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Development of a Posture Assessment Model Using Computer Vision to Analyze Musculoskeletal Injury Risk in Truck Drivers

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Abstract

This study aims to develop an image processing model for assessing truck drivers' sitting posture based on ergonomic principles using the Rapid Upper Limb Assessment (RULA) method, employing Computer Vision technology integrated with MediaPipe Pose Estimation. The reliability of the model was evaluated by comparing joint angle measurements with those obtained by an expert assessor. The developed model is capable of detecting six body landmarks from lateral photographs and computing four joint angles, namely the neck, trunk, upper arm, and lower arm. A Backward Offset technique was developed to adjust landmark positions to correspond with anatomical reference points as specified by the RULA criteria. Testing with a sample of 22 participants revealed that the Intraclass Correlation Coefficients (ICC) for joint angles ranged from 0.777 to 0.995 (good to excellent), and the ICC values for RULA scores ranged from 0.625 to 1.000 (moderate to excellent). These findings demonstrate that the model possesses high reliability in estimating joint angles and can serve as a preliminary ergonomic risk screening tool for truck drivers.

Keywords
Posture Assessment, Computer Vision, Truck Drivers, Ergonomics, Musculoskeletal Disorders.

1. Introduction
Road traffic accidents remain one of the most severe public health and economic challenges in Thailand. According to the road accident analysis report of the Ministry of Transport for the year 2023, Thailand recorded 17,498 fatalities from road traffic accidents, averaging 47 deaths per day, with an additional 3,806 severe injuries. The resulting economic losses amounted to approximately 3.6% of GDP, equivalent to an estimated 610 billion baht (World Bank 2024). Data from the Department of Land Transport in 2024 indicated that 35% of severe accidents involved trucks, with the primary causes attributed to driver behavior, including tailgating, carelessness, excessive speed, and drowsiness resulting from cumulative fatigue due to prolonged continuous driving (Department of Land Transport 2024).

Wise et al. (2019) stated that "prolonged wakefulness, insufficient sleep, extended sleep deprivation, and inadequate recovery from previous work shifts are commonly identified as contributing factors to physical and cognitive fatigue." When cognitive and motor processes are impaired, driver performance deteriorates, leading to an increased risk of errors and accidents. Furthermore, Williamson et al. (2011) reviewed the literature on fatigue and occupational health, identifying relationships among sleep homeostasis, circadian rhythms, and work characteristics with driving safety. This finding is consistent with May and Baldwin (2009), who reported that fatigue and drowsiness are significant contributors to road traffic accidents in numerous countries. Prolonged driving fatigue also leads to work-related musculoskeletal disorders (WMSDs). Asour et al. (2022) investigated the prevalence of WMSDs among Iranian truck drivers and found that the most commonly reported symptoms were back pain, knee pain, and shoulder pain, primarily attributed to extended driving hours, vibration exposure, and sustained static postures. Similarly, Terfa et al. (2022) examined ergonomic risk factors contributing to low back pain among tricycle drivers in Ethiopia and found that sitting posture, steering wheel design, and the working environment were significant risk factors. These findings underscore the importance of sitting posture assessment, which enables drivers to recognize which prolonged sitting postures are most likely to induce fatigue.

In Thailand, several studies have examined the physical risks associated with driving occupations; however, most lack the integration of advanced technology. Porphanitchakorn and Tantipanjaporn (2018) investigated the postures of Songthaew drivers in Phitsanulok Province and found that work experience was significantly associated with lower limb pain ($p < 0.05$), although machine learning was not employed in the analysis. Tubrod et al. (2019) studied factors associated with low back pain among truck drivers and found that 44% experienced pain attributable to driving posture and road conditions, yet conventional observational methods were still utilized. Boonpa et al. (2013) investigated fatigue among bus drivers and found that 60% slept fewer than six hours per day, with 45% reporting moderate to severe fatigue levels. Mongkonkansai et al. (2018) analyzed visual fatigue among drivers and found that 43.3% experienced eye strain from glare exposure. Nanthawong and Chaiklieng (2024) assessed ergonomic risks among public transport drivers and found that 56.67% exhibited high risk in the lower back and arm regions; however, the assessment relied on qualitative evaluation instruments without explicit physical posture analysis.

The Rapid Upper Limb Assessment (RULA) method, developed by McAtamney and Corlett (1993), is a widely accepted tool for evaluating upper body ergonomic risks. However, traditional RULA assessment requires expert observation and manual posture measurement, resulting in limitations related to time constraints, difficulty in collecting large-scale data, and inter-rater variability. This study therefore has two objectives: (1) to develop an image processing model for assessing truck drivers' sitting posture based on ergonomic principles using the RULA method, employing Computer Vision technology integrated with MediaPipe Pose Estimation; and (2) to evaluate the reliability of the model by comparing joint angle measurements with those obtained by an expert assessor, using the Intraclass Correlation Coefficient (ICC).

2. literature review

2.1 Ergonomic Issues among Truck Drivers

Fatigue is a critical factor contributing to accidents, injuries, and fatalities, particularly in the transportation sector (May and Baldwin 2009). Williamson et al. (2011) identified relationships among sleep homeostasis, circadian rhythms, and work characteristics with driving safety, particularly in tasks requiring sustained attention or involving repetitive activities, which significantly reduce work performance. Truck drivers represent an occupational group at high risk for musculoskeletal disorders due to the nature of their work, which involves prolonged static sitting, exposure to whole-body vibration, and limited opportunities for postural adjustment. Asour et al. (2022) investigated the prevalence of musculoskeletal disorders among truck drivers in Iran and found that 73.2% reported low back pain, 52.1% reported neck pain, and 45.8% reported shoulder pain. These findings are consistent with Terfa et al. (2022), who identified the primary risk factors as continuous driving duration, inappropriate sitting posture, and insufficient rest periods.

2.2 Posture Assessment Using the RULA Method

The Rapid Upper Limb Assessment (RULA) is an ergonomic risk assessment tool developed by McAtamney and Corlett (1993), designed to evaluate upper body posture during work activities. The method considers joint angles of the upper arm, lower arm, wrist, neck, trunk, and legs, assigning scores according to predefined criteria. The grand score ranges from 1 to 7, with higher scores indicating greater risk. For example, Halek et al. (2023) applied RULA to assess bus driver postures in Singapore and reported a mean score of 6, indicating a high-risk level.

2.3 Computer Vision and Pose Estimation Technology

Computer Vision technology has advanced rapidly over the past decade, particularly in the field of Pose Estimation, which involves estimating the positions of human body joints from images or video. MediaPipe Pose, developed by Google, is one of the most widely adopted tools due to its capability for real-time processing on standard devices without requiring specialized hardware. It can detect 33 body landmarks covering the face, trunk, arms, and legs. Research on the application of Computer Vision for ergonomic posture assessment has been increasing steadily. Tanthuwapathom et al. (2025) investigated the reliability of RULA-based sitting posture assessment between physical therapist video-based evaluation and the SMART IMU sensor system, reporting ICC values ranging from 0.84 to 0.92. Additionally, Francia et al. (2026) evaluated the accuracy of MediaPipe for joint angle measurement compared with an optoelectronic motion capture system, reporting ICC values exceeding 0.91 for the elbow and 0.77 for the shoulder, demonstrating the potential of this technology for ergonomic applications.

2.4 Related Research in Thailand and Research Gap

Although several studies in Thailand have examined ergonomic risks among drivers, most rely on conventional observational methods or qualitative assessment instruments. There remains a notable absence of research integrating Computer Vision technology with established ergonomic assessment methods such as RULA for the specific context of truck drivers. This study addresses this gap by developing a MediaPipe-based image processing model capable of automatically estimating joint angles and computing RULA scores from lateral photographs, thereby providing an objective, efficient, and scalable screening tool for ergonomic risk assessment.

3. Methods

3.1 Population and Sample

The study population comprised truck drivers operating vehicles of four wheels or larger in Nakhon Ratchasima Province, Thailand, whose primary occupation was driving. Inclusion criteria required participants to be long-haul truck drivers (e.g., freight or agricultural product transport) with a minimum of one year of driving experience, who provided informed consent and permitted photographic documentation of their sitting posture. The sample size was calculated using the formula for testing agreement:

$$N = \left[\frac{(Z_\alpha + Z_\beta)}{C}\right]^2 + 3,\ \text{where } C = 0.5\ \times \text{In}\left(\frac{1+r}{1-r}\right)$$

The significance level was set at $\alpha = 0.05$ ($Z_\alpha = 1.96$), statistical power at 0.80 ($\beta = 0.20$, $Z_\beta = 0.842$), and the expected correlation coefficient at $r = 0.70$, referenced from Tanthuwapathom et al. (2025), who reported ICC values between 0.84 and 0.92. However, since this study employs MediaPipe Pose Estimation from photographs rather than direct IMU sensor measurement, a more conservative r value was adopted. The calculated minimum sample size at $r = 0.70$ was 14 participants. In practice, data were collected from 22 participants, all of whom were male truck drivers operating in Nakhon Ratchasima Province, thereby enhancing statistical power.

3.2 RULA Posture Assessment Criteria

The RULA assessment evaluates four body segments relevant to this study.

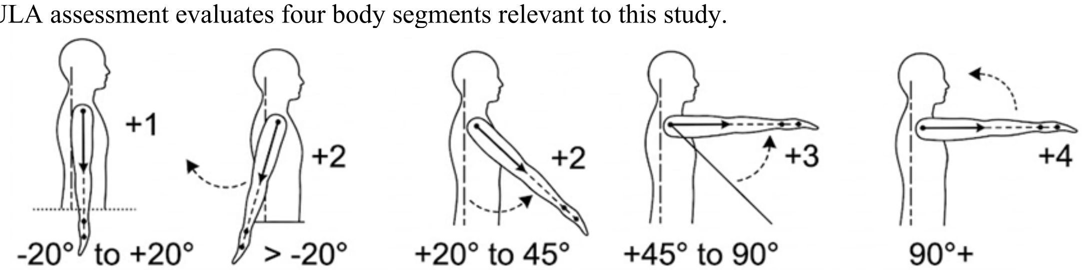

Figure 1. illustrates the postures used for upper arm risk assessment

For the upper arm, the assessment considers the degree of arm elevation from the shoulder to the elbow relative to the vertical axis of the trunk. Higher elevation or backward extension results in higher scores. Adjustment scores are added for shoulder raising or arm abduction. The scoring criteria for the upper arm are presented in Table 1 and Figure 1.

Table 1. Scoring criteria for upper arm posture

Posture	**Score**
Extension 20° to flexion 20°	1
Extension > 20° or flexion 20°–45°	2
Flexion 45°–90°	3
Flexion > 90°	4
Shoulder raised: +1; Arm abducted: +1	Adj.

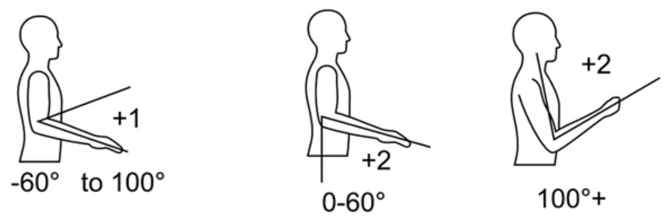

Figure 2. illustrates the postures used for lower arm risk assessment

For the lower arm, the assessment evaluates the angle of the forearm from the elbow to the wrist relative to the vertical axis at the elbow. Greater deviation from the optimal range increases the risk score. The scoring criteria for the lower arm are presented in Table 2 and Figure 2.

Table 2. Scoring criteria for lower arm posture

Posture	**Score**
Elbow flexion 60°–100°	1
Elbow flexion < 60° or > 100°	2
Arm crosses midline or deviates laterally: +1	Adj.

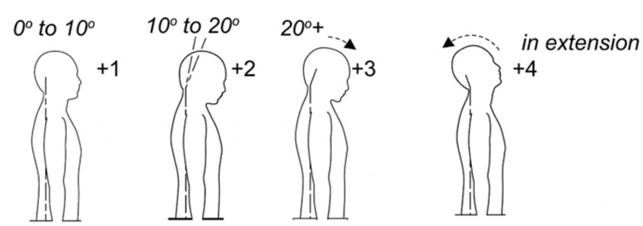

Figure 3. illustrates the postures used for neck risk assessment

The neck assessment considers the degree of head flexion or extension relative to the vertical axis. Greater forward flexion or backward extension increases the load on the cervical muscles, resulting in higher risk scores. The scoring criteria for the neck are presented in Table 3 and Figure 3.

Table 3. Scoring criteria for neck posture

Posture	**Score**
Flexion 0°–10°	1
Flexion 10°–20°	2
Flexion > 20°	3
Extension (backward)	4
Neck twisting: +1; Side bending: +1	Adj.

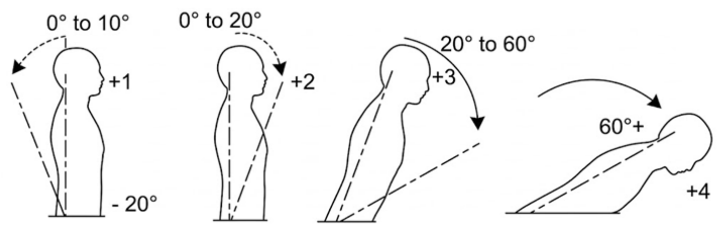

Figure 4. illustrates the postures used for trunk risk assessment

The trunk assessment evaluates the degree of forward flexion. The ideal posture involves sitting upright with full back support, which receives the lowest score. Increasing forward flexion results in progressively higher risk scores. The scoring criteria for the trunk are presented in Table 4 and Figure 4.

Table 4. Scoring criteria for trunk posture

Posture	**Score**
Upright (0°) with back support	1
Flexion 0°–20°	2
Flexion 20°–60°	3
Flexion > 60°	4
Trunk twisting: +1; Side bending: +1	Adj.

3.3 Design and Development of the Image Processing Model

The image processing model for RULA-based ergonomic posture assessment was designed and developed to analyze upper body angles from lateral (sagittal view) photographs. The model comprises two main components: Pose Landmark Definition and Angle Calculation.

3.3.1 Pose Landmark Definition

The model utilizes the MediaPipe Pose library, a machine learning framework capable of detecting and estimating the positions of body joints and key landmarks. For this study, the model estimates landmark positions from lateral photographs of the driver, selecting six key landmarks: Nose, Right Ear, Right Shoulder, Right Elbow, Right Wrist, and Right Hip.

However, directly applying MediaPipe coordinates has limitations because the detected landmarks do not precisely correspond to the anatomical reference points used in RULA assessment criteria. For example, the "shoulder" landmark detected by MediaPipe tends to be positioned anteriorly rather than at the acromion process, and the "ear" landmark corresponds to the pinna rather than the tragus, which serves as the reference point for neck angle measurement in RULA. Therefore, a Backward Offset technique was developed to adjust landmark positions as follows:

Tragus Offset: The RULA method uses the tragus as the reference point for neck angle measurement. The model estimates the tragus position by shifting the MediaPipe "ear" landmark backward along the nose-to-ear vector by 40% of the nose-to-ear distance, approximating the actual tragus location.

Acromion Offset: To obtain the correct shoulder joint position for upper arm angle measurement, the model estimates the acromion process by shifting the MediaPipe "shoulder" landmark backward in the same direction as the Tragus Offset by 35% of the nose-to-ear distance.

C7 Pivot Offset: The true pivot point of the neck is located at the seventh cervical vertebra (C7), which is superior to the shoulder position. The model estimates the C7 position by shifting the "shoulder" landmark upward along the trunk line by 30% of the shoulder-to-ear distance.

Trunk Line Offset: The trunk line drawn between the MediaPipe shoulder and hip landmarks tends to be positioned anteriorly. To approximate the spinal midline more accurately, the model shifts the entire trunk line backward by 6% of the total image width.

3.3.2 Angle Calculation

After obtaining the adjusted landmark positions, the model computes body segment angles using vector mathematics and the dot product formula:

$$\theta = \arccos\left(\frac{\vec{A} \cdot \vec{V}}{||\vec{A}||\,||\vec{V}||}\right)$$

where V = [0, −1] is the vertical reference vector and A is the vector of the adjusted landmark positions (e.g., neck vector, trunk vector, upper arm vector). The model applies this formula to compute angles for each body segment according to the RULA criteria. The vectors used for each body segment are summarized in Table 5 and Figure 5.

Table 5. Summary of vectors used for angle calculation

Body Segment	**Primary Vector (V_1)**	**Reference Vector (V_2)**
Neck	C7 to Tragus	Vertical upward [0, −1]
Trunk	Acromion to Hip (adjusted)	Vertical downward [0, 1]
Upper Arm	Acromion to Elbow	Trunk line (Acromion to Hip)
Lower Arm	Elbow to Wrist	Vertical downward [0, 1]

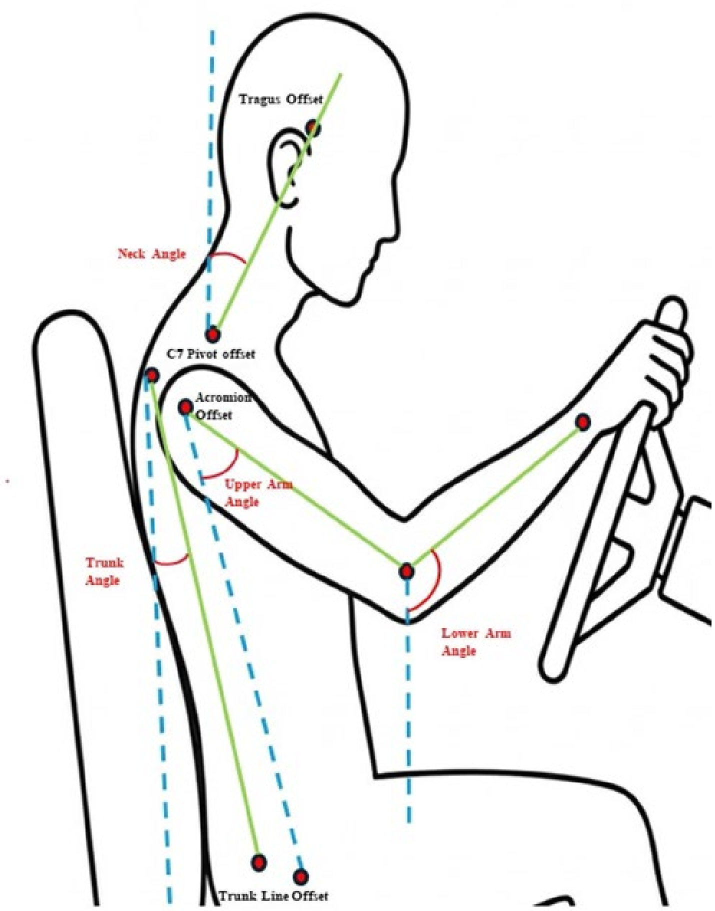

Figure 5. Defined point locations for the designed model

For the trunk angle, the model computes a signed angle, where negative values indicate backward lean (with back support, scored as 1) and positive values indicate forward lean, which is further analyzed according to RULA criteria.

3.4 Data Collection Equipment

A smartphone camera with a 12-megapixel (12MP) lens was mounted on a tripod to capture photographs in a 9:16 (portrait) aspect ratio, recording the driver's sitting posture from a lateral (sagittal plane) perspective, which is the optimal viewpoint for RULA-based posture analysis.

3.5 Statistical Analysis

The reliability of the model was evaluated using the Intraclass Correlation Coefficient (ICC), specifically the ICC(2,1) Two-Way Random Effects, Absolute Agreement model, as recommended by Koo and Li (2016). Analysis was performed using SPSS software, with separate evaluations for angle ICC and RULA score ICC. The ICC interpretation criteria followed Koo and Li (2016): ICC < 0.50 = poor, ICC 0.50–0.75 = moderate, ICC 0.75–0.90 = good, and ICC > 0.90 = excellent.

4. Data Collection

4.1 Demographic Data

The study sample comprised 22 male truck drivers. The demographic characteristics of the participants are presented in Table 6.

Table 6. Demographic characteristics of the sample (n = 22)

Demographic Dimension	Mean	Standard Deviation	Range
Age (years)	31.05	6.31	22–45
Height (cm)	173.32	4.63	165–183
Weight (kg)	73.59	7.09	61–88
BMI (kg/m²)	24.51	2.20	18.2–29.1

4.2 Data Collection Procedure

Data were collected by photographing the sitting posture of participants during actual driving operations. The camera was positioned laterally at a distance of 70 centimeters from the driver, aligned as parallel as possible to the driver in the sagittal plane to clearly capture the upper body posture. The photographed posture represented the most frequently adopted driving position during long-haul operations.

4.3 Image Processing with the Model

The collected photographs were processed through the developed model in the following sequence: (1) input the image into the MediaPipe Pose system to detect six body landmarks; (2) adjust landmark positions using the offset techniques described in Section 3.3.1; (3) compute four joint angles for the neck, trunk, upper arm, and lower arm; and (4) calculate RULA scores according to the predefined criteria. Concurrently, an expert assessor measured joint angles from the same photographs using conventional manual assessment methods to serve as reference values for comparison. After processing the image through the model, the measurement results and key points are obtained as shown in Figure 6.

Figure 6. Model-generated measurement points mapped on the real image

5. Results and Discussion

5.1 Numerical Results

The ICC analysis results for joint angles between the model and the expert assessor are presented in Table 7. The analysis was performed using SPSS with the ICC(2,1) Two-Way Random Effects, Absolute Agreement model.

Table 7. ICC values for joint angles between the model and the expert (n = 22)

Body Segment	ICC	95% CI	Agreement Level	MAE (°)
Lower Arm	0.995	[0.970, 0.999]	Excellent	0.90
Upper Arm	0.992	[0.968, 0.999]	Excellent	1.42
Trunk	0.926	[0.723, 0.991]	Excellent	1.45
Neck	0.777	[0.210, 0.962]	Good	2.37

Table 7 demonstrates that the ICC values for all joint angles were in the good to excellent range (ICC = 0.777–0.995). The lower arm exhibited the highest ICC (0.995, 95% CI [0.970, 0.999]), followed by the upper arm (ICC = 0.992, 95% CI [0.968, 0.999]), trunk (ICC = 0.926, 95% CI [0.723, 0.991]), and neck with the lowest ICC (0.777, 95% CI [0.210, 0.962]). The Mean Absolute Error (MAE) for all segments ranged from 0.90 to 2.37 degrees, which is considered acceptable for ergonomic assessment purposes. The ICC analysis results for RULA scores between the model and the expert assessor are presented in Table 8.

Table 8. ICC values for RULA scores between the model and the expert (n = 22)

Body Segment	ICC	95% CI	Agreement Level	Percent Agreement
Trunk	1.000	[1.000, 1.000]	Perfect	100%
Upper Arm	0.750	[0.092, 0.952]	Good	85.7%
Lower Arm	0.727	[0.042, 0.947]	Moderate	85.7%
Neck	0.625	[−0.146, 0.924]	Moderate	85.7%

Table 8 reveals that the ICC values for RULA scores exhibited greater variability than those for angles. The trunk achieved the highest ICC of 1.000 (perfect agreement), the upper arm was in the good range (ICC = 0.750), the lower arm was moderate (ICC = 0.727), and the neck was moderate (ICC = 0.625). The overall percent agreement was 89.3% (25 out of 28 comparison pairs).

5.2 Proposed Improvements

The results demonstrate that the developed model is capable of estimating joint angles with high accuracy. The ICC values for all joint angles were in the good to excellent range (ICC = 0.777–0.995). These findings are consistent with Francia et al. (2026), who evaluated the accuracy of MediaPipe for joint angle measurement compared with an optoelectronic motion capture system and reported ICC values exceeding 0.91 for the elbow and 0.77 for the shoulder, which are comparable to the results obtained in this study. The findings are also consistent with Tanthuwapathom et al. (2025), who investigated the reliability of RULA-based sitting posture assessment between physical therapists and the SMART IMU sensor system, reporting ICC values between 0.84 and 0.92.

The lower arm achieved the highest ICC (0.995) because the landmarks used for computation, namely the elbow and wrist, are joints that MediaPipe can detect with high accuracy due to their prominent visual features, minimal occlusion by other body parts, and no requirement for offset adjustment. The MAE was only 0.90 degrees, which is lower than the RMSE of MediaPipe reported by Francia et al. (2026), who found RMSE values of approximately 16–19 degrees for full range of motion tasks. This discrepancy is attributable to the limited range of motion inherent in driving postures, which enables MediaPipe to achieve more accurate landmark estimation.

The upper arm achieved the second highest ICC (0.992). Although the acromion point was adjusted using the offset technique, the Acromion Offset (35% of the nose-to-ear distance) effectively approximated the acromion process position. The MAE was 1.42 degrees, with the model tending to slightly underestimate angles compared with the expert (Mean Difference = −1.07 degrees), likely because the estimated acromion position was marginally superior to the actual position, resulting in a narrower upper arm vector angle.

The trunk achieved an excellent ICC (0.926), although lower than both arm segments, because trunk angle computation requires two offset-adjusted landmarks (Acromion and Hip adjusted with Trunk Line Offset), introducing cumulative offset error. Nevertheless, the MAE was only 1.45 degrees, and the Bland-Altman Limits of Agreement ranged from −1.72 to 3.82 degrees, which is within acceptable limits.

The neck achieved the lowest ICC (0.777), although still in the good range according to Koo and Li (2016). The primary cause is the complexity of estimating the tragus position, which requires offset adjustment from the MediaPipe ear landmark. The ear landmark position may vary with head tilt and gaze direction. Individual analysis revealed that some participants exhibited errors as high as 9.34 degrees, potentially due to slight head rotation during photography, causing the ear landmark to deviate from its true position and propagating error through the tragus offset. These findings are consistent with Francia et al. (2026), who reported that MediaPipe accuracy decreases when joint angles are complex or partially occluded.

5.3 Validation

A notable finding is that despite high angle ICC values, the RULA score ICC values decreased markedly for certain segments. This phenomenon, termed the "Threshold Effect," occurs when measured angles fall near the scoring boundary, causing minor angular discrepancies to alter the RULA score.

A clear example is the lower arm, which achieved an angle ICC of 0.995 (excellent) but a score ICC of only 0.727 (moderate). This occurred because some participants had model-measured angles of 99.39 degrees while the expert measured 100 degrees—a difference of only 0.61 degrees—yet the scoring boundary at 100 degrees (< 100° = score 1, ≥ 100° = score 2) caused a one-point score difference. Similarly, the upper arm exhibited an angle ICC of 0.992 but a score ICC of 0.750, as some participants had model-measured angles of 19.32 degrees (score 1) versus expert-measured angles of 22 degrees (score 2), crossing the 20-degree boundary. For the neck, the score ICC was 0.625 (moderate), with some participants showing model-measured angles of 26.34 degrees (score 3) versus expert-measured angles of 17 degrees (score 2), representing the largest angular discrepancy (9.34 degrees) attributable to the tragus detection issue discussed above.

Conversely, the trunk achieved a perfect score ICC of 1.000 because all participants exhibited backward lean during driving, resulting in negative trunk angles computed by the model. This consistently yielded a score of 1 for all participants, matching the expert assessment. This result confirms that the signed angle technique developed for trunk angle measurement can accurately distinguish lean direction, consistent with the RULA principle that backward lean with back support receives a low risk score.

The Backward Offset technique developed in this study plays a crucial role in enhancing joint angle measurement accuracy, particularly for the trunk and upper arm, which require anatomically correct reference points. The trunk ICC of 0.926 and upper arm ICC of 0.992 demonstrate that the Acromion Offset (35% of the nose-to-ear distance) and Trunk Line Offset (6% of the image width) effectively adjust landmark positions. However, the Tragus Offset for the neck still exhibits certain limitations, as reflected by the lower neck ICC, which warrants further refinement in future research.

6. Conclusion

This study developed an image processing model for assessing truck drivers' sitting posture based on ergonomic principles using the RULA method, employing Computer Vision technology integrated with MediaPipe Pose Estimation. A Backward Offset technique was developed to adjust landmark positions to correspond with anatomical reference points. Testing with a sample of 22 participants yielded the following findings:

(1) The ICC values for all joint angles were in the good to excellent range (ICC = 0.777–0.995), with the lower arm achieving the highest value (0.995) and the neck the lowest (0.777). The Mean Absolute Error ranged from 0.90 to 2.37 degrees.

(2) The ICC values for RULA scores ranged from 0.625 to 1.000, with the trunk achieving the highest value (1.000) and the neck the lowest (0.625). The overall percent agreement was 89.3%
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(3) The Threshold Effect was identified as the primary cause of lower score ICC values compared with angle ICC values, particularly when measured angles fell near scoring boundaries.

In conclusion, the developed model demonstrates acceptable reliability for ergonomic posture assessment and can be applied as a preliminary risk screening tool for truck drivers. Future research should focus on extending the model to support three-dimensional analysis, increasing the sample size, and refining the Tragus Offset technique to improve neck angle measurement accuracy.

The study has certain limitations that should be considered. First, the model analyzes photographs from the sagittal plane only, precluding detection of twisting or abduction, which are RULA adjustment factors. Second, image quality affects MediaPipe landmark detection accuracy, particularly under low-light conditions or when body parts are occluded by the steering wheel or vehicle interior. Third, the offset ratios were derived from average anatomical proportions, which may not be optimal for all body types. Finally, although the sample size of 22 participants satisfies the statistical calculation requirements, increasing the sample size would enhance result reliability and narrow the confidence intervals.

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Biographies

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