six-point Likert scale, with responses ranging from ‘Never’ to ‘Nearly all the time’ (See Appendix D).

Additionally, drivers completed the Simulator Sickness Questionnaire (SSQ; Kennedy, Lane, Berbaum & Lilenthal, 1993) before and after commencing their first simulated drive. The SSQ is a 16 item questionnaire rating the degree of various sickness symptoms. Responses on these items are rated on a 4-point scale, with responses ranging from ‘None’ to ‘Severe’.

1.1.3.2 Driving Simulator

Drivers then completed their simulated drives in the Nottingham Integrated Transport and Simulation Facility (NITES), NITES 1. NITES 1 is a high-fidelity Mini BMW simulator with a 360^{o} visual field situated within a projection dome (Figure 6) The Mini BMW contains all of the components expected within a typical car, including pedals, a gear stick, handbrake, steering wheel and indicators. All of which is situated on a motion platform with six degrees of freedom, which gives the impression of movement whilst driving in the simulator.

Figure 6: NITES 1 High-Fidelity Driving Simulator

XPI ISO software (XPI Simulation, London, UK) was used to create the various driving scenarios. The driving scenario created for the familiarisation drive was mostly situated on a single lane carriageway, with a small section of driving within an urban environment in the middle of the scenario. This allowed drivers to practise the navigation of junctions and roundabouts, as well as practise driving along straight stretches of road. Speed limits on single carriageway sections were 60mph, whilst speed limits in the urban section were 30mph. The drives completed during the second simulator session were situated in a virtual version of Nottingham. This virtual world was created and incorporated into XPI using LiDar scanning. As described in the 'Design' section, the first route took drivers from the University of Nottingham, up Derby road, through the city centre and towards West Bridgford. The second route took drivers in the opposite direction, travelling from West Bridgford towards the South entrance of the University. The majority of these roads had a speed limit of 30mph, with the exception of Clifton Boulevard, which had a speed limit of 40mph.

1.1.4 *Audio Diaries*

In order to complete the driving diaries, drivers were given an Olympus WS-853 Digital Voice Recorder. This recorder had a built-in microphone and could record 8GB, or up to 2080 hours, of audio. Once switching the device on, drivers were required to press the 'Record' button to begin recording their diary entry. Pressing the 'Stop' button would finish recording the diary entry and store it into a folder incorporated onto the device. These files were then extracted from the recorder after plugging the recorder's USB stick into the computer and accessing the recorder's folder. The files were then transcribed and anonymised (by Dragon Virtual Assistants).

1.1.5 *Physiological recordings*

Eye tracking was achieved using a series of cameras placed onto the dashboard of NITES 1's Mini BMW. Two of these cameras had infra-red lights which would initially pick up the driver's eyes, and the remaining four cameras would then track the movements of the driver's eyes. FaceLab version 5.0 was used to track the driver's eyes, run two five-point calibrations prior to driving, and record the driver's eye movements. FaceLink version 2.0 was used to transfer this information to XPI software and link it to the driving data.

Prefrontal Cortex (PFC) activity was measured using a BIOPAC 100A continuous wave fNIRS device (BIOPAC Systems Inc., USA). This fNIRS device consists of a headband with 4 sources in its centre that emit near infra-red light at wavelengths of 730nm and 850nm. These wavelengths are absorbed by oxygenated and oxygenated haemoglobin, respectively, in the PFC. A series of 10 light detectors surround the sources at an inter-optode distance of 2.5cm, creating a total of 16 channels where blood oxygenation levels can be measured. fNIRS data was recorded at a frequency of 2HZ using COBI optical brain imaging studio (fNIRS Devices, Polomac, MD, USA). fNIRS data was pre-processed using HomER2 v.2.2., running on Matlab R2012A. To prevent any outside lighting interfering with the device, a bandage was also placed over the headband.

Heart rate was measured using an ear clip attached to a Biopac PPG100C amplifier. Acqknowledge 4.0 was used to record the raw heart rate at a frequency of 62.5 Hz.

After completing the two drives in the third phase of the study, half of the drivers in the study were given an A3 laminated feedback sheet (Figure 7). This sheet contained, across time, details of the driver's speed, acceleration, changes in heart rate, changes in frontal lobe oxygenation, spread of eye movements, and mean fixation durations for each of the two drives. An image of the driver's brain activity was also provided of each drive, comparing levels of activity in 16 different sections of the frontal lobes.

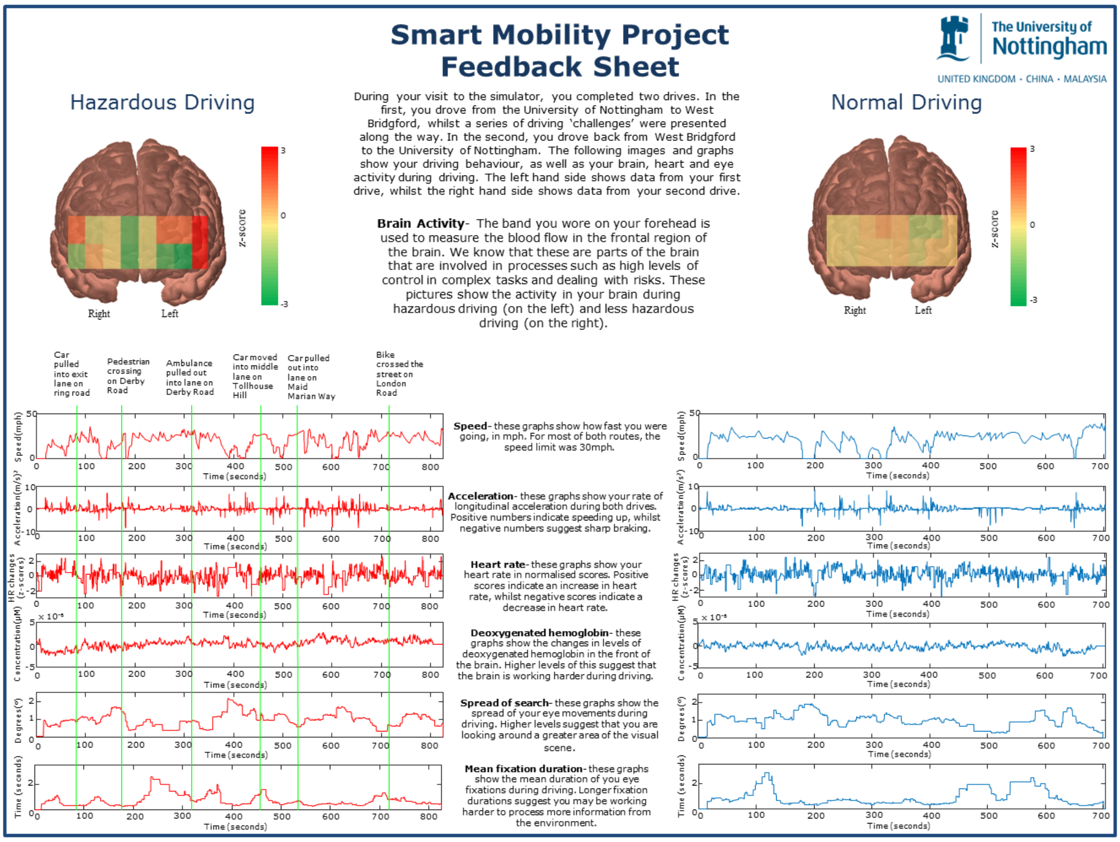

Figure 7: An example of an A3 feedback sheet provided to drivers, either before completing their second set of driving diaries, or after receiving a debriefing at the end of the study.

1.1.6 *Procedure*

Drivers completed the study in a series of four phases. During the first phase, drivers initially completed the demographics, skills and driving behaviour questionnaires, as well as the first of the simulator sickness questionnaires. They were then taken to the driving simulator, where they were told about how it worked and the various safety procedures. Afterwards, drivers were given the opportunity to complete a 10 minute familiarisation drive. This scenario was set in a typical rural area, with a variety of speed limits to adhere to, and a series of turns and roundabouts to complete. Drivers were asked to drive as they normally would, and follow the sat-nav instructions spoken out to them.

Once this familiarisation had been completed, drivers were taken out of the simulator and given a second sickness questionnaire to complete. Provided that drivers did not rate any of their sickness symptoms as 'moderate' or higher, they were then informed that they were eligible to continue with the second phase of the study. Drivers were told that they needed to complete a series of driving diaries over the next seven days, during their normal day to day driving, using the voice recorder provided to them. For every journey that they had completed, the driver had to describe how far they had driven and how long it took them. They then had to describe the best and worst parts of their journey, along with how it made them feel. Afterwards, they were asked to give two ratings on a 5-point Likert scale; the first of these rated how positive the driver felt about the event in question (with '1' meaning 'Very Negative' and '5' meaning 'Very Positive'), and the second of these rated how much control the driver felt they had over the event (with ‘1’ meaning ‘None’ and ‘5’ meaning ‘Complete control’). For safety reasons these recordings were always completed after the car had stopped and the driver had taken the keys out of the ignition.

After this first set of driving diaries had been completed, drivers then returned to the simulator for the third phase of the study. Drivers were taken back into the simulator and told that they would be completing two 10-minute drives whilst a series of eye, brain and heart measures were taken. As with the familiarisation drive, drivers were asked to drive as they typically would, whilst following the instructions spoken out to them by the audio sat-nav. After eye tracking calibration had been completed and a baseline measure of frontal lobe activity had been recorded, these two drives were then completed.

Once the drives had been completed, the drivers were told that they needed to complete another seven days of diaries; however, this time the voice recorders would be posted to them around 24 hours after the current session. This time period was chosen to allow the researchers time to create feedback sheets for half of the participants prior to posting. The A3 sheet gave detailed feedback about their behavioural, physiological and attentional patterns throughout the two drives was posted to half of the drivers (see Materials/Stimuli for more details), along with a new audio recorder. To control for the length of time elapsing before completing this second set of diaries, the control group were also posted an audio recorder, without a feedback sheet, 24 hours after the second simulator session.

This then led onto the fourth phase of the study, the second week of driving diaries. The same procedure was followed here as it was for the first week of driving diaries. After this second set of diaries had been completed, the driver then returned to hand over their second voice recorder to the researcher, where they were then given a debrief and an inconvenience allowance. Any drivers who had been placed in the control group were also then given their own feedback sheet at this point.

1.1.6.1 Driving scenario

Both experimental driving scenarios were based on Nottingham roads. The route took drivers from the South entrance of the University of Nottingham, up towards Derby Road, through the city centre, and towards West Bridgford. However, a series of six hazards were placed within the scenario that drivers needed to avoid in order to prevent a crash. Two of these hazards involved a vehicle pulling out of a minor road at the last minute, two involved a vehicle pulling into the driver’s lane at the last minute, and two involved a pedestrian running or cycling into the road. The second route required drivers to navigate through West Bridgford, through the city centre, up Derby Road, and towards the South entrance of the University. For the majority of the drives, both scenarios had a speed limit of 30mph.

1.1.7 *Measures*

The data recorded in this study consisted of objective measures collected by the driving simulator, an eye tracker, a heart rate monitor and fNIRS. Moreover, participants performed voice recordings during two one-week-long periods in their own car. Measures presented in this report are listed in Table 1(main text)

1.2 Appendix B: Correlations with Simulator Drives

Table 4: Correlation matrix for the hazardous route (* denotes significantly different from 0, $p < 0.05$). Behavioural and physiological measures are highlighted

	Speed	Acceleration	Abs. acceleration	Steering reversal rate	Mean fixation duration	Spread of search	Percent road centre	Total Hb left
Speed								
Acceleration	-0.05*							
Absolute accel'tion	-0.30*	-0.10*						
Steering reversal rate	0.37*	-0.02	-0.10*					
Mean fixation duration	0.07*	-0.04	0.03	-0.01				
Spread of search	-0.22*	0.10*	0.08*	-0.09*	-0.01			
Percent road centre	0.23*	-0.10*	-0.08*	0.13*	0.02	-0.32*		
Total Hb left	-0.17*	-0.08*	0.08*	-0.02	-0.04	-0.06*	0.04	
Total Hb ight	-0.20*	-0.03	0.08*	-0.03	-0.02	-0.01	0.01	0.82*

Table 5: Correlation matrix for the control route (* denotes significantly different from 0, p < 0.05). Behavioural and physiological measures are highlighted

	Speed	Acceleration	Absolute accel'tion	Steering reversal rate	Mean fixation duration	Spread of search	Percent road centre	Total Hb left
Speed								
Acceleration	0.01							
Abs acceleration	-0.23*	0.07*						
Steering reversal rate	0.44*	0.00	0.07*					
Mean fixation duration	-0.03	-0.01	0.01	0.01				
Spread of search	-0.37*	0.00	0.14*	-0.28*	0.03			
Percent road centre	0.27*	-0.03	-0.11*	0.16*	-0.02	-0.39*		
Total Hb left	-0.15*	-0.03	-0.03	-0.12*	-0.09*	0.14*	-0.10*	
Total Hb right	-0.09*	-0.02	-0.02	-0.10*	-0.01	0.12*	-0.05	0.72*

For each drive section average values were computed in order to perform correlation analyses over time, separately for the hazardous and control drives, and for each measure. Because the 10-second-sections were different in each drive, the data were treated as between-subjects data. Hence, using all data segments for each drive (hazard or control), correlation coefficients were calculated for each combination of two measures. In order to normalise the distributions, a Fisher transformation was performed on these correlation coefficients. Subsequently the transformed coefficients were averaged over the number of participants with plausible data for the measures. In order to test whether the correlations were significant, z-scores were calculated. The degrees of freedom (n-3) were defined as the sum of the degrees of freedom of each single drive (n-2), minus 1.

For analysing the differences in the correlations between the hazardous and the control drive, the normalised correlation coefficients were transformed back using the inverse Fisher formula. Subsequently, the z-score could be computed and the significance established.

As expected, vehicle based measures are highly correlated. Speed negatively correlates with the absolute value of acceleration, in both the hazardous (-0.30) and control (-0.23) route but only slightly negatively in the hazardous route when the acceleration is considered (-0.05) Lower speeds are associated with higher variations in speed. In the hazardous route acceleration and absolute acceleration are negatively related (-0.10), and positively in the control drive (0.07). Speed, in turn, correlates strongly with the steering reversal rate in both drives (0.37 and 0.44), implying more steering corrections in situations with higher speeds. The absolute acceleration and steering reversals correlate negatively in the hazardous (-0.10) and positively in the control route (0.07). A characterisation of the driving data with the model built in the data analytics (WP 1) shows that the simulated Nottingham routes carry characteristics of both predominantly urban and predominantly motorway journeys.

1.3 Appendix C: Correlations for average measures over drives

In order to compare overall effects for the drives, the measures, as defined in section 3.2.7, were averaged for the entire drives, before correlation analyses were performed separately for the hazardous and the control routes.

When overall measures for the experimental drives were considered, fewer significant correlations were found. In the hazardous drive there was a positive relationship between percent road centre and mean fixation duration, with 0.41, and a strong negative association (-0.83) between percent road centre and spread of search, indicating that people who were concentrating on the front road centre were exhibiting less horizontal variety in their search behaviour. In the hazardous route there was a strong negative correlation, with -0.62, between acceleration and heart rate, which could point to a link between higher heart rates and more negative accelerations.

In the control drive a few more significant correlations appeared. Speed is positively associated with acceleration (0.57) and steering reversals (0.36), as well as with mean fixation duration (0.46). The mean fixation duration is also positively associated with acceleration, with 0.41. At the same time, fixations tended to be longer for those also concentrating their gaze more towards the road centre, with a coefficient of 0.54. Mean fixation duration and spread of search are negatively correlated, with -0.39, and so are spread of search and percent road centre, with -0.76. At 0.92 the brain activities on both hemispheres are almost perfectly correlated with each other.

Table 6: Correlation matrix for the hazardous route (* denotes significantly different from 0, $p < 0.05$) Behavioural and physiological measures are highlighted

	Speed	Acceleration	Steering reversal rate	Mean fixation duration	Spread of search	Percent road centre	Heart rate	Total Hb left
Speed								
Acceleration	0.04							
Steering reversal rate	0.27	0.01						
Mean fixation duration	0.32	0.31	0.31					
Spread of search	-0.03	-0.07	0.30	-0.35				
Percent road centre	-0.20	0.27	-0.07	0.41*	-0.83*			
Heart rate	-0.38	-0.62*	-0.39	-0.20	-0.14	0.16		
Total Hb left	-0.31	-0.12	-0.25	-0.27	0.10	-0.23	0.10	
Total Hb right	.09	-0.31	-0.29	-0.19	-0.01	-0.26	-0.29	0.69*

Table 7: Correlation matrix for the control route (* denotes significantly different from 0, $p < 0.05$) Behavioural and physiological measures are highlighted

	Speed	Acceleration	Steering reversal rate	Mean fixation	Spread of search	Percent road centre	Heart rate	Total Hb left
Speed								
Acceleration	0.57 *							
Steering reversal rate	0.36 *	0.16						
Mean fixation duration	0.46 *	0.41*	0.15					
Spread of search	0.04	0.01	0.26	-0.39*				
Percent road centre	0.11	0.16	-0.01	0.54*	-0.76*			
Heart rate	0.01	0.06	-0.45	-0.10	-0.15	0.05		
Total Hb left	0.02	0.01	-0.07	0.19	-0.21	0.21	0.30	
Total Hb right	0.00	-0.08	0.00	0.10	-0.10	0.11	0.22	0.92*

Table 8: Differences between hazardous and control correlations (hazardous minus control; * denotes significantly different from 0, p < 0.05) Behavioural and physiological measures are highlighted

	Speed	Acceleration	Steering reversal rate	Mean fixation duration	Spread of search	Percent road centre	Heart rate	Total Hb left
Speed								
Acceleration	-0.53							
Steering reversal rate	-0.09	-0.15						
Mean fixation duration	-0.14	-0.1	0.16					
Spread of search	-0.07	-0.08	0.04	0.04				
Percent road centre	-0.31	0.11	-0.06	-0.13	-0.07			
Heart rate	-0.39	-0.68	0.06	-0.1	0.01	0.11		
Total Hb left	-0.33	-0.13	-0.18	-0.46	0.31	-0.44	-0.2	
Total Hb right	0.09	-0.23	-0.29	-0.29	0.09	-0.37	-0.51	-0.23

Appendix D: Copies of questionnaires

Driving Skill Inventory (Lajunen & Summala, 1995)

For the following questions, please tick or circle the box that best applies to you:

1. Relative to the average driver, how skilful do you think you are?

More Skilful	The Same	Less Skilful

2. Relative to the average driver, how safe do you think you are?

More Safe	The Same	Less Safe

3. Relative to the average driver, do you think you are more or less likely to be involved in a driving accident when you are driving?

More Likely	The Same	Less Likely

Compared to the 'average' British driver please estimate how you believe your abilities measure up in the following aspects of driving.
Please tick **one** box on each line

Item	Much Worse	Worse	Slightly Worse	The Same	Slightly Better	Better	Much Better
1. Fluent driving							
2. Performance in a critical situation							
3. Perceiving hazards in traffic							
4. Driving in a strange city							
5. Paying attention to pedestrians and bicyclists							
6. Driving on a slippery road							
7. Conforming to traffic rules							
8. Managing the car through a slide							
9. Predicting traffic situations ahead							
10. Driving carefully							
11. Knowing how to act in particular traffic situations							

12. Fluent lane-changing in heavy traffic							
13. Fast reactions							
14. Making firm decisions							
15. Paying attention to other road users							
16. Driving fast if necessary							
17. Driving in the dark							
18. Controlling the vehicle							
19. Avoiding competition in traffic							
20. Keeping sufficient following distances							
21. Adjusting your speed to the conditions							
22. Overtaking							
23. Cleaning the car windows on winter mornings							
24. Giving up right of way when necessary							
25. Keeping to speed limits							
26. Avoiding unnecessary risks							
27. Tolerating other drivers' blunders calmly							
28. Obeying the traffic lights carefully							
29. Parking in legal places only							

Driver Behaviour Questionnaire (Reason et al., 1990)

Please read the following questions carefully and tick **one** box on each line:

		Never	Hardly Ever	Occasionally	Quite Often	Frequently	Nearly All the Time
1	How often do you hit something when reversing that you had not previously seen?						
2	How often do you , intending to drive to destination A, "wake up" to find yourself on the road to destination B?						
3	How often do you get into the wrong lane approaching a roundabout or a junction?						
4	How often do you, queuing to turn left onto a main road, pay such close attention to the main stream of traffic that you nearly hit the car in front?						
5	How often do you fail to notice that pedestrians are crossing when turning into a side street from a main road?						
6	How often do you sound your horn to indicate your annoyance to another road user?						
7	How often do you stay in a motorway lane that you know will be closed ahead until the last minute before forcing your way into the other lane?						
8	How often do you fail to check your rear-view mirror before pulling out, changing lanes, etc.?						
9	How often do you brake too quickly on a slippery road or steer the wrong way in a skid?						
10	How often do you pull out of a junction so far that the driver with right of way has to stop and let you out?						
11	How often do you disregard the speed limit on a residential road?						
12	How often do you switch on one thing, such as the headlights, when you meant to switch on something else, such as the wipers?						
13	How often do you on turning left nearly hit a cyclist who has come up on your inside?						
14	How often do you miss "Give Way" signs and narrowly avoid colliding with traffic having right of way?						
15	How often do you attempt to drive away from the traffic lights in third gear?						
16	How often do you attempt to overtake someone that you had not noticed to be signalling a right turn?						
17	How often do you become angered by another driver and give chase with the intention of giving him/her a piece of your mind?						
18	How often do you forget where you left your car in a car park?						
19	How often do you overtake a slow driver on the inside?						
20	How often do you race away from traffic lights with the intention of beating the driver next to you?						

21	How often do you misread the signs and exit from a roundabout on the wrong road?						
22	How often do you drive so close to the car in front that it would be difficult to stop in an emergency?						
23	How often do you cross a junction knowing that the traffic lights have already turned against you?						
24	How often do you become angered by a certain type of a driver and indicate your hostility by whatever means you can?						
25	How often do you realise that you have no clear recollection of the road along which you have just been travelling?						
26	How often do you underestimate the speed of an oncoming vehicle when overtaking?						
27	How often do you disregard the speed limit on a motorway?						

Appendix E: Correlation tables between language variables from the LIWC and the simulator data

Table 9: Correlations between language variables and simulator data from the *hazardous* drive, based on the best driving events from Week One. Significant correlations are highlighted.

	Speed	Speed Variability	Acceleration	Fixation Duration	Spread of Search	Percentage Road Centre	Heart Rate	Total Hb left	Hazard Total Hb right	Steering Reversal Rate
Affective language	-.025	-.346	.158	-.210	.034	-.105	.161	.006	.122	-.078
Positive Words	.077	-.393	.270	-.074	.078	-.093	.274	-.125	.095	-.100
Negative Words	-.223	.320	.482	.086	-.324	-.120	.642	.237	.320	-.379
Drives	-.042	-.038	.173	.080	-.113	.161	-.034	-.198	-.145	.022
Achievement	.209	.399	.505	-.163	-.279	-.001	-.095	.437	.319	-.187
Power	-.136	.173	.272	-.224	.051	-.001	-.631	**.628***	.487	-.399
Reward	.128	.112	.363	-.063	-.248	-.185	.375	.012	.151	-.143
Risk	-.366	.015	.525	.333	-.412	.622	-1.000**	-.416	-.717	.373
Rating of positivity	-.231	-.121	-.191	-.009	-.037	.237	.434	.358	.320	-.150
Degree of control	-.063	-.046	-.042	.039	-.061	-.053	-.064	-.284	-.259	**.516****

Table 10: Correlations between language variables and simulator data from the *control* drive, based on the best driving events from Week One. Significant correlations are highlighted.

	Speed	Speed Variability	l Acceleration	Fixation Duration	Spread of search	Percentage Road Centre	Heart Rate	Total Hb left	Total Hb right	Steering Reversal Rate
Affective language	.186	-.187	**.438***	-.169	-.006	-.046	.102	.136	.221	-.226
Positive Words	.199	-.253	.385	-.061	.034	-.043	.374	.220	.189	-.303
Negative Words	.272	.173	.463	.025	-.267	-.243	.445	-.212	.344	-.510
Drives	.248	.024	.362	.017	-.094	.219	-.137	-.130	.052	-.065
Achievement	.213	.748	-.257	-.158	-.235	-.130	-.074	**-.839***	.274	-.077
Power	-.172	.434	.063	-.253	.143	-.096	-.594	-.506	.480	-.461
Reward	.265	.084	.481	-.020	-.294	-.093	-.127	.315	.133	-.331
Risk	.677	-.083	-.077	.234	-.365	.642	**-1.000****	-.666	-.774	.558
Rating of positivity	-.221	.354	.162	.024	-.015	.192	.454	-.079	**.399***	-.244
Degree of control	.050	-.183	.096	-.027	-.004	-.075	-.017	-.215	-.055	**.429***

Table 11: Correlations between language variables and simulator data from the *hazardous* drive, based on the worst driving events from Week One. Significant correlations are highlighted.

	Speed	Speed Variability	Acceleration	Fixation Duration	Spread of Search	Percentage Road Centre	Heart Rate	Total Hb left	Total Hb right h	Steering Reversal Rate
Affective language	-.122	.059	-.153	-.213	-.051	-.157	-.182	**.530** *	.294	.012
Positive Words	-.291	-.102	.110	.091	.033	.135	-.546	.090	.030	.102
Negative Words	.041	.474	.002	-.282	-.043	-.280	-.188	.704	**.772** *	-.658
Drives	-.195	-.187	-.074	**-.416***	-.004	-.162	.029	**.465** *	.310	-.030
Achievement	-.290	.133	-.182	-.763	-.173	-.085	.810	**.892** *	.644	**-.848***
Power	.111	.018	.062	.183	.040	-.054	.694	-.158	.005	.036
Reward	-.448	-.157	-.045	-.384	.142	.154	.203	.171	.034	.012
Risk	.283	.645	.490	-.594	-.158	-.028	**-1.000****	.846	.776	-.918
Rating of positivity	-.332	-.177	-.028	-.112	.158	-.100	.362	-.069	-.077	.108
Degree of control	-.166	-.107	-.066	.009	-.146	-.041	-.127	-.070	.030	.271

Table 12: Correlations between language variables and simulator data from the *control* drive, based on the worst driving events from Week One. Significant correlations are highlighted.

	Speed	Speed Variability	Acceleration	Fixation Duration	Spread of search	Percentage Road Centre	l Heart Rate	Total Hb left	Total Hb right	Steering Reversal Rate
Affective language	-.310	.188	.169	-.216	.041	-.210	**-.587***	-.230	**.528***	-.153
Positive Words	-.162	-.107	.038	.018	.090	.108	-.612	-.241	.031	.045
Negative Words	-.358	.436	-.055	-.272	-.002	-.357	-.406	.265	**.719***	**-.800***
Drives	-.240	-.060	.013	**-.475***	.039	-.326	-.186	-.193	**.454***	-.073
Achievement	-.554	.546	-.712	-.721	-.091	-.185	.797	-.506	.563	-.804
Power	.006	-.072	.008	.257	-.011	-.056	.667	.229	-.009	-.016
Reward	-.329	.024	-.112	-.433	.130	.007	.339	-.280	.052	.100
Risk	-.423	.943	-.885	-.532	-.084	-.140	**-1.000****	-.152	.675	-.929
Rating of positivity	-.061	-.304	.157	-.148	.176	-.161	.176	-.004	-.083	.147
Degree of control	-.049	-.209	-.107	-.039	-.115	-.086	-.080	.160	-.137	.212

Table 13: Correlations between simulator data from the *hazardous* drive and language used in subsequent best driving events. Significant correlations are highlighted in bold.

	Affect Language	Positive Words	Negative Words	Drives	Achievement	Power	Reward	Risk	Rating of positive	Degree of control
Speed	-.036	-.155	-.246	.021	**.966***	.390	-.037	-.984	-.229	.041
Speed Variability	-.248	-.194	.233	-.278	.942	**.691****	-.191	.700	-.039	.039
Acceleration	-.019	.173	-.737	-.084	-.230	-.521	.297	**1.000****	.138	.083
Fixation Duration	.062	.004	-.623	.081	.534	.058	-.270	.806	.128	-.008
Spread of Search	.028	.041	-.017	-.107	-.703	.390	-.152	-.620	-.192	-.102
Percentage Road Centre	.131	.101	-.336	-.117	.071	-.182	-.337	.555	.268	.044
Heart Rate	.177	.113	**-1.000****	.079	**1.000****	.040	-.419	.^{c}	-.296	-.124
Total Hb left	.027	-.059	**.907***	-.046	-.249	-.277	.272	.076	.385	-.226
Total Hb right h	.161	.128	.068	.056	-.384	-.072	-.066	-.355	.144	-.344
Steering Reversal Rate	.030	-.056	.512	.289	.343	.499	-.039	.482	-.082	**.633****

Table 14: Correlations between simulator data from the *control* drive and language used in subsequent best driving events. Significant correlations are highlighted in bold.

	Affective Language	Positive Words	Negative Words	Drives	Achievement	Power	Reward	Risk	Rating of positivity	Degree of control
Speed	.137	.111	.227	.103	.948	.425	-.022	.992	-.015	.095
Speed Variability	-.189	-.336	.543	**-.545****	.756	.316	-.478	.801	.275	-.071
Acceleration	.133	-.015	.317	-.241	.115	.243	**-.513***	.005	.169	.187
Fixation Duration	.141	.098	-.503	.122	.730	.150	-.367	.386	.134	-.040
Spread of Search	.032	.030	-.088	-.079	-.788	.391	-.082	-.782	-.125	-.065
Percentage Road Centre	.207	.152	-.119	-.079	.275	-.135	-.378	.496	.233	.013
Heart Rate	-.031	-.017	**-1.000****	.103	**1.000****	-.167	-.322	.[c]	-.326	-.322
Total Hb left	.298	.429	**-.909***	.129	-.680	.133	-.494	-.934	-.119	-.249
Total Hb right	-.044	-.224	.336	-.166	-.276	.223	-.101	-.387	.189	-.232
Steering Reversal Rate	-.022	-.124	.521	.324	.541	.353	.195	.825	-.021	**.642****

Table 15: Correlations between simulator data from the *hazardou*s drive and language used in subsequent worst driving events. Significant correlations are highlighted.

	Affective Language	Positive Words	Negative Words	Drives	Achievement	Power	Reward	Risk	Rating of positivity	Degree of control
Speed	.282	.141	.625	.238	-.473	.107	-.225	-.389	-.140	.036
Speed Variability	.105	-.223	.690	-.137	-.468	-.162	-.033	.850	-.137	-.193
Acceleration	.229	.254	-.676	**.400***	-.160	.567	.361	.224	.032	.062
Fixation Duration	.161	.013	-.036	.281	-.455	**.654***	-.340	-.401	-.178	-.129
Spread of Search	.241	.173	**.998****	.087	**.990****	.046	.050	-.901	.027	-.216
Percentage Road Centre	-.018	-.180	-.830	.077	-.785	.209	**-.535***	.933	-.123	-.077
Heart Rate	-.429	-.342	**1.000****	-.429	**-1.000****	.035	-.446	.[c]	-.098	-.429
Total Hb left	-.137	-.042	.212	.094	.734	-.372	.369	-.956	-.146	-.174
Total Hb right	.003	.151	.352	.080	.906	.227	.394	-.990	-.252	-.117
Steering Reversal Rate	.127	.150	.049	-.105	.484	-.154	.201	-.749	.344	**.404***

Table 16: Correlations between simulator data from the control drive and language used in subsequent worst driving events. Significant correlations are highlighted.

	Affective Language	Positive Words	Negative Words	Drives	Achievement	Power	Reward	Risk	Rating of positivity	Degree of control
Speed	**.438***	.229	.455	.030	-.383	.130	-.222	.092	.157	.071
Speed Variability	.062	-.131	.408	-.069	-.040	-.068	-.167	-.408	-.299	-.328
Acceleration	**.457***	**.495***	.240	.211	.674	.017	.070	-.975	.155	-.179
Fixation Duration	.175	.030	.178	.158	-.423	.485	-.420	-.816	-.160	-.163
Spread of Search	.214	.108	.813	.154	**.981***	.057	.004	-.779	.050	-.196
Percentage Road Centre	.097	-.087	-.710	.050	-.898	.115	**-.599***	.956	-.123	-.118
Heart Rate	-.436	-.412	**1.000****	-.337	**-1.000****	.777	-.624	.[c]	-.352	-.246
Total Hb left	.110	.074	-.295	-.344	.277	.256	-.199	-.552	-.133	-.035
Total Hb right	.102	.421	.563	.334	.905	.183	.324	-.984	-.232	-.168
Steering Reversal Rate	.062	-.012	-.199	-.226	.278	-.207	.129	-.371	**.425***	.285