Social values behind the wheel: How does social value orientation shape speeding behaviour across drivers in Europe?

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Abstract

Speeding can be conceptualised as a social dilemma that requires attention to engineering factors such as traffic and roadway conditions as well as psychological traits and individual attributes. These traits and attributes shape whether regulatory and physical signals are internalised as binding constraints, yet most existing studies overlook them. In particular, drivers' Social Value Orientation (SVO) can substantially influence speeding and moderate the effects of other factors. To address this gap, we examined stated preferences to exceed speed limits, and their determinants including SVO, across urban scenarios in the West Midlands (WM), Athens, and Valencia. We used an ordered discrete choice model with random parameters and heterogeneity in means to capture unobserved and latent psychological heterogeneity. Results indicated that road design, traffic density, and speed enforcement were associated with self-reported speeding, with effects varying by context and driver traits. Higher SVO was linked to greater compliance in the WM, mixed effects in Valencia, and norm-congruent behaviour in Athens that could legitimise moderate speeding. Older drivers in Athens reported greater responsiveness to cameras. Age moderated self-reports: in WM and Athens, the stated likelihood of speeding linked to drivers' violation history declined with age; the gender gap widened with age in WM but narrowed in Athens. Overall, the findings demonstrate that the effects of engineering and enforcement are not uniform across all drivers. Their impact is mediated by local norms, perceived credibility, and socially embedded understandings of considerate driving, underscoring the need to integrate social and psychological dimensions into traffic safety interventions.

Keywords: speeding; social value orientation; driving behaviour; behavioural modelling; speeding in Europe; heterogeneity in the means

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1. Introduction

Speeding is one of the main factors contributing to traffic crashes and road fatalities in urban areas around the world. It contributes to around one-third of all fatal crashes in the European Union, making it a top risk factor for road users in this region (Adminaité-Fodor & Jost, 2019), and thus understanding its underlying causes is critical for effective prevention strategies. Previous studies investigating these causes have largely focused on factors related to road infrastructure, traffic characteristics and environmental conditions (Abdel-Aty et al., 2024; Afghari et al., 2018; Donnell et al., 2001; Eluru et al., 2013; Perez et al., 2021). While these factors undoubtedly influence driver behaviour and speeding, they often fall short of capturing the nuanced psychological and behavioural determinants of individuals' decisions to exceed the speed limit. Recent studies have increasingly highlighted the effects of demographics (e.g. age, gender, education levels) and psychological factors (e.g. risk perception) in shaping driving behaviour (Aluja et al., 2023; J. J. Fleiter et al., 2010; J. Fleiter & Watson, 2005; Rhodes & Pivik, 2011). In addition, driving habits and past behaviours have been found to be correlated with non-compliant behaviours among drivers as well (An et al., 2023; Fildes et al., 1991).

Beyond demographics and psychological and habitual factors, personality traits can also play a crucial role in speeding. Research has shown that the way road users interact with one another and with their surrounding environment, in terms of risk aversion, altruism, or competitive tendencies, significantly influence their driving behaviour, explaining substantial variance in individual driving styles (Al-Tit, 2020). One of these personality traits that has been widely studied in behavioural science, particularly due to its ability to capture tendencies towards altruism, cooperation, or competitiveness, is Social Value Orientation (SVO). SVO is defined as an individual’s stable preference regarding how outcomes (e.g. resources, rewards, or costs) should be distributed between themselves and others. It captures motivational orientations ranging from prosocial or altruistic (maximising joint or others’ outcomes), to individualistic (maximising self-interest), to competitive (maximising relative advantage over others) (Murphy et al., 2011).

Integrating SVO into the study of speeding behaviour has the potential to yield particularly valuable insights, as it can provide a deeper understanding of the social motivations underpinning drivers’ decision to go over the speed limit. Recognising how drivers value their own behaviours relative to those of the others can help explain why some individuals choose to speed under certain conditions while others do not, enabling the development of more targeted interventions aimed at reducing risky driving behaviours. Nonetheless, empirical investigation of the effects of SVO on speeding behaviour is not straightforward. Since SVO is a psychological trait, it is quite difficult (if not impossible) to directly observe and measure it in naturalistic settings. Therefore, a form of self-reported survey is often needed to ask people about their SVO (Kalantari et al., 2023; Murphy & Ackermann, 2014). Such a survey can be administered as part of a Stated Preference (SP) study (e.g. van Essen et al., 2020) where respondents are presented with hypothetical but realistic driving scenarios, and their intentions and decision-making processes are assessed under controlled conditions.

However, responses in SP studies are also shaped by unobserved heterogeneity in psychological traits, meaning that individuals with the same observed characteristics may still behave differently. Previous studies have shown that there is unobserved heterogeneity in the effects of psychological traits on the behaviour of road users, which is the variation in individuals' social preferences that is not directly observable or measurable but influences their behaviour (Paetz, 2021). Traditional fixed parameters statistical models assume uniform behavioural responses across the driver population, ignoring these unobserved heterogeneities that are central to psychological research. Random parameters models have been proposed to address this limitation of the traditional models (Hensher & Greene, 2003; Kim, 2023). However, even these models are limited in interpretability. This is particularly important when the goal is to understand why individuals behave differently under the same conditions—not merely that they do.

To overcome these challenges, a more flexible framework is needed, one that preserves the information embedded in ordinal survey responses while accounting for latent psychological variation among individuals. Specifically, hierarchical random parameters ordered probit models (also referred to as random parameters with heterogeneity in means/variances in the literature) provide a principled way to incorporate individual-level heterogeneity into the analysis of Likert-scale responses in SP contexts. These models do not merely relax statistical assumptions; they embed psychological realism into econometric structure by allowing behavioural parameters such as sensitivity to traffic density/volume, speed limits, or enforcement cues to vary systematically across individuals. Importantly, constructs such as SVO can be incorporated both as predictors and as moderators of such variations, offering insights into how and why drivers weigh different factors under identical conditions. For example, in random parameters settings, SVO may shift the distributional mean or variance of the effect of enforcement visibility. These approaches, thus, advance not only prediction but explanation, providing structured, interpretable windows into the mechanisms underlying behavioural diversity on the road.

This study aims to address the above gaps by investigating the effects of SVO, demographics and past driving behaviours on speeding behaviour using a stated preference survey administered across three different regions in Europe, Athens in Greece, Valencia in Spain and the West Midlands (WM) in the UK. A random parameters ordered model with heterogeneity in the means is then developed to account for unobserved heterogeneity in the SP data. This multi-level approach embeds psychological realism within a rigorous econometric framework, revealing how individual differences shape speeding behaviour. It supports more targeted and adaptive road safety strategies by capturing the contextual and motivational diversity of road users.

2. SVO in Transport Literature

In transport systems, many behavioural decisions reflect underlying social dilemmas (i.e. situations in which individuals must weigh personal benefits against potential consequences for others or for the broader traffic system). Choosing whether to comply with speed limits, yield to merging vehicles, or adopt sustainable modes of transport often involves trade-offs between self-interest and collective welfare. Successfully navigating these dilemmas requires individuals to construct mental representations of their social environment and adjust their behaviour based on anticipated actions and expectations of others. In this context, individuals' social preferences, such as those captured by SVO, play a crucial role in determining whether one behaves cooperatively, competitively, or indifferently in traffic-related dilemmas. Rather than acting purely on self-interest or external incentives, drivers may adjust their behaviour based on how much they value the impact of their actions on others, consciously or not. Although SVO has been studied extensively in psychology and behavioural economics, its application in transport science remains relatively sparse and fragmented.

The effect of SVO on individuals’ transport-related decision-making is well-documented in a small but impactful body of research. Van Vugt et al. (1995) demonstrated that commuters’ interpretation of car-versus-public transport options, as environmental or social dilemmas, was significantly shaped by their SVO profiles, with prosocial individuals (i.e. those who do care more about others' welfare) framing choices in more socially considerate terms. Van Lange et al. (1998) conducted field experiments using decomposed game measures of SVO and found that prosocial participants more frequently choose carpooling or public transit over solo driving, even when this entailed personal inconvenience indicating a genuine sensitivity to collective welfare in daily modal decisions. Further reinforcing SVO's transport relevance, Joireman et al. (2001) used SVO assessments alongside evaluations of future-oriented thinking to reveal that prosocial individuals were more willing to fund improvements in public transit, with prosocial orientation predicting greater responsiveness to scheme fairness.

Building on these early findings, subsequent research has applied SVO frameworks to a broader range of travel behaviours and emerging mobility systems. In travel behaviour research, previous studies have shown that people with prosocial SVO profiles are more likely to support sustainable transport options, such as carpooling, public transit, or biking, even at a personal cost (Gärling et al., 2003). In contrast, people with individualistic or competitive SVO profiles might prioritise speed, comfort, or personal freedom, and prefer private car use despite societal costs (Toghi et al., 2021). In ridesharing or carpooling, the success of the system depends on trust, fairness, and willingness to cooperate, all influenced by SVO. A few studies have also used SVO to predict which road users are more likely to participate in these systems (e.g. Chremos & Malikopoulos, 2021).

SVO has also been used to simulate how different types of road users interact in traffic (e.g. yielding behaviour, merging, or pedestrian crossing). A growing body of research highlights the effectiveness of SVO in improving predictive and adaptive capabilities in interactive traffic scenarios. Research has found that incorporating SVO into driver behaviour models can significantly reduce trajectory prediction errors (by up to 25%) in complex interactions such as merging and performing unprotected left turns (Schwarting et al., 2019). Similarly, altruistic automated vehicles (AVs) guided by SVO have been shown to learn cooperative decision-making strategies prioritising collective safety (Rong et al., 2025; Valiente et al., 2022). Extending this concept, a set of motion-planning methods for AVs has been developed that are sensitive to the cooperation levels exhibited by human drivers (Le & Malikopoulos, 2022; Rong et al., 2024). Furthermore, the application of SVO has been broadened to include AV–pedestrian and AV–AV interactions at unsignalised intersections, where SVO-informed autonomous agents showed more human-like yielding, risk-aware behaviour, and cooperative decision-making (Crosato et al., 2021, 2022; Tong et al., 2023; Xie et al., 2024).

Despite these few applications, the full potential of SVO as a psychological construct for socially influenced behaviours across diverse groups of road users remains largely untapped. In particular and in the field of road safety, a notable gap exists in understanding the role of SVO in influencing drivers' speeding behaviour. Drivers with prosocial SVO profiles, who typically prioritise others' well-being, may be less likely to speed due to concerns about endangering others. At the same time, such prosocial tendencies might, in some cases, foster cooperative attitudes that inadvertently encourage conformity to group norms, even if those norms tolerate or promote speeding. Furthermore, the ways in which SVO interacts with normative influences such as peer behaviour and cultural attitudes toward speeding remain underexplored. Given that speeding carries substantial social externalities and poses significant risks to others, SVO may represent an important yet overlooked factor in shaping safer driving behaviours.

3. Methodology

This study employed a SP survey to collect data on individual decisions regarding exceeding the speed limit in specific urban scenarios. The survey was designed to present respondents with a series of hypothetical choice scenarios varying in key attributes of interest. Along with the SP survey, additional questions were asked about individuals demographics, past traffic behaviours and, most importantly, their SVO. The collected responses were then analysed using an ordered probit model with random parameters and heterogeneity in their means, a technique that is appropriate for modelling outcomes with a natural ordering but unknown spacing between categories (e.g. Likert scale responses) (Agresti, 2010). This modelling approach allows for estimation of the influence of various attributes on the likelihood of respondents selecting higher or lower preference categories, while taking unobserved heterogeneity into account. The details of survey design and analytical model are explained in the following.

3.1. Stated Preference (SP) Survey

The design and development of the survey questions were grounded in the premise that speeding behaviour is influenced both at the individual level, by characteristics such as demographics, psychological constructs, and personality traits, and at the road segment level by local traffic and environmental factors.

The final questionnaire consisted of four sections. A filtering question was placed at the beginning to exclude non-drivers or individuals who drive less than one hour per week on average to exclude drivers with minimum exposure. The structure and content of each section, along with the criteria used for question selection, are described below.

Section 1

The first section of the questionnaire collected general demographic information, including age, gender, nationality, and education level. Additional items captured driving-related characteristics such as driving experience, years holding a driver’s licence, frequency of driving per week, and the primary type of vehicle used. Participants were also asked to report the number of crashes they had been involved in during the past two years. This information was collected to assess whether prior crash involvement influenced their driving choices and behaviours.

Section 2

The second section focused on participants' driving habits and behaviours over the past two years. Using a five-point frequency scale (Never, Rarely, Sometimes, Often, Always), participants responded to a series of items adapted from several widely recognised instruments for assessing self-reported driving behaviour, including the DBQ developed by Reason et al. (1990) and validated by Parker et al. (1995), along with more recent behavioural questionnaires addressing mobile phone usage and pedestrian interaction behaviours (e.g. Özkan & Lajunen, 2005; Zhou et al., 2016).

The selected items were chosen based on their relevance to factors that influence speeding behaviour or increase the likelihood of collisions. Examples of the behaviours assessed include:

- Overtaking another driver from the wrong side
- Exceeding the speed limit on urban highways
- Running a red light at an intersection
- Using a handheld mobile phone while driving
- Texting or browsing social media while driving
- Tailgating (following too closely)
- Underestimating the speed of an oncoming vehicle when overtaking
- Failing to notice pedestrians when turning into a side street
- Nearly colliding with a bicycle while turning
- Ignoring a "Give Way" sign and narrowly avoiding a collision
- Adjusting speed to facilitate another driver's overtaking manoeuvre
- Yielding to pedestrians despite having the right-of-way

Section 3

The third section of the survey comprised a SP experiment involving a series of driving scenarios set in selected urban locations within the defined use cases. These SP scenarios were developed using a fractional factorial design to ensure statistical efficiency and adequate variation in attribute levels across choice sets. Participants were presented with hypothetical driving situations that varied by roadway configuration, traffic density (high/low), posted speed limits, and the presence or absence of enforcement measures. The objective was to assess participants' likelihood of engaging in speeding behaviour under different combinations of these conditions. Traffic density was conveyed visually to aid comprehension. The figures reflected actual roadway configurations and traffic conditions from each use-case city. Configurations were selected, in consultation with the use-case technical experts, to represent the most commonly observed layouts; therefore, the set is representative rather than exhaustive, and not all city configurations were included. Time constraints also limited the number of configurations that could be shown. Figure 1 illustrates how traffic density is depicted for a given road layout in the WM use case.

Figure 1. Comparison of Low (left) and High (right) Traffic Scenarios on a Two-Way Multilane Undivided Roadway in the WM

These driving scenarios and their associated factors were selected due to their well-established influence on drivers' speeding behaviour, as reported in previous studies (De Pauw et al., 2014; Schepers et al., 2025; Wilson et al., 2010). Key factors included traffic density, posted speed limits, and the presence of speed enforcement measures (e.g. speed cameras). While additional variables could have been incorporated, doing so would have increased the complexity of the survey design and posed feasibility challenges for the overall study implementation. Participants indicated their likelihood of speeding in each scenario using a five-point Likert scale (Extremely Unlikely, Unlikely, Neutral, Likely, Extremely Likely). Further details on the scenario attributes across the use cases are provided in Table 1.

Table 1. Driving Scenarios within West Midlands (WM), Athens and Valenica

Roadway Configuration	**Figure**	**Traffic Volume**	**Speed limit (mph)**	**Presence of speed camera**
WM				
Two-way undivided urban roadway with single lane in each direction		Low/ High Traffic	20/30	yes/no
Two-way undivided roadway with multiple lanes in each direction		Low/ High Traffic	20/30	yes/no
Two-way divided highway with multiple lanes in each direction		Low/ High Traffic	30/40	yes/no
Athens				
Single Lane one-way street		Low/High Traffic	30/50	yes/no

Table 1. Continued

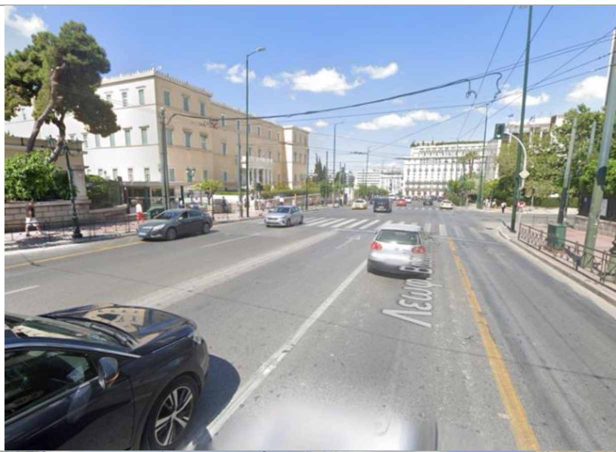
Roadway Configuration	Figure	Traffic Volume	Speed limit (mph)	Presence of speed camera
One-way multi-lane roadway		Low/High Traffic	30/50	yes/no
Two-way undivided highway with multiple lanes in each direction		Low/High Traffic	30/50	yes/no
Two-way divided highway		Low/High Traffic	30/50	yes/no
Valencia				
Single lane one-way road		Low/ High Traffic	20/30	yes/no

Table 1. Continued

Roadway Configuration	**Figure**	**Traffic Volume**	**Speed limit (mph)**	**Presence of speed camera**
Two-way road with one lane in each direction of traffic separated by tram tracks		Low/ High Traffic	30/40	yes/no
Two-lane, one-way road		Low/ High Traffic	20/30	yes/no
Two-way divided road with multiple lanes in each direction		Low/ High Traffic	40/50	yes/no

Section 4

The final section of the survey focused on assessing participants' SVO. Several established methods exist for measuring SVO, among which the Ring Measure (Liebrand, 1984), the Triple-Dominance Measure (Van Lange et al., 1997), and the SVO Slider Measure (Murphy et al., 2011) are the most commonly applied in empirical research. The SVO Slider Measure was adopted for its precision and ease of administration in online and paper-based formats. The task is composed of six primary items and nine secondary items. In each primary item, a fixed monetary endowment is divided between the participant and an anonymous counterpart. The six 'self' and six 'other' allocations are averaged and compared with the neutral 50–50 point; the direction of this average relative to 50–50 is then converted into an angle (in degrees) that serves as a continuous index of social preference. Higher angles indicate more prosocial or altruistic dispositions, values around 45° are interpreted as prosocial, values near 0° as individualistic, and negative angles as competitive. The secondary items do not contribute to the angle; rather, they are used to distinguish whether prosocial choices prioritise maximising joint outcomes or minimising inequality, and to provide internal consistency checks.

3.2. **Analytical Model**

Ordered response models, particularly the ordered probit model, offer a theoretically grounded alternative by assuming that each observed ordinal outcome corresponds to a categorisation of an unobserved continuous latent propensity. This latent propensity is segmented into intervals by a set of estimated thresholds. To capture unobserved heterogeneity such as individual-level variation due to SVO, the model can be flexibly extended with random parameters with heterogeneity in the means, allowing the effects of covariates to vary systematically across respondents. This formulation is particularly well suited for panel data settings, in which repeated ordinal responses are observed across multiple scenarios for each individual.

Let the observed ordinal outcome for individual $i = 1, \dots, N$ at scenario $t = 1, \dots, T$ be denoted as:

$$Y_{it} \in \{0,1, \dots, J\} \tag{1}$$

which is assumed to be a discretisation of an unobserved continuous latent variable $Y_{it}^* \in \mathbb{R}$ such that:

$$Y_{it}^* = X_{it}' \beta_i + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathcal{N}(0,1) \tag{2}$$

where $X_{it}' \in \mathbb{R}^K$ is the vector of observed covariates, $\beta_i \in \mathbb{R}^K$ is the vector of random parameters for individual i and ε_{it} is an independent and identically distributed standard normal error term.

The ordinal response Y_{it} is linked with the latent Y_{it}^* through a series of cut-points or thresholds:

$$Y_{it} = j \quad \text{if} \quad \mu_{j-1} < Y_{it}^* \leq \mu_j, \quad j = 0, \dots, J \tag{3}$$

To ensure identification and ordering, these thresholds must satisfy:

$$\mu_{-1} = -\infty, \quad \mu_J = +\infty, \quad \mu_0 < \mu_1 < \cdots < \mu_{J-1} \tag{4}$$

To account for unobserved heterogeneity across individuals, β_i is specified as:

$$\beta_i = \bar{\beta} + \eta_i, \quad \eta_i \sim \mathcal{N}(0, \Omega) \tag{5}$$

where $\bar{\beta}$ is the population mean vector, η_i captures individual deviations and Ω is the covariance matrix of the random parameters. Note that β_i varies only across individuals (with subscript *i*) and is constant across scenarios (no subscript *t*). This specification allows for continuous heterogeneity in preferences across individuals and accounts for the repeated observations of the same individual i.e. panel setting.

To further investigate the factors underlying random parameters, the mean of each random parameter is allowed to vary systematically with observed individual-level characteristics Z_i. For $k = 1, \ldots, K$,

$$\beta_{ik} = \mu_k + Z_i'\phi_k + \sigma_k v_{ik}, \quad v_{ik} \sim \mathcal{N}(0,1) \tag{6}$$

where μ_k is the unconditional mean of coefficient k, ϕ_k is an $M \times 1$ vector of loadings for the mean function, Z_i is an $M \times 1$ vector of individual covariates (e.g. demographics, psychometrics), and $\sigma_k > 0$ is the standard deviation of the random effect. We assume v_{ik} are independent across k, implying a diagonal covariance $diag(\sigma_1^2, \ldots, \sigma_K^2)$. Hence,

$$\mathbb{E}[\, \beta_{ik} \mid Z_i \,] = \mu_k + Z_i'\phi_k \tag{7}$$

which introduces systematic heterogeneity in parameter distributions. The probability that individual i chooses category j in scenario t, conditional on their random parameters vector, is then given by:

$$P(\, Y_{it} = j \mid X_{it}, \beta_i \,) = \Phi\big(\mu_j - X_{it}'\beta_i\big) - \Phi\big(\mu_{j-1} - X_{it}'\beta_i\big) \tag{8}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

Let $\mathcal{L}_i$ denote the likelihood contribution of individual i across their repeated observations:

$$\mathcal{L}_i = \int \Big[\prod_{t=1}^{T_i} P(\, Y_{it} \mid X_{it}, \beta_i \,)\Big] f(\beta_i; \theta)\ d\beta_i \tag{9}$$

where $f(\cdot)$ is the density of the random coefficients. This model is referred to as *Random Parameters Ordered Probit (RPOP) with Heterogeneity in the Means*. Since the likelihood function is not analytically tractable, it is approximated and estimated using Simulated Maximum Likelihood Estimation. Efficient variance reduction and better convergence are achieved by employing quasi-random Halton sequences instead of purely random draws.

4. Data

The survey questionnaire was distributed to participant panels in three study areas: Athens, Valencia and WM. Distribution was managed by a professional survey provider, with targeting to promote demographic representativeness within each use case. The target sample sizes were 500 respondents each for WM and Athens, and 125 for Valencia. These figures were set in proportion to the population of each area (city or municipality) and in light of available resources and data collection costs. To minimise respondent fatigue and potential measurement error, the instrument was deliberately constrained in length, yielding a mean completion time of approximately 20 minutes. To further ensure data quality, only responses meeting a minimum completion-time threshold were retained; specifically, participants had to spend at least 40% of the expected completion time (i.e. 8 minutes) on the survey. All target sample sizes were achieved. Upon completion of data collection, these targets were successfully achieved. However, after rigorous data cleaning and exclusion of incomplete or invalid responses, the final sample comprised 361 participants for WM, 468 participants for Athens, and 124 participants for Valencia. The size of the final dataset for each use-case is equal to the use-case sample size multiplied by the number of scenarios for that use-case: 8,664 for WM, 14,976 for Athens, and 3,068 for Valencia. These cleaned datasets formed the basis for all subsequent analyses presented in this study. Table 2 provides descriptive statistics of the final sample across the three use cases. Figure 2 shows Social Value Orientation (SVO) profiles for the three study regions (WM, Valencia, and Athens). For each region, the left panel plots individual mean SVO angles from the slider task, and the right panel gives the distribution of SVO profiles. Profiles are classified as Competitive, Individualistic, Prosocial, or Altruistic using the standard cut-offs (≤−12°, −12° to <22.45°, 22.45° to <57.15°, ≥57.15°). The black arrow indicates the regional mean angle.

5. Results

5.1. Behavioural constructs

To prepare for the modelling, the responses to Section 2 of the questionnaire (questions related to the past driving behaviours) were pre-processed to extract valid and reliable latent psychological constructs. In doing so, a set of theoretically grounded and empirically supported behavioural constructs was extracted using Principal Component Analysis (PCA) as in the following. The constructs selected for analysis included speeding tendencies, distraction, deliberate violations, lapses, and positive behaviour. For each construct, a specific subset of survey items was identified based on prior literature and conceptual alignment. Items related to exceeding speed limits on urban highways and residential roads were grouped under the speeding tendencies construct. Behavioural items concerning handheld mobile phone use and texting or browsing while driving were categorised as distraction. Actions such as illegal overtaking (e.g. overtaking on the right in right-hand-traffic countries and on the left in left-hand-traffic countries), red-light running at intersections, and tailgating were classified under deliberate violations. Instances of underestimating the speed of an oncoming vehicle when overtaking, failing to notice pedestrians or cyclists when turning, and missing 'Give Way' signs were considered lapses. Lastly, items reflecting positive driving behaviours, namely adjusting speed to assist overtaking drivers and yielding to pedestrians despite having the right-of-way, were considered proxies for the driver's prosocial tendencies and named positive behaviours.

The internal consistency of each item group was assessed using Cronbach's alpha, with only constructs meeting the reliability threshold ($\alpha \geq 0.70$) carried forward. Items were standardised (z-scores) and subjected to PCA, and in each case the first principal component was extracted to serve as a latent trait score. This component consistently explained the largest share of variance, supporting its interpretation as a unidimensional construct. Construct validity was examined through a multi-step process: unidimensionality was confirmed by requiring the first component to account for a substantial proportion of variance (typically > 50%); items with factor loadings ≥ 0.40 were retained as dominant contributors; and discriminant validity was established by observing low to moderate correlations between constructs, confirming their conceptual independence. The resulting standardised factor scores were then merged with the main dataset and included as continuous covariates in the RPOP model.

Table 2. Descriptive statistics of the studied variables

Variable		Use case	Sample frequency	Sample share (%)
Categorical				
High Traffic		West Midlands	4332	50.0
		Athens	7488	50.0
		Valencia	1416	46.15
Median		West Midlands	2888	33.33
		Athens	3744	25.0
		Valencia	1888	61.53
Presence of speed camera/radar		West Midlands	4332	50.0
		Athens	7488	50
		Valencia	1416	46.15
Speed limit	West Midlands	20 mph	3249	37.5
		30 mph	3971	45.83
		40 mph	1444	16.67
	Athens	30 km/h	7488	50
		50 km/h	7488	50
	Valencia	20 km/h	118	3.84
		30 km/h	1062	34.61
		40 km/h	472	15.38
		50 km/h	1416	46.15
Gender (Male)		West Midlands	4128	47.64
		Athens	7680	51.28
		Valencia	1196	38.98
Education	Secondary education or lower	West Midlands	3888	44.87
		Athens	3264	21.79
		Valencia	936	30.50
	Bachelor's degree	West Midlands	3312	38.22
		Athens	8128	54.27
		Valencia	884	28.81
	Master's degree or higher	West Midlands	1464	16.89
		Athens	3584	23.93
		Valencia	1248	40.67

Continuous	Region	Min	Max	Mean	SD
Age	West Midlands	18	86	44.55	16.06
	Athens	19	83	43.38	11.33
	Valencia	18	69	43	12.57
Driving experience (years)	West Midlands	1	64	20.50	16.99
	Athens	1	60	19.56	11.94
	Valencia	1	50	20.45	12.53
Driving exposure (hrs/week)	West Midlands	1	120	10.36	10.91
	Athens	1	150	12.56	12.78
	Valencia	1	60	8.76	8.70
Number of crashes in the past 2 years	West Midlands	0	8	0.28	0.74
	Athens	0	50	0.57	2.60
	Valencia	0	8	0.2	0.84
SVO angle	West Midlands	-28.21	68.49	27.99	14.29
	Athens	-16.26	61.38	29.47	13.63
	Valencia	-7.81	53.36	29.84	11.99

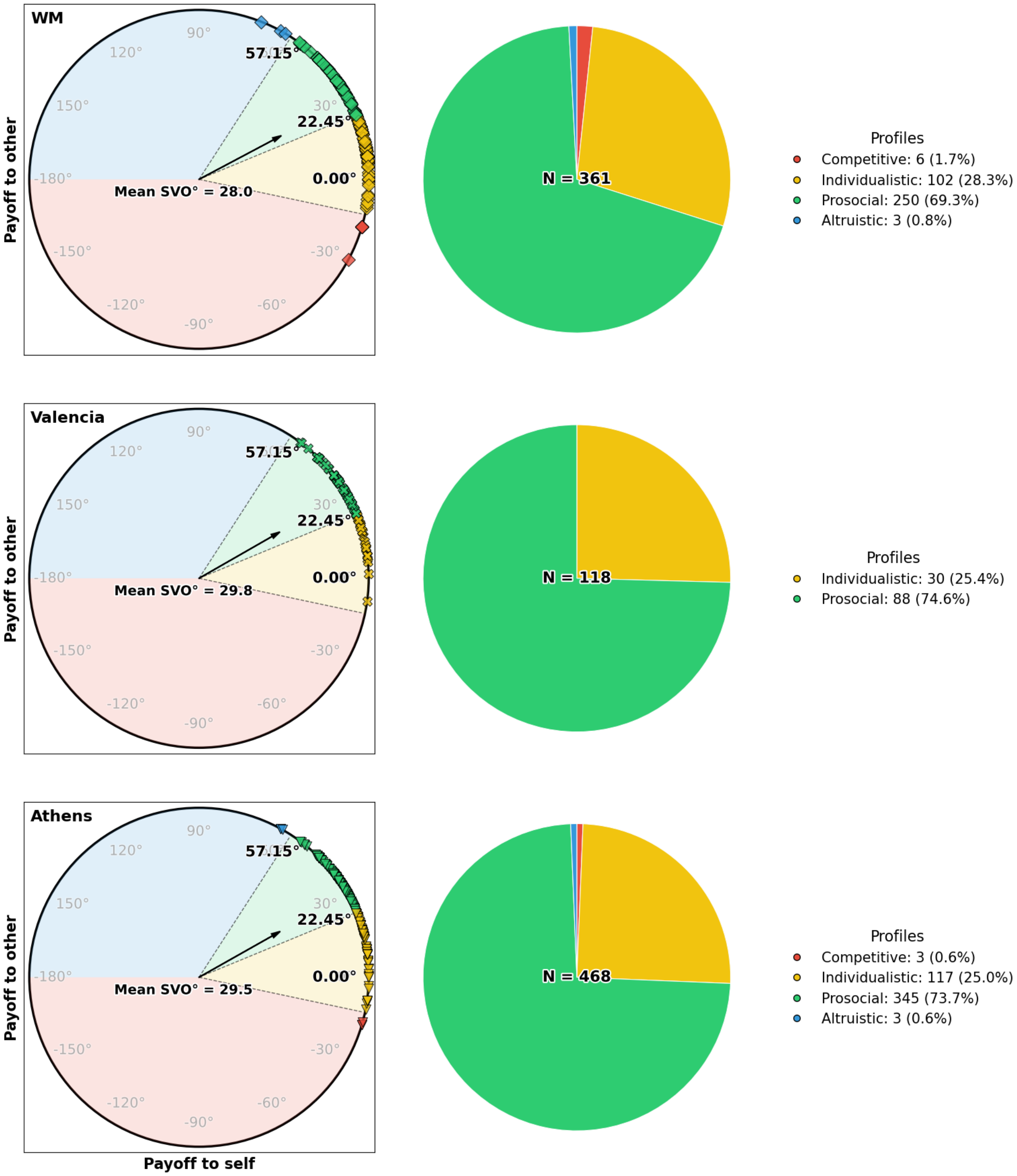


Figure 2. SVO profiles of participants across the three study regions visualised using the SVO Slider Measure developed by Murphy et al. (2011) (left) and corresponding pie charts of profile distributions (right).

5.2. Analytical models

Three RPOP models were estimated against the survey data for the three use cases separately. Explanatory variables were tested for multicollinearity by computing the Pearson/Spearman correlation coefficients, and the variables with unacceptably high (> 0.7) correlation coefficients were not simultaneously introduced into the model. The parameters of all variables were tested for random parameters specification, with SVO and age as the two covariates for the heterogeneity in their means and normal distribution as the distribution of their error terms. The models were estimated using the maximum simulated likelihood approach with 500 Halton draws. The required number of Halton draws was selected so that further increasing the number of draws does not change the estimates significantly. All estimates are assessed using 5% significance level. For better readability, the parameter estimates for the observed covariates within the heterogeneity in the means (Eq 6) are presented separately as interaction effects of those variables on the means of the random parameters.

Table 3 shows the results of the RPOP model for the WM use case. The negative parameters of high traffic (β = –0.222) and presence of a physical median (β = –0.089) were statistically significant indicating that the respondents were, on average, less likely to report going over the speed limit when there is high traffic or a physical median. These effects, however, varied substantially across individuals (σ = 0.286, and 0.371, respectively), reflecting heterogeneity in drivers' responses to traffic conditions.

The presence of speed cameras was one of the strongest predictors of the self-reported speeding (β = –0.535), with drivers reporting lower levels of speeding on roads equipped with such cameras. The effect of this variable on speeding behaviour varied across drivers as well (σ = 0.951).

The negative, statistically significant coefficients on the 30 and 40 mph indicators (vs 20 mph) show that higher posted limits were associated with a lower self-reported likelihood of speeding. This effect varied across drivers at 40 mph (σ = 0.070, z = 2.104) but not at 30 mph (σ = 0.043, z = 1.559).

Male drivers (β = 0.164) and those with higher education levels (β = 0.127) reported higher levels of speeding, with considerable heterogeneity across individuals (σ =1.049 and σ=0.455, respectively). Drivers with higher weekly driving times (exposure) also reported increased levels of speeding (β = 0.233) –albeit with significant heterogeneity in their behaviour. In contrast, the mean effects of driving experience and crash history were not statistically significant for the WM sample. However, the standard deviations of both parameters were significant (σ=0.777 and σ=0.445, respectively), indicating that while some more experienced drivers or those who had crash history reported decreased speeding tendencies, others showed little change or even opposite tendencies.

Finally, most of the behavioural constructs were statistically significant. Higher scores on speeding tendencies (β = 0.597), deliberate violations (β = 0.198), lapses (β = 0.593), and positive behaviour (β = 0.406) associated with an increased self-reported likelihood of speeding, with substantial heterogeneity across individuals (σ=0.728, 0.318, 0.382 and 0.810, respectively). In contrast, distraction (β = 0.037) showed no significant average effect, although its statistically significant variability (σ = 0.281) suggests divergent behavioural responses across drivers.

Table 3. Results of the RPOP Model with Heterogeneous Means for WM Speeding Behaviour

Variable		**Fixed Effects**			**Random Effects**		
		Estimate	**z value**	**95% CI**	**Estimate**	**z value**	**95% CI**
High traffic		-0.222	**-8.764**	[-0.271,-0.172]	0.286	**13.058**	[0.243,0.329]
Presence of physical median		-0.089	**-2.645**	[-0.154,-0.023]	0.371	**15.105**	[0.323,0.419]
Presence of speed camera		-0.535	**-11.728**	[-0.625,-0.446]	0.951	**30.039**	[0.889,1.013]
Speed limit	30 mph	-0.070	**-3.206**	[-0.113,-0.027]	0.043	1.559	[-0.011,0.096]
	40 mph	-0.107	**-3.729**	[-0.163,-0.051]	0.070	**2.104**	[0.005,0.136]
Gender (male)		0.164	**3.434**	[0.071,0.258]	1.049	**23.492**	[0.961,1.136]
Education		0.127	**2.507**	[0.028,0.227]	0.455	**11.894**	[0.380,0.530]
Driving experience		0.024	0.292	[-0.137,0.184]	0.777	**19.549**	[0.699,0.855]
Driving exposure		0.233	**6.518**	[0.163,0.303]	0.404	**7.275**	[0.295,0.513]
Crash history		0.016	0.325	[-0.083,0.116]	0.445	**6.869**	[-0.083,0.116]
Behavioural constructs	Speeding tendencies	0.597	**9.995**	[0.480,0.714]	0.728	**14.927**	[0.632,0.824]
	Distraction	0.037	0.516	[-0.102,0.175]	0.281	**7.601**	[0.208,0.354]
	Deliberate Violations	0.198	**2.302**	[0.029,0.367]	0.318	**8.508**	[0.029,0.367]
	Lapses	0.593	**8.462**	[0.456,0.731]	0.382	**7.001**	[0.274,0.490]
	Positive behaviour	0.406	**7.824**	[0.304,0.508]	0.810	**20.451**	[0.732,0.888]
Thresholds							
		Estimate	z value	p-value	95% CI		
μ_1 (very unlikely to unlikely)		-0.946	**-19.608**	<0.001	[-1.040, -0.851]		
μ_2 (unlikely to neutral)		0.911	**18.885**	<0.001	[0.817, 1.006]		
μ_3 (neutral to likely)		1.893	**37.175**	<0.001	[1.793, 1.993]		
μ_4 (likely to very likely)		3.278	**55.353**	<0.001	[3.162, 3.394]		
Model Fit							

AIC	AIC/N	Log-likelihood	Participants		Observations
			Count	Panel	
15755.94	1.818	-7813.970	361	24	8664

The results of the RPOP model for Greek drivers are presented in Table 4. Similar to the UK sample, high traffic was, on average, associated reduced self-reported speeding (β = –0.177), and this effect varied substantially across individuals (σ = 0.218). Likewise, the presence of a physical median was associated with a reduction in average self-reported speeding (β = –0.046; σ = 0.262), suggesting that roadway design features played a role in moderating speeding behaviour. Greek drivers reported a markedly high propensity, on average, to speed on highways compared to urban roads (β = 0.124; σ = 0.350). In addition, the presence of speed cameras was one of the strongest deterrents, showing a negative average association with self-reported speeding (β = –0.398) and substantial heterogeneity across drivers (σ = 0.551). Elevated speed limit (50 km/h) was associated with reduced self-reported speeding (compared to the 30 km/h speed limit) (β = –0.273; σ = 0.486).

Table 4. Results of the RPOP Model with Heterogeneous Means for Speeding Behaviour in Athens

Variable		**Fixed Effects**			**Random Effects**		
		Estimate	**z value**	**95% CI**	**Estimate**	**z value**	**95% CI**
High traffic		-0.177	**-9.543**	[-0.213,-0.141]	0.218	**15.884**	[0.191,0.245]
Presence of physical median		-0.046	**-2.126**	[-0.089,-0.004]	0.262	**15.506**	[0.229,0.295]
Highway		0.124	**4.623**	[0.072,0.177]	0.35	**22.518**	[0.320,0.381]
Presence of speed camera		-0.398	**-13.926**	[-0.454,-0.342]	0.551	**30.615**	[0.515,0.586]
Speed limit	40 mph	-0.273	**-11.032**	[-0.321,-0.224]	0.486	**25.795**	[0.449,0.523]
Gender (male)		0.049	**1.382**	[-0.021,0.119]	0.919	**34.761**	[0.867,0.971]
Education		-0.125	**-4.067**	[-0.185,-0.065]	0.376	**15.972**	[0.330,0.422]
Driving experience		-0.152	**-5.565**	[-0.206,-0.099]	0.557	**18.558**	[0.498,0.616]
Driving exposure		0.106	**3.597**	[0.048,0.163]	0.419	**14.066**	[0.361,0.477]
Crash history		-0.181	**-3.135**	[-0.294,-0.068]	0.469	**6.199**	[0.321,0.618]
Behavioural constructs	Speeding tendencies	0.602	**20.704**	[0.545,0.659]	0.647	**28.482**	[0.603,0.692]
	Distraction	0.21	**4.826**	[0.124,0.295]	0.446	**13.949**	[0.383,0.508]
	Deliberate Violations	0.299	**8.087**	[0.227,0.371]	0.584	**22.453**	[0.533,0.635]
	Lapses	0.268	**8.842**	[0.209,0.328]	0.439	**23.578**	[0.403,0.476]
	Positive behaviour	0.532	**13.873**	[0.457,0.608]	0.367	**17.012**	[0.325,0.409]
Thresholds							
		Estimate	z value	p-value	95% CI		
μ_1 (very unlikely to unlikely)		-1.29	-49.29	<0.001	[-1.341,-1.238]		
μ_2 (unlikely to neutral)		0.422	17.609	<0.001	[0.375,0.469]		
μ_3 (neutral to likely)		1.624	61.402	<0.001	[1.572,1.676]		
μ_4 (likely to very likely)		3.218	82.156	<0.001	[3.141,3.295]		

Model Fit					
AIC	AIC/N	Log-likelihood	Participants		Observations
			Count	Panel	
15755.94	1.818	-7813.970	361	24	8664

Contrary to the British drivers, gender differences in Athens were not statistically significant on average. However, the large (and statistically significant) variation across individuals (σ = 0.919) indicates that male and female drivers responded quite differently to contextual factors. Higher education was negatively associated with speeding tendencies (β = –0.125; σ = 0.376), suggesting that higher educational attainment is associated with safer driving attitudes. Moreover, more experienced drivers were more likely to report lower levels of speeding (β = –0.152; σ = 0.557). In line with the WM results, Greek drivers with higher road exposure reported higher levels of speeding (β = 0.106; σ = 0.419). Finally, individuals with a crash history were less likely to report speeding (β = –0.181; σ = 0.469), potentially reflecting behavioural adjustments following prior incidents.

All behavioural constructs had statistically significant effects on speeding among the Greek sample. Higher reported tendencies toward speeding were strongly associated with elevated self-reported speeding (β = 0.602; σ = 0.647). Distraction (β = 0.210; σ = 0.446), deliberate violations (β = 0.299; σ = 0.584), and lapses (β = 0.268; σ = 0.439) also increased the likelihood of self-reported speeding, on average, confirming the role of cognitive-behavioural traits in unsafe driving. Interestingly, prosocial orientation displayed a strong positive association with speeding (β = 0.532), contrary to conventional expectations that it should act as a protective factor. However, the significant individual variation (σ = 0.367) suggests that while many prosocial drivers in Athens reported higher speeding tendencies, others may still display safer driving patterns.

The results of the model for Valencia are presented in Table 5. In Valencia, most of the variables did not have statistically significant parameter estimates except for driving experience (β = –0.326) indicating that, on average, they had no influence on the self-reported speeding behaviours. However, the standard deviations of all of those parameters were statistically significant suggesting that there is even more unobserved heterogeneity in this region.

Table 6 presents the comparative parameter estimates for the variables influencing the heterogeneity in the means of the random parameters in all three use cases. Age and SVO are statistically significant covariates that influence the means of random parameters in the models. In the WM, the negative and statistically significant parameters of SVO within the means of high traffic (β = –0.061) and physical median (β = –0.083) suggest that British drivers who were more prosocial and altruistic were even less likely to report speeding in congested conditions or when there was a physical median. SVO, however, had no significant influence on the effects of these two variables in the other use cases.

In Valencia, the negative parameter of SVO within the means of elevated speed limit 50 km/h (β = –0.196) indicates that Spanish drivers who were more prosocial and altruistic were less likely to report speeding in such speed limits, implying that prosocial drivers in this region internalised regulatory constraints more strongly.

In Athens, the negative parameter of age within the means of speed cameras (β = –0.053) indicates that speeding was further moderated by age among Greek drivers and implying that older drivers were more likely than younger drivers to reduce their speed in response to enforcement.

Table 5. Results of the RPPOP Model with Heterogeneous Means for Speeding Behaviour in Valencia

Variable		**Fixed Effects**			**Random Effects**		
		Estimate	**z value**	**95% CI**	**Estimate**	**z value**	**95% CI**
High traffic		0.053	0.386	[-0.217,0.324]	0.199	**6.02**	[0.134,0.264]
Median		0.079	0.529	[-0.213,0.371]	0.229	**6.46**	[0.159,0.298]
Presence of speed radar (SR)		-0.157	-0.709	[-0.592,0.278]	0.885	**14.731**	[0.768,1.003]
Speed limit	30 km/h	-0.23	-0.785	[-0.802,0.343]	0.362	**8.613**	[0.280,0.445]
	40 km/h	-0.253	-1.078	[-0.714,0.207]	0.176	**4.868**	[0.105,0.247]
	50 km/h	-0.433	-1.332	[-1.070,0.204]	0.44	**9.016**	[0.344,0.535]
Gender (Male)		-0.156	-0.46	[-0.821,0.509]	0.408	**5.926**	[0.273,0.543]
Education		-0.204	-0.711	[-0.768,0.359]	0.952	**14.401**	[0.822,1.081]
Driving experience		-0.326	**-2.814**	[-0.553,-0.099]	0.441	**7.029**	[0.318,0.563]
Driving exposure		0.126	0.225	[-0.972,1.224]	0.422	**4.206**	[0.225,0.619]
Crash history		0.300	0.902	[-0.352,0.953]	0.494	**5.059**	[0.303,0.686]
Behavioural constructs	Speeding tendencies	0.118	0.337	[-0.569,0.805]	0.605	**5.089**	[0.372,0.838]
	Distraction	0.293	0.984	[-0.290,0.875]	0.658	**9.499**	[0.522,0.793]
	Deliberate Violations	0.155	0.289	[-0.898,1.209]	0.497	**4.101**	[0.262,0.732]
	Lapses	0.299	0.808	[-0.426,1.023]	0.359	**8.194**	[0.273,0.445]
	Positive behaviour	0.095	0.38	[-0.396,0.586]	0.901	**9.983**	[0.724,1.078]
Thresholds							
		Estimate	z value	p-value	95% CI		
μ_1 (very unlikely to unlikely)		-0.932	-15.494	<0.001	[-1.050,-0.814]		
μ_2 (unlikely to neutral)		0.467	8.381	<0.001	[0.358,0.576]		
μ_3 (neutral to likely)		1.31	22.556	<0.001	[1.196,1.423]		
μ_4 (likely to very likely)		2.535	35.841	<0.001	[2.396,2.673]		
Model Fit							
AIC	AIC/N	Log-likelihood		Participants			Observations
6589.08	2.147	-3226.54		Count	Panel		3068
				118	26		

Table 6. Comparative effects of Age and Social Value Orientation (SVO) on the means of random parameters across West Midlands (WM), Athens, and Valencia in the RPOP models.

Variable	WM				Athens				Valencia			
	Age		SVO		Age		SVO		Age		SVO	
	β	z	β	z	β	z	β	z	β	z	β	z
High traffic	0.010	0.352	**-0.061**	**-2.046**	-0.002	-0.174	-0.020	-1.384	0.131	1.043	-0.063	-1.588
Presence of physical Median	-0.014	-0.404	**-0.083**	**-2.094**	-0.010	-0.588	0.008	0.473	0.044	0.321	0.011	0.262
Highway	-	-	-	-	0.009	0.427	0.037	1.896	-	-	-	-
Speed limit (30 km/h / mph)*	-0.005	-0.234	0.017	0.683	-	-	-	-	-0.094	-0.354	-0.048	-0.566
Speed limit (40 km/h / mph)**	-0.007	-0.245	0.037	1.106	-	-	-	-	-0.060	-0.280	-0.075	-1.086
Speed limit (50 km/h)	-	-	-	-	0.008	0.404	-0.038	-1.815	0.096	0.328	**-0.196**	**-2.060**
Speed camera/radar***	0.053	1.159	0.005	0.115	**-0.053**	**-2.577**	-0.024	-1.209	0.294	1.396	-0.050	-0.728
Gender (Male)	**0.199**	**4.320**	**-0.191**	**-3.943**	**-0.066**	**-2.581**	-0.013	-0.511	-0.121	-0.385	-0.082	-0.833
Education	**-0.123**	**-2.961**	-0.001	-0.019	**0.091**	**3.718**	-0.231	-0.231	-0.266	-0.967	0.010	0.111
Driving experience	-0.053	-0.660	**0.246**	**2.811**	**0.109**	**5.302**	**-0.060**	**-2.805**	-0.214	-1.245	**-0.210**	**-2.342**
Driving exposure	0.063	1.063	0.089	1.791	**-0.162**	**-5.174**	**0.109**	**4.580**	0.004	0.008	-0.191	-1.526
Crash history	**0.220**	**4.308**	0.124	1.057	**-0.160**	**-4.765**	**0.140**	**2.427**	0.007	0.016	**0.496**	**2.997**
Speeding tendencies	0.123	1.806	**-0.495**	**-5.693**	-0.038	-1.938	**0.152**	**6.106**	-0.112	-0.345	0.045	0.327
Distraction	**-0.316**	**-6.878**	0.121	1.446	**-0.272**	**-10.686**	-0.053	-1.474	-0.198	-0.700	-0.222	-1.932
Deliberate Violations	**-0.276**	**-3.335**	**-0.245**	**-2.170**	**-0.088**	**-2.820**	0.016	0.452	0.368	0.756	-0.207	-1.639
Lapses	0.035	0.491	0.064	0.924	**-0.096**	**-3.917**	-0.019	-0.647	0.217	0.647	-0.229	-1.916
Positive behaviour	-0.008	-0.141	**0.252**	**5.351**	**0.181**	**6.240**	**0.073**	**2.711**	0.084	0.356	0.052	0.665

* 30 km/h for Valencia, 30 mph for WM.
**40 km/h for Valencia, 40 mph for WM.
***Speed camera for Athens/WM, radar for Valenica.

In terms of socio-demographic factors, clear cross-contextual differences can be seen from the results. In the WM, the effect of gender is moderated by age (β = 0.199), indicating that older male respondents are more likely to state a higher propensity towards speeding across the experimental scenarios. In contrast, in Athens, the pattern is reversed; age has decreasing influence (β = –0.066) on the effects of gender.

Moreover, SVO moderated gender effects only in WM: the negative parameter within the mean of Gender (male) (β = −0.191) indicates that more prosocial men were less likely to report speeding; no comparable SVO moderation was found in Athens or Valencia. Age moderated Gender in opposite directions across contexts, increasing the male effect in WM (β = 0.199) and reducing it in Athens (β = −0.066), with no clear effect in Valencia.

Education exhibited contrasting age moderation: the education effect declined with age in WM (β = −0.123) but increased with age in Athens (β = 0.091); SVO showed no meaningful moderation of education across sites.

Driving experience displayed distinct patterns. In WM, SVO strengthened the experience effect (β = 0.246). In Athens, the experience effect increased with age (β = 0.109) but was dampened by SVO (β = −0.060). In Valencia, SVO reduced the experience effect (β = −0.210), while age was negligible.

Driving exposure in Athens was negatively moderated by age (β = −0.162) and positively by SVO (β = 0.109). Corresponding moderations in WM and Valencia were not statistically clear.

Crash history showed heterogeneous moderation. In WM, the crash-history effect strengthened with age (β = 0.220). In Athens, it weakened with age (β = −0.160) but increased with SVO (β = 0.140). In Valencia, SVO increased the crash-history effect (β = 0.496), whereas age played little role.

Behavioural constructs also differed by context. For Speeding tendencies, SVO was negative in WM (β = −0.495) and positive in Athens (β = 0.152). Distraction declined with age in both WM (β = −0.316) and Athens (β = −0.272). Deliberate Violations decreased with age in both settings (WM: β = −0.276; Athens: β = −0.088) and additionally declined with higher SVO in WM (β = −0.245). Lapses declined with age in Athens (β = −0.096). Positive behaviour increased with both age (β = 0.181) and SVO (β = 0.073) in Athens, and with SVO in WM (β = 0.252).

6. Discussion

In two of the three use cases, WM and Athens, the presence of a physical median and higher traffic density were consistently associated with reduced self-reported speeding, highlighting the importance of roadway geometry and traffic flow conditions in mitigating risky driving behaviour which resonate well with the literature (Bassani et al., 2014; Porter et al., 2012). Enforcement measures, such as speed cameras and higher posted speed limits, further consolidated this effect. The lowered self-reported propensity to speed in relation to speed cameras, and particularly posted speed limits, suggest that when limits are perceived as credible and aligned with typical driving norms, drivers are less likely to report themselves as ‘speeding’ (Aarts & Van Schagen, 2006; Goldenbeld & van Schagen, 2007). Credibility may narrow the psychological gap between self-perceived behaviour and formal rules, which in turn reduces reported violations. Credible limits might also encourage respondents to perceive themselves as compliant, while enforcement mechanisms such as cameras reinforce adherence at the margins. Crucially, however, these influences were not uniform across individuals but were moderated by age and SVO. In WM, prosocial drivers were more responsive to traffic and design cues; in Athens, older drivers were especially responsive to visible enforcement; and in Valencia, weak average effects with marked between-driver variability suggest uneven rule acceptance.

These cross-regional differences can be situated within broader national cultures of road safety and enforcement. In the UK, automated enforcement has a long tradition and enjoys high public acceptance, which underpins rule legitimacy. Fixed speed camera zones have been shown to reduce personal injury collisions by about 22 percent and fatalities/serious injuries by roughly 42 percent, providing strong institutional support of compliance norms (Pilkington & Kinra, 2005; Wilson et al., 2010). In Greece, where day-to-day compliance has been variable, empirical analyses show that stronger enforcement is associated with improved safety outcomes (Yannis et al., 2008), while European reviews emphasise that visible, well-publicised enforcement is a key deterrent mechanism (Adminaité-Fodor & Jost, 2019). In such contexts, external enforcement cues act as salient safety signals, and adherence may depend more on demographic factors such as age and risk sensitivity than on internalised social orientations. In Spain, attitudes toward speeding and enforcement have been described as more ambivalent, with substantial heterogeneity across drivers. European survey data (ESRA) demonstrate cross-national variation in attitudes toward traffic enforcement and compliance norms, including in Spain (Vias institute, 2024a). This context frames the Valencia case, where weaker average effects of traffic and geometric cues contrasted with more heterogeneous responses to regulatory measures. In Spain's lower-trust enforcement environment, compliance appears to depend less on broad demographic patterns and more on individual orientations. Prosocial drivers were more inclined to interpret credible limits and radar enforcement as legitimate, whereas others remained disengaged, reflecting the cultural ambivalence toward traffic rules that surveys and evaluations have repeatedly noted.

The contrasting findings between the UK and Greece also extended to socio-demographic factors: in the UK, education aligned with compliance, yet older men and prosocial drivers with greater experience were more non-compliant. In Greece, the pattern inverted: ageing was protective, but more educated, prosocial drivers with high exposure, and prosocial crash-involved drivers were linked to greater reported speeding. Moreover, Spain displayed a related paradox, where prosocial experience curbed speeding overall but shifted towards risk among crash-involved drivers. Viewed through a cross-cultural lens, the contrast is consistent with country-level variation in both the acceptability and the self-reported prevalence of speeding (Harkin et al., 2024; Vias institute, 2024b). Against this backdrop, the UK pattern can be read as reflecting stronger internalisation of anti-speeding norms among higher-educated drivers, whereas Greek DBQ evidence documents aberrant-behaviour profiles that contextualise our Athens result as culture-specific rather than education-driven per se (Kontogiannis et al., 2002). Well-established regularities, men reporting more violations and ageing generally reducing them, also vary by culture and subgroup, which is consistent with the inversion we observed for older men across the two countries (Martinussen et al., 2013; Özkan & Lajunen, 2006), and aligns with experimental evidence that gender categories and roles shape attributed driving competence and safety-related anxiety (Degraeve et al., 2025). Mileage/exposure is positively associated with riskier self-reports, helping to interpret the prosocial-by-exposure interaction in Athens. Prosocial effects themselves are context-sensitive and shaped by situational norms, which can produce opposite prosocial × experience patterns across settings (Kaye et al., 2022). Finally, the positive prosocial-by-crash-history association, observed in Greece and Spain, is consistent with evidence that DBQ violations relate to crash involvement and with optimism-bias accounts of persistent risk underestimation after adverse events (de Winter & Dodou, 2010; DeJoy, 1989).

Across WM and Athens, the same behavioural dispositions, speeding tendencies, deliberate violations, lapses, and even self-rated positive behaviour, went with higher self-reported speeding, but the way these links worked differed. In WM, higher SVO values weakened the links for speeding tendencies and deliberate violations, while age reduced distraction (and, to a smaller extent, violations) but left tendencies and lapses much the same. In Athens, by contrast, age reduced distraction, violations, and lapses across the board, whereas higher SVO values made the links stronger for speeding-tendency beliefs and positive behaviour. Valencia differed from both: these constructs showed no consistent average link with speeding and little moderation, with differences showing up mainly between drivers rather than within constructs. Socially and psychologically, the same traits can play out differently under local norms. In WM, a 'considerate driver' self-image tends to work against risky habits, and age shows up mainly as better attention control; higher prosocial values weaken the link between having speeding/violation tendencies and reporting speeding. In Athens, that self-image can quietly license mild speeding unless tied to specific actions; higher prosocial values strengthen the link between 'I tend to speed' or 'I'm a positive driver' and reported speeding, while age relates to fewer slips and less distraction across the board. In Valencia, there is no single average pattern, differences sit between drivers, so identity cues matter less than personal habits and situations.

This study is not without limitations. First, it relies on self-reported, SP data: responses reflect intentions in hypothetical but realistic scenarios rather than observed speeds, so social-desirability, hypothetical-response bias, and common-method variance are possible; external validity should therefore be read with caution, and triangulation with revealed-preference (RP) sources (e.g. telematics/ISA logs, naturalistic speed observations, enforcement records) is a clear next step. Second, although the Spanish (Valencia) sample was drawn using an appropriate statistical sampling design, it was smaller than the UK and Athens samples, which reduces power and may contribute to weaker average effects. Replication with a larger Spanish panel would tighten uncertainty and stabilise moderation estimates. Third, cross-site differences likely reflect context (legal norms, enforcement salience, street design, socio-cultural values) as much as psychology; a multilevel design with explicit country/corridor covariates would separate culture from composition. Fourth, although the RPOP with heterogeneous means captures substantial heterogeneity, the current specification assumes independent, normally distributed random coefficients and fixed thresholds shared within each city. These restrictions cannot capture correlated preference variation or response-style differences (e.g. scale and cut-point use), so some estimated preference heterogeneity may reflect unmodelled covariance or reporting scale. Future work could test correlated random effects, latent-class or semi-parametric mixtures, heteroskedastic scale by site/exposure/scenario, and respondent-level or random thresholds to better separate preferences from response style. Robustness can be strengthened by sensitivity to the number and type of simulation draws and seeds, alternative links (ordered logit versus probit, partial proportional-odds, heteroskedastic links), alternative threshold parameterisations, and out-of-sample prediction. External validity can be improved via triangulation with RP sources (telematics, roadside/camera data). Finally, SP realism and cross-site comparability can be enhanced with short video vignettes to convey motion/density and with measurement-invariance checks on psychological scales (configural, metric, scalar; differential item functioning).

7. Conclusions

This study investigated how roadway and traffic conditions, socio-demographic factors, and SVO jointly shape self-reported speeding behaviour across three European cities using a RPOP model capable of capturing unobserved heterogeneity and accounting for latent psychological influences. Overall, our results suggest a two-layer process: road design, traffic density and enforcement set a baseline deterrent, but whether drivers internalise and act on these cues depends on who they are (age, prosocial orientation) and where they drive (local norms and rule legitimacy). Prosocial orientation (i.e. higher SVO values) can support compliance when limits and cameras are seen as protective of others, as in WM and, selectively, in Valencia, but it can also track local norms, which in Athens sometimes meant justifying ‘a little over’ when speeding felt socially acceptable. Older drivers tended to be more responsive to visible enforcement (especially cameras), consistent with greater risk sensitivity and norm adherence with age. In short, engineering and enforcement do not operate in a vacuum: their effects are filtered through social meanings, credibility, legitimacy, and what counts as considerate driving in each place.

In summary, speeding is not a fixed trait but a social practice shaped by what drivers consider normal, competent and considerate in their setting, and by how and how much they drive. A practical implication is to help at the moment a speed choice is made, turning identity and intention into one simple action. One workable option is a zone-entry prompt that appears when a vehicle enters a new limit and asks: 'Set speed to the legal limit?'. With one tap, the driver sets Intelligent Speed Assistance (ISA) or cruise control to the posted speed; if the car drifts a few km/h over, a brief, non-punitive reminder appears. The driver can override at any time. Where ISA is unavailable, the same prompt can run in navigation apps; in cars with driver assistance, it updates the system's target speed while preserving driver control. This cue-to-action approach fits our results: in WM, where prosocial tendencies supported compliance, it helps those tendencies become consistent behaviour; in Athens, where norms sometimes tolerated 'a little over', it quietly resets the default at the point of choice and complements cameras; in Valencia, where average effects were weaker but differences between drivers were larger, it offers a light-touch option that many can accept.

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CRediT authorship contribution statement

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