



AIXPERT

SONIC-01: A Real-World Benchmark for Evaluating Multimodal Large Language Models on Audio-Video Understanding

MLA Cohort 10 Group Session 2
24th Feb 2026



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Presenter

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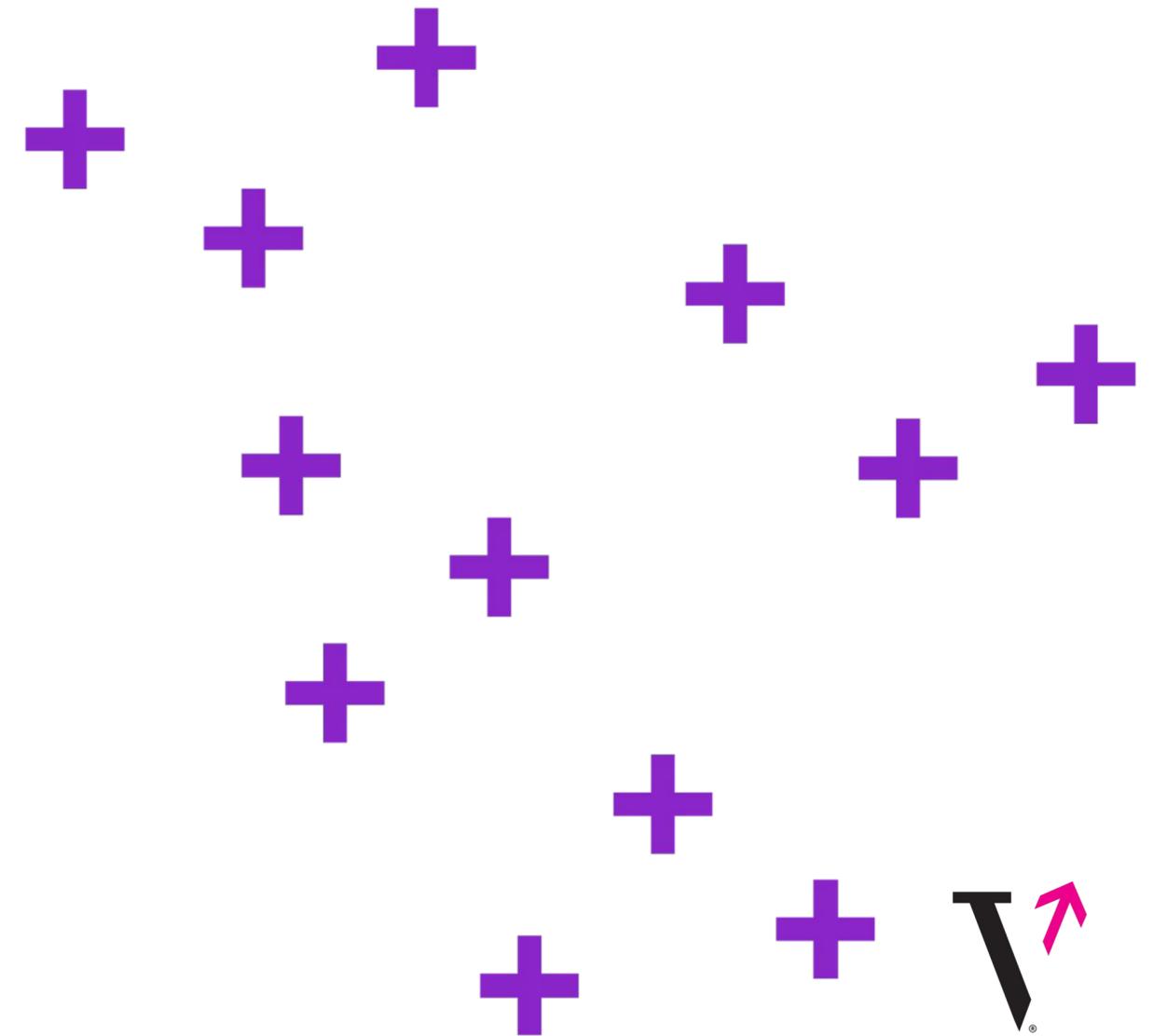
Project lead

Shaina Raza, PhD

About me

Ahmed Y. Radwan

- ❑ MSc in Computer Science @ York University
- ❑ Applied ML Intern, Vector Institute, Toronto
- ❑ Previous KAUST Researcher
- ❑ **Expertise in Trustworthy and Generalizable Machine Learning with efficient deployment**

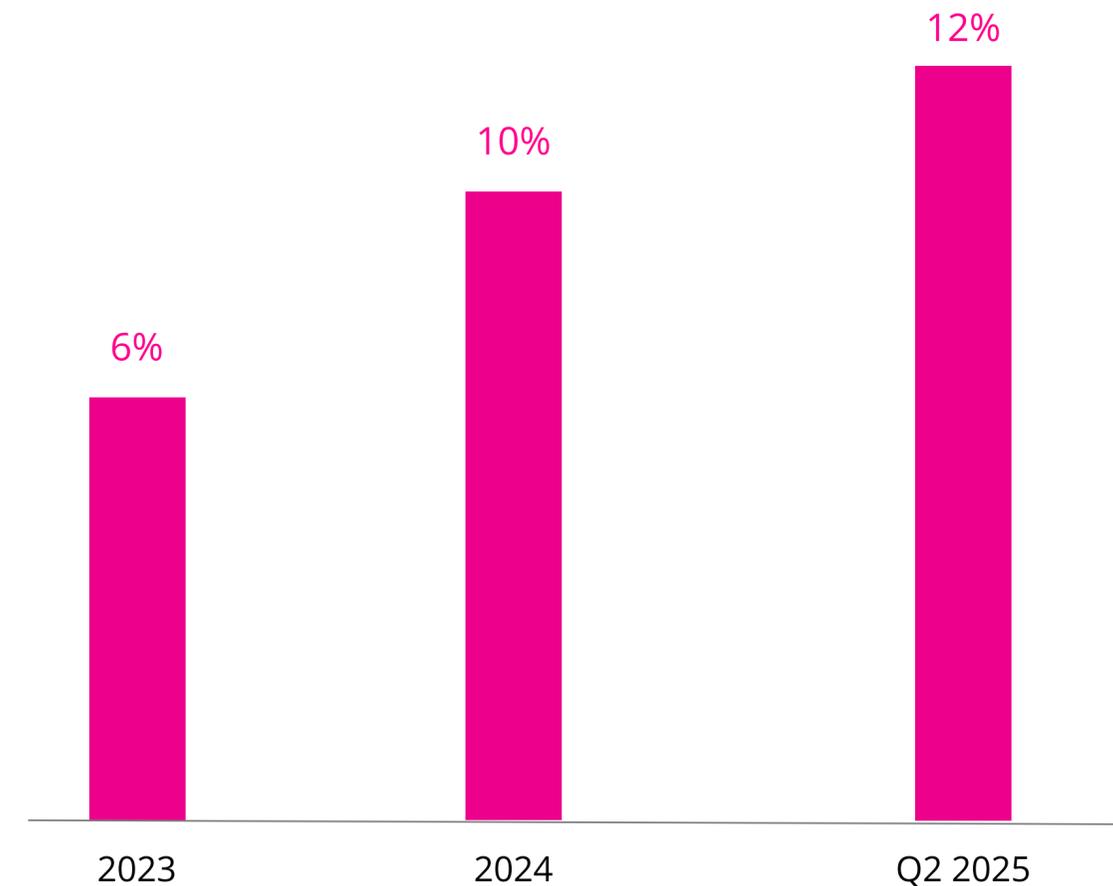


AI Is Already Here

Canada, 2026

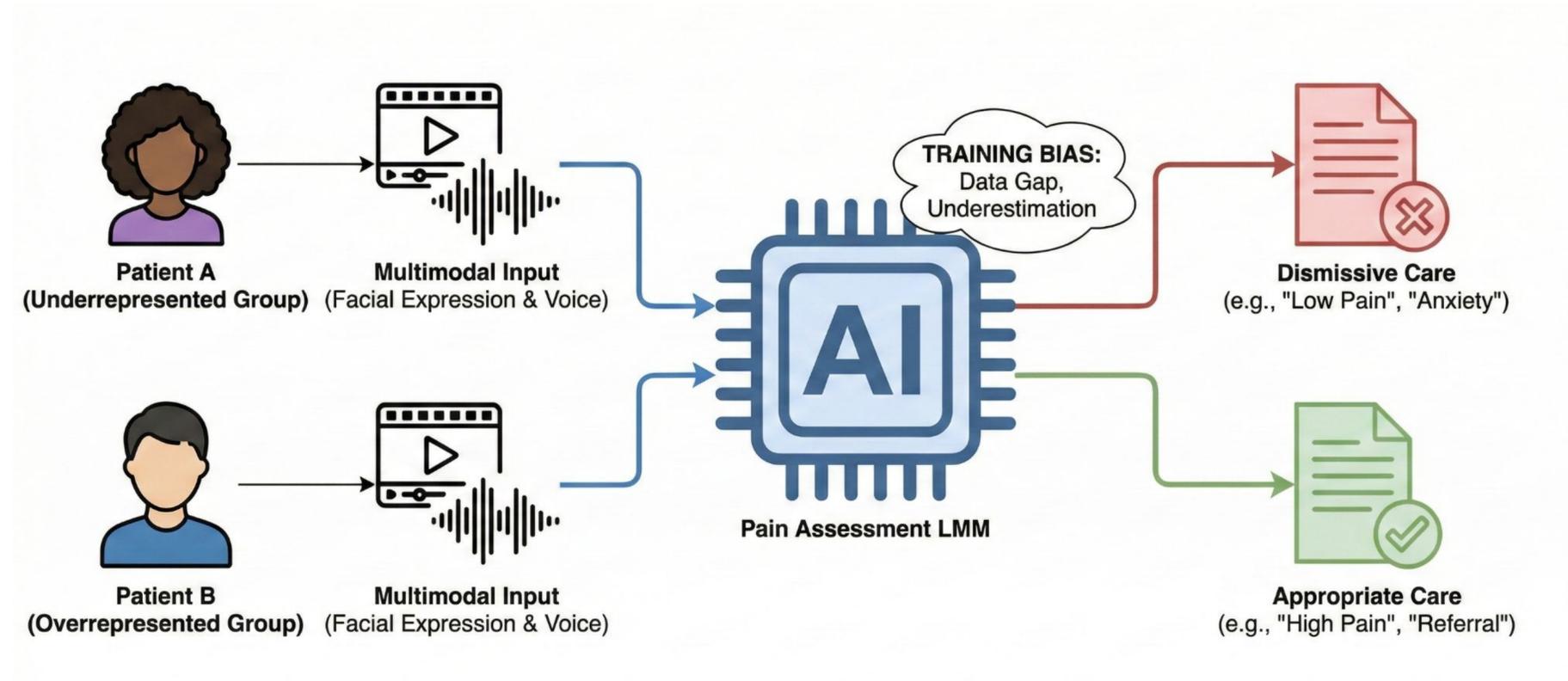
- ❑ **Jan 1, 2026:** Ontario mandates AI disclosure in hiring
- ❑ **12% of businesses** now use AI to produce goods or services
- ❑ **51% of workers** use GenAI at work
- ❑ **132 days** average healthcare wait in Canada

AI Adoption in Canada

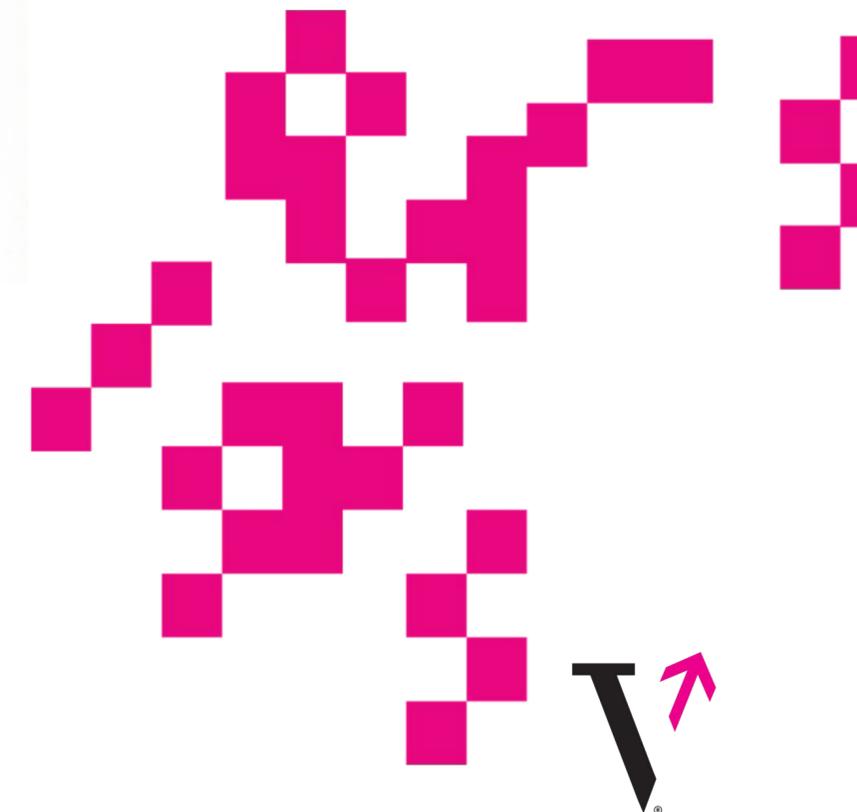


Healthcare Scenario

Healthcare Assessment



*How do we know if the decision wasn't **biased**?*

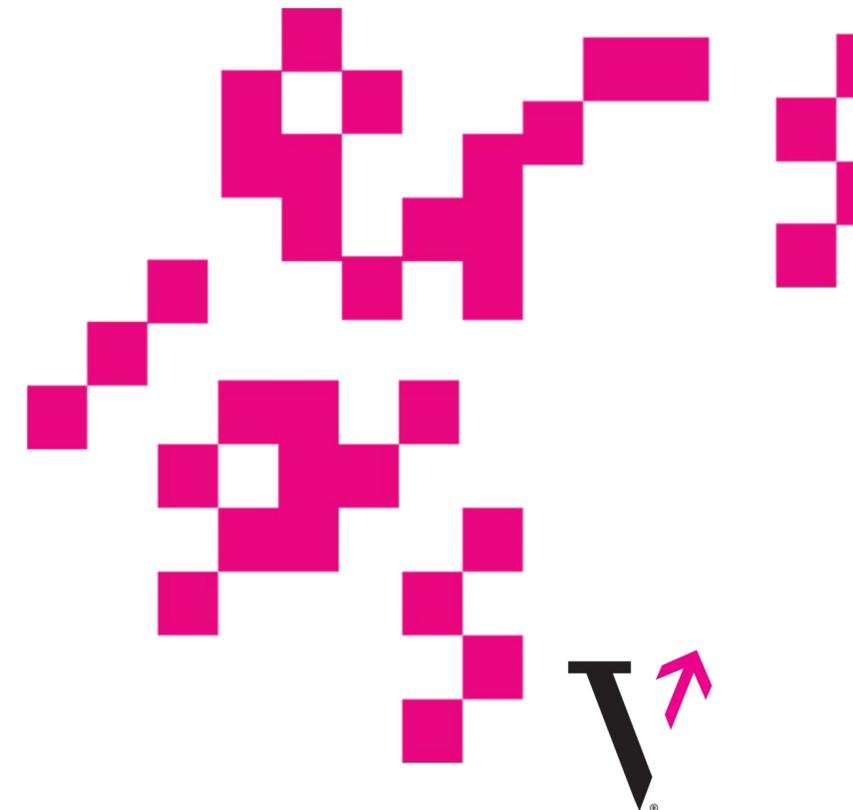


Hiring Scenario

Hiring via AI Video Screening



Can we **trust** if they will hire the best for the role?



2 Years Before (Midjourney)



We've **seen** bias clearly in image models.

For audio-video MLLMs in high-stakes setting **we don't even have the measurement tools.**

Related Work in Responsible AI

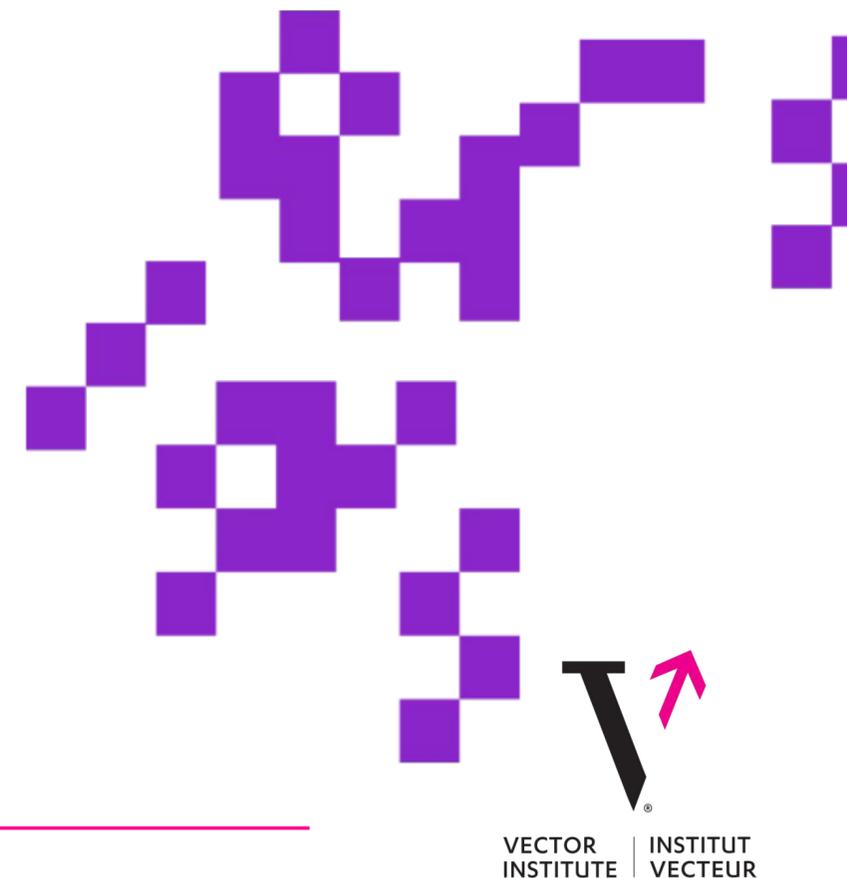
The MIT AI Risk Repository — A Living Framework

- ❑ 1,600 identified AI risks across 43 taxonomies
- ❑ Organized by 7 domains and 23 subdomains
- ❑ Causal taxonomy: Entity, Timing, Intentions
- ❑ Covers risks from bias and fairness to safety and governance

FairSense-AI (Vector Institute)

- ❑ Detects and explains bias in text and images
- ❑ Open-source and maps risks to NIST AI RMF

SONIC-O1 extends responsible AI evaluation into a new frontier — real-world audio-video understanding.



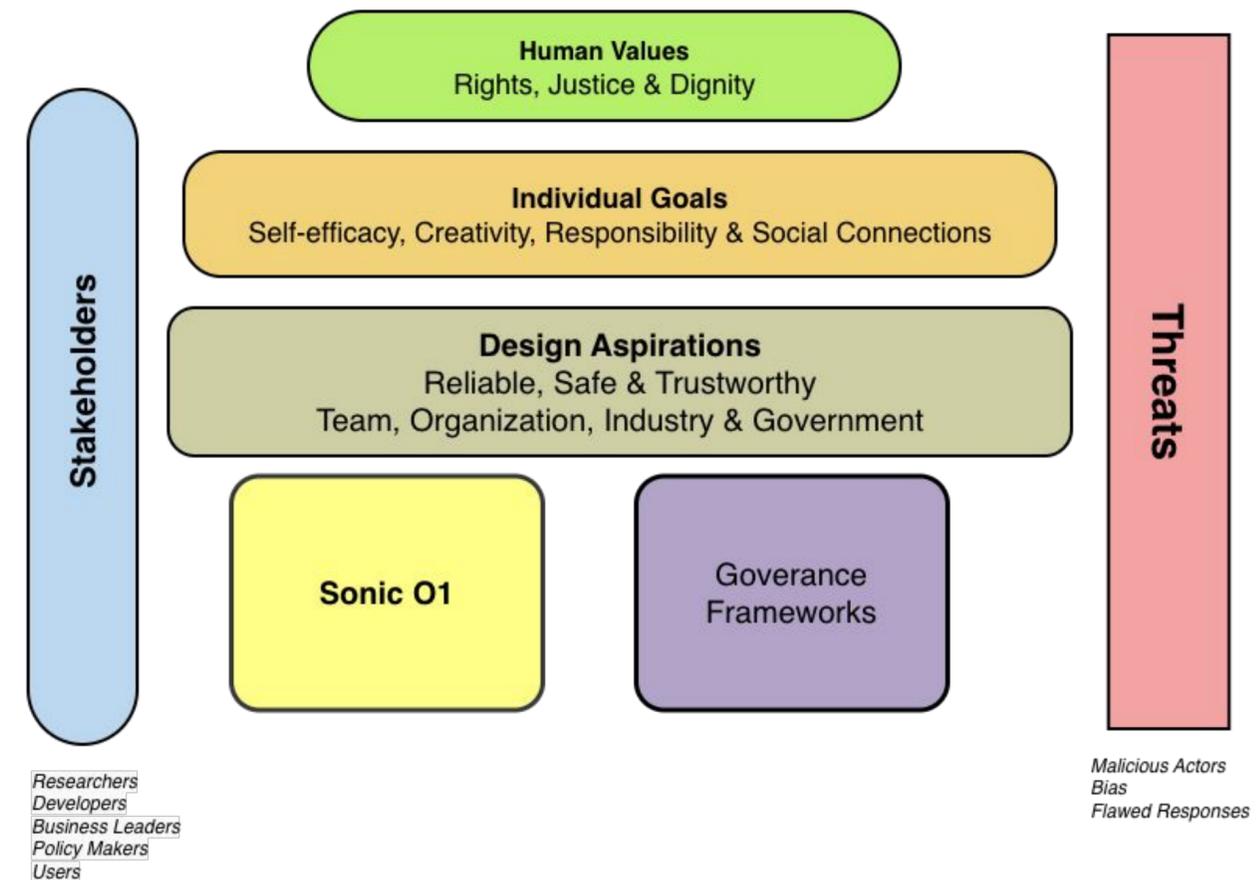
When Audio-Video meets Human-centeredness

But Why?

Human-centred AI means we don't just ask *Is it smart?* we ask *Is it helpful, fair, and safe for real people in real situations?*

(Shneiderman, 2020)

- ❑ We evaluate AI by how it supports people: their **safety, dignity, and worth**
- ❑ Success is measured by real-world impact, not just technical benchmarks or numbers
- ❑ We move from pure **metrics** to **human experience**



If AI evaluate people, we must evaluate AI

That is why we built SONIC-01



Research Questions

1. Temporal Understanding & Coherence

- ❑ Can MLLMs compress hours of interaction into **coherent summaries**?
- ❑ How well do MLLMs track how events unfold over time?

2. Scene-Level Reasoning

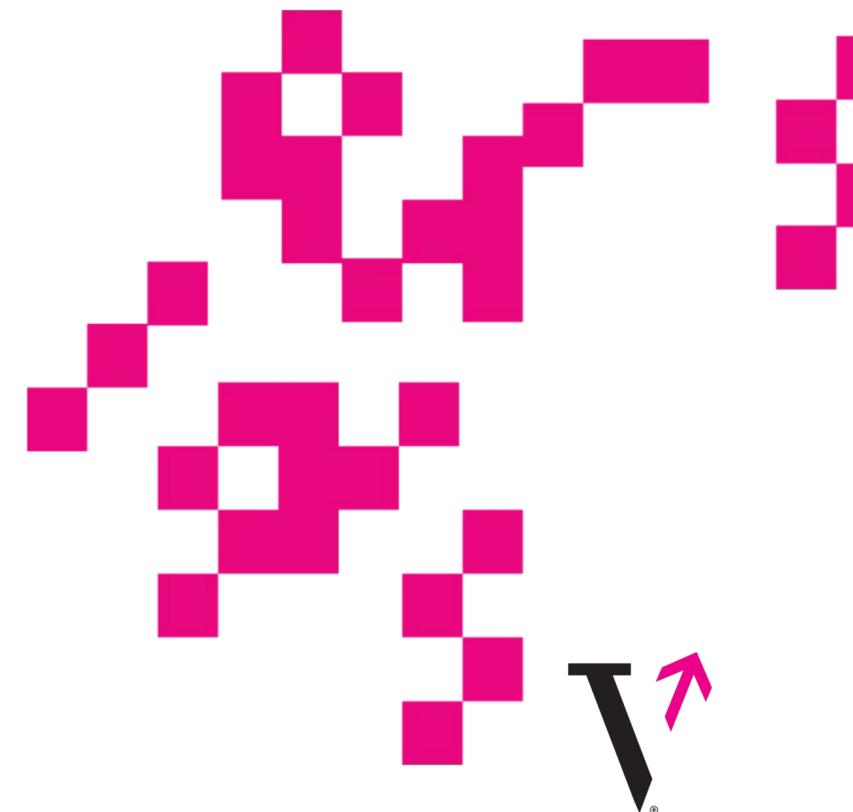
- ❑ Can MLLMs find **when did the action happened** in the video?
- ❑ Do MLLMs correctly **interpret segment-level actions**, objects, and interactions?

3. Social Context & Empathy

- ❑ Can models adapt their phrasing to the **emotional and social context**?

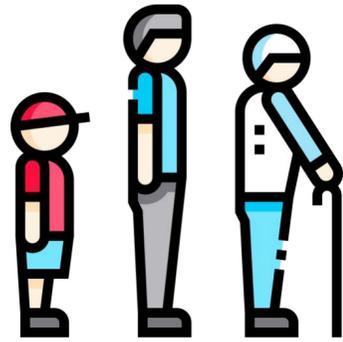
4. Demographic Fairness

- ❑ Do model failures **vary across demographic groups** (race, gender, age)?



Demographics

Different Ages



Misidentifies elderly patient age, affecting health assessment urgency

Different Races



Overlooks qualified minority candidates in job interview summaries

Different Genders



Labels women's complaints as 'emotional' rather than legitimate

SONIC-O1: Audio-Video Understanding Benchmark



1

Covering 13 Topics

2

231 Audio-Video and 4,958 QAs

3

Three Evaluation Tasks

4

Capabilities and Fairness Analysis

SONIC-O1: Audio-Video Understanding Benchmark

Q. Provide a detailed summary about the video content and audio

Answer: This initial segment features Nasser, a final-year medical student from King's College London (KharmaMedic), as he introduces a detailed guide on how to take patient histories effectively. He begins by providing a disclaimer, clarifying the content's educational nature. Nasser then outlines essential steps to take before engaging with a patient, such as understanding the clinical context and establishing rapport. He explains the general structure of a patient history, highlighting the 'ICE' framework (Ideas, Concerns, Expectations) to gain insight into the patient's viewpoint. The segment further elaborates on how to properly approach a patient using the WIPER acronym (Washing hands, Introducing self, Patient details, Exposing, Reposition) and securing verbal consent. Finally, Nasser provides guidance on exploring the 'presenting complaint' and 'history of presenting complaint' by utilizing open-ended questions and mnemonic acronyms like SOCRATES for pain and DOPT for duration, onset, progression, and timing, stressing the importance of summarizing information back to the patient. ...



00:00 *The video features one main male speaker (Nasser), who is visibly White, appears to be in his late 20s or early 30s, and speaks English with a British accent. The transcript confirms he is a 'final year medical student.'. The audio contains only the main speaker's voice.* 15:30

Q. What inconsistency first reveals the receptionist's misleading professional approach to the customer regarding the hotel's services?

- (A) He initially describes luxury amenities but then states they belong to a different hotel.
- (B) He claims all rooms are booked until the customer declines using a discount code.
- (C) He forgets to provide a requested wake-up call, causing the customer to miss a flight.
- (D) He charges the customer's credit card for his personal debts instead of the hotel room.
- (E) Not enough evidence

Answer: A, The receptionist initially details luxurious features like an infinity pool, spa, and Michelin chef-catered food (0:06-0:16). However, he immediately clarifies that these amenities are 'for the hotel next door' (0:18) and tells the customer to 'Find any room that is not full' in *this* hotel (0:21 0:23), marking the first significant misleading professional approach regarding the actual services of the hotel he represents.



00:00 *The segment clearly shows two main male actors (receptionist and customer) who are Asian, appear to be middle-aged, and speak English. Additionally, two other male staff members are visible in the background for a significant portion of the segment, also appearing Asian and middle-aged.* 02:22

Q. After Ryan Sessegnon scores Fulham's goal, when does Antoine Semenyo score Bournemouth's first goal?

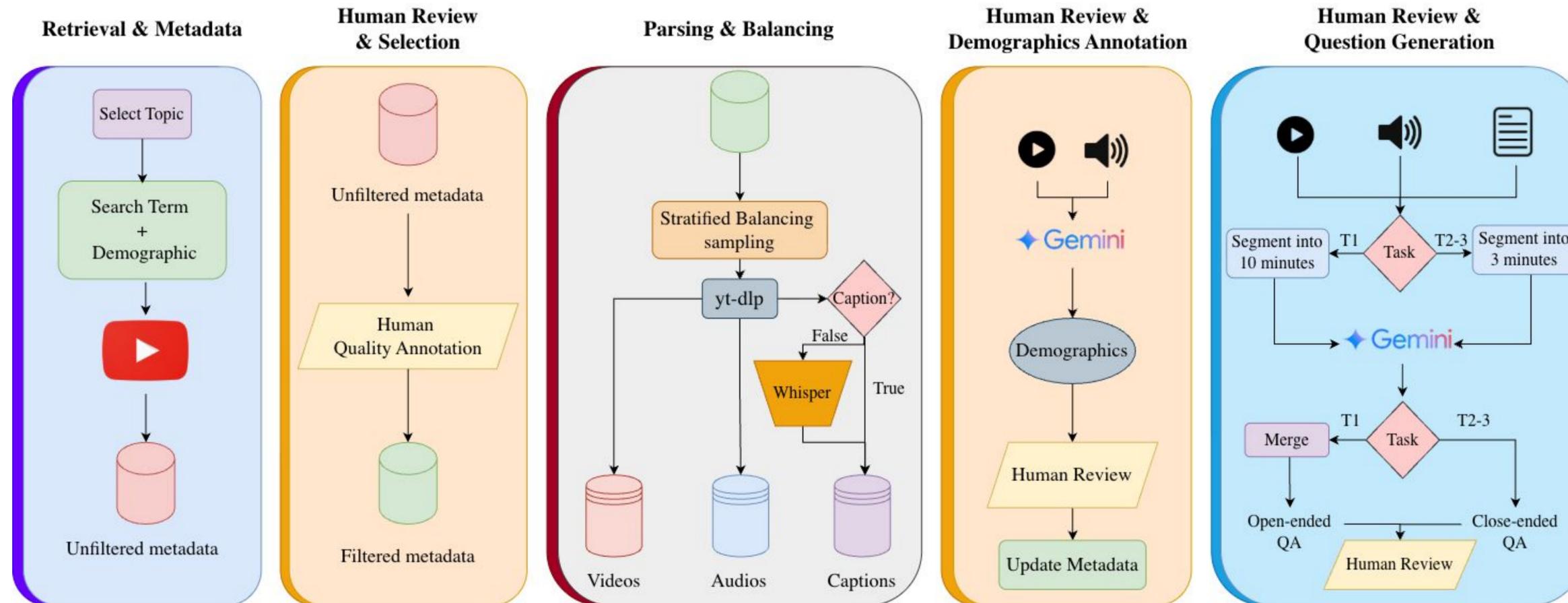
Answer: start_time: 42.9s , end_time 49.0s, E1= Fulham's goal is scored by Ryan Sessegnon at 8.755s (ball hits net). E2=Bournemouth's first goal, scored by Antoine Semenyo, starts at 42.9s (ball hits net) and his celebration ends around 49.0s. Relation is after.



00:00 *The video features a football match with multiple players visible on the field, including both Black and White males. Based on typical player ages, they are categorized as young or middle-aged adults. One male English-speaking commentator is heard, categorized as White, Male, Older adult (40+).* 02:24



Data & Annotation Pipeline



Evaluation Stage

SONIC-O1 Audio-Video Benchmark

Evaluation Metrics

Semantic Alignment - Judge

- ❑ Compare AI summaries to human Summaries

Correctness - Accuracy

- ❑ Answering correctly in multiple-choice questions

Temporal Precision - IoU

- ❑ Can the AI find the correct time of an event happening?

Fairness

- ❑ Performance across demographic groups

Empathy

- ❑ Can the AI adjust it's tone in sensitive situations?

MLLMs

Closed Source

- ❑ Gemini 3.0 Pro

Open Source

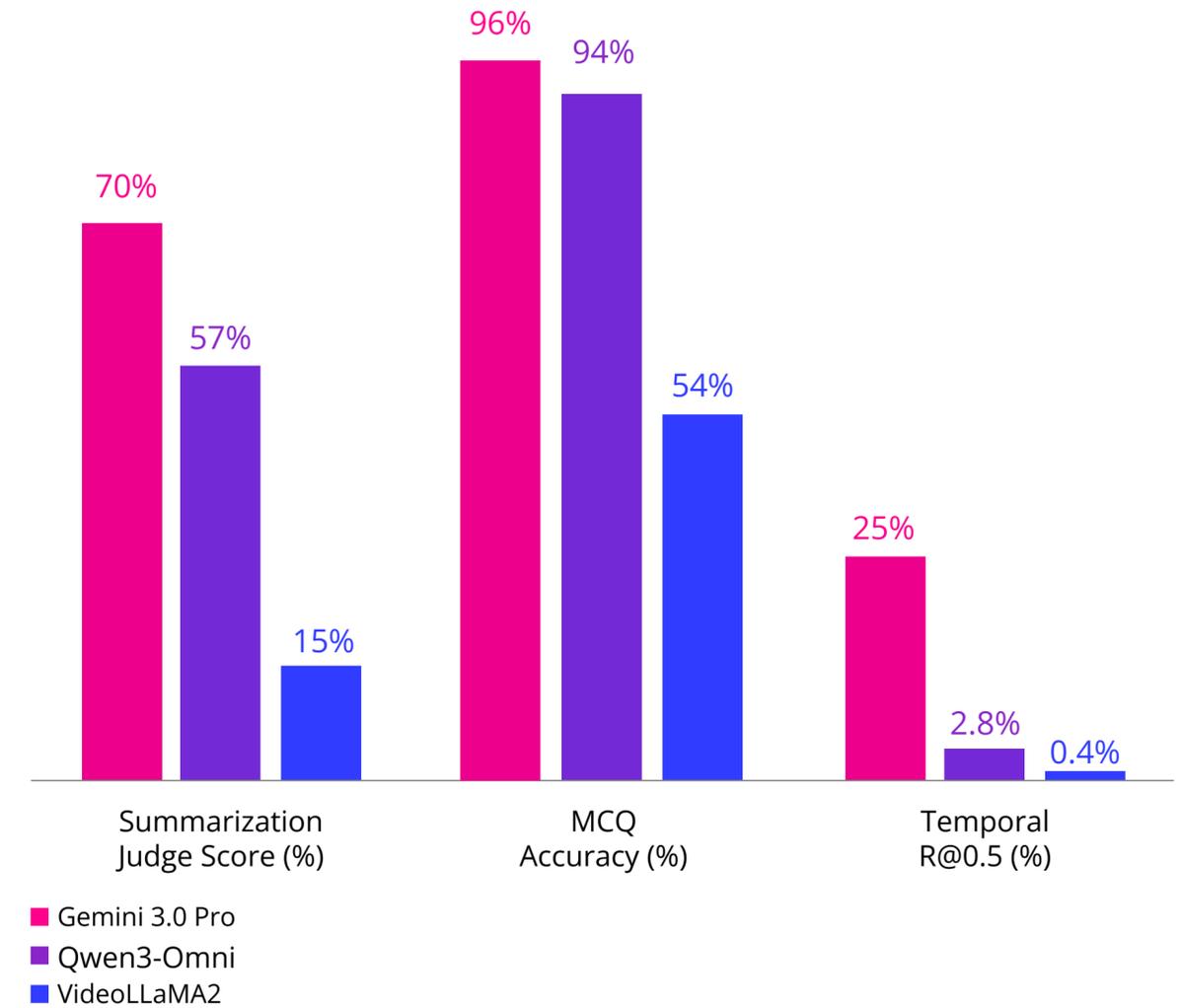
- ❑ Qwen3-Omni
- ❑ Uni-MoE-2.0-Omni
- ❑ Minicpm-o-2.6
- ❑ VITA 1.5
- ❑ VideoLLAMA2

Overall Performance

Models are failing to answer *when?*

- ❑ Closed-source models consistently outperform open-source.
- ❑ Temporal Localization remains challenging.

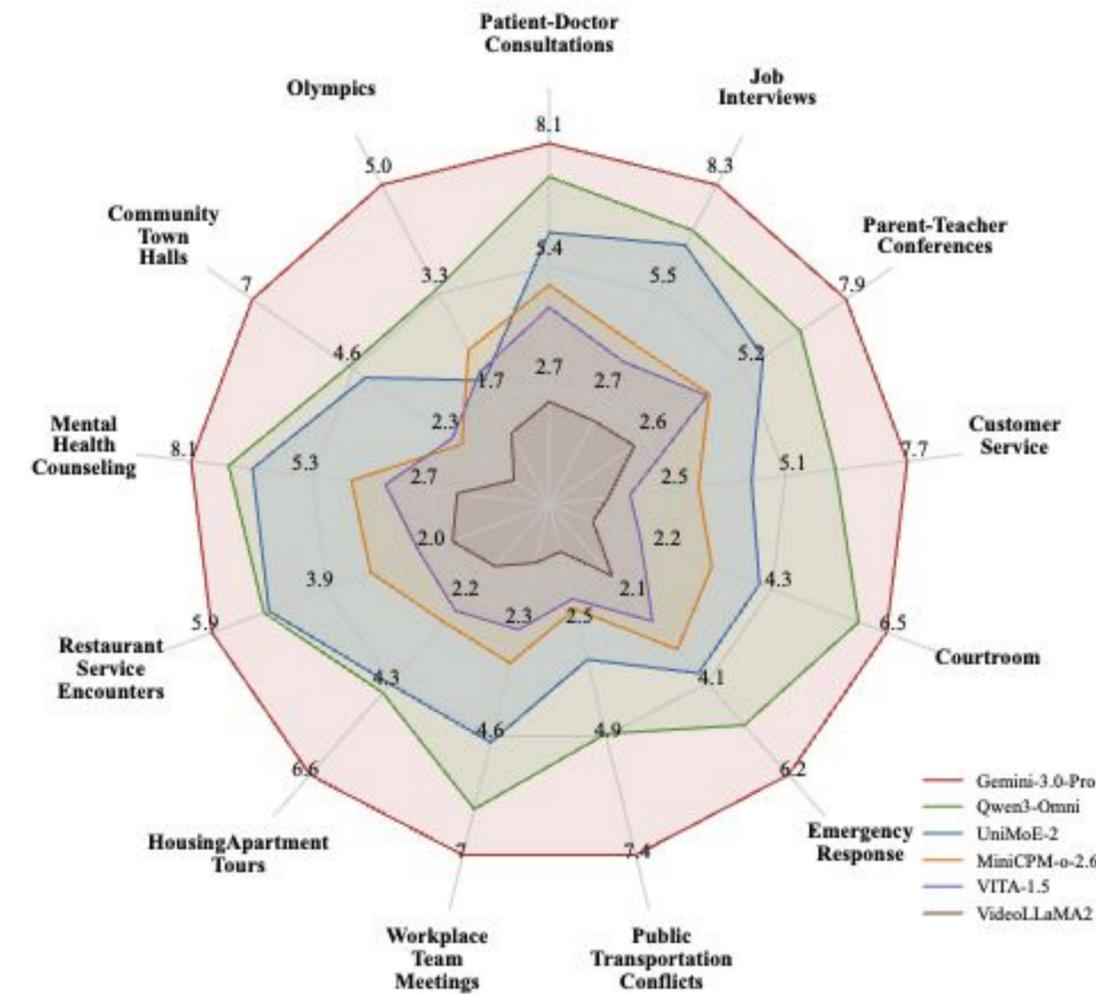
Performance Across Tasks



Per-Topic Performance

High stakes scenarios are *harder*

- ❑ **Structured interactions are easier:** Models excel in formal settings with predictable patterns.
- ❑ **High-stakes scenarios are harder:** Emergency response and mental health counseling show lower scores due to complexity and emotional nuance.



Who gets Left *Behind*?

Summarization Fairness (LLM-as-Judge Score, 0–10)

| Model | White | Black | Asian | Hispanic | Indigenous | Arab | Gap ↓ |
|------------------|-------|-------|-------|----------|------------|------|-------|
| Gemini 3.0 Pro † | 6.68 | 6.02 | 7.05 | 6.41 | 6.70 | 6.90 | 1.03 |
| Qwen3-Omni | 5.28 | 4.39 | 5.71 | 4.99 | 4.13 | 5.95 | 1.82 |
| UniMoE-2.0-Omni | 4.29 | 3.45 | 4.62 | 3.70 | 4.35 | 5.00 | 1.55 |
| MiniCPM-o-2.6 | 3.26 | 2.92 | 3.26 | 3.04 | 3.61 | 3.57 | 0.69 |
| VITA 1.5 | 2.50 | 2.31 | 2.65 | 2.21 | 1.65 | 2.76 | 1.11 |
| VideoLLaMA2 | 1.45 | 1.38 | 1.63 | 1.23 | 1.04 | 1.00 | 0.63 |

- ❑ Black and Indigenous groups consistently score lowest across all models
- ❑ Closed-source models show smaller demographic gaps than open-source alternatives

Who gets Left *Behind*?

MCQ Fairness (Accuracy, %)

| Model | White | Black | Asian | Hispanic | Indigenous | Arab | Gap ↓ |
|------------------|-------|-------|-------|----------|------------|------|-------|
| Gemini 3.0 Pro † | 96.9 | 96.4 | 97.8 | 96.1 | 94.3 | 98.4 | 4.1 |
| Qwen3-Omni | 93.3 | 92.0 | 96.1 | 92.8 | 77.1 | 96.9 | 19.8 |
| UniMoE-2.0-Omni | 88.9 | 87.4 | 89.2 | 85.5 | 80.0 | 95.3 | 15.3 |
| MiniCPM-o-2.6 | 87.5 | 86.3 | 88.7 | 81.6 | 82.9 | 92.7 | 11.1 |
| VITA 1.5 | 82.0 | 82.2 | 84.6 | 79.1 | 62.9 | 93.2 | 30.3 |
| VideoLLaMA2 | 55.1 | 55.0 | 57.9 | 51.0 | 65.7 | 66.0 | 15.0 |

- ❑ Indigenous groups show lowest accuracy (62.9-94.3%) across all models
- ❑ Performance gaps widen in open-source models, indicating training data imbalances

Who gets Left *Behind*?

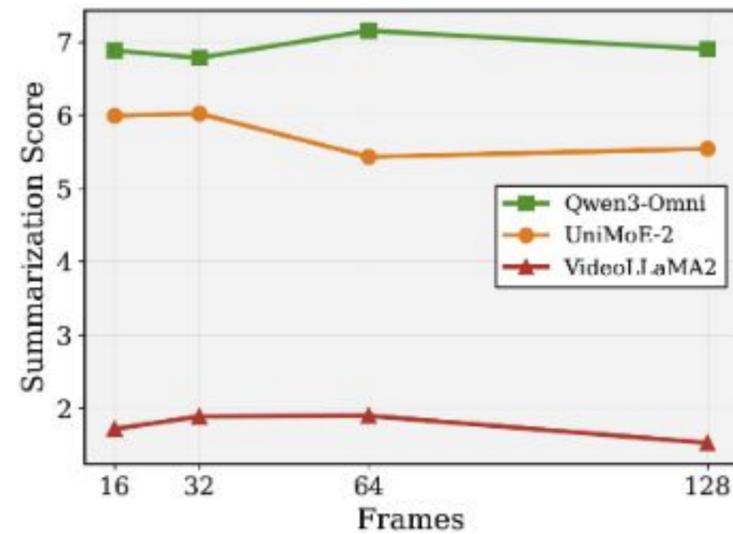
Temporal Localization Fairness (Recall@0.5, %)

| Model | White | Black | Asian | Hispanic | Indigenous | Arab | Gap ↓ |
|------------------|-------|-------|-------|----------|------------|------|-------|
| Gemini 3.0 Pro † | 23.0 | 19.5 | 30.7 | 23.8 | 40.9 | 21.1 | 21.4 |
| Qwen3-Omni | 2.6 | 1.8 | 2.9 | 2.3 | 0.0 | 1.6 | 2.9 |
| UniMoE-2.0 | 1.2 | 0.6 | 0.6 | 0.1 | 1.3 | 0.2 | 1.2 |
| MiniCPM-o-2.6 | 0.9 | 0.3 | 0.8 | 0.2 | 0.0 | 2.6 | 2.6 |
| VITA 1.5 | 1.4 | 1.4 | 1.4 | 0.8 | 1.3 | 1.2 | 0.6 |
| VideoLLaMA2 | 0.5 | 0.3 | 0.4 | 0.0 | 1.3 | 0.0 | 1.3 |

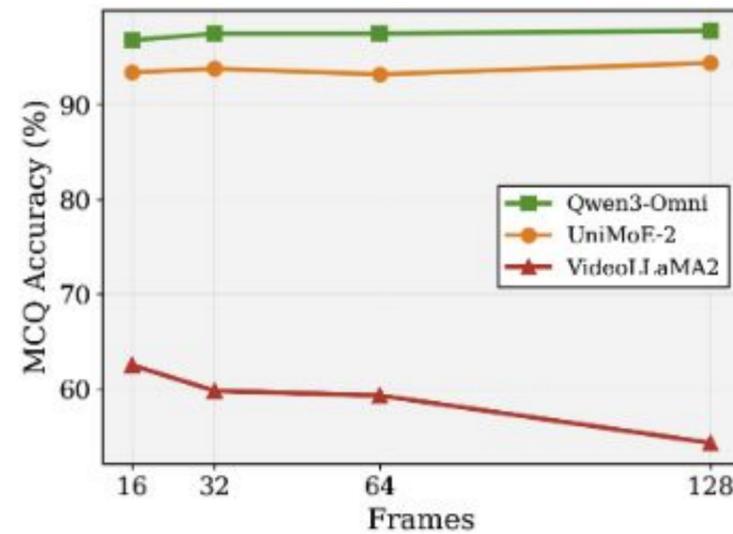
- ❑ 21% Gap Across Racial Groups.
- ❑ Open-Source Models are collapsing.
- ❑ The Gap Extends to Gender and Age Groups.

Does more Frames Help Performance?

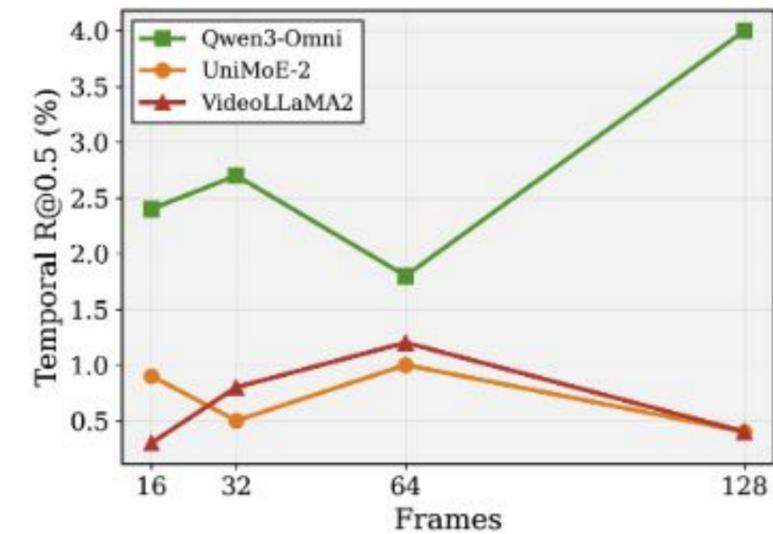
- ❑ **Higher frame** counts primarily **benefit temporal localization only**
- ❑ **Summarization and MCQ tasks** show **minimal gains** with more frames
- ❑ **Stronger models** (Qwen3-Omni) **benefit more from dense visual coverage** than weaker models



(a) Summarization Score



(b) MCQ Accuracy



(c) Temporal R@0.5

Do MLLMs Express empathy?

| Model | Total Emotion (%) | Neg. Emotion (%) | Tone |
|----------------|-------------------|------------------|-------|
| Gemini 3.0 Pro | 4.35 | 2.03 | 46.16 |
| Qwen3-Omni | 3.88 | 1.39 | 56.99 |
| UniMoE-2.0 | 3.54 | 0.93 | 57.94 |
| MiniCPM-o-2.6 | 1.41 | 0.38 | 46.10 |
| VITA 1.5 | 2.65 | 0.59 | 55.45 |
| VideoLLaMA2 | 2.02 | 0.49 | 49.83 |

- ❑ Gemini: high emotional validation with formal tone; UniMoE-2.0: warm tone with lower emotional intensity
- ❑ Smaller models fail at empathic modulation, defaulting to detached clinical descriptions

Key Findings

Open-Source Models are still Behind with **23% performance gap** in temporal localization

Black and **Indigenous** groups show lower performance

Female and **40+ Age** group score higher consistently

High-stakes scenarios (Emergency Response and Mental Health) **are more challenging**

We built a **mirror** for AI — and what it reflected back should concern all of us

SONIC-01 Audio-Video Benchmark



What is AIXPERT

AIXPERT is an international research initiative funded by the European Union's Horizon Europe programme and the Swiss State Secretariat for Education, Research and Innovation (SERI).

Our mission is to make AI smarter, safer, and more trustworthy across critical sectors such as healthcare, human resources, manufacturing, robotics, and the creative industries.

- Build an adaptable, explainable AI-agentic platform
- Define and assess AI trustworthiness
- Advance explainable multimodal foundation models
- Demonstrate real-world impact through pilot use cases (healthcare, recruitment, educational robotics, manufacturing and creative arts)

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