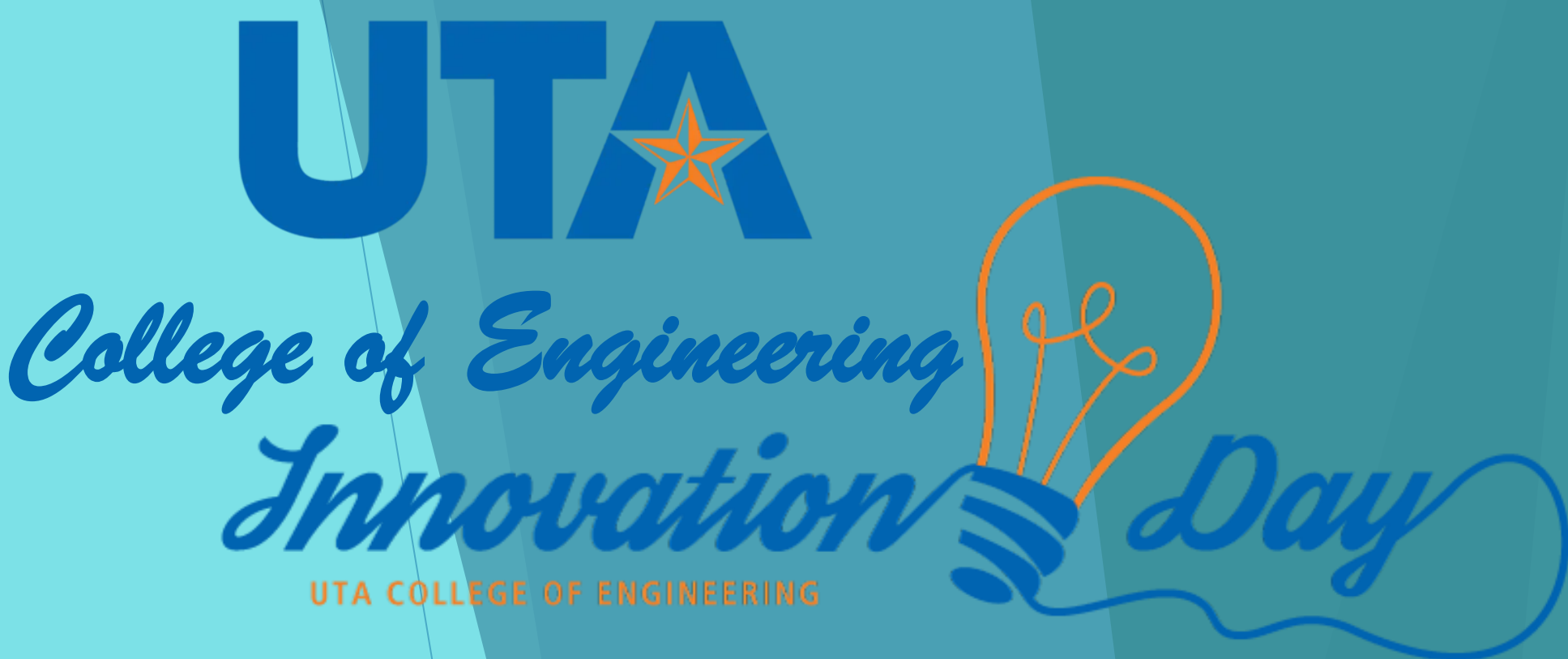


POSTURE: Posture Observation System for Task-based User Risk Evaluation

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Executive Summary

- This project developed an interactive AI system for ergonomic risk assessment using multi-camera computer vision, intended as an assistive tool allowing repeatable screening & documentation where continuous expert observation is limited
- The system automates REBA and RULA scoring continuously using 3 synchronized camera views with adaptive angle selection instead of manual sampling
- Final results achieved close agreement with expert scoring:
 - REBA: CV mean 7.0 vs expert 6.25
 - RULA: CV mean 5.5 vs expert 4.83
- Interactive dashboard adds a review layer through timestamped risk flags, AI generated posture insights, & suggested corrections
- Findings demonstrate a pathway for ergonomic risk assessment that is both explainable and scalable

Background

- 2.5 million nonfatal workplace injuries were reported in U.S. private industry (2024)[1]
- Total recordable case rate: 2.3 per 100 full-time workers
- ~30% of injuries away from work are musculoskeletal disorders (MSDs)[2]
- REBA & RULA are validated ergonomic tools[3, 4], but:
 - Require manual observation and expert scoring
 - Are time-intensive and difficult to scale
- The current gap:
 - Existing automation scores without interpretation
 - Lacking continuous, scalable, and explainable assessment due to need for manual expert review



Figure 1: Illustration of musculoskeletal discomfort

Experimental Results

- Overall System Performance:
 - Scores tracked closely human expert reviews
 - System's error margins fell within natural range of expert-to-expert variability
 - Demonstrates practical reliability for initial risk screening

Metric	REBA	RULA	Outcomes
Mean (CV/Expert)	7.00 / 6.25	5.8 / 4.83	Slight positive bias (+0.75 REBA, +0.67 RULA)
Mean Absolute Error (MAE)	1.08	0.83	Close to human expert baseline
Expert to Expert Variability	0.83	1.67	Performed within or better than human variance
Adjacent Agreement	4/6 (67%)	4/6 (67%)	System consistently placed cases in the correct action range
Max Absolute Difference	2	2	Highest observed deviation from the expert mean

- Component-Level Accuracy Gradient:
 - Performance analysis revealed a clear proximal-to-distal accuracy gradient
 - Larger segments are easily detected while smaller markers (like the wrist) introduce noise, consistent with known pose-estimation limits

- Reviewable Peak Risk Moments and AI Interpretation:
 - System automatically extracts peak-risk frames & score timelines, allowing ergonomists to instantly inspect high risk moments without scrubbing full videos
 - VLM and LLM identified task context and summarized risk based on computed scores to ensure traceability with the established ergonomic grading patterns
 - Generated insights provided useful review assistance, but consistency remains dependent on how well specific task parameters are identified

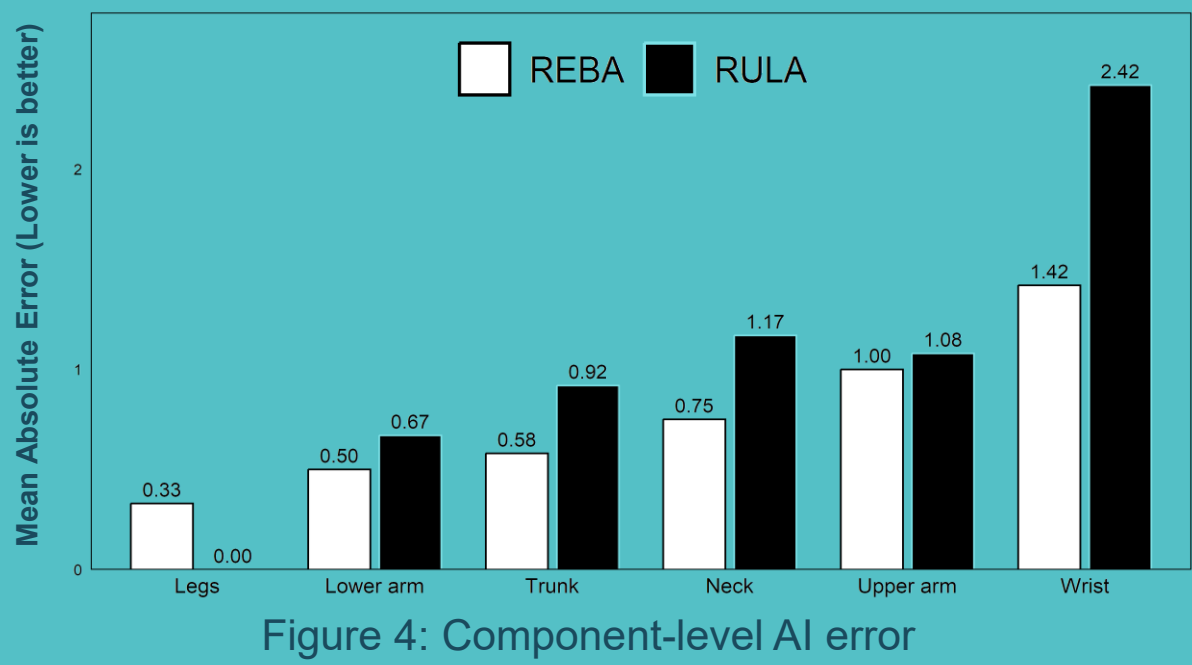


Figure 4: Component-Level AI error

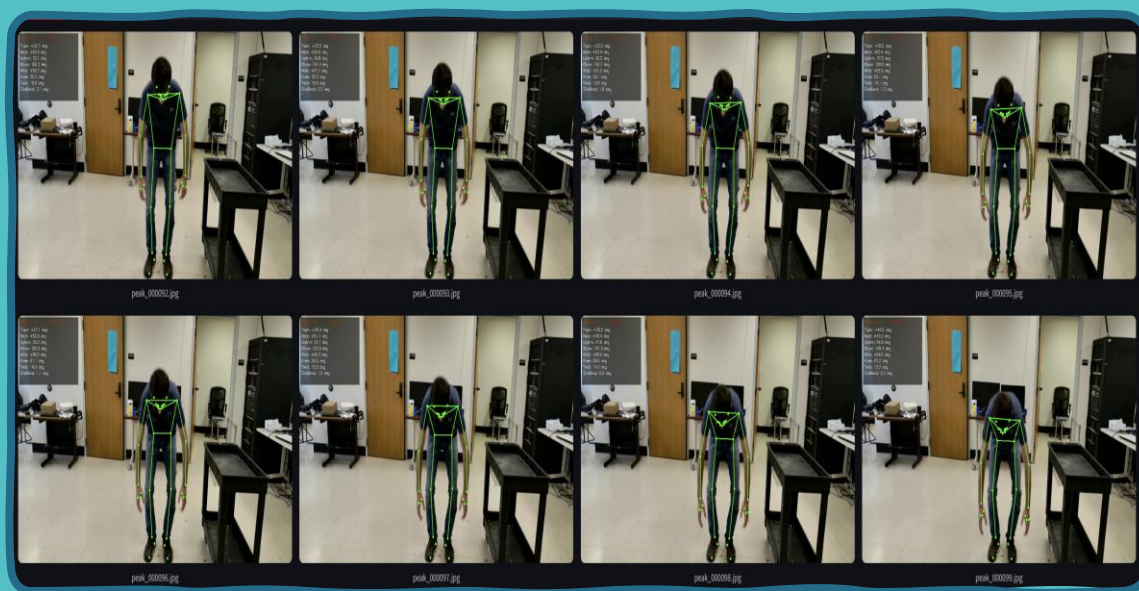
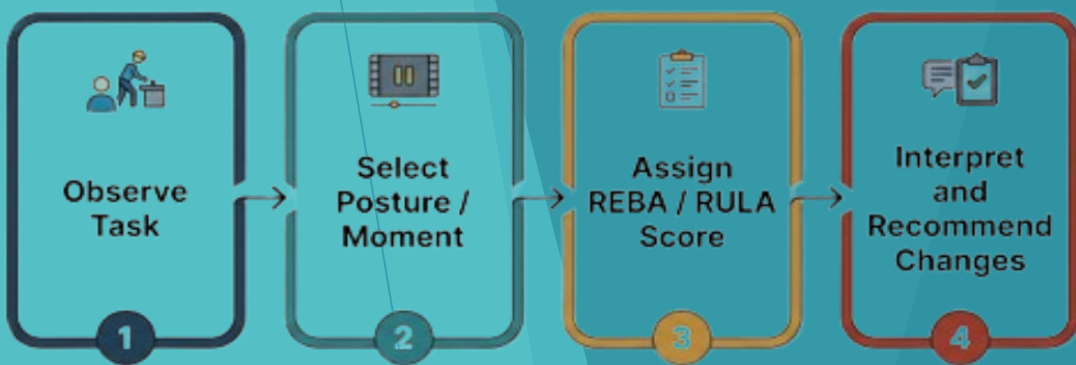


Figure 5: Reviewable peak-risk moments identified by the system

Conclusions

- Multi-camera CV allows for continuous, automated REBA/RULA scoring with expert-level agreement
- System achieves practical and consistent reliability comparable to human raters
- LLM layer improves usability and explainability:



- Multi-view helps mitigate occlusion & depth ambiguity
- First steps toward scalable, explainable, & interactive ergonomic risk assessment
- Current limitations:
 - Small validation sample
 - Based on controlled data and environment
 - Reduced accuracy in distal joints & depth reconstruction
- Next steps:
 - Expand sample size and expert validation
 - Improve wrist and distal joint tracking
 - Make AI reports consistent with ergonomist style
 - Publish the interactive dashboard tools

Experimental Setup & Test Plan

- Challenges in Single-Camera Systems[5-7]:
 - Occlusion and depth ambiguity
 - Weak tracking of distal joints
- Our Capture Setup: 3 synchronized OBSBOT Tiny 2 RGB cameras (front, side, & isometric)
- Dynamically selects the optimal camera angle instead of averaging all inputs. System swaps to best available view when visibility is poor
- Participants: 8 individuals

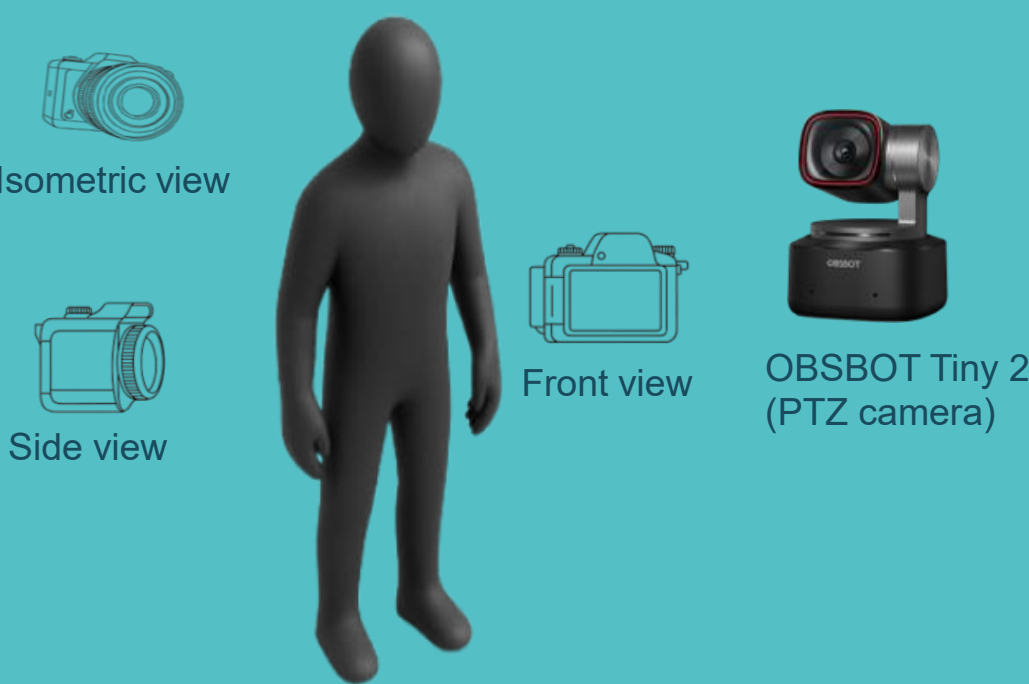


Figure 2: Multi-view camera setup

- Tasks:
 - 1) Floor-to-waist lifting
 - 2) Overhead stocking
 - 3) Waist-level screwdriving
- Pipeline:
 - Pose estimation → Temporal smoothing → Selecting best view → REBA/RULA scoring → LLM/VLM review → Dashboard output

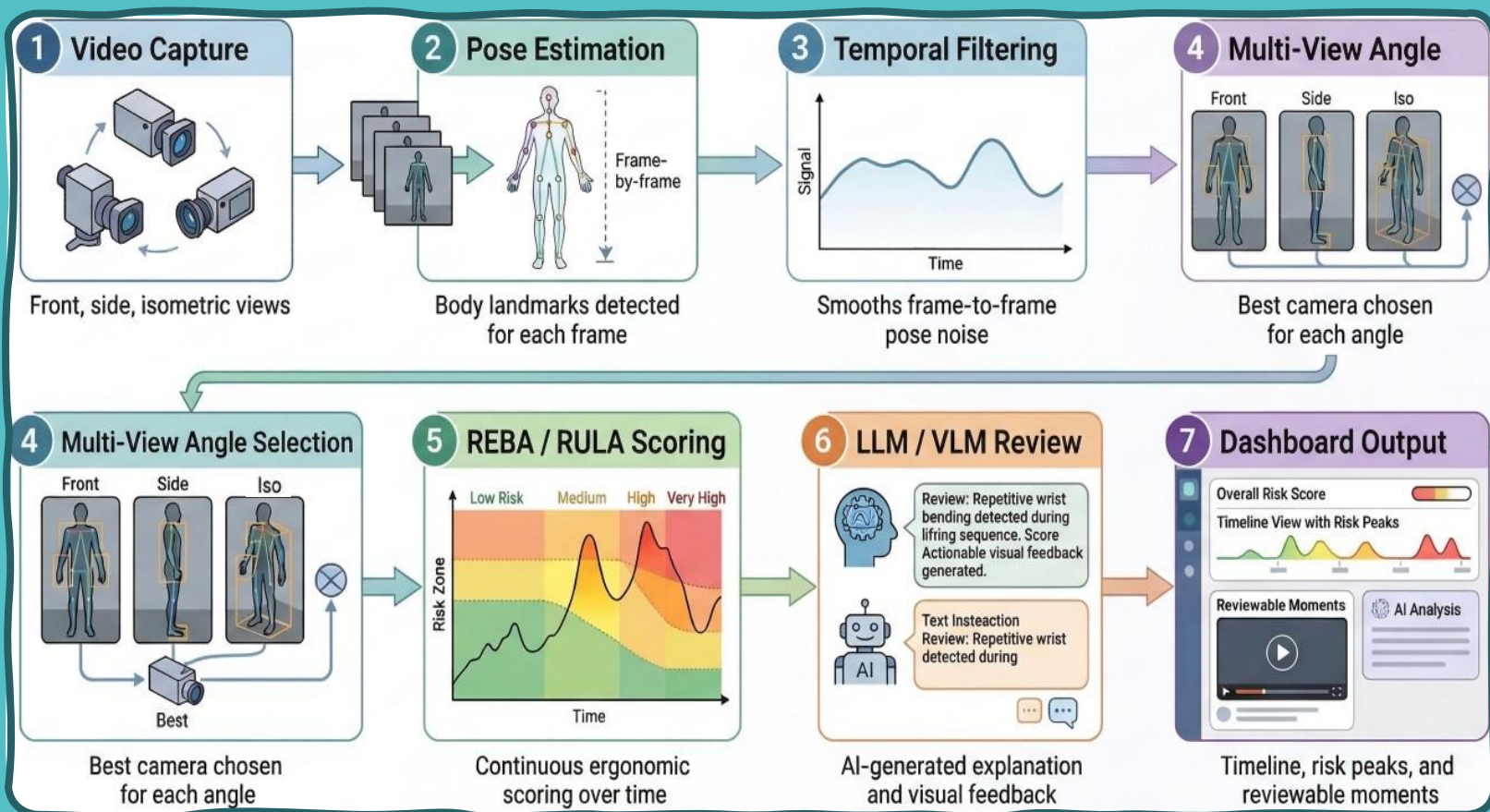


Figure 3. A: End-to-end pipeline for continuous ergonomic scoring and AI assisted review

- Comparison method: Experts reviewed same peak-risk frames
- Evaluation subset (proof-of-concept):
 - 2 participants, 2 expert raters
 - 6 peak-risk postures
- Metrics:
 - Bias, MAE, max absolute difference
 - Exact/adjacent agreement
 - Risk category agreement
 - Expert-to-expert variability



Figure 3. B: Dashboard analytics for visibility, angles, and risk distribution

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