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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 shaped by road and traffic conditions, enforcement, and individual psychological differences. Yet most studies have overlooked how such differences condition drivers' responses to speed-management cues. We examined drivers' speeding propensity across urban scenarios in the West Midlands (WM), Athens, and Valencia, focusing on Social Value Orientation (SVO) and its moderating role. Random-parameters ordered probit models with heterogeneity in the means were used to capture unobserved heterogeneity and systematic variation linked to driver traits. Results show that road design, traffic density, and speed enforcement are associated with self-reported speeding, but these associations vary across contexts and drivers. SVO-related moderation was clearest in the WM, where stronger prosocial orientation weakened the links between behavioural-risk constructs and self-reported speeding and increased sensitivity to traffic and road-design conditions. In Athens, the pattern differed, with stronger prosocial orientation mainly strengthening the link between speeding tendencies and speeding propensity. In Valencia, SVO-related evidence was more selective and less pervasive. Age also moderated these relationships: in Athens, speed cameras were more strongly associated with lower stated speeding among older drivers, while in the WM and Athens the links between behavioural-risk constructs and stated speeding generally weakened with age. Overall, engineering and enforcement measures were not associated with stated speeding uniformly across drivers or study contexts. Speed-management strategies may therefore be more effective when physical design and enforcement are paired with communication that presents speed limits as credible, locally relevant, and clearly connected to the safety of other road users.

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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 Europe, making it a top risk factor for road users in this region (Adminaité-Fodor & Jost, 2019), and thus understanding its underlying factors is critical for effective prevention strategies. Previous studies investigating these factors have largely emphasized 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; Fleiter & Watson, 2005; Rhodes & Pivik, 2011). In addition, driving habits and past behaviours have also been shown to be associated with non-compliant driving behaviours such as speeding (An et al., 2023; Fildes et al., 1991; Liu et al., 2025; Rachad et al., 2024).

Beyond demographics, psychological factors, and driving habits, personality traits may also play an important role in speeding. Road users' tendencies toward risk aversion, altruism, or competitiveness can shape how they interact with others and with the traffic environment, and may therefore influence driving behaviour (Al-Tit, 2020). One of these personality traits that has been widely studied in behavioural science, particularly due to its ability to capture tendencies toward altruism, cooperation, or competitiveness, is Social Value Orientation (SVO). SVO refers to an individual's relatively stable preference for how outcomes, such as resources, rewards, or costs, are allocated between themselves and others. It captures motivational orientations ranging from altruistic and prosocial preferences, which reflect concern for others' outcomes, joint outcomes, or equality, to individualistic preferences centred on self-interest, and competitive preferences emphasising relative advantage over others (Murphy et al., 2011). This construct is particularly relevant to traffic safety because speeding is not only an individual risk-taking behaviour but also a socially consequential decision. Higher speeds increase both crash likelihood and injury severity, and even small increases in mean speed are associated with disproportionate increases in fatal crash risk (Aarts & Van Schagen, 2006; World Health Organization, 2019; World Health Organization, 2024). Drivers may therefore trade private benefits, such as time or convenience, against safety costs partly borne by pedestrians, cyclists, passengers, and other drivers. Because SVO captures how individuals weigh their own outcomes relative to those of others (Murphy & Ackermann, 2014; Murphy et al., 2011), it provides a theoretically relevant lens for understanding why some drivers may be more willing than others to accept or externalise such risks.

Integrating SVO into the study of speeding behaviour can therefore help explain why drivers differ in their propensity to exceed speed limits under similar conditions. Empirically, however, SVO is difficult to observe directly in naturalistic driving settings and is therefore commonly measured using self-reported survey instruments (Kalantari et al., 2023; Murphy & Ackermann, 2014). These measures can be incorporated into Stated Preference (SP) studies, where respondents evaluate hypothetical but realistic driving scenarios under controlled conditions (e.g. van Essen et al., 2020).

At the same time, SP responses may also reflect unobserved psychological heterogeneity, meaning that individuals with similar observed characteristics may still differ in their stated propensity to speed. Previous research has shown that such heterogeneity can influence how psychological traits relate to road-user behaviour (Paetz, 2021). Fixed-parameter models assume uniform behavioural responses across the population, whereas random-parameter models allow the effects of explanatory variables to vary across individuals (Hensher & Greene, 2003; Kim, 2023). However, random-parameter models are most informative when this variation can be linked to observed individual characteristics, rather than merely showing that responses differ. This motivates the use of a random-parameters ordered model with heterogeneity in the means, which is appropriate for ordinal stated-preference responses and allows part of the variation in behavioural sensitivities to be related to covariates such as SVO and demographics.

Although SVO has been applied in transport decision-making and interactive traffic research, its role in empirical speeding-behaviour studies remains underexplored, particularly within ordered-response models that account for unobserved and systematic heterogeneity. Taken together, the literature points to two key gaps: the limited empirical attention given to SVO in speeding behaviour, and the limited understanding of how SVO-related effects vary across individuals and contexts. These gaps motivate the present study. We aim to answer the following research questions: (1) How does SVO shape drivers' propensity to engage in speeding behaviour, and to what extent are its effects consistent across different contexts? (2) How do demographic characteristics and past driving behaviours interact with SVO in influencing speeding decisions, and what do these interactions reveal about the underlying behavioural mechanisms?

Accordingly, this study investigates how SVO, demographic characteristics, and past driving behaviours are associated with stated speeding behaviour using an SP survey administered across Athens, Valencia, and the WM. Random-parameters ordered probit models (RPOP) with heterogeneity in the means are estimated to account for unobserved heterogeneity in the stated-preference data and to examine systematic variation linked to individual characteristics. This modelling framework embeds psychological heterogeneity within a rigorous econometric structure, revealing how individual differences are associated with stated speeding responses and supporting more targeted and context-sensitive road safety strategies.

2. Literature review

In transport systems, many behavioural decisions involve trade-offs between individual benefits and collective outcomes. Decisions such as complying with speed limits, yielding to other road users, or choosing sustainable modes of transport are therefore not shaped only by external incentives or infrastructure, but also by social preferences. In this context, SVO provides a useful framework for examining whether individuals respond cooperatively, competitively, or individualistically in traffic-related dilemmas.

The role of SVO in transport-related decision-making has been examined in a small but influential body of work. 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 place greater weight on others' welfare) framing choices in more socially considerate terms. Van Lange et al. (1998) examined commuting preferences as a social dilemma and showed that SVO and trust shape preferences for cooperative commuting alternatives such as carpooling and public transport. Joireman et al. (2001) further showed that prosocial individuals were more willing to fund public-transit improvements, especially when schemes were perceived as fair.

Subsequent research extended this perspective to route choice, shared mobility, and network-level outcomes. Avineri (2009) examined how travellers' SVO may affect route-choice behaviour within a social-dilemma framework and how traffic-equilibrium outcomes may depend on the distribution of social preferences across individuals. Related shared-mobility research has examined how system design, social welfare, and traveller–vehicle assignment affect market stability (e.g. Chremos & Malikopoulos, 2021). More recently, van Essen et al. (2020) empirically investigated travellers' compliance with social routing advice using both stated and revealed preference data, showing that compliance with system-optimal routes depends on behavioural motivations, information framing, and individual characteristics, including social preferences.

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; Toghi et al., 2021; Valiente et al., 2024). Extending this concept, a set of motion-planning methods for AVs has been developed that are sensitive to the cooperation levels shown 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; Crosato et al., 2023; Tong et al., 2023; Xie et al., 2024).

Despite these applications, the role of SVO in empirical speeding-behaviour research remains limited. This is an important gap in road safety because drivers with prosocial orientations, who typically place greater weight on others' welfare, may be less likely to speed due to concerns about endangering others. At the same time, prosocial tendencies may interact with local norms in more complex ways, including conformity to group norms that tolerate or normalise speeding. This is consistent with recent evidence showing that speeding and speed-limit compliance can carry social value and normative meanings (Varet et al., 2023). These considerations suggest that SVO may shape not only drivers' propensity to speed, but also how broader contextual and behavioural influences are associated with speeding intentions. However, this moderating role remains largely untested in empirical speeding-behaviour research, particularly across different urban contexts.

3. Methodology

A stated-preference (SP) survey was employed to collect data on drivers' stated likelihood of exceeding speed limits in specific urban scenarios. The survey presented respondents with a series of hypothetical driving scenarios that varied key attributes of interest. In addition to the scenario-based responses, the survey collected information on individual demographic characteristics, past traffic behaviours, and SVO. The collected responses were analysed using RPOP models with heterogeneity in the means, an approach appropriate for modelling outcomes with a natural ordering but unknown spacing between categories, such as Likert-scale responses (Agresti, 2010). The survey design and analytical model are described in the following sections. Fig. 1 presents the study architecture linking the survey design, analytical inputs, modelling framework, and interpretive outputs.

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 and individuals who drive less than one hour per week on average. The structure and content of each section, along with the criteria used for question selection, are described below.

3.1.1. 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, measured as years of active driving, 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 experienced while driving a car in the past two years, where a crash was defined as any incident involving a vehicle that resulted in personal injury, damage to a vehicle, or damage to other property.

3.1.2. Section 2

The second section focused on participants' driving habits and behaviours over the past two years. Using a five-point frequency

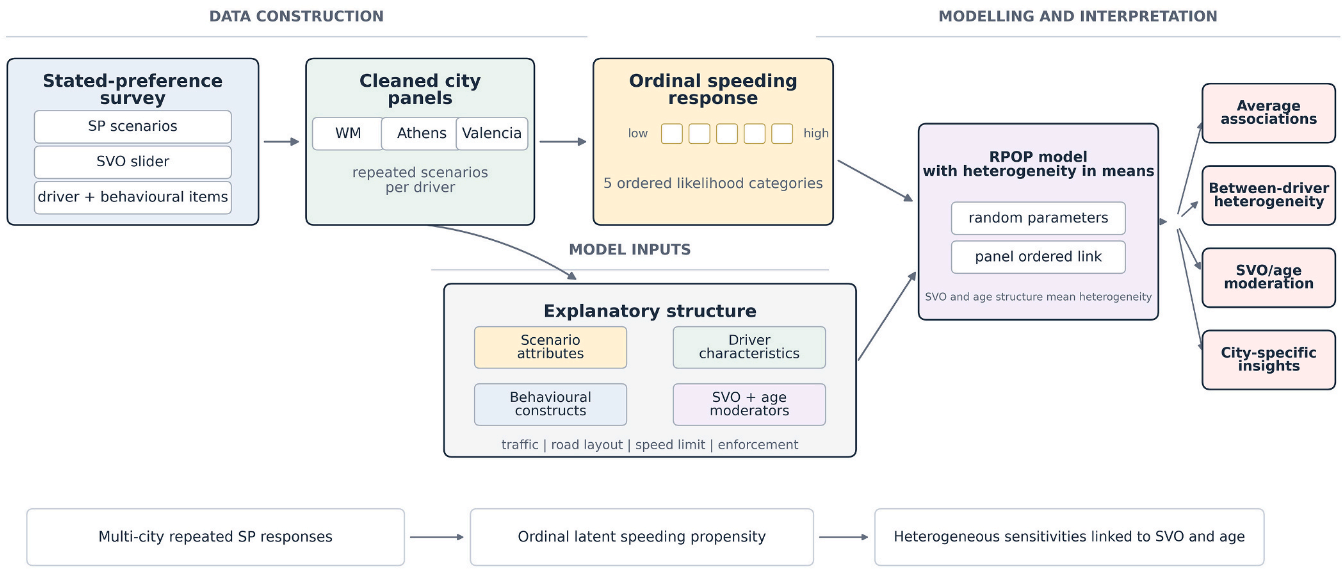

Fig. 1. Study architecture linking the multi-city stated-preference survey, cleaned city panels, ordinal speeding response, explanatory inputs, RPOP model with heterogeneity in means, and interpretive outputs.

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 Driver Behaviour Questionnaire (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 influencing speeding behaviour and crash risk, as elaborated in Section 5.1.

3.1.3. Section 3

The third section of the survey comprised an SP experiment involving a series of driving scenarios set in selected urban locations across the three use cases. The scenarios were developed using a fractional factorial design to ensure statistical efficiency and adequate variation in attribute levels across scenario sets. Participants were presented with hypothetical driving situations combining context-specific roadway images and short textual prompts. For each scenario, respondents first viewed an image representing a realistic urban road environment from the corresponding use-case city and were asked to imagine driving their own car in that setting, typically as part of a daily trip. The accompanying text specified the key scenario attributes, including roadway configuration, traffic condition, posted speed limit, and the presence or absence of enforcement measures such as speed cameras. For example, participants were instructed: "*Please look at the figure below. Consider yourself driving your car for your daily trips on a two-way undivided urban roadway with a single lane in each direction under low traffic, and select how likely it would be for you to go over the speed limit in the following situations.*" The objective was to assess participants' stated likelihood of exceeding the speed limit under different combinations of these attributes. Traffic density was conveyed visually using paired low- and high traffic images for each roadway configuration. This approach is consistent with SP survey design, where perceptual realism and consistent interpretation across respondents are prioritised over precise numerical representations of traffic flow. The configurations were selected in consultation with use case technical experts to capture a representative range of urban road typologies and traffic conditions within each city. Accordingly, the scenario sets were designed to be realistic and context-representative rather than identical across cities, reflecting the functional and regulatory diversity of urban road environments while maintaining behavioural relevance across use cases. Fig. 2 illustrates how traffic density was depicted for a given road layout in the WM use case.

The scenario attributes were selected because of their established influence on drivers' speeding behaviour, as reported in previous studies (De Pauw et al., 2014; Schepers et al., 2025; Wilson et al., 2010). Speed-limit levels were selected separately for each use case, in consultation with local partners, to reflect posted limits commonly observed on the representative urban roadway types included in that city, with lower limits assigned to local streets and higher limits to multilane or higher-capacity urban roads. Although additional variables could have been incorporated, doing so would have increased the complexity of the survey design and posed feasibility challenges for implementation. Participants reported their stated likelihood of speeding in each scenario using a five-point Likert scale: Extremely Unlikely, Unlikely, Neutral, Likely, and Extremely Likely. Further details on the scenario attributes across the use cases are provided in Table S1 of the Supplementary Material.

3.1.4. Section 4

The final section of the survey assessed participants' SVO. Several established methods exist for measuring SVO, including the Ring Measure (Liebrand, 1984), the Triple-Dominance Measure (Van Lange et al., 1997), and the SVO Slider Measure (Murphy et al., 2011). The SVO Slider Measure was adopted because it provides a continuous measure of social preference and is suitable for administration in both online and paper-based survey 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 mean allocation to the self and the mean allocation to the other across the six primary items are then compared with the neutral 50–50 allocation and converted into an SVO angle in degrees, which serves as a continuous index of social preference. Higher angles indicate more prosocial or altruistic orientations, with standard cut-offs distinguishing competitive, individualistic, prosocial, and altruistic profiles. 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. An example SVO Slider item used in this section is provided in Fig. S1 in the Supplementary Material.

3.2. Analytical model

The analytical objective is to identify the factors associated with drivers' stated propensity to exceed the speed limit across the three

Fig. 2. Comparison of Low (left) and High (right) Traffic Scenarios on a Two-Way Multilane Undivided Roadway in the West Midlands (WM).

study areas, while also examining whether SVO and age systematically moderate these relationships. Given the ordinal nature of the dependent variable and the panel structure of the data, in which multiple responses are observed for each respondent across scenarios, RPOP models with heterogeneity in the means are employed. This approach treats the observed Likert-scale response as a categorisation of an underlying latent propensity to speed. Random parameters allow the effects of explanatory variables to differ across individuals, while heterogeneity in the means allows part of this variation to be systematically explained by covariates such as SVO and age. The model is therefore well suited to capturing the ordered response structure, repeated observations, and both unobserved and systematic differences in drivers' speeding behaviour.

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

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

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:

$$Y_{it} = j \quad \text{if} \quad \tau_{j-1} < Y_{it}^{*} \leq \tau_j, \quad j = 0, \ldots, J \tag{3}$$

To ensure identification and ordering, these thresholds must satisfy:

$$\tau_{-1} = -\infty, \quad \tau_J = +\infty, \quad \tau_0 < \tau_1 < \ldots < \tau_{J-1} \tag{4}$$

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

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

where $\overline{\beta}$ is the population mean vector, η_i captures individual-specific deviations and Ω is the covariance matrix of the random parameters. Note that β_i varies only across individuals (with subscript i).

The heterogeneity-in-means specification extends this random-parameter structure by allowing the mean of each random parameter to vary systematically with observed individual-level characteristics Z_i For $k = 1, \ldots, K$,

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

where μ_k is the unconditional mean of coefficient k, φ_k is an M × 1 vector of loadings for the mean function, Z_i is an M × 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,

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

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

$$P(Y_{it} = j X_{it}, \beta_i) = \Phi(\tau_j - X_{it}'\beta_i) - \Phi(\tau_{j-1} - X_{it}'\beta_i) \tag{8}$$

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:

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

where $f(\cdot)$ is the density of the random coefficients. 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

4.1. Procedure and recruitment

The survey questionnaire was created in Qualtrics and distributed through a professional panel provider to participants across three study areas: Athens, Valencia, and the WM. Recruitment targeted the relevant geographic areas within each use case and was restricted to adult respondents from the general population who met the study eligibility criteria. As this study focuses on speeding behaviour, only drivers with sufficient driving exposure were retained for analysis. The survey was designed to be device-agnostic to facilitate participation across desktop and mobile platforms.

The target sample sizes were set a priori at 500 respondents for WM, 500 for Athens, and 125 for Valencia. These figures were informed by the population of each study area and considering available resources, data collection costs, and regional panel availability. In the case of Valencia, the target population consisted of residents of the city of Valencia rather than the wider metropolitan region, resulting in a comparatively smaller population frame.

To minimise respondent fatigue and potential measurement error, the instrument was deliberately constrained in length, with an expected completion time of approximately 20 min. 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, equivalent to at least 8 min, completing the survey.

Before full deployment, the survey underwent a soft launch through the professional panel provider. The survey was initially opened until 50 complete responses were obtained in each use case. These pilot responses were inspected to verify survey functionality, completion time, missingness, response patterns, and the distributions of key variables. No major wording, scale, or programming issues requiring redesign were identified, after which the full survey launch proceeded.

4.2. Participants

Upon completion of data collection, the target sample sizes were reached before data cleaning. After excluding incomplete or invalid responses, the final analytical sample comprised 361 participants for the WM, 468 for Athens, and 118 for Valencia. The corresponding datasets contained 8664 observations for the WM, 14,976 for Athens, and 3068 for Valencia, reflecting the number of retained participants multiplied by the number of scenarios completed in each use case. These cleaned datasets formed the basis for all subsequent analyses presented in this study.

Table 1 summarises the analytical sample and scenario-level attributes across the three use cases. Participant-level characteristics are reported as participant counts and percentages or as mean values with standard deviations and ranges, while scenario-level attributes are reported as observation frequencies and shares within each use case. Fig. 3 presents the SVO profiles for the three study regions. For each region, the left panel plots individual SVO angles from the slider task, and the right panel shows the distribution of SVO profiles. Profiles are classified as competitive, individualistic, prosocial, or altruistic using the standard SVO cut-offs: $< -12.04^\circ$, -12.04° to $<22.45^\circ$, 22.45° to $<57.15^\circ$, and $\geq 57.15^\circ$, respectively. The black arrow indicates the regional mean angle.

5. Results

5.1. Behavioural constructs

To prepare the behavioural variables for modelling, responses to Section 2 of the questionnaire were processed to derive PCA-based behavioural construct scores. Based on prior literature and conceptual alignment, the analysed constructs were defined as speeding tendencies, distraction, deliberate violations, lapses, and positive behaviour. Table 2 reports the questionnaire items used to operationalise each construct.

The construct definitions were informed by theory and the behavioural interpretation of the underlying items. Items referring to exceeding speed limits on urban highways and residential roads were grouped under speeding tendencies. Items related to handheld

Table 1
Descriptive statistics of the studied variables.

Variable	WM	Athens	Valencia
Panel A. Analytical sample			
Participants, n	361	468	118
Scenario observations, n	8664	14,976	3068
Scenarios per participant, n	24	32	26
Age, mean (SD) [range]	44.55 (16.06) [18–86]	43.38 (11.33) [19–83]	43.00 (12.57) [18–69]
Male, n (%)	172 (47.64)	240 (51.28)	46 (38.98)
Secondary education or lower, n (%)	162 (44.87)	102 (21.79)	36 (30.50)
Bachelor's degree, n (%)	138 (38.22)	254 (54.27)	34 (28.81)
Master's degree or higher, n (%)	61 (16.89)	112 (23.93)	48 (40.67)
Driving experience (years), mean (SD) [range]	20.50 (16.99) [1–64]	19.56 (11.94) [1–60]	20.45 (12.53) [1–50]
Driving exposure (hrs/week), mean (SD) [range]	10.36 (10.91) [1–120]	12.56 (12.78) [1–150]	8.76 (8.70) [1–60]
Crashes in past 2 years, mean (SD) [range]	0.28 (0.74) [0–8]	0.57 (2.60) [0–50]	0.20 (0.84) [0–8]
SVO angle, mean (SD) [range]	27.99 (14.29) [−28.21–68.49]	29.47 (13.63) [−16.26–61.38]	29.84 (11.99) [−7.81–53.36]
Panel B. Scenario attributes			
High traffic present, n (%)	4332 (50.00)	7488 (50.00)	1416 (46.15)
Physical median present, n (%)	2888 (33.33)	3744 (25.00)	1888 (61.53)
Speed camera/radar present, n (%)	4332 (50.00)	7488 (50.00)	1416 (46.15)
Speed-limit distribution, n (%)	20 mph: 3249 (37.50) 30 mph: 3971 (45.83) 40 mph: 1444 (16.67)	30 km/h: 7488 (50.00) 50 km/h: 7488 (50.00)	20 km/h: 118 (3.84) 30 km/h: 1062 (34.61) 40 km/h: 472 (15.38) 50 km/h: 1416 (46.15)

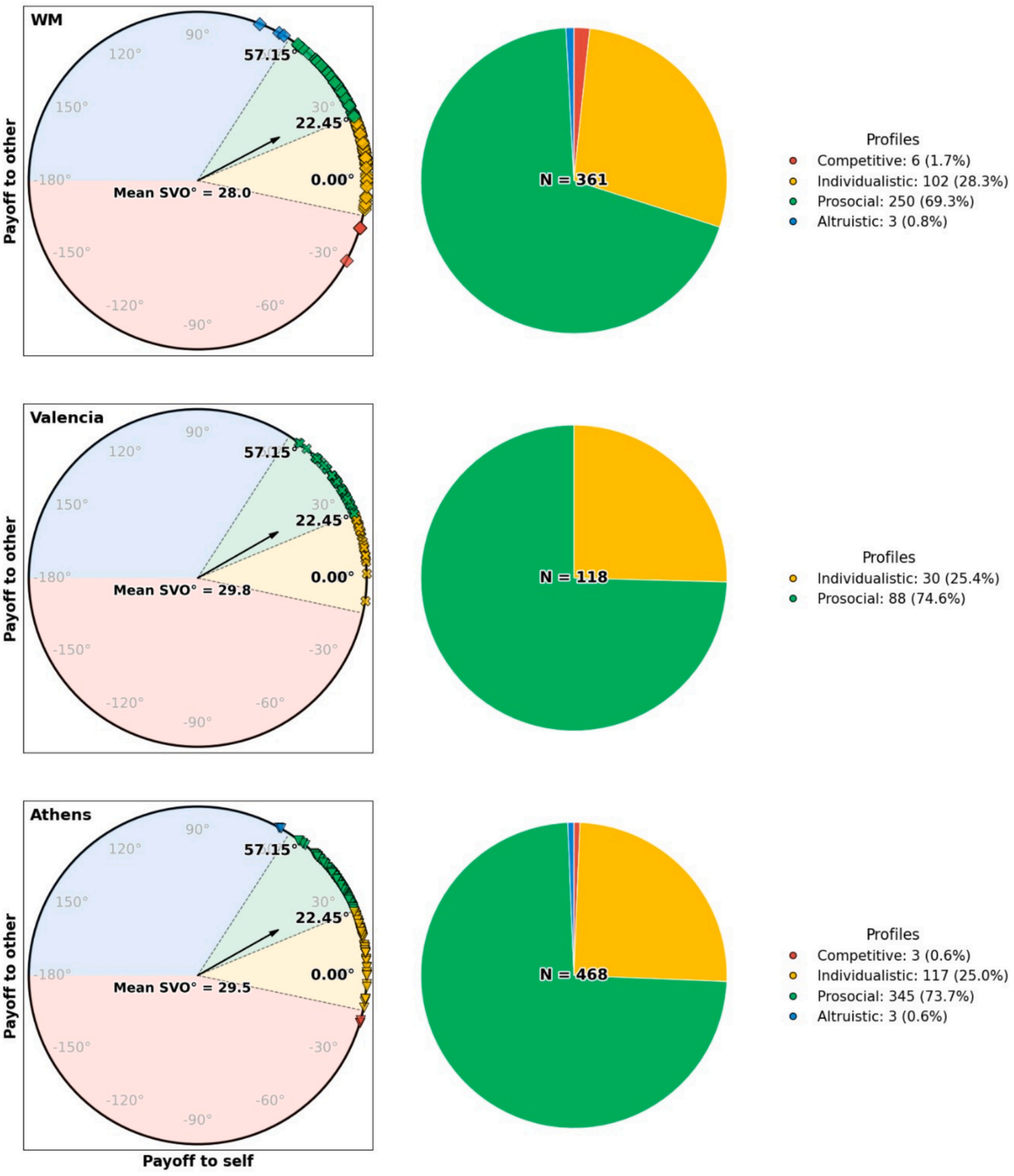

Fig. 3. SVO profiles of participants across the three study regions visualised using the SVO Slider Measure (left) and corresponding pie charts of profile distributions (right).

mobile phone use and texting or browsing while driving were grouped under distraction. Behaviours reflecting intentional rule-breaking, such as illegal overtaking, red-light running, and tailgating, were classified as deliberate violations. In contrast, behaviours reflecting misjudgements or failures of attention, including underestimating the speed of oncoming vehicles when overtaking, failing to notice pedestrians or cyclists when turning, and missing ‘Give Way’ signs, were classified as lapses. Finally, behaviours describing courteous or facilitative driving actions, such as adjusting speed to assist overtaking drivers and yielding to pedestrians despite having the right-of-way, were grouped under positive behaviour, reflecting prosocial driving tendencies.

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 using z-scores and subjected to Principal Component Analysis (PCA). For each construct, the first principal component was extracted and used as the corresponding behavioural construct score. The first component explained the largest share of variance within each item group, supporting its use as a summary measure of the

Table 2
Latent behavioural constructs and corresponding survey measurement items.

Latent construct	Measurement item(s)
Speeding tendency	I disregard the speed limit on urban highways.
	I disregard the speed limit on residential roads.
Distraction	I engage in handheld mobile phone conversations while driving.
	I engage in texting and surfing my social media platforms while driving.
Deliberate violations	I overtook a slower driver on the right (left).
	I disregard the red light at an intersection.
	I enter an intersection knowing that the traffic lights have already changed against me.
	I drive so close to the car in front that it would be difficult to stop in an emergency.
Lapses	I fail to notice that pedestrians are crossing when turning into a side street from a main road.
	When making a right (left) turn, I almost ran over a cyclist approaching from my right.
	I miss seeing a "Give Way" sign and just avoid colliding with traffic having the right of way.
	I underestimate the speed of an oncoming vehicle when overtaking on an undivided two-way road.
Positive behaviour	I adjust my speed to help a driver trying to overtake.
	I let pedestrians cross, even if I have the right-of-way.

corresponding behavioural dimension. 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 absolute component loadings of at least 0.40 were identified as dominant contributors. Construct correlations were inspected to assess overlap between behavioural dimensions. Where higher correlations were observed, particularly between conceptually related unsafe-driving constructs, these were further considered in the multicollinearity checks and sensitivity assessment before model inclusion. The resulting PCA-derived construct scores were then merged with the main dataset and included as continuous covariates in the RPOP model. Construct-validation diagnostics by use case and behavioural construct can be found in Table S2 of the Supplementary Material.

5.2. RPOP model results

Three RPOP models were estimated separately for the three use cases. Before model estimation, explanatory variables were screened for multicollinearity using pairwise Pearson or Spearman correlation coefficients, depending on the measurement scale of the variables. Variables showing high pairwise correlations, using 0.70 as a screening threshold, were not introduced simultaneously into the same model specification.

Candidate coefficients were tested for random-parameter specification, with SVO and age considered as covariates in the heterogeneity-in-means functions for the retained random parameters. Normal mixing distributions were used for the random parameters because the modelled effects could plausibly vary in both positive and negative directions across individuals. Alternative bounded two-sided distributions, including uniform and triangular specifications, were explored as robustness checks but did not provide a consistent improvement across the three study areas. Sign-constrained alternatives, such as lognormal distributions, were not retained because they would impose one-sided effects that were not theoretically appropriate for all parameters.

The models were estimated using simulated maximum likelihood with 500 Halton draws. The number of draws was selected based on stability checks indicating that further increases did not materially change the estimates. Statistical significance was evaluated using the 5% level as the main threshold. For readability, the covariate effects from the heterogeneity-in-means functions in Eq. (6) are presented separately as terms shifting the means of the random parameters.

Table 3
Results of the random parameters ordered probit model with heterogeneity in means for the West Midlands (WM) speeding behaviour.

Variable	Mean effect, β (95% CI)	Random-effect SD, σ (95% CI)
Road, traffic, and enforcement attributes		
High traffic	−0.222 [−0.271, −0.172]	0.286 [0.243, 0.329]
Presence of physical median	−0.089 [−0.154, −0.023]	0.371 [0.323, 0.419]
Presence of speed camera	−0.535 [−0.625, −0.446]	0.951 [0.889, 1.013]
Speed limit: 30 mph	−0.070 [−0.113, −0.027]	0.043 [−0.011, 0.096]
Speed limit: 40 mph	−0.107 [−0.163, −0.051]	0.070 [0.005, 0.136]
Driver characteristics		
Gender (male)	0.164 [0.071, 0.258]	1.049 [0.961, 1.136]
Education	0.127 [0.028, 0.227]	0.455 [0.380, 0.530]
Driving experience	0.024 [−0.137, 0.184]	0.777 [0.699, 0.855]
Driving exposure	0.233 [0.163, 0.303]	0.404 [0.295, 0.513]
Crash history	0.016 [−0.083, 0.116]	0.445 [0.318, 0.572]
Behavioural constructs		
Speeding tendencies	0.597 [0.480, 0.714]	0.728 [0.632, 0.824]
Distraction	0.037 [−0.102, 0.175]	0.281 [0.208, 0.354]
Deliberate violations	0.198 [0.029, 0.367]	0.318 [0.245, 0.391]
Lapses	0.593 [0.456, 0.731]	0.382 [0.274, 0.490]
Positive behaviour	0.406 [0.304, 0.508]	0.810 [0.732, 0.888]

Threshold estimates and model-fit statistics for the final RPOP models are reported in Table S3 of the Supplementary Material. Model comparisons against simpler ordered-response specifications are reported in Table S4, including log-likelihood, AIC, AIC/N, and BIC values for each use case.

5.2.1. WM

Table 3 presents the results of the RPOP model for the WM use case. In the table, fixed effects refer to the estimated mean coefficients of the random-parameter distributions, while random effects refer to the estimated standard deviations of the corresponding random parameters. The negative coefficients for high traffic ($\beta = -0.222$) and the presence of a physical median ($\beta = -0.089$) were statistically significant, indicating that respondents were, on average, less likely to report going over the speed limit under these conditions. These effects, however, varied substantially across individuals ($\sigma = 0.286$, and 0.371, respectively), reflecting heterogeneity in drivers' responses to road and traffic conditions.

The presence of speed cameras was one of the strongest predictors of self-reported speeding ($\beta = -0.535$), with WM drivers reporting lower levels of speeding on roads equipped with such cameras. This effect also varied substantially across drivers ($\sigma = 0.951$), suggesting that while speed cameras were associated with a substantially lower stated likelihood of exceeding the speed limit on average, drivers differed considerably in their responsiveness to enforcement.

The negative, statistically significant coefficients on the 30 and 40 mph speed-limit indicators (relative to 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 ($\sigma = 0.070$, $z = 2.104$) but not at 30 mph ($\sigma = 0.043$, $z = 1.559$), suggesting noticeable heterogeneity at higher posted limits.

Male drivers ($\beta = 0.164$) and those with higher education levels ($\beta = 0.127$) reported higher levels of speeding, with considerable heterogeneity across individuals ($\sigma = 1.049$ and $\sigma = 0.455$, respectively). Drivers with higher weekly driving exposure also reported increased levels of speeding ($\beta = 0.233$), 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 ($\sigma = 0.777$ and $\sigma = 0.445$, respectively), indicating substantial heterogeneity across drivers. This suggests that while some more experienced drivers, or drivers with a crash history, may report lower speeding tendencies, others may show little change or the opposite pattern.

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

5.2.2. Athens

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 with lower self-reported speeding ($\beta = -0.177$), and this effect varied substantially across individuals ($\sigma = 0.218$). Likewise, the presence of a physical median was associated with a reduction in average self-reported speeding ($\beta = -0.046$; $\sigma = 0.262$), suggesting that roadway design features may play a role in shaping speeding behaviour. Drivers reported a markedly high propensity, on average, to speed on highways compared to urban roads ($\beta = 0.124$; $\sigma = 0.350$). In addition, the presence of speed cameras showed one of the strongest negative associations with self-reported speeding ($\beta = -0.398$) and substantial heterogeneity across drivers ($\sigma = 0.551$). Furthermore, the higher speed-limit indicator (50 km/h, relative to 30 km/h) was associated with lower self-reported speeding ($\beta = -0.273$; $\sigma = 0.486$).

Contrary to the WM drivers, gender differences in Athens were not statistically significant on average. However, the large and

Table 4
Results of the random parameters ordered probit model with heterogeneity in means for speeding behaviour in Athens.

Variable	Mean effect, β (95% CI)	Random-effect SD, σ (95% CI)
Road, traffic, and enforcement attributes		
High traffic	−0.177 [−0.213, −0.141]	0.218 [0.191, 0.245]
Presence of physical median	−0.046 [−0.089, −0.004]	0.262 [0.229, 0.295]
Highway	0.124 [0.072, 0.177]	0.350 [0.320, 0.381]
Presence of speed camera	−0.398 [−0.454, −0.342]	0.551 [0.515, 0.586]
Speed limit: 50 km/h	−0.273 [−0.321, −0.224]	0.486 [0.449, 0.523]
Driver characteristics		
Gender (male)	0.049 [−0.021, 0.119]	0.919 [0.867, 0.971]
Education	−0.125 [−0.185, −0.065]	0.376 [0.330, 0.422]
Driving experience	−0.152 [−0.206, −0.099]	0.557 [0.498, 0.616]
Driving exposure	0.106 [0.048, 0.163]	0.419 [0.361, 0.477]
Crash history	−0.181 [−0.294, −0.068]	0.469 [0.321, 0.618]
Behavioural constructs		
Speeding tendencies	0.602 [0.545, 0.659]	0.647 [0.603, 0.692]
Distraction	0.210 [0.124, 0.295]	0.446 [0.383, 0.508]
Deliberate violations	0.299 [0.227, 0.371]	0.584 [0.533, 0.635]
Lapses	0.268 [0.209, 0.328]	0.439 [0.403, 0.476]
Positive behaviour	0.532 [0.457, 0.608]	0.367 [0.325, 0.409]

statistically significant variation across individuals (σ = 0.919) indicates substantial heterogeneity in the gender-related effect. Unlike WM drivers, higher education was negatively associated with speeding tendencies (β = −0.125; σ = 0.376), suggesting that more educated drivers show lower stated likelihood of speeding. Moreover, more experienced drivers were less likely to report higher levels of speeding (β = −0.152; σ = 0.557). In line with the WM results, greater driving exposure in Athens was associated with higher stated speeding propensity (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 adjustment 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, consistent with a role of cognitive-behavioural traits in unsafe driving. Interestingly, positive behaviour 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 substantial heterogeneity across individuals, showing that this relationship does not operate uniformly across drivers in Athens.

5.2.3. Valencia

Table 5 presents the results of the RPOP model for the Valencia use case. In contrast to the WM and Athens models, most explanatory variables in Valencia did not show statistically significant mean effects. Driving experience was the only explanatory variable with a statistically significant average association (β = −0.326), indicating that more experienced drivers were, on average, less likely to report exceeding the speed limit in the presented scenarios.

Overall, the Valencia results provide limited evidence of consistent average associations between contextual, demographic, and behavioural variables and stated speeding. This should be interpreted cautiously given the smaller Valencia sample, wider confidence intervals, and the fact that speed-limit coefficients are estimated relative to the 20 km/h reference category, which was represented by comparatively few observations.

Nevertheless, the standard deviations of all retained random parameters were statistically significant, indicating substantial heterogeneity across drivers. Thus, stated speeding in Valencia appears to be characterised less by uniform average effects and more by individual-level variation in responses to road, enforcement, demographic, and behavioural conditions.

5.2.4. Heterogeneity-in-means effects of age and SVO

Table 6 presents the heterogeneity-in-means effects for age and SVO across the three study contexts. These coefficients indicate how age and SVO shift the mean of each random-parameter distribution. Accordingly, positive values shift the corresponding effect in a more positive direction, while negative values shift it in a more negative direction.

Moderation patterns for road-environment variables varied across contexts. In the WM, stronger prosocial orientation (higher SVO) was associated with stronger negative associations between stated speeding and both high traffic (β = −0.061) and physical median presence (β = −0.083). In Athens, the speed-camera coefficient became more negative with age (β = −0.053), suggesting a stronger negative enforcement-related association among older drivers. In Valencia, stronger prosocial orientation was associated with a more negative 50 km/h speed-limit coefficient (β = −0.196), although most other road-environment moderation effects were not statistically clear.

For socio-demographic and driving-history variables, gender and education showed contrasting moderation patterns across contexts. The male-related coefficient became more positive with age in the WM (β = 0.199), but more negative with age in Athens (β = −0.066). In the WM, stronger prosocial orientation was associated with a weaker positive male-related association with stated

Table 5
Results of the random parameters ordered probit model with heterogeneity in means for speeding behaviour in Valencia.

Variable	Mean effect, β (95% CI)	Random-effect SD, σ (95% CI)
Road, traffic, and enforcement attributes		
High traffic	0.053 [−0.217, 0.324]	0.199 [0.134, 0.264]
Presence of physical median	0.079 [−0.213, 0.371]	0.229 [0.159, 0.298]
Presence of speed radar	−0.157 [−0.592, 0.278]	0.885 [0.768, 1.003]
Speed limit: 30 km/h	−0.230 [−0.802, 0.343]	0.362 [0.280, 0.445]
Speed limit: 40 km/h	−0.253 [−0.714, 0.207]	0.176 [0.105, 0.247]
Speed limit: 50 km/h	−0.433 [−1.070, 0.204]	0.440 [0.344, 0.535]
Driver characteristics		
Gender (male)	−0.156 [−0.821, 0.509]	0.408 [0.273, 0.543]
Education	−0.204 [−0.768, 0.359]	0.952 [0.822, 1.081]
Driving experience	−0.326 [−0.553, −0.099]	0.441 [0.318, 0.563]
Driving exposure	0.126 [−0.972, 1.224]	0.422 [0.225, 0.619]
Crash history	0.300 [−0.352, 0.953]	0.494 [0.303, 0.686]
Behavioural constructs		
Speeding tendencies	0.118 [−0.569, 0.805]	0.605 [0.372, 0.838]
Distraction	0.293 [−0.290, 0.875]	0.658 [0.522, 0.793]
Deliberate violations	0.155 [−0.898, 1.209]	0.497 [0.262, 0.732]
Lapses	0.299 [−0.426, 1.023]	0.359 [0.273, 0.445]
Positive behaviour	0.095 [−0.396, 0.586]	0.901 [0.724, 1.078]

Table 6
Heterogeneity-in-means effects of age and Social Value Orientation (SVO) on random-parameter means.

Variable	WM		Athens		Valencia	
	Age	SVO	Age	SVO	Age	SVO
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)
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	−0.005 (−0.234)	0.017 (0.683)	–	–	−0.094 (−0.354)	−0.048 (−0.566)
Speed limit: 40	−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)
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 (−0.931)	−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)

Note. Values are reported as beta (z). Coefficients indicate shifts in the means of the corresponding random-parameter distributions. Bold values indicate $|z| \geq 1.96$. Dashes indicate that the variable was not included in the corresponding use-case model. For speed-limit rows, 30 and 40 refer to mph in the WM and km/h in Valencia; 50 km/h applies to Athens and Valencia. Speed camera/radar refers to speed camera in the WM and Athens and speed radar in Valencia.

speeding (β = −0.191). Education showed a similar cross-context contrast: the education-related coefficient became more negative with age in the WM (β = −0.123), but more positive with age in Athens (β = 0.091).

Driving experience also showed context-specific moderation. In the WM, stronger prosocial orientation was associated with a positive shift in the experience-related coefficient (β = 0.246), although the mean effect of driving experience was not statistically significant. In Athens, age partly offset the negative experience-related association (β = 0.109), whereas SVO made it more negative (β = −0.060). In Valencia, SVO was likewise associated with a stronger negative experience-related association (β = −0.210). Driving exposure was clearly moderated only in Athens: the positive exposure-related association was weaker with age (β = −0.162) but stronger with stronger prosocial orientation (β = 0.109).

Crash-history moderation was also context dependent. In the WM, age moved the crash-history coefficient upward (β = 0.220), although the mean effect was not statistically significant. In Athens, age strengthened the negative crash-history association (β = −0.160), while SVO partly offset it (β = 0.140). In Valencia, SVO moved the crash-history coefficient upward (β = 0.496), whereas the age-related moderation was not statistically significant.

Behavioural constructs showed some of the clearest moderation patterns. For speeding tendencies, SVO was associated with opposite moderation directions in WM and Athens: it weakened the positive speeding-tendency association in the WM (β = −0.495), but strengthened it in Athens (β = 0.152). Age weakened the positive distraction-related association in both the WM (β = −0.316) and Athens (β = −0.272). Deliberate violations also showed weaker positive associations with increasing age in both contexts (WM: β = −0.276; Athens: β = −0.088), and this association was further weakened by higher SVO in the WM (β = −0.245). Lapses followed a similar age-related pattern in Athens (β = −0.096). By contrast, the positive-behaviour coefficient became more positive with both age (β = 0.181) and SVO (β = 0.073) in Athens, and with SVO in the WM (β = 0.252).

Overall, the heterogeneity-in-means effects reveal three broad patterns across contexts. First, SVO-related moderation was most pronounced in the WM, where stronger prosocial orientation weakened the positive associations of several behavioural-risk constructs with stated speeding, while also strengthening the negative associations of some road-environment variables. Second, age-related moderation was strongest in Athens, where increasing age generally weakened the positive associations of behavioural-risk constructs with stated speeding and strengthened the negative association of speed cameras. Third, Valencia showed more selective and less pervasive moderation patterns than the WM and Athens, with significant effects concentrated in a smaller subset of variables. Overall, these findings suggest that both SVO and age are associated with systematic heterogeneity in stated speeding responses, but their roles differ across study contexts.

To aid behavioural interpretation of the latent-scale coefficients, Fig. S2 in the Supplementary Material presents predicted probabilities of reporting “Likely” or “Extremely likely” to exceed the speed limit under selected illustrative traffic and enforcement scenarios.

6. Discussion

This study examined how SVO, demographic characteristics, and past driving behaviours are associated with stated speeding across different European contexts, and how these associations vary across individuals. In two of the three use cases, the WM and Athens, the presence of a physical median and higher traffic density were consistently associated with lower self-reported speeding, which is consistent with previous evidence on the relevance of roadway geometry and traffic-flow conditions for speed choice (Bassani et al., 2014; Porter et al., 2012). The estimated scenario effects for speed-camera presence and posted speed-limit level further reinforce this interpretation. The reduced speeding propensity in the presence of speed cameras, and especially under higher speed limits, may indicate that credible and context-consistent speed limits are more readily perceived as binding constraints (Aarts & Van Schagen, 2006; Goldenbeld & van Schagen, 2007). Credibility may narrow the psychological gap between self-perceived behaviour and formal rules, encouraging respondents to perceive compliance as both appropriate and attainable, while enforcement mechanisms such as cameras may be associated with greater adherence at the margins.

Crucially, however, these influences were not uniform across individuals but were moderated by age and SVO. In the WM, prosocial drivers were more responsive to traffic and road design cues; in Athens, older drivers were especially responsive to visible enforcement; and in Valencia, weak average effects with marked between-driver variability suggest less uniform responses to the presented regulatory and roadway conditions.

These cross-regional differences can be situated within broader national cultures of road safety and enforcement. In the UK, automated enforcement has a long history and has been extensively evaluated as a road-safety intervention. Fixed speed camera zones have been shown to reduce personal injury collisions by about 22% and fatalities and serious injuries by roughly 42%, supporting the interpretation that enforcement cues can be salient in the WM scenarios (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 settings, external enforcement cues can act as salient safety signals, although their behavioural meaning may still depend on local norms, demographic characteristics, and risk sensitivity. 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, 2024b; Vias institute, 2024c). This context frames the Valencia case, where weaker average effects of traffic and geometric cues contrasted with substantial between-driver variability in responses to regulatory measures. Given the smaller Valencia sample and the resulting lower statistical power for detecting weaker average or moderation effects, these patterns should be interpreted cautiously as evidence of heterogeneous stated responses, rather than as direct evidence of enforcement trust, legitimacy, or disengagement. Nevertheless, they suggest that stated speeding in this context may be less amenable to uniform interventions and more dependent on individual-level heterogeneity and context-sensitive speed-management approaches.

The contrasting findings between the WM and Athens also extended to socio-demographic, driving-history, and SVO-related effects. Rather than identifying a stable demographic profile of the speeding-prone driver, the results suggest that education, driving experience and exposure, crash history, age, and prosocial orientation are conditioned by local behavioural and enforcement contexts. In the WM, education and selected age- and SVO-related heterogeneity terms were associated with higher stated speeding propensity. In Athens, by contrast, education, driving experience, and crash history were more closely associated with lower stated speeding propensity, while SVO altered the associations of exposure and crash history with speeding in ways that were not uniformly protective. Valencia also showed a more fragmented SVO-related pattern: prosocial orientation appeared less as a uniformly protective tendency than as a context-dependent filter through which prior experience and crash-related histories were associated with stated speeding responses. The Valencia pattern is consistent with broader country-level variation in both the acceptability and the self-reported prevalence of speeding (Harkin et al., 2024; Vias Institute, 2024b). Taken together, these findings suggest that socio-demographic markers and prosocial orientation do not carry fixed behavioural meanings across contexts. In the WM, education and experience-related heterogeneity appear to operate within a locally specific compliance environment, whereas Greek DBQ evidence on aberrant-driving profiles helps contextualise the Athens findings as culture-specific rather than education-driven per se (Kontogiannis et al., 2002). Frequently observed patterns, such as men reporting more violations and ageing generally reducing them, also vary by culture and subgroup, which is consistent with the inversion observed for older men across the two settings (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).

The counterintuitive SVO-related moderation patterns therefore warrant a more nuanced interpretation. Driving exposure provides useful context for the Athens findings, where prosocial orientation appeared to strengthen the exposure-related association with stated speeding. More broadly, prosocial orientation may be context-sensitive and shaped by situational norms, which could help explain why its moderating role differs across driving exposure, driving experience, and crash-history effects across settings (Kaye et al., 2022). The positive prosocial-by-crash-history association observed in Athens and Valencia is also 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). One possible explanation is that, in some contexts, prosocial orientation may be expressed through adaptation to perceived traffic flow and surrounding driver behaviour rather than strict adherence to formal speed limits. However, the present study did not directly measure descriptive norms, injunctive norms, rule legitimacy, or drivers' perceptions of what other road users typically do or believe should be done. Future research should examine this possibility by explicitly measuring perceived descriptive norms, injunctive norms, rule legitimacy, and expectations about other drivers' behaviour.

The behavioural constructs further show that similar self-reported driving tendencies did not carry the same behavioural meaning across contexts. Their associations with stated speeding were relatively systematic in the WM and Athens, but more diffuse in Valencia, where the main signal was between-driver heterogeneity rather than a consistent average construct-level pattern. In the WM, stronger prosocial orientation appeared to temper the link between risky behavioural tendencies and stated speeding, suggesting that concern for others may constrain the expression of speeding and violation tendencies. In Athens, by contrast, age was more consistently associated with weaker links between distraction, violations, lapses, and stated speeding, while SVO showed a more mixed moderating role. Valencia showed no single average behavioural pattern, suggesting that differences in stated speeding were more strongly attributable to between-driver heterogeneity than to a uniform construct-level relationship.

6.1. Practical implications

Because the outcome is stated speeding, the findings should be used as an implementation filter alongside observed speed data and road audits. Their practical value is in helping authorities decide where enforcement, design changes, or communication should be prioritised, and where further local diagnosis is needed before large-scale intervention.

In Athens, where speed cameras were strongly associated with lower stated speeding and this association varied by age, visible enforcement should be prioritised at locations where observed speeding overlaps with high vulnerable-road-user exposure, such as approaches to crossings, schools, public-transport stops, and mixed-use corridors. Camera enforcement and speed monitoring should be publicised through short, location-specific messages explaining why lower speeds are needed and which road users are being protected. The age-specific speed-camera association and the context-sensitive role of SVO suggest that these messages should be tailored and pre-tested across age and behavioural groups.

In the WM, speed management should combine physical speed cues, enforcement, and communication that frames speed compliance as a shared-responsibility behaviour. Where observed speeds are close to the intended limit, signing, visible enforcement, and communication may help maintain compliance. Where observed speeds remain above the target limit, physical measures such as gateway treatments, visual narrowing, lane-width reduction, raised tables, and pedestrian- or cyclist priority features should be considered. Because stronger prosocial orientation weakened the links between speeding tendencies, deliberate violations, and stated speeding, campaigns should emphasise harm reduction for pedestrians, cyclists, passengers, and other drivers, especially among frequent drivers and locally identified high-speeding groups.

In Valencia, the weak average effects and substantial heterogeneity point to diagnosis and piloting before scale-up. Authorities should first map where speeding is concentrated using observed speed distributions, proportions exceeding the limit, radar data, crash or conflict records, road type, time of day, and vulnerable-road-user exposure. If road audits indicate that the layout supports speeds above the posted limit, design changes should be prioritised; if speeding is concentrated at specific locations or times, targeted radar enforcement is more appropriate. The SVO-related heterogeneity further supports message piloting before wider rollout. Interventions should be evaluated using excessive-speed prevalence, speed dispersion, and corridor-level effects, rather than average speed reduction alone.

6.2. Limitations

This study is not without limitations. First, the study relies on self-reported stated-preference data. Although the scenarios were designed to be realistic, the responses represent stated intentions rather than observed driving behaviour. Social-desirability and hypothetical-response biases may therefore be present, and the external validity of the findings should be interpreted with caution. Although the survey underwent a soft-launch pilot before full deployment, a separate cognitive pre-test was not conducted to further optimise questionnaire wording and scale interpretation. Future research could strengthen both survey refinement and external validity by combining stated-preference designs with cognitive pre-testing and by triangulating the results with observed behavioural data, such as naturalistic driving observations, roadside speed measurements, camera-based data, or telematics.

Second, the smaller Valencia sample may have reduced statistical power, particularly for detecting weaker effects and moderation effects. This may partly explain the weaker average effects and wider uncertainty observed for Valencia. Replication with a larger Valencia sample would improve precision and allow a more robust assessment of heterogeneity in this use case.

Third, cross-site differences may reflect both psychological differences and broader contextual factors, including legal norms, enforcement practices, street design, traffic culture, and socio-cultural values. The present modelling approach captures differences across use cases but does not fully separate cultural context from sample composition or corridor-level conditions. Future studies could use multilevel designs with explicit country-, city-, and corridor-level covariates to better distinguish these sources of variation.

Fourth, although the RPOP model with heterogeneity in means captures substantial individual-level variation, it relies on several modelling assumptions. The current specification assumes independent normally distributed random coefficients and city-specific fixed thresholds. These assumptions may not fully capture correlated preference variation, scale heterogeneity, or response-style differences in the use of ordinal categories. Future work could examine correlated random parameters, latent-class or semi-parametric mixtures, heteroskedastic scale specifications, and respondent-level or random thresholds. Robustness could also be assessed using alternative link functions, threshold parameterisations, simulation draws, random seeds, and out-of-sample prediction.

Finally, future survey designs could further improve realism and cross-site comparability. Short video vignettes could better convey motion, traffic density, and dynamic interaction cues than static images. In addition, measurement-invariance checks for the psychological scales, including configural, metric, scalar, and differential item-functioning tests, would help assess whether constructs such as SVO and behavioural tendencies are interpreted similarly across use cases.

7. Conclusions

This study examined how roadway and traffic conditions, socio-demographic factors, and SVO are jointly associated with self-reported speeding across three European study areas, using an RPOP model that captures unobserved heterogeneity and observed psychological differences. The findings point to a two-layer process: road design, traffic density, and enforcement may define a baseline deterrent context, but how these cues are reflected in stated speeding depends on driver characteristics and local conditions. Prosocial orientation may support speed compliance when speed limits and enforcement cues are perceived as protecting other road users, as suggested by the WM results and, more selectively, by the Valencia patterns. In Athens, however, the findings suggest a different mechanism, whereby prosocial orientation may partly reflect sensitivity to perceived traffic flow and surrounding driver behaviour in contexts where minor speeding is more socially tolerated. In addition, the presence of speed cameras in Athens was more strongly associated with lower stated speeding propensity among older drivers, suggesting that visible enforcement may be especially salient for this group. Overall, roadway engineering factors and speed enforcement should not be interpreted in isolation: their associations with stated speeding appear to be filtered through driver characteristics, social meanings, perceived credibility, and what counts as considerate driving in each place. Speeding therefore emerges not only as an individual tendency, but also as a context-sensitive behaviour shaped by local expectations, behavioural tendencies, and driving exposure.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process.

During the preparation of this work, the authors used ChatGPT-5 to improve the writing of the manuscript. After using this tool, they reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Amir Hossein Kalantari: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Amna Chaudhry:** Methodology, Data curation, Conceptualization. **Mark Burke:** Writing – review & editing, Funding acquisition, Conceptualization. **Ana María Pérez-Zuriaga:** Writing – review & editing, Funding acquisition, Conceptualization. **Apostolos Ziakopoulos:** Writing – review & editing, Funding acquisition, Conceptualization. **Eleonora Papadimitriou:** Writing – review & editing, Funding acquisition, Conceptualization. **Shanna Lucchesi:** Funding acquisition, Conceptualization. **Amir Pooyan Afghari:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors have no conflicts of interest to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2026.103710.

Data availability

Data will be made available on request.

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