# Exploring smart device sensor potential to assess simulated vulnerable road user head injury risk

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## I. INTRODUCTION

Vehicle sensors are increasingly being used to predict injury risk in road traffic collisions (RTCs) [1, 2]. Event data recorder (EDR) based collision detection systems are not always able to detect vulnerable road user (VRU) collisions, especially with pedestrians, despite them accounting for a large proportion of global disease burden [1, 3]. In particular, head injury is a critical cause of early death following RTCs, and highly prevalent in pedestrians [4-5]. Therefore, we explore the feasibility and potential for sensors beyond the vehicle (particularly EDR) to assess injury risk. 54% of the world now owns a smart phone [6]. Smartphones are equipped with accelerometers and gyroscopes which could feasibly provide an assessment of collision dynamics, with many Google/Apple devices (phones, watches) capable of basic collision detection from 2019 and 2022 respectively [1]. Smart device data is not known to be accessible in a public dataset, and therefore we use simulation to investigate feasibility.

## II. METHODS

Madymo multibody models simulated frontal pedestrian-car impacts. We use a validated, similar-to-average hatchback car model [1, 9]. A coefficient of friction of 0.7 (asphalt) was used [1]. We varied parameters:

1. Impact speed: 22mph and 31mph from average travel speeds in UK urban speed limit areas [1, 10].
2. Pedestrian ellipsoid multibody model: AF05 (1.53m, 50kg), AM50 (1.74m, 76kg) and AM95 (1.91m, 101kg).
3. Stance: UK pedestrians were crossing (51%) and walking (47%) [1]. 10 walking stances were taken [11].
4. Pedestrian speeds: 1.0m/s, 1.5m/s and 2.0m/s as taken from population variation in literature [1, 12].
5. Approach angle: 0˚, 45˚, 90˚, 135˚, 180˚, 215˚, 270˚, 315˚ relative to the vehicle direction of travel.
6. Pedestrian-car offset: 0.0m, 0.3m, 0.6m horizontal displacement (vehicle central line to pedestrian).

Linear and rotational accelerometers were mounted to the hip region and wrist of the pedestrian as digital proxy sensors for a smartphone in a pocket and watch worn on the wrist. A total of 4,320 pedestrian-car impacts were simulated for 1.5 seconds each. The initial 400ms (vehicle) and latter 1100ms (ground) contacts were considered.

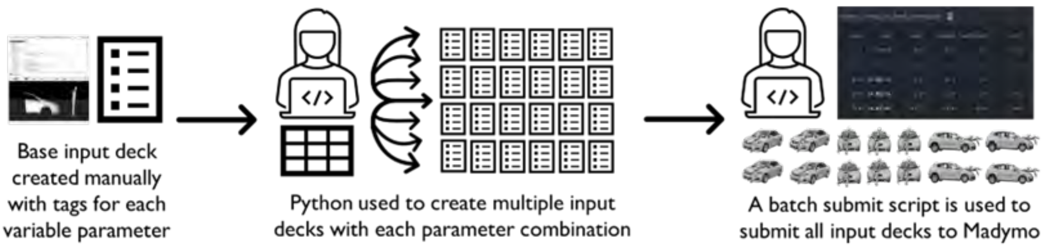


*Figure 1. Python is used for automatic input deck creation (from parameters) and Madymo batch submission.*

Peak values from the virtual 'watch' (wrist accelerometer) and 'smartphone' (hip accelerometer) sensors and a range of head kinematics from the 4,320 simulations were used to create logistic regression models predicting distinct head injury kinematic risk thresholds from literature (results shown in Fig. 2 [13-18]. 5-fold cross-validation was repeated 200 times using Python's scikit learn. The average risk, 95% confidence intervals (calculated using the 50th, 2.5th and 97.5th percentile ranked risk values) and area under the receiver operator characteristic curve (ROC-AUC) were determined by averaging over 1,000 iterations. Mann-Whitney U tests are used to compare the distributions across different groups including impact speeds and pedestrian models.

## III. INITIAL FINDINGS

4320 simulations produced a range of head kinematics. Fig. 2 shows the head kinematic distributions separated by initial vehicle and latter ground impact, grouped by impact speed and pedestrian model. There were generally higher values in the latter 1100ms than the initial 400ms of the 1.5s simulated impact. When comparing the initial 400ms at 22mph and 31mph or the latter 1100ms at 22mph or 31mph, the higher impact speed induced higher head kinematics, as expected. When comparing pedestrian type, apart from throw distance, where AF05 travelled further [$U_{MW}$=1667550.0, p=0.0001], the AF05 head kinematics were generally lower than the combined AM50-AM95 model group. AF05 pedestrian had lower initial 400ms peak rotational acceleration (PRA) [$U_{MW}$=2162072.5, p=0.0003], latter 1100ms BrIC [$U_{MW}$=2162072.5, p=0.0003] (and both peak rotational velocities, $p_{initial\ 400ms}$=0.0159, $p_{latter\ 1100ms}$<0.0001), peak linear acceleration (both initial 400ms and latter 1100ms: p<0.0001), HIC [$U_{MW}$=2696675.0, p<0.0001] and contact force (both initial 400ms and latter 1100ms: p<0.0001). In general, the latter 1100ms capturing ground impact shows greater variation than the initial 400ms (vehicle impact).

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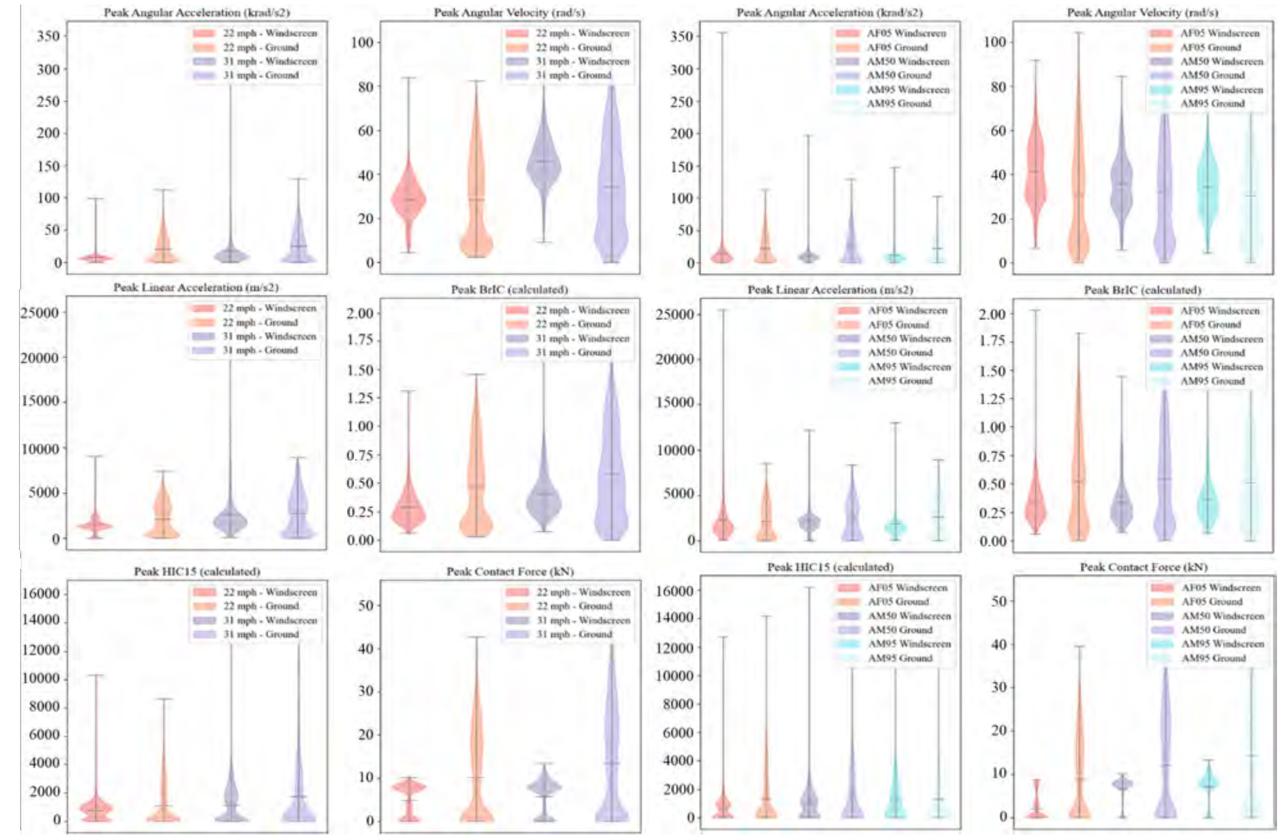

*Figure 2. Head kinematic distributions for the initial 400ms (vehicle - 'windscreen') and latter 1100ms impact.*

Distinct injury risk functions with injury classes from different rotational and linear kinematic thresholds showed different accelerometer-based simulated sensors had similar ROC-AUC predictions (Fig. 3). The wrist 'watch' was generally less able to predict the simulated injury class (initial 400ms: 0.52-0.65; latter 1100ms: 0.65-0.79) compared to the upper leg 'smartphone' (initial 400ms: mostly 0.63-0.71; latter 1100ms: 0.62-0.74).

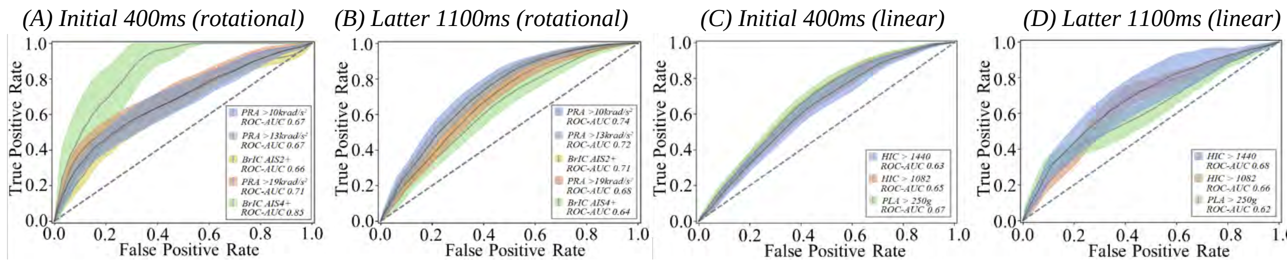

*Figure 3. Hip accelerometer ROC-AUCs for rotational (L) and linear (R) head kinematic literature thresholds.*

## IV. DISCUSSION

Simulated sensors differentiated between simulated pedestrian head injury in frontal car collisions. Linear metrics provide insight about focal injuries (e.g. skull fractures) and rotational metrics about diffuse injury (e.g. axonal damage or bleeding). Simulated accelerometer data (hip/wrist) was able to differentiate between subdural haematoma (PRA>10krad/$s^2$ simulated injury class) or skull fracture (HIC simulated injury class). This begins to address how smart devices could one day predict TBI, as accelerations could feasibly be collected by smart devices and relayed in real-time, this provides an exciting possibility to increase global post-crash care. Future work should explore scenarios beyond frontal pedestrian to average-dimension hatchback impacts; varied vehicle contact characteristics and ground impact phase interpretation. Simulated accelerometers were unrealistically 'perfect' so noise and time-series data from other smart device sensor proxys (e.g. gyroscopes) could be explored.

## V. REFERENCES

[1] Baker CE, PhD thesis, 2023; [2] Lee E, NHTSA AACN report, 2019; [3] WHO, 2021-2030 report, 2022; [4] Baker CE et al., Brain Commun, 2022; [5] Brazinova A et al., J. Neurotrauma, 2016; [6] GSMA, mobile connectivity report, 2023; [9] Baker CE et al., Accid Anal Prev, under review 2024; [10] Nightingale GF et al., PLoS One, 2021; [11] Untaroiu C et al., Int J Impact Eng, 2009; [12] Park J et al., J Korean Geo Inf Sci, 2012; [13] Depreitere B et al., J Neurosurg, 2006; [14] ECE22.06 regulation, 2020; [15] Yoganandan N, et al., IUTAM Symp, 2005; [16] Takhounts E et al., Stapp Car Crash J, 2013; [17] Wu H et al., Front Bioeng Biotechnol, 2021