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Temporal fluctuations in driving demand:
the effect of traffic complexity on subjective measures of workload and driving performance

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Abstract

Traffic density has been shown to be a factor of traffic complexity which influences driver workload. However, little research has systematically varied and examined how traffic density affects workload in dynamic traffic conditions. In this driving simulator study, the effects of two dynamically changing traffic complexity factors (Traffic Flow and Lane Change Presence) on workload were examined. These fluctuations in driving demand were then captured using a continuous subjective rating method and driving performance measures. The results indicate a linear upward trend in driver workload with increasing traffic flow, up to moderate traffic flow levels. The analysis also showed that driver workload increased when a lane change occurred in the drivers' forward field of view, with further increases in workload when that lane change occurred in close proximity. Both of these main effects were captured via subjective assessment and with driving performance parameters such as speed variation, mean time headway and variation in lateral position. Understanding how these traffic behaviours dynamically influence driver workload is beneficial in estimating and managing driver workload. The present study suggests possible ways of defining the level of workload associated with surrounding traffic complexity, which could help contribute to the design of an adaptive workload estimator.

Keywords: Driver workload; Traffic density; Lane change; Subjective measurement

1 Introduction

Driving a vehicle is a highly dynamic, safety critical task. Drivers are constantly exposed to a vast array of information and have to select what is relevant in order to make decisions and execute appropriate responses. These decisions are shaped by their expectations of the road, traffic scenarios and the conditions they encounter (Oppenheim et al., 2010). For safe driving, drivers have to perceive, identify and correctly interpret the relevant objects and elements in the current traffic situation. Drivers then construct and maintain a mental representation of the current situation which forms the basis of driver's decisions and actions (Endsley, 1995). Failure to process safety-relevant information may lead to errors. In dynamic changing traffic conditions, the task of driving fluctuates with the surrounding situation and the requirement to manoeuvre the vehicle appropriately. Task demand is defined as the demands of the process of achieving a specific and measurable goal using a prescribed method (Cacciabue & Carsten, 2010). Workload is the amount of information-processing resources used per time unit, to meet the level of performance required (Wickens & Hollands, 2000). Workload serves as an indication of the effect the task demand has on the driver as well as the driver state. In a dynamic traffic environment, the operator may occasionally experience periods of particularly high task demand and fluctuations in driver capabilities. From the human factors perspective of safe traffic and transport systems, the match between the driver's capabilities and the demands of the actual driving task determines the outcomes in terms of safer or less safe driving behaviour. This relationship has been modelled by Fuller (2000, 2005), as the task-capability interface model (TCI) of the driving process. Driving demand in dynamic conditions depends on the combination of environmental features, such as traffic complexity, other road users' behaviour, characteristics of the vehicle and its speed and position on the road. Driver capability is limited by personal competence (experience, age, attitude etc) and shaped by momentary variations in driver states (such as fatigue, alcohol, time pressure). In the case when there is a mismatch between the task demand and the driver capabilities, the corresponding task difficulty which arises from the dynamic interaction between them, may be reflected in the changes in task performance.

With the interface between the driving demand and momentary driver capability being important for road traffic safety (Fastenmeier and Gstalter, 2007), the accurate modelling of driver workload is regarded as crucial in the context of driver assistance systems that aim to optimise drivers' workload. Automobile companies are developing intelligent systems such as workload managers to control in-vehicle communications based on the assessed workload of the driving situation. To date, research on workload manager systems had focused mainly on the distractions within the vehicle, such as studies on the effect in-vehicle warnings on driver workload (Hibberd *et. al*., 2012, in press). However these systems have yet to consider external demands such as weather and traffic complexity in driver workload assessment. Research shows that traffic density affects driver workload; Brookhuis et al. (1991) reported that drivers' subjective mental effort was higher on a busy ring road compared to when driving on a quiet motorway. De Waard (2008) showed that increased traffic density has been shown to increase workload and the probability that error will lead to accidents. Hao et al. (2007) found that driving performance did not worsen with increasing traffic, although mental workload (physiological and subjective assessment) increased and situation awareness worsened with increasing traffic. Schieβl (2008) also reported a significant effect of traffic density on strain or workload; measuring subjective strain continuously via a 15-point rating scale, she found it rose up to a medium traffic density, thereafter plateauing and remaining the same afterward, whereas physiological strain decreased. Although Schieβl (2008) argued that the continuous subjective rating measure was sensitive to the fluctuations in workload resulting from the surrounding traffic density, the analyses were computed based on a dataset which was rather limited (n=6). Moreover, participants were instructed to give a new rating when they perceived a change in their subjective workload as opposed to being prompted at particular time points.

Changes in traffic demands can be sudden, urgent and unpredictable, such as a vehicle pulling-in from an adjacent lane. When such a critical situation occurs, driving task demand increases with the event occurring in the ‘field of safe travel’ (Gibson and Crooks, 1938). While some studies have reported that driving task demand increases when the absolute number of vehicles in the forward scene increases (Zhang, Smith, Witt, 2009; Schweitzer & Green, 2007), it is unknown if the behaviour of the vehicles’ lane changes such as their proximity and the direction of lane change affects driver workload.

Workload assessment has involved measurement of performance, subjective impressions of workload and physiological indicators (O’Donnell & Eggemeier, 1986). Sheridan (1980) suggests that operator ratings are the most direct indicators of workload. Subjective measures of mental workload are obtained from subjects’ direct estimates of task difficulty and under repeated exposures to the same tasks, the reliability coefficients for subjective measures of mental workload using uni-dimensional ratings have been reported as high as or higher than 0.90 (Gopher & Browne, 1984). Since subjective measures are easy to obtain and excel in face validity as the measures depend directly on the subject’s actual experience of workload (Gopher & Donchin, 1986), it is possible that subjective measures are more accurate in tapping into driver’s current workload as compared to some objective measures. It is argued that physiological measures are able to provide information about mental workload that cannot easily be obtained from performance or subjective measures (Humphrey and Kramer, 1994). Heart rate for example, has the longest history of use in assessing operator workload and many studies have reported that heart rate variability measures are sensitive to variations in task demand. However, this rationale is not always supported as the body also responds physiologically to things other than mental workload. Physiological measures may therefore only capture certain elements and performance measures may not correspond to workload. Dissociations between the measures could also be resulted due to how the measures are taken. Therefore care should be taken to ensure that the measures utilised could provide explanations about the level of mental effort used. While there are not many studies use performance measures to evaluate workload, the studies that do make comparisons between the subjective and objective measures of workload often find dissociation (Yeh & Wickens, 1988). Although subjective measures are often collected at the end of a mission or task risking earlier experiences being forgotten, they are more sensitive to processes which require awareness (or attention) as they rely on subjects' conscious, perceived experienced with regard to the interaction between the operator and the system. Often, subjective experiences of overload take precedence when an operator is performing a task, even when objective measures do not indicate an overload (Moray, Johanssen, Pew, Rasmussen, Sangers, & Wickens, 1979). Therefore, regardless of the limitation of subjective measures, subjective workload represents the degree to which an individual experiences workload demands, and this experience itself has potential consequences for performance levels. Hence, subjective measures of workload are used in the present investigation to characterise how much mental effort is experienced in performing driving tasks in varying traffic conditions.

To further verify subjective measures of workload, driving performance such as longitudinal and lateral driving performance measures were also employed to examine whether driver's driving behaviour varied with changes in driving demand. Research has shown that headway from the lead vehicle (Green, 2004), time-to-collision (Kondoh et al., 2007; Wada et al., 2010), and variation of speed (Cacciabue, 2007) are key factors examined for primary task demand relating to traffic. Although the aim of the study is to explore driver's temporal workload in response to changes in immediate traffic, understanding possible adaptation in driving behaviour may provide clarification of changes in driver workload and thus verify the utility of subjective measures in quantifying these external demands.

In summary, the dynamic aspect of workload in the face of fluctuating traffic conditions has not been examined thoroughly in the literature. Traffic density, measured in terms of traffic flow, has not been systematically manipulated in previous studies and in addition it is not clear how these relative temporal demands can be measured directly using subjective measures. Moreover, the influence of lane changes undertaken by other traffic on driver workload has not been explored at all. Better understanding of whether driving demand is also influenced by the behaviour of those vehicles help identify potential situations where drivers experience high workload. Therefore, the aim of this study was to examine the relationship between a number of traffic complexity factors, namely Traffic Density and Lane Changes of Other Traffic and measures of continuous subjective driver workload and driving performance. It is hypothesised that as Traffic Density increases, driving task difficulty will also increase due to drivers needing to process more information in the external traffic environment in order to manoeuvre the vehicle safely. In relation to Lane Changes of Other Traffic, it is hypothesised that subjective workload increases when they occur and those that occur in close proximity are more workload-inducing than those that occur further ahead. Following the estimation of driving task difficulty via subjective measures, data acquired relating to the vehicle and the driving environment (for example, speed, time headway and steering) can also be used to assess the driving task demand. In general, driving task demand increased with a reduction in headway and with increasing number of objects in the forward scene (i.e. traffic flow and presence of lane changes).

2 Method

2.1 Simulator

The experiment took place in the moving-base, high-fidelity University of Leeds Driving Simulator (UoLDS), see Figure 1.

Figure 1 The University of Leeds Driving Simulator

The UoLDS is based on a complete 2005 Jaguar S-type vehicle housed within a dome, with all of its basic controls and dashboard instrumentation fully operational.

The projection system within the dome provides a total horizontal field of view of 250° and vertical field of view is 45°. The central rear channel (60°) is viewed through the vehicle's rear view mirror, whilst LCD panels are built into the Jaguar's wing mirrors to provide the two additional rear views. Data were collected at 60Hz.

2.2 Participants

Drivers were recruited from both an existing database and responses to the University of Leeds website and local poster advertisement. Forty six drivers participated in the study. All participants were holders of a valid driving license for over five years, with a reported minimum annual mileage of 16,000 km. They all had normal or corrected-to-normal vision. Ten participants did not complete the experiment due to simulator sickness and simulator technical complications. Eighteen males and eighteen female participants successfully completed the study. Their age ranged between 25 and 50 years old; mean age was 37 years (S.D.= 6.9 years). All drivers were paid for their participation (£15).

2.3 Experimental design

Three roads were modelled, each being a 19km two-lane divided motorway where the behaviour of the traffic was dynamically scripted to change lanes, overtake and stay in front of or behind the participant’s vehicle. The three roads varied in their average traffic flow and therefore the number of lane changes that occurred as shown in Table 1.

Table 1 Average traffic flow and number of lane changes for each drive

	Drive 1 Low Traffic Complexity	Drive 2 Medium Traffic Complexity	Drive 3 High Traffic Complexity
Average Traffic Flow (vehicles/lane/hour)	416	810	1654
Total No. of Lane Changes (count)	1065	1428	2688

Example screenshots of the three simulated drives are shown in Figure 2.

Figure 2 Three simulated roads with varying Traffic Complexity (left to right: Low, Medium, High)

Due to the naturalistic nature of the choreographed traffic, for the purposes of data analysis each road was divided into 252m long sections. The first 3km of data in each road were excluded to allow participants to adjust to the traffic conditions and to allow the simulated traffic to build up to the appropriate flow level. The following 16km road geometry was consistent across the three roads, with 75% of sections being straight and 25% being curved. In order to eliminate the carryover effects between sections (e.g. accelerating out of a curve or decelerating into one), the data recorded in the first and the last 26m of each 252m straight section were excluded from the analyses, as detailed in Figure 3. This resulted in there being 63 road sections for inclusion in the analysis.

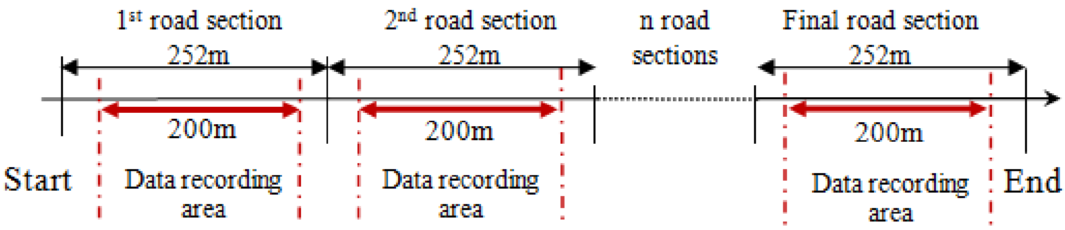

Figure 3 Data recording at each road section

These road sections could then be defined according to their traffic complexity in terms of Traffic Flow and Lane Change Presence, Proximity and Direction.

i. Traffic Flow was characterised according to the Level of Service (LOS) as defined in the Highway Capacity Manual (2000); these range between LOS A (minimal traffic) and LOS F (traffic congestion). According to the Highway Capacity Manual (2000), the traffic in LOS F can be considered as erratic and unstable. There occurred very few instances of LOS F in this study, making it difficult to draw statistically robust conclusions. Therefore, the LOS F data were excluded from the analysis, leaving five levels of this independent variable as shown in Table 2.

Table 1 Description of number of vehicles in each Level of Service (LOS) (Source: Highway Capacity Manual, 2000)

LOS	A	B	C	D	E
Density (vehicles/km/hr)	7	11	16	22	25

ii. Lane Change Presence within 252m of the front of the participant's vehicle was considered, creating a dichotomous independent variable (present/absent).

iii. When a lane change by a vehicle ahead occurred, its proximity to the participant varied and they were subsequently categorised as being in either the near-zone or far-zone. The near-zone was defined as the area between the participant's vehicle and the lead vehicle, whilst the far-zone was defined as the area between lead and preceding lead vehicle, see Figure 4.

iv. Lane Change Direction was also varied, with vehicles either moving away from the participant's lane or towards it.

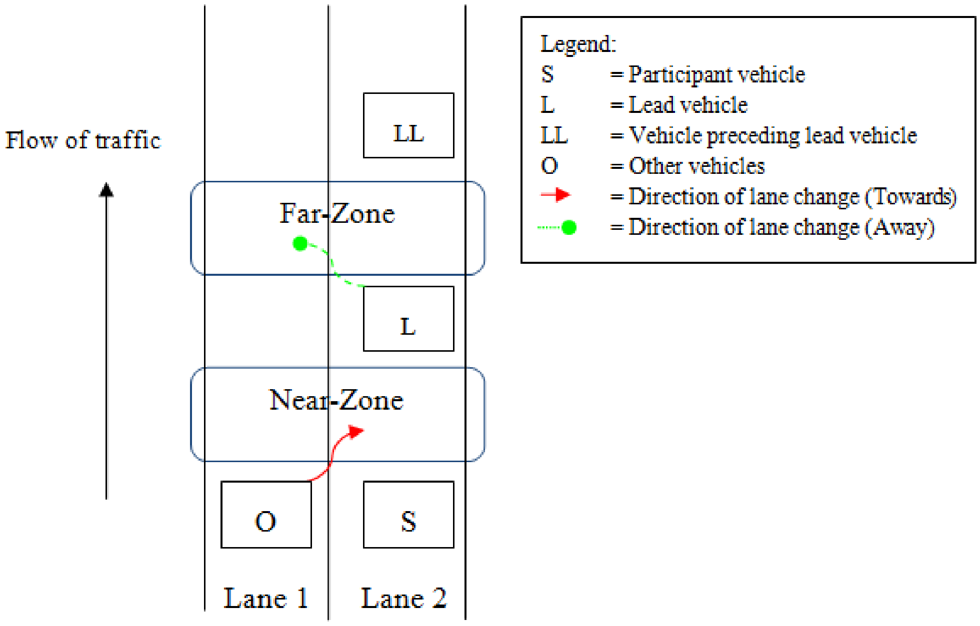

Figure 4 Description of type of Lane Change

A within-subjects design was used, whereby the order in which the participants drove the three roads was counterbalanced. The other vehicles consisting passenger vehicles such as highway maintenance vehicles and heavy good vehicles were scripted to change lanes when certain conditions were met (e.g. available gap). To encourage participants to interact with the surrounding traffic, they were instructed to drive with an element of urgency whilst adhering to the traffic regulations (i.e.

speed limit). The following instructions were given to the participant prior to the start of the drive,

"You are late for a meeting. You will arrive on time if you drive at 110km/h."

A 10 minute practice of the experimental road preceded the experiment to ensure a certain level of competence with the simulator controls and familiarisation with the rating scales.

2.4 Measures of subjective workload

Overall (i.e. after each drive) and continuous (i.e. during each drive) measures of subjective workload were elicited. An informal post-study interview session was also conducted at the end of study to expand the understanding of ease of use of workload ratings and to discuss factors that influenced driver's ratings.

i. *Overall workload (NASA-RTLX and RSME).* It is common to assess workload over a long period of time (Verwey & Veltman, 1996) as a global measure of operator demand. In this study, after the completion of each of the three drives, the two most commonly used techniques of eliciting subjective mental workload were administered; the Raw NASA-Task Load Index (NASA-RTLX; Byers, Bittner, & Hill, 1989) and RSME (Zijlstra, 1993). The NASA-RTLX is a multi-dimensional instrument consisting of six subscales exploring Mental Demand, Physical Demand, Temporal Demand, Own Performance, Effort, and Frustration Level. Each subscale is 10-cm long depicting a scale of 0 to 100, with the endpoints of the response scale anchored 'low' and 'high'. The NASA-RTLX has successfully been used to measure small changes in workload (Jahn, Oehme, Krems, & Gelau, 2005), specifically in mental and temporal demands. The RSME is a uni-dimensional rating scale developed by Zijlstra (1993) to investigate mental effort only. Perceived mental effort is rated on a 15-cm long vertical line marked at 1-cm intervals and reflects a scale of 0-150. The scale has nine anchor points ranging from 'absolutely no effort' (close to the 0 point), to 'rather much effort' (approximately 57 on the scale) to 'extreme effort' (approximately 112 on the scale). This scale has been widely used in traffic research (De Waard, 1996) since it is a fast and easy method; however it provides no diagnostic information about the sources of workload (Zjilstra, 1993).

ii. *Continuous Subjective Rating (CSR)*. As well as the workload measures taken post-drive, in the present study ratings were also collected continuously during each drive to assess the fluctuations in participant's workload. De Waard (1996) notes that where performance measures might be insensitive to increases in workload, changes in continuous workload ratings may well give an indication of effort exerted. A pilot study using a 15 point rating scale similar to that of Schieβl (2008), suggested response-bias with participants' scores clustering around multiples of 5. Participants also indicated a preference for a smaller scale and therefore a 10-point scale was used here. The rating scale consisted a 1-10 point scale, explained verbally as representing low (1-3), medium (5-6) and high (8-10). Participants were asked to provide a workload rating by an auditory prompt, approximately every 8 seconds (i.e. in each 252m road section).

2.5 Measures of driving performance

During the trials, driving behaviour in terms of speed, steering, and vehicle position (lateral position, time headway) were sampled and calculated for each road section (each 252 m) as detailed previously in Figure 3. Curve sections (which comprise of 25% of the total sections) were removed when examining the lateral control measures.

i. *Mean and Standard Deviation of Speed.* Ratings of workload systematically increase with speed (Fuller, McHugh and Pender, 2008) since task difficulty has been suggested to be analogous to mental workload (Fuller, 2005). Since very little change of speed occurs in the case of roads with constant geometry (straight or low curvature roads), standard deviation of speed would be an indication of changes in traffic conditions (Cacciabue, 2007) and thus suggesting variation on driving demand while controlling the roadway features. This is particularly applicable in more dense traffic conditions where space is restricted, causing drivers to proceed more cautiously with lower speed.

ii. *Mean Time Headway.* Headway is a measure of longitudinal risk to understand whether a following vehicle is travelling too close to a lead vehicle compared with a recommended safe following distance (Roskam et al., 2002). In previous studies of estimating driver workload, Green et al. (2011) suggested that headway from the lead vehicle should be considered when measuring the influence of other road users on driver workload and this measure had been included in workload estimator equations such as the SAVE-IT project (Green, 2011). In this study, the continuous workload ratings collected requires the driver to constantly monitor the surrounding traffic, thus it is possible that workload rating may be influenced by the overall headway experienced. Since the traffic flow manipulated in this study may affect the participant's driving speed, time headway is therefore examined and compared over conditions.

iii. *High Frequency Component of Steering Angle.* A detailed analysis of lateral deviation performances can be conducted by focusing on the variation of steering wheel angle by means of a spectral analysis of the steering signal. This involves transforming the signal to a frequency domain (by means of Fourier transform) and analysing those frequency bands affected by different factors. Mc Lean and Hoffman (1975) found that the frequency content in the 0.35-0.6 Hz band is sensitive to variations in both primary and secondary task load, thus an effective indirect measure of the driver workload since any variations on drivers' attention affect the steering wheel frequency variation (Ostlund et al., 2004). In this study, the high frequency component is defined as the proportion between the power in frequency band between 0.3 and 0.6 Hz and the total steering activity signal (i.e. power of frequency band between 0 – 0.6 Hz).

iv. *Standard Deviation of Lateral Position (SDLP).* Lateral position variation is influenced by unintentional lateral variations caused by the difficulty to drive within the safe path of travel. SDLP is a primary task performance measure which is sensitive to high workload in conditions where driver performance is not optimal (de Waard, 1996). In this present study, it is assumed that changes in lateral position would be significant when driver workload significantly increased with the changes in traffic conditions. In a study conducted by Green et al. (1994) that examined the relationship between road geometry and workload ratings, standard deviation of lateral position was found to correlate with workload ratings when workload was light and traffic absent. In the present study, it is assumed this variation is capable of detecting the driver workload changes caused by the impact of the traffic conditions.

3 Results

Data were tested for normality and sphericity before proceeding to parametric analyses (ANOVA). The Greenhouse-Geisser correction was applied where necessary. Gender was included as a between subjects factor.

In order to compare the sensitivity of the three measures of subjective workload, the average CSR was computed across all road sections for each of the three drives and compared to the overall workload scores obtained post-drive (NASA-RTLX and RSME).

The RSME, NASA-RTLX and mean CSR scores were standardized to a 100 point scale and correlations were computed between CSR and RSME ($r=0.720$, $p<0.001$), CSR and NASA-RTLX (0.739, $p<0.001$) and RSME and NASA-RTLX ($r=0.834$, $p<0.001$). A one-way repeated MANOVA conducted using the three workload scores, found main effect of Traffic Complexity ($F(6,29)=110.138$, $p<0.001$). Post-hoc pairwise comparisons revealed there were significant differences ($p<0.001$) between each of the Traffic Complexity conditions for each workload measure, see Figure 5.

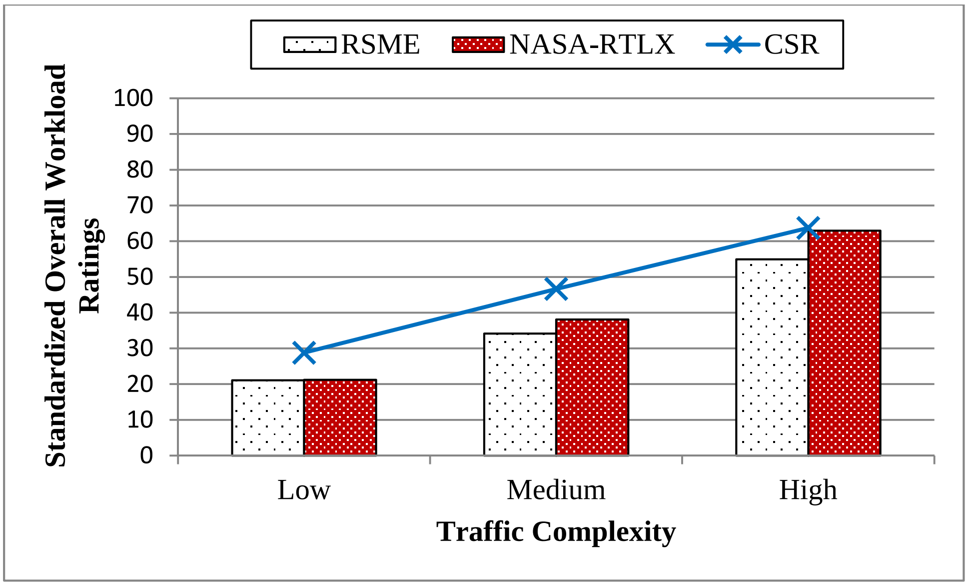

Figure 5 Mean subjective mental workload scores by Traffic Complexity

One-way repeated MANOVA analysis of the six dimensions of NASA-RTLX revealed significantly higher mental demand (F(2,68)=132.745, p<0.001), physical demand (F(2,57.56)=61.246, p<0.001), time pressure (F(2,68)=81.234, p<0.001), poorer own performance (F(2,68)=44.346, p<0.001), greater effort (F(2,68)=73.431, p<0.001) and frustration (F(2,68)=75.214, p<0.001) in medium and high traffic complexity, compared to low traffic complexity. There was no significant effect of gender.

Following this analysis of overall workload, the data were then stratified by road section, allowing the investigation of the effect of the four independent variables (outlined in Section 2.3) on CSR scores. This allowed the examination of how temporal fluctuations in Traffic Complexity might affect workload. The experimental design was not a full factorial one as not every factor was tested at every level of all of factors (e.g. where a lane change was absent there was no associated level of proximity or direction). Therefore we first considered if there were effects of Traffic

Flow and the Presence of Lane Changes on subjective workload and then proceeded to examine the characteristics of those Lane Changes in more detail (Proximity and Direction).

3.1 Effect of Traffic Flow and Lane Change Presence on subjective workload

First, the segmented CSR data were subjected to two-way ANOVA repeated measures analyses. There were significant main effects of Traffic Flow (F (3.024, 105.841) =126.075, p<0.001) and Lane Change Presence (F (1, 35) =47.104, p<0.001) on CSR ratings as shown in Figure 6. There was no significant interaction between Traffic Flow and Lane Change Presence.

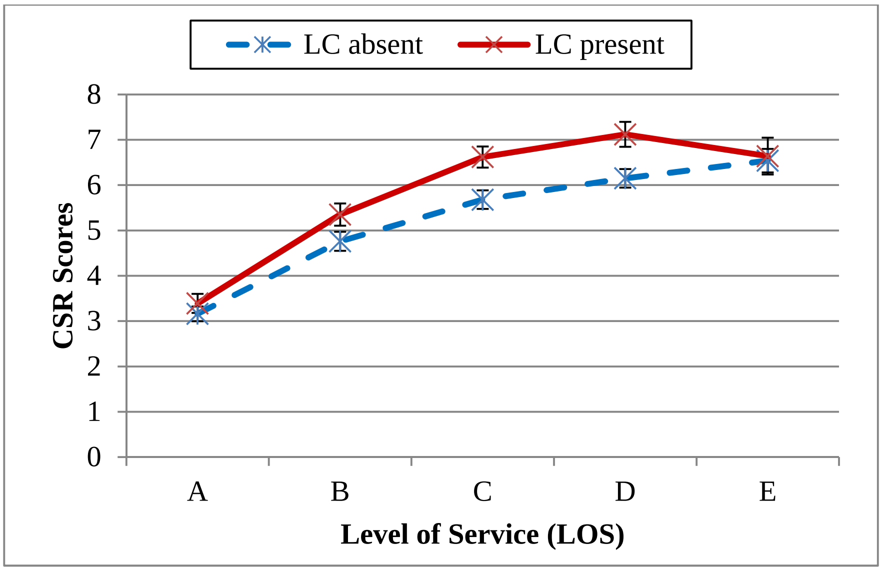

Figure 6 Mean CSR by Traffic Flow and Lane Change Presence

Post-hoc polynomial contrasts showed a significant quadratic effect of Traffic Density (F (1, 35) =71.407, p<0.001) on CSR, suggesting that workload increases and then levels off beyond LOS D. There was no significant effect of gender.

3.2 Effect of Traffic Flow and Lane Change Presence on Driving Performance

Lateral and longitudinal data were analysed with mixed MANOVA repeated measures analyses and gender as the between-subject factor. At the Bonferonni adjusted alpha level of 0.01, findings showed that there were significant effects of the Traffic Flow (F(20,15)=65.477, p<0.001) and Lane Change Presence (F(5,30)=53.917, p<0.001) and their interaction (F(20, 438.744)=3.922, p< 0.001) on the combined dependent variables. No significant effect of gender was found.

Analysis of the dependent variables individually showed effects of Traffic Flow on longitudinal measures only. However effects of Lane Change Presence were found for all except high steering frequency. Two-way ANOVAs were conducted on significant measures (i.e. all except non-significant high steering frequency measures) revealed by MANOVA and Greenhouse Geisser correction was employed where the sphericity assumption was violated.

ANOVA showed main effect of Traffic Flow with a significant reduction in average mean speed (F(3.244, 113.548)=249.897, p< 0.001) and increase in standard deviation of speed (F(2.914, 102.002)=37.207, p<0.001)(Figure 7). Similar trend was also found with main effect of Traffic Flow in average mean speed (F(1,35)=7.766, p=0.009) and variation in speed (F(1,35)=66.138, p<0.001) in traffic conditions involving lane changes. There was no significant interaction between Traffic Flow and Lane Change Presence on standard deviation of speed suggesting that main effect of Traffic Flow is present regardless of Lane Change Presence and vice versa. In contrast, a significant interaction was found with mean speed (F(2.753, 96.351)=729.932, p=0.004). Simple effects analysis (paired sample t-test comparisons of presence and absence of lane changes for each Traffic Flow condition) showed an effect of Lane Change Presence for all except LOS A, t(35)=0.504, p=0.618.

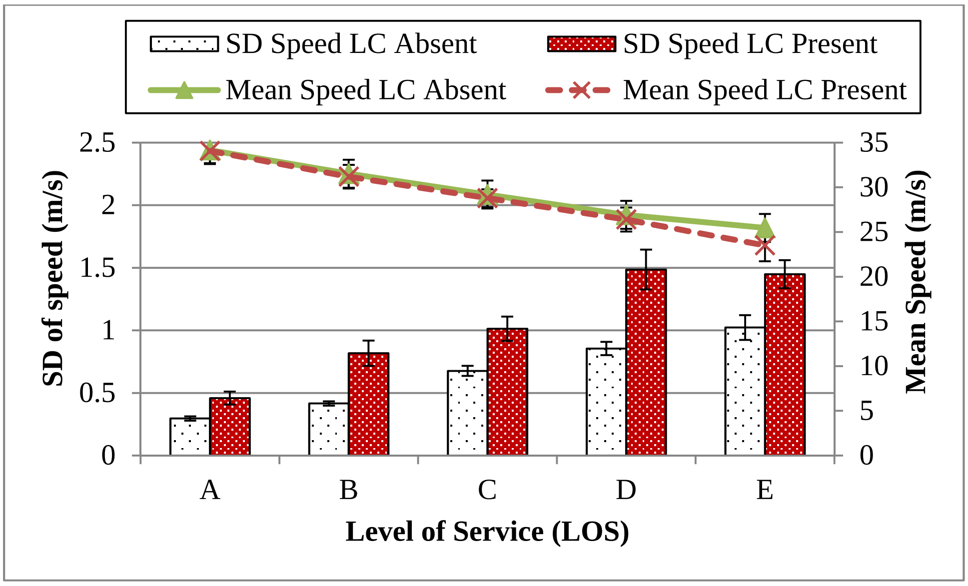

Figure 7 Comparison of mean and standard deviation of speed (and standard errors)

Since effects on speed were found across LOS, time headway were compared over conditions. Significant effects of Traffic Flow, F(1.077,37.688)=135.199, p<0.001), Lane Change Presence, F(1,35)=73.819, p<001) and an interaction F(1.621,56.750)=9.095, p=0.001 for time headway were found. Pair-sampled t-test indicates there was a significant effect of Lane Change Presence on all LOS. Mean time headway increased in the presence of lane changes in all traffic flow conditions where participants keep a mean time headway 0.926 s (95% CI – 0.707 to 1.145) longer than they did during the no Lane Change Presence conditions (Figure 8).

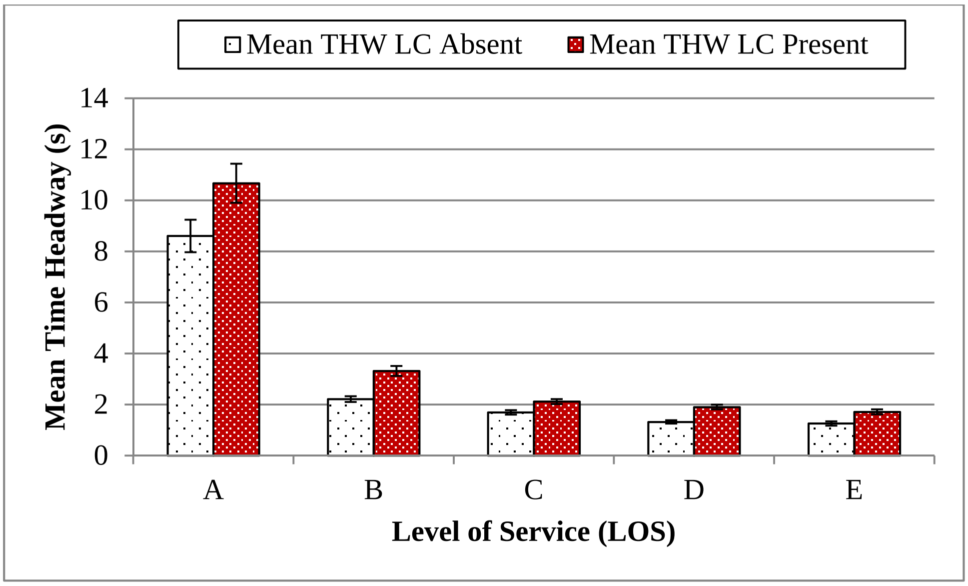

Figure 8 Mean time headway (and standard error) by Traffic Flow and Lane Change Presence

There was a significant main effect of Lane Change Presence on variations in lateral position (F(1,35)=8.973, p=0.005). Participants deviated more in lateral position when lane changes were present (M=0.099m) than when absent (M=0.88m)(Refer to Figure 9).

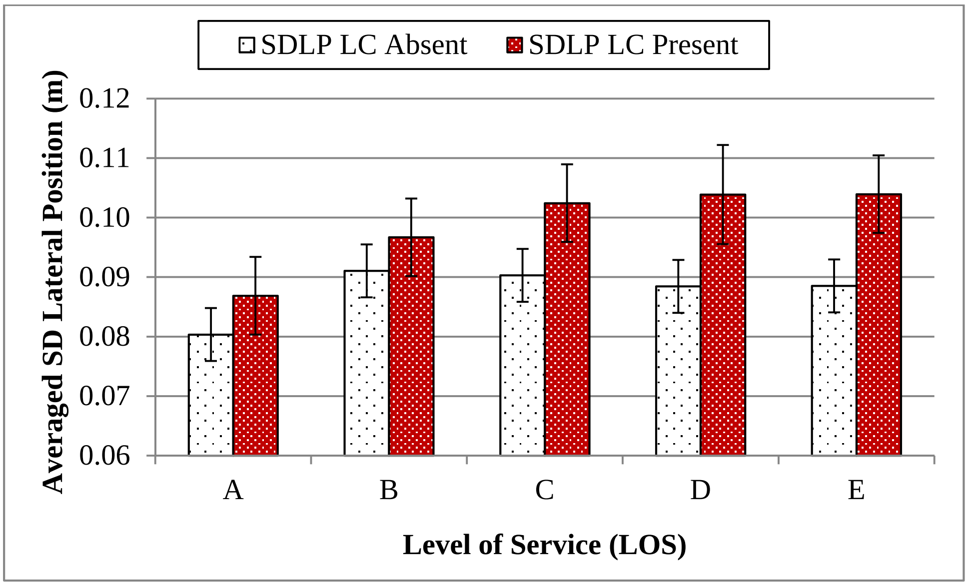

Figure 9 Averaged standard deviation of lateral position (and standard error) by Traffic Flow and Lane Change Presence

3.3 The effect of lane change characteristics

Given that the presence of lane changes impacts on driver workload and driving performance, further analyses were undertaken to establish if Lane Change Proximity and Lane Change Direction were significant factors. The near-zone was defined as the area between the participant's vehicle and the lead vehicle (569 lane changes took place here), whilst the far-zone was defined as the area between lead and preceding lead vehicle (2147 lane changes). However only 31 participants experienced both characteristics of lane changes, therefore data for the 5 participants were excluded. Two way repeated ANOVA showed a significant main effect of Lane Change Proximity, (F(1,30) = 8.445, p<0.005) with CSR scores obtained when the lane change occurred in the near-zone being higher than those obtained with lane changes in the far-zone (see Figure 10). There was, however, no significant main effect of Lane Change Direction on CSR ratings. No significant interaction between Lane Change Direction and Proximity was found.

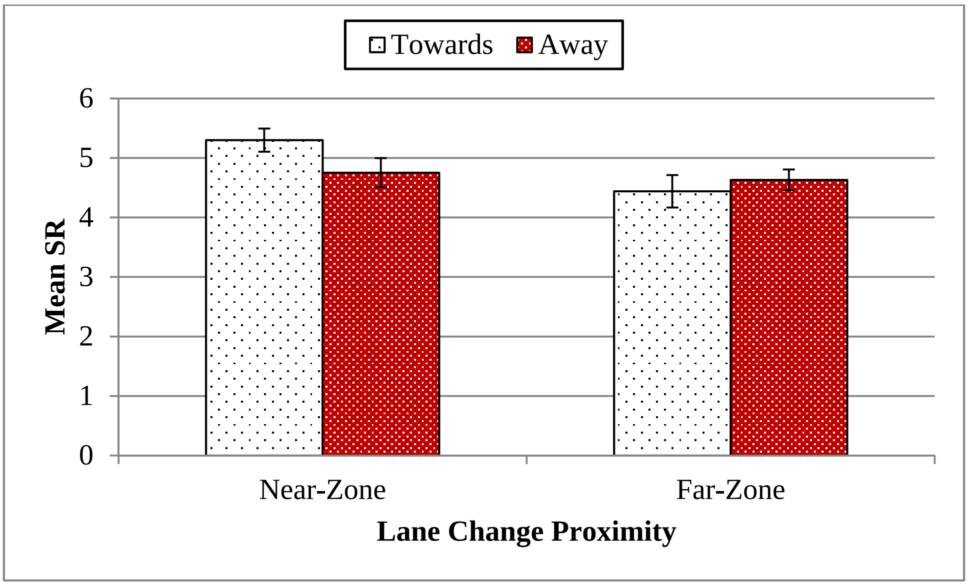

Figure 10 Mean CSR (and standard error) by Lane Change Proximity and Direction

Although no significant effect of Lane Change Direction was found on any of the performance measures, there was an effect of Lane Change Proximity on mean speed (F(1,30)=19.586, $p<0.001$) and standard deviation of lateral position (F(1,30)=8.430, $p=0.007$). Results indicate that participants drove at a lower mean speed of 30.293ms^{-1} s (i.e. an average reduction of 2.182ms^{-1} in mean speed) and performed poorer in maintaining lateral position with an average increase of 0.024m in SDLP when experiencing lane changes in the near-zone. Although other factors such as the criticality of these lane changes (for example, time-to-collision at which they occur) could offer an explanation to changes in primary task performance, this factor was not explored further due to insufficient data for statistical testing.

4 Discussion

The main aim of the present study was to investigate the relationship between dynamic traffic behaviour factors and subjective workload. Measures of self-reported workload elicited after each of three twenty-minute drives significantly increased as traffic complexity increased, as characterised by traffic density and the lane changes encountered. Based on the correlations between the three workload measures, it can be concluded that mean CSR is as reliable measure of overall driver workload as the widely validated uni-dimensional RSME and multi-dimensional NASA-RTLX scales.

Establishing the feasibility of using a simple scale to detect changes in reported workload allowed the subsequent analysis of temporal fluctuations in workload by dividing the road into 250m sections. Each road section was characterised by its momentary traffic flow and lane changes. Subjective workload, as measured by CSR, varied in the hypothesised direction, increasing systematically as traffic flow increased. Schieβl (2008) who also found similar results argued that mental load is higher in high traffic flow due to drivers being restricted in the actions available to them. Feedback from the post-study interviews in this study indicated that participants rated higher when they experienced a ‘boxed-in’ effect with the presence of the vehicles, especially heavy goods vehicles, in dense traffic. Participants also indicated higher ratings when a highway maintenance vehicle (misjudged as a traffic police vehicle) was present in the nearby surroundings. Other traffic factors which influenced their ratings included frustration when traffic was operating at non-normal speed i.e. when vehicles on the slow lane were moving faster and less congested than the fast lane. The driving performance measures demonstrated changes in longitudinal and lateral control, an effect that was linear up to moderate traffic. However from moderate traffic to high traffic density conditions, the driving task is more heavily influenced by other vehicles thus requiring participants to adapt their speed and headway with respect to the surrounding traffic. Driver workload measured subjectively indicates that driving task difficulty increases with required driver input and attentional demand from traffic monitoring.

However, this study not only wished to establish how the density of traffic influenced workload, i.e. the number of vehicles that drivers were required to monitor, but also whether the specific behaviour of those vehicles was influential. Whilst undoubtedly there are other behaviours that can be considered, such as a lead car braking, we chose to focus on lane changes due to the relative lack of research observed in the literature. Moreover, drivers reported increases in workload when a lane change occurred in their forward field of view, with further increases when that lane change occurred in close proximity. This is congruent with the notion of a safety margin (Endsley, 1995) which influences a driver's interactions with other road users under normal driving conditions (e.g. distance keeping) and in their risk assessment if a critical situation occurs. This concept was first conceived as the "field of safe travel" by Gibson and Crooks (1938) and later adapted by e.g. Kontaratos (1974) who defined two safety zones (termed collision and threat zones). If another vehicle entered these zones, then the driver undertakes an emergency reaction. Ohta (1993) defined these safety margins as four zones, with the most critical being when a following vehicle is within 0.6 s of a lead vehicle. In this zone, drivers experience feelings of being in danger of colliding with the vehicle ahead. Ahead of this critical zone is the danger zone (0.6 s to 1.1 s headway) whose upper border corresponds to the minimum subjective safe following distance. The normal (or comfort) driving zone then extends to 1.7 s headway, beyond which is the pursuit zone. In the current study, the near-zone lane change events occurred in all four zones, thus allowing the possibility of measuring the criticality of these lane changes and evaluating the effect of this factor on driver workload.

Intuitively, driver workload and driving behaviour varies as a function of traffic complexity. However, as far as we are aware, there are no reported studies that have systematically varied complexity factors and measured the resulting workload, in a dynamically changing traffic environment. This study has attempted to do just that, albeit in a simulated context. In order to advance our knowledge in the modelling of driver workload, it was more efficient to undertake the study using a driving simulator: in an on-road study it would not have been possible to control the surrounding traffic or expose the participants to identical experimental conditions. Whilst simulator studies can invite criticism for their lack of validity, we argue that the lack of fundamental understanding in the domain of traffic complexity and workload is partly due to the difficulties in manipulating it in the real world: hence, a simulated environment is ideal. Another advantage of using such a highly controlled experimental setting is the ability to prompt participants to provide a workload rating to a pre-specified schedule: this continuous measurement of driver workload is superior to that of conventional post-drive scales, given the natural fluctuations in traffic complexity that can be observed in real-life settings. The range of workload scores obtained suggests the method is sensitive to these fluctuations and has face-validity. Both these characteristics will aid the design of a workload manager that is reliable and acceptable to drivers.

However, self-report measures can be prone to response bias (for example, Green et al*.* (2011) found ratings tended to be clustered at lower ends of the range and significantly favouring rounded numbers) and considering that workload is multidimensional and multifaceted construct, it is unlikely that the manifestations of workload would be captured by one unique, representative measure. In this study, driving behaviour such as speed, time headway and lateral position were found to vary with the traffic complexity. Although further analysis is required to examine the direct relationship between subjective rating of driving performance and objective performances measures, however this study had indicated that categorising the traffic complexity variables influence on driver workload and driver performance may prove useful in estimating driver workload as traffic demands could now be determined and weighted accordingly. Following the findings from this study, lane change characteristics could be explored further to examine the varying criticality on driver workload. Understanding of possible problematic traffic behaviours may help in optimising the design of a real-time workload estimator which considers not only the driver’s distraction within the vehicle but also the dynamic workload resulting from surrounding traffic demand.

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