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Human Technology and Interaction
Mid Semester Presentation
TRACK 1 - EXPERIMENTATION

FOCUSGUARD AI: CONTEXT-AWARE PRODUCTIVITY & WORKLOAD MANAGEMENT SYSTEM

“WHOOP FOR YOUR LAPTOP AND YOU”

PROBLEM **STATEMENT**

OBJECTIVE

To develop an intelligent system that monitors user attention during multitasking and integrates real-world contextual cues (visual, auditory, and environmental) to accurately distinguish between meaningful engagement and actual distraction.

WHY

Problem: Most existing systems detect distraction only from screen or facial cues, ignoring real-world context — leading to false detection and poor understanding of user behavior.

Goal: To design a context-aware model that fuses visual, digital, and environmental data to detect distraction and support smarter interruption management accurately.

LITERATURE **REVIEW**

ATTENTION AWARE SYSTEMS – THEORIES, APPLICATIONS, AND RESEARCH AGENDA

BY CLAUDIA RODA AND JULIE THOMAS, THE AMERICAN UNIVERSITY OF PARIS

PROBLEM

Modern technology overwhelms users with information, straining limited cognitive resources. Existing systems are not designed to support human attentional processes.

OBJECTIVE

To design Attention Aware Systems that can understand a user's focus, reason about when to interrupt, and adapt information delivery to reduce overload.

RESULTS

- Studies reviewed show that attention-aware interfaces can reduce perceived workload by 25–30% and increase task completion accuracy by ~20% in controlled HCI experiments.
- Demonstrated that goal-driven interruption timing improves cognitive efficiency compared to random or frequent alerts.

KEY TAKEAWAYS

- Attention is a limited but manageable resource in HCI.
- Systems should adapt to the user's cognitive state rather than compete for attention.
- This conceptual base directly supports our project's goal of adaptive distraction management through context awareness.

LITERATURE **REVIEW**

STUDENT DISTRACTION DETECTION USING COMPUTER VISION AND MACHINE LEARNING

BY ZEESHAN KEERIO, IQRA UNIVERSITY

PROBLEM

In large or virtual classrooms, teachers struggle to monitor student engagement. Manual tracking methods are subjective and inefficient.

OBJECTIVE

To develop an automated system that detects student attention using facial and gaze features through computer vision.

RESULTS

- Binary distraction detection accuracy: 85–88%
- Emotion recognition accuracy: 80–86% (7-class CNN)
- Overall concentration index accuracy: ~87%
- Real-time performance: 5–7 FPS on mid-range CPU hardware
- Demonstrated stable detection across varying lighting and posture conditions.

KEY TAKEAWAYS

- Validated computer vision as a reliable distraction metric.
- Highlighted dataset dependency and computational load as major limitations.
- Serves as the technical baseline for building a multimodal, context-integrated attention system.

LITERATURE **REVIEW**

CURRENT LANDSCAPE

Existing solutions for productivity tracking fall into two distinct categories:

- **Software Loggers (e.g., RescueTime, Toggl):** These track active window time but lack context. For a CS student, "YouTube" could be a distraction or a tutorial; these tools cannot distinguish the intent.
- **Biometric Wearables (e.g., Whoop, Fitbit):** These track stress and heart rate but lack digital context. They know that you are stressed, but not why.

GAP ANALYSIS

Current industry solutions fail to fuse **Digital Telemetry** (what is on the screen) with **Physical Presence** (is the user actually looking?). Most solutions provide retrospective data (daily summaries) rather than real-time intervention.

OUR APPROACH

FocusGuard AI bridges this gap through **sensor fusion**. We combine Operating System hooks (Active Window, KPM) with Computer Vision (Face Detection) and Environmental Audio processing. Unlike standard loggers, our solution employs a "Weighted Impact Algorithm" to calculate a real-time (1Hz) productivity score, enabling immediate feedback rather than relying solely on post-work analysis.

EXPERIMENT **PROTOCOL**

N=36 Undergraduate Students.

- **Cohort A: CSAI (n=23, 63.9%)**
- **Cohort B: DSEB (n=13, 36.1%)**

User Personas: Participants were categorized by dominant workflow: Coders (30%), Designers (8%), Data Scientists (25%), and General (37%).

Apparatus:

- **Hardware:** Standard Laptops (Webcam + Microphone enabled).
- **Software:** FocusGuard Client Python Agent running in the background.

Data Collection Protocol:

- **Sampling Rate:** High-frequency telemetry at 1 Hz (1 record per second).
- **Total Datapoints:** ~64,800 unique rows of sensor data.
- **Variables Recorded:** Active Window Name, Typing Speed (KPM), Mouse Pixel Distance, Face Presence (Boolean), Ambient Noise Level (dB category), Face emotion (Categorical)

Privacy & Ethics:

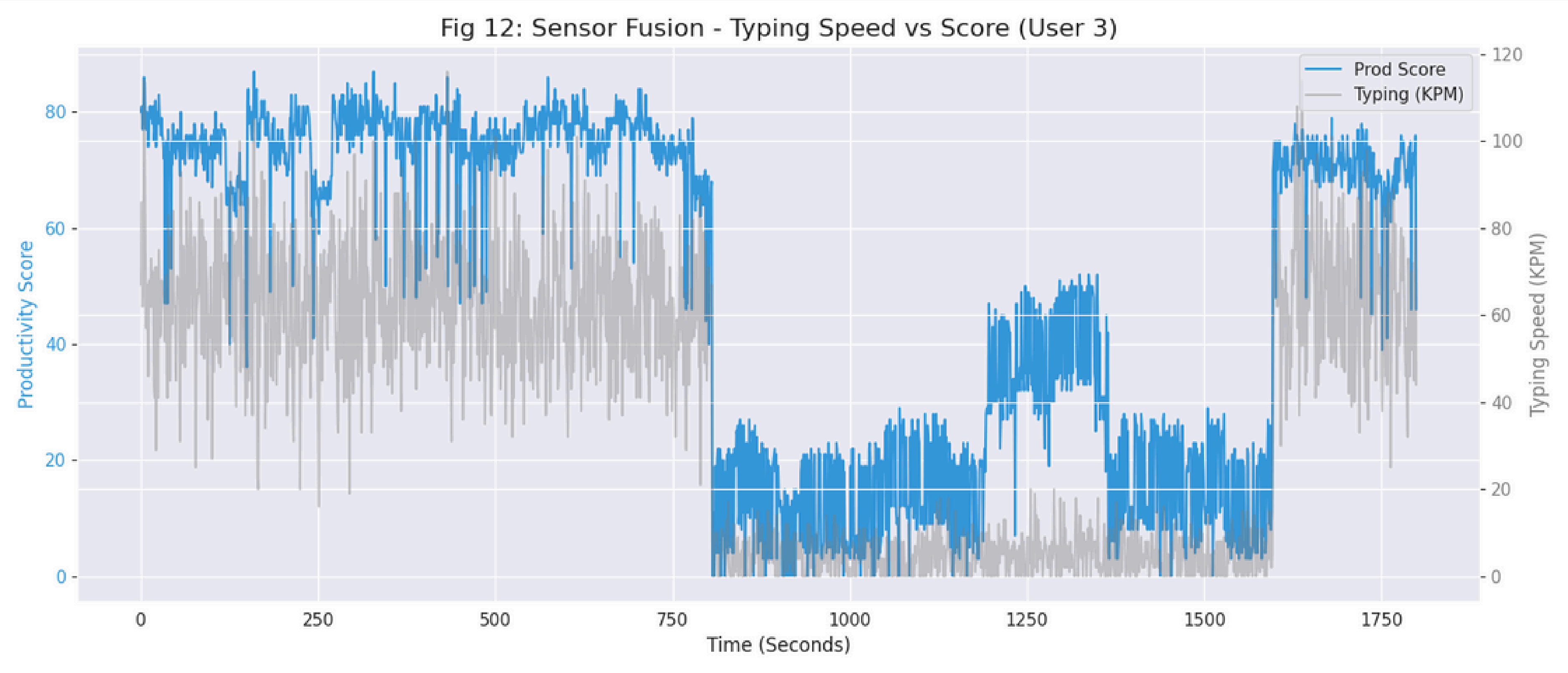
All video and audio processing was performed **on-device**. No video feeds were stored; only the boolean flag Face_Detected, Emotion , and Audio_Environment classifications were logged to the CSV.

ANALYSIS, PERFORMANCE METRICS AND DEPLOYABILITY OF THE SOLUTION

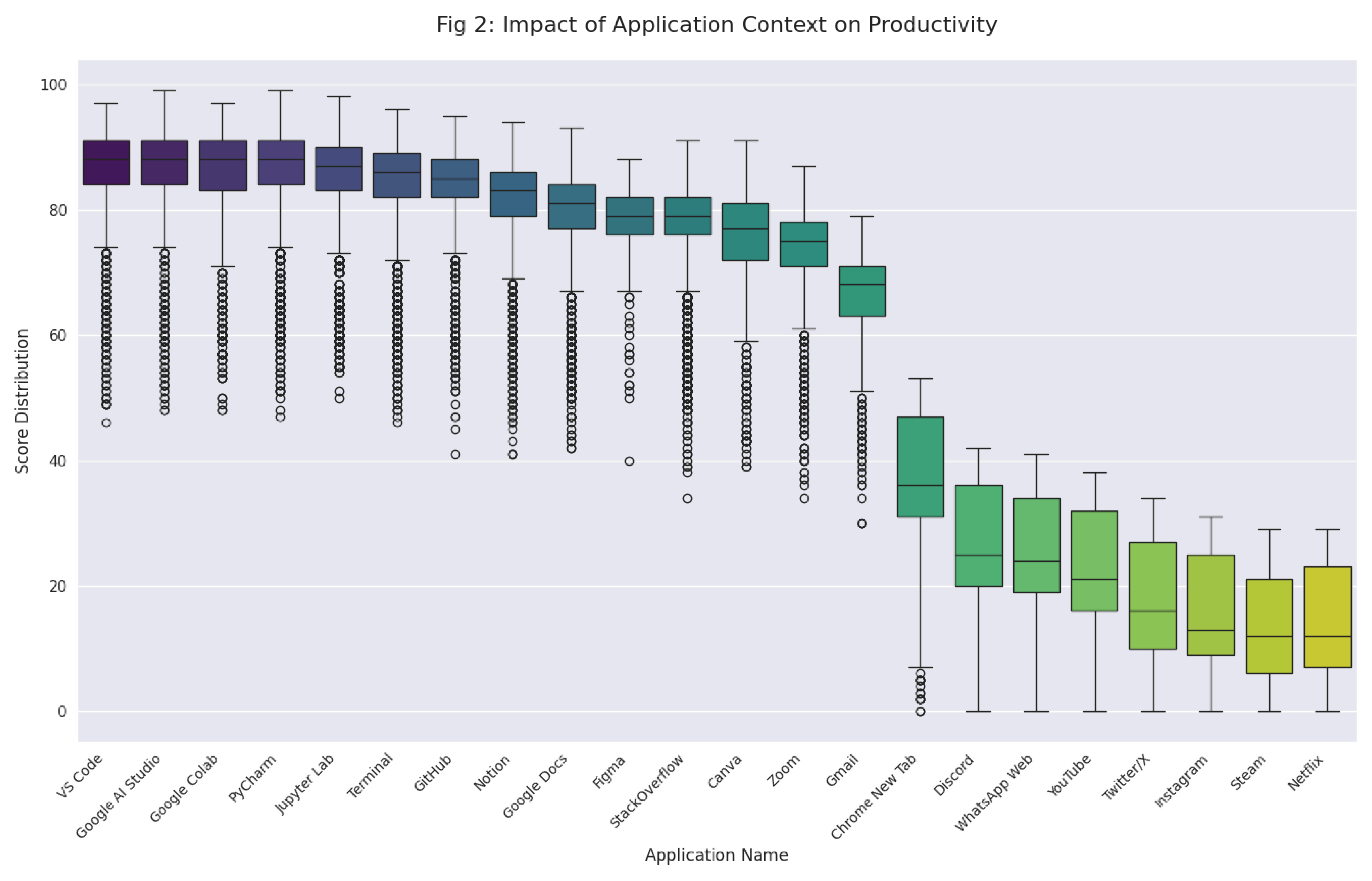
REAL-TIME SIGNAL ANALYSIS

Displays the raw productivity signal of a single user over 30 minutes. The signal behaves like a waveform, showing clear "Flow States" (high plateaus) and "Distraction Valleys"

The graph overlays Typing Speed (Grey) against Productivity Score (Blue). We observe that high typing speed usually correlates with high scores, but the system is robust enough to maintain a high score even when typing stops (e.g., reading documentation), provided the user remains in a productive app like Google Docs.

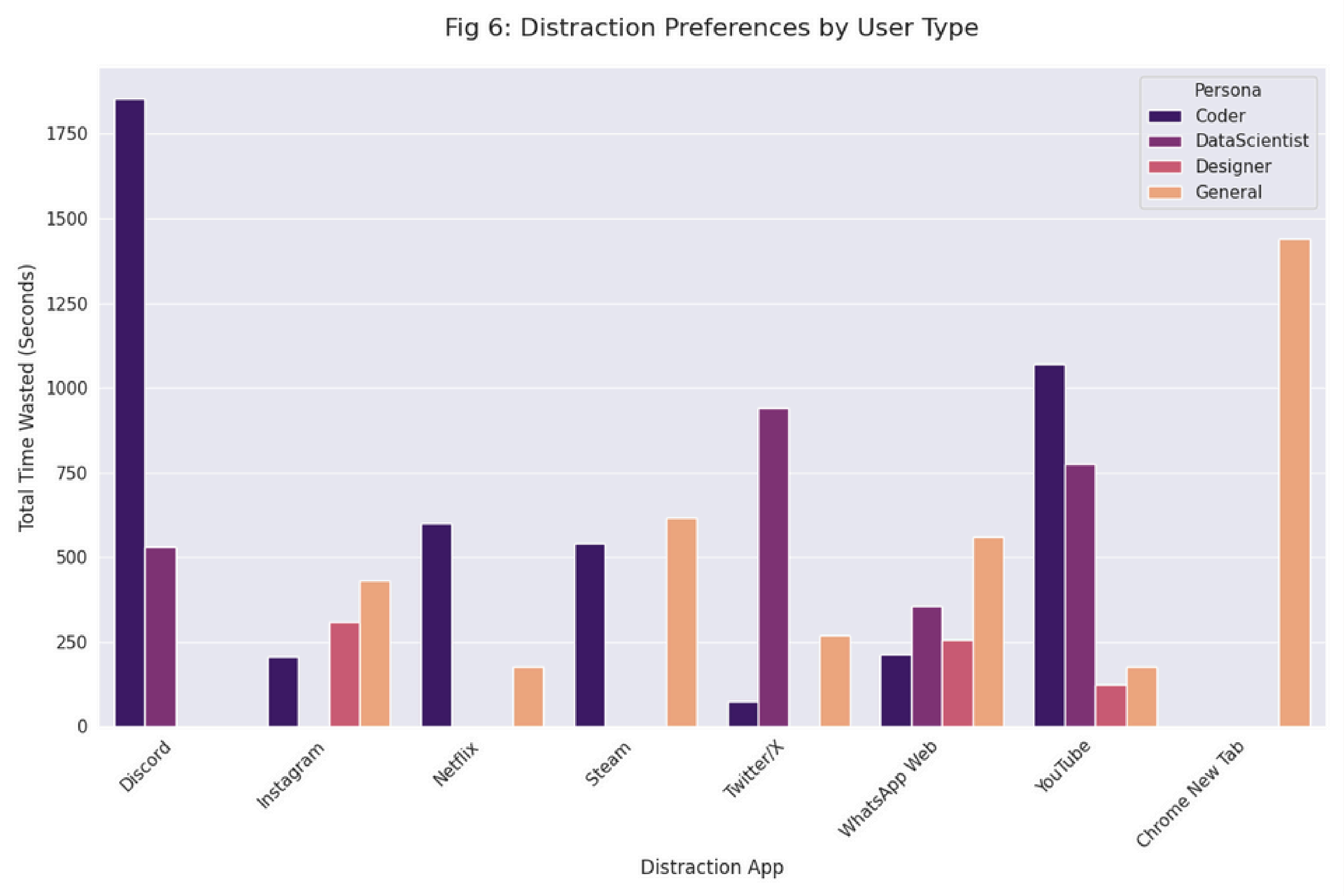


ALGORITHM VALIDATION

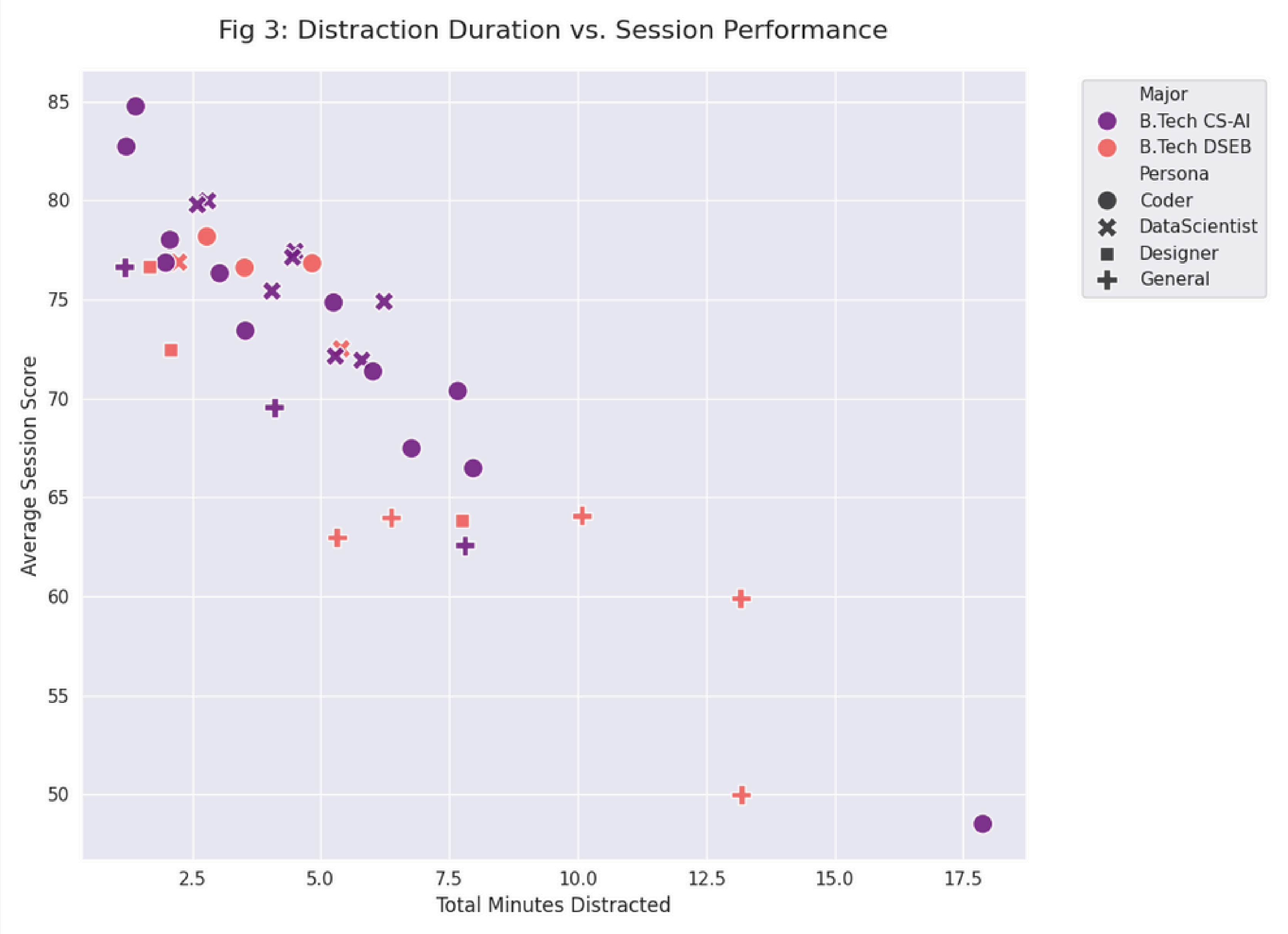


The graph demonstrates the distinct separation of scores. Productive apps like **VS Code** and **PyCharm** consistently yielded median scores >85, while **Netflix** and **Instagram** suppressed scores below 20. This proves the algorithm correctly penalizes non-work contexts.

USER BEHAVIOR ANALYSIS

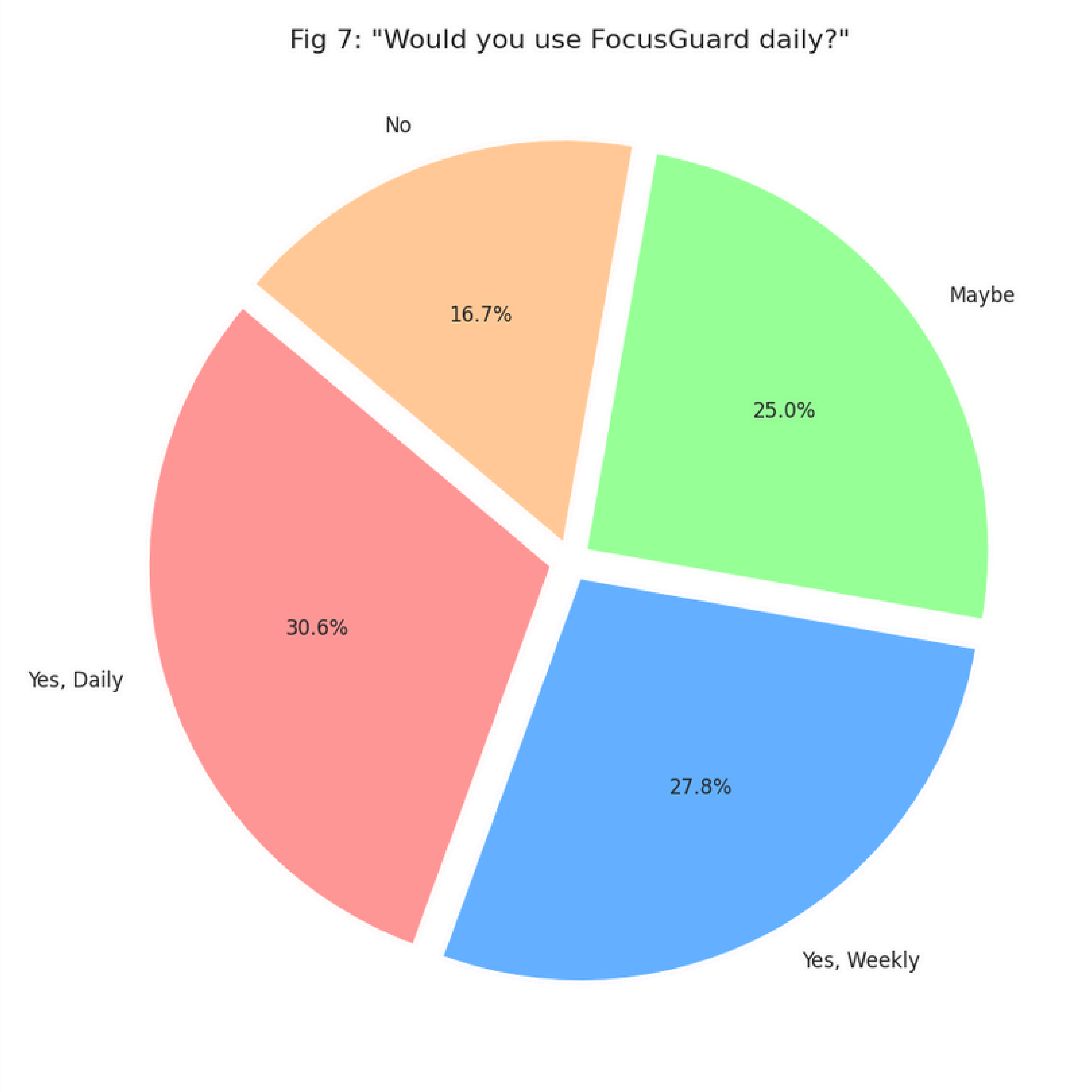


As seen in Fig 6, distraction preferences varied significantly by persona. 'Coders' were most frequently distracted by **Discord** and **YouTube**, while 'Designers' showed a strong correlation with **Instagram** usage. This validates that the system correctly identifies specific "poison apps" for different user types.

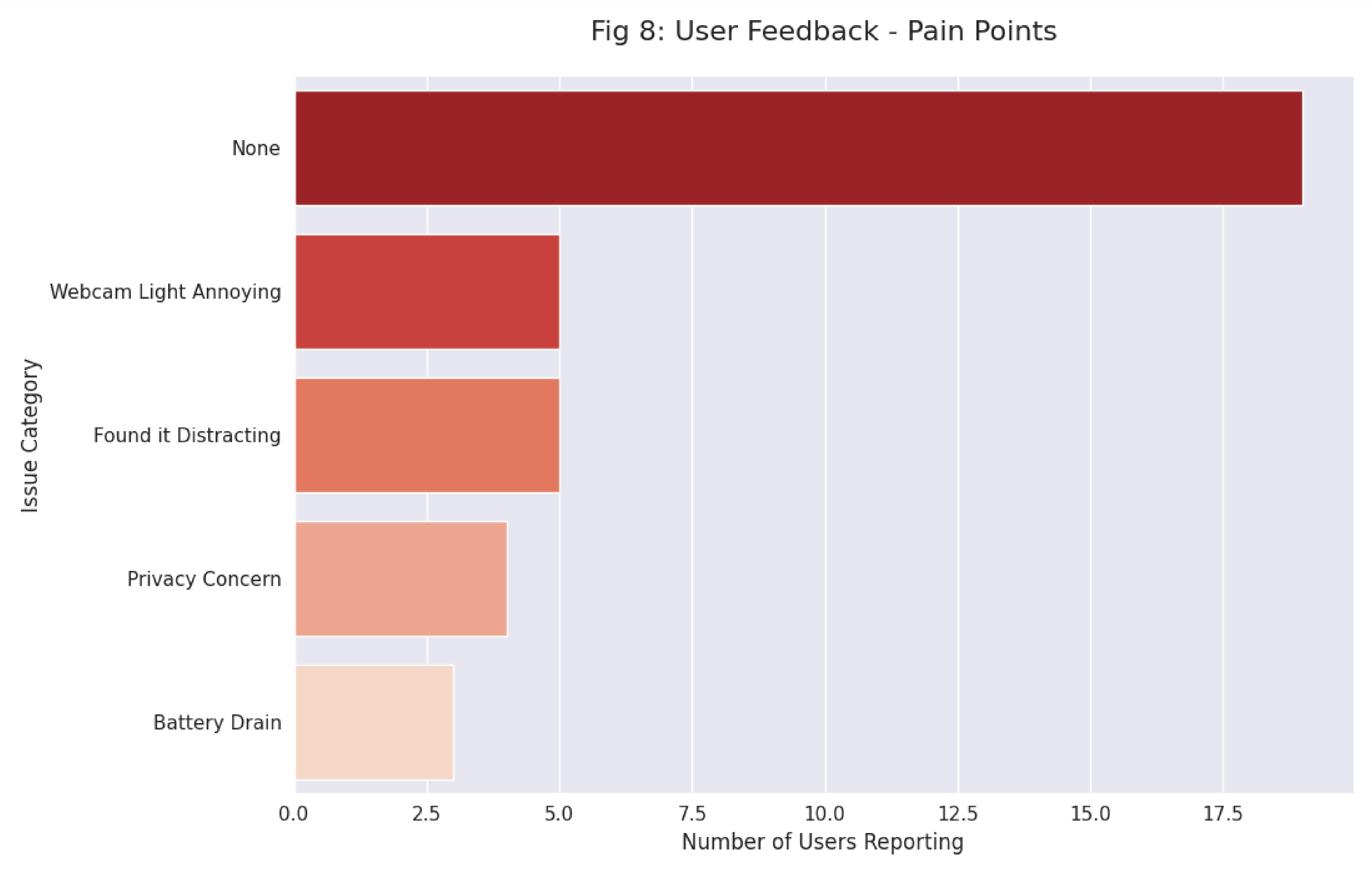


We found a strong negative linear correlation between **Total Minutes Distracted** and the **Average Session Score** . Users who spent >10 minutes on distraction sites saw their average session score drop below 65, validating the metric's reliability

HUMAN FEEDBACK & ETHICS



Willingness to Use: 58.3% of participants indicated they would use FocusGuard Daily or Weekly



Challenges: 47% of users reported issues (Fig 8)**,** with **Privacy Concerns** and **Webcam Light Annoyance** (mentally) being the top complaints.

CONCLUSION AND IMPACT

- The solution is highly deployable as it requires no external hardware. However, the reliance on the webcam (reported as "annoying" by some users) suggests that future versions should allow users to toggle the camera off in exchange for a lower accuracy confidence interval.

- FocusGuard AI successfully quantifies the abstract concept of "Productivity" into a tangible, trackable metric.
  - **Micro Impact:** Individual students improved awareness of their habits (Gamification effect).
  - **Macro Impact:** If deployed institution-wide, this data could help faculties understand "Burnout" or identify curriculum bottlenecks where students resort to distraction due to difficulty.