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Analysing speeding behaviour: A multilevel modelling approach

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ABSTRACT: This paper examines the variability in speeding for 147 motorists over a five-week period using data collected from Global Positioning System (GPS) technology. A multilevel modelling approach is employed to decompose speeding behaviour into four major levels of variation, namely: inter-individual variation, temporal variation, trip-level variation, and segment level variation. Initially, we estimate a null model (i.e., excludes the explanatory variables) to assess the variations at each level. Results suggest that the driver is more of a factor in speeding as the speed limit increases but that the majority of variation in speeding goes unexplained. This is followed by progressively including explanatory variables (e.g., age, gender, vehicle type, trips purpose etc) at each of the four levels to assess how much more of the variation in speeding can be explained. Results suggest that the reduction in unexplained variance in speeding varies markedly by speed zone, indicating the disproportionately different impacts of explanatory factors.

KEY WORDS: ***Speeding; multilevel modelling; GPS technology.***

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1. Introduction

Despite campaigns and strategies to the contrary, speeding and its consequences remain a major problem on Australia's roads. For instance, in 2007, evidence from New South Wales (*1*) and South Australia (*2*) showed that almost one-third of licensed drivers were caught speeding. The consequences of speeding in terms of increasing both the risk and severity of a crash are well documented. For instance, in 2007, speeding in New South Wales was a causal factor in 32 percent of fatal crashes and 16 percent of all crashes resulting in injuries (*1*). Despite this, many motorists still do not consider speeding to be dangerous (*3*) with the majority of drivers admitting to exceeding the speed limit at least occasionally by 10 km/h or more (*4*).

Efforts to understand the characteristics of speeding (who, where, when, why, by how much) have uncovered a range of contributory factors pertaining to the driver, vehicle, trip, street environment and weather (*5, 6, 7, 8*). Analyses have generally relied on speeding enforcement records or self-reported speeding behaviour, both of which have serious limitations when it comes to understanding the magnitude and prevalence of speeding for drivers over space and time. An alternative is to capture data while motorists are driving through instrumentation of the vehicle using Global Positioning System (GPS) technology (*7*). The advantage here is that motorists are monitored while driving around as per their normal daily routines providing the opportunity to study the factors impacting speeding in more depth. Clearly, the potential disadvantages are the sample sizes and the possible impacts of the monitoring itself on driver behaviour.

With this in mind, the current paper presents a multilevel modelling analysis of speeding behaviour using data captured from a major study of driving behaviour in Sydney using GPS technology (*9*). A multilevel approach is chosen because of the inherently hierarchical nature of the interdependencies that exist between the key elements behind speeding, namely the driver, vehicle, temporal, trip characteristics and road conditions. Such an approach provides greater flexibility in breaking out the variation in speeding by these different 'levels' as well as examining interactions between the various levels.

The paper is structured as follows. First, we provide a brief review of the main factors found to impact speeding followed by applications of multilevel models in transport analyses. We then go on to detail the development of the multilevel models together with the data source and structure. Results are presented for the null model (i.e., no explanatory variables included) to assess the variations at each level followed by progressively including explanatory variables at each of the four levels to assess how much more of the variation in speeding can be explained. Finally key conclusions are drawn about the approach and findings.

2. Literature review

2.1 Factors impacting speeding

Previous research has identified a number of factors impacting speeding pertaining (broadly) to the driver, vehicle, characteristics of the trip, and road/environmental conditions. From the perspective of the driver, age, gender and personality type have (arguably) received the most scrutiny. In terms of age, evidence points to drivers under the age of 34 being more likely to speed on average than drivers over the age of 55 although there is marked heterogeneity within these groups (*7, 10, 11*). The importance of gender as a stand-alone factor in speeding behaviour is less conclusive with some studies finding males to be more likely to speed (*12*), while others do not find gender to be significant (*10, 13*). However, some studies show that gender is a factor in speeding for certain age groups or at certain speed limits (*4, 7*). Relationships between personality traits and speeding have also been investigated by researchers. These studies have found personality characteristics such as Type-A personalities and those with a propensity for 'sensation seeking' to be correlated with speeding (e.g., *14, 15, 16*). In contrast, altruism and risk aversion have the opposite effect (*15, 17*).

Speeding also appears to be influenced by the vehicle with previous research showing that drivers of newer vehicles are more likely to speed (*7, 10, 11*) as are those using higher performance vehicles (*18*). At the trip and street level, the trip purpose (*4*), number of passengers in the car (*8, 19*), speed limit of the road (*4, 7*) and other 'street-environment' factors (*5, 20*) are all factors in speeding behaviour. Although the aforementioned factors all appear to influence speeding per se, research suggests that there are significant interaction effects between these factors. This means that the direction and magnitude of speeding is influenced by a combination of these factors including age, gender, the presence of passengers (*19*) and the speed limit of the road (*4, 7, 15*).

In terms of factors leading to reductions in speeding, it is evident that the perceived likelihood of being caught and punished is the most crucial issue (*4*). For instance, evidence from the United Kingdom shows that speed cameras lead to a reduction in mean speeds (4.1 percent) and the proportion of vehicles speeding (32.9 percent) in the locations where they are installed (*21*). However, a not insignificant proportion of vehicles continue to exceed the speed limit despite the presence of speed cameras. Furthermore, drivers report that they are more likely to abide by the speed limit when there is overt police enforcement (*22*). Efforts to change attitudes to speeding have largely come through anti-speeding campaigns focused on both the danger and (certainly in Australia) the anti-social nature or 'uncool' nature of speeding (*23*). It is difficult to gauge the effects of these campaigns per se on behavioural change, but what is again clear is that speeding enforcement is a necessary component (*24*).

2.2 Multilevel modelling

Multilevel modelling is an extension to existing variance decomposition techniques, which attempts to account for the inherently hierarchical nature of many phenomena. For instance, in comparing exam scores across schools, this reflects the ability of the children, which in turn may be influenced by 'higher level' effects coming from the school they attend and possibly the school district. Multilevel modelling breaks out the variance attributable to the children (level 1), the schools (level 2), and school districts (level 3) as well as isolating the interactions between the different levels and the various component factors at each level (*25*).

Within the field of transport-related research, multilevel approaches are becoming more widely used (*26*). In a recent application, Chikaraishi et al. (*27*) detail how multilevel modelling was used to analyse the observed variation in departure time over several weeks. They delineated five levels of variation components namely; inter-individual variation, inter-household variation, day-to-day variation, spatial variation and intra-individual (unexplained) variation. Among the main conclusions drawn were that there is large variability by activity type and (perhaps not surprisingly) intra-individual variation consistently explains by far the most variation. The findings of the study draw attention to the need to simultaneously deal with unobserved variation from the macro-level to micro-level (i.e., individual) and can be attained by using multilevel models.

In terms of transport safety, multilevel modelling has been used in accident analyses. For instance, Jones and Jorgensen (*28*) used a multilevel binary logistic regression approach to model outcomes among occupants of vehicles involved in road accidents in Norway. Using a hierarchy of casualties, accidents, and municipalities they conclude that 83% of the variation happens at level 1 (between individuals), 16% at the accident level and the rest which is 1% is associated with the municipalities of Norway where the incidents happened. Yanis et al. (*29*) use multilevel approaches to study the spatial variation of the effect of alcohol enforcement in Greece and report that 10% of the total variation in accident counts was attributed to the regional classification. In another application, Vanlaar (*30*) compares the results of a conventional logistic model and two-level logistic model on data of seatbelt behaviour to demonstrate the consequences of ignoring the hierarchical structure of the data.

To the authors' knowledge, the only prior instance in which multilevel modelling has been applied to the study of speeding per se was by Vanlaar as part of the European Union 'SafetyNet' project (*26*). The aim here was to demonstrate the application and interpretation of multilevel modelling through an artificial example created from speeding data collected at various road sites around Belgium. Although useful for instruction on how to use multilevel modelling the approach is quite different from that followed in this paper where the focus is on decomposing the variance in speeding collected from individual drivers over several weeks to isolate the major levels of variation (inter-individual, temporal, trip-level, road segment level) underlying speeding.

3. Data and data structure

The primary source of data used for this study was second-by-second GPS data collected from 147 motorists in Sydney as part of a wider investigation into driving behaviour (*9*). Briefly, the objectives of the study were to investigate changes in driving behaviour in response to a charging regime based on kilometres driven, night-time driving, and speeding. This involved a five-week period of GPS monitoring (the 'before' period) to ascertain 'regular' driving routines followed by a further five-week period of monitoring (the 'after period) following imposition of the charging regime. GPS data were downloaded in real-time, processed and then uploaded to a website where participants were able to see their trips and provide additional information for each recorded trip including who was driving, number of passengers, and trip purpose. Given the objectives of the study, it was important in the before period that the true purpose of the data collection was carefully masked, because of the potential that this in itself could artificially impact driving behaviour, including speeding. It is the data from the before period that is used in the analysis presented here. As well as the GPS data, information was captured about the driver, vehicle, trip and weather conditions (specifically whether it was raining). In addition to driver demographics, measures of personality correlated with (self-reported) speeding behaviour were collected, including Aggression, Excitement, and Altruism measured on a ten point scale ranging from 'Not at All' to 'Very Much' (*31*). Perceptions of risk were also collected based on a five-point Worry and Concern Scale (*32*) and three cognition-based scales, namely a Likelihood of Accident (both for self and other drivers) ten point scale, an Efficacy five-point scale and an Aversion to Risk five-point scale (*17*).

For the purposes of this analysis, the 'raw' GPS data comprising millions of records proved problematic to use and interpret necessitating aggregation. Clearly, aggregation always comes at a loss of some information, so must be done carefully. Following experimentation with various aggregation schemes including time, distance, and trip it was concluded that the most logical approach was to aggregate by speed limit segments – this involved creating a new segment each time the speed limit changed within a trip. The rationale here was drawn from preliminary analysis that showed significant variation in the magnitude of speeding by speed limit (Figure 1) and that it still preserved much of the richness of the 'raw' GPS data.

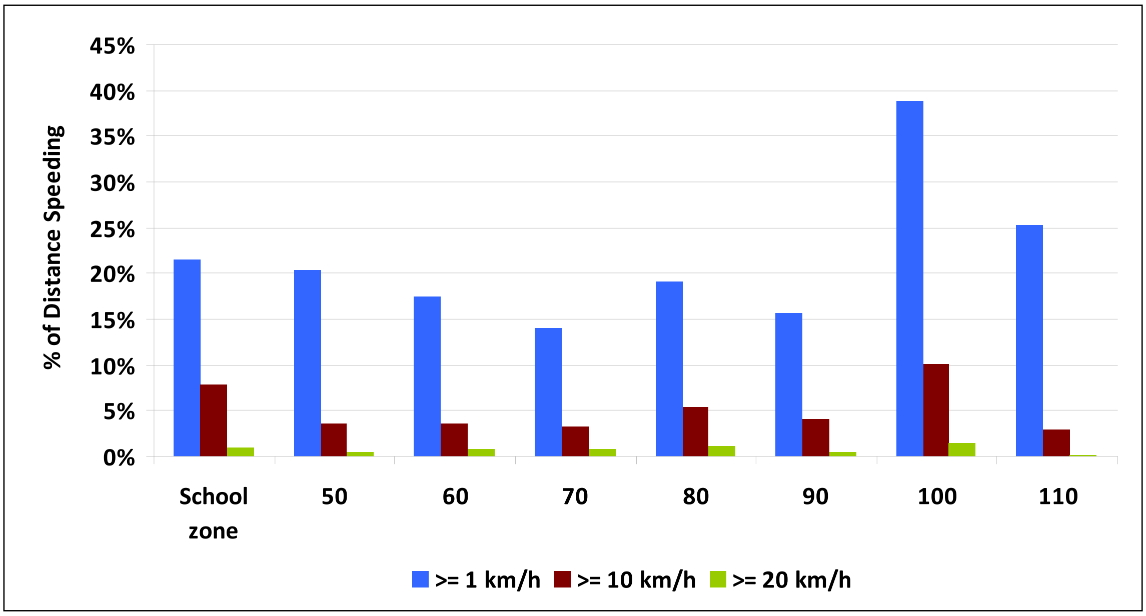

Figure 1: Percentage of distance speeding by speed limit from the GPS data

This aggregation by speed limit segment necessitated consideration of how to identify speeding at a segment level. Essentially this came down to establishing a threshold for defining speeding as some percentage of distance above the speed limit for that segment. While defining this threshold is clearly subjective and open to debate, the crucial issues are that it has some underlying rationale and that the impacts on results of using different thresholds are explored. The logical starting point was to look at the overall speeding percentage from the original GPS data, which was 25 percent. However, this disguised the fact that for the majority of speed limit segments (Figure 1), overall speeding was closer to 20 percent. This seemed to represent (at a segment level) a reasonable compromise between capturing systematic speeding versus the occasional discrepancy. To explore the impacts of different thresholds, experimental models were developed using thresholds of 20, 30 and 50 percent with little difference in results – therefore the final models assumed a threshold of 20 percent. To clarify, if (say) we had a one kilometre segment and at least 200 metres of that segment were spent above the speed limit, that segment would be identified as speeding and assigned a value of one. Conversely if the segment had less than 200 metres above the speed limit, it would be assigned a value of zero. The other major methodological decision was how to define speeding in terms of magnitude. For the purposes of this analysis, speeding was defined as being above the speed limit primarily because this reflects current (zero tolerance) laws in New South Wales.

For the purposes of the multilevel modelling, data were split into four levels, namely the segment (Level 1), trip (Level 2), day (Level 3), and individual (Level 4) for each speed limit segment – the structure is depicted in Figure 2 with the number of segments by level shown in Table 1. The rationale for such a structure was based on intuition as well as evidence from elsewhere that drivers within a speed zone are more alike than drivers in another speed zone, because their behaviour is influenced (within a certain extent) by the speed limit in that zone (*30*). In addition, CHAID analysis conducted on the data clearly showed that this was the most logical way to define the levels. Ignoring this degree of dependence between the speed zone and driver behaviour could cause the standard errors of the regression coefficients to be underestimated.

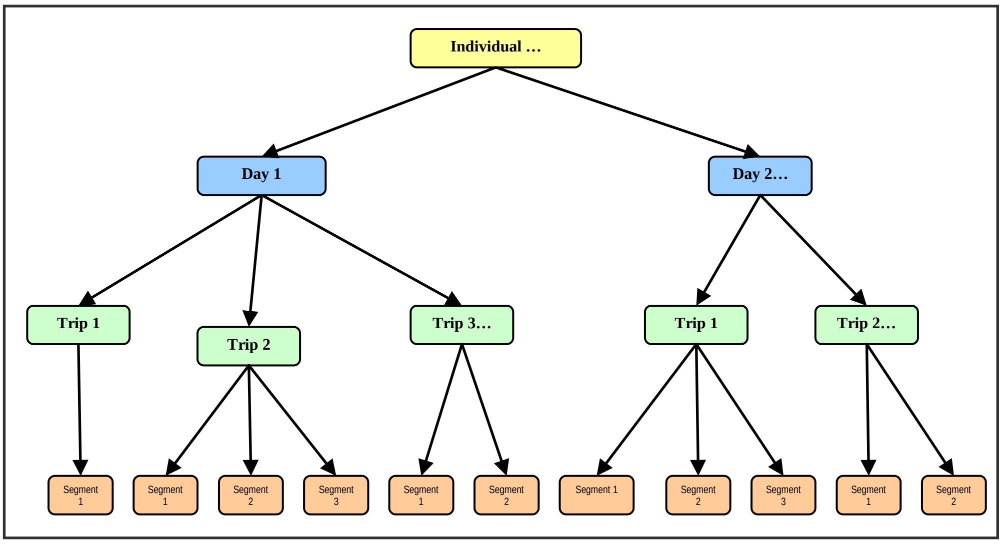

Figure 2: Structure of segment records at different speed limits

Table 1: Segment records

Level	Number	Average per level	Minimum	Maximum
Individual (Level 4)	147	-	-	-
Day (Level 3)	4,016	27.3	7	35
Trip (Level 2)	17,275	117.5	14	316
Segment (Level 1)	107,667	732.4	107	2,541

Other variables used in the analysis together with their assignment to the different levels are shown in Table 2 – note, the bolded values refer to the reference category for each variable where applicable. The figures in italics refer to the proportion of segments for which a particular value occurred – so for instance, speeding was observed on 25% of segments, males were represented on 48% of segments and so on.

Table 2: Variables used in the analysis

Variable	**Description** *(proportion of segments in italics)*
Dependent Variable	
SpeedSD	**0 = No** (*75%*)**,** 1 = Yes (*25%*)
Individual (Level 4)	
Gender	**1 = Male** (*48%*), 2 = Female (*52%*)
Age	**0 = 18-30** (*25%*), 1 = 31-45 (*40%*), 2 = 46-65 (*34%*)
Aggression (AggN Ave)	Scale from 0 to 100 (Mean: 46)
Altruism (AltruN Ave)	Scale from 0 to 100 (Mean: 70)
Excitement (ExcitN Ave)	Scale from 0 to 100 (Mean: 28)
Worry and Concern (WorryN Ave)	Scale from 0 to 100 (Mean: 29)
Chance of having an accident in next 12 months (QPARTB_B_1)	**1 = <= 10%** (*51%*), 2 = 11-20% (*20%*), 3 = 21-30% (*9%*), 4 = 31-40% (*5%*), 5 = 41-50% (*11%*), 6 = 51-60% (*2%*), 7 = 61-70% (*2%*)
Transmission	**1 = Automatic** (*74%*), 2 = Manual (*26%*)
Vehicle Body (VehBody)	**1 = Sedan** (*48%*), 2 = Hatchback (*34%*), 3 = Other (*18%*)
Vehicle year of manufacture (YearOfMan)	**1 <=1999** (*21%*), 2 = 2000-2004 (*42%*), 3 = 2005+ (*37%*)
Day (Level 3)	
Day of the week (DayWeek)	**0 = Sunday** (*11%*), 1 = Monday (*14%*), 2 = Tuesday (*15%*), 3 = Wednesday (*16%*), 4 = Thursday (*16%*), 5 = Friday (*16%*), 6 = Saturday (*12%*)
Trip (Level 2)	
Trip purpose (TripPurp6)	**1 = Returning home** (*31%*), 2 = Commuting to Work/Work-Related (*19%*), 3 = Education/Childcare (*5%*), 4 = Social/Recreation (*14%*), 5 = Shopping / Personal Business (*17%*), 6 = Other (*14%*)
No. Of Passengers (NumPas)	**0** (*49%*), 1 (*28%*), 2 (*15%*), 3 (*6%*), 4+ (*2%*)
Time of Day (TimeWk6)	**1 = Weekday Night** (*6%*), 2 = Weekday Morning (*20%*), 3 = Weekday Day (*22%*), 4 =Weekday Afternoon/Evening (*29%*), 5=Weekend Night (*2%*), 6=Weekend Day (*21%*)
Segment (Level 1)	
Rain	**0 = Not Raining** (*98%*), 1 = Raining (*2%*)
Interactions	
Interaction of driver age and no. Of passengers (Age30xNumPas)	18-30x1, 18-30x2, 18-30x3, 18-30x4+

*Bolded values refer to the reference categories.

4. Multilevel model development

Keeping in mind how speeding was defined for this analysis, the dependent variable has a binary outcome (i.e., 1 = speeding, 0 = not speeding) making logistic regression an appropriate technique. Given the objective of the analysis was to divide the total variation in speeding among the various levels, multilevel logistic regression was used. Dividing the variance of a binary dependent variable is non-trivial in comparison to a continuous dependent variable as is discussed later.

4.1 The null model

The null model (intercept-only model) refers to a model where no independent variables are included. The null model describes a dependent variable as a function of an average value, in this case the intercept, and is specified to vary at random across the levels enabling investigation of the variance proportion of variation at different levels.

The four-level null model can be described as:

$$\log it(\pi_{ijkl}) = \log\left(\frac{\pi_{ijkl}}{1-\pi_{ijkl}}\right) = \beta_0 + f_{0l} + v_{0kl} + u_{0jkl} + e_{0ijkl} \qquad (1)$$

Here, the parameter β_0 is the average of *logit*(π_{ijkl}) across groups i,j,k,l with f_{0l} (the random effect at individual level) , v_{0kl} (the random effect at the day level) , u_{0jkl} (the random effect of trip level) , are assumed to be normally distributed with mean 0 and corresponding variances σ_f^2, σ_v^2 and σ_u^2 respectively and e_{ijkl} is a segment level error term distributed as Bernoulli constant (3.29).

4.2 The four-level random intercept model

The model described in (1) can be extended to allow for other effects on the probabilities of speeding. The model that is formulated here is the random intercept model, also known as the variance component model, which enables variation of the probability of speeding across other levels. Looking at the structure of the data we have a binary outcome y_{ijkl} of segment i of trip j of day k for individual l takes the value of 1 as opposed to 0. Suppose that we have a set of independent variables measured at segment level then the four-level random intercept can be described as follows:

$$\log it(\pi_{ijkl}) = \log\left(\frac{\pi_{ijkl}}{1-\pi_{ijkl}}\right) = \beta_0 + \beta_1 x_{1ijkl} + \beta_2 x_{2ijkl} + \ldots + \beta_n x_{nijkl} + f_{0l} + v_{0kl} + u_{0jkl} + e_{0ijkl} \qquad (2)$$

Here π_{ijkl} is the probability of an *i*th segment of the *j*th trip of the *k*th day of *lth* individual that is categorised as speeding, e_{ijkl} is a segment level error term distributed as Bernoulli constant and β_0 is a vector of unknown parameters, u_{0jkl} is the random effect of trip level, v_{0kl} is the random effect at the day level, and f_{0l} is the random effect at individual level.

Assumptions are as follows:

$f_{0l} \sim N(\sigma_f^2), v_{0kl} \sim N(\sigma_v^2)$, and $u_{0jkl} \sim N(\sigma_u^2)$.

The model development process comprised of starting with the null model (Model 1) to provide a reference point before progressively adding independent variables at the various levels in a series of models:

Model 1 Null model

Model 2 includes individual-level variables (e.g., Gender, age, attitudes)

Model 3 includes individual-level variables and day-level variables (e.g., Day of the week)

Model 4 includes individual-level variables, day-level and trip-level variables (e.g., Purpose, number of passengers)

Model 5 includes individual-level variables, day-level and trip-level variables, trip-level variables and segment-level variables (e.g., Rain, distance of segment)

Model 6 Full model, which includes individual-level variables, day-level and trip-level variables, trip-level variables, segment-level variables and interaction variables.

4.3 Variance partition coefficient

The percentage of the variation for the different levels with respect to the total variation is in general called the variance partition coefficient (VPC). The VPC for a 4-level random intercept for the null model described in (1) is the proportion of the total variance which is attributable to a certain level. When there are no explanatory variables the VPC can easily be determined using the following definitional formulae.

For the 4-level model described in (2) the Latent Variable approach for the level 4 VPC has the form:

$$VPC_l^{(4)} = \frac{\sigma_f^2}{\sigma_f^2 + \sigma_v^2 + \sigma_u^2 + \pi^2/3} \tag{3.a}$$

Similarly for level 3, level 2 and level 1 we have:

$$VPC_{kl}^{(3)} = \frac{\sigma_v^2}{\sigma_f^2 + \sigma_v^2 + \sigma_u^2 + \pi^2/3} \tag{3.b}$$

$$VPC_{jkl}^{(2)} = \frac{\sigma_u^2}{\sigma_f^2 + \sigma_v^2 + \sigma_u^2 + \pi^2/3} \tag{3.c}$$

$$VPC_{ijkl}^{(2)} = \frac{\pi^2/3}{\sigma_f^2 + \sigma_v^2 + \sigma_u^2 + \pi^2/3} \tag{3.d}$$

nder this methodology the level 1 variance used in the calculation of the VPC is fixed at $\pi^2/3$ = 3.290.

4.4 The variance partition coefficient when independent variables are added

In our case because **SpeedSD** is originally a continuous variable the logistic model can be taken to be a threshold model such that:

$$y_{ijkl} = \begin{cases} 1 & if\ y_{ijkl}^* > 0.20 \\ 0 & otherwise \end{cases} .$$

Thus we have,

$$y_{ijkl}^{*} = \beta_0 + \beta_1 x_{1ijkl} + \beta_2 x_{1ijkl} + \ldots + \beta_h x_{1ijkl} + f_{0jkl} + v_{0kl} + u_{0l} + e_{0ijkl} \tag{4}$$

where $e_{ijkl} \sim \log istic(0, \pi^2/3)$ here, $\pi = 3.141$.

If we are using the threshold model shown, we can examine the proportion of explained variation proposed by Snijders and Bosker (*33*).

From (4) the fixed part is:

$$\hat{y}_{ijkl} = \beta_0 + \beta_1 x_{1ijkl} + \beta_2 x_{1ijkl} + \ldots + \beta_h x_{1ijkl} \tag{5}$$

This variable is called the *linear predictor of Y* and the variance is denoted by σ_F^2. The level 1 variance denoted by σ_e^2 is fixed to be equal to $\pi^2/3$ for the logistic model (*33*). So for a randomly drawn level 1 unit *i* in a randomly drawn level 2 unit *j*, randomly drawn level 3 *k* and randomly drawn level 4 unit *l* the total variance of y_{ijkl}^{*} can be defined as:

$$Var\left(Y_{ijkl}^{*}\right) = \sigma_F^2 + \sigma_f^2 + \sigma_v^2 + \sigma_u^2 + \sigma_e^2 \tag{6}$$

where σ_F^2 is the explained part and $\sigma_f^2 + \sigma_v^2 + \sigma_u^2 + \sigma_e^2$ the unexplained part.

Using a similar definition from Snijders and Bosker (*33*) we can describe the proportion of explained variance (PEV) using the following:

$$PEV = \frac{\sigma_F^2}{\sigma_F^2 + \sigma_f^2 + \sigma_v^2 + \sigma_u^2 + \sigma_e^2} \tag{7}$$

In this way we can have an estimate of the explained variance. The PEV will be used to look at the explained variation and changes of variance proportion at the different levels when compared to the VPC of the null model.

In theory the estimated unexplained variation components of the random components in the full model is less than their corresponding components random part in the null model. This is because σ_F^2 explains a portion of the total variation. The problem with the logistic regression is that the lowest level is assumed to have a variance of $\pi^2/3$. So without losing this assumption we can estimate the variance proportion at each level with respect to the proportion of explained variation.

For the purpose of this analysis, the special-purpose multilevel modelling software, Mlwin was used (*25*). It has a graphical user interface for specification and fitting of wide range of multilevel models. For more complex models one can enter commands in the command interface window (*25*). It uses several estimation methods that include maximum likelihood and Markov Chain Monte Carlo (MCMC). In this analysis the approximation of parameters were done using 1st order marginal quasi-likelihood (MQL) to have a starting value and then use 1st order predictive quasi-likelihood (PQL) for the final estimates.

5. Results

Model 1 – the null model

A four-level null model (i.e., without explanatory variables) was estimated for both the overall data and different speed limits. The proportion of variation attributable to the different levels was estimated using the definitional formula in (3.a) to (3.d) and results are shown in Table 3 (a). Note that we are talking here about unexplained variations proportions and that differences in proportions are attributed to the classification only (i.e., the levels) since there are no independent variables included in the model. The results show that individual-level variables contribute more to the proportion of unexplained variation in speeding as the speed limit increases, ranging from 13.86% (50 km/h zones) to 42.08% (100 &110 km/h zones). This must be interpreted carefully as it is *not* indicating that speeding is more prevalent in particular speed zones, rather it is saying that the driver is more of a factor behind the unexplained variance in speeding as the speed limit increases. Day-to-day variation contributes 2.48% to 8.11% of the unexplained variation in speeding, while trip level variation is of little importance, ranging from 0% to 4.69%. As expected the majority of the unexplained variation in speeding is at the segment level, which (broadly speaking) represents network-level effects (gradient, lane width, traffic effects, traffic control devices etc). The pattern here is the reverse of the individual-level effects, with the unexplained variance decreasing as the speed limit increases from 80.88% (50 km/h zones) to 52.19% (100 &110 km/h zones).

Table 3: Variance proportion for (a) null model, (b) model 2 and (c) full model at different speed limits

(a) Null model

Speed Limit	Individual (Inter-individual)	Day to Day variation	Trip variation	Segment variation
50 km/h	13.86%	3.39%	1.87%	80.88%
60 km/h	22.49%	3.92%	4.69%	68.90%
70 km/h	27.06%	2.48%	4.17%	66.29%
80 km/h	32.11%	6.38%	0.00%	61.52%
90 km/h	35.05%	8.11%	0.53%	56.31%
100 & 110 km/h	42.08%	3.49%	2.24%	52.19%

*Note, these are *unexplained* variations partitioned using the multilevel modelling indicating the proportion with respect to the levels only (i.e., *not* the independent variables)

(b) Model 2 (add individual level variables)

Speed Limit	Individual (Inter-individual)	Day to Day variation	Trip variation	Segment variation	Explained Variation
50 km/h	10.34%	3.05%	1.68%	72.71%	12.22%
60 km/h	15.24%	3.30%	3.96%	58.11%	19.39%
70 km/h	18.44%	2.10%	3.53%	55.61%	20.33%
80 km/h	21.50%	4.95%	0.00%	47.85%	25.70%
90 km/h	24.35%	6.21%	0.29%	43.39%	25.76%
100 & 110 km/h	19.85%	1.22%	2.91%	40.90%	35.13%

(c) Full model

Speed Limit	Individual (Inter-individual)	Day to Day variation	Trip variation	Segment variation	Explained Variation
50 km/h	10.01%	2.82%	1.31%	71.91%	13.95%
60 km/h	14.71%	3.10%	3.60%	56.72%	21.86%
70 km/h	17.96%	1.66%	3.39%	54.10%	22.89%
80 km/h	20.87%	4.62%	0.00%	45.90%	28.60%
90 km/h	24.61%	4.05%	0.00%	40.13%	31.21%
100 & 110 km/h	17.43%	0.79%	2.51%	38.82%	40.45%

When independent variables are introduced it is expected that the unexplained variation *should* decrease in general. The problem with the multilevel logistic regression is the assumption that the lowest level has variance equal to 3.29. While several methods are recommended for the estimation of the variance partition coefficients, the method proposed by Snijders and Bosker (*33*) is used in here. Different impacts are noticed on the unexplained variance and explained variations when the independent variables are included in the models for the different speed limits.

Model 2 – add individual level variables

The introduction of individual level variables (see Table 2) causes the individual unexplained variations to decrease for all speed limits as shown in Table 3 (b). The impact is (perhaps not surprisingly) greatest at the 100 & 110 km/h speed limit where more than 20 percent of the individual level variation is explained by introducing the individual level variables. What is also notable is both the day-to-day variation and the segment variation go down for all speed limits, with the trend generally downwards also for the trip-level variation - again, however, it should be stressed the trip-level variation is of marginal importance and results should be interpreted accordingly. Also shown in Table 3 (b) is the explained variation in speeding (computed using Equation 7), which ranges from 12.22% (50 km/h zones) to 35.13% (100 & 110 km/h zones). It should be noted, while not directly comparable to a coefficient of determination (r-square) this does give some indication of how well the model is explaining the data.

Models 3-5 – add day-level, trip level, segment level

As anticipated, retaining the individual level variables and adding the day level variables lowers the unexplained day-to-day variation for all speed zones marginally (results not shown). The explained variation also increases marginally ranging from 13.07% (50 km/h zones) to 37.83% (100 & 110 km/h zones). Adding the trip level variables makes a very marginal difference, given the low levels of variance to begin with. Similar results were found for the segment level, which was unsurprising given it only included rain – clearly, there is a need to build in other segment level variables (e.g., lane width, gradient, presence of speed cameras etc) to improve performance at this level.

Model 6 – the full model

Results from the full model, which include an interaction between age and number of passengers, are shown in Table 3 (c). Comparing this with the null model, all the corresponding variations at different levels are lower than the corresponding unexplained variation of the null model. The explained variation for the full models for the different speed limit zones range from 13.95% in 50 km/h to 40.45% in 100 & 110 km/h zones. In general the independent variables considered in this exercise have different impacts on the different speed limits as manifested by the different percentages of the explained variation. It is also useful to visualise the reduction rate of variation in the full model relative to that of the null model following an approach presented in (*27*). Here a graph is presented indicating the reduction rate of variation in the full model relative to that of the null model to compare the variations between the two models (Figure 3). The graph illustrates that the relative decrease in unexplained variation generally increases with speed limit across all the levels, essentially reinforcing the fact that more of the variance can be explained as the speed limit increases.

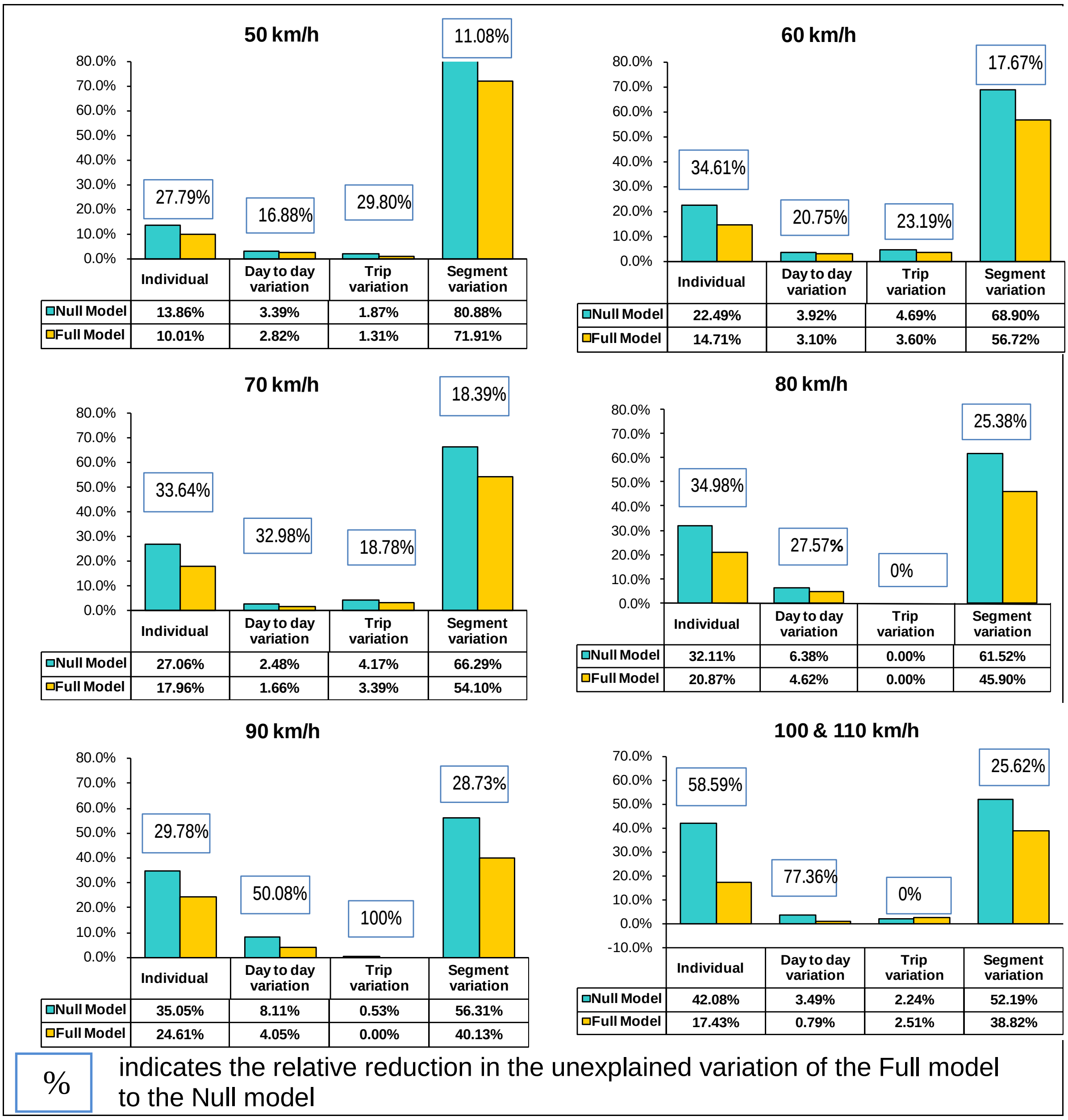

Figure 3: Relative reduction in unexplained variance of speeding between the null and full models

Table 4 shows the estimated parameters and corresponding relevant information for the full models for different speed limit zones. General observations are that few of the coefficients are significant and effects vary across speed limits so accepting this, the focus is on the general trends per se. In terms of age and gender, while overall males and younger drivers appear more likely to speed, this is not observable across all the speed limits. Most interestingly (arguably) is that females and 46-65 year-olds may be more likely to speed at the 100 & 110 km/h roads, something that could be simply a sample effect. In terms of vehicle characteristics, the coefficients suggest that those driving newer vehicles and automatic transmissions are more likely to speed. The personality/risk variables suggest that aggression and excitement are associated with an increased chance of speeding, while altruism is associated with a decreased chance of speeding, which appear intuitive. Increases in risk, as evidenced by the self-reported chance of an accident in the next 12 months, suggests that the higher the risk the less likely the speeding, which is what one would hope to observe. Temporal effects indicate that speeding is generally more prevalent on a Sunday, but this does vary markedly by speed limit. A clearer picture emerges in terms of the time-of-day categories, indicating that speeding is generally more likely on weekday nights compared to all other times of the day apart from weekend days. In terms of trip purpose, higher odds of speeding are generally associated with commuter trips and social/recreation trips with the picture less clear for shopping and education-related trips. The number of passengers does not indicate any general trends and in terms of the weather speeding is less likely when raining, which is intuitive.

	Full model 50 km/h			Full model 60 km/h			Full model 70 km/h			Full model 80 km/h			Full model 90 km/h			Full model 100 & 110 km/h		
Variables	β	(S.E.)	*p-value*	β	(S.E.)	*p-value*	β	(S.E.)	*p-value*	β	(S.E.)	*p-value*	β	(S.E.)	*p-value*	β	(S.E.)	*p-value*
Intercept	**-0.806**	*(0.758)*	*0.287*	**-0.953**	*(1.027)*	*0.353*	**-2.284**	*(1.184)*	*0.054*	**-0.053**	*(1.398)*	*0.975*	**0.055**	*(1.674)*	*0.975*	**-0.074**	*(1.278)*	*0.954*
Female	**-0.001**	*(0.140)*	*1.000*	**-0.005**	*(0.188)*	*0.975*	**0.162**	*(0.230)*	*0.482*	**-0.356**	*(0.281)*	*0.206*	**-0.029**	*(0.363)*	*0.938*	**0.534**	*(0.368)*	*0.147*
31-45	**0.098**	*(0.168)*	*0.558*	**-0.028**	*(0.227)*	*0.903*	**0.685**	*(0.281)*	*0.015*	**-0.613**	*(0.355)*	*0.084*	**-0.574**	*(0.454)*	*0.206*	**-0.195**	*(0.468)*	*0.677*
46-65+	**0.079**	*(0.171)*	*0.644*	**-0.275**	*(0.230)*	*0.231*	**0.610**	*(0.283)*	*0.031*	**-0.725**	*(0.355)*	*0.041*	**-0.194**	*(0.475)*	*0.682*	**0.236**	*(0.486)*	*0.627*
Hatchback	**0.311**	*(0.162)*	*0.055*	**0.306**	*(0.220)*	*0.164*	**0.447**	*(0.267)*	*0.094*	**0.160**	*(0.333)*	*0.631*	**-0.484**	*(0.483)*	*0.316*	**0.391**	*(0.463)*	*0.398*
Other	**0.465**	*(0.173)*	*0.007*	**0.533**	*(0.235)*	*0.023*	**0.203**	*(0.291)*	*0.486*	**0.478**	*(0.370)*	*0.197*	**0.240**	*(0.456)*	*0.598*	**1.159**	*(0.485)*	*0.017*
2000-2004	**0.491**	*(0.173)*	*0.005*	**0.334**	*(0.238)*	*0.160*	**0.255**	*(0.292)*	*0.383*	**0.031**	*(0.378)*	*0.933*	**0.154**	*(0.457)*	*0.736*	**-0.676**	*(0.523)*	*0.196*
2005+	**0.344**	*(0.173)*	*0.047*	**0.401**	*(0.238)*	*0.092*	**0.067**	*(0.295)*	*0.821*	**0.186**	*(0.372)*	*0.616*	**0.014**	*(0.456)*	*0.975*	**-1.352**	*(0.508)*	*0.008*
Manual	**-0.284**	*(0.149)*	*0.057*	**-0.093**	*(0.202)*	*0.647*	**-0.495**	*(0.253)*	*0.050*	**-0.332**	*(0.322)*	*0.302*	**0.531**	*(0.430)*	*0.217*	**-0.151**	*(0.436)*	*0.729*
Aggression	**0.000**	*(0.005)*	*1.000*	**0.000**	*(0.006)*	*0.950*	**-0.003**	*(0.008)*	*0.687*	**0.007**	*(0.010)*	*0.479*	**0.014**	*(0.013)*	*0.277*	**0.002**	*(0.014)*	*0.911*
Altruism	**-0.105**	*(0.048)*	*0.028*	**-0.150**	*(0.065)*	*0.021*	**-0.178**	*(0.082)*	*0.030*	**-0.106**	*(0.105)*	*0.312*	**-0.144**	*(0.135)*	*0.286*	**-0.013**	*(0.149)*	*0.931*
Excitement	**0.070**	*(0.038)*	*0.066*	**0.106**	*(0.053)*	*0.046*	**0.178**	*(0.065)*	*0.006*	**0.004**	*(0.084)*	*0.964*	**0.060**	*(0.108)*	*0.576*	**0.029**	*(0.108)*	*0.785*
Worry and Concern	**0.079**	*(0.062)*	*0.200*	**0.008**	*(0.004)*	*0.045*	**0.001**	*(0.005)*	*0.827*	**-0.006**	*(0.006)*	*0.322*	**0.007**	*(0.008)*	*0.387*	**0.017**	*(0.009)*	*0.060*
Chance <=10%	**-0.586**	*(0.724)*	*0.418*	**-0.822**	*(0.982)*	*0.403*	**-0.008**	*(1.200)*	*0.994*	**-0.961**	*(1.313)*	*0.994*	**-1.105**	*(1.553)*	*0.477*	**-0.984**	*(1.167)*	*0.399*
Chance 11-20%	**-0.758**	*(0.730)*	*0.299*	**-0.833**	*(0.988)*	*0.399*	**-0.189**	*(1.129)*	*0.867*	**-1.445**	*(1.331)*	*0.958*	**-1.751**	*(1.589)*	*0.270*	**-1.640**	*(1.264)*	*0.194*
Chance 21-30%	**-0.558**	*(0.738)*	*0.449*	**-0.693**	*(1.002)*	*0.488*	**-0.207**	*(1.149)*	*0.858*	**-1.046**	*(1.348)*	*0.858*	**-2.087**	*(1.636)*	*0.202*	**-1.685**	*(1.361)*	*0.216*
Chance 31-40%	**-0.707**	*(0.775)*	*0.361*	**-1.252**	*(1.062)*	*0.238*	**-0.827**	*(1.220)*	*0.498*	**-0.892**	*(1.445)*	*0.498*	**-1.334**	*(1.674)*	*0.426*	**-1.888**	*(1.324)*	*0.154*
Chance 41-50%	**-0.589**	*(0.738)*	*0.425*	**-0.827**	*(1.002)*	*0.409*	**0.013**	*(1.147)*	*0.992*	**-1.311**	*(1.362)*	*0.992*	**-2.536**	*(1.621)*	*0.118*	**-2.318**	*(1.284)*	*0.071*
Chance 51-60%	**-0.785**	*(0.834)*	*0.346*	**-1.543**	*(1.141)*	*0.176*	**-0.998**	*(1.336)*	*0.455*	**-1.251**	*(1.604)*	*0.455*	**-1.048**	*(2.369)*	*0.658*	**-0.079**	*(1.694)*	*0.963*
Chance 61-70%	**-0.228**	*(0.827)*	*0.783*	**0.034**	*(1.121)*	*0.975*	**-0.563**	*(1.289)*	*0.662*	**-0.793**	*(1.520)*	*0.662*	**-2.426**	*(1.756)*	*0.167*	**-2.786**	*(1.566)*	*0.075*
Monday	**0.075**	*(0.075)*	*0.317*	**0.037**	*(0.087)*	*0.674*	**-0.072**	*(0.151)*	*0.636*	**0.195**	*(0.214)*	*0.362*	**0.164**	*(0.261)*	*0.531*	**-0.311**	*(0.388)*	*0.422*
Tuesday	**0.054**	*(0.075)*	*0.468*	**-0.046**	*(0.087)*	*0.597*	**0.071**	*(0.148)*	*0.632*	**0.350**	*(0.212)*	*0.099*	**0.028**	*(0.265)*	*0.916*	**-0.076**	*(0.371)*	*0.838*
Wednesday	**0.091**	*(0.074)*	*0.218*	**-0.005**	*(0.086)*	*0.950*	**-0.066**	*(0.147)*	*0.652*	**0.345**	*(0.207)*	*0.095*	**-0.062**	*(0.265)*	*0.815*	**-0.248**	*(0.379)*	*0.512*
Thursday	**-0.074**	*(0.074)*	*0.319*	**-0.113**	*(0.087)*	*0.193*	**0.010**	*(0.150)*	*0.950*	**0.412**	*(0.210)*	*0.050*	**0.147**	*(0.266)*	*0.580*	**-0.339**	*(0.371)*	*0.361*
Friday	**-0.013**	*(0.074)*	*0.858*	**-0.093**	*(0.087)*	*0.284*	**0.009**	*(0.149)*	*0.950*	**0.343**	*(0.209)*	*0.101*	**0.103**	*(0.259)*	*0.692*	**-0.409**	*(0.375)*	*0.275*
Saturday	**-0.068**	*(0.058)*	*0.238*	**-0.115**	*(0.068)*	*0.092*	**0.139**	*(0.115)*	*0.226*	**0.134**	*(0.162)*	*0.409*	**0.294**	*(0.207)*	*0.155*	**0.458**	*(0.245)*	*0.061*
Weekday Morning	**-0.172**	*(0.064)*	*0.007*	**-0.399**	*(0.072)*	*0.000*	**0.111**	*(0.130)*	*0.392*	**-0.629**	*(0.194)*	*0.001*	**-1.550**	*(0.274)*	*0.000*	**-0.251**	*(0.337)*	*0.456*
Weekday Day	**-0.220**	*(0.059)*	*0.000*	**-0.136**	*(0.067)*	*0.042*	**0.129**	*(0.119)*	*0.279*	**-0.566**	*(0.174)*	*0.001*	**-0.381**	*(0.218)*	*0.081*	**-0.157**	*(0.332)*	*0.637*
Weekday Afternoo/Evening	**-0.327**	*(0.055)*	*0.000*	**-0.300**	*(0.064)*	*0.000*	**-0.140**	*(0.113)*	*0.216*	**-0.840**	*(0.162)*	*0.000*	**-0.847**	*(0.197)*	*0.000*	**-0.306**	*(0.310)*	*0.324*
Weekend Night	**0.280**	*(0.089)*	*0.002*	**0.169**	*(0.099)*	*0.088*	**0.068**	*(0.171)*	*0.692*	**-0.320**	*(0.269)*	*0.234*	**-0.993**	*(0.338)*	*0.003*	**0.031**	*(0.409)*	*0.939*
Weekend Day	**0.000**	*(0)*		**0.000**	*(0)*		**0.000**	*(0)*		**0.000**	*(0)*		**0.000**	*(0)*		**0.000**	*(0)*	
Commuting to Work/Work Related	**0.025**	*(0.047)*	*0.595*	**0.306**	*(0.052)*	*0.000*	**0.091**	*(0.090)*	*0.312*	**0.106**	*(0.136)*	*0.437*	**0.330**	*(0.192)*	*0.086*	**0.254**	*(0.223)*	*0.254*
Education/Childcare	**0.014**	*(0.075)*	*0.847*	**0.218**	*(0.085)*	*0.010*	**-0.592**	*(0.192)*	*0.002*	**0.234**	*(0.268)*	*0.383*	**-0.742**	*(0.527)*	*0.159*	**-1.168**	*(0.79)*	*0.139*
Social/Recreation	**0.130**	*(0.045)*	*0.004*	**0.174**	*(0.052)*	*0.001*	**-0.119**	*(0.089)*	*0.180*	**0.328**	*(0.121)*	*0.007*	**-0.098**	*(0.172)*	*0.568*	**0.029**	*(0.198)*	*0.884*
Shopping/Personal Business	**-0.206**	*(0.041)*	*0.000*	**-0.187**	*(0.049)*	*0.000*	**-0.429**	*(0.092)*	*0.000*	**-0.224**	*(0.131)*	*0.087*	**-0.347**	*(0.176)*	*0.048*	**0.010**	*(0.218)*	*0.964*
Other	**0.045**	*(0.044)*	*0.306*	**0.050**	*(0.051)*	*0.328*	**-0.098**	*(0.095)*	*0.185*	**-0.129**	*(0.136)*	*0.343*	**-0.049**	*(0.192)*	*0.797*	**0.229**	*(0.233)*	*0.326*
Passenger 1	**0.006**	*(0.077)*	*0.938*	**0.072**	*(0.088)*	*0.412*	**-0.286**	*(0.152)*	*0.059*	**0.306**	*(0.225)*	*0.174*	**-0.247**	*(0.283)*	*0.384*	**-0.057**	*(0.299)*	*0.849*
Passengers 2	**0.099**	*(0.093)*	*0.285*	**0.188**	*(0.103)*	*0.069*	**-0.171**	*(0.201)*	*0.395*	**-0.720**	*(0.291)*	*0.013*	**-0.804**	*(0.368)*	*0.029*	**-0.610**	*(0.500)*	*0.222*
Passengers 3	**-0.157**	*(0.145)*	*0.278*	**-0.275**	*(0.201)*	*0.171*	**0.033**	*(0.315)*	*0.916*	**0.480**	*(0.448)*	*0.284*	**-0.498**	*(0.423)*	*0.239*	**1.021**	*(0.785)*	*0.194*
Passengers 4	**0.002**	*(0.173)*	*0.996*	**0.121**	*(0.202)*	*0.549*	**-0.538**	*(0.652)*	*0.409*	**0.356**	*(0.853)*	*0.677*	**-1.344**	*(0.794)*	*0.091*	**0.128**	*(0.915)*	*0.889*
Raining	**-0.277**	*(0.108)*	*0.010*	**-0.135**	*(0.117)*	*0.250*	**-0.347**	*(0.228)*	*0.127*	**-0.930**	*(0.350)*	*0.008*	**0.287**	*(0.380)*	*0.451*	**-1.080**	*(0.485)*	*0.026*
18-30 x Passenger 1	**-0.046**	*(0.089)*	*0.605*	**-0.167**	*(0.103)*	*0.106*	**0.155**	*(0.178)*	*0.385*	**-0.299**	*(0.260)*	*0.250*	**-0.320**	*(0.337)*	*0.342*	**-0.346**	*(0.382)*	*0.365*
18-30 x Passengers 2	**-0.238**	*(0.110)*	*0.031*	**-0.208**	*(0.124)*	*0.093*	**-0.066**	*(0.238)*	*0.783*	**1.079**	*(0.342)*	*0.002*	**0.219**	*(0.457)*	*0.632*	**0.197**	*(0.587)*	*0.737*
18-30 x Passengers 3	**-0.177**	*(0.167)*	*0.290*	**-0.025**	*(0.224)*	*0.909*	**0.282**	*(0.356)*	*0.429*	**-0.857**	*(0.508)*	*0.092*	**-0.129**	*(0.573)*	*0.823*	**-0.583**	*(0.887)*	*0.511*
18-30 x Passengers 4	**-0.219**	*(0.234)*	*0.348*	**-0.154**	*(0.283)*	*0.587*	**-0.366**	*(0.758)*	*0.629*	**-0.985**	*(0.981)*	*0.315*	**1.311**	*(0.914)*	*0.152*	**-0.591**	*(1.121)*	*0.598*
Random Effects																		
Individual	**0.458**	*(0.060)*	*0.000*	**0.853**	*(0.110)*	*0.000*	**1.086**	*(0.159)*	*0.000*	**1.496**	*(0.237)*	*0.000*	**2.018**	*(0.373)*	*0.000*	**1.477**	*(0.332)*	*0.000*
Day	**0.129**	*(0.018)*	*0.000*	**0.180**	*(0.023)*	*0.000*	**0.101**	*(0.049)*	*0.000*	**0.331**	*(0.070)*	*0.079*	**0.332**	*(0.112)*	*0.000*	**0.067**	*(0.106)*	*0.527*
Trip	**0.060**	*(0.027)*	*0.000*	**0.209**	*(0.032)*	*0.000*	**0.206**	*(0.072)*	*0.000*	**0.000**			**0.000**			**0.213**	*(0.157)*	*0.175*
Segment	**3.290**	-		**3.290**	-		**3.290**	-		**3.290**	-		**3.290**	-		**3.290**	-	

Table 4: Full model coefficients and standard errors for different speed limits

6. Conclusions

This paper employs a multilevel modelling approach to analyse speeding behaviour of 147 motorists over a five-week period. Speeding behaviour is decomposed into four major categories, namely: inter-individual variation, temporal variation, trip-level variation, and segment level variation. The null model in which no explanatory variables are included suggests that the driver is more of a factor in the unexplained variance in speeding as the speed limit increases but that the majority of unexplained variation in speeding is at the road segment level. This may be a function of more opportunities for unconstrained speeding on higher speed roads. Introducing explanatory variables (e.g., age, gender, vehicle type, trip purpose etc) into the model reduces the unexplained variance in speeding by markedly different rates across the different speed zones indicating disproportionately different impacts.

Multilevel modelling has intuitive appeal but comes with many challenges both in application and interpretation of results, particularly over the coefficients. The results presented here have helped understand the sources of variation and indicated where modifications are needed to improve model performance. In terms of the definition of levels themselves, there appears to be little gained by differentiating by the trip level and (arguably) the day. Clearly, there is a need to include other parameters, particularly at the segment level to reflect roadway characteristics (e.g., gradient, lane width, presence of a median), traffic mix, presence of speed cameras and other attributes affecting speed. Other key issues surround the assumptions made, particularly about the definition of speeding in terms of magnitude and duration. Current work is focused on a breaking the dependent variable into speeding categories (0-10, 11-20, 20+) to try to isolate the characteristics behind more serious violations of the speed limit. Finally, on a more general note, it must be stressed the results are very sensitive to how the data are defined and organised and we would caution against generalising the findings presented here.

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