Measuring Attentiveness Across Workplace Environments

Bhavi, Divith Narendra, Shaurya Mann

problem statement

Analyzing attentiveness across different environments metrics during decision-making tasks.

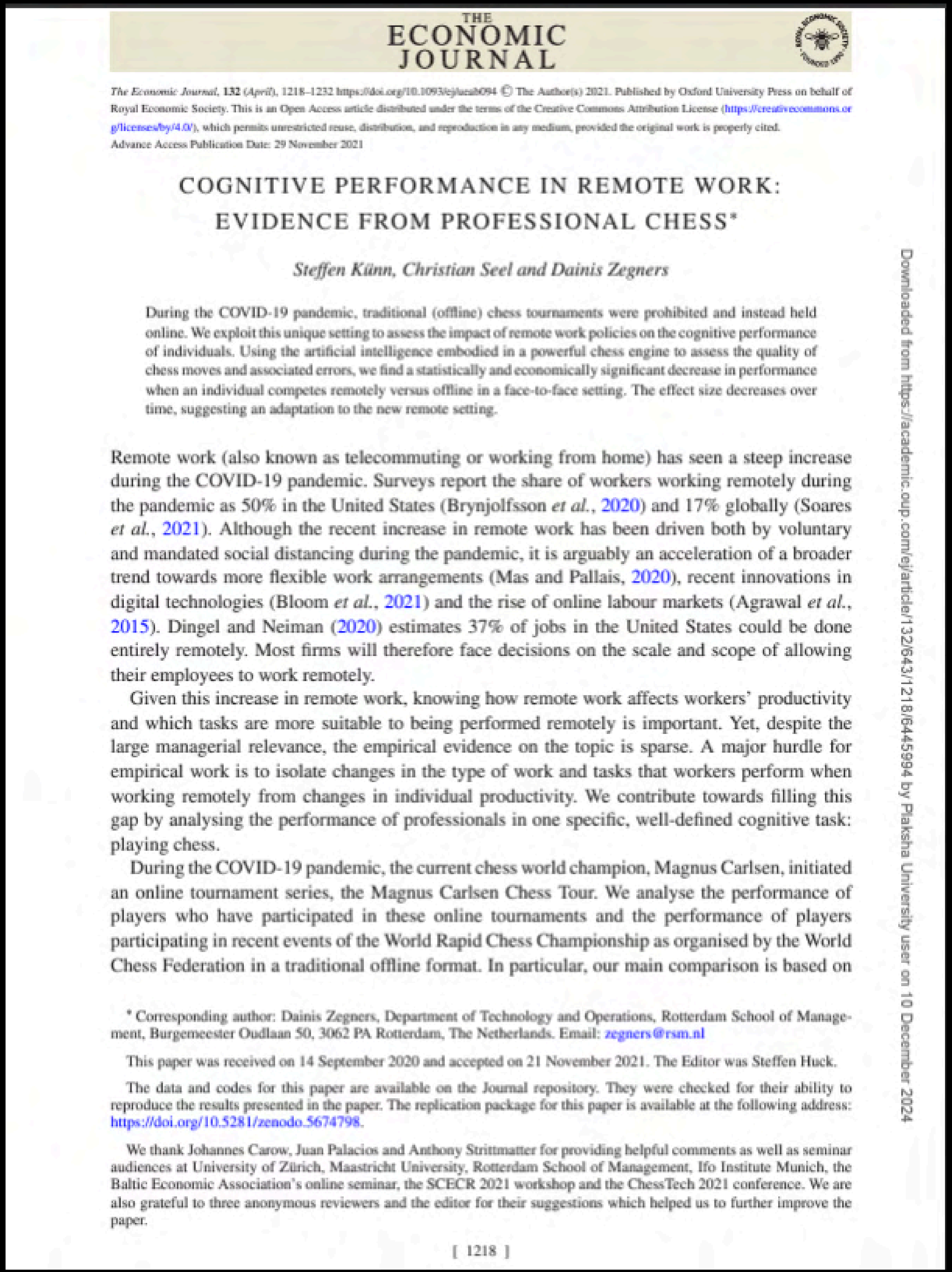
contribution

Our study builds on existing literature by leveraging HTI to validate their findings by tracking physiological metrics for attentivness which enhances generalization across different fields.

We foresee an adoption of this metric to assess broader impact of social media and provide validation for the same.

Literature Review

Remote vs In-Person



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COGNITIVE PERFORMANCE IN REMOTE WORK: EVIDENCE FROM PROFESSIONAL CHESS*

Steffen Künn, Christian Seel and Dainis Zegners

During the COVID-19 pandemic, traditional (offline) chess tournaments were prohibited and instead held online. We exploit this unique setting to assess the impact of remote work policies on the cognitive performance of individuals. Using the artificial intelligence embodied in a powerful chess engine to assess the quality of chess moves and associated errors, we find a statistically and economically significant decrease in performance when an individual competes remotely versus offline in a face-to-face setting. The effect size decreases over time, suggesting an adaptation to the new remote setting.

Remote work (also known as telecommuting or working from home) has seen a steep increase during the COVID-19 pandemic. Surveys report the share of workers working remotely during the pandemic as 50% in the United States (Brynjolfsson *et al.*, 2020) and 17% globally (Soares *et al.*, 2021). Although the recent increase in remote work has been driven both by voluntary and mandated social distancing during the pandemic, it is arguably an acceleration of a broader trend towards more flexible work arrangements (Mas and Pallais, 2020), recent innovations in digital technologies (Bloom *et al.*, 2021) and the rise of online labour markets (Agrawal *et al.*, 2015). Dingel and Neiman (2020) estimates 37% of jobs in the United States could be done entirely remotely. Most firms will therefore face decisions on the scale and scope of allowing their employees to work remotely.

Given this increase in remote work, knowing how remote work affects workers' productivity and which tasks are more suitable to being performed remotely is important. Yet, despite the large managerial relevance, the empirical evidence on the topic is sparse. A major hurdle for empirical work is to isolate changes in the type of work and tasks that workers perform when working remotely from changes in individual productivity. We contribute towards filling this gap by analysing the performance of professionals in one specific, well-defined cognitive task: playing chess.

During the COVID-19 pandemic, the current chess world champion, Magnus Carlsen, initiated an online tournament series, the Magnus Carlsen Chess Tour. We analyse the performance of players who have participated in these online tournaments and the performance of players participating in recent events of the World Rapid Chess Championship as organised by the World Chess Federation in a traditional offline format. In particular, our main comparison is based on

* Corresponding author: Dainis Zegners, Department of Technology and Operations, Rotterdam School of Management, Burgemeester Oudlaan 50, 3062 PA Rotterdam, The Netherlands. Email: zegners@rsm.nl

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The data and codes for this paper are available on the Journal repository. They were checked for their ability to reproduce the results presented in the paper. The replication package for this paper is available at the following address: https://doi.org/10.5281/zenodo.5674798.

We thank Johannes Carow, Juan Palacios and Anthony Strittmatter for providing helpful comments as well as seminar audiences at University of Zürich, Maastricht University, Rotterdam School of Management, Ifo Institute Munich, the Baltic Economic Association's online seminar, the SCECR 2021 workshop and the ChessTech 2021 conference. We are also grateful to three anonymous reviewers and the editor for their suggestions which helped us to further improve the paper.

Validates the Use of Chess

The study helped us in validating the utilization of chess for the experiment protocol by identifying an increase in cognitive load while playing chess.

Online vs Offline Debate

Players made more errors when playing online, with an average increase in error magnitude of 1.7% compared to offline settings.

Increased Adaptation

The adverse impact of playing online diminished over successive tournaments, indicating players adapted to remote settings.

Elite Population Pool

High ELO rated players competing across different platforms and peer effects failed to be considered.

computer vision methodologies to measure attentiveness

There have been many studies using Eye Gaze [1], Facial Expressions [2], and Head Pose [3] individually for estimating attentiveness.

here, we see literature using all 3 to measure attentiveness using video data

[1] Huang, D., Yu, Y., Fu, Y., & Huang, T. S. (2013). Detecting user engagement with direct gaze estimation. In 2013 IEEE International Conference on Multimedia and Expo (ICME) (pp. 1-6). IEEE.
[2] Li, Y., Liu, H., & Zhang, C. (2018). Automatic recognition of student engagement using facial expression analysis. IEEE Transactions on Affective Computing, 9(2), 217-228.
[3] Doshi, A., & Trivedi, M. M. (2009). Real-time head pose estimation for driver attention monitoring. In 2009 IEEE Intelligent Vehicles Symposium (pp. 905-910). IEEE.

computer vision

Develop an intelligent, real-time, vision-based system that monitors and evaluates students' behavior, attention levels, and emotions in the classroom.
YOLOv5 to monitor engagement using:

- action/behavioral data that they label, followed by training
- emotional recognition model on both masked and unmasked faces using AffectNet dataset

Results:
1.action/behviour: eating food- highest mAP of 0.92, reading book- lowest mAP of 0.689
2. emotion recognition- Happy: mAP = 0.942 Surprised: mAP= 0.948 (highest) Neutral: mAP = 0.743 (lowest)

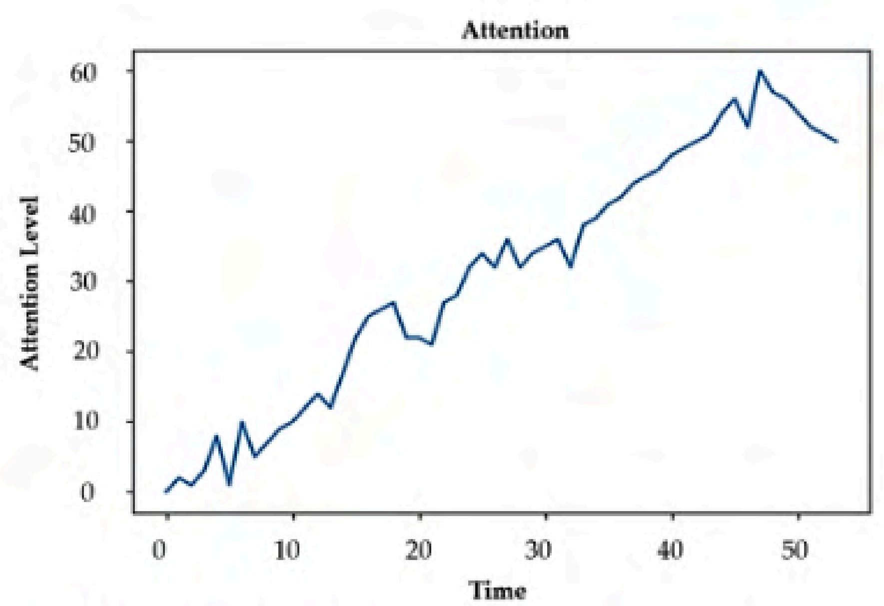


Figure 15. Attention level of student 2 is plotted on the graph.

A	B	C	D	E
Student	Action/Behaviour detected	Attention State	Emotions	Time
Student 1	Focused	Attention	Happy	13:10:22
Student 2	Focused	Attention	Happy	13:10:22
Student 3	Bored	No attention	Sad	13:10:22
Student 4	Raising hand	Attention	Neutral	13:10:22
Student 5	Using Phone	No attention	Neutral	13:10:22
Student 6	Focused	Attention	Sad	13:10:22
Student 7	Using Phone	No attention	Neutral	13:10:22

Figure 16. Student information is saved in a CSV format.

A	B	C	D
Date	Time	Lecture/Code	Student
12.02.2022	13:08:02	Computer Networks(CN-0200D)	NCB002
12.02.2022	13:08:03	Computer Networks(CN-0200D)	NCB003
12.02.2022	13:08:03	Computer Networks(CN-0200D)	NCB004
12.02.2022	13:08:03	Computer Networks(CN-0200D)	NCB005
12.02.2022	13:08:04	Computer Networks(CN-0200D)	NCB006
12.02.2022	13:08:04	Computer Networks(CN-0200D)	NCB007
12.02.2022	13:08:05	Computer Networks(CN-0200D)	NCB008
12.02.2022	13:08:05	Computer Networks(CN-0200D)	NCB009

Figure 17. Student attendance data is saved in a CSV format.

Using both these, the final attentiveness score is computed

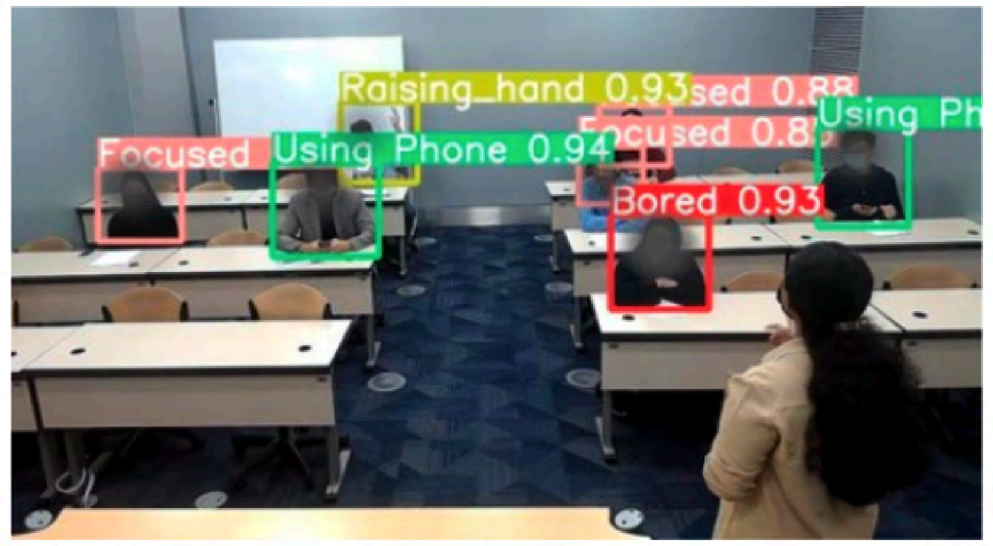


Figure 9. Classroom setup for experimentation on seven students. Each student's action is detected and color-coded. Three students are focused, two are using their phones, one is bored, and the other is raising his/her hand.

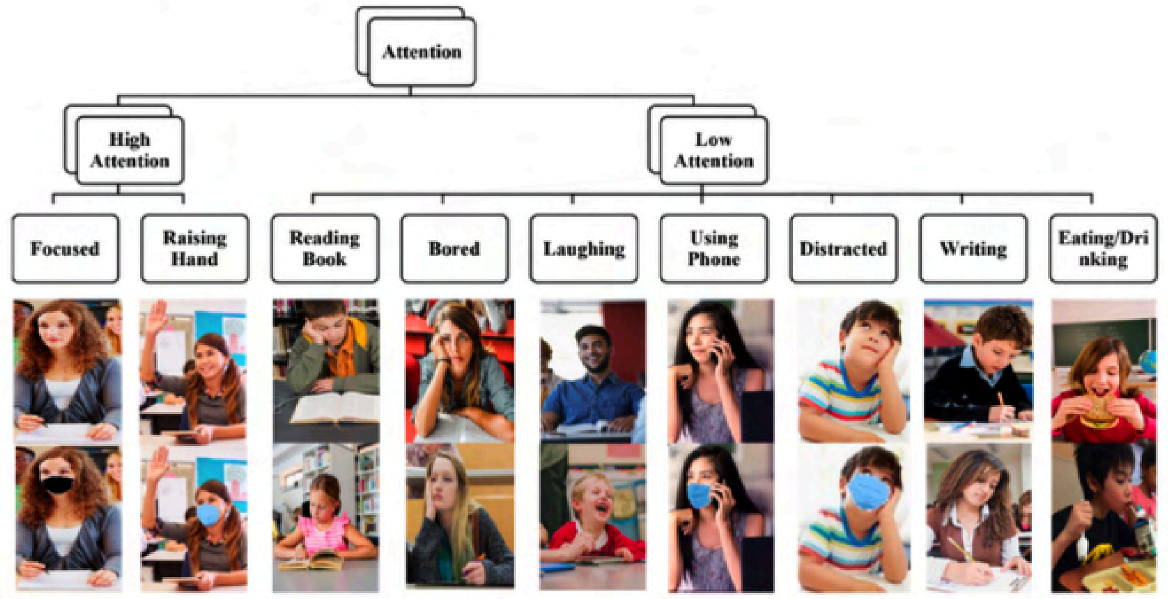


Figure 2. Classification of action/behavior based on attention.

Trabelsi, Z., Alnajjar, F., Parambil, M. M. A., Gochoo, M., & Ali, L. (2023). Real-time attention monitoring system for classroom: A deep learning approach for student's behavior recognition. Big Data and Cognitive Computing, 7(48). https://doi.org/10.3390/bdcc7010048

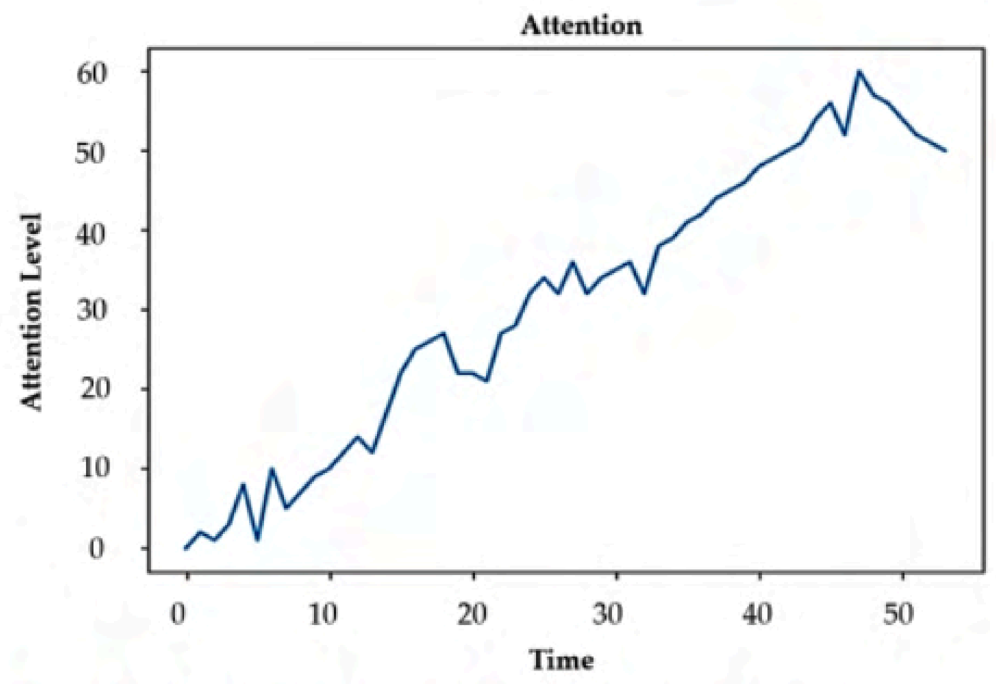
Real-Time Attention Monitoring System for Classroom: A Deep Learning Approach for Student’s Behavior Recognition

Final Attentiveness Score:

- The attentiveness score for each student is updated based on the combination of actions and emotions. The system assigns an initial score and adjusts it throughout the lecture. The final attentiveness score can range from 0 to 100, where:
  - 100 indicates maximum attentiveness (high-attention actions combined with positive emotions).
  - 0 indicates no attentiveness (low-attention actions combined with negative emotions).
- The system continuously tracks each student's behavioral actions and emotions, incrementing or decrementing the score as the student displays certain behaviors or emotions.

Example:

- If a student is focused on the instructor and displays a happy or neutral emotion, their attentiveness score increases. For example, if the score starts at 50, the system might add 10 points for each high-attention behavior detected, raising the score to 60, 70, or higher.
- If the student becomes distracted (e.g., uses their phone) and shows signs of boredom or frustration, the score might decrease by 10 or more points for each detected instance, lowering the score.



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12.02.2022	13:08:03	Computer Networks(CN-0200D)	NCB004
12.02.2022	13:08:03	Computer Networks(CN-0200D)	NCB005
12.02.2022	13:08:04	Computer Networks(CN-0200D)	NCB006
12.02.2022	13:08:04	Computer Networks(CN-0200D)	NCB007
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12.02.2022	13:08:05	Computer Networks(CN-0200D)	NCB009

Figure 17. Student attendance data is saved in a CSV format.

shortcomings

Limited Population

Comprised of a pool that was mainly players with a relatively significant ELO rating which limits it’s generalization across a broad population.

Econometric Analysis

Primarily using varieties of regressions which fail to account for physiological effects and generalization across populations.

Peer Effects Misaccounted

Studies fail to accommodate the ‘streamer effect’. Most players from the Magnus Carlsen Tour was a hybrid tournament..

Selection Bias within Productivity

The study's productivity measure is skewed by selection effects; better players remain active longer, inflating older age groups' productivity metrics.

EXPERIMENTAL DESIGN

SETUP

Baseline

1. A non decision making task- watching Youtube for each subject → 3 trials per person
2. We are able to provide a tentative starting point.
3. Limit to 3 minutes.

Chess

1. We control for difficulty selecting players across all ELO ratings (800-1800).
2. 3 trials per environment collect for 10 subjects.
3. Trial → 3 min blitz.
   a. Online Game of Chess
   b. Offline Game of Chess

Meetings

1. A 10 min time constraint.
2. 6 subjects considered for the trials.
3. Two trials per subject conducted per environment
   a. Online Meetings
   b. Offline.

ethics

1. Informed Consent
2. Voluntary Participation
3. Data Retention Policy - EoS
4. Non-invasive setups
5. Debriefing and Transparency.
6. Consent Surveys.
7. Minimizing Experimental Bias

Chess Game Data

Please note this will be your experimental setup:

Location: Quiet and well-lit indoor space with minimal distractions.
Lighting:
Ensure uniform lighting on the participant's face (no strong shadows or backlighting).
Position the light source in front of the participant, slightly above the eye level.
Chair and Desk: Provide a stable chair and desk to keep the participant steady during recording.

Guidelines on Setup:
Camera Placement:
Place the laptop camera at eye level and centered to the participant's face.
Maintain a distance of 50-70 cm (20-30 inches) from the camera.
Framing:
Ensure the participant's face occupies at least 70% of the frame.
Include the upper shoulders for better context in head pose estimation.
Orientation:
The participant should face the camera directly, with minimal head movement.

Section 1 ...

1. We would like you to play a few games of chess. This is the following format. - 3 games of online chess [A combination of Engine vs Players]- 3 games of offline chess. [Matchmaking against other trials within the study]- Baselines.
   Do you consent?

   Enter your answer

2. Did the match end with win/loss/draw?

   Enter your answer

3. We promise to maintain the sanctity of your data and ensure it's safe erasure at the end of the semester. Do you consent?

   Enter your answer

4. We will be utilizing your face data (a visual medium) to conduct experiments in order to contribute to a growing body of literature. Do you consent?

   Enter your answer

PROTOCOL

Environment

Location: Quiet and well-lit indoor space with minimal distractions.

Lighting:

- Ensure uniform lighting on the participant's face (no strong shadows or backlighting).
- Position the light source in front of the participant, slightly above the eye level.

Chair and Desk: Provide a stable chair and desk to keep the participant steady during recording.

Framing and Orientation

Camera Placement:

- Place the laptop camera at eye level and centered to the participant's face.
- Maintain a distance of 50-70 cm (20-30 inches) from the camera.

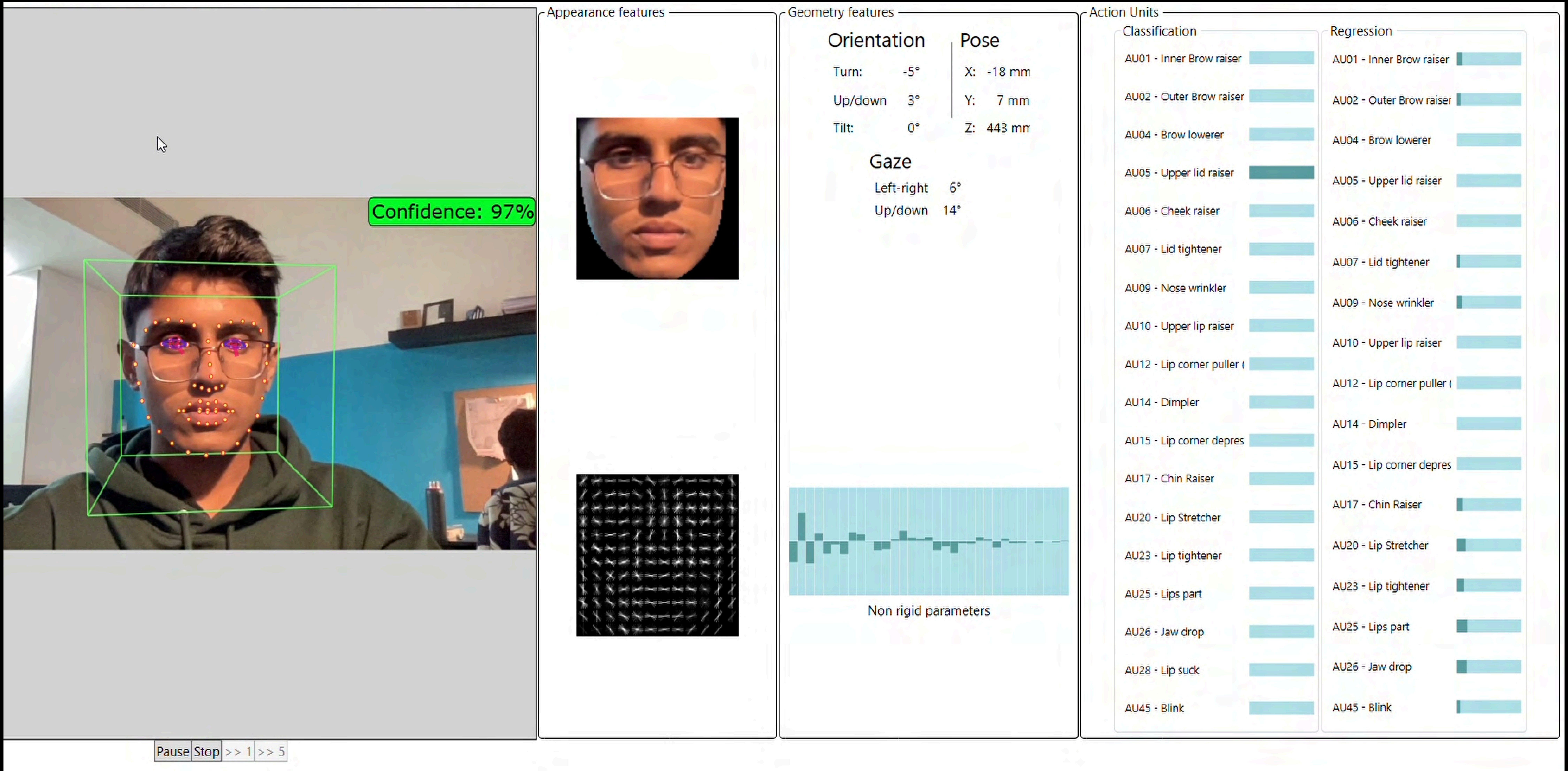
- Framing:
  - Ensure the participant's face occupies at least 70% of the frame.
  - Include the upper shoulders for better context in head pose estimation.
- Orientation:
  - The participant should face the camera directly, with minimal head movement.

Anshul - Offline Chess

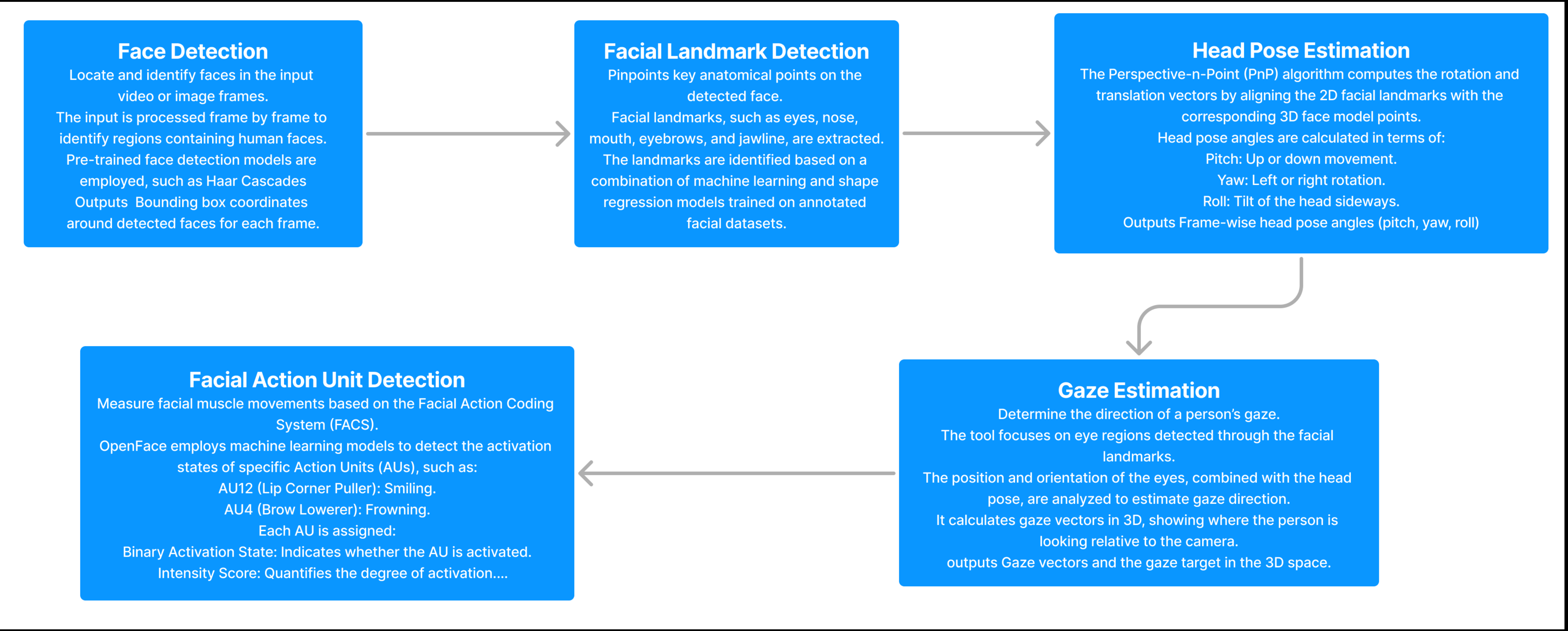
Khushi - Offline Meeting

Sanidhya - Online Chess

Suhani - Online Meeting


Confidence: 97%
Appearance features
Geometry features
Orientation
Turn: -5°
Up/down 3°
Tilt: 0°
Pose
X: -18 mm
Y: 7 mm
Z: 443 mm
Gaze
Left-right 6°
Up/down 14°
Non rigid parameters
Action Units
Classification
Regression
AU01 - Inner Brow raiser
AU02 - Outer Brow raiser
AU04 - Brow lowerer
AU05 - Upper lid raiser
AU06 - Cheek raiser
AU07 - Lid tightener
AU09 - Nose wrinkler
AU10 - Upper lip raiser
AU12 - Lip corner puller
AU14 - Dimpler
AU15 - Lip corner depres
AU17 - Chin Raiser
AU20 - Lip Stretcher
AU23 - Lip tightener
AU25 - Lips part
AU26 - Jaw drop
AU28 - Lip suck
AU45 - Blink
Pause
Stop
>> 1
>> 5

openface overview



FEATURES:

Gaze Features:

- Gaze Angles
  - gaze_angle_x: Horizontal gaze angle.
  - gaze_angle_y: Vertical gaze angle.

Head Pose Features:

- Pose Rotation: Measures head orientation.
  - pose_Rx, pose_Ry, pose_Rz: Rotation angles (roll, pitch, yaw).

Facial Action Units (FAUs):

- Presence Scores: Binary values indicating activation (1 = active, 0 = inactive).

SENSOR:

- Camera: Any RGB camera or webcam to record the facial video input.

BIOMARKERS:

- Eye Movement Biomarkers: gaze angles
- Facial Expressions: FAUs measure facial muscle activity
- Head Orientation: Pose rotation
- Temporal Dynamics: Frame-by-frame variations in gaze, pose, and FAUs

LANDMARKS:

- Eyes
- Eyebrows
- Nose
- Mouth
- Jawline

FPS

ended up using 13 frames per second - total 7800 for meetings, 4680 for chess, 2340 for baseline

FAUs

FAU	Description	Threshold	Reference
AU1	Inner Brow Raiser	Active (AU1_c == 1)	Shao et al. (2017) (arXiv)
AU2	Outer Brow Raiser	Active (AU2_c == 1)	Hutt et al. (2018) (ACM)
AU4	Brow Lowerer	Active (AU4_c == 1)	Whitehill et al. (2021) (Frontiers)
AU5	Upper Lid Raiser	Active (AU5_c == 1)	Ekman & Friesen (1978) (FACS)
AU7	Lid Tightener	Active (AU7_c == 1)	Baltrusaitis et al. (2017) (arXiv)
AU25	Lips Part	Active (AU25_c == 1)	Essa & Pentland (2004) (Springer)
AU45	Blink	Active (AU45_c == 1)	Nakano et al. (2013) (Nature)

Shao, Z., Zhou, Y., Cai, J., & Zhu, H. (2017). Automatic Analysis of Facial Action Units for Affect Recognition.

Hutt, S., Mills, C., White, S., Donnelly, P. J., & D'Mello, S. K. (2018). The Eyes Have It: Gaze-based Detection of Mind Wandering During Learning with an Intelligent Tutoring System. In Proceedings of the 2018 ACM CHI Conference on Human Factors in Computing Systems (CHI 2018).

Whitehill, J., Serpell, Z., Lin, Y. C., Foster, A., & Movellan, J. R. (2021). Inferring Learning Engagement from Affective and Behavioral Cues in an Intelligent Tutoring System. Frontiers in Artificial Intelligence.

Ekman, P., & Friesen, W. V. (1978). Facial Action Coding System (FACS). Consulting Psychologists Press.

Baltrusaitis, T., Robinson, P., & Morency, L. P. (2017). OpenFace: An Open Source Facial Behavior Analysis Toolkit.

Essa, I., & Pentland, A. (2004). Facial Expression Recognition Using Support Vector Machines. Springer Advances in Neural Information Processing Systems.

Nakano, T., Yamamoto, T., & Kitajo, K. (2013). Blinking is Believing: Blink Synchronization Influences Human Attentiveness. Nature Scientific Reports.

Pose and Gaze data

Gaze Ranges:

1. gaze_angle_x:
   - Radians: −0.44 to 0.45
   - Degrees: −25.21° to 25.76°
2. gaze_angle_y:
   - Radians: −0.80 to 0.26
   - Degrees: −45.84° to 14.90°

Pose Ranges:

1. pose_Rx (Pitch):
   - Radians: −0.80 to 0.09
   - Degrees: −45.84° to 5.15°
2. pose_Ry (Roll):
   - Radians: −0.12 to 0.12
   - Degrees: −6.87° to 6.87°
3. pose_Rz (Yaw):
   - Radians: −0.65 to 0.61
   - Degrees: −37.24° to 34.96°

Dataset Overview

frame	face_id	timestamp	confidenc	success	gaze_angl	gaze_angl	AU01_c	AU02_c	AU04_c	AU05_c	AU06_c	AU07_c	AU09_c	AU10_c	AU12_c	AU14_c	AU15_c	AU17_c	AU20_c	AU23_c	AU25_c	AU26_c	AU28_c	AU45_c
1	0	0	0.98	1	0.082	0.398	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0.033	0.98	1	0.076	0.371	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3	0	0.067	0.98	1	0.094	0.334	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
4	0	0.1	0.98	1	0.087	0.298	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0.133	0.98	1	0.102	0.285	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0.167	0.98	1	0.12	0.325	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0.2	0.98	1	-0.019	0.188	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0.234	0.98	1	0.054	0.038	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Computing Attention

```
attentive = (gaze_angle_x in [-0.44, 0.45]) and \
        (gaze_angle_y in [-0.80, 0.26]) and \
        (pose_Rx in [-0.80, 0.09]) and \
        (pose_Ry in [-0.12, 0.12]) and \
        (pose_Rz in [-0.65, 0.61]) and \
        (AU1_c == 1 or AU2_c == 1 or AU4_c == 1 or AU5_c == 1 or AU7_c == 1 or AU25_c == 1 or AU45_c == 1)
```

OUTPUT:

each frame is assigned attentive (1) or not attentive (0)

Key Metrics

A two-fold measure of performance metrics was provided at the behest of extensive discussion and deliberation. We aim to propose the measure of attentiveness as a representation of either - a proportion of time during which these combination of AUs activations.

Baseline

43.64%

Chess

online- 71.18%
offline- 87.3%

Meetings

online- 56.8%
offline - 73.2%

deployable Metrics

Mean Attention Across Condition

$$\text{Mean Attention Across Conditions} = \frac{\text{Sum of Attention Percentages Across All Conditions}}{\text{Number of Conditions}}$$

Calculates the average attention percentage across multiple experimental conditions, such as online and offline tasks.

Relative Increase (Offline vs. Online):

$$\text{Relative Increase (Offline vs. Online)} = \frac{\text{Offline Attention} - \text{Online Attention}}{\text{Online Attention}} \times 100$$

Measures the percentage increase in attentiveness in offline settings compared to online settings for a specific task

Overall Percentage Change (Offline vs. Online)

Determines the overall difference in mean attention between offline and online conditions across all tasks.

$$\text{Overall Percentage Change (Offline vs. Online)} = \frac{\text{Mean Offline Attention} - \text{Mean Online Attention}}{\text{Mean Online Attention}} \times 100$$

Deployable Metrics

Attention Difference (Decision-Making vs. Baseline)

Quantifies the relative increase in attention for decision-making tasks compared to a neutral baseline condition.

$$\text{Attention Difference (Decision-Making vs. Baseline)} = \frac{\text{Mean Decision-Making Attention} - \text{Baseline Attention}}{\text{Baseline Attention}} \times 100$$

Percentage Change (Online/Offline vs Baseline)

Evaluates the improvement in attention for offline or online conditions relative to baseline attentiveness.

$$\text{Percentage Change (Offline vs. Baseline)} = \frac{\text{Mean Offline Attention} - \text{Baseline Attention}}{\text{Baseline Attention}} \times 100$$

Findings

online vs offline attentiveness

Average Attention Across Decision Making Tasks:
- Online: 63.99%
- Offline: 80.25%

Percentage Increase in Offline vs. Online Attention:
- Chess: 22.65% more attention in offline chess compared to online.
- Meetings: 28.87% more attention in offline meetings compared to online.
- Average Across Both Tasks: 25.41% more attention in offline settings compared to online.

The attentiveness in offline settings is 25.41% higher than in online settings.

comparison with baseline

Average Attention:
- Decision-Making Tasks (Chess and Meetings): 72.12%
- Non-Decision-Making Task (Baseline): 43.64%

Comments →
- Offline attention (80.25%) is 83.89% higher than the baseline (43.64%).
- Online attention (63.99%) is 46.63% higher than the baseline (43.64%).

Attention in decision-making tasks is 65.26% higher compared to the baseline

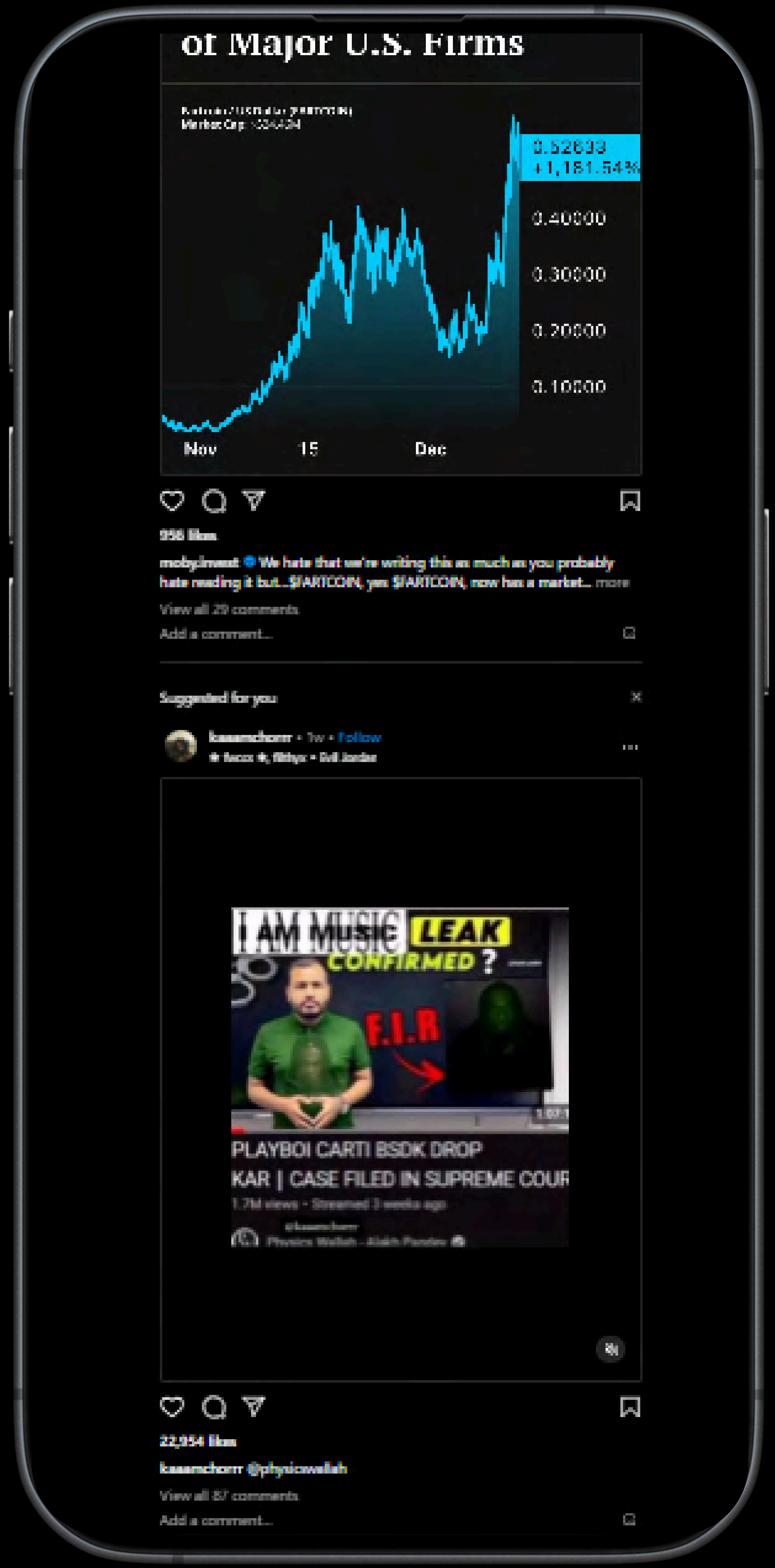
Findings: Inter-subject

Task	Environment	Mean	Std Dev	Min	Q1- 25%	Q2- 50%	Q3- 75%	Max
Baseline	-	43.64	3.5	38	41.12	43.64	46.16	49
Chess	Online	71.18	5.8	62	67.08	71.18	75.28	80
Chess	Offline	87.3	4.7	80	83.6	87.3	91	95
Meetings	Online	56.8	5.2	48	53	56.8	60.6	65
Meetings	Offline	73.2	5	66	69	73.2	77.4	81

- Offline chess has lower variability (Std Dev: 4.70%) compared to online chess (5.80%), with higher attentiveness across subjects.
- Offline meetings show more consistent attentiveness than online meetings.
- Subjects exhibit higher variability in online task.
- Baseline attentiveness is consistently low (Mean: 43.64%, Std Dev: 3.50%) across all subjects.

Deployable Soln.

We propose leveraging this attentiveness measure to contribute by generating a quick notification system allowing users to notified on a drop in their regular attentitiveness.



Impact of Deployable Solution

Task design should consider attentional demands

In-person interactions remain critical for attention-intensive activities, strategy-building. Online formats may work better for independent, structured activities but underperform in collaborative or discussion-heavy contexts.

Advancements in platforms helps bridge engagement gaps.

A subjects passion is a significant driver of overall attentiveness. The significant attention gaps in online Meetings highlight the need for better engagement strategies in virtual environments.

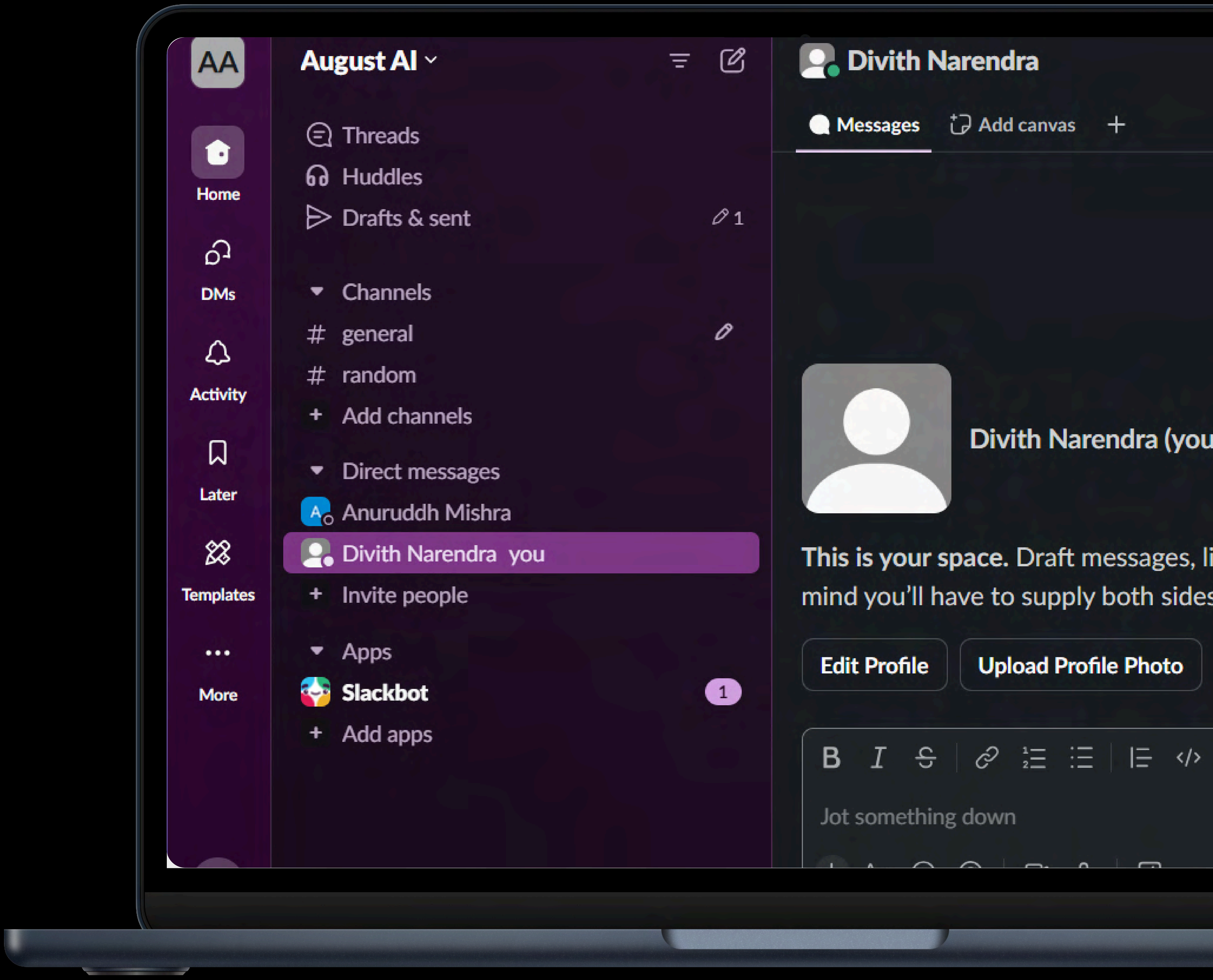
Task-Specific Hybridization

The higher Attention Consistency Index (ACI) for Chess indicates that some tasks are less sensitive to environmental shifts, making them more adaptable to remote or hybrid models.

Office Spaces

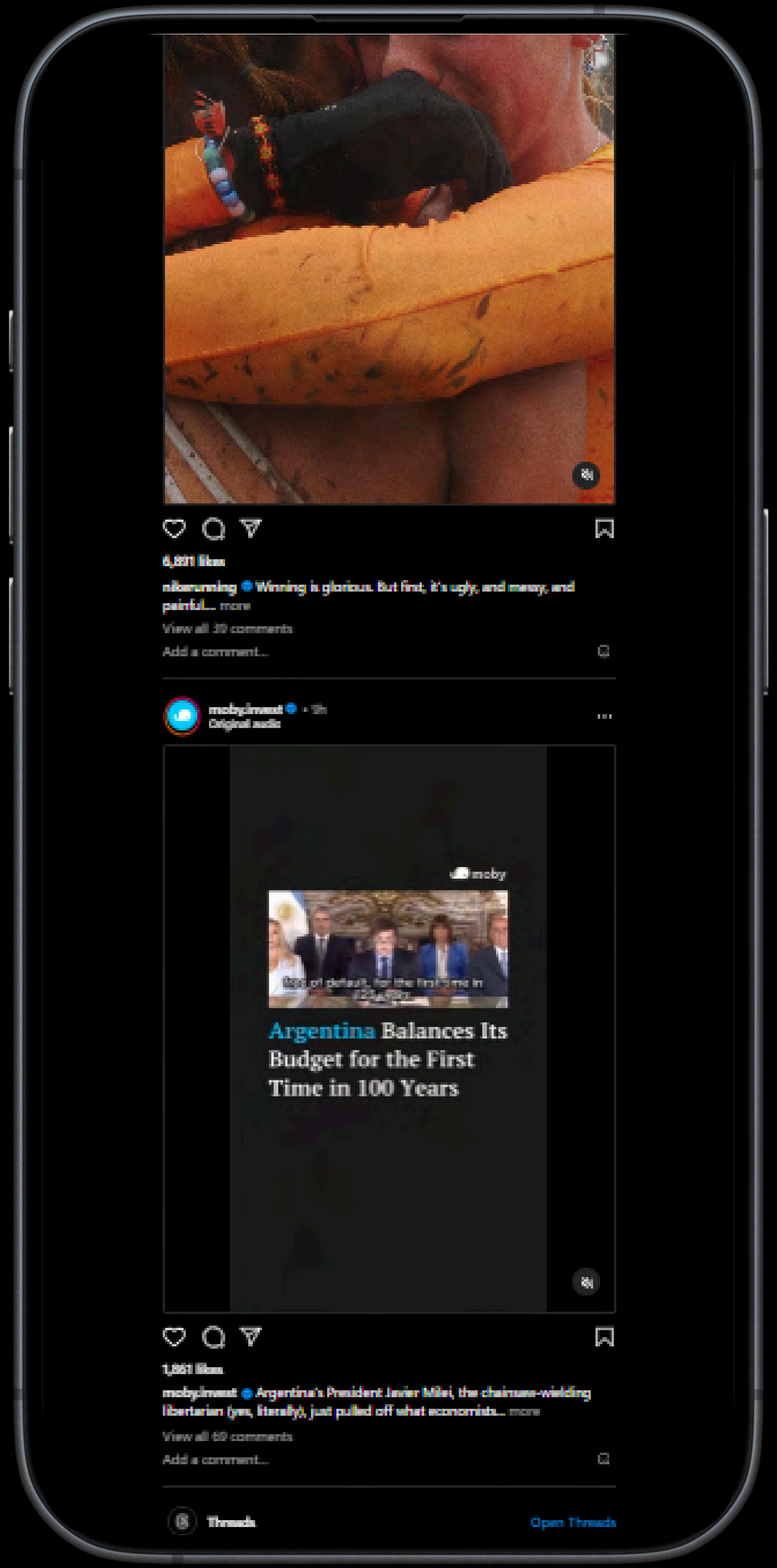
Providing a feasibility analysis to check whether office spaces are really impactful [Leveraging the attentiveness metrics, comparing across open and closed office spaces.

For, every 100 attentive minutes online, offline meetings produce 128.87 minutes—an additional 28.87 minutes.



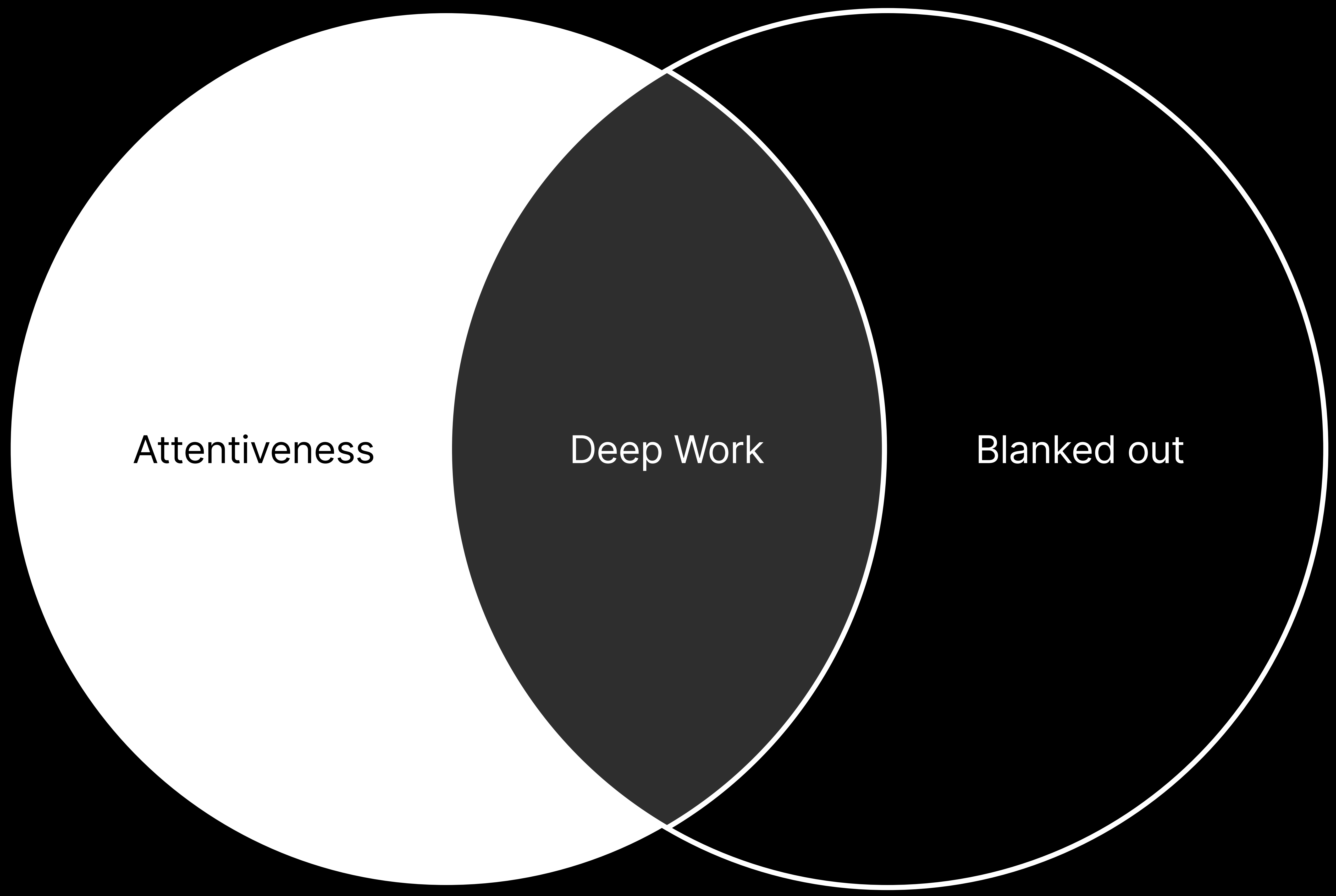
Doomscrolling

We can solve doomscrolling by developing alerts, in the case that your attentiveness frames are constant over time



Attentiveness Breaks

Blank spacing out can be highlighted whenever an individual spaces out and notifying them that they need a break.

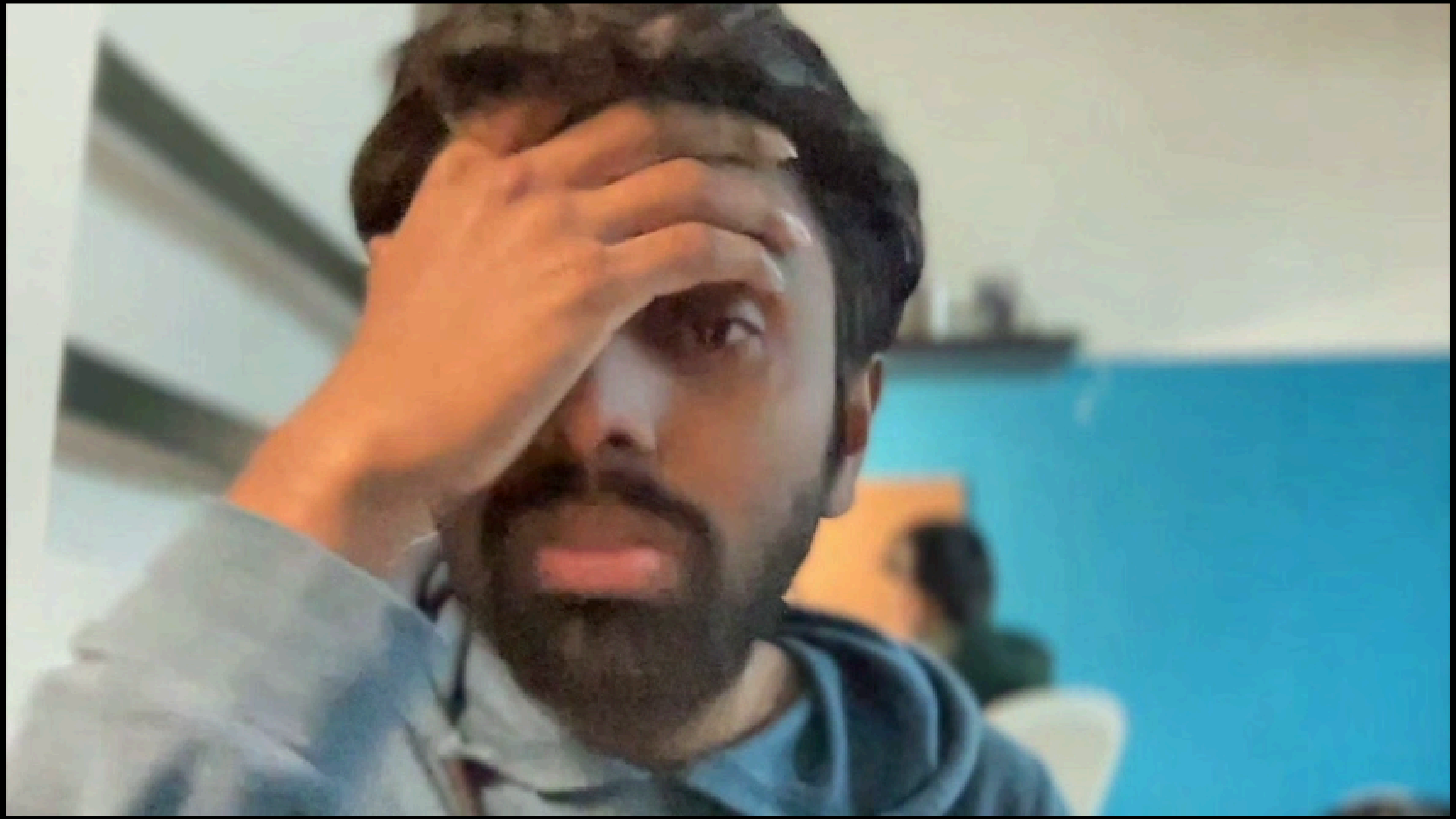


Sir, a specific impact

Our study reconciles with literature arguing that transitioning to offline formats would help increasing retention rate, i.e. not much rote learning.

Challenges in Data Collections

Subject moving continiously



Subject covered face

Limitations

Short Meetings May Lack Depth

- Short meetings may not provide sufficient time to capture comprehensive data or observations. This limitation can result in missing critical cues or patterns that require extended interaction or analysis to emerge.

Facial Action Units (AUs) Alone Are Insufficient

- Solely relying on facial Action Units (AUs) for analysis may not yield robust or reliable conclusions. Additional data points, such as pupil dilation or other physiological markers, are necessary for a holistic understanding.

Incorporate More Decision-Making Tasks

- To enhance the robustness of the analysis, integrating additional cognitive and decision-making tasks, such as memory recall tests, Stroop tests, or other problem-solving activities, can provide deeper insights. These tasks introduce complexity and stressors that may elicit more informative and nuanced responses.

Using More Sensors

- We have only used a single camera sensor, that is physiological features. Integrating pupil dilation, EEG data, etc. would give us more accurate results.

thank you!