Intrusion Characteristics and Occupant Body Size in Driver Entrapment: An Attention-Based Analysis of Real-World Crash Data

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I. INTRODUCTION

Occupant entrapment following motor vehicle crashes is consistently associated with severe injury outcomes [1-2] and has been used as an early indicator in post-crash injury severity prediction systems [3]. Structural deformation of the vehicle interior, particularly the intrusion of components into the occupant compartment, is widely recognised as a major physical mechanism leading to entrapment. Despite this, a systematic quantitative understanding of how specific intrusion patterns interact with occupant characteristics to produce entrapment remains limited in the literature. This study investigated entrapment of drivers in passenger vehicles using the combined data from National Automotive Sampling System Crashworthiness Data System (NASS-CDS) and Crash Investigation Sampling System (CISS). A key analytical challenge was that a crash may involve multiple intrusion records associated with the driver's seat, spanning different structural components, and it was often unclear which record, or combination thereof, was responsible for trapping the occupant, let alone how occupant body size modulated these contributions. We addressed this through an attention-based multiple-instance learning framework that explicitly modelled interactions among intrusion records and their interplay with occupant anthropometry. The attention analysis was intended to summarise model-salient intrusion/body-size patterns associated with entrapment prediction rather than to establish direct physical causation.

II. METHODS

Data and features

This study used the NASS-CDS (2010-2015) and CISS (2017–2024), focusing on driver-seat occupants of passenger sedans. Variables of interest are defined in the NASS-CDS and CISS Analytical User's Manual [4]: occupant body-size variables HEIGHT and BMI, and intrusion variables INTCOMP (intrusion component), INTDIRECT (intrusion direction: Vertical / Longitudinal / Lateral), and INTMAG (intrusion magnitude, ordinal 0–6). INTCOMP was reclassified into 10 structural regions (Steering, InstPanel, Footwell, Pillar, SidePanel, Door, Roof, Glazing, Seat, and Other); analyses focused on the nine named components. The outcome variable ENTRAP was binarised to retain only cases of no entrapment and mechanical restraint ("entrapped/pinned"). Records with unknown or missing values in any remaining variable were likewise excluded. The analytic sample comprised 2,727 vehicles with 7,362 intrusion records (2.7 per vehicle; range 1–14). In total, 263 vehicles (9.6%) had ENTRAP = 1.

Model

We constructed an attention-based model [5] for entrapment prediction. Since the number of intrusion records per crash varies (1–14), we followed the Deep Sets framework [6] and treated each crash as a permutation-invariant set of m instances (Fig. 1). All inputs were first mapped to $\mathbb{R}^d$: each intrusion record's feature vector was encoded to h_j by a shared two-layer feed-forward network, while HEIGHT and BMI were each projected to a latent token by a separate linear layer, forming body-size matrix $B = [b_{ht}, b_{bmi}]$.

The intrusion records then interact via self-attention: each record gathers context from all co-occurring intrusions in the crash. The self-attended output H_j' is a weighted sum of all record representations, where weight a_{jk} measures the relevance of record k to record j: $H_j' = \sum_k a_{jk} h_k$, $a_{jk} = softmax_k\left(\frac{h_j^\top h_k}{\sqrt{d}}\right)$.

Each context-enriched record H_j' then queries the occupant's body-size tokens via cross-attention. The resulting per-record weight $\alpha_j = [\alpha_{ht}, \alpha_{bmi}] \in \mathbb{R}^2$ quantifies which body dimension (stature or adiposity) more strongly modulates the entrapment risk of that intrusion: $\alpha_j = softmax\left(\frac{H_j' B^\top}{\sqrt{d}}\right) \in \mathbb{R}^2$. Body-conditioned records are mean-pooled and passed to a binary classifier to yield $P(\mathrm{ENTRAP} = 1)$. Five-fold stratified CV was used.

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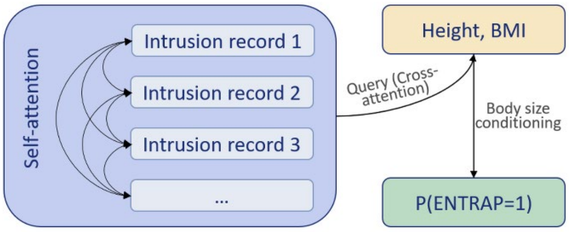

Fig. 1. Model overview.

III. INITIAL FINDINGS

The model achieved mean AUC = 0.857 ± 0.027 across five folds, indicating adequate discriminative capacity for the attention-weight analysis that follows. **(a) Self-attention focus:** self-attention weights reflect how much each record is used as a contextual reference by co-occurring records: a higher weight means other records treat this record as the primary contextual reference when forming their own representations. Table I reports mean attention received per component in entrapment crashes. InstPanel and Steering received the highest attention (0.247 and 0.230), identifying fore-cabin structural collapse as the dominant contextual anchor in entrapment crashes; Glazing was the least attended (0.093). By severity, attention increases with INTMAG, confirming the model's focus on the most severe intrusions in multi-record crashes. **(b) Cross-attention focus:** cross-attention weights α_{ht} and α_{bmi} quantify whether HEIGHT or BMI more strongly modulates predicted entrapment risk for each intrusion record. Table II reports per-component weights in entrapment crashes. HEIGHT attracted more attention for fore-cabin components, with the strongest preferences occurring at Steering (0.558), InstPanel (0.558), and Footwell (0.531). BMI was slightly favored for Roof (0.534), Pillar (0.526), Door (0.525), and Seat (0.522), whereas SidePanel and Glazing showed near-balanced HEIGHT/BMI weights (0.509 / 0.491).

TABLE II
SELF-ATTENTION WEIGHTS RECEIVED BY EACH INTRUSION COMPONENT IN ENTRAPMENT CRASHES

Component	InstPanel	Steering	Footwell	Pillar	SidePanel	Door	Roof	Seat	Glazing
$\bar{w}_{SA}$	0.247	0.230	0.164	0.162	0.139	0.134	0.134	0.105	0.093

TABLE II
MEAN CROSS-ATTENTION WEIGHTS IN ENTRAPMENT CRASHES (ENTRAP = 1) PER COMPONENT

Component	Seat	Footwell	Glazing	Steering	InstPanel	Door	Pillar	Roof	SidePanel
$\bar{\alpha}_{ht}$	0.478	**0.531**	**0.509**	**0.558**	**0.558**	0.475	0.474	0.466	**0.509**
$\bar{\alpha}_{bmi}$	**0.522**	0.469	0.491	0.442	0.442	**0.525**	**0.526**	**0.534**	0.491

IV. DISCUSSION

Self-attention weights show that the model identifies a structural hierarchy in multi-record crashes: fore-cabin records (InstPanel, Steering) serve as dominant contextual anchors. Cross-attention weights suggest that HEIGHT receives greater model attention for fore-cabin components, consistent with a geometric mechanism in which stature influences whether limbs and torso exceed residual clearance. BMI received slightly greater attention for Roof, Pillar, Door, and Seat, suggesting that body bulk may be more relevant for overhead, lateral, door, and seat deformation. These patterns suggest weighting intrusion severity by occupant stature for fore-cabin components, with heightened attention to body bulk at roof, pillar, door, and seat deformation. Several limitations apply. Attention weights reflect model-internal salience rather than physical causation, so the body-size patterns reported here should be interpreted as hypothesis-generating rather than confirmatory. The analysis was restricted to drivers of passenger sedans, and the findings have not been validated on an independent dataset.

V. REFERENCES

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