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Standards for passenger comfort in automated vehicles: Acceleration and jerk

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A R T I C L E I N F O

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A B S T R A C T

A prime concern for automated vehicles is motion comfort, as an uncomfortable ride may reduce acceptance of the technology amongst the general population. However, it is not clear how transient motions typical for travelling by car affect the experience of comfort. Here, we determine the relation between properties of vehicle motions (i.e., acceleration and jerk) and discomfort empirically, and we evaluate the ability of normative models to account for the data. 23 participants were placed in a moving-base driving simulator and presented sinusoidial and triangular motion pulses with various peak accelerations ($A_{\max}0.4-2\ \mathrm{ms}^{-2}$) and jerks ($J_{\max}0.5-15\ \mathrm{ms}^{-3}$), designed to recreate typical vehicle accelerations. Participants provided discomfort judgments on absolute 'Verbal Qualifiers' and relative 'Magnitude Estimates' associated with these motions. The data show that discomfort increases with acceleration amplitude, and that the strength of this effect depends on the direction of motion. We furthermore find that higher jerks (shorter duration pulses) are considered more comfortable, and that triangular pulses are more comfortable than sinusoidal pulses. ME responses decrease (i.e., reduced discomfort) with increasing pulse duration. Evaluations of normative models of vibration and shock (ISO 2631), and perceived motion intensity provide mixed results. The vibration model could not account for the data well. Reasonable agreement between predictions and observations were found for the shock model and perceived intensity model, which emphasize the role of acceleration. We present novel statistical models that describe motion comfort as a function of acceleration, jerk, and direction. The present findings are essential to develop motion planning algorithms aimed at maximizing comfort.

1. Introduction

Automation of vehicle functionalities is becoming ever more common, with optimistic accounts suggesting that SAE Level 5 vehicles may enter the consumer market over the next few decades (Kyriakidis et al., 2015; Wadud et al., 2016). Automated vehicles (also referred to as autonomous vehicles/cars, driver-less cars, self-driving cars, or robotic cars) are often presented as the embodiment of freedom, allowing their occupants to work or engage in leisurely activities during otherwise unproductive travel time. In order to ensure broad adoption of the technology, vehicle motion planning and control algorithms must provide levels of motion comfort that are at least sufficiently high to allow such projected benefits to materialize. Implementation of comfortable algorithms requires a comprehensive understanding of how the experience of comfort relates to vehicle motion.

Motion comfort has many facets (see e.g. (de Winkel et al., 2021; Edelmann et al., 2021; Will et al., 2021; Shyrokau et al., 2018; Mirakhorlo et al., 2022),). The presence of low frequency motions endured over a long period of time can lead to motion sickness (Irmak et al., 2021a). In addition to the unpleasant symptoms of motion sickness (including nausea and vomiting), there may also be a drop in cognitive task performance (Matsangas et al., 2014) and increases in subjective workload (Irmak et al., 2021b), as well as increase in fatigue and lethargy (Lackner, 2014). Long duration exposures to high frequency whole body vibrations may also lead to discomfort, may interfere with the ability to perform tasks, and may have adverse health effects, such as

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(chronic) lower back pain (Griffin and Erdreich, 1991; Burström et al., 2015). There is a third class of motions, which leads to an acute sense of discomfort. These motions are typically transient and can be described as discrete pulses that may be characterized in terms of acceleration and jerk, related through motion frequency (Förstberg, 2000; de Winkel et al., 2020). Such discrete events include lane changing, accelerating, braking and curve taking, characteristic for transportation by car.

Whereas some standards on accelerations and jerks may be found in official norms, it is uncertain to what extent these generalize to travel in an automated vehicle. For instance, ISO norm 22179 on *Full Speed Range Adaptive cruise control systems* notes acceleration limits of $+4/-5$ ms^{-2} down to $+2/-3.5$ ms^{-2}, and negative jerk limits of $-5/-2.5$ ms^{-3}; for vehicles travelling at 20 and 5 ms^{-1}, respectively, but the norm does not provide empirical grounds for the chosen values (ISO 22179:2009(E), 2009); ISO norm 2631 provides methods to classify comfort of vibration and shock for lateral and longitudinal motion with frequencies of 0.5–10 Hz, similar to what may be encountered in a car. However, it is noted that the experience of comfort may vary: "a particular vibration may be considered to cause unacceptable discomfort in one situation but may be classified as pleasant or exhilarating in another" (ISO 2631, 2001).

The scientific literature on how acceleration and jerk relate to (dis-) comfort is also inconclusive. A survey of comfort in public transportation by Hoberock (1976) argues that steady non-emergency longitudinal accelerations of 1.08–1.47 ms^{-2} most probably fall in the acceptable range, and that jerks higher than 2.94 ms^{-3} are unlikely to be acceptable. More recent studies by Andersson and Nilstam (1984) in Swedish rail found that the magnitude of tolerable acceleration and jerk was lowest for walking passengers, followed by standing, and subsequently by sitting. Förstberg (2000) built on the study by Andersson and Nilstam (1984), investigating comfort for discrete lateral motions in Swedish rail transport. It was found that a 20% discomfort reporting threshold coincided with a maximum lateral acceleration of 0.84 ms^{-2} and a maximum jerk of 0.42 ms^{-3}. The 50% comfort threshold for lateral acceleration was 1.18 ms^{-2}, which is in agreement with Hoberock (1976), but the 50% comfort threshold for lateral jerk was smaller, at 0.6 ms^{-3}. A limitation of the Andersson and Nilstam (1984) and Förstberg (2000) studies is that the acceleration and jerk were filtered. Andersson and Nilstam (1984) low pass filtered the jerk at 0.3 Hz, presumably to reduce the noise introduced by differentiating acceleration. Förstberg (2000) evaluated two filtering combinations, one of which was a 0.6–1.5 Hz bandpass filter for the lateral acceleration with a 0.3 Hz high-pass filter for the jerk. The other filtering combination was 0.2–0.6 Hz bandpass filter for both lateral acceleration and jerk. The second filter combination gave slightly different comfort thresholds than the initial combination; with maximum lateral acceleration being at 0.52 ms^{-2} and a maximum jerk of 1.18 ms^{-3}. Results therefore imply there may be a frequency relationship, but this was not evaluated.

In the present study we aim to provide clear and unambiguous parametrizations of expected discomfort given acceleration pulses following different characteristic profiles, with acceleration magnitudes and jerks (and, by extension, frequencies) typical for automotive domain. We hypothesize that: (1) subjective discomfort increases linearly with acceleration magnitude and jerk; (2) high jerks do not elicit discomfort if they occur over short periods of time (i.e., an interaction effect exists between frequency and acceleration, such that high frequency accelerations do not elicit discomfort); and (3) lateral and backward motions are more uncomfortable than forward motion due to decreased seat support.

To test these hypotheses, we designed an experiment where comfort responses were collected for motion pulses with various combinations of peak acceleration and jerk. Using the collected empirical data, we evaluate how well existing normative models of comfort for vibration and shock (ISO 2631, 2001), and a model of perceived motion intensity (Soyka et al., 2011; de Winkel et al., 2020), can account for comfort responses of transient motions typical of travelling by car.

2. Methods

2.1. Overview

In the experiment, participants were seated in the driver seat of a moving base motion simulator and were passively subjected to a series of physical motion pulses that were similar to perturbations experienced in traffic. Hence, participants were, in effect, passengers. Participants were tasked to rate the discomfort they felt during each perturbation. These ratings were cross-matched to verbal qualifiers to allow an interpretation of the ratings as well as comparisons between individuals. Statistical models were fitted to the data to determine which characteristics best predicted comfort. The findings of these analyses were then used to evaluate existing normative models.

2.2. Ethics statement

The experiment was performed in accordance with the Declaration of Helsinki. The study was approved by the Human Research Ethics Council of Delft University of Technology (Delft, The Netherlands; application number 1981). All participants gave their written informed consent prior to participation in the study.

2.3. Participants

23 participants (mean age = 28.8, SD = 4.7, 7 females, 16 males) were recruited from amongst university staff and students. All participants were informed of the experimental goals and procedures as per the requirements of informed consent. Participants were offered a 10 voucher as a compensation for their time.

2.4. Apparatus

The study was performed using the Delft Advanced Vehicle Simulator (DAVSi) (Khusro et al., 2020). The DAVSi consists of the front half of a vehicle (Toyota Yaris), mounted to a Stewart motion platform and surrounded by a cylindrical projection screen (Fig. 1). Participants were seated in the driver seat and wore a cervical collar and safety belt as safety measures. External noises were not blocked to ensure that the experimenter and participants could communicate at all times.

2.5. Task & procedure

The main experimental task was a Magnitude Estimation task (ME (Stevens, 1957),), in which participants attributed numbers

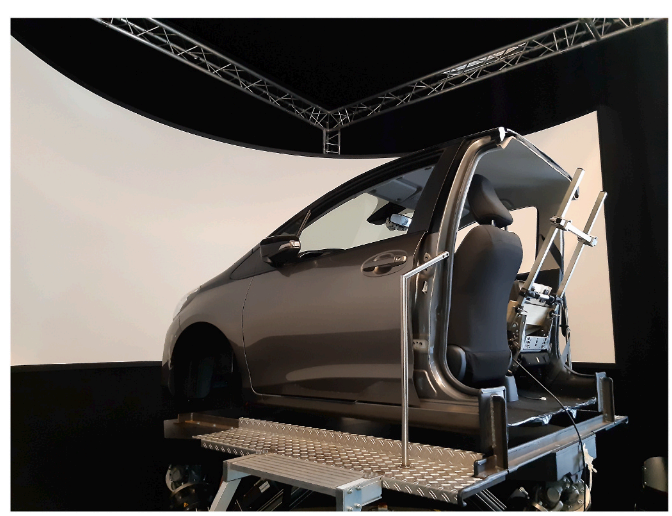

Fig. 1. The DAVSi simulator.

representing their experience of *discomfort* to motion pulses. Motion pulses were presented in a series of experimental trials. There were three training trials followed by 136 experimental trials. In the three training trials, a motion pulse was applied that represented the average of the characteristics varied in the actual experiment (see: Stimuli). The order of motion pulses was randomized within and between participants to counteract effects of time. Participants were instructed to attribute this average motion the arbitrary value '100', and to scale their responses in the actual experiment relative to this motion. To further clarify this, the following explanation was given: "a motion twice as uncomfortable would be attributed the value '200'; and a motion half as uncomfortable would be attributed the value '50'. It was also explicitly stated that any scaling was allowed, as long as participants felt that their responses accurately represented their subjective experiences.

Participants were instructed to assume a comfortable position, keep their hands on their laps, and to keep their eyes closed for the duration of the experiment. Each experimental trial was started manually by the experimenter following the sound of a single beep. Participants were cued to respond by the sound of a double beep, presented upon completion of each pulse. Responses were given verbally and noted by the experimenter. After a response was noted, the simulator was moved back to the simulator centre position over 5 s, following a sinusoidal waveform acceleration profile. The peak acceleration for this homing motion was chosen proportionally to the distance travelled during the experimental trial. All stimuli were presented in random order in a single session.

During debriefing, participants were also asked to provide a key that allowed us to interpret and compare their ratings between individuals. To this end, they were asked to associate numbers to seven 'Verbal Qualifiers' (VQ) using the same scaling they chose to use in the actual experiment. The VQ were: 'Excellent', 'Very Good', 'Good', 'So-so', 'Bad', 'Very Bad', 'Terrible' (Venrooij et al., 2015; de Winkel et al., 2022). The VQ were presented on a single sheet of paper, and participants were allowed to fill in the numbers themselves in any desired order. It was emphasized that the mapping of numbers to VQ does not have to be linear, and that it was not necessary to have experienced them all during the experiment, such that, for example, if a participant never experienced a motion that they found terribly uncomfortable, they could assign a number outside the range of numbers provided as responses during the experimental trials.

Including instructions and debriefing, the experiment took approximately 1 h to complete.

2.6. Stimuli

Participants were presented with a range of different motion stimuli. The motions were either sinusoidal (subscript $*_s$) or triangular (subscript $*_t$) pulses, with acceleration profiles defined as:

$$A_s(t) = A_{max}\sin(2\pi ft), \tag{1}$$

and

$$\begin{aligned} A_t(t) \quad &= A_{max}\ (\ [t < T/4]\ (4t/T) \\ &+[t >= T/4\ \&\ t < 3T/4]\ (-4t/T + 2) \\ &+ [t >= 3T/4]\ (4t/T - 4)\ ), \end{aligned} \tag{2}$$

respectively. Here A_{max} is peak acceleration, f is frequency, and t is time, which could take on values between $[0, T]$. T is the period of the pulse,

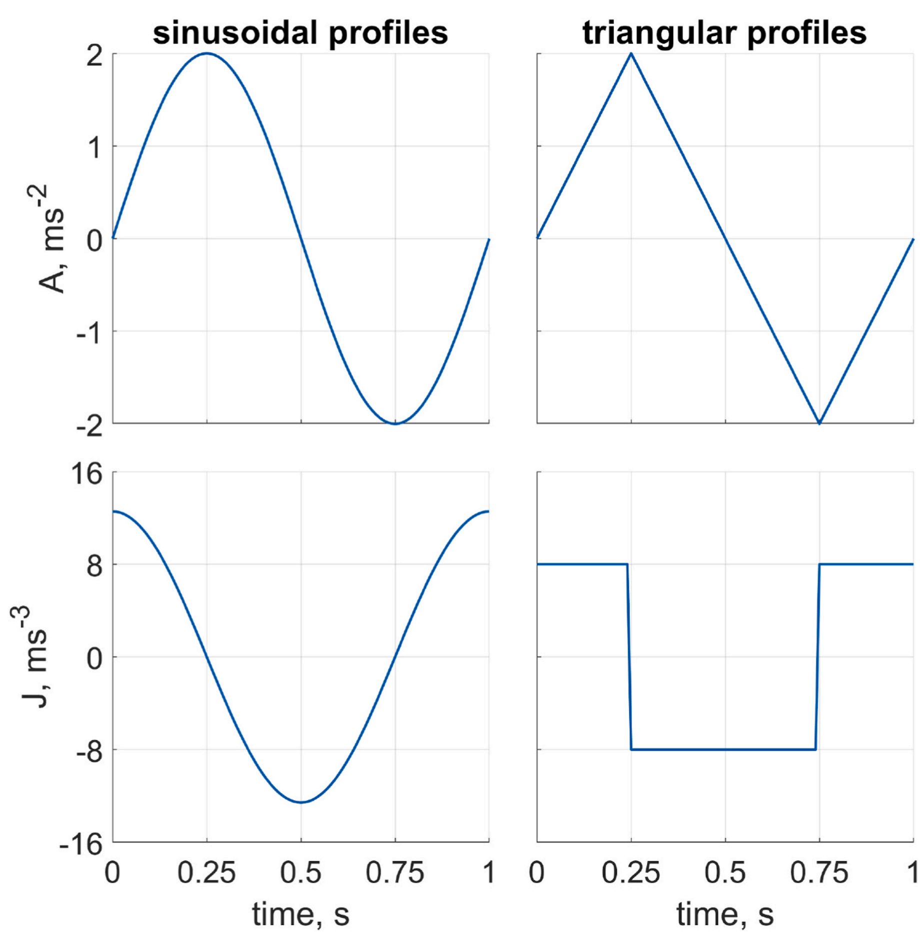

Fig. 2. Characteristic acceleration (top row) and jerk (bottom row) profiles for sinusoidal (left column) and triangular (right column) pulses, using as a frequency of 1 Hz and peak acceleration of 2 ms^{-2} as an example.

defined as $1/f$. Note that Equation (2) is a piecewise function, meaning that the expressions between square brackets are conditional statements that evaluate to true (1) or false (0) depending on the value of t.

The acceleration and jerk profiles for sinusoidal and triangular pulses are shown in Fig. 2.

A comprehensive naturalistic driving study by Feng et al. (2017) shows that the 99th percentile acceleration event was 2.85 ms^{-2}. Similarly, in data we collected during urban driving (in The Hague, The Netherlands), the 99th percentile was 2.2 ms^{-2}. Based on these observations, and also considering the limitations of the simulator motion envelope, we chose to use the following peak accelerations: $A_{max} = \{0.4, 0.75, 1.1, 1.45, 1.7, 2\}$ ms^{-2}.

Data on the magnitude of jerks encountered during driving is less reliable. Feng et al. (2017) noted 2.6 ms^{-3} as the 99th percentile jerk experienced during naturalistic driving. This maximal jerk is similar to the jerk thought to be at the comfort limit by Hoberock (1976). However, Feng et al. (2017) smoothed the vehicle acceleration using a 1 s window and then computed the jerk over an acceleration time window of 0.3 s; similar to the filtering operations used by Andersson and Nilstam (1984) and Förstberg (2000). It is possible that the filtering operations performed in these studies removed what would otherwise be uncomfortable jerks. Therefore, we chose to study jerks up to 15 ms^{-3}: $J_{max} = \{0.5, 1, 2, 4, 8, 15\}$ ms^{-3}.

Consequently, we obtain a 6 × 6 grid of *desired* combinations of peak accelerations A_{max} and peak jerks J_{max}. Due to limitations on the workspace (±0.51m relative to centre position) and velocity ±0.81 ms^{-1} of the platform, not all combinations could be reproduced. Particularly, due to excessive translations or velocities, none of the J_{max} = 0.5 ms^{-3} conditions and some combinations of low jerks and high accelerations could not be reproduced. Fig. 3 provides an overview of the motions that could be reproduced, and were used in the experiment. For sinusoidal pulses, 15/36 profiles could be reproduced; for triangular profiles 19/36. The associated frequency range for sinusoidal pulses is approximately 0.40–5.97 Hz; and 0.63–9.38 Hz for triangular pulses.

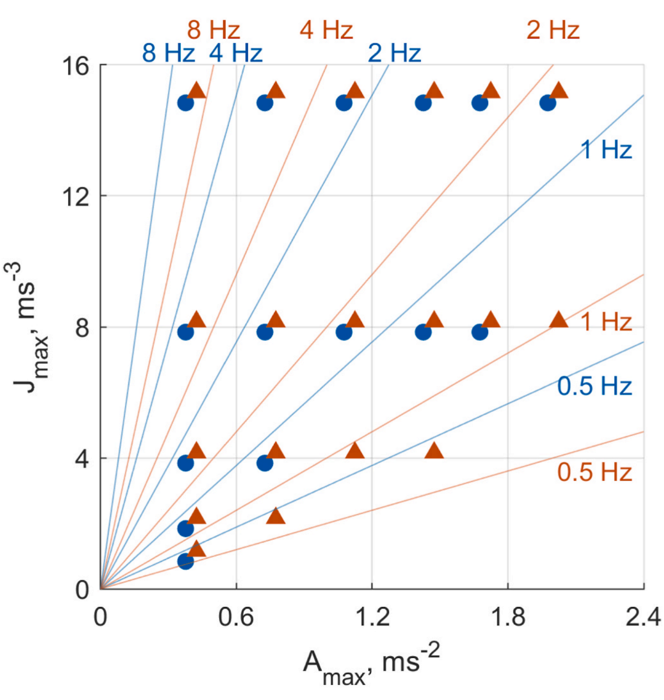

Fig. 3. Stimulus peak accelerations (A_{max}) and peak jerks (J_{max}). Each dot/triangle represents a combination presented in the experiment. Blue dots represent sinusoidal profiles; orange triangles represent triangular profiles. A small offset in x and y was applied to the dot positions to visually separate them. The relation between acceleration, jerk and pulse frequency is visualized using contour lines that indicate frequencies of 0.5, 1, 2, 4, and 8 Hz. Frequency increases in counter-clockwise direction relative to the x-axis. Note how combinations of large accelerations and low jerks, or equivalently, low frequency, could not be produced by the platform. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

All profiles were presented in forward, rightward, backward and leftward directions, resulting in a total of 4(direction) × (15(sinusoidal) + 19(triangular)) = 136 stimuli.

The subscripts $*_{max}$ referring to peak values for acceleration and jerk will be dropped in the description of the statistical analyses for convenience.

2.7. Statistical analyses

The statistical analyses were performed on the individual level. Thus we evaluate which motion characteristics best predict the responses without implicitly assuming that the nature of effects is equal between individuals (i.e, the ‘Ecological Fallacy’ (Freedman, 1999)). We then identify commonalities between individuals and attempt to explain qualitative interpersonal differences by available demographic covariates (i.e., length, weight, age and/or gender). Training trials were omitted from the data analyses.

2.7.1. Data preprocessing

To assess commonalities between individuals and derive estimates of central tendency in the sample, we need to account for interpersonal variability in the scaling chosen for the ME responses. A common way of doing this is by applying a z-score transformation, also called ‘standardization’. This operation scales responses such that the mean equals 0 and the standard deviation equals 1. It does not alter the shape of the distribution. In the present case, standardizing the responses allows comparison between individuals, but does not facilitate interpretation, as increments in terms of comfort response standard deviations are not immediately intuitive. Therefore, we chose to apply a transformation that scales responses in terms of the VQ. We do this by first fitting functions of the form $ME = a \times VQ_n^b$ (Stevens, 1957) to the scaling keys participants provided, with as VQ_n the numerical order of the VQ. The exponent b had a median value of 1.33 (25th − 75th percentile: 0.97–1.48), which suggests that discomfort increases exponentially. The function accounted for the provided keys nearly perfectly (median R^2_{adj} = 0.981, IQR = 0.026). We then normalized the actual ME responses using the inverse of this function. This procedure linearizes the responses and converts each individual’s responses to a common scale. This operation is comparable to standardization, but has the advantage that the results can be interpreted in terms of the VQ. Specifically, a score of 1 on this scale corresponds to the VQ ‘Excellent’, and a score of 7 to ‘Terrible’. The statistical analyses and model fits were performed on the normalized ME.

2.7.2. Stepwise linear regression

For each participant, a stepwise linear regression analysis was performed to identify which (interactions between) independent variables peak acceleration A, peak jerk J, ’motion direction’ d and ’motion profile’ p should be considered as predictors in a model of discomfort. The procedure includes/excludes possible predictors based on improvement of a chosen criterion. Here, we chose to use the Bayesian Information Criterion (BIC). The BIC is based on the model likelihood and includes a penalty for the number of predictors (Schwarz et al., 1978). The procedure was performed using the stepwiselm function of the MATLAB Statistics and Machine Learning Toolbox (MATLAB. version 9, 2017). We also ran the above procedure to evaluate how well responses could be predicted using RMS acceleration A_{rms} and the pulse crest factors A_{crest}, instead of A. These latter analyses yielded lower model R^2_{adj}: for A we found a median $R^2_{adj} = 0.75$ (25st − 75th percentile 0.66–0.80; for A_{rms} $R^2_{adj} = 0.57$ (0.09–0.72), and for A_{crest} $R^2_{adj} = 0.48$

(0.24–0.59). For brevity, we will only present the analyses using A as predictor variable, along with the other predictors J, d and p. The role of frequency will be addressed in separate analyses.

2.7.3. Ordinal regression

An assumption made in the stepwise linear regressions is that the relation between responses and continuous predictors A, J is linear. Since the data preprocessing indicated that this assumption does not hold, we also performed an ordinal regression analysis (Scott Long, 1997) as a control. In ordinal regression, responses are assumed to be ordered, but no assumption is made on the distance between response classes. Because participants did not classify responses in terms of the verbal qualifiers (VQ) directly, we performed this classification for them; using the mapping between ME and VQ that was obtained from each participant during the debriefing. We subsequently predicted the VQ classifications C as a function of peak acceleration A, peak jerk J, their interaction AJ, a categorical 'motion direction' variable d with three levels (forward, lateral, and backward, where forward is the reference level), and a categorical 'motion profile' variable p (where sinusoidal is the reference level). In the model, classification categories j receive their own intercept, or threshold, β_j, which can account for spacing between levels. The model can be written as:

$$\log\left(\frac{\Pr(C \leq j)}{\Pr(C > j)}\right) = \beta_j + \beta_A A + \beta_J J + \beta_{AJ} AJ + \beta_d d + \beta_p p. \tag{3}$$

The model was fitted using the `mnrfit` function from the MATLAB Statistics and Machine Learning Toolbox (MATLAB. version 9, 2017)).

2.8. Linear time-invariant systems modeling

Provided that perceived comfort depends on the frequency content of a signal, it is possible to predict the comfort response for any pulse based on its frequency content using an LTI model. We evaluate two LTI models proposed in the literature.

The first is a model of (dis)comfort as a function of vibration (ISO 2631, 2001; Rimell and Mansfield, 2007). The specific version of the model used is referred to as W_d in the norm, and applies to fore-aft and lateral seat vibrations. The model is a combination of a high-pass filter, a low-pass filter, and an acceleration-velocity transition filter. Predictions of comfort are based on the RMS of filtered acceleration time histories.

The second model is a human perception model of translational acceleration (Soyka et al., 2011; de Winkel et al., 2020), which may apply when we assume that discomfort increases linearly with perceived motion intensity. The model provides a description of the vestibular otolith organs, which act like accelerometers, and subsequent processing of their output performed by the brain. We filtered the pulse acceleration time histories using the model. The result of this operation can be interpreted as a perceived motion intensity. We then used the peak value of the rectified output signal as a predictor of (dis)comfort. We evaluate the tenability of the models by using the model outputs as the sole predictor (apart from an intercept) of ME responses in individually fitted linear models. Doing so, we account for interpersonal differences in the ME response scale.

In addition to the above analysis, we compare the model frequency responses to the observed frequency response. To this end, we first need to deal with conflating effects of acceleration magnitude. Therefore.

(1) we divided the normalized ME responses by the measured peak acceleration to correct for effects of motion amplitude. This simple division was adequate due to the linear relation between the normalized ME and acceleration.

Next, (2) we binned the responses by taking together each two subsequent frequencies and then calculated a mean normalized response for each bin. This was done separately for the two pulse profiles to avoid assuming a common effect. Because there is an unequal number of frequencies observed for sinusoidal and triangular profiles, 7 and 9 bins were created for the two profiles, respectively. To evaluate the correspondence of the model behaviour and responses in the frequency domain, we then fitted the LTI models to the binned data by choosing gain parameters that minimized the sum of squared differences between the response predicted by the model and the observations.

3. Shock model

In addition to models on the effects of vibration, ISO 2631 also includes models of adverse health effects of shock (ISO 2631, 2001). There are two versions; one model to predict the lumbar spine accelerations for seated individuals in response to horizontal impulses, and a model for the spinal response to vertical motion. Here we use the model for horizontal directions. The model uses a digital filter to describe the response of the spine. An acceleration dose D_k is then calculated by counting the number of peaks in the filtered signal, weighted by their magnitude, as follows

$$D_k = \left[\sum_i A_{ik}^6\right]^{1/6}, \tag{4}$$

where i is the i-th peak and k is a subscript referring to motion direction (x, y or z).

As an illustration of the filtering, Fig. 4 shows the predicted spinal response for an arbitrarily chosen sinusoidal and triangular pulse, with $A_{\max} = 1.1$ ms^{-2} and $J_{\max} = 8$ ms^{-3}.

As was done in the evaluation of the LTI models, we use the acceleration dose as a single predictor in individually fitted linear models. In ISO 2631-5 (ISO 2631, 2001), the outcome of the equation given for the derivation of the first order term of the filter model denominator (i.e., parameter b(2)) differs from the value given in the example MATLAB script. We were unable to resolve the cause of this discrepancy. Using the value given in the script and resampling our signals accordingly, we

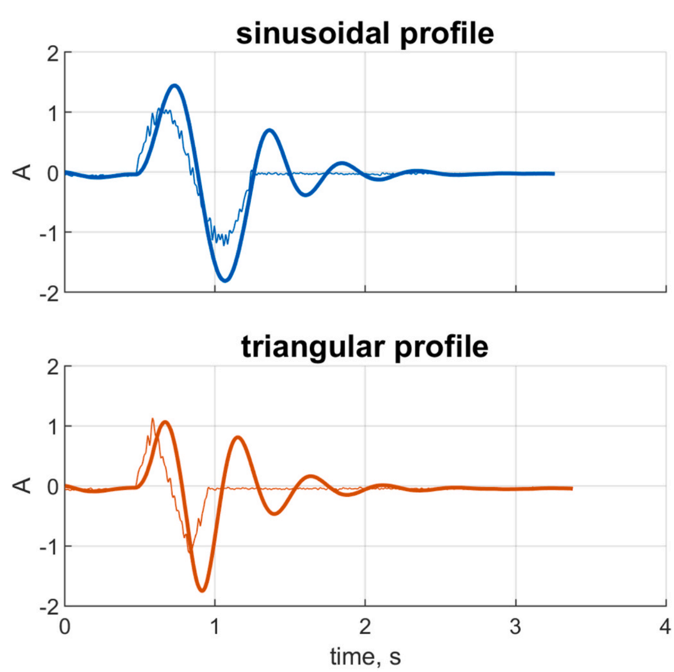

Fig. 4. Examples of the spinal response predicted by the shock model of (ISO 2631, 2001); for the sinusoidal (top panel, blue lines) and triangular (bottom panel, orange lines) pulse profiles. The thin lines show recorded accelerations for pulses with $A_{\max} = 1.1$ ms^{-2} and $J_{\max} = 8.0$ ms^{-3}, and the thick lines show the model prediction. Acceleration dose values are calculated by calculating the 6th root of the sum over the acceleration peaks to power 6. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

obtain slightly *worse* fits than when using the equation to determine model parameters, with median $R^2_{\text{adj}} = 0.61$ (25th − 75th percentiles: 0.50–0.67) versus $R^2_{\text{adj}} = 0.62$ (25th − 75th percentiles: 0.48–0.68). However, the model output is over an order of magnitude larger than the input when using the equation to calculate parameter b(2). We therefore report the results of the analysis using the value of b(2) presented in the norm example script.

4. Results

4.1. Statistical analyses

As an illustration of the findings, data and regression model fits obtained for a typical participant[1] are shown in Fig. 5. The figure shows that magnitude estimates (ME) *increase* for higher accelerations, and that ME *decrease* for higher jerks. In the following, we evaluate the effects of the experimental manipulations using statistical methods.

4.1.1. Stepwise linear regression

The individual regression models accounted for the data well, with a median R^2_{adj} over participants of 0.75 (25th − 75th percentiles: 0.66–0.80). The stepwise fitting procedure revealed several effects that were more or less consistent among participants: peak acceleration $A_{\max}$ had a positive effect for 22 participants, with a median coefficient of $\beta_A = 2.36$ (Inter-Quartile Range, IQR = 1.08). The remaining participant had an atypical response to the motion stimuli, with the function relating ME to A and J resembling a saddle function. For this person we also obtained the lowest $R^2_{\text{adj}} = 0.43$ overall (id 12, see the appendix). Backward motion comfort differed from forward motion for 18/23 participants, being less comfortable for 12/23 but more comfortable for 6/23 participants (median $\beta_{d\,=\,\text{backward}} = 0.11$, IQR = 0.44), and lateral motion was generally more uncomfortable (18/23, median $\beta_{d\,=\,\text{lateral}} = 0.46$, IQR = 0.74). There were positive interaction effects between acceleration and direction, indicating that the effect of acceleration tended to be stronger for backward than for forward motion (9/23, median $\beta_{A,d\,=\,\text{backward}} = 0.47$, IQR = 0.98), and even more so for lateral motion (9/23, median $\beta_{A,d\,=\,\text{lateral}} = 1.30$, IQR = 0.42). Furthermore, triangular profiles were more comfortable than sinusoidal profiles (20/23, median $\beta_{p\,=\,\text{triangular}} = -0.54$, IQR = 0.68), and there was also an interaction effect of profile with acceleration for 7/23 participants (median $\beta_{A,p\,=\,\text{triangular}} = -0.88$, IQR = 0.64). An effect of jerk was also found for a majority of participants (18/23), but the effect was small and there was considerable interpersonal variability, with a positive effect for 6/23, but a negative effect for 12/23 (median $\beta_J = -0.05$, IQR = 0.13). The variability in β_J could not be accounted for by participant height ($\rho = 0.343$, $p = 0.109$), weight ($\rho = 0.015$, $p = 0.946$), age ($\rho = -0.166$, $p = 0.450$) or sex ($t(21) = 1.133$, $p = 0.270$). This means that there is no evidence that responses are related to these body characteristics.

The appendix, available as supplementary material, shows the estimated coefficients for predictors included in the final model for each individual participant.

To obtain a predictive model for the general population, we applied stepwise regression to the joint data of all participants. This yields the following model:

$$\text{ME}_{\text{norm.}} = \beta_0 + \beta_A A + \beta_J J + \beta_d d + \beta_p p + \beta_{A,d} A d + \beta_{A,p} A p. \tag{5}$$

The model reflects the typical individual findings, and includes main effects for acceleration ($\beta_A = 2.297$), jerk ($\beta_J = -0.052$), direction (β_d(backward) = −0.005, β_d(lateral) = 0.005), and profile (β_p(triangular) = −0.283); and interaction effects with A for direction ($\beta_{A,d\,=\,\text{backward}} = 0.247$, $\beta_{A,d\,=\,\text{lateral}} = 0.690$) and profile ($\beta_{A,p\,=\,\text{triangular}} = -0.317$)).

4.1.2. Ordinal regression

Ordinal regressions were performed on a classification of the ME responses according to the VQ provided by each participant. Qualitatively, the findings are similar to those of the linear regressions. Note that due to the model definition, the interpretation of the sign of effects is inverted. For 22/23 participants, a positive effect was found for acceleration, with a median $\beta_A = -5.73$ (IQR = 3.07); backward motion was more uncomfortable than forward motion for 5/23 participants (median $\beta_{d\,=\,\text{backward}} = -1.39$, IQR = 0.98), and lateral motion was worse than forward motion for 21/23 participants (median $\beta_{d\,=\,\text{lateral}} = -1.66$, IQR = 0.71). The triangular profiles were more comfortable than the sinusoidal profiles for 20/23 participants (median $\beta_{p\,=\,\text{triangular}} = 1.57$, IQR = 0.82). The directional effects and the effect of pulse profile can be seen in Fig. 6, which shows the relative frequency of each classification in each direction; separately for the two profiles. An effect of jerk was found for 13/23 participants (median $\beta_J = 0.24$, IQR = 0.16), which was negative in all but two of the 13 cases.

As an indication of the central tendency in the sample, we calculated acceleration thresholds for each subsequent classification by solving the ordinal regression model for A, and using the median value of the observed predictor coefficients. These calculations were made setting log-odds of 0.5, at the median peak jerk value $J = 8$ ms^{-3}, for forward sinusoidal pulses motion ($p = 0$, $d = 0$). The results of these calculations, along with offsets for variation of profile and direction are given in Table 1.

4.2. Linear time-invariant systems models

Fig. 7 shows the medians and IQR of the obtained acceleration normed ME responses for each of the frequency bins. From this figure, it appears that discomfort decreases with increasing frequency and thereby with shorter pulses.

Because the frequency bins differed between the pulse profiles, separate one-way ANOVA tests were performed to evaluate whether the normed ME responses differed between bins. Effects were observed both for sinusoidal ($F(6, 154) = 4.31$, $p < 0.001$) and triangular pulses ($F(8, 198) = 9.42$, $p < 0.001$). Post hoc tests revealed that responses in the first frequency bin (edges: 0–0.749 for sinusoidal pulses; 0–0.667 for triangular pulses) were higher than in the other bins ($p < 0.01$) for both pulse profiles. One exception was the comparison between the first and second bin for sinusoidal profiles, which could not be told apart ($p = 0.220$).

For the ISO 2631 vibration model, the gain K that minimized the difference between the model and observed medians was 4.97; for the Soyka et al. (2011) model, the gain K was 0.13. Neither model appears able to capture the trend observed in the data. Whereas the models predict an increase of discomfort (ISO 2631, 2001) and increased perceived intensity (Soyka et al., 2011) over the range of frequencies covered in this study, the data show an opposite trend, with discomfort decreasing for higher frequencies.

According to the vibration model, predictions on comfort can be made using the RMS of the filtered acceleration signal. Using these metrics as the sole predictor of the normalized ME in a linear model yielded, summarized over all participants, a median R^2_{adj} of 0.24 (25th − 75th percentiles: 0.01-0.61). The RMS of the filtered acceleration had a correlation of $r = 0.49$ ($p \ll 0.001$) with the peak acceleration.

Using the perception model (Soyka et al., 2011), and taking the peak of the predicted perceived motion intensity as predictor of the normalized ME responses in a linear model, we obtain a median R^2_{adj} of 0.64 (25th − 75th percentiles: 0.54–0.69). The peak perceived motion intensity had a correlation of $r = 0.98$ ($p \ll 0.001$) with peak acceleration.

[1] 'typical' is defined as the smallest sum of squared deviations of model parameter estimates from their corresponding median values.

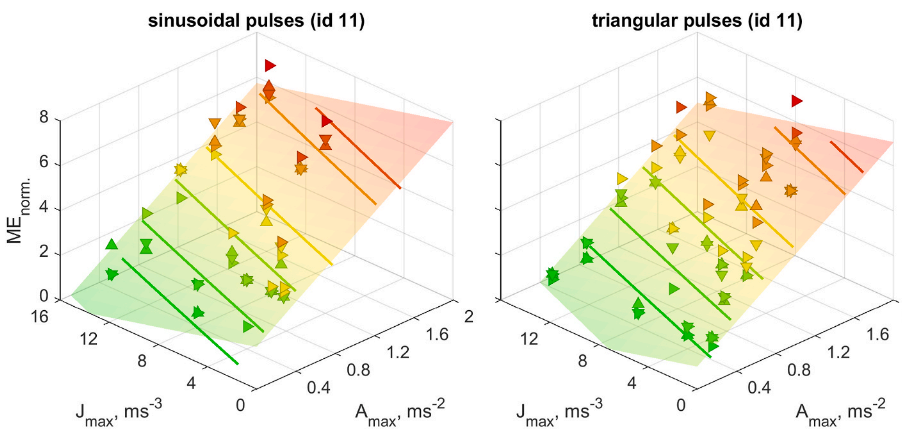

Fig. 5. Normalized ME responses and model fits for a typical participant (id 11). The two panels of the figure separately represent the findings for the two different pulse profiles. Each triangle represents a response for an experimental trial. The x and y coordinates represent the pulse peak acceleration and jerk values; the z-coordinate represents the response. The orientation of the triangles corresponds to the direction of the motion pulse (e.g., 'up' means forward). Individual responses are colored using the mapping of ME to VQ that the participant provided during debriefing. Colors vary from green via yellow to red, where green corresponds to feeling 'Excellent', and red to 'Terrible'. The surface fitted through the responses is the final regression model obtained from the stepwise procedure. The lines represent predictions from the ordinal regression model. Note the positive effect for acceleration ($\beta_A = 3.03$), and the negative effect for jerk (linear regression $\beta_J = -0.14$). The ordinal regression model predictions match the linear model predictions well, supporting the linear model. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

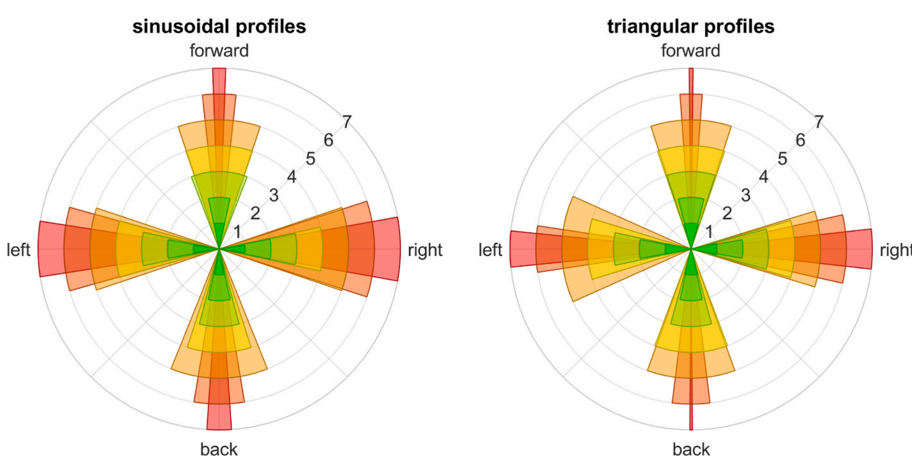

Fig. 6. Relative frequencies of each classification per direction. The two panels of the figure separately represent the findings for the two different pulse profiles. Eccentricity and color correspond to the verbal qualifiers; ranging between 1/green for 'Excellent', and 7/red for 'Terrible'. Note how more mass is concentrated at the higher (more uncomfortable) ratings for lateral motions compared to backward and forward motions, and how more mass is concentrated at the higher ratings for sinusoidal profiles. As data for all accelerations and jerks was aggregated to create these figures, they do not show effects for these variables.

Table 1
Estimated acceleration thresholds A_τ for each Verbal Qualifier, calculated for the study median peak jerk value of $J = 8$ ms^{-3}. For triangular profiles, the thresholds are 0.26 ms^{-2} *higher*, indicating a higher acceleration tolerance. Thresholds for backward and lateral motion were a constant 0.10 ms^{-2} and 0.25 ms^{-2} *lower*, respectively. This indicates reduced tolerance compared to forward motions.

	Verbal Qualifier						
	'Excellent'	'Very good'	'Good'	'So-so'	'Bad'	'Very Bad'	'Terrible'
A_τ	≤ 0.28ms^{-2}	≤ 0.56ms^{-2}	≤ 0.89ms^{-2}	≤ 1.23ms^{-2}	≤ 1.89ms^{-2}	≤ 2.12ms^{-2}	> 2.12ms^{-2}

4.3. Shock model

The shock model presented in ISO 2631-5 (ISO 2631, 2001) describes the acceleration response of the spine to external perturbations. Predictions on adverse health effects are made by using the model to predict the spinal response to an acceleration pulse; then identifying the peak accelerations of the filtered signal and exponentiating these values to the sixth power; summing the obtained values; and finally taking the sixth root of the outcome. When we use these values D_k as the sole predictor of normalized ME in individually fitted linear models, we obtain a median R^2_{adj} of 0.61 (25th − 75th percentiles: 0.50–0.67). D_k had a correlation of $r = 0.93$ ($p \ll 0.001$) with peak acceleration.

5. Discussion

The design of control algorithms governing Advanced Driver Assistant Systems (ADAS) or automated-driving functionality requires reliable standards for vehicle accelerations and jerks that ensure passenger comfort (Zheng et al., 2021). The present study was designed to establish such standards. We identified acceleration and jerk values typical for car driving and determined the associated (dis)comfort by presenting a sample of participants with these motions and registering their comfort ratings.

Vis-à-vis the hypotheses, the key observations are:

(1) Discomfort increases in an approximately linear fashion with acceleration magnitude, and acceleration is the most important predictor of comfort. The central tendencies in the study sample are that sinusoidal longitudinal accelerations up to 0.28 ms^{-2} feel

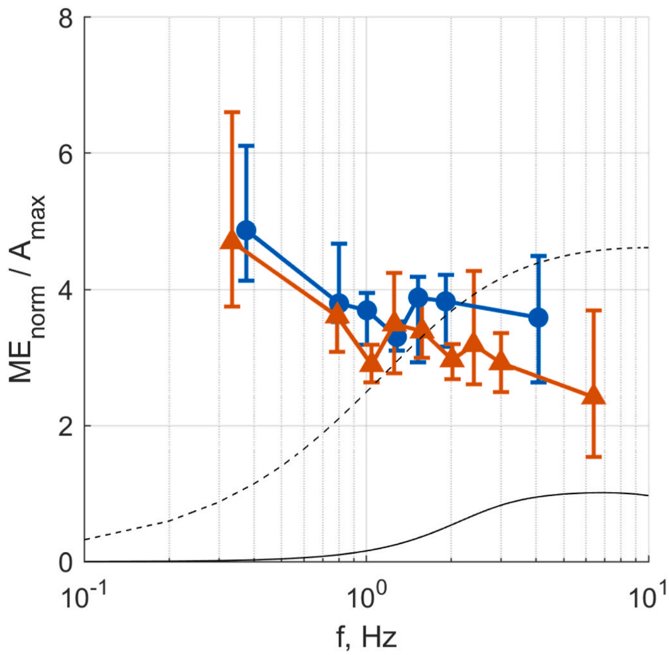

Fig. 7. The distribution of acceleration normed ME responses over participants per frequency bin; separately for sinusoidal (blue line/dots) and triangular (orange line/triangles) pulse profiles. The x-axis location represents the mean of each frequency bin. The dots/triangles represent the median normed ME responses; the error bars represent the IQR. The solid black line shows the frequency weighting model for vibration comfort in ISO 2631 (ISO 2631, 2001); the dashed black line shows the prediction on perceived motion intensity from Soyka et al. (Soyka et al., 2011). For both models, the gain was set to match the observations as closely as possible. Note how the models predict an increase in discomfort or perceived intensity, whereas the data indicate a reduction of discomfort for higher frequencies. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

'Excellent'; and accelerations above 2.12 ms^{-2} feel 'Terrible'. The average 'So-so' point, which may be interpreted as a threshold for acceptable acceleration, was 1.23 ms^{-2}. These findings are in agreement with the expected upper limit of 1.47 ms^{-2} for acceptable longitudinal accelerations in public transportation given by Hoberock (1976). For lateral motion, we find that thresholds were 0.25 ms^{-2} lower, resulting in a limit of 0.98 ms^{-2}. This value is close to a 20% discomfort threshold of 0.84 ms^{-2} reported for lateral accelerations in rail transport (Andersson and Nilstam, 1984).

(2) On average, the effect of jerk appears to be *negative*, meaning that higher jerks are associated with less discomfort. Triangular pulses, which feature jerk plateaus, were also judged more comfortable than sinusoidal pulses (controlling for peak jerk). Likewise, the analyses performed to evaluate LTI models (discussed below) indicate that discomfort decreased with increasing frequency. This observation appears counterintuitive when we consider jerk analogous to the experience of a 'kick'. However, higher jerks also meant shorter duration pulses, such that the highest jerks were experienced for the shortest pulses. During debriefing, some individuals remarked that the briefness of pulses with higher jerks made the discomfort of the pulse negligible, whereas others remarked that a stronger kick was more uncomfortable. We did not consider block shaped accelerations leading to extreme jerk peaks, which do occur in abrupt braking, and jerk was limited to 15 ms^{-3}. Taken together, we cannot exclude the possibility that higher jerk levels aggravate discomfort, and we believe that both effects of jerk and duration may need to be considered.

(3) Discomfort depends on direction. Overall, forward motion is most comfortable, followed by backward motion, and lateral motion is most uncomfortable. Interaction effects were also observed between peak acceleration and direction, which indicated that the effect of acceleration on discomfort is stronger for backward motion than for forward motion, and even stronger for lateral motion.

Because the experiments included only longitudinal accelerations under eyes-closed conditions, the findings should generalize to other seating locations (i.e., passenger side, back-seat), and other seating arrangements (e.g., facing backwards), provided that the direction of acceleration is interpreted as relative to the direction faced by the passenger.

Whereas the choice to perform the experiments in eyes-closed conditions allows for generalization of the findings to other seating positions and arrangements, the experience of comfort may differ when an out-the-window view *is* available. Although the visual system is not adept at perception of accelerations per se (Peter et al., 1992), it was apparent from debriefings that participants found the fact that the motions were unpredictable in itself uncomfortable. It is therefore likely that having an out-the-window view could reduce discomfort in situations where it allows anticipation of events.

To account for the comfort responses, we evaluated the applicability of normative models provided in ISO 2631 for comfort of sustained vibrations and shock (ISO 2631, 2001), as well as a model designed to account for perceived motion intensity based on vestibular stimulation and subsequent cortical processing (Soyka et al., 2011).

The vibration model provides a frequency weighting function and predicts discomfort from the RMS of a filtered acceleration input. A comparison of the frequency response for this model to the relation between pulse frequency and normalized ME responses revealed a discrepancy, in that the model predicts an *increase* of discomfort with frequency, whereas the observations suggested a *decrease* of discomfort with frequency. Out of the evaluated models, the predictive ability of this model was the poorest (median $R^2_{adj} = 0.24$). Given that discomfort was found to correlate strongly with peak acceleration, a likely cause for the poor performance is that the frequency weightings distort this relation. This is evidenced by a relatively low correlation of the model output with acceleration (i.e., $r = 0.49$). We therefore conclude that the vibration model is not suitable for prediction of comfort for motion pulses typical for vehicle travel.

Considerably better performance was observed for the shock model, which predicts comfort as a weighted sum of the number of peaks in the spinal response to perturbations (median $R^2_{adj} = 0.61$). Predictions *Dk* show a strong correlation with acceleration ($r = 0.93$). This accounts for the improved predictive ability.

The perception model had comparable performance to the shock model (median $R^2_{adj} = 0.64$), with predictions also correlating strongly with peak acceleration ($r = 0.92$).

The best performance overall was obtained for our statistical model (median $R^2_{adj} = 0.75$). The statistical model differs from the other models in that it does not consider the time history of the pulses per se, but takes peak acceleration, peak jerk and pulse profile as inputs, and predicts comfort as a weighted sum of those inputs. Although the model performed best, the downside of statistical models like this is that the effect of any variation in the motion profile has to be determined and quantified empirically. In other words, the model does not generalize to arbitrary pulse profiles.

Considering only predictions for the present data, the primary difference between the statistical model and the other models is the inclusion of a directional effect. Neither the shock model nor the perception model include explicit directional effects. Given that predictions were made taking as input recorded simulator accelerations, in our application these models do not account for the support provided by the seat and head rest when moving forwards, and to a lesser extent, laterally. Consequently, it should be noted that better performance may be obtained for these models when accounting for dampening provided by the seat; the effect of the presence of a seat on the spinal response for the shock model; or by using accelerations of the head as inputs to the perception model instead.

CRediT authorship contribution statement

Ksander N. de Winkel: Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Supervision, Project administration. **Tugrul Irmak:** Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Writing – Review & Editing. **Riender Happee:** Writing – Review & Editing, Supervision, Funding acquisition. **Barys Shyrokau:** Conceptualization, Software, Resources, Writing – Review & Editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apergo.2022.103881.

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