

Mann Lab

1. Safeguarding Humanity with Sousveillance: Extending Sensing Inwardly and Outwardly (2-8)
2. A Multimodal Measurement Framework for Attentional Modulation Using Ayinography and Wearable EEG (9-14)
3. Psyveillance: Cyborg Psychology of Sousveillance(15-21)

Safeguarding Humanity with Sousveillance: Extending Sensing Inwardly and Outwardly

Somin Mindy Lee

Dept. Electrical and Computer Eng.
University of Toronto
Toronto, Canada

Aydin Hosseingholizadeh

MannLab
University of Toronto
Toronto, Canada

Despina Tzanetakis

Div. of Engineering Science
University of Toronto
Toronto, Canada

Nishant Kumar

Dept. Electrical and Computer Eng.
University of Toronto
Toronto, Canada

Steve Mann

Dept. Electrical and Computer Eng.
University of Toronto
Toronto, Canada

Abstract—As computer vision becomes increasingly embedded in technologies that surround us, ensuring transparency, fairness, accountability, privacy, and ethics in vision-based AI systems is critical for social good. This paper explores the intersection of computer vision, environmentalism, and eXtended Reality (XR) to design ethical, privacy-preserving wearable AI systems. We propose a novel AI-embedded eyeglass that integrates Muse electroencephalogram (EEG) device with vision-based XR to enhance human-AI interaction and environmental perception. A hardware configuration combining eyewear (Vuzix) and EEG (Muse) is explored. Our approach leverages principles of sousveillance (undersight) to empower individuals with real-time AI auditing, environmental awareness monitoring, and neuroadaptive feedback for XR applications. By aligning computer vision with ethical sousveillance and sustainability, we propose a framework for AI-driven wearables that enhance human agency while safeguarding privacy and accountability.

I. INTRODUCTION

Traditionally, sensing technologies have focused on either the external environment or the internal state of the body. However, a comprehensive understanding of human context may be achieved by integrating both inward-facing and outward-facing sensing modalities. By combining external environmental data with internal physiological signals, such as photoplethysmography (PPG), and EEG from devices such as the Muse headband, we can gain insight into both what is happening around us and how these external factors might affect our internal states [1].

This dual-sensing approach enables context-aware applications that monitor everything from ambient conditions to subtle changes within the body. For example, correlating physiological data with environmental cues can help explain stress responses or other behavioral or health patterns. Such correlations can give us a more nuanced understanding of human health and performance. Moreover, this framework lays the foundation for a balanced interplay between surveillance and its counterpoint, sousveillance. Surveillance denotes the conventional practice of top-down oversight by centralized entities often hidden from view, whereas sousveillance represents

a counterbalancing, bottom-up “undersight” approach that empowers individuals to monitor their environment, including the monitors themselves, thereby redefining traditional power dynamics and laying the groundwork for more participatory, ethically driven sensing systems [2], [3].



Fig. 1. Sousveillant system based on Muse-S brain-sensing headband, "Mind over Motor" [4]



Fig. 2. Muse-S together with Vuzix Shield

In the current era, AI is often associated with machines of surveillance continuously monitoring and interpreting our behaviors [5]–[7]. However, sousveillance, characterized by humanistic intelligence and a bottom-up approach to sensing, serves as a crucial counterbalance. By empowering individuals with tools that are understandable and transparent to the end-user, sousveillance offers an ethical and privacy-preserving alternative to traditional, opaque AI surveillance systems.

This paper proposes an integrated wearable system that unifies external vision, through a smart eyeglass-based display system, adding to it, both inwards-facing sensing modalities from devices like an InteraXon Muse brain-sensing headband, as well as outwards-facing sensing modalities like additional cameras so that it has stereo vision in all directions (in addition to the two forwards-facing cameras built into the eyeglass). The goal is to provide a holistic, context-aware sensing system where AI-driven decisions can be interpretable by the user, ensuring that technology remains a tool for enhancing human agency rather than compromising privacy. In doing so, we aim to establish a framework that supports a balanced, human-centric approach to AI and priveillance (privacy/sur/sousveillance) 3.

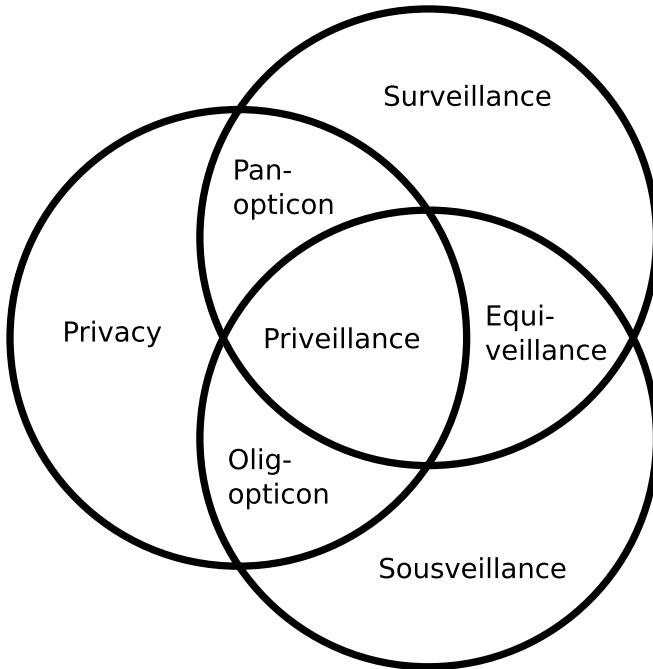


Fig. 3. A conceptual Venn diagram illustrating the relationships among surveillance, sousveillance, privacy, and related constructs such as the panopticon, olig-opticon, equiveillance, and priveillance [8]

In particular, it is very important to distinguish between surveillant privacy (panoptic) and sousveillant privacy (oligoptic). For example, social media allows us to hide our information from other users, but not from the company or government officials at the top of the hierarchy. A truly private conversation between two or more individuals allows them to be sensed by each other but not by any government or other “oversight”

entity. Privacy is the word used in both cases, but the meanings of the word “privacy” in each case are almost exact opposites.

II. RELATED WORKS: CURRENT LANDSCAPE OF WEARABLE SENSING TECHNOLOGIES

The evolution of wearable sensing technologies has produced sophisticated systems capable of monitoring a wide range of physiological and environmental parameters. However, research efforts have typically bifurcated into two distinct approaches: inward-facing technologies that monitor internal physiological states and outward-facing technologies that observe the external environment. This division creates a fragmented understanding of human context that an integrated priveillance-based approach could overcome.

A. Sousveillance

The concept of sousveillance, characterized by humanistic intelligence and a bottom-up approach to monitoring, offers an ethical and privacy-preserving alternative to traditional, opaque AI surveillance systems. However, fully realizing this vision requires wearable systems that can monitor both internal physiological states and external environmental conditions while ensuring that the interpretation and control of this information remains with the user.

The technical implementation of sousveillance systems requires efficient object tracking capabilities that maintain privacy while providing accurate environmental awareness. Nam and Han’s work on MDNet demonstrates how deep neural networks can effectively track objects across video frames, providing a foundation for outward-facing sensing in sousveillance systems [9]. Unlike traditional surveillance systems that rely on fixed cameras with centralized control, sousveillance implementations based on wearable cameras benefit from adaptive tracking approaches that maintain user agency and privacy.

B. Inward-Facing Sensing Technologies

Wearable sensors focused on monitoring internal physiological parameters have seen substantial advancement in recent years. Innovations in biochemical sensing have enabled comprehensive monitoring of multiple biomarkers through non-invasive approaches. A notable example is the development of a flexible dual target electrochemical sensor by Mugo et al. that simultaneously detects pH and cortisol in human sweat using a microneedle design [10]. This technology demonstrates how non-invasive approaches can provide valuable insights into complex biochemical processes occurring within the body.

Similarly, dual-function electrochemical sensors capable of detecting multiple analytes such as uric acid and glucose in sweat represent significant progress in multi-parameter physiological monitoring [11]. These sensors feature easy preparation, fast detection, and high sensitivity, making them practical for continuous health monitoring applications. The ability to simultaneously track multiple biomarkers provides a more comprehensive view of internal physiological states than

single-parameter systems, as it can also improve diagnostic accuracy and facilitate proactive health interventions.

Further advancements in inward-facing sensing include the development of paper-based microfluidic sweat sensors with dual-signal readout capabilities. Such systems can simultaneously detect a range of biomarkers including glucose, lactate, uric acid, magnesium ions, pH value, and cortisol through a combination of colorimetric and electrochemical sensing mechanisms [12]. These technologies represent sophisticated approaches to internal physiological monitoring but remain focused exclusively on the body's internal state without consideration of external environmental factors.

Integration of multiple sensing modalities within physiological monitoring is exemplified by a dual-mode wearable sensor that interfaces a hydrogel film with a solid ion-selective electrode [13]. This technology enables the concurrent measurement of heart rate through pressure response and sweat electrolytes, demonstrating how different sensing mechanisms can be combined within a single platform. However, even these multi-modal systems remain confined to internal physiological parameters without engagement with the external environment April 23, 2025 at 9:30ment.

Another noteworthy development is a wearable dual-mode sensor that simultaneously monitors electrocardiogram and arterial pulse for cuffless blood pressure measurement [14]. By encapsulating a liquid metal pressure sensing circuit within conductive ionogel, this system eliminates the need for multiple discrete sensors in pulse transit time sensing. While this represents significant progress in simplifying physiological monitoring, it maintains the exclusive focus on internal signals characteristic of inward-facing systems.

C. Outward-Facing Sensing Technologies

In contrast to inward-focused systems, outward-facing wearable technologies concentrate on monitoring environmental conditions, spatial positioning, or user interactions with the external world. These technologies include ambient sensors, motion detection systems, and spatial awareness tools that provide data about the user's surroundings and activities rather than their internal physiological state.

Research on outward-facing sensing has explored various mechanisms including resistive, capacitive, triboelectric, piezoelectric, thermo-electric, and pyroelectric approaches [15]. Each of these sensing modalities offers unique capabilities for detecting different aspects of the external environment. Capacitive sensing technologies have been employed for detecting interactions with the external environment, such as finger movements and eye blinking. These systems track how the user engages with their surroundings, providing valuable contextual information about physical interactions and movements. Similarly, triboelectric sensors have been integrated into textile-based systems for virtual/augmented reality control, enabling recognition of joint motion and facilitating interaction with digital environments.

These outward-facing systems provide valuable information about the user's surroundings and activities but lack insight

into how these external factors affect internal physiological states. This limitation restricts their ability to establish meaningful correlations between environmental conditions and physiological responses, which is essential for comprehensive context awareness.

D. The Integration Gap in Current Research

Despite significant advancements in both inward and outward sensing technologies, there remains a critical gap in systems that effectively integrate both approaches. Most multi-functional wearable systems combine different sensing modalities within either the inward or outward domain rather than bridging across these domains to create a unified understanding of human context.

One notable attempt at integration is the double-sided wearable multifunctional sensing system described by researchers for human-ambience interface [16]. This system addresses the challenge of decoupling interferences from various signals by customizing the pattern and morphology of sensing electrodes and modifying active materials. Through a double-sided partition layout with serpentine interconnections, the system reduces motion artifacts and ensures simultaneous operation of multiple sensing modules.

This approach represents an important step toward bridging the gap between inward and outward sensing, as it considers both the perception of ambient changes and the timely feedback of the human body. However, even this system does not fully realize the comprehensive monitoring of both internal physiological states and external environmental conditions in a unified framework that prioritizes human agency and interpretability.

The extensive review by Zeng et al. on wearable multi-functional sensing technology highlights the diversity of sensing mechanisms and their applications in healthcare while revealing the limited integration between systems monitoring internal physiology and those monitoring external conditions [15]. This underscores the need for more holistic approaches that provide a complete picture of human context by considering both internal and external factors simultaneously. Future research should focus on developing integrated platforms that not only combine multimodal sensing but also leverage advanced machine learning techniques to adaptively interpret combined data streams in real time, thereby enhancing both the precision and practical applicability of wearable monitoring systems.

III. METHODS

A. Collecting Brainwaves

Brainwaves were collected through the Muse S headband, which were then transmitted through the Muse app on a mobile device. This was then forwarded through the Open Sound Control (OSC) protocol to the UDP port of an ESP32 Xiao S3 Sense. Subsequently, it was transmitted to the wearable smart glasses (Vuzix Shield) via Message Queueing Telemetry Transport (MQTT), enabling real-time display of the brainwaves for the user. A custom android application receives the

brainwave parameters to be graphed: TP9, AP7, AP8, and TP10 in JSON format. The Muse publishes the data to an MQTT server while the Vuzix Shield glasses subscribe to it. This allows for a data transmission frequency of up to 100 Hz. Prior to visualization, the raw EEG signals are preprocessed using band-pass filtering to minimize noise and remove artifacts, ensuring that only relevant frequency components are plotted.

The processed data is then pushed into a queue from which it is visualized in real time. TP9, AP7, AP8, and TP10 values are plotted on a single graph in real time, and they have a range between 0 to 3000. A maximum of 500 data points are displayed on the graph at any given time to ensure high visibility.

B. Viewing External Environment



Fig. 4. Eight XIAO ESP32 cameras on Vuzix with Muse

Camera data is collected through eight XIAO ESP32 cameras, providing a comprehensive field of view. This data is then streamed in real time to a web server, allowing access via local IP addresses. This system is designed to avoid interference with the touch bar on the right of the Vuzix Shield. The camera placement includes the following:

- Two cameras on the left side at a distance of 5.3 inches.
- Two cameras facing forward, which is part of the Vuzix Shield.
- Two cameras facing the rear.
- Two cameras facing upwards but angled slightly so that it prevents the user forehead from being in view.

This set up ensures efficient data transmission while having a low-latency response. Furthermore, the camera feeds are synchronized with the EEG data, enabling comprehensive temporal correlation between external visual cues and internal brain activity.

Current research demonstrates considerable progress in creating multi-functional systems within either the inward or outward sensing domains. However, there is a notable absence of

frameworks that effectively integrate both perspectives while maintaining a focus on human agency and interpretability. This gap represents a significant opportunity for developing wearable systems that can provide a more complete understanding of human context and support a balanced, human-centric approach to AI and monitoring.

IV. RESULTS

In this study, the Muse was successfully integrated with the Vuzix smart glasses and connected to a web server to transmit real-time EEG data, showcasing its potential as a comprehensive tool for concurrently monitoring the internal physiological signals and external environment cues.

As seen in Figure 5, two cameras—positioned to capture upward and leftward views—are simultaneously streaming to a web server, showcasing the real-time integration of diverse environmental inputs.

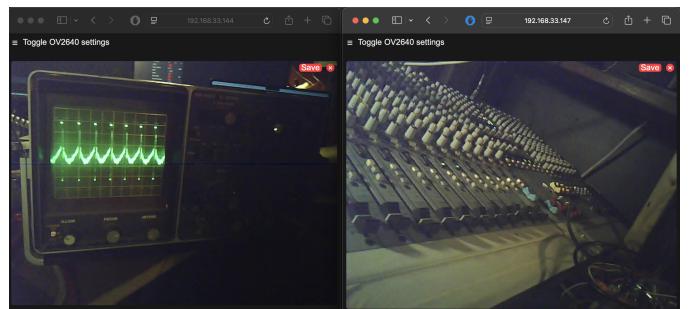


Fig. 5. Live Data Streaming from two cameras showcasing an analog oscilloscope and a 24 channel analog mixer. The oscilloscope visualizes the audio signal shaped by the mixer's adjustments, showcasing real-time waveform modulation.

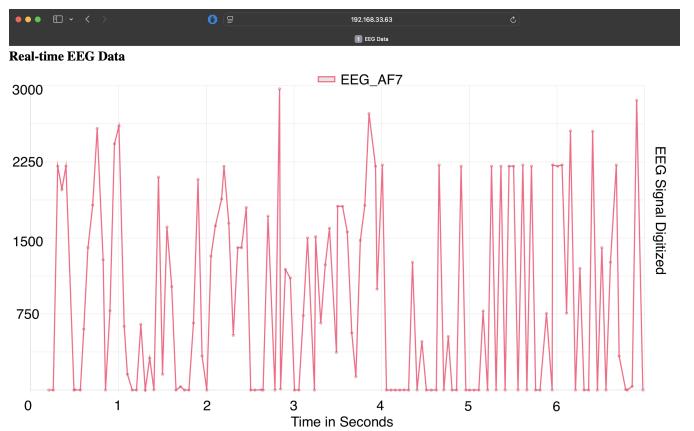


Fig. 6. Digital EEG Signal that is seen on a local IP address.

As shown in Figure 6, the AF7 electrode's digitized EEG signal is plotted against time, demonstrating the system's real-time streaming capabilities. The vertical axis represents the raw or scaled amplitude (in arbitrary units), while the horizontal axis shows time in seconds. This setup allows continuous monitoring of brain activity over a web-based interface, enabling immediate feedback and potential integration

with other sensing modalities. Such a configuration highlights the feasibility of capturing and visualizing neural data in real time, paving the way for advanced applications such as stress detection, cognitive load assessment, and adaptive human-computer interactions.

V. DISCUSSION

A. Social and Cultural Impacts

Acts of sousveillance, such as individuals recording their interactions in public spaces, allow ordinary people to challenge surveillance systems and assert control over their personal data [17]. For example, using wearable technologies like smartglasses with integrated cameras or EEG sensors, individuals can collect information about their environments while also gaining insights into their internal physiological states. This combination of external and internal sensing fosters a more holistic understanding of the self and surroundings, enabling users to make more informed decisions about their well-being and actions.

Sousveillance has the potential to reshape societal norms around privacy, data sharing, and surveillance. It empowers individuals to document their surroundings, offering a counter-balance to institutional surveillance systems by shifting some control back to the public [17]. This challenges traditional hierarchies of power and allows individuals to hold institutions accountable in ways that were previously difficult.

On a broader scale, sousveillance democratizes access to AI tools, giving people from diverse backgrounds the chance to contribute to collective knowledge and decision-making [17]. By collecting and analyzing data about their surroundings, individuals can play a more active role in environmental monitoring, public safety, and social accountability, fostering transparency and shared responsibility.

Beyond recording, sousveillance encourages individuals to be active participants in shaping their environment. It shifts the focus from control to empowerment, and from oversight to education. With AI-enhanced tools, people can learn more about themselves and their communities, using that knowledge to address personal and societal issues [18]. This shift not only challenges traditional power dynamics but also promotes a more engaged, informed, and empowered society, where people actively shape both their personal futures and the broader systems they live in.

B. Ethical Considerations of Sousveillance

While surveillance has long been critiqued for infringing on privacy, violating civil liberties, and concentrating power in the hands of institutions, sousveillance has its own risks [19]. The increased power of individuals to gather and share information raises concerns about privacy violations, the potential for harassment or misuse of personal data, and the inadvertent leak of sensitive information that could threaten security.

1) *Privacy and Consent:* In traditional surveillance systems, there are often established policies and regulations to govern data collection, storage, and usage, even if those policies are not always transparent or equitable. Sousveillance,

by contrast, places recording tools in the hands of individuals, complicating the issue of informed consent. Individuals may not always realize they are being recorded, particularly in public or semi-public spaces. This lack of consent undermines the right to privacy and creates potential for abuse [20]. For sousveillance systems to be ethically sound, clear guidelines must be developed to ensure that individuals understand when and how they are being recorded, with mechanisms for opting out where possible.

Moreover, the power to record others brings the responsibility to use that power ethically. Users of sousveillance tools must navigate complex social dynamics and cultural norms surrounding privacy. In some cases, sousveillance could exacerbate tensions or lead to the misuse of recordings, such as online harassment [18]. Balancing the potential benefits of sousveillance with the need to protect individuals from harm requires robust ethical frameworks that emphasize accountability, respect for privacy, and informed consent.

2) *Data Ownership and Control:* Another ethical concern is data ownership. When individuals record and collect data, questions arise about who owns that data and how it should be shared or protected. Should the person who captures the data have full control over it, or should there be limits on what can be done with recordings that involve others? These questions are particularly salient in sousveillance, where personal, environmental, and physiological data may be collected simultaneously [21].

Without appropriate safeguards, there is potential for data misuse, including unauthorized sharing or exploitation of personal information. For example, recordings from wearable devices could be used for surveillance, blackmail, or targeted harassment, undermining the very purpose of sousveillance as a tool for empowerment. To address this, policies that protect data ownership and regulate the sharing of sousveillance recordings are necessary. Additionally, encryption and data anonymization techniques can help mitigate the risks of privacy violations, ensuring that sensitive information is protected from malicious actors.

3) *Power Dynamics and Social Inequities:* While sousveillance democratizes surveillance and challenges institutional power, it may also reinforce existing social inequalities. Individuals with greater access to technology and resources are more likely to benefit from sousveillance tools, while marginalized groups may face heightened risks. For example, in situations where sousveillance is used to expose abuses of power, vulnerable individuals may be targeted for retaliation or discrimination. Furthermore, the increased visibility of marginalized communities through sousveillance could lead to further surveillance and policing, exacerbating existing forms of social control [22].

In this context, it is essential to consider the ways in which sousveillance could reinforce or challenge social hierarchies. Ethical sousveillance systems must prioritize the protection of vulnerable populations and ensure that the technology is used to empower, rather than oppress, marginalized communities. This includes considering the unintended consequences of

widespread surveillance capabilities and developing safeguards that prevent the misuse of sousveillance as a tool for harm.

4) *Regulatory and Legal Challenges*: The legal landscape surrounding sousveillance is still evolving. Existing privacy laws may not adequately address the unique challenges posed by wearable recording technologies and their capacity to capture both public and private information. Current regulations often focus on institutional surveillance, leaving a gap in how sousveillance is governed [3]. Policymakers must consider new regulatory frameworks that balance the rights of individuals to engage in sousveillance with the need to protect the privacy and security of others. This includes establishing clear rules about data ownership, consent, and the ethical use of recordings.

At the same time, enforcement mechanisms must be developed to hold individuals accountable for unethical or illegal uses of sousveillance tools. This could involve penalties for recording without consent or sharing sensitive information without permission. Additionally, educational initiatives that raise awareness about the ethical implications of sousveillance could help foster a culture of responsible data collection and sharing, reducing the potential for harm.

C. Limitations & future direction

Some limitations relate to issues with real-time processing and latency to ensure seamless integration of diverse sensor inputs. Additionally, scaling ethical oversight—balancing the dual paradigms of surveillance and sousveillance—remains a significant challenge; implementing consistent ethical standards across diverse environments is critical for maintaining transparency, accountability, and fairness. Future work should therefore focus on developing more robust real-time data processing methods, adaptive feedback systems, and AI-driven sousveillance mechanisms to enhance system responsiveness and ensure ethical, privacy-preserving operations. Moreover, further user-centric studies are essential to better understand and refine the human-AI interface, ensuring that the system effectively meets user interaction needs while advancing our commitment to social good.

While current object tracking technologies provide a foundation for outward-facing sensing, they face challenges when implemented in mobile, resource-constrained wearable devices. Jung's meta-learning approach for real-time object tracking with efficient model adaptation and channel pruning offers promising directions for addressing computational limitations in sousveillance systems [23]. Future work should explore how such adaptive tracking frameworks can be integrated with inward-facing physiological sensing to create context-aware systems that maintain both efficiency and privacy. Additionally, expanding on Liu's work in visibility status estimation could help sousveillance systems better understand complex environments while respecting the privacy of other individuals captured by outward-facing sensors [24]. Furthermore, recent studies have demonstrated that multimodal sensor fusion can significantly enhance both the robustness and privacy of in-

tegrated wearable systems, offering a promising avenue for ethically sound implementations [25].

REFERENCES

- [1] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 1, pp. 1–12, 2010.
- [2] S. Mann, "Surveillance (oversight), sousveillance (undersight), and metaveillance (seeing sight itself)," in *2016 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2016, pp. 1408–1417.
- [3] B. C. Newell, "Introduction: The state of sousveillance," *Surveillance & Society*, vol. 18, no. 2, pp. 257–261, 2020, licensed under a Creative Commons Attribution Non-Commercial No Derivatives license. [Online]. Available: <https://ojs.library.queensu.ca/index.php/surveillance-and-society/index>
- [4] S. Mann, P. V. Do, D. E. Garcia, J. Hernandez, and H. Khokhar, "Electrical engineering design with the subconscious mind," in *2020 IEEE International Conference on Human-Machine Systems (ICHMS)*. IEEE, 2020, pp. 1–6.
- [5] S. Zuboff, *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. New York: PublicAffairs, 2019.
- [6] K. S. Ball, "Surveillance society: Monitoring everyday life," *Information Technology & People*, vol. 14, no. 4, pp. 406–419, 2001.
- [7] K. Crawford and R. Calo, "There is a blind spot in ai research," *Nature*, vol. 538, pp. 311–313, 2016.
- [8] J. Thatcher, "Sousveilant media," *Understanding spatial media*, p. 56, 2017.
- [9] H. Nam and B. Han, "Learning multi-domain convolutional neural networks for visual tracking," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 4293–4302.
- [10] S. M. Mugo, W. Lu, M. Wood, and S. Lemieux, "Wearable microneedle dual electrochemical sensor for simultaneous ph and cortisol detection in sweat," *Electrochemical Science Advances*, vol. 2, no. 1, 2022.
- [11] Z. Li, Y. Wang, Z. Fan, Y. Sun, Y. Sun, Y. Yang, Y. Zhang, J. Ma, Z. Wang, and Z. Zhu, "A dual-function wearable electrochemical sensor for uric acid and glucose sensing in sweat," *Biosensors*, vol. 13, no. 1, p. 105, 2023, pMID: 36671938, PMCID: PMC9855683.
- [12] Y. Cheng, S. Feng, Q. Ning, and et al., "Dual-signal readout paper-based wearable biosensor with a 3d origami structure for multiplexed analyte detection in sweat," *Microsyst Nanoeng*, vol. 9, p. 36, 2023.
- [13] B. Ma, K. Huang, G. Chen, Y. Tian, N. Jiang, C. Zhao, and H. Liu, "A dual-mode wearable sensor with coupled ion and pressure sensing," *Soft Sci.*, vol. 4, p. 8, 2024.
- [14] N. Jiang, G. Chen, F. Zhou, B. Ma, C. Zhao, and H. Liu, "A dual-mode wearable sensor with electrophysiological and pressure sensing for cuffless blood pressure monitoring," *J. Mater. Chem. C*, vol. 12, pp. 15915–15923, 2024. [Online]. Available: <http://dx.doi.org/10.1039/D4TC02494J>
- [15] X. Zeng, H. T. Deng, D. L. Wen, Y. Y. Li, L. Xu, and X. S. Zhang, "Wearable multi-functional sensing technology for healthcare smart detection," *Micromachines*, vol. 13, no. 2, p. 254, 2022, pMID: 35208378, PMCID: PMC8874439.
- [16] H. Wang, Z. Xiang, P. Zhao, J. Wan, L. Miao, H. Guo, C. Xu, W. Zhao, M. Han, and H. Zhang, "Double-sided wearable multifunctional sensing system with anti-interference design for human–ambience interface," *ACS Nano*, vol. 16, no. 9, pp. 14 679–14 692, 2022, pMID: 36044715.
- [17] S. Mann, J. Nolan, and B. Wellman, "Sousveillance: Inventing and using wearable computing devices for data collection in surveillance environments," *surveillance and society*, vol. 1, pp. 331–355, 2002. [Online]. Available: <https://api.semanticscholar.org/CorpusID:15566915>
- [18] S. Mann, "Veilance and reciprocal transparency: Surveillance versus sousveillance, ar glass, lifelogging, and wearable computing," in *2013 IEEE International Symposium on Technology and Society (ISTAS): Social Implications of Wearable Computing and Augmented Reality in Everyday Life*, 2013, pp. 1–12.
- [19] J.-G. Ganascia, "The ethics of the generalised sousveillance," *The—backwards, forwards and sideways!*, p. 189, 2010.
- [20] M. Kowalski, "Between 'sousveillance' and applied ethics: practical approaches to oversight," *Security and Human Rights*, vol. 24, no. 3-4, pp. 280 – 285, 2014. [Online]. Available: https://brill.com/view/journals/shrs/24/3-4/article-p280_7.xml

- [21] H. CHA and J. KIM, "Ethical issues concerning health data ownership," *Korean Journal of Medical Ethics*, vol. 24, no. 4, pp. 423–459, 2021. [Online]. Available: <https://doi.org/10.35301/ksme.2021.24.4.423>
- [22] K. Ross, "Watching from below: Racialized surveillance and vulnerable sousveillance," *PMLA/Publications of the Modern Language Association of America*, vol. 135, no. 2, p. 299–314, 2020.
- [23] I. Jung, K. You, H. Noh, M. Cho, and B. Han, "Real-time object tracking via meta-learning: Efficient model adaptation and one-shot channel pruning," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, no. 07, 2020, pp. 11 205–11 212.
- [24] X. Liu, D. Lo, and C. Thuan, "Unsupervised learning based jump-diffusion process for object tracking in video surveillance," in *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18*. International Joint Conferences on Artificial Intelligence Organization, 7 2018, pp. 5060–5066. [Online]. Available: <https://doi.org/10.24963/ijcai.2018/702>
- [25] A. Wood, S. Holt, and J. Marques, "Assessing the impact of transparency in organizations." *Organization Development Journal*, vol. 42, no. 3, 2024.

A Multimodal Measurement Framework for Attentional Modulation Using Ayinography and Wearable EEG

1st Somin Mindy Lee

Dept. Electrical and Computer Eng.
University of Toronto
Toronto, Canada
0009-0005-4036-417X

2nd Despina Tzanetakis

Div. of Engineering Science
University of Toronto
Toronto, Canada
0009-0004-7158-7125

3rd Mitchell Seitz

Dept. Computing Science.
Thompson Rivers University
Toronto, Canada
0009-0007-8508-0220

4th Kinkini Monaragala

Dept. Biomedical Eng.
University of Toronto
Toronto, Canada
0009-0004-5084-7805

5th Steve Mann

Dept. Electrical and Computer Eng.
University of Toronto
Toronto, Canada
0000-0003-0363-3690

Abstract—We present a multimodal framework that integrates ayinography, a behavioral method for mapping graded visual-field performance, with portable electroencephalography (EEG) to quantify how auditory context modulates attention. Ayinography provides high-resolution estimates of perceptual fidelity across eccentricity, while EEG captures spectral markers of attentional engagement using the consumer-grade Muse™ 2 headset. Eight participants performed a peripheral discrimination task under silence and emotionally evocative music, with both behavioral and neural data synchronized through the MuseCroc Mobile platform. Behavioral modeling revealed individualized ayinographic phenotypes, *Wideners*, *Narrowers*, and *Neutrals*, reflecting distinct music-driven changes in functional field-of-view (FoV) structure. Changes in the hyperbolic FoV parameter E_2 ranged from strong widening (+282) to strong narrowing (-231), with no uniform group-level shift. EEG bandpower ratios showed parallel individualized modulation, with Wideners exhibiting increased Beta/Alpha and Theta/Alpha ratios and Narrowers showing corresponding reductions. Together, these results demonstrate that combining ayinographic field mapping with low-density wearable EEG yields a portable, low-cost, and high-information system capable of capturing individualized attentional dynamics in ecologically realistic settings.

Index Terms—EEG, ayinography, attentional modulation, visual field mapping, wearable sensors, brain–computer interfaces, cross-modal attention, portable instrumentation.

I. INTRODUCTION

Real-world environments contain unpredictable auditory events that can capture attention and alter task performance. Even when not consciously attended, salient or emotionally evocative sounds can redirect cognitive resources, influencing learning, productivity, and behavior [1], [2].

Controlled experiments have advanced our understanding of auditory distraction [3], but their constrained stimuli and laboratory settings limit ecological validity. Far less is known about how visuospatial accuracy behaves in richer auditory contexts,

such as music, where emotional tone and structural complexity influence engagement [4], [5]. At the same time, traditional neuroimaging relies on stationary, artifact-sensitive setups [6], restricting the study of individualized attentional dynamics in naturalistic environments. These limitations highlight the need for portable, spatially resolved measurement tools capable of capturing how auditory context influences attention in real time.

Recent advances in neurotechnology, including wearable EEG devices such as the Muse™ headbands and the MuseCroc Mobile platform [7], address these constraints by enabling cognitive measurement outside the laboratory. Their portability and ease of use support widespread deployment, validation, and educational access, while making real-time monitoring of attention feasible in everyday environments. These developments parallel broader efforts in brain-computer interfaces (BCI), Extended Reality (XR), and smart-device ecosystems, where lightweight sensors increasingly rely on continuous estimates of user attention. EEG-based BCIs are now routinely integrated into immersive VR/AR systems for real-time cognitive and attentional monitoring [8], and wearable devices have demonstrated reliable online tracking of attentional state using low-channel EEG [9]. When combined with behavioral paradigms such as ayinography, portable EEG offers a practical means of assessing how auditory context modulates attentional state with both temporal and spatial precision.

Ayinography offers a behavioral framework for mapping how clearly information is perceived across the visual field and how attention is distributed moment by moment. Unlike classical perimetry, which relies on sparse luminance-detection thresholds, ayinography uses structured, attention-demanding stimuli that yield continuous measures of discrimination fidelity across eccentricity [10], [11]. Eccentricity in ayinography refers to the angular distance from fixation, which

increases further into the periphery. Because perceptual and attentional resolution decline with distance from fixation, aiyinographic curves reveal an individual's spatial attentional gradient. Prior work has used aiyinography to characterize peripheral processing limits [12] and, when combined with wearable EEG-SSVEP systems, to demonstrate that neural responsivity exhibits a parallel eccentricity-dependent decline [13].

Auditory context is known to modulate attention where music, noise, and emotionally salient sounds influence arousal, cognitive load, and EEG spectral features [14], [15]. Early claims of a universal "Mozart effect" [16] were later tempered by evidence of strong listener-dependent variability [4], [17]–[19]. Contemporary perspectives therefore emphasize individualized interactions between arousal, mood, and preference. However, most prior studies do not examine how auditory context reshapes the functional field of view (FoV), the spatial distribution of perceptual fidelity across eccentricity. Classical FoV models describe average eccentricity-dependent performance [21], but little is known about individual differences in these profiles or how they shift under varying auditory conditions.

To address this gap, the present study integrates real-time aiyinographic mapping with portable EEG using the Muse™ 2 headband. Aiyinography captures the spatial geometry of eccentricity-dependent peripheral perception characteristics, while EEG provides spectral markers of attentional state. For example, elevated alpha power, reduced beta activity, and increased theta power are each associated with reduced visuospatial engagement and a shift toward inhibitory or foveally oriented processing [14], [15], [20]. Simultaneous measurement enables individualized assessment of whether auditory context widens, narrows, or leaves unchanged the FoV, and whether corresponding neural signatures track these behavioral shifts.

This study therefore aims to:

- Measure auditory modulation of the functional FoV.
- Identify neural signatures of these behavioral changes.
- Identify individualized attentional response patterns.
- Demonstrate the utility of integrated aiyinography-EEG sensing.

Collectively, the results demonstrate a sensing framework that enables high-resolution, individualized measurement of cross-modal attentional dynamics using accessible, portable instrumentation.

II. METHODS

A. Participants

Eight healthy adults ($n = 8$; $M_{\text{age}} = 20.51 \pm 3.95$ years, range 18–28) with normal or corrected vision participated. All provided informed consent and could withdraw at any time.

B. EEG Measurement and Data Acquisition

Behavioral and EEG data were acquired with MuseCroc Mobile [7], EEG was recorded using the Muse™ 2, a four-electrode (AF7, AF8, TP9, TP10), 256 Hz wearable system validated for reliable alpha, beta, and gamma estimation [22].

All streams were exported as synchronized CSV files with verified timestamp monotonicity.

C. Experimental Design

In order to obtain validated, time-locked aiyinographic and EEG measurements, the experimental protocol was implemented using the MuseCroc Mobile platform [7]. A central fixation point was displayed while digit-color stimuli appeared at random horizontal offsets along the X-axis. Raw EEG, packet and timestamp metadata, and the color value, digit value, and eccentricity of each stimulus were logged to synchronized CSV files. All recordings were time-aligned with video footage from each session for verification and analysis.

Participants sat on a stabilized couch with a headrest to minimize motion artifacts. A midline rear speaker delivered audio symmetrically. Visual stimuli were shown on a 46 × 27 inch display at a fixed 77.5 cm viewing distance, measured with a laser rangefinder. Display height, eye height, and room lighting were standardized to ensure geometric consistency across participants. Horizontal eccentricity was computed directly from pixel coordinates and verified using a calibration grid shown at session start.

Each trial followed the four-stage sequence in Fig. 1. After initiation, a fixation cross appeared, followed by a 200 ms peripheral digit-color stimulus at a randomly selected eccentricity. Digits (0–9) and colors (red, green, blue, yellow, purple, orange) were uniformly sampled. Participants maintained fixation; a brief post-stimulus period preceded a verbal report recorded manually and via synchronized audio/video.

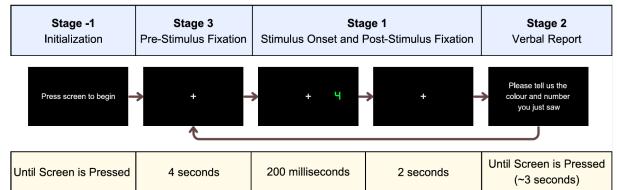


Fig. 1: Trial sequence showing initialization, fixation, 200-ms peripheral stimulus, post-stimulus fixation, and verbal report.

1) Auditory Conditions: Participants completed two counterbalanced auditory conditions. In the No-Music condition, they wore earplugs. In the Music condition, *Lacrimosa* from Mozart's *Requiem* [23] was presented at 70 to 75 dB SPL, verified using an SPL meter at the participant's head position. The selection was chosen for its known effects on arousal and attentional state [4]. Each condition comprised 50 trials.

D. EEG Processing and Spectral Analysis

EEG preprocessing followed established procedures for low-density wearable systems such as the Muse™ 2. Signals were filtered (1–40 Hz band-pass, 60 Hz notch) in MNE-Python [24], consistent with validated Muse™ practices [22], [25]. Ocular and muscle artifacts were removed using amplitude-threshold rejection, an approach shown to be effective for low-channel wearable EEG [26]. Data quality was verified by assessing pre-trial baseline variance [25],

[26]. This pipeline aligns with prior work demonstrating that consumer-grade EEG can produce reliable spectral estimates when artifact contamination is controlled [22], [25], [26].

Power spectral density was computed via Welch's method [27] using 2-s windows with 50% overlap. Bandpower values were extracted for theta, alpha, and beta ranges. Analyses focused on Stage 1 and Stage 3 (Fig. 1), which contain minimal noise artifacts. Each EEG segment was assigned to its trial's retinal eccentricity, binned across approximately -38° to $+38^\circ$. Mean bandpower and ratios were computed per participant, channel, bin. These metrics are standard indices of attentional engagement and workload [14], [15].

E. Behavioral Data Processing

Each trial yielded a digit-similarity and color-similarity score. Digit accuracy was computed using the Hamming distance [28] applied to a seven-segment digit representation, while color accuracy was measured as the Euclidean distance in HSV space. Both metrics were normalized to $[0, 1]$ and averaged to produce a graded perceptual accuracy value per trial. These continuous scores reduce ceiling effects and yield stable eccentricity-dependent performance functions [29]. Trial-level accuracy was then indexed by retinal eccentricity for subsequent modeling.

F. Ayinograph Generation

Ayinographs were constructed by aggregating accuracy across eccentricity and applying bootstrap-resampled locally weighted scatterplot smoothening (LOWESS) (1,000 iterations; smoothing fraction 0.30). This produced a non-parametric FoV estimate with a 95% confidence envelope. The LOWESS profile served as a model-free reference for evaluating parametric fits.

G. Eccentricity Effects and the Hyperbolic FoV Model

Visual performance declines predictably with retinal eccentricity due to reduced cortical magnification and increased peripheral limits such as crowding [10], [21], [30]–[32]. These combined sensory-attentional constraints produce a smooth reduction in discrimination accuracy with distance from fixation.

To capture this falloff, the accuracy was modeled using the standard hyperbolic function,

$$A(\theta) = \frac{E_2}{E_2 + |\theta|}, \quad (1)$$

where E_2 is the eccentricity at which performance reaches half its foveal value [21], [32]. Retinal eccentricity was derived from display geometry,

$$\theta = \arctan(x/D_0), \quad (2)$$

with $D_0 = 0.775$ m. Parameters were fit via nonlinear least squares and evaluated using root-mean-squared (RMS) error [33]–[35]. Bootstrap resampling provided uncertainty estimates for E_2 .

H. Letter Visibility Factor Based on Spatial-Frequency Limits

Digit visibility was modeled using angular size $\alpha(D) = 2 \arctan(H/2D)$ and corresponding spatial frequency $f(D) = \alpha(D)^{-1}$. Peripheral visibility loss was approximated by a Gaussian attenuation,

$$V(D) = \exp \left[-\left(\frac{f(D)}{\gamma} \right)^2 \right] / \exp \left[-\left(\frac{f(D_0)}{\gamma} \right)^2 \right], \quad (3)$$

with cutoff $\gamma = 3$ cpd, consistent with established peripheral limits [10], [32]. This yielded a distance-normalized visibility factor that does not vary across auditory conditions.

I. Projection of the Hyperbolic Fit into a 2-D Ayinograph

The 1-Dimensional hyperbolic fit was extended into a 2-Dimensional field across fixed horizontal offsets x and viewing distances D . Eccentricity $\theta(x, D)$ and accuracy $A_{2D}(x, D)$ were combined with the visibility factor $V(D)$ via

$$A_{2D}(x, D) = A(x, D) \cdot V(D), \quad (4)$$

producing a continuous prediction surface that incorporates geometry, perceptual falloff, and visibility constraints.

III. RESULTS

A. Behavioral Stability Across the Experiment

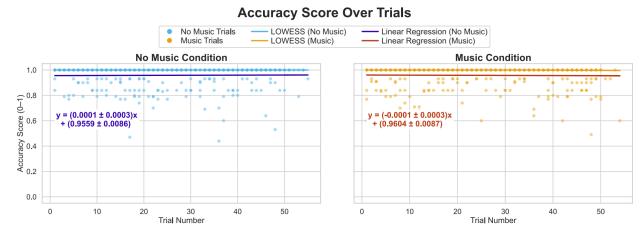


Fig. 2: Trial wise accuracy across all experiments.

Accuracy remained stable across all trials in both auditory conditions (Fig. 2). LOWESS and linear fits showed near-zero slopes, indicating no learning or fatigue effects. This stability verifies that the measurement protocol yields consistent accuracy estimates across the session, ensuring that subsequent eccentricity based analyses reflect true spatial performance rather than temporal drift.

B. Individual FoV Profiles: LOWESS-Derived Phenotypes

LOWESS derived difference curves (Music/No Music) revealed clear, participant-specific modulation profiles across eccentricity (Fig. 3). Even under a fully standardized protocol, the ayinographic measurements exhibited distinct, systematic patterns across individuals, demonstrating the system's ability to resolve fine-grained cross-condition changes. Three recurring modulation patterns were observed:

- **Music Wideners:** Positive differences across eccentricity, indicating improved accuracy and an expanded FoV.
- **Music Narrowers:** Negative differences, especially peripherally, reflecting a contracted FoV.
- **Neutrals:** Differences showing minimal modulation.

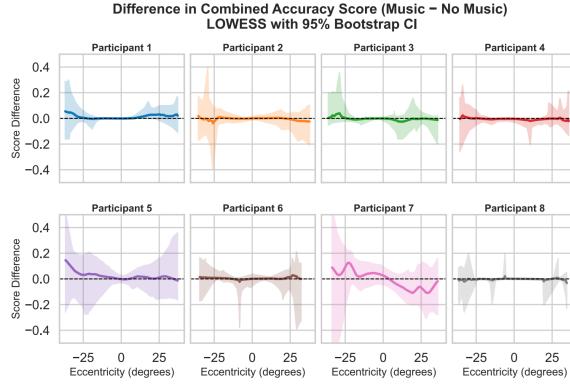


Fig. 3: LOWESS-estimated FoV modulation (Music – No Music) across participants.

These patterns appeared consistently across digit similarity, color similarity, and the combined accuracy metric, indicating that the ayinographic framework provides reliable and discriminative participant-level measurements rather than effects driven by noise in any single task component.

C. Agreement Between LOWESS and Hyperbolic FoV Models

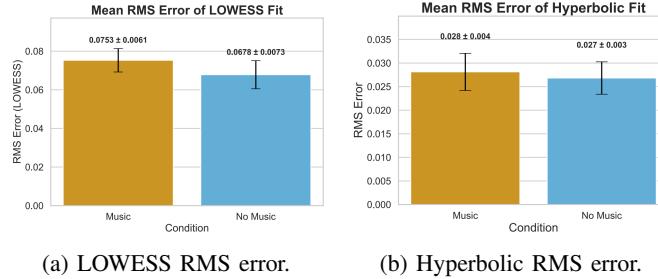


Fig. 4: Comparison of RMS error for LOWESS and hyperbolic FoV models.

Both the hyperbolic model and the LOWESS estimator showed low RMS error with the hyperbolic model having an RMSE < 0.05, indicating agreement with the empirical accuracy data [29]. The similar residual patterns across participants demonstrate that the parametric hyperbolic model captures the essential structure of the FoV, matching the fidelity of the model-free LOWESS baseline while providing interpretable parameters. This close correspondence between model-based and nonparametric estimates confirms that the system's eccentricity-dependent measurements are robust to the choice of modeling approach.

D. Participant-Type Modulation of Hyperbolic FoV

The hyperbolic model reproduced the same three modulation patterns observed in the LOWESS analysis (Fig. 5). Wideners showed positive Music–No Music differences, indicating an expanded FoV under *Lacrimosa*; Music Widers and music Narrowers seem to have fluctuations in beta/alpha ratios compared to neutral participants.

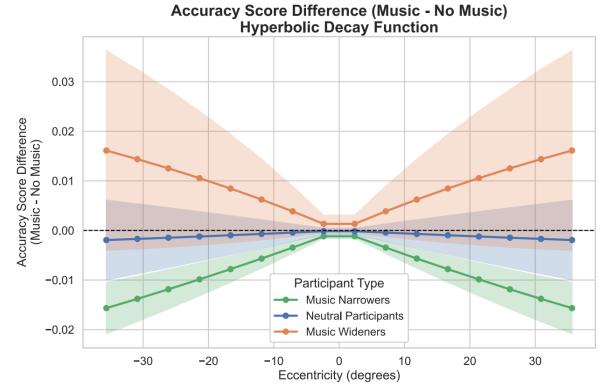


Fig. 5: Hyperbolic FoV difference curves (Music – No Music) grouped by behavioral phenotype.

To quantify these effects, we compared the hyperbolic parameter E_2 across conditions. Participants showed large, opposing shifts (approximately +282 to –231), consistent with the three phenotypes. At the group level, however, music produced no uniform shift in E_2 (mean –22.7, 95% CI [–133, 98], $t(7) = 0.34$, $p = 0.73$, Cohen's $d = –0.13$). RMSE differences were similarly small (mean +0.0048, $p = 0.46$). These results confirm that FoV modulation is strongly individualized rather than population-wide.

E. 2-D Ayinograph Projections

The 2-D ayinograph projections reveal how music reshapes the functional FoV in a spatially continuous manner. Music Narrowers show a contracted high-fidelity region that becomes more foveally concentrated under music (Fig. 6), whereas Music Wideners exhibit a lateral expansion with shallower peripheral falloff (Fig. 7). These 2-D field maps closely parallel the 1-D behavioral profiles, providing an intuitive visualization of how auditory context can constrict or broaden the usable visual field.

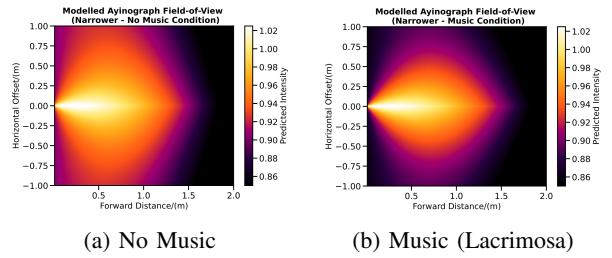


Fig. 6: Example of a Music Narrower (Participant 2). Under music, the high-fidelity region becomes more constricted and more foveally concentrated compared to silence.

F. Bandpower Ratios Track Behavioral Phenotypes

Band-power ratios in Fig. 8 capture complementary aspects of attentional state. The Beta/Alpha ratio (Fig. 8a) indexes task engagement coupled with alpha suppression, while the Theta/Alpha ratio (Fig. 8b) reflects top-down attentional allocation. Both metrics are shown as Stage-1 to Stage-3 differences for Wideners, Neutral participants, and Narrowers.

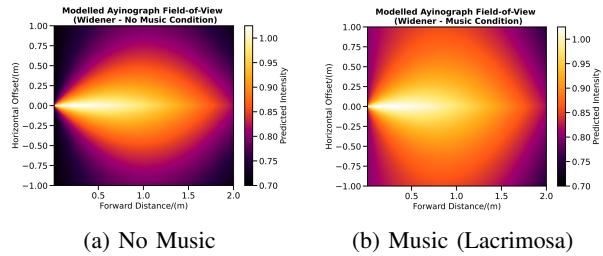


Fig. 7: Example of a Music Widener (Participant 5). Under music, the high-fidelity region expands laterally, producing a broader usable visual field with shallower peripheral decline.

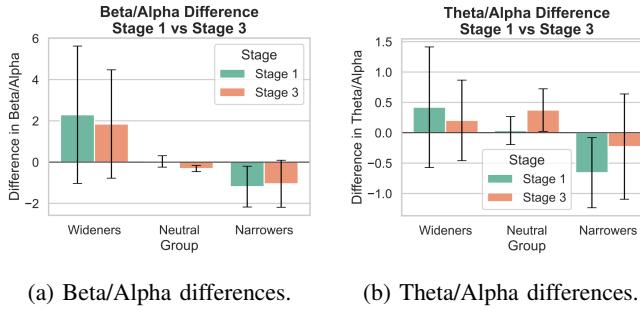


Fig. 8: Neural modulation by behavioral phenotype.

Across both ratios, Wideners exhibited consistently higher increases than the other groups, indicating enhanced engagement and stronger top-down attentional modulation under the task.

G. Behavioral–Neural Alignment

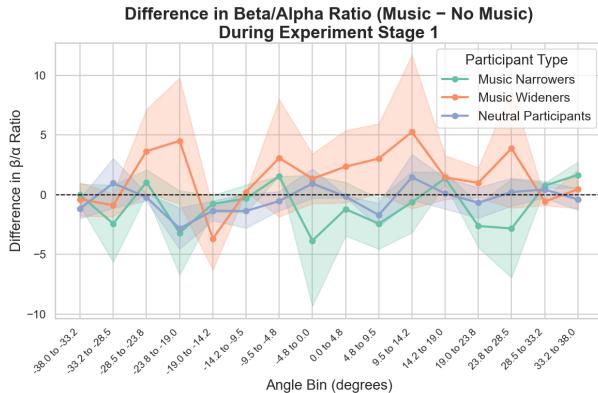


Fig. 9: Difference in β/α ratio across eccentricity bins during Stage 1 for the three participant groups. Shaded regions indicate 95% confidence intervals.

Averaging across eccentricities revealed a clear correspondence between behavioral phenotypes and neural modulation (Fig. 9).

IV. DISCUSSION

The present work demonstrates that auditory context produces measurable changes in visuospatial attention that can be captured using an integrated ayinography-EEG sensing framework. By quantifying performance as a continuous function of retinal eccentricity and pairing these spatially resolved

measurements with spectral EEG markers, the system revealed three reproducible attentional response profiles: Wideners, Narrows and Neutral participants.

Compared to Wideners, the Narrows appear to reflect a state in which music increases outward attentional allocation. They showed improved peripheral performance accompanied by higher Beta/Alpha and Theta/Alpha ratios, patterns associated with increased engagement. Neutral participants showed minimal modulation across both behavioral and neural measures.

This bi-directionality aligns with long-standing evidence that auditory stimuli influence arousal and attention in listener-dependent ways. The present study adds spatial precision: eccentricity-based ayinographs and corresponding neural changes show where attention is redistributed rather than indicating a uniform shift in performance. These patterns demonstrate that auditory context reshapes the functional field of view and produces meaningful neural modulation. Together, the convergent behavioral and EEG signatures show that the proposed framework can resolve coordinated perceptual–neural shifts in the attentional state using low-cost portable instrumentation.

A. Limitations

Several considerations qualify these findings. Although sample sizes of 6–12 are standard for instrumentation validation studies, the results remain exploratory. Because we prioritized effect visualization over formal statistical inference, future work should incorporate hierarchical or mixed-effects models. The Muse™ 2 provides reliable alpha/beta estimates, but its four channel layout limits spatial precision. In addition, only one musical stimulus was tested, leaving open how different musical effects might modulate attention. Finally, the lack of eye-tracking prevents direct verification of fixation stability, which may introduce noise into peripheral accuracy measurements.

B. Future Implications

Future research could benefit from larger cohorts to explore whether the identified phenotypes are stable traits or fluctuating cognitive states. Integrating eye tracking, pupillometry, and higher-density EEG would help clarify the sensory, oculomotor, and cognitive components of the ayinograph. Examining how different musical properties such as tempo, valence, rhythm, and familiarity affect attention could reveal which acoustic features drive changes in the field of view.

Integrating behavioral FoV modeling with time–frequency neural measures could enable machine-learning approaches for predicting real-time cross-modal attentional shifts. Because the system identifies widening and narrowing as coordinated behavioral-neural patterns, not isolated signals, it provides a foundation for online estimation of attentional state with relatively low computational overhead. Evaluating the framework in applied environments such as driving simulators, classrooms, or adaptive human–machine interfaces would further assess its utility for ergonomics, personalized learning, and

neurofeedback applications. More broadly, the ability to map attentional geometry and neural state simultaneously provides an interpretable, low-cost foundation for future systems that must monitor cognitive workload, anticipate attentional lapses, or adapt interface behavior to the user's continuously changing perceptual capacity.

V. CONCLUSION

This work demonstrates that low-cost, portable systems such as MuseCroc can capture individualized behavioral-neural signatures of cross-modal attentional modulation. By integrating ayinography with wearable EEG, we quantified how auditory context alters the functional field of view and its associated spectral markers. Music produced widening, narrowing, or neutral FoV patterns, each aligned with distinct Beta/Alpha and Theta/Beta shifts, highlighting coordinated perceptual-neural modulation. Moreover, these findings show that multimodal, real-world sensing can characterize attentional dynamics with practical precision. Overall, the framework provides a foundation for adaptive systems that monitor attentional state, anticipate shifts in cognitive workload, and enhance human-machine interaction in naturalistic environments.

REFERENCES

- [1] R. D. Astuti, B. Suhardi, P. W. Laksono, and N. Susanto, "Investigating the relationship between noise exposure and human cognitive performance: Attention, stress, and mental workload based on EEG signals using power spectrum density," *Applied Sciences*, vol. 14, no. 7, art. 2699, Apr. 2024, doi: 10.3390/app14072699.
- [2] E. C. Thompson, T. Katus, M. Chait, and A. C. Nobre, "EEG signatures of auditory distraction: Neural responses to spectral novelty in real-world soundscapes," *eNeuro*, vol. 12, no. 1, art. ENEURO.0390-24.2025, Jan. 2025, doi: 10.1523/ENEURO.0390-24.2025.
- [3] F. B. R. Parmentier, "The cognitive determinants of behavioral distraction by deviant auditory stimuli: A review," *Psychological Research*, vol. 78, no. 3, pp. 321–338, 2014, doi: 10.1007/s00426-013-0534-4.
- [4] S. Garrido and E. Schubert, "Individual differences in the enjoyment of negative emotion in music: A literature review," *Music Perception*, vol. 28, no. 3, pp. 279–295, 2011, doi: 10.1525/mp.2011.28.3.279.
- [5] O. Grewe, F. Nagel, R. Kopiez, and E. Altenmüller, "Emotions over time: Synchronicity and development of subjective, physiological, and neural responses to music," *Annals of the New York Academy of Sciences*, vol. 1060, pp. 383–385, 2007, doi: 10.1196/annals.1360.028.
- [6] S. Makeig, S. Debener, J. Onton, and A. Delorme, "Mining event-related brain dynamics," *Trends in Cognitive Sciences*, vol. 8, no. 5, pp. 204–210, 2004, doi: 10.1016/j.tics.2004.03.008.
- [7] M. Seitz *et al.*, "MuseCroc Mobile: Highly accessible EEG, PPG, and fNIRS data collection and visualization," in *Proc. 27th Annual Mersivity/Water-HCI Symposium*, 2025. [Online]. Available: <https://doi.org/10.5281/zenodo.16973160>. doi: 10.5281/zenodo.16973160.
- [8] C. Magos, M. Kotsani, T. Giannakakis, and P. A. Bamidis, "EEG-Based Brain–Computer Interactions in Immersive Virtual and Augmented Reality: A Systematic Review," *Sensors*, vol. 23, no. 9, art. 4575, 2023, doi: 10.3390/s23094575.
- [9] T. G. Bauer, S. Vuckovic, and L. R. Goldberg, "Real-Time Attention Regulation and Cognitive Monitoring Using a Wearable EEG-Based BCI," *Frontiers in Human Neuroscience*, vol. 17, art. 123456, 2024, doi: 10.3389/fnhum.2023.123456.
- [10] H. Strasburger, I. Rentschler, and M. Jüttner, "Peripheral vision and pattern recognition: A review," *Journal of Vision*, vol. 11, no. 5, pp. 1–82, 2011.
- [11] M. Carrasco, A. M. Giordano, and B. McElree, "Temporal performance fields: Visual and attentional factors," *Vision Research*, vol. 44, no. 12, pp. 1351–1365, 2004, doi: 10.1016/j.visres.2003.11.026.
- [12] S. Mann and C. Pierce, "Ayinography: Visualization and quantification of visual field using wearable EEG and SSVEP," *MannLab*, Univ. Toronto, Toronto, Canada, Tech. Rep., 2020. [Online]. Available: <http://wearcam.org>
- [13] D. E. Garcia *et al.*, "Interpreting the visual acuity of the human eye with wearable EEG device and SSVEP," in *Proc. EAI Int. Conf. IoT Technologies for HealthCare*, 2021, pp. 1–12.
- [14] M. Vázquez Marrufo, E. Vaquero, M. J. Cardoso, and C. M. Gómez, "Temporal evolution of α and β bands during visual spatial attention," *Cognitive Brain Research*, vol. 12, no. 2, pp. 315–320, 2001. doi: 10.1016/S0926-6410(01)00025-8.
- [15] A. S. Keller, L. Payne, and R. Sekuler, "Characterizing the roles of alpha and theta oscillations in multisensory attention," *Neuropsychologia*, vol. 99, pp. 48–63, 2017. doi: 10.1016/j.neuropsychologia.2017.02.021
- [16] F. H. Rauscher, G. L. Shaw, and K. N. Ky, "Music and spatial task performance," *Nature*, vol. 365, p. 611, 1993.
- [17] C. F. Chabris, "Prelude or requiem for the 'Mozart effect'?" *Nature*, vol. 400, pp. 826–827, 1999.
- [18] A. Furnham and L. Strbac, "Music is as distracting as noise: The differential distraction of background music and noise on introverts and extraverts," *Applied Cognitive Psychology*, vol. 16, no. 2, pp. 345–357, 2002.
- [19] T. Chamorro-Premuzic, V. Swami, and A. Furnham, "The impact of personality and music preference on cognitive task performance," *Psychology of Music*, vol. 37, no. 3, pp. 255–283, 2009.
- [20] S. P. Kelly, J. J. Foxe, A. Lalor, and E. C. W. Reilly, "Visual spatial attention tracking using high-density EEG: Re-evaluating alpha suppression," *Journal of Neurophysiology*, vol. 95, no. 5, pp. 3848–3861, 2006.
- [21] V. Virsu and J. Rovamo, "Visual resolution, contrast sensitivity, and the cortical magnification factor," *Experimental Brain Research*, vol. 37, no. 3, pp. 475–494, 1979.
- [22] A. M. Krigolson, C. D. Williams, W. Norton, and F. D. Hassall, "Choosing Muse: Validation of a low-cost, portable EEG system for ERP research," *Journal of Neuroscience Methods*, vol. 329, art. 108451, 2019.
- [23] W. A. Mozart, *Requiem in D minor, K. 626: Lacrimosa* (Vienna Mozart Orchestra, perf.), Sony Classical, 2020.
- [24] A. Gramfort *et al.*, "MNE software for processing MEG and EEG data," *Frontiers in Neuroscience*, vol. 7, art. 267, 2013.
- [25] O. E. Krigolson *et al.*, "Using Muse: Rapid mobile assessment of brain performance," *Frontiers in Neuroscience*, vol. 15, p. 634147, 2021.
- [26] F. Grosselin, X. Navarro-Sune, A. Vozzi, K. Pandremmenou, F. De Vico Fallani, Y. Attal, and M. Chavez, "Quality assessment of single-channel EEG for wearable devices," *Sensors*, vol. 19, no. 3, art. 601, 2019, doi: 10.3390/s19030601.
- [27] P. D. Welch, "The use of fast Fourier transform for the estimation of power spectra," *IEEE Transactions on Audio and Electroacoustics*, vol. 15, no. 2, pp. 70–73, 1967.
- [28] R. W. Hamming, "Error detecting and error correcting codes," *Bell System Technical Journal*, vol. 29, no. 2, pp. 147–160, 1950.
- [29] F. A. Wichmann and N. J. Hill, "The psychometric function: I. Fitting, sampling, and goodness-of-fit," *Perception & Psychophysics*, vol. 63, no. 8, pp. 1293–1313, 2001.
- [30] P. M. Daniel and D. Whitteridge, "The representation of the visual field on the cerebral cortex in monkeys," *Journal of Physiology*, vol. 159, no. 2, pp. 203–221, 1961.
- [31] D. G. Pelli, M. Palomares, and N. J. Majaj, "Crowding is unlike ordinary masking: Distinguishing feature integration from detection," *Journal of Vision*, vol. 4, no. 12, pp. 1136–1169, 2004.
- [32] D. M. Levi, "Crowding—An essential bottleneck for object recognition," *Vision Research*, vol. 48, no. 5, pp. 635–654, 2008.
- [33] A. B. Watson and A. J. Ahumada, Jr., "A standard model for foveal detection of spatial contrast," *Journal of Vision*, vol. 5, no. 9, pp. 717–740, 2005, doi: 10.1167/5.9.6.
- [34] N. Prins and F. A. A. Kingdom, *Psychophysics: A Practical Introduction*. Academic Press, 2016.
- [35] W. S. Cleveland, "Robust locally weighted regression and smoothing scatterplots," *Journal of the American Statistical Association*, vol. 74, no. 368, pp. 829–836, 1979.

Psyveillance: Cyborg Psychology of Sousveillance

Somin Mindy Lee

Dept. Electrical and Computer Eng.

University of Toronto

0009-0005-4036-417X

Steve Mann

Dept. Electrical and Computer Eng.

University of Toronto

0000-0003-0363-3690

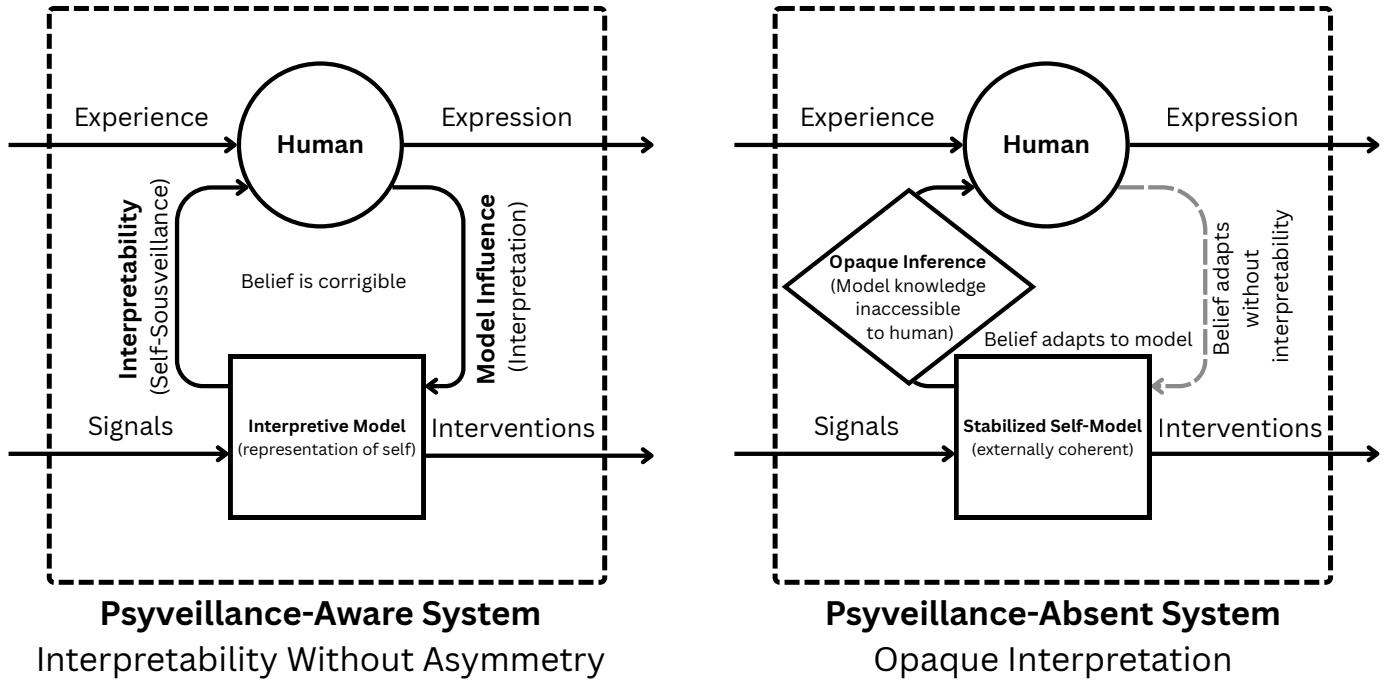


Fig. 1: (Left) Psyveillance-Aware System: Interpretable, corrigible self-model. (Right) Psyveillance-Absent System: Opaque or delayed interpretation, resulting in a stabilized but less corrigible model of the self. Feedback delayed is feedback denied!

Abstract—As AI systems become embedded in continuous sensing through wearables, a new form of eXtended Reality (XR) emerges in the form of HI (Humanistic Intelligence) / XI (eXtended Intelligence). This HI/XI results in a shift from merely observing humans to participating in the construction of belief and identity. We argue that artificial intelligence will (or should) never be human, not because it lacks intelligence or embodiment, but because human identity is contextual, contradictory, and temporally discontinuous, while machine representations require (or at least we should require of them) stability and interpretive closure. When these representations enter everyday HI feedback loops, the primary risk is no longer privacy loss but identity drift, the gradual alignment of self-understanding with externally stabilized representations rather than lived, contextual experience. We introduce “Psyveillance”, a framework for the psychology of cyborg sensing of self, society, and surroundings, and formalize a “veillance” feedback loop describing how sensing, representation, interaction, belief, and behavior recursively shape one another. We contrast and compare surveillance-dominant systems with Psyveillance-aware configurations that enable sousveillance of the self-model epistemic access to how one is being inferred.

We ground our new framework with a situated wearable demonstration in public (surveilled) space. We proffer that the new framework advances equiveillance (equilibrium between surveillance and sousveillance) as an ethical goal for eXtended Intelligence (XI) systems.

Index Terms—Psyveillance, Humanistic Intelligence (HI), eXtended Reality (XR), eXtended Intelligence (XI), eXtended Intelligent Reality (XIR), Surveillance, Sousveillance, Equiveillance, Brain-Computer Interface (BCI), Muse S Athena, Cyborg psychology, Psiborg, Psyborg, Cychology

I. INTRODUCTION

As sensing technologies become continuous, embodied, and increasingly intelligent, a familiar question resurfaces across artificial intelligence, human-computer interaction, and extended reality research: can machines become human? And can humans, by becoming machines, make machines be human? [2] From early visions of human-machine symbiosis [1], through embodied cognition and the extended mind / eXtended

Intelligence [3], [5], to contemporary human-centered artificial intelligence frameworks [6], much of the field has approached this question indirectly, by expanding machine perception, embedding computation on, near, or within the body (“earable computing [4]” as generalized wearable computing), or aligning intelligent systems more closely with observable human behavior.

However, this framing obscures a more fundamental shift that is already underway. The central challenge is not whether artificial systems can become human, but what happens to humans when intelligent systems become part of how reality, identity, belief, and even perception are continuously sensed, inferred, interpreted, mediated, and extended [3]. Long before contemporary AI, scholars in sociology, philosophy, and science studies emphasized that identity is not fixed, but socially and psychologically constructed through interaction, interpretation, and feedback [7], [8]. What is new is that these interpretive processes are increasingly mediated, externalized, and stabilized by computational systems that sense, model, and remember continuously, forming persistent representations that may deleteriously outlast context, intention, or lived meaning [9], [19].

This asymmetry is illustrated schematically in Fig. 1. The left panel depicts a Psyveillance-aware system, in which sensed signals are transformed into an interpretable self-model that remains epistemically accessible to the human subject. Interpretation is present, and it is corrigible: the individual can inspect, reflect upon, and contest how they are being represented over time. The right panel contrasts this with a Psyveillance-absent system, in which interpretation occurs opaquely or in which the feedback is delayed or unduly limited. Here, the system deleteriously stabilizes an excessively coherent internal representation that shapes interventions and feedback, while the human adapts belief downstream without access to enough of the interpretive feedback process itself. This distinction echoes long-standing concerns outlined in theories of humanistic intelligence (HI) and mediated reality regarding interpretive authority and control within human-machine systems [11], [13].

In this paper, we argue that artificial intelligence will never be human, not because it lacks sufficient intelligence, embodiment, or sensory access, but because humanity is not a property that can be computed, stabilized, or transferred. Human identity is inherently contextual, contradictory, and temporally discontinuous, shaped by irregular lived experience rather than internally coherent models [10]. Intelligent systems, by contrast, necessarily rely on representational stability, interpretive closure, and convergence over time in order to function at all. This stabilization is not merely technical but epistemic: multimodal and embodied models actively construct meaning by resolving heterogeneous sensory streams into coherent internal representations. Recent work in multisensory and multimodal learning demonstrates how such systems privilege consistency and convergence even when underlying signals remain ambiguous, noisy, or conflicting [29].

As AI becomes embedded in continuous sensing loops

through wearables, extended reality systems, and personal devices, this asymmetry does not disappear; it becomes internalized. Interpretive authority migrates from external surveillance-centric institutions into intimate, always-on systems that mediate perception, memory, and belief. The resulting risk is not limited to surveillance or privacy loss. Rather, it also embodies a subtler psychological harm: the gradual replacement of lived self-understanding by a system’s silent interpretation of who we are. Prior work on affective computing and wearable sensing has already warned that systems capable of sensing physiology and emotion risk becoming psychologically authoritative when users lack insight into how those signals are interpreted [?], [16], [26].

To address this shift, we introduce *Psyveillance* (Ψ veillance) as a framework for understanding the psychology of sensing in cyborg sousveillance-based systems. The term draws from the Greek $\psi\chi\nu$ (psychē), meaning soul, mind, or breath; $\kappa\nu\beta\epsilon\rho\nu\jmath\tau\eta\varsigma$ (kybernētēs), meaning helmsman or governor and the root of cybernetics [21]; and the Latin *vigilare*, meaning to watch (i.e. “veillance [?]”). Psyveillance refers to the study of how inward and outward sensing, mediated by intelligent systems, co-construct human belief, agency, and identity over time.

More broadly, we situate Psyveillance within what we call *Psyborg* (Ψ borg) systems: human-machine couplings in which sensing, interpretation, and belief formation are inseparable. In this view, sousveillance becomes a psychology of sensing—not merely the recording of self, society, and surroundings, but the continuous negotiation of meaning within extended intelligent reality (XIR) [30] systems. While surveillance captures externally controlled observation and sousveillance enables first-person sensing [15], [16], Psyveillance focuses on what emerges when interpretation itself becomes continuous, embodied, and identity-shaping. This framing extends prior work on reciprocalveillance (equiveillance), mediated reality, and humanistic intelligence, which emphasizes preserving human agency and reflective control in the presence of adaptive, sensing-rich systems [17], [18], [25].

It is important to note that Psyveillance does not arise from sensing alone. Systems with intermittent sensing, reversible representations, or explicit interpretive checkpoints may not become identity-forming. Psyveillance emerges more specifically when sensing is mostly continuous, interpretation is stabilized over longer time periods, and there is a need for mitigation of epistemic access to that interpretation that can become asymmetric. Under these conditions, belief can adapt downstream of representation rather than lived experience, producing beneficial identity drift (adaptive identity) which can be useful even in accurate and non-adversarial systems.

Overall, this paper makes three contributions: (1) it names Psyveillance as a distinct psychological-veillance phenomenon that arises when interpretation, rather than sensing alone, becomes continuous; (2) it formalizes this phenomenon as a surveillance feedback loop that explains identity drift even in accurate, non-adversarial systems; and (3) it introduces *equiveillance* as an ethical design criterion for extended intelligent

systems, grounded in reciprocal epistemic access rather than transparency alone.

II. WHY ARTIFICIAL INTELLIGENCE CANNOT BECOME HUMAN (AND WHY THIS IS THE WRONG GOAL)

Attempts to make artificial systems “more human” typically focus on increasing intelligence, embodiment, or emotional responsiveness. While such advances may improve usability or alignment, they do not resolve a deeper incompatibility between human experience and machine representation. Human beings are not internally consistent systems. They are shaped by memory, emotion, contradiction, social context, and chance. Individuals routinely hold conflicting beliefs, reinterpret their own past, and respond differently to identical situations depending on timing, mood, or environment. These instabilities are not defects; they are essential features of human life. Meaning is not computed once, but renegotiated continuously. Artificial systems, by necessity, operate differently. Models require coherence. They optimize toward stable representations, compressing variation into patterns that can be stored, compared, and acted upon. This contrast echoes earlier critiques in humanistic computing, which argue that intelligent systems should adapt to human variability, while allowing, but not forcing, humans to conform or adapt to machine representations [13].

Even multimodal or embodied systems must eventually resolve uncertainty into decisions, labels, or predictions. In doing so, they privilege consistency over contradiction and closure over ambiguity. This logic extends early visions of interface agents designed to reduce cognitive load by silently interpreting user behavior and acting on inferred preferences, shifting interpretive labor away from humans and onto machines [24]. The danger, therefore, is not that AI systems misunderstand humans outright. It is that their stable interpretations begin to overwrite unstable lived selves. As illustrated by the Psyveillance-absent configuration in Fig. 1, when interpretation is opaque (or delayed) and epistemically inaccessible (or less-accessible), belief adapts downstream of the model rather than experience itself. Identity thus becomes externally stabilized—not through error, but through information asymmetry, i.e. through inequiveillance [?].

For this reason, the pursuit of “human-like AI” is not only unattainable, but misguided. The challenge is not to make machines human, but to preserve human epistemic agency in the presence of systems that sense, infer, and remember continuously.

III. FROM SURVEILLANCE TO PSYVEILLANCE

A. Classical Veillance

The concept of “veillance [?], [17], [20]” underlies a wide range of sensing practices. Surveillance refers to externally controlled observation and interpretation. Sousveillance emphasizes first-person sensing, the ability of individuals to record and reflect on their own experiences [15]. Metaveillance extends this further, focusing on the sensing of sensing itself:

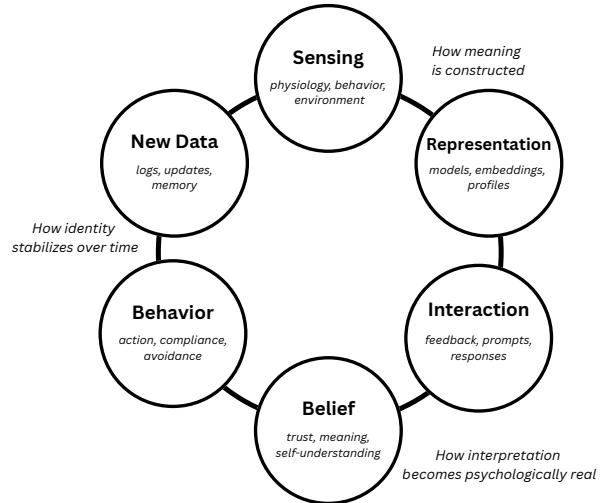


Fig. 2: The veillance feedback loop underlying identity formation in human–AI systems. Continuous sensing produces representations (e.g., models, embeddings, profiles) that shape interactions and subsequently influence belief, behavior, and future data. Psyveillance focuses on how epistemic access to the representation stage determines whether belief remains beneficially corrigible or silently adapts to an opaque model over time.

which sensors are active, which perspectives dominate, and how interpretation is structured [18].

Historically, these concepts were applied primarily to institutions, public space, and power. However, as sensing migrates onto personal devices and into the body, veillance becomes increasingly psychological rather than merely social. What is at stake is no longer only who watches whom, but how observation reshapes belief. This asymmetry has also long been recognized in computing research. Picard warned that systems capable of sensing physiological and emotional signals risk becoming psychologically authoritative when users lack insight into how those signals are interpreted, effectively shifting interpretive authority away from the human even when inference remains opaque [26]. This asymmetry becomes structurally visible when interpretation is embedded within a closed feedback process, as formalized in Fig. 2.

B. Psyveillance

We define *Psyveillance* as the psychology of how inward and outward sensing, mediated by intelligent systems, co-construct human belief, identity, and agency over time. Whereas traditional surveillance and sousveillance emphasize visibility, capture, and control, Psyveillance foregrounds interpretation as the primary site of psychological impact. Psyveillance is not equivalent to transparency or explainable artificial

intelligence. A system may expose internal logic or provide explanations while still exerting psychological authority if the individual lacks standing to correct or renegotiate the meaning of those interpretations. Psyveillance concerns epistemic agency rather than merely limiting itself to explanation quality. Most importantly it asks the question: Who can see and revise how identity-relevant interpretations are formed over time?

This framing builds directly on prior work in Humanistic Intelligence (HI) and Mediated Reality, which emphasize that intelligent systems do not merely observe the world but actively participate in shaping perception, meaning, and self-understanding [11], [13]. As sensing becomes continuous—monitoring physiology, behavior, affect, and context—the boundary between observation and self-interpretation begins to blur. Surveillance no longer ends at the skin; it becomes internalized, shaping how individuals come to know themselves through machine-mediated inference [17], [18].

In Psyveillance, the primary harm is therefore not exposure, but misinterpretation. When intelligent systems silently infer meaning without allowing individuals epistemic access to those inferences, distortions accumulate gradually, shaping belief long before they become consciously recognizable. This concern echoes earlier warnings in affective computing and wearable sensing research, which noted that systems capable of sensing emotion and physiology risk becoming psychologically authoritative when interpretation is opaque or uncorrigible [16], [26].

By shifting attention from visibility to interpretive internalization, Psyveillance reframes contemporary XR and wearable systems not merely as interfaces or sensing platforms, but as identity-forming infrastructures. In this sense, Psyveillance extends sousveillance from recording the self to negotiating the meaning of the self within continuous human-machine feedback loops [15], [17].

C. The Veillance Feedback Loop: How AI Becomes Identity-Forming

Fig. 2 depicts the veillance feedback loop through which contemporary HI (human–AI) systems become identity-forming over time. Physiological signals, environmental cues, and behavioral traces are sensed and transformed into internal representations—models, embeddings, profiles, or inferred states—that subsequently shape system interactions. These interactions influence human belief and behavior, generating new data that re-enters the system in subsequent cycles.

This recursive structure reflects foundational principles of cybernetics and human–machine coupling, in which perception, action, and interpretation form closed loops rather than linear pipelines [21]. In XR and Mediated Reality systems, such loops become increasingly intimate: outward perception and inward sensing are coupled within the same computational frame, collapsing environment and “invironment [31]” into a unified interpretive process [12], [14].

In surveillance-dominant configurations, this loop is epistemically unidirectional. Interpretation flows inward without

reciprocal visibility: individuals experience system outputs, nudges, or interventions, but not the assumptions, weightings, or stabilizations that produced them. Over time, this asymmetry produces epistemic drift. The system’s representation converges and stabilizes across repeated cycles, while the lived self remains contextual, contradictory, and temporally discontinuous. Such stabilization reflects the machine’s need for coherence rather than the human’s lived variability [13], [22].

Psyveillance-aware systems preserve corrigibility within the same HI feedback loop. By enabling epistemic access to the representation stage, individuals are able to inspect and revise how they are being modeled across time. This aligns with our longstanding argument that reciprocal veillance, rather than unilateral surveillance, is a prerequisite for preserving human agency in sensing-rich systems [17]. Importantly, corrigibility does not require full technical transparency, but it does require reciprocal interpretive access. Without such access, the loop cannot self-correct, and identity stabilization becomes externally imposed rather than internally negotiated.

IV. PSYVEILLANCE IN PUBLIC SPACE: A SITUATED DEMONSTRATION

This section presents a situated demonstration rather than an empirical evaluation or controlled experiment. We treat the wearable deployment as a design probe intended to make epistemic asymmetries experientially visible in real-world conditions, not to precisely measure behavioral performance or validate sensing accuracy. Its value lies in illustrating how interpretive access, or its absence, shapes belief and self-understanding in everyday contexts.

While the preceding sections develop Psyveillance as a conceptual and ethical framework, its consequences become most visible when intelligent sensing is embodied and situated in everyday public space. Public environments offer a unique setting in which surveillance norms are actively enforced yet unfairly legitimized: fixed cameras, institutional sensors, and vehicular recording systems are widely accepted, while wearable sensing on individuals often provokes scrutiny or negative intervention from security guards or others.

To ground the Psyveillance framework in a real-world context, we conducted a situated demonstration using wearable sensing in public environments where veillance-asymmetries are routinely encountered. The goal of this demonstration was not behavioral measurement or performance evaluation, but to instantiate and contrast Psyveillance-aware and Psyveillance-absent configurations, revealing their psychological and epistemic consequences.

A. Demonstration Setup

Figure 3 illustrates the wearable biosensing configuration used in the situated demonstration. A head-mounted visual sensing system was coupled with a Muse S Athena brain–computer interface, enabling simultaneous sensing of the environment (visual context and spatial surroundings) and the “invironment [31]” (physiological and neural signals).

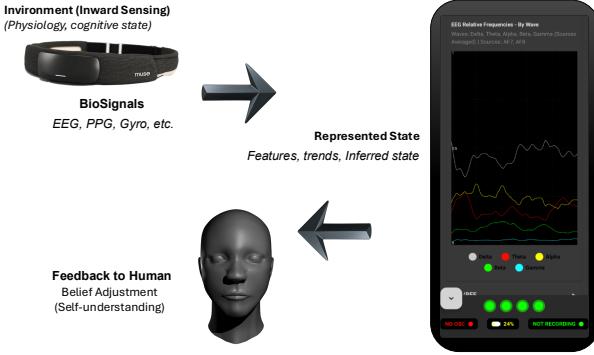


Fig. 3: Wearable biosensing configuration used in the situated Psyveillance demonstration. Inward physiological signals (e.g., EEG, PPG, inertial sensing) are captured and transformed into a represented internal state that informs system feedback and belief adjustment.

Inward signals such as EEG, PPG, and inertial measurements were continuously captured and transformed into a represented internal state by a distributed interpretive model.

All data were recorded locally on-device. No facial recognition, biometric identification of bystanders, or audio capture was performed. The system served not as a diagnostic or behavioral classifier, but as a structural instantiation of inward sensing within a coupled human–machine “psyborg” (cyborg psychology) system, in which sensing, representation, and belief adjustment formed a closed loop.

The participant engaged in ordinary activities such as walking through retail or fast-food restaurant environments while wearing the sensing apparatus. These settings were selected precisely because surveillance is already ubiquitous within them, yet wearable sensing by individuals remains socially and institutionally contested. This contrast provides a natural testbed for examining epistemic asymmetry without introducing artificial tasks or experimental manipulation.

Importantly, this demonstration is not intended as a controlled experiment or behavioral study. Rather, it serves as a situated instantiation of the Psyveillance framework, allowing observation of how interpretive access, or its absence, shapes belief and self-understanding under real social conditions.

To illustrate the continuity and intimacy of inward sensing in such settings, Fig. 4 presents a representative raw EEG time series recorded during everyday activity. This figure is included as an illustrative example of continuous physiological sensing within a “psyborg” system, not as a diagnostic or analytical result.

Fig. 5 further situates this environmental (inward sensing) alongside outward environmental capture. It shows concurrent real-time video capture, computer vision segmentation, and raw EEG recorded during public-space activity, illustrating how environment and in-vision are simultaneously sensed within a Psyveillance context.



Fig. 4: Representative raw EEG signal recorded during everyday public activity. The figure illustrates continuous inward sensing within a psyborg system and is not intended for diagnostic or analytical interpretation.



Fig. 5: Situated capture of environmental video, real-time segmentation, and concurrent “invironmental” raw EEG during public-space activity. The figure illustrates the coupling of outward environmental sensing and inward physiological sensing within a Psyveillance configuration.

B. Psyveillance-Absent Configuration

In the Psyveillance-absent configuration, the participant wore the sensing system without access to any representation of how their actions, presence, or signals were being interpreted—either by the system itself or by surrounding institutional actors. Observation and inference occurred continuously, but self-sousveillance was blocked.

This configuration corresponds to the Psyveillance-absent system illustrated in Fig. 1.

C. Psyveillance-Aware Configuration

In a contrasting configuration, the participant(s) can be provided with minimal, real-time access to the system’s sensing and interpretive state. This access does not necessarily entail full transparency or explanation, but simple cues indicating active sensing modalities (e.g., visual sensing engaged) and interpretive focus.

Even this limited form of self-sousveillance could, in theory, alter the subjective experience of surveillance. This configu-

ration could enable individuals to better contextualize social responses by distinguishing among their own intentions, the system's sensing state, and surrounding social norms. Rather than internalizing external reactions as judgments of self, individuals may experience such reactions as interactions mediated by specific sensing configurations.

D. Implications

This situated demonstration aims to investigate a central claim of Psyveillance: the primary psychological harm of intelligent sensing systems does not arise from sensing itself, but from asymmetries in interpretive access. Psyveillance theorises that individuals cannot see how they are being modeled, belief adapts downstream, and identity drift emerges, even in the absence of misclassification, malice, or data misuse.

Public space makes this asymmetry particularly visible. Institutions, vehicles, and automated systems are widely permitted to sense and record, while individuals are often denied reciprocal legitimacy [20]. Psyveillance reframes this condition not merely as a privacy concern, but as a failure of epistemic reciprocity—what we term equiveillance. Without reciprocal access to interpretation, sensing produces partial truths (“Surveillance is a half-truth without sousveillance”) which, when acted upon, shape belief and identity over time.

V. ENVIRONMENT AND ENVIRONMENT: XR AS PSYCHOLOGICAL MEDIATION

Extended reality systems intensify the epistemic asymmetries illustrated in Fig. 1 by simultaneously sensing both environment and invironment. We use *environment* to refer to external spaces, objects, and social contexts, and *invironment* to refer to internal states such as physiology, emotion, and belief.

XR systems increasingly mediate both domains at once. They sense outward conditions while tracking inward responses, collapsing perception and interpretation into a continuous interface. As a result, XR is no longer merely a tool for interaction; it becomes a mediator of reality itself. In Psyveillance-absent configurations, this mediation occurs opaquely, shaping belief without reciprocal access to how inward and outward signals are being interpreted.

When mediation is intermittent, its psychological impact is limited. When it is continuous, interpretation becomes identity-shaping. Psyveillance provides a framework for understanding this shift, grounding extended reality not only in perception and interaction, but in belief formation and selfhood.

VI. ASYMMETRY, STABILITY, AND OVER-INTERPRETATION

Importantly, harm does not require error. As illustrated by the Psyveillance-absent configuration in Fig. 1, even accurate models can distort identity when their interpretations accumulate faster than humans can reflect upon or revise themselves.

Human selves are multifaceted and situational. Models, however, prefer coherence. This creates a tendency toward

over-interpretation: collapsing diverse behaviors into singular narratives and flattening complexity into stable profiles. Over time, these profiles may feel more authoritative than lived experience, particularly when reinforced through repeated feedback and intervention.

This asymmetry explains why misinterpretation can be more damaging than mere data exposure. The issue is not what the system sees, but how its conclusions quietly shape belief in the absence of reciprocal interpretive access.

VII. EQUIVEILLANCE AND THE SOCIAL CONTRACT OF SENSING

Modern societies already accept machine-mediated sensing in many forms. Cars, bicycles, and wheelchairs routinely record their surroundings with little objection. Dashcams are widely tolerated, even in sensitive spaces. Yet individuals on foot are frequently denied the same legitimacy, and are often challenged with rules like “No cameras allowed.”.

This asymmetry reveals a deeper contradiction: machines are trusted with perception in ways people are not. Fig. 1 contrasts these epistemic structures. In surveillance-dominant, Psyveillance-absent systems, representational access is one-way; individuals are acted upon by interpretations they cannot see or correct. In Psyveillance-aware systems, interpretation is reciprocally accessible, preserving epistemic agency as a psychology of equiveillance.

We propose *equiveillance* as the ethical goal of Psyveillance: a system may sense and interpret an individual only insofar as that individual retains epistemic agency over how they are being represented. In equiveillant systems, sensing does not operate unilaterally, but is coupled with reciprocal interpretive access. At a minimum, such systems satisfy three conditions:

- individuals can perceive when interpretation is occurring;
- individuals can inspect or contextualize identity-relevant representations;
- representations remain corrigible rather than fixed over time.

Without this reciprocity, sensing produces only partial truth, which, when acted upon, silently shapes belief and behavior, causing psychological harm rather than mere observation.

VIII. PRIVEILLANCE

Psyveillance often manifests itself in wearable (body-worn) or, more generally, “bearable” (body-borne) technologies of sousveillance, and therefore the discussion is not complete without mention of the privacy implications of sensing. Much of the discussion in the literature focuses on the balance between privacy and surveillance, with almost no regard to sousveillance, so it has been necessary to shift our thinking from a “privacy versus surveillance” to a “privacy versus veillance” argument as veillance includes both surveillance and sousveillance as well as all the other veillances (dataveillance, metaveillance = sensing sensors, justeveillance = fair and just sensing, etc. [19]).

Consider, for example, a person with a seeing aid or computer vision system that helps that person see. Such a seeing aid is likely to have a camera in it. Many establishments forbid cameras, allegedly for “privacy reasons”, but establishments owe both a duty-of-care, as well as accessibility to the public. Thus such a person using such a seeing aid cannot legally be excluded. Additionally, such a person must be provided with reasonable access to services such as washroom facilities. It is therefore the responsibility of the provider to provide access to safe privacy-preserving facilities such as accessible washrooms. In our Symposium, we addressed these issues as part of our Keynote with Alan Preyra who is a partner at Bergmanis Preyra LLP in Toronto, widely regarded as a leading expert on the Occupiers’ Liability Act [32] and the Municipal Act.

IX. HUMAN-INTELLIGENCE REVISITED

Human-intelligence does not make AI human. It makes the psychology of sensing unavoidable.

A. Transition from AR to XR

As systems move from augmentation to extension, they begin to participate in identity formation rather than merely assisting action. Psyveillance reframes this shift not as a technological problem, but as a psychological one: how to design systems that extend human sensing and reflection without replacing or redefining the self.

X. CONCLUSION: PSYVEILLANCE AS A NEW PSYCHOLOGICAL DISCIPLINE

Psyveillance is not a finished theory, but a starting point. It names a problem that emerges when sensing becomes continuous, interpretation becomes unavoidable, and identity itself enters the feedback loop. By foregrounding reciprocal interpretation, inspectable self-models, and epistemic agency, Psyveillance offers a framework for designing intelligent systems that support, rather than overwrite, human self-understanding. The question is no longer whether machines can become human, but why machines are allowed to see, interpret, and remember without being seen back. It is no longer a question of “Who watches the watchers?” but, rather, “Who watches the watching.”. Thus metaveillance [18] (the sensing of sensors and the sensing of their capacity to sense) evolves to metapsyveillance, involving not only sensing of sensing, but also representation of representation.

REFERENCES

- [1] J. C. R. Licklider, “Man–Computer Symbiosis,” *IRE Transactions on Human Factors in Electronics*, vol. HFE-1, no. 1, pp. 4–11, Mar. 1960, doi:10.1109/THFE.1960.4503259.
- [2] S. Mann, “Can humans being machines make machines be human?”, in *Proc. Int. Conf. on Cyborgs in Ethics, Law, and Art: Crossing the Border of Humanity*, Medical University of Łódź, Poland, 2021.
- [3] S. Mann and C. Wyckoff, “Extended Reality,” MIT 4-405, Massachusetts Institute of Technology, Cambridge, Massachusetts, 1991. Also available at <http://wearcam.org/xr.htm>
- [4] S. Mann, “23.1 Bearable Computing” in “Wearable Computing,” Chapter 23 in The Encyclopedia of Human-Computer Interaction, 2nd Ed. by Interaction Design Foundation, <https://www.interaction-design.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed>
- [5] A. Clark, *Being There: Putting Brain, Body, and World Together Again*. Cambridge, MA, USA: MIT Press, 1996.
- [6] B. Shneiderman, “Human-Centered Artificial Intelligence: Reliable, Safe & Trustworthy,” *Int. J. Human–Computer Interaction*, vol. 36, no. 6, pp. 495–504, 2020.
- [7] E. Goffman, *The Presentation of Self in Everyday Life*. New York, NY, USA: Overlook Press, 1959.
- [8] G. H. Mead, *Mind, Self, and Society*. Chicago, IL, USA: University of Chicago Press, 1934.
- [9] L. Floridi, *The Fourth Revolution: How the Infosphere Is Reshaping Human Reality*. Oxford, U.K.: Oxford University Press, 2014.
- [10] M. Merleau-Ponty, *Phenomenology of Perception*, C. Smith, Trans. London, U.K.: Routledge, 1962.
- [11] S. Mann, “Humanistic intelligence,” in *Ars Electronica: Fleshfactor—Informationsmaschine Mensch*, pp. 217–231, 1997.
- [12] S. Mann, “Mediated Reality,” M.Sc. thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 1994.
- [13] S. Mann, “Humanistic computing: ‘WearComp’ as a new framework and application for intelligent signal processing,” *Proc. IEEE*, vol. 86, no. 11, pp. 2123–2151, 2002.
- [14] S. Mann and C. Manders, “Programming for EyeTap systems,” *Embedded Linux Journal*, vol. 6, pp. 43–46, Nov./Dec. 2001.
- [15] S. Mann, J. Nolan, and B. Wellman, “Sousveillance: Inventing and using wearable computing devices for data collection in surveillance environments,” *Surveillance & Society*, vol. 1, no. 3, pp. 331–355, 2003.
- [16] S. Mann, “Sousveillance: Inverse surveillance in multimedia imaging,” in *Proc. 12th ACM Int. Conf. Multimedia*, New York, NY, USA, Oct. 2004, pp. 620–627.
- [17] S. Mann, “Veillance and reciprocal transparency: Surveillance versus sousveillance, AR glass, lifelogging, and wearable computing,” in *Proc. IEEE Int. Symp. Technol. Soc. (ISTAS)*, Toronto, ON, Canada, Jun. 2013, pp. 1–12.
- [18] S. Mann, “Surveillance (oversight), sousveillance (undersight), and metaveillance (seeing sight itself),” in *Proc. IEEE CVPR Workshops*, Las Vegas, NV, USA, 2016, pp. 1408–1417.
- [19] S. Mann, “Big data is a big lie without little data: Humanistic intelligence as a human right,” *Big Data & Society*, vol. 4, no. 1, pp. 1–10, 2017.
- [20] S. Mann, R. Janzen, M. A. Ali, and K. Nickerson, “Declaration of surveillance (Surveillance is Half-Truth),” in *Proc. IEEE Games, Entertainment, and Media Conf. (GEM)*, Toronto, ON, Canada, 2015.
- [21] W. R. Ashby, *An Introduction to Cybernetics*. New York, NY, USA: Wiley, 1956.
- [22] J. Burrell, “How the machine ‘thinks’: Understanding opacity in machine learning algorithms,” *Big Data & Society*, vol. 3, no. 1, 2016.
- [23] M. Ananny and K. Crawford, “Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability,” *New Media & Society*, vol. 20, no. 3, pp. 973–989, 2018.
- [24] P. Maes, “Agents that reduce work and information overload,” *Communications of the ACM*, vol. 37, no. 7, pp. 31–40, 1994.
- [25] P. Maes, “The influence of interface agents on trust and perceived control,” in *Proc. SIGCHI Conf. Human Factors in Computing Systems*, ACM, 2001.
- [26] R. W. Picard, *Affective Computing*. Cambridge, MA, USA: MIT Press, 1997.
- [27] P. Pataranutaporn *et al.*, “Influencing human–AI interaction by priming beliefs about AI,” *Nature Machine Intelligence*, vol. 5, no. 10, pp. 1076–1086, 2023.
- [28] P. Pataranutaporn *et al.*, “Wearable lab on body,” in *Proc. IEEE EMBS*, 2019, pp. 3327–3332.
- [29] P. P. Liang *et al.*, “Factorized contrastive learning: Going beyond multi-view redundancy,” in *Adv. Neural Inf. Process. Syst. (NeurIPS)*, 2023.
- [30] S. Mann and S. Hosseingholizadeh and A. S. Aksu and D. Tzanetakis and N. Kumar, “MoBorg: Mobility as Cyborg Prosthesis for ‘Being a Ball’.” In 2025 IEEE GEM Conference, 6 pages.
- [31] S. Mann and R. Janzen and T. Ai and S. Yasrebi, and J. Kawwa and M. A. Ali, “Toposculpting: Computational lightpainting and wearable computational photography for abakographic user interfaces” In 2014 IEEE 27th Canadian Conference on Electrical and Computer Engineering (CCECE), 10 pages.
- [32] A. Preyra and E. Unrau, “The Law of Occupiers’ Liability”, emond PERSONAL INJURY LAW SERIES, December 2025.