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From Lab to Field: Facilitating Cooperative Work with Interruption Management Systems in Praxis

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Abstract. Workplace interruptions significantly disrupt productivity and well-being, particularly during periods of high cognitive load. Existing intelligent management solutions often fail to account for the complex social boundaries and strict privacy requirements inherent to in-situ deployments. We introduce a comprehensive set of design guidelines for future cognitive load-based systems that bridge this gap between controlled laboratory settings and the real world. Our approach integrates 'Privacy by Architecture' and 'Contextual Lifecycle Awareness' into cooperative systems to ensure data sovereignty while utilising eye tracking for physiological state assessment. These guidelines facilitate the development of fail-safe systems that effectively mitigate disruptive interruptions while fostering user trust and acceptance.

Keywords. Cooperative Work, Coordination, Interruption Management Systems, Cognitive Load, Eye Tracking, Privacy by Design, Design Guidelines, Edge Computing

1 Introduction

Workplace interruptions are essential for distributing relevant information and foster social connectedness (Gross & von Kalben 2023; McFarlane & Latorella 2002). Interruption management systems aim to balance positive and negative effects. Automatic approaches follow the principle that interruptions are less disruptive during periods of low cognitive load (Bailey & Iqbal 2008; Schaule *et al.* 2018). To identify such periods, eye tracking has been applied as a reliable method (Eckstein *et al.* 2017; Zagermann *et al.* 2016).

There is a gap between controlled laboratory settings and real-world environments where the actual praxis is taking place. Laboratory interruption management systems using eye tracking often ignore the complex social and temporal boundaries inherent to real-world environments. To the best of our knowledge, we are the first to systematically derive design guidelines that bridge this gap, addressing the need for systems that are fail-safe, trust-building, and strictly privacy-preserving in the wild.

We present a comprehensive set of design guidelines and requirements for future cognitive load-based Intelligent Interruption Management Systems (IIMS). The key contributions are: Identification of Challenges in the Wild; Qualitative Insights on User Acceptance; and Design Guidelines for Future Systems.

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2 Related Work

Interruptions present a duality in the workplace. They can impede performance, lead to longer completion times, and reduce accuracy (Gross & von Kalben 2023; McFarlane & Latorella 2002; Schaule *et al.* 2018; Yuan & Zhong 2024), but they are also essential for distributing relevant information and improving social connectedness (Gross & von Kalben 2023; McFarlane & Latorella 2002). The goal is to optimise the management of interruptions.

Research has shown that the impact of an interruption is highly dependent on timing (Bailey & Iqbal 2008; Schaule *et al.* 2018). Technological approaches often identify opportune moments based on task models (Bailey & Iqbal 2008), availability cues (Shivakumar *et al.* 2020), contextual factors (Cha *et al.* 2020) or real-time cognitive load assessments (Maleck & Gross 2024; Maleck & Gross 2025).

To assess the user's state in real-time, eye tracking—specifically the measurement of pupil diameter—has emerged as a powerful modality, reflecting the user's cognitive load (Eckstein *et al.* 2017; Zagermann *et al.* 2016). The interpretation of such physiological signals presents a challenge, because users find it difficult to differentiate between mental workload and related states like stress (Chen *et al.* 2025).

Pupillometry can entail privacy challenges due to the high sensitivity of the data. The pupil diameter reveals deceptive answers (Dionisio *et al.* 2001; Maleck & Gross 2023; Wang *et al.* 2010), predicts decisions (de Gee *et al.* 2014), and indicates emotion, attention, and uncertainty (Eckstein *et al.* 2017; Zénon 2019). The exposure can lead to a significant loss of privacy (Gahlan & Sethia 2025).

To address the risks associated with sensitive biometric data, architectures should protect user privacy by default. A foundational framework for this is 'Privacy by Design' (Cavoukian 2009). One principle emphasises 'Respect for User Privacy' by keeping the system user-centric and ensuring strong privacy defaults (Cavoukian 2009). Technologically, this can be realised through Edge Computing. This paradigm decentralises computation, moving processing resources away from centralised data centres and closer to the source of data sensing and generation (Abreha *et al.* 2022; Bablu & Rashid 2025).

While Privacy by Design and Edge Computing provide the architectural tools to secure data, their practical application to eye-tracking-based interruption management remains under-explored.

3 Challenges in the Wild

Laboratory systems often operate under ideal conditions that ignore the complex social, temporal, and technical boundaries of in-situ deployments (Eckstein *et al.* 2017). Based on related literature and practical limitations identified in previous research, we abstract challenges that IIMS should overcome.

Challenge 1: Temporal & Social Boundaries. The first challenge arises from the discrepancy between controlled laboratory settings and the dynamic reality of in-situ deployments. In a controlled study, the system is active for a specific duration of a task. In the wild, users have individual working hours, private breaks, and distinct social roles (Anderson *et al.* 2016). The rise of remote and hybrid work has further blurred these boundaries, increasing the potential for work-family conflict (Gibbs *et al.* 2023; Leroy *et al.* 2021). Further, user interruptibility is contingent upon the social presence of co-located individuals and established daily routines (Cha *et al.* 2020). A system that functions on an 'always on' basis risks violating these delicate borders. Therefore, a significant challenge is enabling the system to recognise and respect these temporal and social limits.

Challenge 2: Workflow & Context Integration. Pupillometry offers high precision in measuring mental effort (Eckstein *et al.* 2017), but should not be the single source (Cha *et al.* 2020). A user might have low cognitive load while waiting for a process, yet remain unavailable due to a meeting or conversation. Without semantic context, sensor-based metrics become irrelevant if the user's calendar is full. Consequently, the IIMS must integrate external 'blockers'—like calendar events and physical presence—to prioritise situational constraints.

Challenge 3: Trust & Resilience. Field-based environmental factors are unpredictable—for instance, fluctuating lighting conditions can compromise pupil diameter data quality (Eckstein *et al.* 2017). Furthermore, the introduction of biometric sensors like eye trackers into a workspace can engender mistrust or feelings of being observed. Systems should be maximally fault-tolerant—that is, able to handle data loss or sensor failure gracefully without disrupting workflows. Trust relies on the combination of technical stability and the transparent processing of biometric information (Gahlan & Sethia 2025). The challenge is to design an architecture that is resilient to the "chaotic" nature of the real world while actively gaining user trust through reliability and transparency.

4 User Acceptance of Eye-Tracking Hardware

To understand the barriers to deploying eye-tracking based interruption management in the wild, we deployed a cognitive load-based IIMS over three full days in the wild. We conducted semi-structured interviews with $N=4$ participants (2 female, 2 male, 0 non-binary) with age from 25 to 29 years (M = 27.25, SD = 1.79). The insights reveal that user acceptance is a complex interplay of physical obtrusiveness, environmental context, and trust.

Hardware Obtrusiveness and Physical Constraints. Desk-mounted eye-tracking hardware drew mixed reactions, highlighting the difficulty of integrating sensors into established workflows. While some users eventually acclimated, an initial feeling of being "observed" or "internally stressed" was common, with some feeling pressured to remain focused on the PC. Furthermore, stationary hardware created physical constraints; one participant felt restricted to a single monitor despite a multi-screen workflow. Consequently, users preferred smaller, unobtrusive hardware integrated directly into the workstation to reduce distraction.

Context Dependency: Office vs. Private Spaces. The system acceptance depends heavily on environmental context; hardware accepted in a corporate office may be rejected in a home office. Participants, comfortable with the device at work, resisted its presence in her “private space”. This resistance stems from both privacy concerns and health anxieties, such as potential radiation, indicating that perceived physical safety is as vital as data security. These context-dependent concerns mirror issues with vision-based agents in shared living spaces. Consequently, future IIMS must tailor sensing modalities to the specific physical context.

Mitigation Strategies through Transparency. Despite the sensitivity of biometric data, our findings suggest that proactive communication and transparent architecture can effectively mitigate privacy concerns. Pre-briefing participants on data handling was highly successful; all reported no concerns during the study. Crucially, the “Privacy by Design” approach—where raw data remains on the local machine—was decisive. Participants noted that local processing successfully allayed her initial privacy fears, underscoring that trust is contingent on a clear understanding of data sovereignty.

5 Design Guidelines for Cognitive Load-Based Interruption Management Systems

Drawing on these challenges, we present design guidelines for IIMS.

Guideline 1: Contextual & Lifecycle Awareness

An effective IIMS must operate within the temporal and social boundaries of each user’s work and everyday life. Physiological data alone is insufficient to determine availability; a system must incorporate contextual and lifecycle awareness.

Calendar Integration. The system must be aware of external commitments. If a user’s calendar indicates a scheduled meeting, the cognitive load metric becomes irrelevant for interruptibility. In such cases, the system must defer to the calendar as the primary source of truth.

After-Hours Logic. To prevent the intrusion of work into private life, the system must implement strict intra-day blockers (e.g., lunch breaks) and after-hours logic. During such events, the system must cease all monitoring and interruption activities to respect the user’s right to disconnect. Ideally, this status should synchronise automatically with existing time-tracking or workforce management systems. Lacking such infrastructure, the system must maintain user agency via low-barrier manual controls—such as a physical toggle on the eye-tracker—to enable or disable monitoring instantly.

Guideline 2: Privacy by Architecture

To address the sensitivity of biometric data, privacy must be a fundamental architectural constraint, not an add-on feature.

Local Processing of Raw Data. Raw sensor data, such precise pupil diameter measurements, must never leave the local hardware. All processing that are required to infer the cognitive states of the user must occur locally on the edge device.

Data Minimisation via Abstraction. Only abstract, non-identifiable states—such as a classification of 'High Load', 'Medium Load', or 'Low Load'—must be permitted to leave the local environment. This ensures that even in the event of a network interception, no sensitive biometric data is compromised.

Guideline 3: Transparent Data Handling

Trust is a prerequisite for the acceptance of invasive sensing technologies in the workplace. To build and maintain this trust, systems must adhere to transparent data handling, ensuring users are fully informed about the system's operations.

Pre-Briefing Relevance. Users must always know exactly what is measured and how data is used. A comprehensive pre-briefing on data flow and privacy—such as the non-storage of raw images—is essential to define system boundaries and allay fears. This transparency fosters acceptance and informed consent. Beyond external communication, this can be integrated into the system via a digital onboarding phase at initial launch to reinforce privacy guarantees.

Accessible Terminology. To bridge the gap between abstract metrics and user comprehension, accessible terminology should replace technical jargon. As noted by Chen *et al.* (2025) regarding mental workload tracking, direct conceptualisation is often challenging; failing to provide a clear rationale can diminish system acceptance. However, to accommodate varying expertise, the IIMS should offer multiple levels of abstraction.

Implementation Scenario: A Deployment Vignette

To illustrate the practical application of these guidelines, we present a deployment vignette of an in-situ IIMS: Consider a user, Alice, who integrates the system into her daily workflow. Prior to deployment, she completes a comprehensive digital pre-briefing that transparently details the local processing architecture and strict data minimisation protocols. This transparency successfully mitigates her initial concerns regarding camera-based observation (Guideline 3). At her workstation, the eye-tracking hardware assesses her pupil diameter, processing the raw physiological data entirely on a local edge device (Guideline 2).

During a period of high cognitive demand, the system infers a state of high workload. However, to ensure data sovereignty, it only transmits an abstracted 'High Load' indicator to a shared coordination dashboard, safeguarding sensitive biometric data (Guideline 2). Later, when her digital calendar registers a scheduled meeting, the IIMS prioritises this external blocker, automatically overriding the physiological metrics to set her status to ‘Unavailable’ (Guideline 1). To maintain social boundaries during her lunch break, Alice utilises a low-barrier physical toggle on the hardware to instantly disable all monitoring, preserving her right to disconnect (Guideline 1). Throughout the day, the system interface employs accessible terminology—such as ‘Deep Work’ or ‘Available’—rather than raw technical metrics, fostering mutual understanding and trust amongst co-workers (Guideline 3).

This scenario illustrates that the practical application of our framework remains flexible. Not all systems will need to apply all guidelines. For instance, data minimisation via abstraction might work well in scenarios where the users only want and need crude information on each other’s availability. In scenarios where the users might want more precise information (e.g., percentages of availability) the abstraction is less strong.

6 Conclusions and Future Work

We presented design guidelines to bridge the gap between laboratory studies and the dynamic workplace. Our analysis indicates that future IIMS must prioritise contextual awareness, respecting temporal boundaries and integrating with external blockers. Furthermore, ‘Privacy by Design’ via local processing and transparent data handling are essential prerequisites for user trust.

While our qualitative insights are limited by a small sample size (N=4), they provide a foundation for larger, longitudinal studies across diverse organisations. Future research could focus on deeper integration with workplace ecosystems and calendar services to enhance accuracy and reduce activation effort. Additionally, exploring social contexts and role-based interruptibility could prevent cross-role disruptions. Ultimately, for widespread acceptance, IIMS must be fundamentally privacy-first and adaptable to the user's specific physical context.

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