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Possible New Directions in Occupational Safety

(Advantages and Limitations)

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Instrumentation in Human Factors and Monitoring in Ergonomics

WHY THIS MATTERS NOW

The scale of the occupational safety challenge

Global figures that explain why instrumentation and monitoring are moving from optional to essential

2.78M
deaths per year from work-related accidents and disease (Intl. Labour Org., ILO, 2024)

374M
non-fatal workplace injuries per year (ILO, 2024)

~2%
of GDP lost to work-related musculoskeletal disorders (WMSDs)

ZERO
EU Vision Zero target for work-related deaths by 2030

WMSD = work-related musculoskeletal disorder

An injury or disorder of muscles, nerves, tendons, joints, or spinal discs caused or aggravated by work tasks — for example from repetitive motion, awkward posture, or sustained physical load. WMSDs are the single largest category of occupational ill-health in industrialised economies, and they are exactly the category of risk that is hardest to see with the naked eye and easiest to miss with a purely observational checklist.

TALK ROADMAP

Ten parts, one running question: advantages vs. limitations

For every instrumentation approach we will ask the same two questions, side by side

0-1 **Foundations**
How machine reasoning works; from reactive to predictive safety

2 **Wearable instrumentation**
Sensing the body: IMU, EMG, fall detection, sensor fusion

3 **Exoskeletons**
Objectifying ergonomic benefit with EMG and simulation

4 **Digital human modeling**
Simulating the worker before the workstation is built

5 **Cognitive ergonomics**
Eye tracking, pupillometry, EEG — monitoring the mind

6 **Human-in-the-loop & cobots**
Teleoperation, digital twins, collaborative robots

7 **Computational intelligence**
Fuzzy logic and decision support for ergonomic risk

8 **Privacy-preserving sensing**
Beyond cameras and wearables: radar-based monitoring

9-10 **Adoption & synthesis**
Worker trust, standards, and an integrated view

1 2 3 4 5 6 7 8 9 10

Parts 6 and 7 build on themes from Thursday's research day

BEFORE WE START

A short primer on terms used throughout

Every abbreviation will be explained again at first detailed use — this is just an overview

AI (Artificial Intelligence)

Umbrella term for systems that detect patterns in data and draw inferences from them, rather than following only fixed, hand-written rules.

ML (Machine Learning)

The branch of AI where a system improves its performance from examples (data) rather than from explicit programming for every case.

Sensor / instrumentation

A device that converts a physical quantity (motion, muscle activity, gaze, radio reflection) into a measurable, recordable signal.

Fusion

Combining signals from two or more sensors or models to get a more reliable estimate than any single source alone.

PARADIGM SHIFT

From reactive to predictive safety

Occupational safety is moving from recording what happened to anticipating what could happen

Reactive practice	Proactive Prevention focus	Predictive	Adaptive Agentic practice
Investigate after an accident has occurred	Periodic inspections and scheduled risk assessments, identifies hazards in advance	Continuous sensor data flags react rising risk before an incident	The system itself adjusts (e.g. a cobot slows down) in real time.

Today's focus sits at the predictive and adaptive end: instrumentation that captures human state continuously, rather than at scheduled checkpoints.
Safety by design: the core idea behind –safety considerations get built into the system architecture from the start rather than bolted on afterward.

PART 2

Wearable instrumentation

Today's real focus: instrumenting the human body directly

IMU	sEMG	HR / HRV	CAWES	sEMG uncertainty
Motion & posture	Muscle load & fatigue	Stress & exertion	Multimodal fusion + tactile feedback	Wireless dropout (Prauzek 2026)

A taxonomy of wearable sensing

Five broad categories — each abbreviation explained, each measuring something different

IMU

Inertial Measurement Unit: accelerometer + gyroscope (+ magnetometer), tracks motion and orientation.

sEMG

Surface electromyography: electrical activity of muscles, measured non-invasively through the skin.

HR / HRV

Heart rate and heart-rate variability: physiological load and stress proxy.

EDA

Electrodermal activity (skin conductance changes linked to the autonomic nervous system's arousal response): sensitive to temperature/humidity.

Environmental

Gas, noise, vibration, and climate sensors worn on or near the body.

Modern systems rarely use just one — the next slides show why combining sensors (fusion) matters

Surface EMG: power and its measurement uncertainty

sEMG (surface electromyography) measures muscle load directly — but the signal is fragile

What sEMG captures

Electrodes on the skin surface detect the electrical activity generated when a muscle contracts — giving a direct, objective readout of muscular effort and fatigue, without asking the worker anything.

Used throughout this talk: exoskeleton evaluation, fatigue detection, and fusion with lifting-risk models.

A 2026 uncertainty study (Prauzek et al.)

Prauzek and colleagues addresses something practitioners don't discuss enough:

- Wireless dropouts — transmission gaps cause missing signal segments, not just noisy ones
- Quantifiable uncertainty — the resulting data gaps can be propagated into a measurable uncertainty bound on the workload score itself
- Reconstruction helps — a local linear trend method can restore signal continuity and shrink that uncertainty

An ergonomic compliance decision can account for how much the missing data could have shifted the result.

CAWES: a cognitive architecture for wearable sensors

Multimodal fusion that gives physical feedback for the worker in real-time,— not just a dashboard

CAWES does

Built on ACT-R (Adaptive Control of Thought—Rational): a cognitive-science model of how human cognition processes information,
CAWES fuses data streams from multiple wearable sensors on a worker's body in real time, and delivers tactile feedback the moment when an ergonomics rule is broken.

Aerospace case study

Validated under laboratory conditions; real working-environment tests are planned next.

Why it's notable

Tactile feedback closes the loop immediately for the worker, instead of an ergonomist reviewing a dashboard later.

Oyekan et al., Journal of Manufacturing Systems, 61 (2021), 391–405

Wearable instrumentation: advantages

What the evidence from this section actually supports

Objectivity

Continuous, quantified measurement replaces subjective, retrospective self-report.

Real-time feedback

Workers and supervisors are alerted in the moment, not after an injury report is filed.

Redesign loop

Aggregated data drives workstation improvements, not only individual correction.

Scalability

Once deployed, the marginal cost of monitoring an extra worker or shift is low compared to manual observational assessment.

Wearable instrumentation: limitations

None of this invalidates the advantages - but a rigorous evaluation has to hold both sides at once.

Calibration & individual variation

The same hardware can give different results depending on placement and anatomy.

Comfort and compliance

Rigid, visible sensors can be uncomfortable over a full shift — leading to inconsistent wear.

Durability

Dust, moisture, vibration, and temperature extremes degrade reliability over time.

Standardisation gap

No universal agreement on which fusion algorithm, which sampling rate, or which threshold values should be used across studies, which makes cross-study comparison difficult.

Exoskeletons in industry

Wearable mechanical or powered devices that support specific body segments during physical tasks

Passive

Springs or elastic elements; no power source.

Active

Motorised; can adapt assistance to the task in real time.

Upper-body

Supports back, shoulders, or arms.

Lower-limb

Supports legs and lower back.

The promise: reduce mechanical load on the body during repetitive or overhead work.
The question for ergonomics science: how do we objectively prove it?

Exoskeletons: advantages and limitations

ADVANTAGES

- Objectively measurable reduction in muscle load and metabolic cost (multi-study EMG evidence)
- Simulation tools (AnyBody) allow design evaluation before physical prototyping
- Directly targets the costliest injury category: musculoskeletal disorders

LIMITATIONS

- No universally agreed assessment standard — results are hard to compare across studies
- Standards (ISO 11228 and similar) largely predate exoskeleton-specific use cases
- Comfort and full-shift wearability remain real adoption barriers regardless of EMG numbers show

Simulate before you build

Digital Human Modeling (DHM): simulating the worker and the workstation before either exists physically

The core idea

Simulate the human body's interaction with a workstation virtually, so ergonomists can identify reach problems, awkward postures, and fatigue risks at the design stage — when changes are cheap — rather than after construction, when they are expensive.

A conceptual parallel: "simulate and prevent" appears instead of "inspect and fix" — the same logic behind the reactive-to-predictive shift we can see.

AI-driven human simulation from a single photo

Siemens announced an AI-driven enhancement to their Tecnomatix human-simulation software that lets an ergonomics engineer lowering the technical barrier to DHM.

How it works

- An engineer photographs a concerning task or posture
- Uploads it to the cloud-based platform
- AI image processing generates a detailed 3D human model automatically
- The system assigns body size, hand-force exertion, action frequency, and returns an automated safety analysis

A phone photo can now be the starting point of a DHM analysis — previously this required someone trained in manually posing as a virtual manikin.

Not yet widely validated independently — worth watching closely.

ErgoReality: VR + motion capture

Overcoming DHM's posture-prediction limitations with observed, not predicted, movement (VR = virtual reality)

The known DHM limitation

Traditional DHM software has a well-known limitation: its posture-PREDICTION algorithms - the part that guesses what posture a worker will actually adopt for a given task - often fail to capture the full range and variability of real human behavior. Real workers do not all move identically.

Amazon Science researchers addressed this with ErgoReality

Virtual Reality application Workers physically perform tasks inside a simulated VR workspace while motion capture records their ACTUAL movements — not a predicted, idealised posture.

This generates genuinely observed kinematic data instead of an algorithm's best guess.

A closely related approach was independently validated by Kačerová et al. (2022) on 20 automotive-production operators, comparing classic biomechanical analysis, a motion-capture suit, and VR-linked measurement.

PART 4 — SYNTHESIS

Digital Human Modeling: advantages and limitations

ADVANTAGES

- Identify and fix ergonomic problems before physical construction, at a fraction of late-stage redesign cost
- Built-in RULA (upper-limb risk), NIOSH (lifting-limit), and OWAS (whole-body posture) scoring standardises assessment in one platform
- AI-photo and VR-motion-capture extensions lower the technical barrier and improve realism

LIMITATIONS

- Classic posture-prediction algorithms still struggle with the variability of real human movement
- The newest AI-driven tools (photo-to-3D) are not yet thoroughly independently validated
- Any simulation is only as accurate as its underlying anthropometric/biomechanical model - it cannot fully replace eventual real-world validation.

PART 5

Cognitive ergonomics & neuroergonomics

Eye tracking & pupillometry

Beyond the body: monitoring the mind

Lightweight workload proxy (HFES 2025)

EEG
Direct neural index (Kosachenko 2023)

fNIRS
Blood-oxy proxy, less movement-sensitive

EEG + pupillometry
Multimodal combination — 2026 preprint

Eye tracking & pupillometry — key terms

The most mature tool for inferring cognitive workload without a questionnaire

Fixations

Moments when the eye holds relatively still on a point of interest.

Saccades

The rapid jumps between fixations.

Gaze entropy

How scattered or focused a visual attention pattern is — higher = more searching/distraction.

Pupillometry

Measures changes in pupil diameter; a larger pupil (beyond lighting effects) indicates increased cognitive effort.

Blink rate also matters — a faster blink rate is a classic fatigue signal

2025 RESEARCH SPOTLIGHT

Pupillometry + machine learning workload classification

HFES 2025 — predicting cognitive workload automatically from pupil data

The study design

20 university students performed a complex Lego-building task while wearing eye-tracking glasses recording pupil diameter continuously.

After preprocessing, a clustering algorithm classified the data into moderate versus high cognitive workload levels, and the researchers then trained three different machine learning models.

Three models compared

- Random Forest
- XGBoost
- LSTM (Long Short-Term Memory, a recurrent neural network) — the clear winner

This matters because it demonstrates that pupillometry combined with the right machine learning model can predict workload automatically and continuously.

Opens the door to real-time cognitive-load dashboards in safety-critical, high-attention occupations.

EEG: a more direct window into mental state

Electroencephalography — what it offers, and its practical tradeoff

What EEG measures

Electrodes placed on the scalp measure the brain's electrical activity directly, organised into frequency bands associated with different mental states.

Offers something pupillometry cannot.

The practical tradeoff

Far more direct, high-temporal-resolution neural insight than pupillometry — but traditionally requires a multi-channel cap and is far more sensitive to movement artefacts and electrical noise.

Wearable, simplified EEG systems are slowly closing this practicality gap.

2026 PREPRINT — REANALYSIS OF THE KOSACHENKO (2023) DATASET

HOW DO WE COMBINE (Multimodal neuroergonomics) EEG + pupillometry combined

Genuelly unresolve challenge: Not choosing one sensor over another — understanding how to combine complementary signals

EEG is resource-intensive but neurally direct; pupillometry is lightweight and wearable but more indirect. How do we combine both into one practical, interpretable monitoring system?

Essentially, mapping out the actual shape of the pupil's response curve under increasing demand, not just a simple linear relationship.

2026 preprint: combining the signals

86 participants test performed a working-memory digit-span task while wearing a pupillometer alongside a 64-channel EEG system, revealing a triphasic pattern in how pupil size evolves as memory load rises toward overload (Kosachenko et al., 2023); a 2026 preprint re-applies machine learning to classify cognitive load from the combined EEG+pupillometry signal.

Cognitive & neuroergonomic monitoring: advantages and limitations

ADVANTAGES

- Continuous, objective, real-time proxies replace retrospective questionnaires (e.g. the NASA Task Load Index, NASA-TLX)
- Pupillometry is lightweight and field-deployable; EEG offers direct neural insight
- Combining modalities (EEG + pupillometry + fNIRS, functional near-infrared spectroscopy) captures more than any single signal alone

LIMITATIONS

- Strong environmental confounds, especially lighting and temperature/humidity
- No agreed-upon workload thresholds across studies, tasks, or individuals
- Continued gap between laboratory validation and rugged, real industrial deployment

PART 6 — ROBOTICS & DIGITAL TWINS

Human-in-the-loop robotics & digital twins

When a human controls, supervises, or works physically alongside a machine

Cobots	Overassistive paradox	NeuroErgo	Human-in-loop twins
Posturography-validated benefit (Bibbo 2025)	Natural variability as protective factor	AI-driven postural optimization (ICRA 2022)	Biosensor data from the operator

Collaborative robots (cobots) and ergonomic instrumentation

Robots designed to work safely alongside humans, without traditional safety cages

The promised benefit

Cobots take over the most physically demanding or repetitive sub-tasks, improving posture, reducing biomechanical load, and removing humans from awkward or hazardous positions.

"Promised" benefit and "measured, instrumented" benefit are two different things — the next slides show the research community instrumenting cobot collaboration directly, rather than assuming the benefit exists.

2025 RESEARCH SPOTLIGHT

Posturography-based assessment of cobot collaboration

Published in JMIR Human Factors — direct, objective measurement instead of assumption

Posturography, defined

Direct, objective measurement of postural stability and balance — used here to evaluate workers performing standing tasks under different levels of human-robot collaboration.

Why it matters

Postural adjustments and balance directly reflect biomechanical loading and effort. If a cobot genuinely reduces physical strain, that should show up as measurable postural-stability improvement — not just in subjective reports.

A methodological step forward: from "the literature assumes cobots help" to a direct biomechanical measurement of how much, and under which collaboration mode

A COUNTER-INTUITIVE 2024 FINDING

The "overassistive cobot" paradox

More robot assistance is not automatically better for the human body

What "overassistive" means

A cobot that repeatedly selects helpful actions optimizing for short-term task efficiency can force the human into highly repetitive movement patterns — suppressing the NATURAL variability in how a person normally performs a task.

The paradox

Natural movement variability is itself a protective factor against musculoskeletal disorders. An overassistive cobot can therefore INCREASE long-term MSD risk, even while each individual interaction feels easier.

NeuroErgo: AI-driven postural optimization

Teaching the robot to move in ways that are easier on the human body

What NeuroErgo does

Using AI directly inside the robot's control loop to optimize for human ergonomic comfort, not just task efficiency or basic safety distance.

A deep neural network method, first presented at ICRA 2022 and extended in a 2024 follow-up study into ergonomic path-planning by the same research group, that adjusts a robot's motion planning specifically to improve the human partner's postural ergonomics during collaboration — learned from data, not a fixed rule.

A meaningful shift: ergonomics moves from something we measure AFTER the fact, to a parameter the robot actively optimizes for, in real time, alongside its primary task.

What is a digital twin?

Digital twin — defined

A continuously updated, virtual replica of a physical system — a machine, a robot, even a worker's body or workspace — that mirrors its real-world counterpart's state in close to real time, typically using live sensor data.

Differs from a static DHM simulation (Part 4), which represents a designed or predicted state — a digital twin tracks the actual, current, LIVE state of its physical counterpart continuously.

Physical system · machine · robot · worker → live sensor data → **Digital twin · continuously updated virtual replica**

2025-2026 RESEARCH SPOTLIGHT

Human-in-the-loop digital twins

Incorporating real-time data FROM the human operator, not just the machine

The emerging framing

This brings together everything from our cognitive ergonomics section - EEG, pupillometry, physiological monitoring - with the digital twin and robotics world, in a single integrated research direction.

A digital twin architecture that incorporates real-time biosensor data from the human operator — so the system can adapt to human limitations, rather than assuming a constantly alert, constantly capable operator.

Applies across:

The reasoning is that automated systems - whether self-driving vehicles, air traffic control support tools, surgical robots, or teleoperated industrial robots - all depend critically on understanding how the human operator's cognitive and physiological state changes moment to moment.

PART 6 — SYNTHESIS

Human-in-the-loop, cobots & digital twins: advantages and limitations

ADVANTAGES

- Direct posturography now instruments cobot benefit objectively, rather than assuming it
- AI-driven motion planning (NeuroErgo) can actively optimize robot behaviour for human comfort
- Human-in-the-loop digital twins integrate physiological/cognitive monitoring directly into robot control

LIMITATIONS

- The overassistive-cobot finding shows more automation is not automatically better for long-term MSD risk
- Much of this research remains at laboratory/pilot-study stage rather than widespread deployment

PART 7 — COMPUTATIONAL INTELLIGENCE

Computational intelligence & decision support

From raw sensor data to a defensible risk decision

Classic tools (RULA/REBA)	Fuzzy logic	MCDM frameworks	IVFFS + hybrid (2026)
Discrete categories — no in-between	Continuous membership, no threshold cliff	Multiple criteria in one assessment	Six classic methods combined simultaneously

Why classic ergonomic tools struggle with uncertainty

RULA, REBA, and OWAS share a structural limitation

The mismatch

REBA (Rapid Entire Body Assessment) and similar tools were designed as static, snapshot-based scoring systems — a posture is captured at one moment and assigned a discrete risk category.

But real work is continuous

Posture changes second by second; risk does not actually jump abruptly between categories the way discrete scoring suggests. This mismatch is exactly the problem fuzzy logic was mathematically designed to solve.

Fuzzy logic, in brief

A mathematical framework from the 1960s, a natural fit for continuous human data

The rigid alternative

"Posture risk is either LOW or HIGH" — a joint angle snaps from one label to another at an arbitrary threshold.

The fuzzy alternative

Membership functions allow degrees of membership in multiple categories simultaneously — a joint angle might be 80% "acceptable" and 20% "concerning" at the same time, smoothly.

Real postural and physiological data is inherently continuous and gradual, not naturally discrete

Interval-Valued Fermatean Fuzzy Sets + MCDM

Six classic ergonomic methods unified under one uncertainty-aware MCDM (Multi-Criteria Decision-Making) framework

Six methods, one framework

RULA · REBA · OWAS · OCRA (Occupational Repetitive Action index) · QEC (Quick Exposure Check) · SI (Strain Index) — integrated simultaneously, not separately.

The stated motivation

These six traditional methods are individually limited by subjectivity and by their inability to handle interdependent criteria — no existing framework had combined them under a shared treatment of uncertainty until now.

PART 7 — SYNTHESIS

Computational intelligence & decision support: advantages and limitations

ADVANTAGES

- Meaningfully reduced subjectivity and faster assessment (Govindan & Li, 2023)
- Validated against real injury data, not only expert opinion
- A genuine mathematical solution to the mismatch between continuous movement and discrete classic categories

LIMITATIONS

- Most systems still rely on expert-defined membership functions and rules — subjectivity is relocated, not eliminated
- Validation studies tend to be facility-specific, raising generalisability questions
- Adds mathematical/computational complexity requiring specialised expertise to build and audit

PART 8 — THE NEWEST FRONTIER

Privacy-preserving, non-contact sensing

⊘ Wearable discomfort
Physical burden over a full shift — compliance drops with wear time

⊘ Biometric privacy
Workers resist camera recording & continuous physiological monitoring

→

✓ mmWave radar sensing
No device worn · no identifiable image captured
Both adoption barriers resolved simultaneously

Beyond cameras and wearables: radar-based sensing

The two biggest barriers to instrumentation adoption that have come up repeatedly today: physical discomfort from **wearable** devices over a full shift, and privacy concerns - about being recorded on camera.

How it differs from a camera

The answer emerging in the very recent literature is radar-based sensing.

mmWave radar does not capture a visual image at all. It emits radio waves and measures their reflection to determine position, distance, and velocity — producing a sparse 3D point cloud, not a photograph.

What it can do

- Detect motion, posture, even falls
- Without recording an identifiable face or scene
- Works regardless of lighting conditions

mmWave (millimetre-wave radar) — a fundamentally different sensing principle

2025 RESEARCH SPOTLIGHT

mmFree-Pose: a privacy-preserving pose dataset

The first dedicated mmWave radar dataset for privacy-preserving human pose estimation

What was built

Described as the first dedicated mmWave radar dataset specifically designed for privacy-preserving human pose estimation.

A visual-free data-collection framework, synchronizing radar with a separate, validated motion-capture suit purely to establish accurate ground-truth annotations — not for the deployed system itself. Provides 23-joint skeletal annotations, covering basic gestures through complex falls.

Eliminating ethical and technical risks associated with optical sensors, while still achieving medical-grade annotation accuracy — entirely without any optical or visual sensor.

Directly APPLIED EXAMPLE

Non-contact fall detection with 4D imaging radar

Solving both adoption barriers in a single deployed system

How it works

4D imaging radar (3 spatial dimensions + Doppler velocity) combined with a CNN (convolutional neural network) classifies standing, sitting, or lying — and distinguishes a fall from simply lying down based on speed and pattern of position change.

Results shown via a Unity-engine avatar — a supervisor sees an animated figure, never an actual image of the worker.

Both barriers, solved at once

- No wearable device discomfort
- No privacy concern associated with image-based monitoring

PART 8 — PRIVACY-PRESERVING SENSING

Where this is headed next

Very recent (2026) extensions of the same underlying principle

Occupancy monitoring & people counting

~8m effective range per sensor; explicit privacy-preserving alternative to camera-based occupancy systems for lighting, heating, and safety control.

"Strictly privacy-sensitive" settings

Radar-based activity recognition demonstrated for elderly bathroom-monitoring care — the same principle applies to confidential or camera-resistant industrial settings.

PART 8 — SYNTHESIS

Privacy-preserving, non-contact sensing: advantages and limitations

ADVANTAGES

- Zero wearable discomfort — nothing touches the body
- Fundamentally better privacy protection by design — no identifiable image is ever captured
- Works regardless of lighting conditions

LIMITATIONS

- Genuinely early-stage — most research published within the past year
- Cost and integration complexity for industrial-scale deployment remain largely unproven

PART 9

The human factor in adoption

We have now covered the full range of instrumentation technologies. None of this delivers value if workers do not trust it or refuse to use it

Trust in data accuracy
Biometric data accuracy questioned by respondents

Comfort concerns
Discomfort with continuous monitoring

Climate validation
No solutions for hot/humid climates

Source: Mosly, I. (2026) — 567 construction professionals, Saudi Arabia

A 2025 CONCEPT

"Functional transparency" — beyond consent forms

Building on themes raised by Aloisi & De Stefano, 2025 — algorithmic management at work

Informed consent

Tells a worker THAT data is being collected.

Functional transparency

Workers actually understand HOW the system works and makes decisions — what triggers an alert, how a score is calculated, what happens to the data afterward.

Two further findings

Lack of employee involvement in actually SELECTING devices is itself a major adoption barrier.

Across multiple studies, trust and perceived ease-of-use are the strongest predictors of acceptance — stronger than raw technical accuracy.

An integrated view

None of today's technologies work best in isolation — the value emerges from integration of the solutions

Wearables & EMG

Non-contact radar sensing

Exoskeletons

WORKER SAFETY & WELLBEING

Fuzzy decision support

Digital Human Modeling

Cobots & digital twins

Cognitive monitoring

Worker trust and acceptance research determines which of these technologies actually gets adopted — regardless of how scientifically sound it is

Thank you

Possible New Directions in Occupational Safety

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