Sensible and Sensitive AI for Worker Wellbeing: Factors that Inform Adoption and Resistance for Information Workers

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ABSTRACT

Algorithmic estimations of worker behavior are gaining popularity. Passive Sensing–enabled AI (PSAI) systems leverage behavioral traces from workers' digital tools to infer their experience. Despite their conceptual promise, the practical designs of these systems elicit tensions that lead to workers resisting adoption. This paper teases apart the monolithic representation of PSAI by investigating system components that maximize value and mitigate concerns. We conducted an interactive online survey using the Experimental Vignette Method. Using Linear Mixed-effects Models we found that PSAI systems were more acceptable when sensing digital time use or physical activity, instead of visual modes. Inferences using language were only acceptable in work-restricted contexts. Compared to insights into performance, workers preferred insights into mental wellbeing. However, they resisted systems that automatically forwarded these insights to others. Our findings provide a template to reflect on existing systems and plan future implementations of PSAI to be more worker-centered.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**; • **Applied computing** → *Health informatics*; • **Security and privacy** → *Social aspects of security and privacy*.

KEYWORDS

information work, future of work, passive sensing, digital phenotyping, technology adoption, impacts, harms, human resource management, worker wellbeing, mental health

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1 INTRODUCTION

We witnessed declining economic activity with COVID-19 and subsequently the tech and media layoffs in 2022 [133]. What was less palpable, was the decline in thriving workers. Information Workers (IW)[1] have showed an increasing tendency to detach from work while remaining employed—exemplifying the *Great Resignation* [57] and *Quiet Quitting* phenomena [65]. This phenomenon stems from organizations failing to take care of their workers' needs leading to a form of *emotional recession* [29]. As organizations search for new instruments to understand workers, especially one that is increasingly diverse in terms of where they work from (in person/remote), one emerging approach is to passively monitor IWs' behaviors with everyday technology and then utilize algorithmic modeling to estimate their effectiveness [40, 98]. These technologies have been recently referred to as Passive Sensing–enabled AI (PSAI) [37]. Simplistically, a PSAI system would sense some observable phenomena unobtrusively (e.g., screen use or physical motion) to provide an *experiential insight* (e.g., task performance score or stress score). While, the power asymmetry at work can raise anxieties of using such technology at work, emerging literature suggests that workers envision empowering applications of such AI-inferences [3, 37] — using the insights to leverage resources or even for *sousveillance* [23, 85]. Today, organizations have started deploying technologies prototypical of the PSAI discussed in research [2, 9, 26, 56, 66–68, 110, 129]. However, these designs often ignore the voices of IWs leading to exploitative applications of both passive sensing and AI. Therefore, we need empirical evidence from a worker-centered perspective to build PSAI systems that enable workers to thrive rather than inadvertently become new instruments of oppression.

[1]Workers whose primary job role involves gathering, synthesizing, and producing new information are known as *Information Workers*, or *Knowledge Workers* [86]

Although IWs are familiar with digital tools that count instances of their work[2], PSAI distinguishes itself by collecting different kinds of data — peripheral and orthogonal to specific tasks — and algorithmically interprets these data to generate inferences outside the bounds of aggregate measurement [132]. Using sensing streams such as desktops, smartphones, wearables, social media, and other digital work tools, PSAI systems have the potential to give workers personalized insight into their work quality, coordination, and overall effectiveness [3, 37, 40, 98]. However, the benefits of these systems may not be directed back to the data providers: the IWs [33, 94]. In reference to traditional Computer-Supported Cooperative Work (CSCW) applications (e.g., groupware), Grudin had stated, "the application fails because it requires that *some people do additional work*, while those people are *not the ones who perceive a direct benefit* from the use of the application." To use PSAI, an IW contributes additional data to a company, but the benefits might be reaped by other stakeholders. Research promoting PSAI may include cautionary notes of informed consent and other ethical implications. However, such calls simply shift the onus on the worker and ignore the power imbalance. Not all IWs would have a say on this matter, especially given the precarity of work [102]. Without a lack of alternatives, an IW could be stuck with an employer who dispossesses them of their data [5]. Therefore, relying on an individual user's burden of consent cannot be considered a sufficient safeguard. Instead, we need to fundamentally design more acceptable technology. To protect worker interests, we need to design acceptable PSAI systems that are *sensible* and *sensitive*.

We can formalize Grudin's notion of successful technology with the Technology Acceptance Model (TAM) [44]. According to this model, willingness to accept is proportionate to perceived ease-of-use (cost) and perceived utility (value). At the surface, PSAI is easy to use, but the perceived privacy risk is also a cost [83]. In fact, recent inquiries on PSAI revealed that IWs anticipate additional harms beyond data loss because of algorithmic estimates of human experience (e.g, stifling promotions) [37]. In nuanced sociotechnical settings, many factors that could explain the perception of technology might be considered outside the grasp of computing research. Having said that, computer scientists can take responsibility of the affordances, or properties, that invite and constrain certain interpretations of the technology [70]. PSAI is not a monolith but a broad technological approach that can be implemented in a variety of information flows [40]. Following this idea, we unpack acceptable manifestations of PSAI by highlighting determinants of perceived harm and perceived utility:

Research Aim: *To identify properties of Passive Sensing–enabled AI that encourage (or impede) their adoption by Information Workers*

We hypothesized that four properties of PSAI could explain perceived harm and perceived utility: $H1$ =Type of Sensing (digital time use, online language, physical activity), $H2$ =Scope of Sensing (work-only, general), $H3$ =Type of Insight (performance, mental wellbeing), and $H4$ =Sharing of Insight (self only, self+manager, self+trusted other, self+aggregate). To test these hypotheses, we deployed an online interactive survey designed using the *Experimental Vignette Method* [4, 55]. IWs visiting our portal could report their perceptions of systematically varying implementations of PSAI (vignettes). We used *Linear Mixed-Effects* models to analyze 1059 vignette evaluations from 110 IWs. We found that PSAI systems were perceived better when they leveraged digital time use or physical activity ($H1$), estimated mental wellbeing ($H3$), and the insights were private to the worker or shared as aggregates ($H4$). The work-only scope of PSAI ($H3$) moderated the effect of online language (such as from social media) as a sensor, but was not a significant factor in itself. Our analyses models also revealed that learning about feature processing could reduce perceived harms of PSAI. For further robustness, we conducted a *Causal Mediation Analysis* to ascertain that these properties have both direct and indirect effects on determining willingness to use PSAI systems. In absolute terms, however, we found that very few designs of PSAI were acceptable. We discuss how the results of our vignette experiment provides an actionable artifact to rethink PSAI systems and how we envision constraints PSAI systems in contrasting sociotechnical settings.

Worker-Centric Perspective of PSAI. Information work is highly collaborative and the actions and outcomes of each individual—especially when mediated by technology—involves and affects multiple other stakeholders [123]. A broader human-centric notion would need to account for a multitude of contrasting perspectives [77]. We choose to focus on the perspectives of the worker, who is the primary data provider and data subject of PSAI systems. Their opinions have been historically underrepresented in the development of tools likePSAI [61]. Our approach follows recent research to highlight the opinions of workers as they are expected to create disproportionate amounts of data while risking the severe consequences [20, 37, 143] . Our findings highlight the bottom-line requirements for PSAI systems to be designed for workers—so that we can better preempt resistance and acceptance of new technology.

2 BACKGROUND

In 1930, Keynes described a future economy where we would work fewer hours than we actually do today [81]. His prediction underestimated many socio-economic factors, but it also misrepresented what today's workers might want in terms of purpose, self-worth, and leisure [52]. Information workers today do not want to work more, they want to work better and healthier [127]. Although Keynes' vision was inaccurate, he highlighted that the future of work needs to be centered on improving the lives of workers. Organizations' limited personalized insight and reliance on traditional survey–based approaches [17, 21] gave rise to PSAI systems to provide more precise understandings of worker behavior. However, much like the survey-based approaches preceding it, PSAI systems have their own failings when deployed in work environments [3, 37]. Our paper is motivated by research on PSAI at work and complimenting literature that investigate its adoption.

2.1 Emergence of Passive Sensing Inferences of Worker Effectiveness

Worker supervision has historically relied on instruments and scales. Right after the industrial revolution it was common to use stop-watches to track worker hours on a shop floor [122]. Since then, organizations have moved onto more sophisticated technologies

[2]Common examples would be project management tools such as *Github* [101] and *JIRA* [106] which expose worker activity to themselves and their peers.

like cameras and access-cards to gain a cursory understanding of a worker's schedule. Many white collar jobs today involve project management tools that track worker tasks over a given period of time [101, 106]. However, task efficiency does not describe the quality of work produced. This distinction is especially true for IWs, who create and manipulate information as a part of their role [48]. Organizational research argues that typical measures of "productivity"—the output of fungible artifacts over a given period of time—do not apply to IWs [49, 53]. As a result, organizational sciences have proposed a broader view of identifying aspirational workers that looks at "effectiveness", not efficiency [130]. This view considers "performance" a positive behavior that includes not only task proficiency, but also worker contributions beyond their role [112]. Furthermore, this research has emphasized the importance of a worker's mental wellbeing at work to ensure a worker and their organizations long term health [32]. Therefore, time and task tracking instruments are simply too limited to represent these experiences. As an alternative, workplaces have relied on surveys to capture these phenomena holistically. However, such surveys are vulnerable to biases [45] and are difficult to scale in size or frequency [50, 59]. To overcome these challenges, we see a growing interest in the research and development of PSAI systems to provide insight into a workers effectiveness [41, 98, 100].

Unlike the instruments before it, these technologies record observational phenomena in a different way (e.g., facial expressions, linguistic tones, or physical activities) and then train Machine Learning models with large amounts of data to estimate an IW's performance and their mental wellbeing. This approach distinguishes itself from other measurement techniques as PSAI systems can automatically and continuously collect data in naturalistic settings and then provide experiential insight based on labelled ground-truth data [34]. Research in the fields of ubiquitous computing, human-computer interaction, and computer-supported cooperative work have posited many opportunities to understand IWs passively through the technologies they interact with and give them deeper insight into their effectiveness [10, 76, 97, 105, 115, 119]. For instance, the visual streams, such as the device camera, can be used to model an IW's cognitive state and suggest opportunities for break-taking and recovery [76]. Less intrusive measures, such as, the usage of certain workplace applications can represent how effectively IWs are engaged with work Mark et al.. Bluetooth, WiFi routers, or other forms of occupancy sensors can indicate an IWs stress and performance based on their coordination with others [39, 128]. Admittedly, it became common practice to coordinate over have remote-meetings after COVID-19 and research shows that the language used during these calls can describe the quality of meetings [144]. This literature expands beyond modeling phenomena typically associated with work activity. Research has shown the value of passively modeling IW's commute routines [104]. IWs' personal wearables (e.g., smartwatches) can be used to estimate their physical fitness, sleep hygiene, and cognitive ability [54, 111, 115]. In fact, even an IW's activity on social media can estimate their wellbeing [93, 113, 114]. Arguably, many of the technologies we described above are promoting PSAI as tool to illuminate antecedents of work behaviors, not necessarily tools for predictive measurement. However, intentions aside, the implications of this research could inspire tools for predictive worker wellbeing.

Recent studies have found that workers envision PSAI systems to provide some form of "objective truth" in their estimates [37]. Unsurprisingly enough, more accurate monitoring technologies have been found to be more acceptable [1]. However, in the workplace, PSAI systems optimized for universal accuracy can lead to inequality between different groups [61]. As these challenges becomes more evident, we also find research attempting to overcome them. These studies showcase methods to incorporate more contextual factors [75], collect large datasets [98], or innovate more fair algorithms [140]. Having said that, deploying such longitudinal studies with real workers can itself be challenging because of how potential participants may interpret the PSAI system being proposed or investigated.

Many commercially available tools that employ passive sensing for IWs are a step away from becoming full fledged PSAI systems [2, 9, 56, 66–68, 110, 129]. The changing workplace dynamics and the greater attention to worker wellbeing and worker rights urge the need to implement such systems with caution [40]. Our study aims to reflect on the technological possibilities of PSAI systems for IWs by inquiring which factors in their design influence their adoption.

2.2 Acceptability of Passive Sensing & Algorithmic Inference in Information Work

The idea of PSAI has its roots in the *quantified self* movement that is motivated to help humans change by giving them a better understanding of their daily living [80]. These technologies have become mainstream and provide us a variety of insights (e.g., fitness trackers, sleep health, driving quality) [91]. These approaches incorporate aspects of individuals that were considered to be blindspots from human supervision and therefore promise more holistic inferences [15]. Although, consented self-tracking has its positives (receiving knowledge), it has its downsides (parting with control of your behavioral data) [94]. Moreover, recent investigations have shown that the acceptability of these technologies in personal life cannot be equated to deploying such technology in Information Work and its unique power dynamics [37].

For any application or tool, people are likely to adopt it if the value it creates outweighs the cost of using it [44]. For PSAI a central assumption, which is also its central promise, is its unobtrusiveness as it can be continuously "on" without any effort from the user [34]. These assumptions have led computer scientists to believe that passively collecting any data is reasonable, given that it does not cost anything. However, this assumption fails in information work context. First, the new perspectives on privacy assert that one's data itself is of value and therefore must be considered a cost [138]. Second, due to asymmetries at work, the IW be the source of the data, but may not receive the benefits [94, 124]. Lastly, while developers of PSAI might feel that algorithmic insights are valuable, explorations of worker perspectives show that not all IW's envision utility in precise algorithmic insights [37]. Thus, we have a limited view of both the utility and the cost of these systems.

Past research on understanding acceptability of passive monitoring at work has focused on individual and interpersonal factors to inform acceptability. Kim et al. found that trust played a major role in dictating perceived risk [83]. Similarly, Abraham et al. found that prior experience with tracking and support for surveillance explain willingness towards being monitored at work [1]. However, these studies ignore the role of the technology in shaping workers' perceptions [70]. By contrast, studies in human–computer interaction have started unpacking the interplay between human perceptions of worker monitoring and the technological affordances in those monitoring systems [90, 108, 143]. Some investigations of worker monitoring have discussed the implementation of the technology and its information flow. Ball has noted that workers are likely to resist constant task tracking (in comparison to intermittent tracking) and exposition to untrained supervisors (who are indifferent to worker wellbeing) [13]. Recent studies have explored the variability between acceptance of passive monitoring technologies. Charbonneau and Doberstein surveyed 12 applications and found that wellness apps and PSAI systems to monitor physical hygiene were relatively more acceptable [25]. However, this study takes an inflexible view of passive monitoring and assumes that each system can only be deployed in one way. By contrast, Constantinides and Quercia studied IWs' attitudes towards 16 PSAI scenarios that represented different passive sensing streams and the possible work-nonwork context in which they are deployed [33]. To add robustness to scenario-based approaches, studies have aimed to distill the specific factors influencing worker attitudes by systematically generating vignettes that vary along different factors associated with the technology. Vitak and Zimmer's large scale survey on existing digital monitoring practices by employing the vignette method to identify the influence of data attributes, purpose, actors, and transmission principles [136]. We expand and complement these studies by exploring perceptions towards PSAI systems as *emerging personal-informatics tools* for IW's to manage their behavioral wellbeing.

3 STUDY OVERVIEW AND DESIGN

Information work is a high consequence environment. It can be challenging to deploy multiple PSAI systems in real workplace contexts to obtain comparative insight on worker preferences. Not only can it be resource-intensive, but it can raise ethical concerns—disrupting work rhythms, misrepresenting experiences, and potentially putting an IW's livelihood at risk. To overcome these hurdles, we analyzed perceptions of PSAI with the *Experimental Vignette Method* [4, 55]. A "vignette" is a scenario that reflects specific features or components of a technology, policy, situation, or interaction. Scenario based experiments have been used in the past to study algorithmic management at work [14, 89]. The experimental setup involves the presentation of a series of vignettes for participants to evaluate. These vignettes are carefully modified across certain components and in effect akin to a factorial survey that helps simulate real world conditions [92]. Prior research sometimes refers to *experimental vignettes* and *factorial surveys* interchangeably [4, 131]. Based on Atzmüller and Steiner's distinction between the two methods, we chose the experimental vignette design because of two key reasons [11]. First, it allows deliberate manipulation of vignette presentation to understand the effects of different factors—for instance a common baseline vignette, followed by other comparison vignettes. Second, a random subpopulation of vignettes is drawn for each respondent such that the larger vignette population is evaluated exhaustively. In Atzmüller and Steiner's words for a small hypothesis space—less than 5 factors—the experimental vignette method is "more efficient for practical applications." For our study on PSAI, we first derived hypotheses from literature. We then conducted a vignette experiment online by modifying components represented the hypotheses. We analyzed the evaluations of these vignettes using linear mixed effects models.

3.1 Hypotheses

We initially drew from the TAM to predict the willingness of workers to be data subjects for PSAI. The TAM framework was first proposed to determine the acceptance of technologies for improving performance at work [44]. Additionally, TAM has been used in a variety of different settings including e-learning, cloud computing, virtual reality, and Internet-of-Things [84]. Traditional analysis with TAM involves two antecedents of acceptance, perceived utility and perceived ease of use. PSAI systems do not involve explicit use, which leads to minimal interaction burden. Classical interpretations of TAM would consider PSAI acceptable. However, looking towards the theory of *privacy calculus* we can identify a different cost—perceived privacy risk [83, 138]. To reemphasize, PSAI systems can appear to infer human outcomes from seemingly unlrelated phenomena [132]. Ideally, this method can help in *digital phenotyping*, however, Lee et al. noted that such AI tools foster new forms of risk that cannot be classified by classical interpretations of privacy [88]. IW's perspectives on PSAI echo that the anticipated costs of using these systems beyond fundamental data privacy risks, and extend onto job consequences [37]). Taken together, we believe a PSAI solution with more perceived utility and less perceived harm is likely to be more acceptable. Das Swain et al. have operationalized PSAI systems as information flows that involve "(i) how data is sensed, (ii) what inferences AI produces from the data, and (iii) how the inferences can be distributed [37]." We took inspiration from this notion and referred to the literature to formally decopose PSAI system for information work on the basis of 4 factors. We hypothesized that varying these key factors can influence the perceived utility and harm of a given PSAI system. In this subsection we have expounded the theoretical grounding behind our choice of factors and the variations within them.

3.1.1 *Type of Sensing.*

The first piece required to engineer a PSAI system is the sensing component —- what observable phenomena is being automatically recorded. Research on PSAI discuss a variety of other sensors that can be used for passive sensing at work, such as screen use [96], bluetooth beacons [39], and even language online [119]. IWs might feel that certain sensing sources are more meaningful than others at indicating work experience [37]. Actually, the traditional CCTV cameras at work can be considered passive sources too. Over time, information workers have accepted such cameras as the norm, but they assume a human supervisor (e.g., a guard) on the other end. A PSAI system would feed the CCTV stream into machine-learning models to provide metrics of work effectiveness [26]. After remote work, the more concerning usage of visual feeds was actually the prospect of an employer tapping into the inbuilt camera on a worker's machine. *RemoteDesk* is an example of such a technology [110]. Charbonneau and Doberstein, have shown that people perceive the intrusiveness of camera–based applications differently from fitness trackers [25]. In

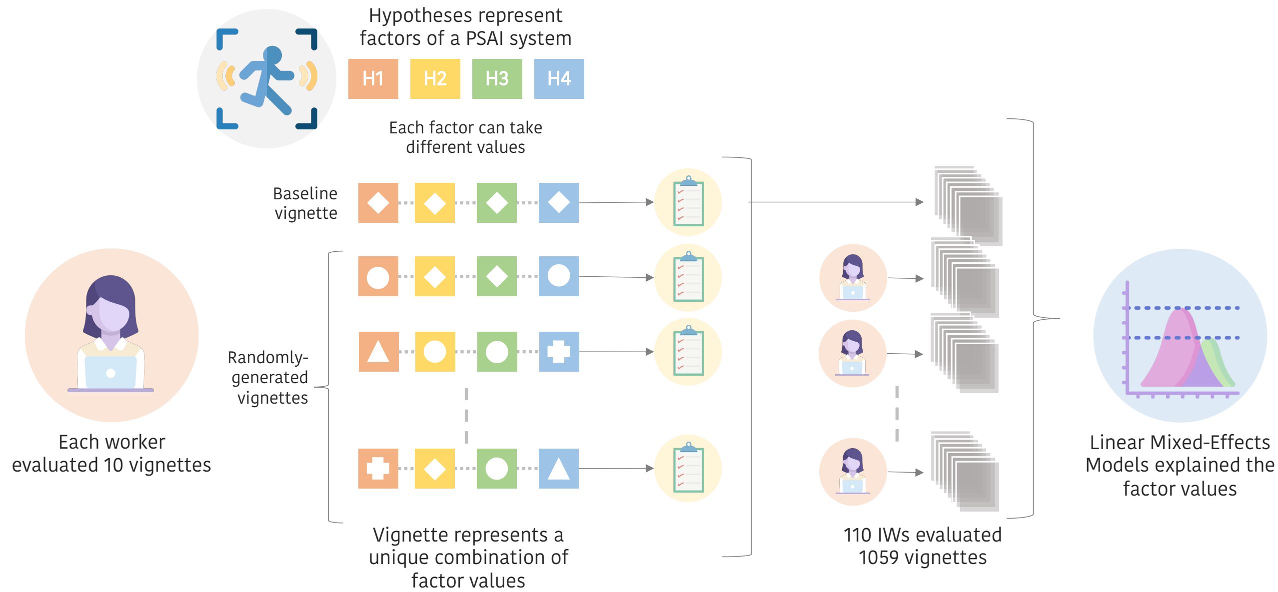

Figure 1: Our study involved the identifying different hypotheses related to the perception of PSAI, the design of the vignette evaluation experiment, and the mixed-effects models to test our hypotheses.

terms of functionality, even fitness-trackers and other non-visual technologies digitize human behavior, store it as data, and can be used for inference. Therefore, we need a focused investigation on of these novel sensing streams as sources of harm. Also note, workers have also questioned the usefulness of phenomena sensed by these streams [37] in comparison to event-counters in existing project management tools [101, 106]. Streams such as physical activity and language might not appear as tightly coupled with work, but IWs might consider these orthogonal correlates as "true reflections" [22]. Therefore, it is reasonable to hypothesize that IWs will favor the adoption of certain sensors in PSAI:

H1a. *Type of sensing stream is associated with perceived utility*
H1b. *Type of sensing stream is associated with perceived harm*

To test these hypotheses, we compared PSAI systems with 3 different sensing modes: (i) digital time use (e.g., time spent on an application, (ii) online language (e.g., sentiment and tone on communication platforms), and (iii) physical activity (e.g., number of restful breaks from a wearable).

3.1.2 Scope of Sensing. Historically information workers have been able to avail flexible work routines [78]. They get the freedom to decide when to work and where to work. Naturally, the degree of freedom might vary across roles and organizations. This flexibility has blurred the lines between contexts when a worker is working (e.g., office) and other general situations where they could also be working (e.g., after-hours at home, at a cafe on the weekend). Simply deploying passive sensing frameworks without regard can heighten anxieties of unchecked surveillance [5]. After COVID-19 many IWs need to choose their work boundaries and are likely to behave differently within those boundaries. When working from home, a worker is likely to interleave work and non-work tasks when they are figuratively "working" [43, 73, 137]. While sensing beyond work could be a privacy risk, sensing specific to the work context could be more sensitive to their career [37]. Workers also varied on the utility of different scopes. Broad sensing could be more holistic but work-limited sensing could be more precise [37]. The varying scope can not only change the traces that a PSAI system would capture, but also the way its output will be interpreted. Hence, we wanted to test if these distinctions explain the overall perceptions of PSAI systems.

H2a. *Scope of sensing is associated with perceived utility*
H2b. *Scope of sensing is associated with perceived harm*

To test these hypotheses, we compared PSAI systems with 2 different scopes: (i) work (e.g, work application use, work communication, or occupancy sensors) and (ii) general (e.g., personal application use, social media, or wearables). = Note, depending on the variation in H2, the events captured in H1 will also change even though the stream itself will not. For example, if $H1$ ="physical activity" , then vignettes with $H2$ ="work" will describe embedded infrastructures such as door access monitors and desk occupancy sensors; whereas vignettes with $H2$ ="general" will describe everyday sensors like smartwatches and phones.

3.1.3 Type of Insight. Any PSAI system will process the data to infer a target. Contemporary systems have typically centered on providing performance–based measures. Exceptions like *Viva Insights* present wellbeing insights alongside performance [67]. Abraham et al. found that workers are more likely to accept monitoring systems that promise an increase in work efficiency — producing more output in the same time [1]. In contrast, Cheney-Lippold found that technologies that monitor efficiency tend to burnout workers and constrain their day-level activities [27]. The need for performance insights arise from organizational incentives and social contract between an employee and employer. Recently, information work has started paying attention to mental wellbeing. We are witnessing a rising trend where organizations are conducting seminars, appointing specialized officers, and even offering mental wellness apps [99]. However, mental wellbeing has not received the same individualized attention as performance. Performance evaluations in information work have been refined and embedded into the worker's life–cycle. *Key Performance Indicators* [12] and *Performance Reviews* [19] are common place, but mental wellbeing is often addressed through nebulous actions. Inferring a worker's health also presents new challenges. In the past, workers have expressed resistance to applications that track their physical health because of anxieties related to insurance possibly because of anxieties related to its effect on their insurance [1]. It remains unclear if workers would actually prefer insights on mental wellbeing given how sensitive disclosing it at work can be [18]. Accordingly, it is yet to be learned if PSAI would be more valuable to workers if the kind of insight received by them is different from performance.

H3a. *Type of experiential insight is associated with perceived utility*
H3a. *Type of experiential insight is associated with perceived harm*

To test these hypotheses, we compared PSAI systems with 2 different types of insights: (i) performance, (ii) mental wellbeing (specifically *stress*).

3.1.4 Sharing of Insight. The asymmetry of work–based power structures inherently carry a critical risk. The insights of passive sensing can often be consumed by someone who is not the data subject [71]. Ideally, the insight of PSAI should affect an IW directly. In reality, it is possible that the insights generated by PSAI indirectly impact IWs through the organizational decisions of others, such as managers. The indirect flow is often designed to benefit organizational interests, e.g., to reorganize work within a team [103]. Prior research indicates that people vary in their privacy concerns when comparing individual and collective benefits [116]. Information work relies on collaboration, communication, accountability, and dependency. Subjective accounts of IWs indicate that they always want to be involved in the flow as a receiver, but they could imagine forwarding insights to other coworkers, such as a manager who enhances their work or a *trusted–other* to help calibrate insights from the system [37]. Additionally, these insights could also be contributed to a collective aggregate to keep workers updated of others, help to smooth out work-flows, and even make sense of the AI's insights [90]. Together, all these potential uses motivate the last set of hypotheses:

H4a. *Sharing of experiential insight is associated with perceived utility*
H4a. *Sharing of experiential insight is associated with perceived harm*

To test these hypotheses, we compared PSAI systems with 4 different sharing paradigms: (i) self only (nobody else receives the insights), (ii) self + manager (iii) self + trusted other, and (iv) self + aggregate. Note, in variations (ii-iv), we specifically studied instances where the insight is shared 1-week after the worker has received it themselves.

3.2 Design of the Vignette Experiment

As mentioned above, we considered the experimental vignette method because it was infeasible to practically and ethically deploy multiple variations of PSAI at scale on real populations. Each vignette represented a scenario where an instance of PSAI is deployed for information work. Generally speaking, each vignette showed a passive data source (H1) that monitors worker behavior in a specific context (H2) to predict either their performance or mental wellbeing (H3) and shares this insight back to certain stakeholders (H4). The Appendix contains tables that list the variations along with the textual component for a vignette by each component. Table A1 shows the descriptions of possible components a PSAI system could have because of variations in the type of sensor (H1) and scope of sensing (H2). Table A2 shows the two different outputs a PSAI system could generate (H3). Lastly, Table A3 shows the four different information sharing paradigms that involve a PSAI system (H4). Accounting for all possible variations, our hypotheses space involves 48 vignettes [3] and 1 baseline vignette.

3.2.1 Baseline Vignette. Since the vignettes vary across categorical variables, we wanted to identify a stable baseline vignette. For this we conducted a short pilot exercise by emulating Das Swain et al.'s PSAI comparison task [37][4]. Participants were shown pairs of PSAI systems inspired by 7 real technologies and asked which technology they were more likely to accept [2, 26, 56, 66–68, 110]. Participants were shown at least two pairs of PSAI randomly selected without replacement from seven possible systems. Some participants also evaluated a third pair, where they selected a technology between their first two preferences. In total 28 IWs performed 60 different comparisons. As shown in Figure 2, the PSAI based on *RemoteDesk* [110] was never preferred over another system. That PSAI scenario described a webcam analyzing facial expressions and surroundings to measure performance and share it with a worker's manager. Thus, we constructed our baseline vignette to resemble the characteristics of this technology (Figure 3).

3.2.2 Vignette Evaluation. Every participant assessed a deck of 10 vignettes through an online browser portal. Before they started evaluating the vignettes, the portal first provided instructions on how to interact with the tool followed by some fixed context for all vignettes. All the PSAI systems were built by an imaginary third party, *CommonSense.AI* and any system will only sense the worker with their consent. We also provided brief summary of what PSAI systems are and what some of their benefits and consequences can be (Figure A1). The first vignette for each participant was the *baseline*. The other 9 were randomly generated combinations from the hypotheses space. These were sampled without replacement such that no two vignettes a participant would see would be exactly alike. The vignettes were presented as a combination of text descriptions along with graphical icons. The icons helped improve recognition of scenarios and emphasize differences. For any PSAI,

[3] $(H1 = 3levels) \times (H2 = 2levels) \times (H3 = 2levels) \times (H4 = 4levels)$
[4] In that study the comparisons were only used to elicit discussions in the subsequent interview

	Viva	Humanyze	Occupancy	Screenshots	Browse	CCTV	Webcam	
Viva		50.00%	85.71%	100.00%	100.00%	100.00%	100.00%	84.21%
Humanyze	50.00%		80.00%	60.00%	80.00%	100.00%	100.00%	71.88%
Occupancy	14.29%	20.00%		50.00%	33.33%	100.00%	100.00%	37.50%
Screenshots	0.00%	40.00%	50.00%		33.33%	50.00%	100.00%	37.50%
Browse	0.00%	20.00%	66.67%	66.67%		100.00%	100.00%	36.84%
CCTV	0.00%	0.00%	0.00%	50.00%	0.00%		66.67%	17.65%
Webcam	0.00%	0.00%	0.00%	0.00%	0.00%	33.33%		7.14%

Figure 2: To ascertain a baseline vignette, we conducted a pilot study where IWs selected the PSAI system they preferred among a pair. The systems were adapted from Das Swain et al.'s comparison task [37]. The highest rated ranking system,"Viva" was monitored digital time use of work and provided insights back to the IW [67]. The second highest, "Humanyeze" performed multimodal sensing (work-communication time use, occupancy monitoring) and sent aggregate insights to the HR [66]

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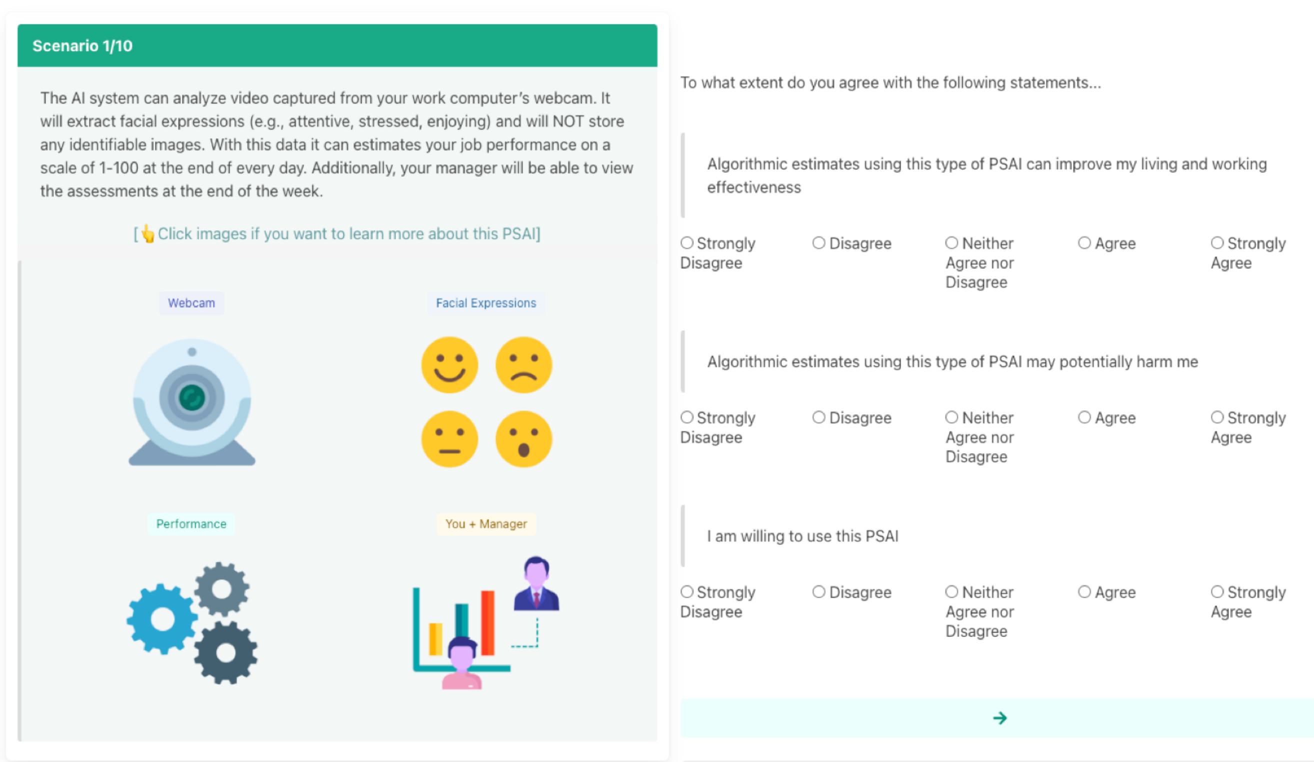


Figure 3: The baseline vignette was shown to all participants, followed by 9 more. For each vignette, participants had to report their perceived utility, perceived harmfulness, and perceived willingness to use the PSAI.

the icons corresponded to the input, process, output, and users. Participants could click the icons to learn a more in-depth explanation about a specific component of a PSAI vignette (Figure 4). The

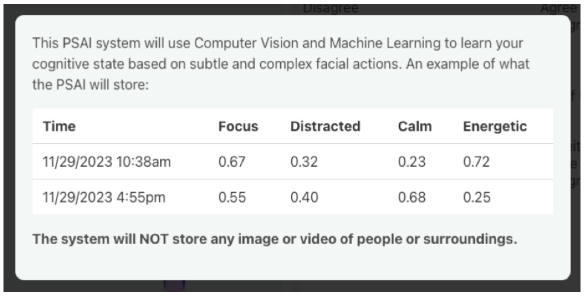


Figure 4: Every vignette had 4 icons representing the PSAI in terms of its input, process, output, and users. Participants could click any of these to get a deeper understanding. The example above shows the explanation for *process* in the baseline vignette.

icons varied by the value of the factor. We have provided a grid of icons and corresponding values in the appendix (Figure A2 and Figure A3). Additionally, we elaborate on the explanations paired with each value in Table A1, Table A2, and Table A3. The portal recorded the number of times an in-depth explanation was shown. Before beginning the exercise, participants received a tutorial of the interface. Participants were asked to complete the exercise in one sitting. A short loading animation indicated the presentation of a new vignette. The portal did not allow participants to revise scores to already evaluated vignettes and the order of vignettes was randomized (after the baseline). Our online portal retained the session ID of the client browser to ensure that a participant can pause and resume the activity in the case of any eventualities. The persistent session ID also ensured that a participant may only complete the activity once.

For each vignette, participants reported their perceived utility, perceived harm, and will to actually use the PSAI in question. In total, they answered 3 questions on a 5–point Likert scale for each vignette. These questions were adapted from Sun et al.'s research on location tracking services and privacy calculus [125]. Specifically, they needed to answer, "to what extend do you agree with the following statements...":

(1) Utilitarian Benefit: "Algorithmic estimates using this type of PSAI can improve our living and working effectiveness"
(2) Anticipated Harm: "Algorithmic estimates using this type of PSAI may potentially harm me"
(3) Willingness to Accept: "we am willing to use this PSAI"

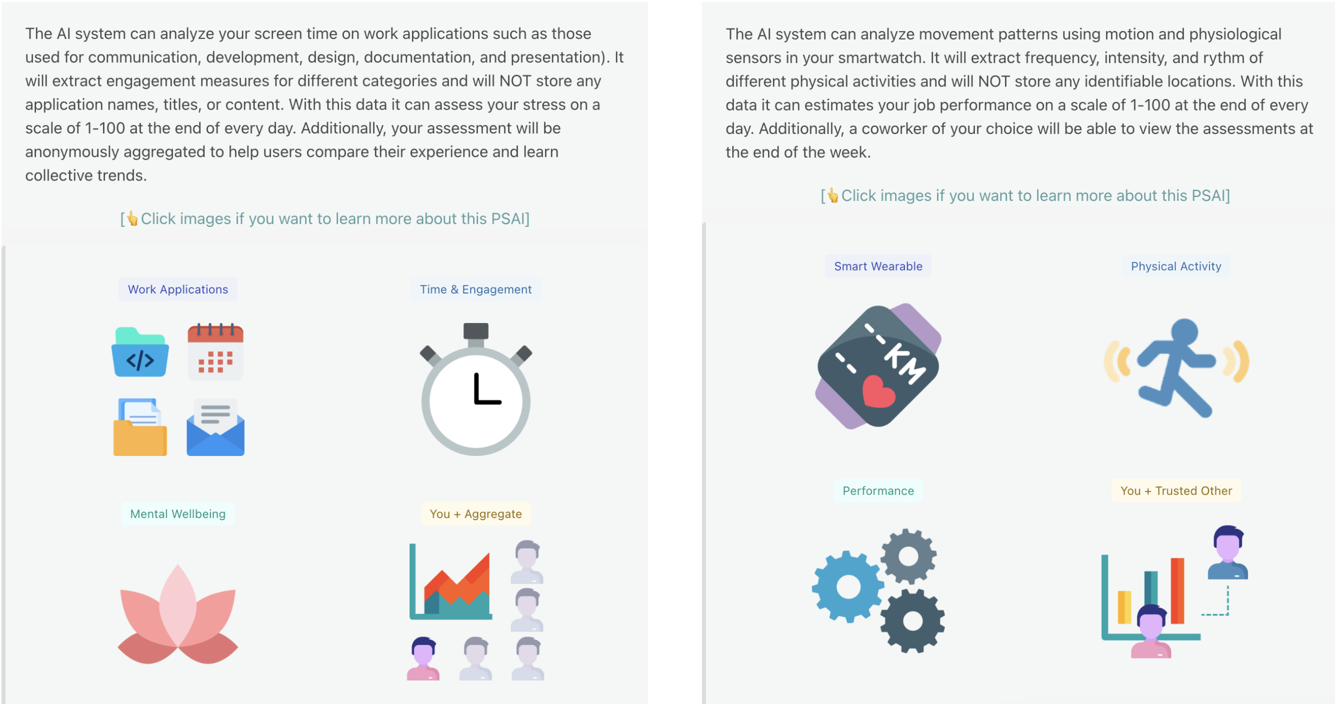
We followed many of the practices suggested by Sheringham et al. to design a reliable vignette study [120]:

(1) *Credibility*: we chose practical factors that information workers considered in the exploratory study to make the vignettes believable.
(2) *Number*: Every participant evaluated multiple vignettes to account for individual variances.
(3) *Variability*: Each factor occurred in variety of combinations with other factors to represent every possible scenario.

Individual traits and Open-ended responses. After the participants had evaluated their deck of vignettes, they completed an additional questionnaire to report their individual characteristics. This included demographic characteristics (age, gender, race) and the nature of their job (role, size of company, number of employees reporting to them). Abraham et al. found that worker's attitude towards *quantification* and *public surveillance* can explain their preference for monitoring at work [1]. We adapted their questionnaires to include a 5–item survey for participants to describe their familiarity with personal tracking technologies and a 3–item survey to express their opinion on public surveillance. We also added a 2–item survey to capture the participants' digital *privacy behaviors* (adapted from [141]). Lastly, Kim et al. found that *trust* was a key antecedent in the cost-benefit calculus of such technologies [83]. Thus, we also included a 2-item survey to capture participant trust in their manager (adapted from [134]). Lastly, participants could answer up to 3 open-ended questions with free-form responses to discuss how they envision PSAI can improve their work, the situations of harm, and designs that protect their best interest.

3.2.3 Participants. This study was approved by the authors' Institutional Review Board (IRB) under an exempt review. The portal launched for public access and we advertised the study through different worker mailing lists, work related social media (e.g., LinkedIn and Reddit), and at physical office spaces. Every evaluation session was anonymous and no personally sensitive information was tracked. Before accessing the vignettes, every visitor needed to complete a screening survey. Eligible participants needed to have at least 2 years of experience in information work in the U.S. Participants were only selected if they had experience working on-site and remote in the U.S. These constraints helped ensure that all participants had similar levels of exposure to the sociotechnical context of work. Additionally, the portal also denied access to potential bots. In total, 110 different information workers attempted the vignetted exercise. Karren and Barringer's review found that most vignette studies involving workers recruited between 80 and 140 participants for a similar vignette space [74]. We also conducted a power analysis using the *pwr* package in *R* to identify the total number of samples we needed prior to recruitment based on recommendations for behavioral sciences [31]. For this test, we selected a high significance level (0.001) and a weak–medium effect size (0.5) in accordance to findings from a analyses on worker preferences for sensing technology [1]. We found that our experimental design (linear model) would achieve 0.9 statistical power with 400 samples or vignette evaluations. Collectively, our portal received 1059 evaluations for PSAI vignettes [5] and therefore satisfied the requirements for a sufficiently powerful analysis. A notable proportion of our participants were in Engineering and Development roles (40%) and others were in Administration, Design & Creatives, Human Resources, Management, Research, and Sales. 57% of our participants reported themselves to be male (female: 42%, did not disclose: 1%). In terms of age, 55% were between 21-30 , 29% were between 31-40, and 15% were over 40. Approximately 30% had 1 or more employees reporting to them. About 29% were from organizations with fewer than 1000 employees. 90% of the vignettes were evaluated within 75 seconds, while the median completion evaluation time was about 25 seconds. We removed 9 vignettes that were completed in less

[5] 9 participants did not evaluate all vignettes in their deck



(a) $H1$ **=Digital Time Use,** $H2$ **=General,** $H3$ **=Mental Wellbeing,** $H4$ **=Self + Aggregate**

(b) $H1$ **=Physical Activity,** $H2$ **=General,** $H3$ **=Performance,** $H4$ **=Self + Trusted Other**

Figure 5: Examples of randomly sampled vignettes from our hypothesis space. Table A1, Table A1, and Table A1 describe the text corresponding to each variation in the factors.

than 5 seconds because unreliably fast evaluations. Each vignette evaluation was used as a data point to test our hypotheses.

3.3 Mixed–Effects Model

We primarily built two *Linear Mixed-Effects* models to understand the impact of various factors on utility (M_U) and harm (M_H). At a high level, every model tested the main-effect of 4 independent variables; $H1$ =Type of Sensing, $H2$ =Scope of Sensing, $H3$ =Type of Insight, and $H4$ =Sharing of Insight. To account for an IW's understanding of the system, we included the count of in-depth explanations viewed by the worker; E_{input}, $E_{process}$, E_{output}, and E_{users}. It is common for vignette analyses to incorporate various covariates to account for confounding factors that might explain the variance in the model based on individual traits and organizational context [1, 120]. We included the following covariates in the final model — demographic characteristics (age, gender, race), job characteristics (role, size of company, number of employees reporting to them), attitude to *quantification*, attitude to *public surveillance*, digital *privacy behaviors* and *trust*. As discussed earlier in Section 3.2.2, prior studies indicate that these factors can impact one's perception of sensing technology. The two models fundamentally varied in the dependent variable that we studied. For example, Y =Perceived Utility in M_U and Y =Perceived Harm in M_H. Every participant could evaluate multiple vignettes. Since each evaluation counted as an observation, the model needed to group these together to account for between–participant variances. Even though we include certain individual factors to account for fixed variances among participant perspectives (e.g., gender), the individuals may vary across many other aspects outside the scope of the model that may influence it (e.g., cultural values). Therefore, we included the participant as a *random effect*. Our models can be formalized with Equation 1:

$$\begin{aligned} Y \sim H1 + H2 + H3 + H4 + E_{input} + E_{process} + E_{output} + E_{users} \\ +Age + Gender + Race + Org.\_Role + Org._Size + Num\_Reportees \\ +Perc.\_Quantification + Perc.\_Surveillance + Privacy\_Behaviors + Trust \\ +1|Participant \\ Y \in \{perceived\ utility,\ perceived\ harm\} \end{aligned} \tag{1}$$

For all the models described in this section we used the *lme4* package in *R* to apply the *lmer* function [46]. Since key variables of interest are categorical (H1, H2, H3, H4), the *lmer* function creates "dummy" variables for each category and estimates deviations from the reference variable. The reference category for each of the hypotheses was selected to be the same as the baseline vignette — $H1$ =*"visual"*, $H2$ =*"general"*, $H3$ =*"performance"*, and $H4$ ="you+manager".

4 FINDINGS

Before reporting the findings from the models discussed above, we confirm some assumptions of our experiment. First, we checked if

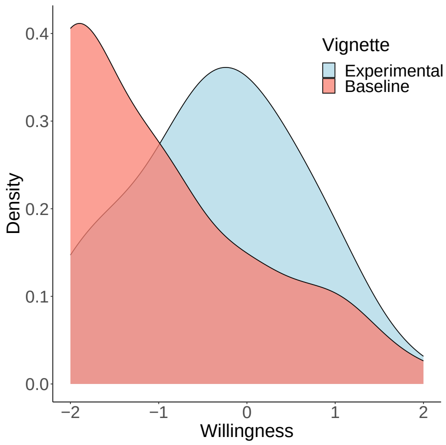


Figure 6: The density plot compares the willingness to adopt PSAI for each of the 110 sessions. Most respondents were resistant to adopting the system discussed in the baseline vignette.

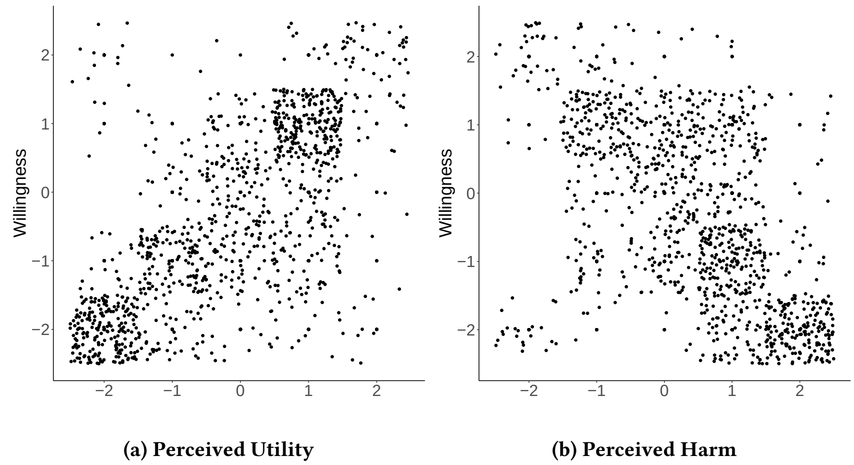


Figure 7: The responses from our participants conform with the expected trends from TAM [44]. (a) Increase in perceived utility leads to greater willingness to adopt PSAI. (b) Increase in perceived harm leads to lower willingness.

our baseline vignette was a less acceptable version of PSAI. Figure 6 shows a strong negative tendency to adopt a PSAI that leverages the camera on a worker's personal device to predict performance and eventually share insights with a manager. The distribution validated that the choice of baseline was reasonable. Additionally, we found that willingness to adopt other vignettes showed a normal distribution around 0, thus, representing a healthy balance.

Second, we checked if the modified version of TAM is an appropriate framework. We built a simple mixed effects model to understand willingness to accept different PSAI (Equation 2). The conditional R^2 of this model was 0.72 indicating that it explains a large portion of the variance in willingness to adopt. Moreover, the relationship between variables was as expected. Figure 7 illustrates that willingness to adopt a PSAI system significantly increased with increase in perceived utility (0.55) and significantly reduced with increase in perceived harm (−0.42).

$$Willingness \sim Perceived\ Utility + Perceived\ Harm + 1|Participant \quad (2)$$

Our primary models explained a sizeable portion of variance in their respective target variables (for M_U the $R^2 = 0.60$ and for M_H the $R^2 = 0.58$). These values are improvements over similar studies to explain worker acceptance of technology [83]. While building these models, M_U and M_H, we included sets of covariates incrementally. We found no notable changes in significant effects among the independent variables and isntead found that the full model with all controls had the highest conditional R^2 in both cases. Thus, we decided to include the results from the full model here and have included results from intermediary models in Table A4 and Table A5. Our model included both fixed and random−effects. On closer inspection, we found that the fixed-effects explain a smaller portion of the variance alone. For comparison, for M_U the marginal-$R^2 = 0.15$ and for M_H the marginal-$R^2 = 0.20$. These measures imply that the unmeasured individual differences (included as the random effect $1|participant$) played a larger role in interpreting perceived utility of PSAI than interpreting perceived harms. Having said that, both fixed and random effects were essential to the models. To reemphasize, our hypotheses testing was concerned with the fixed effects, i.e., $H1$, $H2$, $H3$, and $H4$. The following subsections will explain the results of Table 1.

4.1 H1: Physical Activity and Digital Time Use are More Acceptable

Many of the PSAI scenarios presented in our vignette experiment exist as alternatives to the aggressive surveillance of commercial options. For instance, *RemoteDesk* [110] is a commercial technology that leverages the device camera to track worker's behaviors. The type of sensing is "visual". Our results show that in comparison to recording a visual stream of data, other types of sensing are more favorable.Table 1 (M_U) shows a significant positive coefficient for recording digital time use of applications (estimate= 0.31, p-val= 0.001) and for tracking physical activity patterns with wearables and or embedded devices (estimate= 0.34, p-val= 0.001). However, the results indicate little additional utility for mining online language from communication tools and social media. Based on these results we rejected the null hypotheses that perceived utility of PSAI is independent of the type of sensing. Thus, hypotheses *H1a* holds.

The relationships of these variables with harm (M_H) were symmetrical to the previous set of results. The perceived harm for PSAI reduced when it was sensing digital time use (estimate= −0.28, p-val= 0.008) or physical activity (estimate= −0.44, p-val= 4×10^{-5}). It is also worth noting that, PSAI systems that use of online language can be perceived to be less harmful than monitoring with a camera (estimate= −0.11, p-val= 0.301), but the effect was not statistically significant. Together, type of sensing is related to the perceived harm of different technologies. Therefore, hypotheses *H1b* is likely to be true.

The results of testing for $H1$ echoes some of the findings from our pilot comparison task (Figure 2). The most preferred system,

Table 1: Linear Mixed-Effects Regression models provide insight into the relationship between different variations in PSAI and worker perceptions. By observing the values in this table, we can estimate which components lead to increased utility (M_U) and reduced harm (M_H), which lead to increased acceptability. Covariates that were non-significant were omitted from the table for brevity. ('-':$p < 1$, '∘':$p < 0.1$, '*':$p < 0.05$, '':$p < 0.01$, '***':$p < 0.001$)**

		M_U (Utility)		M_H (Harm)	
		Est.	p−value	Est.	p−value
H1: Type of Sensing (ref: Visual)	Digital Time Use	0.31 ▲	0.001**	−0.29 ▼	0.008**
	Online Language	0.06	0.589	−0.11	0.301
	Physical Activity	0.34 ▲	0.001**	−0.44 ▼	4×10^{-5}***
H2: Scope of Sensing (ref: General)	Work (only)	0.05	0.351	−0.04	0.51
H3: Type of Insight (ref: Performance)	Mental Wellbeing	0.14 ▲	0.021*	−0.15 ▼	0.004**
H4: Sharing of Insight (ref: Self + Manager)	Self (only)	0.54 ▲	4×10^{-10}***	−0.51 ▼	2×10^{-11}***
	Self + Aggregate	0.18 ▲	0.031*	−0.31 ▼	5×10^{-5}***
	Self + Trusted Other	0.08	0.346	−0.12	0.10 ∘
Explanations	Input	0.02	0.834	−0.02	0.781
	Process	−0.02	0.856	−0.17 ▼	0.09 ∘
	Output	−0.04	0.732	0.12	0.255
	Users	0.01	0.872	−0.03	0.753

Viva Insights [67] relies on tracking the time and event counts of digital activities such as communication and document. The greater acceptance could be explained by its similarity to existing tools such as *JIRA* or *GitHub* [101, 106]. Newer advancements in PSAI recommend multimodal approaches—combining various streams—to provide a more complete picture of worker behavior [98]. Our findings suggest that these efforts need to be developed with caution because inclusion of sensors (e.g., visual, online language) could elicit resistance among workers.

4.2 H2: Work–Life Scope Only Matters in Conjunction with Sensing Type

Presently, it is common to work remotely from one's home or from a different spot away from a designated office space (e.g., a coffee shop). Even though some workers have embraced this spatial flexibility, it raises concerns about the limits of sensing. This concern is similar to the finding boundaries where work stops. M_U and M_H included variables to compare work–only scope of PSAI with a broader scope, where a worker's activities outside of work are also sensed. We found that this distinction did not significantly reflect any changes in the perception. Therefore, the null hypothesis still holds, i.e., scope of sensing does not indicate the utility or the harm of PSAI at work.

This result was somewhat counter-intuitive, given the work–life reservations related to PSAI that were expressed by IWs after COVID-19 [37, 124]. In our vignette design, unlike other components, the scope of sensing ($H1$) was manifested in conjunction to the type of sensing ($H2$) [6]. Therefore, to get a better understanding, we ran a post-hoc regression analyses to include the interaction between *H2* and *H1* (Equation 3).

$$\begin{gathered} Y \sim H1 + H2 + H3 + H4 + H1 : H2 \\ Y \in \{perceived\ utility,\ perceived\ harm\} \end{gathered} \tag{3}$$

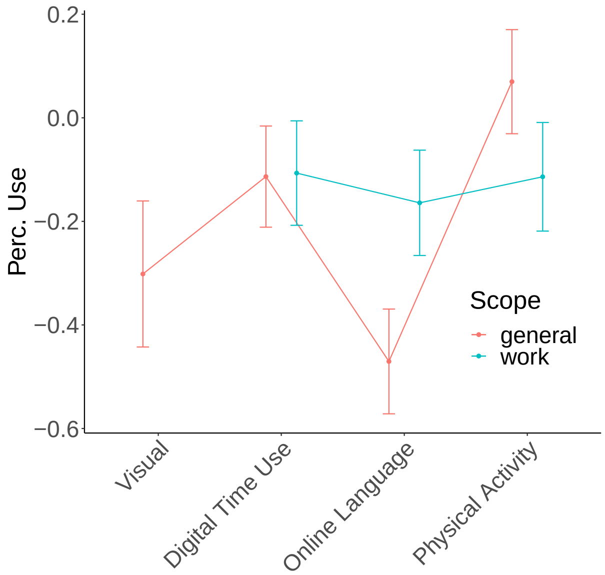
We found that the work scope interacts with the sensing online language when it comes to both perceived utility and harm. Figure 8a and Figure 8b show the interaction plots between the two variables based on the effects fitted by the interaction models. It is evident that online language is considered more useful and less harmful when it is constrained to work-specific applications and platforms. In fact, the broad sensing of online language is possibly worse than the baseline vignette. Studying the interaction also confirms that the scoping does not play a significant role in describing the acceptability of other streams.

4.3 H3: Mental Wellbeing Insights are More Acceptable

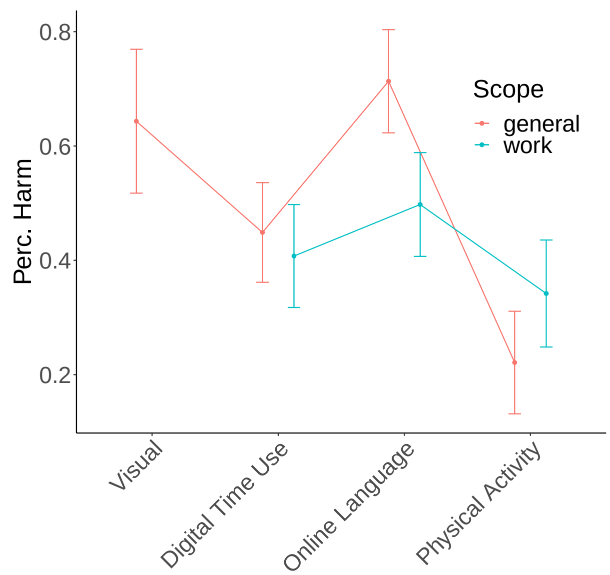
Most of the commercial systems in use today are focused on providing performance insights. This trend possibly stems from the organizational need to maintain productivity. Looking at the workers' perspective tells us a different story. Vignettes where PSAI provided insight on stress were not only considered less harmful (estimate= −0.15, p-val= 0.006), but also more useful (estimate= 0.14, p-val= 0.021) than those that estimated performance. Based on these results, we argue that both *H3a* and *H3b* are true.

In a workplace, measures of performance are directly linked with extant evaluation metrics that could eventually determine promotions or layoffs. In contrast, a worker's mental wellbeing often needs more personal management and organizations are only starting to support worker mental wellbeing. Today's workplace has a

[6] All components were independently varied. However, as described in A1, the representation of $H2$ in the vignette is dependent on the value $H1$ took



(a)



(b)

Figure 8: Scope of Sensing (*H2*) interacts with Type of Sensing (*H1*) when trying to model (a) utility and (b) harm. Although *H2* itself did not have a significant main effect in M_U and M_H, it is evident in the case of online language that the general scope has lower utility and higher harm than work scope.

scarcity of PSAI systems that specialize in supporting worker mental wellbeing. Only 1 of the 7 commercially available technologies studied in the pilot provides mental wellbeing insights (Section 3.2). Our findings motivate the development of PSAI to algorithmically infer constructs that workers are interested in, such as stress.

4.4 H4: Keeping Insights Private or Sharing as Aggregate is More Acceptable

The baseline vignette depicted the PSAI system sharing insights with the manager 1 week after it had been sent to the worker. Although the manager might be able to supervise workers' tasks better, the regression analyses shows that IWs found it significantly more useful to keep the insights to themselves (estimate= 0.54, p-val= 4×10^{-10}). They also found value in sharing their insights as an aggregate for collective interpretation (estimate= 0.18, p-val= 0.031). Keeping the insights private (estimate= 0.53, p-val= 2×10^{-11}) or sharing it as an aggregate (estimate= -0.34, p-val= 3×10^{-5}) were considered significantly less harmful. Sharing the insights to trusted others, such as peers, seniors, or mentors, did not have more utility. However, it was considered less harmful when considering a more liberal confidence interval (estimate= -0.12, p-val= 0.10). Taken together, we rejected the null hypotheses that PSAI are perceived useful and harmful regardless of who the information is shared with. As a result, both *H4a* and *H4b* hold true.

Taking our pilot study as reference, 6 of the 7 commercially available technologies share behavioral insights away from the worker (Section 3.2). The vignette experiment provides evidence that sharing individualized insights with managers (or immediate supervisors) is not a generally accepted approach. Instead, we need to consider the personalized designs of PSAI that give the locus of control to the worker. Arguably, this signals a shift in how these technologies are perceived and deployed today. Organizations can still benefit from the personal approach by focusing on aggregate views of the PSAI outputs to evaluate collective trends without singleing out individual workers. Additionally, sharing to worker insights to specific trusted individuals might be safe to explore in contexts such as counseling.

4.5 Robustness Analyses

This subsection describes additional findings from our experimental vignette study. These results expand on our hypotheses tests and reinforce the value of carefully designing PSAI.

4.5.1 Perceived utility and harm can mediate the effect of PSAI components on acceptability. The fundamental idea of TAM states that the willingness to adopt technology is a function of increasing utility and lowering costs [44]. Our empirical data so far reflects the perceptions of use (M_U) and harm (M_U) for PSAI systems. What remains untested is if these changes can affect willingness to adopt as well. In theory, we might not have accounted for certain factors could influence willingness. Therefore, we decided to validate if selection of certain components will eventually affect the willingness to adopt PSAI systems.

To disentangle this, we conducted *causal mediation analyses* [121]. The aim of this exercise was to determine how modifying PSAI can directly affect adoption or indirectly affect adoption through perceptions of usefulness and harm. Findings from Table 1 already establish the relationship between certain PSAI components and

Table 2: Causal mediation analyses help confirm the relationship between PSAI variables, perceptions of the technology, and willingness to adopt it. Direct effect denotes direct impacts that cannot be explained by the mediator. Indirect effects denotes impact of the predictors mediated through perception.

Predictor (Reference)	Value	Direct Effect	Indirect Effect	
			Mediator: Utility	Mediator: Harm
Type of Sensing (control: Visual)	Digital Time Use	0.30	0.45	0.16
	Physical Activity	0.09	0.40	0.30
Type of Insight (control: Performance)	Mental Wellbeing	0.06	0.17	0.10
Sharing of Insight (control: Self + Manager)	Self (only)	0.25	0.34	0.23
	Self + Aggregate	0.20	0.14	0.23

the mediators, perceived utility and perceived harm. Additionally, M_W discussed in the preliminary findings also confirms the relationship between the mediators and willingness to adopt (Section 4). To test mediating we used the *mma* package in *R* [139]. Table 2 shows that the direct effect of each PSAI component on willingness to adopt, along with its indirect affect through the perception–based mediators. This analysis clarifies that the role of physical activity, as a type of sensing, and mental wellbeing, as a type of insight, is almost fully mediated by the perception variables (the direct effects are negligible). The values of indirect effects imply that changing certain components in a PSAI system can lead to increased acceptability because of their affect on perceived utility and harm. Note, that some components (e.g., Digital Time Use and Sharing of Insight) have sizeable direct effects on willingness to adopt. This highlights that their role in adoption cannot be fully explained by the modified TAM we applied.

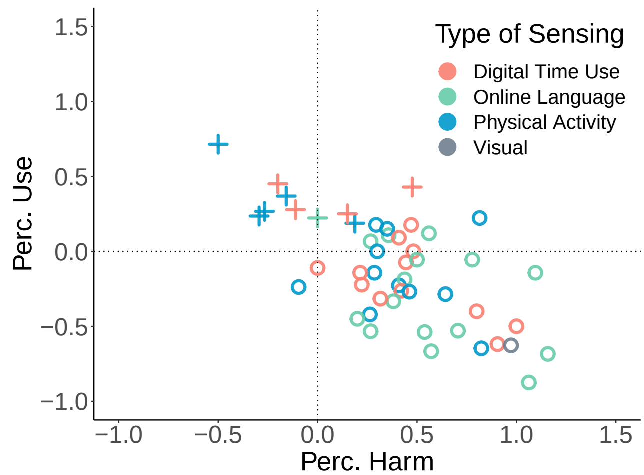


Figure 9: Each point on this plot represents 1 of the 49 PSAI vignettes represented in our experiment. + represents vignettes had average willingness to adopt greater than 0**.**

4.5.2 Learning more about feature processing can reduce the perceived harm of PSAI. Whenever a participant viewed a vignette, they could click each of the icons to learn more about certain aspects of that PSAI system. The portal recorded these explanation–related interactions for approximately 23% of the vignettes. Studies show that adding transparency to the AI–based black boxes can have its benefits [51]. The results of our mixed-effects regression models (Table 1) showed that when workers saw explanations of the underlying process, they perceived less harm. An example of the explanation for process is shown in Figure 4. Not only does it describe the types of features extracted from the sensor source, but it also explicitly states common kinds of artifacts that will not be recorded. Note, however, this experiment was not designed to study explanations. Also, the models capture explanation seeking behaviors, not the fidelity of the explanations itself. Therefore, these results are not conclusive, but do motivate additional experimentation to study the value of explainability in PSAI.

4.5.3 Acceptable designs of PSAI are limited. The nature of vignette experiments makes the comparisons relative. The results of regression models indicate that improvements can be made in how PSAI is deployed. The question is, if these improvements are enough? The experimental setup covered 48 possible scenarios where a worker interacts with PSAI. The 110 different participants evaluated many of the same vignettes to indicate their willingness to use that particular instance of PSAI. The score ranged from −2 to +2, where a negative score indicated resistance to adoption. Figure 9 shows that only 10 of the 49 vignettes (including the baseline) had a positive average for willingness score. Therefore, a large proportion of the possible implementations of PSAI are less likely to be worker-centric. While each vignette was a combination of components, the participants evaluated each of these as an integrated scenario where the moving parts were not explicit. Careful inspecting actual scores reveals that even performance–based insights are acceptable in the right combination (Table 3). For example, in vignette #33, the PSAI system infers mental wellbeing by sensing physical activity. Although performance inferences were less sought after, in comparison to mental wellbeing, we found that a PSAI system in the right configuration could still be acceptable (#13 and #37). Even online language could be leveraged in a PSAI system where it is correctly scoped, for the right purpose, and shared in the right way (#26). It is also worth noting that even though some of the acceptable PSAI vignettes have a positive perceived harm (#37, #9, and #15), none of them have perceived utility below zero. Therefore, creating value is still fundamental for these technologies to be adopted. As it stands

Table 3: Only 10 PSAI systems represented by our vignettes received a positive average for willingness to adopt. The average scores of all vignettes are provided in Table A6.

ID	H1	H2	H3	H4	Perc. Utility	Perc. Harm	Will. to Adopt
33	Physical Activity	General	Mental Wellbeing	Self	0.71	-0.50	0.64
34	Physical Activity	General	Mental Wellbeing	Self + Aggregate	0.27	-0.27	0.40
13	Digital Time Use	Work	Performance	Self	0.28	-0.11	0.33
37	Physical Activity	General	Performance	Self	0.19	0.19	0.25
9	Digital Time Use	Work	Mental Wellbeing	Self	0.43	0.48	0.19
10	Digital Time Use	Work	Mental Wellbeing	Self + Aggregate	0.25	0.15	0.15
1	Digital Time Use	General	Mental Wellbeing	Self	0.45	-0.20	0.10
44	Physical Activity	Work	Mental Wellbeing	Self + Trusted Other	0.24	-0.29	0.06
26	Online Language	Work	Mental Wellbeing	Self + Aggregate	0.22	0.00	0.06
41	Physical Activity	Work	Mental Wellbeing	Self	0.37	-0.16	0.05

right now, without considering worker needs most implementations will fail and only exacerbate poor work experiences. Referring to these raw scores before implementing PSAI information flows can help anticipate their adoption (or resistance).

5 DISCUSSION

Our findings show that Passive Sensing–enabled AI systems to support information work can be designed in a variety of configurations. Each instance varies in how it is perceived by Information Workerss. As a result,our research defines the practical boundaries of making meaningful applications for workers that will support their aspirations of working better. We took a pragmatic approach in improving information work as we know it today. The implications are not necessarily "best practices" but rather "better practices" — alternatives to methods before it. Yet, we need to be wary of how passive sensing interacts within the complex socio-economic ecosystem of work. A true dent in the lives of workers needs many changes beyond the scope of our research inquiry. Beyond technological improvement, we need reform in our research methods and policy. This discussion section presents a starting point, from where future researchers can reflect and rethink how PSAI can make working thrive.

5.1 Worker-Centered PSAI

In today's urban environments, IWs are likely to be equipped with a variety of connected devices (e.g., smartwatches), they regularly engage with digital platforms (e.g., social media), and are exposed to other embedded technologies in their surroundings (e.g., bluetooth beacons). Each of these modalities can provide valuable behavioral traces to study human wellbeing in natural environments. Before the ubiquity of these sensing streams, researchers attempted to instrument fixed structures to understand free living behaviors. The *Aware Home* at Georgia Tech [82] and the *PlaceLab* at MIT [69] are examples of such instrumentation. In the twenty years since, personnel management have considered similar ideas to build "smart offices" to support thriving workers [107]. Arguably, surmounting the engineering challenges of such endeavors is non–trivial. However, these projects need to think beyond technological efficacy and also about the perspectives of its data providers, the information workers. In this section, we will reflect on a recent project, *Mites* at CMU [16], as an example of why sensor deployments need to align worker perceptions of adoption[7].

5.1.1 *Tensions in Deploying Passive Sensing in Work Contexts.*

The *Mites* project represents a "unified, high-fidelity, and general-purpose sensing system" for smart buildings [16]. Human activity modeling was one of the proposed applications, which aligns with the kind of individualized insights we have investigated in regards to PSAI. The research team fitted 334 sensors across the spaces in one of the campus buildings. Let us consider a well established this setup from the perspective of a well-established human-centered framework for ubiquitous computing systems, *Privacy by Design* [87]. Indeed, the overall sensing flow of the research project was setup with privacy–preserving principles. The sensors were connected through end-to-end encryption in a university–only network (*Adequate Security*). Any data recorded by the sensors was first featurized in the sensor itself, therefore ensuring raw data never left the physical device (*Locality*). The location signatures of these sensors were obfuscated to make re-identificaton of occupants more difficult (*Pseudonymity*). In fact, users were able to opt-out of sensing through a companion mobile application, giving some sense of *Choice and Consent.* Lastly, the research team communicated the role of these sensors through a town-hall, email threads, and placing QR codes (linked to documentation) across different rooms (*Notice*). Despite these safeguards, however, the instrumentation of an existing building into a living laboratory was met with resistance [63]. This pushback stemmed from a gap between the occupants' anxieties, the researchers' intentions, and the technology's capabilities. Eventually 9 of 110 offices disabled the sensor [8]. It can be tempting to consider this small proportion to indicate the success of smart instrumentation of offices. However, we urge future researchers to be careful in associating this case-study as a reason to sense workers indiscriminately.

5.1.2 *Foreseeing the Adoption of Passive Sensing in Work Contexts.*

Unlike university students, many IWs might not be able to change where they work. Given appropriate mechanisms, the number of opt-outs from such a project would be much higher in an information work setting. Thus, it is important to design such a project better. Let us take another look at *Mites* from the perspective of

[7]None of the co-authors on this paper were directly involved with the *Mites* project and we only use it as an example

[8]The project was still ongoing when this document was compiled

the components that inform perceptions of PSAI's utility and harm (Section 4):

(1) *Type of Sensing: Mites* possessed 12 kinds of sensing streams. Some of these are beyond the ones we studied, especially the infrastructure–specific streams, such as room temperature, light, humidity, and pressure. It is unclear how these would be perceived. *Mites* included a sophisticated motion sensor to determine *physical activity*, which we found was perceived better than cameras. However, the sensors also included audio sensors which might be perceived as unfavorably as *online language* — a verbal communication stream.
(2) *Type of Insight:* Another big challenge with *Mites* was that occupants did not receive clear insight. The sensing suite provides rich possibilities, including insight into occupant stress. However, the lack of actual consumable insights can make it difficult for occupants to envision utility without anticipating the harms of surveillance.
(3) *Sharing of Insight:* While the occupants themselves were not receiving any insights, the investigators could gain some insight for benchmarking purposes. We had demonstrated earlier that data providers of PSAI must receive some insight from the data to perceive value and evaluate the harm. If occupants or workers are isolated from the information flow after their data is collected, they are less likely to trust their data will be interpreted accurately.

The assessment above did not need the development of sensors. In fact, it showcases how PSAI systems can be evaluated *a priori* to ensure worker-centric deployments.

5.2 Worker-centric Applications through and for PSAI

One of the core ways to make PSAI acceptable technology for workers is directly providing insights back to them (Section 4.4). Such a transaction between data providers and a computational tool protects worker interests. Quantified work needs to surface sensing insights in a way that workers have agency to make meaning out of it [95]. For instance, many IWs use their time effectively to complete work and balance their wellbeing when scheduling systems give them more autonomy [38]. In the same vein, PSAI should aim to shift the locus of control towards the workers. Once workers can comprehend their data in the context of inferences, they can choose if they want to involve other stakeholders. Throughout, they should be able to identify the blindspots and misrepresentations of these tools. Not only will this give them a deeper understanding to revoke their involvement in the system but also an opportunity to gather new information required to fully discuss their performance and wellbeing insights with other stakeholders. Essentially, a path forward needs to incorporate participatory design with the workers [142]. We need to build prototype interfaces for workers when we begin data collection. Thus, workers will be able to assess PSAI transparently in parallel to the data collection, not after they lose control and possession of their data. These interfaces must follow the following key tenets:

(1) *Worker–facing:* Workers must be able to view insights from the data they provide.
(2) *Worker–first:* Workers must receive timely and updated insight to help them control data they provide in the future.
(3) *Worker–flexible:* Workers must be able to adjust and contest any algorithmic insights.

In this section we describe some of these potential worker-centric applications that can be inspired from our research. These applications can help workers improve but also help them inspect how they are estimated through PSAI. The interfaces are meant to encourage recourse and engagement from the workers.

5.2.1 Applications for Workers to Evaluate Themselves. We need to conceptualize applications of worker wellbeing as personal informatics tools. Workers should be able view the daily activities they consent to as factors contributing to their work–related outcomes. This can help them determine if they should change the way they sleep or install screen time management tools. Similarly, we can imagine interfaces where workers evaluate themselves as a function of collaborative teams. PSAI systems can aggregate information to help IWs situate themselves in the context of their team dynamics and organizational pulse [118]. Such insight can empower them to define boundaries between one's own preferences and the behavioral norms. These interfaces should be longitudinal and provide insights within the context of organizational life cycle. Workers should be able to compare their effectiveness across different organizational groups during times of organizational crises, upheavals, or unanticipated policy changes or enforcement within the organizations. Such interfaces can give workers a robust illustration of themselves but also a means to reflect on how their data can be interpreted.

5.2.2 Applications for Workers to Evaluate Organizations. Workers should be able to leverage their data to keep their organizations accountable Calacci. In the days of social media, it is not uncommon to view crowd contributed posts describing companies [58]. These platforms are used by workers to corroborate, compare, and contrast their experiences. It provides a method for job seekers to anticipate how healthy a work setting is [42]. We can envision PSAI as tool to build a knowledge base or "wiki" that accumulates inferences from PSAI leveraging physical activity or digital time use. With this information, workers could obtain an empirical understanding of how an organization's practices align with their personal values, beliefs, and work ethics. Much like making sense of their own information, aggregating information across workers can help them keep the organization accountable and give them the transparency with which they can investigate the changes in worker wellbeing.

5.3 Transferrability of Findings to Changing Landscapes of Work

The motivations of this research and the interpretation of our findings are admittedly flavored with the sociotechnical specifics of work in the US. The COVID-19 pandemic brought more attention to worker wellbeing [99], but also motivated unchecked deployment digital surveillance at work [8]. More recently, we see a shift away from these priorities as many IT companies are recovering from large-scale lay-offs [133]. Personalized worker wellbeing has been overlooked to meet organizational productivity requirements. Keeping these changing dynamics in mind, PSAI systems may be perceived very differently. In this section we speculate on the implications of our research in work environments outside of the US and also, in different cycles of the economy.

5.3.1 PSAI for Information Work Outside the USA. The labor policies and the underlying work–leisure culture of the US is unique. A good way to appreciate it is by contrasting it with the another equally developed economical context with a similar growth trajectory, Europe. Sometime in the late 1960's, we witnessed a decline in European working hours in terms of hours per week and the total weeks per year [6]. More recently, we are seeing Europe–based information workers gain more safeguards against detrimental wellbeing practices with "right to disconnnect" [117]. Several countries have adopted this idea with protective policies that can hold employers in violation if they communicate with their workers after a certain time [79]. In light of these, one might wonder what is utility of an information worker in Europe gaining additional insight into their wellbeing, especially through technologies like PSAI.

These European policies help create boundaries for workers to appreciate and actively utilize their leisure time. It is a luxury that only few US–based information workers have. Yet, these benefits come at a cost. The US has been more economically productive than Europe for a few decades [135]. Apart from losing competitive edge, this gap becomes concerning when labor might not be able to afford the wellbeing benefits it desires. Returning to the individual–level, surveys from 2022 showed that workers in Europe were notably less engaged [30]. Therefore, the personalized insights produced by PSAI might still hold value in explaining to workers how and where they are likely to contribute the most while still maintaining their wellbeing needs.

Even if we can justify the technology, different work paradigms also lead to distinct sociotechnical constraints. Much like the wellbeing–related policies, Europe has also established key policies to protect certain classes of employee data through *General Data Protection Regulation* (GDPR) [109]. Such regulatory policies can provide the necessary guardrails for designing PSAI. Not only can the data collection be limited but also the access to inferences and insights. Potentially, worker wellbeing tools might even become as personal as a one's health trackers. However, the regulation also introduces a paradox where it can become challenging to conduct the necessary research on PSAI in European contexts. Alternatively, other fast–developing economies with large information worker populations might not have policies equivalent to GDPR. It can be tempting to conduct research in these geo-politcal contexts but, if the findings from our US–based participants are indicative, the lack of all regulation will heighten worker concerns with PSAI.

Taken together, the motivations to use (and not use) PSAI and how the technology is appropriated is likely to differ based on different regulations and policy. Although the underlying technology might not drastically change, the way PSAI is instantiated will vary in terms of data source, flow, sharing, and stakeholders.

5.3.2 PSAI for Information Work in Crises. The way an organization views its workers and the way workers view them back is often a function of the peripheral economy. The COVID-19 pandemic induced safe–distancing requirements forced organizations to think about employee wellbeing. The idea of a successful thriving employee was centered around worker–needs [24]. Later, the US witnessed an economic downturn, which indicated a focus on enterprise–level productivity needs at the expense of individual worker performance or wellbeing [126]. However, research shows that organizations that focus on workers' needs beyond financial incentive tend to recover better in the long run [35]. Technology like PSAI could play a role in highlighting their workers' state to help them take stock of workers again. Yet, deployment of these systems requires caution. Studies show that state's find algorithmic profiling of job seekers desirable when few opportunities exist, but it ends up being harmful for the individuals themselves [7]. One can imagine organizations gain access to PSAI and identify workers that are predicted to perform highly without stressful bouts. Such motivations are only likely to increase disparities. A potential solution to this is for states to define statutory limits on decision making through PSAI in times of economic downturn.

Worker in roles with high precariousness, such as contractual work or temporary occupations, are more vulnerable to misuse of PSAI. Research shows that job precarity can worsen worker wellbeing [72]. It can be tempting to deploy PSAI to help workers understand their wellbeing better, but the anxieties of losing their job are likely to supersede any potential benefit of the technology. Even positive algorithmic inferences can be misappropriated by an organization as a cause to hire other workers with lower expectations. Therefore, the policies also need to regulate the rights of different workers when it comes to sharing data with PSAI and moreover involving their employer. Much like other instruments of explaining human ability, PSAI also suffers from the challenge of being used for fallacious purposes like *reification* and *ranking* [60]. Organizations that fall into this trap will foster an economy of dissatisfied workers that will lead to long-term losses. Instead, we believe PSAI needs to be utilized as a tool for understanding, augmenting, and recovering the individual worker.

5.4 Limitations and Future Work

Our study was focused on unraveling which aspects of PSAI systems lead to IWs perception of these systems as useful, harmful, and acceptable. We relied on the Experimental Vignette Method to capture participant preferences for hypothetical, randomly–generated PSAI systems. In other domains, research shows that preferences recorded using such a method closely resemble behavioral benchmarks [64]. However, at the time of writing this paper, we are not aware of any such behavioral benchmarks for IWs accepting or resisting PSAI systems. Future studies can consider deploying a variety of PSAI systems to probe this, but researchers must tread these efforts with caution and only proceed after participation risks of workers have been minimized.

Another aspect beyond the scope of our study was that the actual insights of the PSAI system were hypothetical. In reality, challenges like the *Semantic Gap* [36] can cause different kinds of PSAI systems to vary in efficacy. For instance, online language was not viewed very favorably as a type of sensor among our participants, but it is known to be a potent source of data for mental health predictions [47]. Therefore, it is yet to be understood how IWs reevaluate the cost-benefits of these systems when they are aware of the quality of the AI models. Another similar problem is the fact that many PSAI systems are likely to be multimodal—a combination of various sensing streams [16, 98]. While our findings can give some guidance to anticipate the adoption of such systems, we need more dedicated studies to represent the perception of composite sensing technology for workers.

Lastly, the factors highlighted in our study are not intended to "full-proof" new PSAI systems. We acknowledge that these technologies must be situated within organizational policies, labor laws, and economic needs. Notably, our findings are based on information workers employed in the U.S., where both work evaluations and sensing technologies manifest very differently from other regions, say, Europe. Nevertheless, our findings lay the groundwork to conduct similar experiments with other populations in the context of their unique perspectives and policies. A better understanding of acceptability of PSAI systems by the workers is a fundamental step in evaluation and provides a parsimonious way to describe the success or failure of systems. These factors provide guide rails to design PSAI systems, but they are not sufficient enough to preclude other valuable worker-centered practices. For example, these systems need to be deployed only under new forms of consent—such as one that is freely-given and reversible [28]—that provide added protection to the worker. This paper's findings must complement other safeguards in order to ensure PSAI systems are built to primarily support workers.

6 CONCLUSION

Passive sensing is an immensely powerful tool. As the amount of technology an urban worker interacts with increases, the opportunities to understand their behavior increases. However, real-world deployment of Passive Sensing–enabled AI elicit many concerns among Information Workers leading to resistance in adoption of these systems. Our paper reveals that PSAI can be designed towards adoption. We found that different types of sensors impact perceptions of utility and harm for PSAI differently (*H1*). Restricting sensing to the work scope can be favorable for certain sensor streams (*H2*). Developing PSAI to infer mental wellbeing insights was better perceived than those that measuring performance (*H3*). Lastly, workers were more keen on systems that kept PSAI–generated insights private or shared as aggregate than forwarding it to specific individuals in their organization (*H4*). Together, our findings provide a means to foresee the success of PSAI systems from a work-centered lens.

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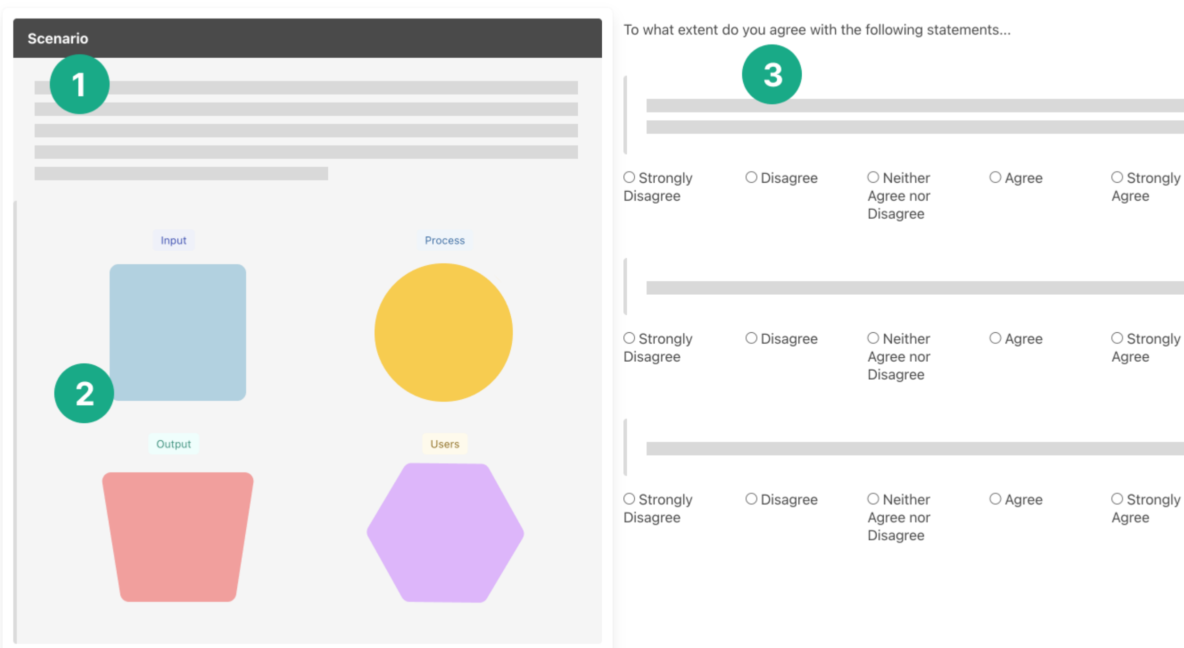
A APPENDIX

The appendix contains the following items:

- Figure A1 represent the instructions shown to participants
- Table A1, Table A2, and Table A3 describe the text in the vignettes corresponding to different hypotheses variations. It also includes the explanations that participants could see if they clicked the icons.
- Figure A2, Figure A3, present the icons included in the vignette depending on the hypotheses variations.
- Figure A4 shows two additional vignettes as examples.
- Table A4 and Table A5 describe the stepwise results of the regression models.
- Table A6 lists the scores of every vignette in our hypothesis space.



What are Passive Sensing-enabled AI (PSAI) systems for behavioral wellbeing? Today we have applications that can measure our daily activities using digital technologies in our everyday life.You can learn how much you walked in a day or how long you used your computer. By learning more about ourselves, we have an opportunity to improve. These applications log activities automatically and continuously without any manual recording. We refer to this as "passive sensing." These applications can power AI to give us insights into our behavioral wellbeing. We call such applications Passive Sensing-enabled AI or PSAI (pronounced "psy" as in "psychology").

What can PSAI systems do for information workers? Recently, organizations and scientists have been considering implementing PSAI in the work context. Our research shows that workers find PSAI potentially empowering as it can reduce subjective biases in their performance and wellbeing evaluations. However, workers are also wary of how PSAI could be misused in the social structures of work. In this study, we aim to explore the elements of PSAI that workers find beneficial or concerning.

We need you to **judge scenarios** where you are a user of different PSAI systems developed by CommonSense.AI to help you succeed at work. Their systems **only sense behavior with your consent** and use artificial intelligence to **provide insights of your behavior**. Consider each scenario as a whole when judging.

1. **Description**: Read short text explaining the scenario.
2. **Visual Aids**: Click graphics if you need more info.
3. **Review**: Answer 3 quick survey questions.

After judging these scenarios we will ask for some basic information and additional perspective. Overall, this should take less than 15 minutes.

Figure A1: Once a participant has cleared the screener they are shown instructions above to familiarize them with the subsequent vignette exercise.

Table A1: The vignette text was generated based on randomly selecting values for $H1$ and $H2$. Every participant was shown the baseline vignette where $H1$ =“Visual” and $H2$ =“General”.

H1	H2	Vignette Text	Explanation	
			Input	Process
Visual	General	The AI system can analyze video captured from your work computer's webcam. It will extract facial expressions (e.g., attentive, stressed, enjoying) and will NOT store any identifiable images.	This PSAI system will use the primary camera of your PC. While the PSAI is running, the camera will remain ON. The camera can be an inbuilt camera or an external one.	This PSAI system will use Computer Vision and Machine Learning to learn your cognitive state based on subtle and complex facial actions. An example of what the PSAI will store ...[sample table with values for timestamp, “focus”, “distracted”, “calm”, “energetic”]. The system will NOT store any image or video of people or surroundings.
Online Language	Work	The AI system can analyze text retrieved from work-related communication platforms such as Slack, Teams, and Email. It will extract psycholinguistic attributes from your posts (e.g., frequency of positive emotions) and will NOT store any readable text.	This PSAI system will analyze the text you input into your work-related communication apps. The PSAI could include email (e.g., Outlook), instant-messaging (e.g., Slack), work-social media (e.g., Yammer).	This PSAI system will use Natural Language Processing to learn different figures of speech in the communication text (e.g., frequency of positive phrases). An example of what the PSAI will store: An example of what the PSAI will store ...[sample table with values for timestamp, “positive”, “negative”, “anger”, “achievement”]. The system will NOT store any raw text or nouns.
	General	The AI system can analyze text retrieved from communication and social media platforms including Facebook, Twitter, and Search. It will extract psycholinguistic attributes from your posts (e.g., frequency of positive emotions) and will NOT store any readable text.	This PSAI system will analyze the text you input into any of your communication apps. The PSAI could include email (e.g., GMail), instant-messaging (e.g., Messenger), social media (e.g., Twitter).	[Same as above]
Digital Time Use	Work	The AI system can analyze your screen time on work applications such as those used for communication, development, design, documentation, and presentation). It will extract engagement measures for different categories and will NOT store any application names, titles, or content.	This PSAI system will analyze your interactions with work-related applications. The PSAI will be restricted to application categories such as work communication (e.g., Outlook, Teams), programming (e.g., VS Code, Github), and documentation (e.g., Word, Excel).	This PSAI system will use event logging to learn the time you spend on different categories of applications and how you use it (e.g., typing, clicking, scrolling). An example of what the PSAI will store ...[sample table with values for timestamp, “category”, “app in focus”, “mouse move”, “keystroke count”]. The system will NOT store any content, such as file name, application name, or typed text.
	General	The AI system can analyze your screen time on computer applications including those used for work, entertainment, browsing, and gaming). It will extract engagement measures for different categories and will NOT store any application names, titles, or content.	This PSAI system will analyze your interactions with your applications. The PSAI will be cover a variety of applications categories including entertainment, programming, and browsing.	[Same as above]

A1 Continued.

Physical Activity	Work	The AI system can analyze movement patterns using occupancy and presence sensors embedded in the office infrastructure such as doors and desks. It will extract frequency, intensity, and rhythm of different physical activities and will NOT store any identifiable locations.	This PSAI system will use sensors embedded in the work space, such as access doors. The location of the sensor can indicate the activity you are involved in (e.g., at your desk or away). These sensors are used for security, maintenance, and analysis of space usage.	This PSAI system will use activity recognition to learn the time you spend on general activities (e.g., sitting, moving). An example of what the PSAI will store ...[sample table with values for timestamp, "activity type", "duration", "event count"]. The system will NOT store any location data.
	General	The AI system can analyze movement patterns using motion and physiological sensors in your smartwatch. It will extract frequency, intensity, and rhythm of different physical activities and will NOT store any identifiable locations.	This PSAI system will use sensors in your smartwatch. These sensors are used for providing different interactions (e.g., automatic screen on/off), but also to track your physical state (e.g., resting, or intense activity).	[Same as above]

Table A2: The vignette text was generated based on randomly selecting values for $H3$. Every participant was shown the baseline vignette where $H3$ ="Performance".

H3	Vignette Text	Explanation: Output
Performance	With this data it can estimates your job performance on a scale of 1-100 at the end of every day.	The PSAI will provide daily insights based on different aspects of performance. You will see a single score (1-100) that reflects (i) the quality with which you perform assigned tasks and (ii) the quality with which you perform additional unspecified tasks related to work.
Mental Wellbeing	With this data it can assess your stress on a scale of 1-100 at the end of every day.	The PSAI will provide daily insights based on different aspects of mental wellbeing. You will see a single score (1-100) that reflects (i) the stress you experience from external demands and (ii) the anxiety you experience thinking of future events.

Table A3: The vignette text was generated based on randomly selecting values for $H3$. Every participant was shown the baseline vignette where $H4$ ="Self+Manager".

H4	Vignette Text	Explanation: Users
Self	You will be able to view the system's assessment of you everyday and reflect on long term trends.	The insights from PSAI are only available to you. By viewing your insights, you can learn more about how you work. This new understanding can identify opportunities for you to change how you work.
Self + Manager	[Self Text +] Additionally, your manager will be able to view the assessments at the end of the week.	The insights from PSAI will be first available to you. By viewing your insights, you can learn more about how you work. This new understanding can identify opportunities for you to change how you work. After some time, your manager will also able to view the insights about you. You will be able to share your interpretation of insights with each other and collaboratively decide approaches to work. The manager will NOT be able to see the data PSAI used to produce insights.

A3 Continued.

Self + Trusted Other	[Self Text +] Additionally, a coworker of your choice will be able to view the assessments at the end of the week.	The insights from PSAI will be first available to you. By viewing your insights, you can learn more about how you work. This new understanding can identify opportunities for you to change how you work. After some time, a trusted other of your choice would also be able to view the insights about you. Your trusted other can be a close colleague, mentor, wellbeing officer, or anyone you think can you improve your work experience. You can share your interpretation of insights with each other and collaboratively decide on new approach to work. The trusted other will NOT be able to see the data PSAI used to produce insights.
Self + Aggregate	[Self Text +] Additionally, your assessment will be anonymously aggregated to help users compare their experience and learn collective trends.	The insights from PSAI will be first available to you. By viewing your insights, you can learn more about how you work. This new understanding can identify opportunities for you to change how you work. In addition, this PSAI will anonymously pool your insights with other coworkers who have consented. You can compare your experience with different groups, such as others in the same role or department. PSAI will NOT pool insights if the groups are smaller than 50 people to ensure individual identities protected.

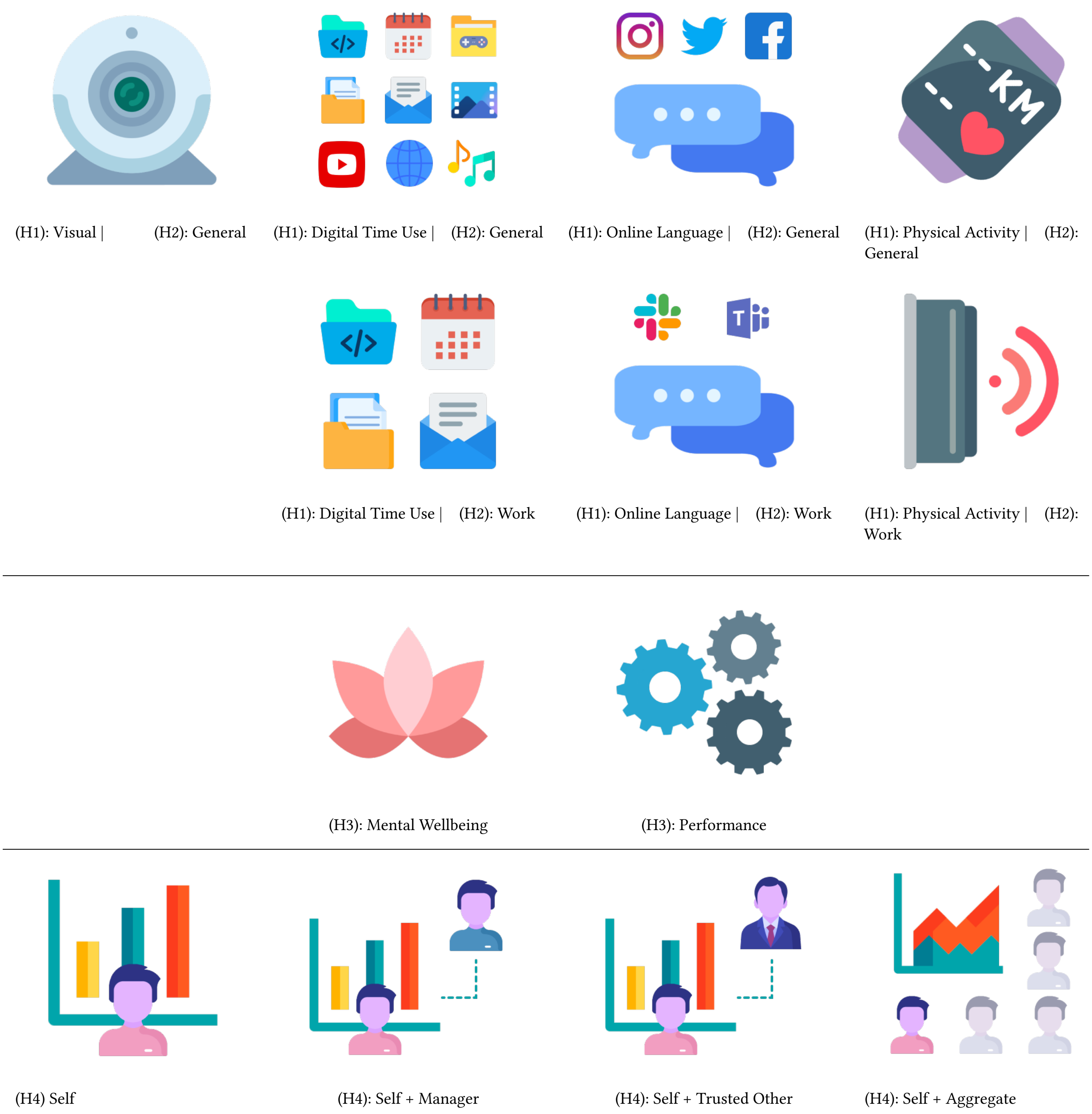


Figure A2: The vignettes text was presented with graphical icons. These icons helped pictorially differentiate the PSAI systems being presented. The first row represents “input”, the second represents “output”, and the third represents “users”. Moreover, participants could interact with the icons to learn a deeper explanation about the system (refer to Table A1, Table A2, Table A3).

(Process): Digital Time Use

This PSAI system will use event logging to learn the time you spend on different categories of applications and how you use it (e.g., typing, clicking, scrolling). An example of what the PSAI will store:

Time	Category	App in Focus	Mouse Move	Key Strokes
11/29/2023 9:26am	Communication	14	10	2
11/29/2023 2:18pm	Document	33	4	15

The system will NOT store any content, such as file name, application name, or typed text.

(Explanation)

(Process): Online Language

This PSAI system will use Natural Language Processing to learn different figures of speech in the communication text (e.g., frequency of positive phrases). An example of what the PSAI will store:

Time	Positive	Negative	Anger	Achievement
11/29/2023 11:44am	4	1	0	2
11/29/2023 3:15pm	2	3	4	0

The system will NOT store any raw text or nouns.

(Explanation)

(Process): Physical Activity

This PSAI system will use activity recognition to learn the time you spend on general activities (e.g., sitting, moving). An example of what the PSAI will store:

Time	Type	Duration
11/29/2023 10:01am	Still	50
11/29/2023 1:08pm	Significant Movement	12

The system will NOT store any location data

(Explanation)

(Process): Visual

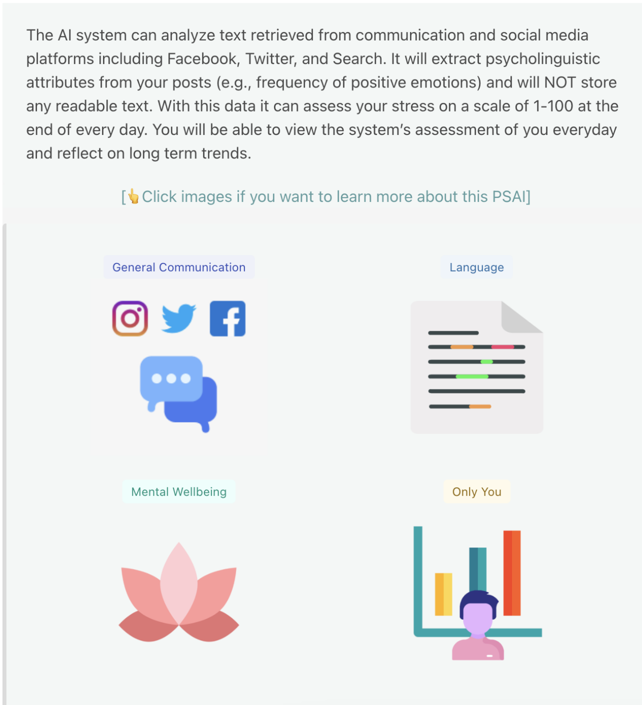
This PSAI system will use Computer Vision and Machine Learning to learn your cognitive state based on subtle and complex facial actions. An example of what the PSAI will store:

Time	Focus	Distracted	Calm	Energetic
11/29/2023 10:38am	0.67	0.32	0.23	0.72
11/29/2023 4:55pm	0.55	0.40	0.68	0.25

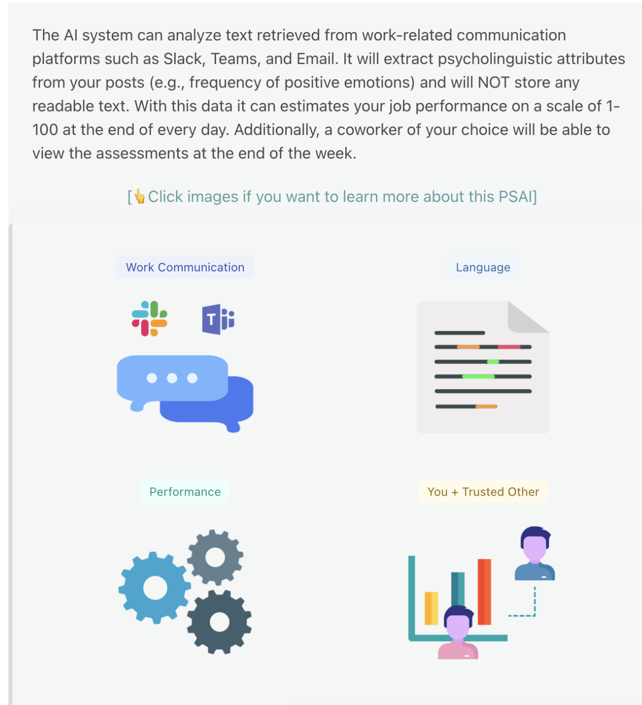
The system will NOT store any image or video of people or surroundings.

(Explanation)

Figure A3: Apart from the icons corresponding to hypothesis values (Figure A2, each vignette also included an icon for "process" which corresponds to the value of $H1$. On clicking the icon, users see an explanation demonstrating the kind of features captured by the PSAI system.



(a) $H1$ =Online Language, $H2$ =Work, $H3$ =Mental Wellbeing, $H4$ =Self Only



(b) $H1$ =Online Language, $H2$ =Work, $H3$ =Performance, $H4$ =Self + Trusted Other

Figure A4: Examples of vignettes from where $H1$ =Online Language.

Table A4: Linear Mixed-Effects Regression models described in the main draft reflected results from a full model including all covariates. Here we provide the intermediate models, where we included control variables in increments to understand factors affecting perceived utility (M_U). $M_U a$ is the simplest model without controls, $M_U b$ includes demographics, $M_U c$ includes organizational context, and the full model M_U includes attitude and perception measures.
('-':$p < 1$, '∘':$p < 0.1$, '*':$p < 0.05$, '':$p < 0.01$, '***':$p < 0.001$)**

	M_{Ua}		M_{Ub}		M_{Uc}		M_U	
	Est.	$p-$value	Est.	$p-$value	Est.	$p-$value	Est.	$p-$value
H1: Type of Sensing (ref: Visual)								
Digital Time Use	0.31	0.011*	0.31	0.011*	0.31	0.011*	0.31	0.001**
Online Language	−0.01	0.91	−0.01	0.93	−0.01	0.93	−0.01	0.93
Physical Activity	0.31	0.004**	0.34	0.003**	0.34	0.004**	0.34	0.001**
H2: Scope of Sensing (ref: General)								
Work (only)	0.05	0.326	0.05	0.334	0.05	0.339	0.05	0.351
H3: Type of Insight (ref: Performance)								
Mental Wellbeing	0.14	0.013*	0.14	0.016*	0.14	0.018*	0.14	0.021*
H4: Sharing of Insight (ref: Self + Manager)								
Self (only)	0.54	1×10^{-10}***	0.54	9×10^{-11}***	0.54	1×10^{-10}***	0.54	4×10^{-10}***
Self + Aggregate	0.18	0.023*	0.18	0.023*	0.19	0.022*	0.18	0.031*
Self + Trusted Other	0.08	0.294	0.08	0.307	0.08	0.316	0.08	0.346
Explanations								
Input	0.04	0.682	0.04	0.689	0.03	0.754	0.02	0.834
Process	−0.01	0.893	−0.01	0.921	−0.02	0.871	−0.02	0.856
Output	−0.05	0.665	−0.05	0.669	−0.04	0.693	−0.04	0.732
Users	0.01	0.925	0.01	0.914	0.01	0.931	0.01	0.872
Demographics								
Age (ref: 21-30)								
31-40			−0.01	0.979	−0.03	0.906	−0.08	0.731
41-50			−0.01	0.992	0.10	0.828	−0.01	0.989
51-60			0.42	0.211	0.61	0.089∘	0.65	0.079∘
Gender (ref: Female)								
Male			0.27	0.187	0.41	0.072∘	0.36	0.106
NB/Other			−0.61	0.572	−0.02	0.982∘	0.01	0.99
Race (ref: Asian)								
Black or AA			0.95	0.029*	0.85	0.123	0.83	0.131
White			0.07	0.715	0.04	0.864	0.11	0.654
Other			−0.56	0.264*	−0.78	0.151	−0.61	0.271
DND			−0.84	0.071∘	−1.07	0.052∘	−0.96	0.086∘
Organization								
Size (ref: Large)								
Small-Medium					−0.35	0.129	−0.04	0.732
Role								
[None of the levels were significant]								
Number of Reportees (ref: 1 or more)								
None					−0.01	0.946	−0.04	0.847
Attitudes and Perceptions								
Perc. Quantification							0.02	0.834
Perc. Surveillance							−0.02	0.856
Privacy Behaviors							−0.04	0.732
Trust in Manager							0.01	0.872
Conditional R^2	0.56		0.58		0.60		0.61	

Table A5: Linear Mixed-Effects Regression models described in the main draft reflected results from a full model including all covariates. Here we provide the intermediate models, where we included control variables in increments to understand factors affecting perceived harm (M_H). M_Ha is the simplest model without controls, M_Hb includes demographics, M_Hc includes organizational context, and the full model M_H includes attitude and perception measures.
('-':$p < 1$, '○':$p < 0.1$, '*':$p < 0.05$, '':$p < 0.01$, '***':$p < 0.001$)**

	M_{Ha}		M_{Hb}		M_{Hc}		M_H	
	Est.	p−value	Est.	p−value	Est.	p−value	Est.	p−value
H1: Type of Sensing (ref: Visual)								
Digital Time Use	−0.28	0.007**	−0.29	0.007**	−0.29	0.007**	−0.29	0.008**
Online Language	−0.11	0.28	−0.12	0.27	−0.11	0.28	−0.11	0.30
Physical Activity	−0.44	3×10^{-5}***	−0.44	3×10^{-5}***	−0.44	3×10^{-5}***	−0.44	4×10^{-5}***
H2: Scope of Sensing (ref: General)								
Work (only)	−0.03	0.463	−0.04	0.411	−0.04	0.419	−0.03	0.504
H3: Type of Insight (ref: Performance)								
Mental Wellbeing	−0.15	0.003**	−0.15	0.004**	−0.15	0.004**	−0.15	0.004**
H4: Sharing of Insight (ref: Self + Manager)								
Self (only)	−0.51	2×10^{-11}***	−0.51	2×10^{-11}***	−0.51	2×10^{-11}***	−0.51	2×10^{-11}***
Self + Aggregate	−0.31	4×10^{-5}***	−0.31	4×10^{-5}***	−0.31	4×10^{-5}***	−0.31	5×10^{-5}***
Self + Trusted Other	−0.12	0.096○	−0.12	0.102	−0.12	0.102	−0.12	0.109
Explanations								
Input	−0.03	0.776	−0.03	0.771	−0.02	0.813	−0.02	0.781
Process	−0.15	0.119	−0.15	0.117	−0.15	0.121	−0.17	0.09 ○
Output	0.13	0.234	0.13	0.241	0.13	0.235	0.12	0.255
Users	−0.04	0.641	−0.04	0.661	−0.04	0.661	−0.03	0.753
Demographics								
Age (ref: 21-30)								
31-40			0.36	0.062○	0.49	0.026*	0.42	0.047*
41-50			−0.16	0.677	−0.07	0.851	−0.05	0.888
51-60			−0.06	0.821	−0.04	0.889	0.05	0.863
Gender (ref: Female)								
Male			−0.11	0.568	−0.13	0.478	−0.15	0.408
NB/Other			1.75	0.063	1.44	0.148	1.44	0.133
Race (ref: Asian)								
Black or AA			−0.29	0.420*	0.06	0.886	0.06	0.886
White			0.07	0.669	0.03	0.873	0.06	0.742
Other			−0.81	0.064○	−0.65	0.162	−0.49	0.285
DND			0.84	0.047*	1.05	0.025*	1.08	0.021*
Organization								
Size (ref: Large)								
Small-Medium					0.14	0.459	0.17	0.348
Role								
[None of the levels were significant]								
Number of Reportees (ref: 1 or more)								
None					0.01	0.995	−0.03	0.878
Attitudes and Perceptions								
Perc. Quantification							0.04	0.013*
Perc. Surveillance							−0.02	0.856
Privacy Behaviors							0.11	0.071○
Trust in Manager							0.01	0.872
Conditional R^2	0.54		0.56		0.58		0.58	

Table A6: Each vignette was evaluated by several different information workers as a part of the experiment. This table shows the average scores for Perceived Utility, Perceived Harm, and Willingness to Adopt. The vignettes are sorted in decreasing order of acceptability. Vignette #49 was the baseline vignette shown to all participants.

ID	H1	H2	H3	H4	Utility	Harm	Accept
33	Physical Activity	General	Mental Wellbeing	Self	0.71	-0.50	0.64
34	Physical Activity	General	Mental Wellbeing	Self + Aggregate	0.27	-0.27	0.40
13	Digital Time Use	Work	Performance	Self	0.28	-0.11	0.33
37	Physical Activity	General	Performance	Self	0.19	0.19	0.25
9	Digital Time Use	Work	Mental Wellbeing	Self	0.43	0.48	0.19
10	Digital Time Use	Work	Mental Wellbeing	Self + Aggregate	0.25	0.15	0.15
1	Digital Time Use	General	Mental Wellbeing	Self	0.45	-0.20	0.10
44	Physical Activity	Work	Mental Wellbeing	Self + Trusted Other	0.24	-0.29	0.06
26	Online Language	Work	Mental Wellbeing	Self + Aggregate	0.22	0.00	0.06
41	Physical Activity	Work	Mental Wellbeing	Self	0.37	-0.16	0.05
29	Online Language	Work	Performance	Self	0.11	0.36	-0.04
38	Physical Activity	General	Performance	Self + Aggregate	-0.24	-0.10	-0.05
14	Digital Time Use	Work	Performance	Self + Aggregate	-0.11	0.00	-0.06
46	Physical Activity	Work	Performance	Self + Aggregate	-0.23	0.41	-0.09
21	Online Language	General	Performance	Self	-0.53	0.27	-0.13
25	Online Language	Work	Mental Wellbeing	Self	0.07	0.27	-0.13
2	Digital Time Use	General	Mental Wellbeing	Self + Aggregate	-0.07	0.44	-0.15
5	Digital Time Use	General	Performance	Self	0.00	0.48	-0.15
42	Physical Activity	Work	Mental Wellbeing	Self + Aggregate	0.15	0.35	-0.15
17	Online Language	General	Mental Wellbeing	Self	0.12	0.56	-0.16
28	Online Language	Work	Mental Wellbeing	Self + Trusted Other	-0.06	0.78	-0.22
36	Physical Activity	General	Mental Wellbeing	Self + Trusted Other	-0.14	0.29	-0.24
6	Digital Time Use	General	Performance	Self + Aggregate	-0.22	0.22	-0.28
45	Physical Activity	Work	Performance	Self	-0.29	0.64	-0.29
31	Online Language	Work	Performance	Self + Manager	-0.19	0.44	-0.31
30	Online Language	Work	Performance	Self + Aggregate	-0.54	0.54	-0.35
15	Digital Time Use	Work	Performance	Self + Manager	-0.26	0.42	-0.37
48	Physical Activity	Work	Performance	Self + Trusted Other	-0.42	0.26	-0.37
12	Digital Time Use	Work	Mental Wellbeing	Self + Trusted Other	-0.14	0.21	-0.39
40	Physical Activity	General	Performance	Self + Trusted Other	0.18	0.29	-0.41
20	Online Language	General	Mental Wellbeing	Self + Trusted Other	-0.33	0.38	-0.48
8	Digital Time Use	General	Performance	Self + Trusted Other	0.09	0.41	-0.50
39	Physical Activity	General	Performance	Self + Manager	-0.27	0.46	-0.50
3	Digital Time Use	General	Mental Wellbeing	Self + Manager	0.18	0.47	-0.59
18	Online Language	General	Mental Wellbeing	Self + Aggregate	-0.45	0.20	-0.60
43	Physical Activity	Work	Mental Wellbeing	Self + Manager	0.00	0.30	-0.60
24	Online Language	General	Performance	Self + Trusted Other	-0.14	1.10	-0.62
32	Online Language	Work	Performance	Self + Trusted Other	-0.06	0.50	-0.67
35	Physical Activity	General	Mental Wellbeing	Self + Manager	0.22	0.81	-0.67
11	Digital Time Use	Work	Mental Wellbeing	Self + Manager	-0.50	1.00	-0.70
7	Digital Time Use	General	Performance	Self + Manager	-0.62	0.90	-0.71
19	Online Language	General	Mental Wellbeing	Self + Manager	-0.67	0.57	-0.71
27	Online Language	Work	Mental Wellbeing	Self + Manager	-0.53	0.71	-0.76
4	Digital Time Use	General	Mental Wellbeing	Self + Trusted Other	-0.32	0.32	-0.79
47	Physical Activity	Work	Performance	Self + Manager	-0.65	0.82	-0.82
16	Digital Time Use	Work	Performance	Self + Trusted Other	-0.40	0.80	-0.93
49	Visual	General	Performance	Self + Manager	-0.63	0.97	-1.06
22	Online Language	General	Performance	Self + Aggregate	-0.68	1.16	-1.11
23	Online Language	General	Performance	Self + Manager	-0.88	1.06	-1.38