How awareness of a user's cognitive state can improve human-AI teams

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Abstract. Much of the discussion about human-AI teams has focused on artificial intelligence technologies; however, recent works have focused on the role of humans. Situation awareness has been used to describe awareness about human environmental factors (e.g., mental workload) on task performance and has recently been applied to new discussions about performance in human-AI teams. These discussions have neglected many cognitive factors that can now be incorporated into human-AI team dynamics, thanks to advances in cognitive neuroscience and technology. In this chapter, I will describe how these advances enable situation awareness of cognition that opens new possibilities for human-AI collaboration.

Keywords: Situation awareness, cognition, attention, vigilance, mind wandering

1 Introduction

Imagine that you are a security officer at a shopping mall, a team member responsible for monitoring and securing the stores late into the night. After closing your email, your eyes start to feel heavy, and your sight blurs. You had a hard time sleeping this morning, and it's clear that you are feeling sluggish. Your colleague informs you that she will patrol today so that you can take it easy. She empties the coffee pot into her cup before starting on her journey around the mall, leaving you alone with your other "teammate," SAM ("situation aware machine"), an artificial video monitoring agent integrated with the security surveillance system, designed to inform you of potential security risks in the facility.

Over the next hour, SAM monitors images of the video feed and discovers two issues: an open door by the back exit and the presence of a cardboard box by the jewelry store. The agent informs you of these potential security issues using its standard process of an on-screen warning message. After observing the screens, you do not notice anything unusual; the jewelry store's CCTV camera looks normal, and SAM sends you many of these messages every night. For example, SAM informed you that the bay door was left open yesterday, but it was just the custodian taking a smoke break. In the past, it has been enough to file a report so that your supervisor can investigate it in the morning. You nonetheless try to take a closer look, but as you sit back and watch the screens, your mind begins wandering. What did you eat yesterday that kept you awake? Was it stress? You are not sure. As the minutes pass, you blankly stare at the videos as nothing happens. Eventually, with heavy eyes and a yawn, you realize it would feel better to log the incident and move on. You turn towards the coffee maker to make a fresh pot and do not notice as the box in front of the jewelry store slowly moves away towards the open door, with a person inside, with thousands of dollars of goods.

Though this story is fictional, it is based on real computer vision technology, such as that developed by Ambient AI [1], and a true story of how US marines were able to outsmart video surveillance algorithms using cardboard boxes [2]. There are also plenty of real examples of threats where improved AI systems could prevent disasters. Autonomous driving agents have been responsible for at least 11 driving-related deaths in 2022 [3], which might have been prevented using a similar approach. Safety motivations have prompted research into new approaches to measuring human error using artificial agents and human hybrid processes. There have also been high-profile calls for research on human-AI teams that incorporate greater awareness about human cognitive contexts [4].

Situation awareness is the ability of an agent to comprehend its environment in space and time [5]. While this concept was initially used to describe a model for incorporating human environmental factors, e.g., mental workload, on task performance, researchers have recently become interested in how situation awareness can be incorporated into autonomous AI systems and human-AI teams [6]. With improved situation awareness, AI systems can incorporate information about a user's state into its processes, improving the human-AI team's outcomes. If the SAM system had been designed to detect habituation to its security messages or a wandering mind, it might have adapted to prevent a security threat. The SAM would have benefitted from situation awareness of its human's cognitive state.

In this chapter, I outline measures from cognitive psychology and cognitive neuroscience that can be used to improve situation awareness of human-AI teams. While this discussion can apply to cognitive states broadly, my focus is on vigilance and mind wandering, two cognitive functions that share a common root in the brain's attention networks [7]. These functions are exemplified by the SAM example but are also relevant to a wide range of work applications and tasks where AI can be helpful, such as long-haul driving [8] and online learning [9]. I will begin with a discussion of these two concepts from the cognitive neuroscience perspective before describing measures that can be incorporated into a human-AI workplace system. My goal is to ultimately contribute to the ongoing conversation about situation awareness in human-AI teams by making a case for situation awareness of cognition.

2 Vigilance and wandering minds

Reconsider the challenges described in the hypothetical example. The first challenge concerned the repetitiveness of notifications and the user's habituation to the notifications. The second challenge concerned how the AI system misinterpreted the user's mental state and mind wandering. While it is possible that existing measures of situation awareness could have accounted for these, the measures would have been indirect. The most commonly employed techniques for measuring situation awareness are the Situation Awareness Global Assessment Technique, an objective questionnaire probe measure concerning the user's perception of the environment, and the Situation Awareness Rating Technique, a subjective psychometric questionnaire measure [10]. These techniques measure a user's overt perceptions about their environment and their subjective perceptions of their situation awareness behaviors rather than their cognitive state. These can thus be further improved by incorporating techniques used by cognitive psychologists and neuroscientists for measuring attentional states.

Concerning the first challenge, if the SAM had incorporated situation awareness about the user's habituation with the notifications, it could have attempted a different approach that might have made the user more responsive. Habituation is defined as a "behavioral response decrement that results from repeated stimulation and that does not involve sensory adaptation/sensory fatigue or motor fatigue" [11, p. 136], and attentional habituation is often observed when humans are exposed to repetitive stimuli. In information technologies, attentional habituation has been demonstrated to negatively impact users' responsiveness to cybersecurity notifications [12], which likely generalizes to this context. Like in the example, when humans are repeatedly exposed to notifications, they become used to them and are less likely to adhere to or act on them. As Vance et al. [12] demonstrated, repeated exposure to notifications degrades users' perception of their saliency, causing users to ignore them.

Some cognitive psychologists and neuroscientists have described the capacity to maintain a high degree of sensitivity to stimuli as vigilance, sometimes also referred to as alerting [13]. The human capacity for vigilance determines whether someone can receive information or attend to a notification in the first place. In the prominent model of attention described by Posner and Petersen [7], they described three attentional brain systems, which each contribute to an individual's ability to process information. While vigilance consists of a distinct function, it works closely with orienting, the ability to align one's sense with a sensory signal, as well as executive control, which is the process of resolving conflicting sensory experiences. By incorporating measures of these attentional capacities, an AI system could improve its performance and attainment of a task.

The second challenge concerned the user's tendency to direct their attention from the world around them and inward towards task-unrelated thoughts. This experience is often referred to as mind wandering, an internally directed cognitive process whereby our attention becomes detached from the external world [14]. Mind wandering is a mechanism that can impair one's ability to attend to a task, such as a video screen, requiring sustained attention over long periods. Researchers have found relationships between mind wandering and boredom [15] and have observed that wandering minds have decreased general awareness, as exemplified by poor driving behaviors [8] and poor retention from lectures [9].

Mind wandering likely occurs due to two distinct functions of our brain, which can be observed on the neurophysiological level [16]. The first function is the passive resting cognitive state resulting from the brain's default mode network. This network of neurons was initially observed in early functional magnetic resonance imaging studies when they noticed active brain activity as study participants lay idle. This network is now thought to be responsible for past and future thinking [17] and spontaneous thoughts [18]. The second brain function is a lapse in cognitive control stemming from the brain's executive networks. The frontoparietal control brain network governs higher thinking, such as response inhibition and selective attention [19]. It is often thought that under normal circumstances, our brains can resist the emergence of spontaneous thoughts generated by our default mode network. However, in situations where our executive cognitive control is compromised, such as when abnormally fatigued, as in the hypothetical example, or if an individual has ADHD [20], then undesirable mind wandering is more prevalent.

In recent years, researchers have begun to further distinguish varieties of mind wandering, such as a distinction between deliberate and spontaneous mind wandering. Deliberate mind wandering occurs when someone wishes to think about something else, possibly because they are passively engaged in an undemanding task or enjoying the present experience. Spontaneous mind wandering, by contrast, occurs against one's wishes [21]. The distinction between deliberate and spontaneous mind wandering has been similarly observed on a neurophysiological level [16] and has sparked a wider discussion about the very nature of mind wandering [22] as well as its possible impacts on the experience of using information technology [23]. Regardless of mind wandering's ultimate nature, when it is understood as the presence of spontaneous thoughts, it can negatively impact the fulfillment of sustained attention tasks. However, this impact is probably lessened if it is deliberate mind wandering. A system that could detect spontaneous mind wandering specifically could thus adapt to a user's context and situation to provide an improved outcome.

3 Attentional measures for AI agents

How, then, would a human-AI system go about incorporating information about sustained attention and mind wandering? Researchers have developed many approaches for measuring attentional states, though many of these approaches are challenging to incorporate into a machine-readable process. Attentional states can be measured using a behavioral test, which implicitly measures attention based on performance at a task. Attention can also be inferred by observing physiological measures that are known to be associated with attentional processes. Either way, researchers have also further distinguished varieties of attention which can be identified with performance at specific tasks and correlated with specific measures. In the aforementioned advanced by Posner and Petersen [7], for example, alerting can be distinguished from orienting, which is in-turn distinguishable from executive control. Each of these functions has been distinguished by varying behavioral and physiological measures.

One of the most deeply explored techniques for measuring attentional capacities is the attention networks test (ANT) [25]. The ANT measures three attention networks through a combination of computer-generated flanker tests designed to measure response inhibition and response time to cuing tasks. While the ANT has been demonstrated to produce reliable measures of an individual's attentional capacities over time

[26], there are considerable limitations to their application. Many of these tasks cannot be reliably employed in an ecologically valid context because it is a long and boring task, although there have been attempts to adapt them for broader contexts [13].

Yet, there is emerging research which suggests that attention can be measured indirectly by observing performance at certain tasks. Wilson et al. [27] demonstrated how the Sustained Attention Response Task, a similar cuing paradigm which involves withholding button presses on infrequent targets [28], can be adapted to the context of friendly fire simulation military training. Performance at a friendly fire military exercise training exercise was found to be correlated with the validated attentional task. Other research by Kozhevnikov et al. [29] demonstrated that participation in action video games can lead to temporary states of enhanced spatial attention. These results suggest that measures of computer-measured tasks, whether these be games or work-related computer use (e.g. chat tasks or assigned duties), may be adapted as indirect measures of vigilance or other aspects of attention.

One approach for adapting sustained attention paradigms to practical applications is to measure computer behavior, such as mouse or motion tracking. Brinton-Anderson and colleagues demonstrated that warning and task habituation can be measured using mouse cursor tracking and that such measures could be more widely applied as a measure of explicit attention during information technology use broadly [30]. Other studies have suggested that mouse tracking is a reliable correlate of eye gaze patterns [31] and have found that mouse patterns can be applied to industrial applications, such as in e-commerce web search [32]. Similarly, researchers have also demonstrated that attention can be reliably measured through other online behaviors such as chat use and video. This was well-demonstrated by Kuzminykh and Rintel [33], who described two studies that leveraged a combination of speech and video behavior to capture attention features during online meetings. Such behaviors could then be used to capture sustained attention using deep learning.

Another related technique is to observe eye patterns, often referred to as *eye tracking*. While eye tracking has been most extensively employed to measure overt or explicit varieties of spatial attention [34] often through gaze tracking, eye movements have also been established to be reliable indicators of covert attention, the function of general attentiveness to stimuli that may not be where someone's eyes are fixated. It has been suggested that covert attention functions are at play when observing attention-related phenomena during technology use [35] and researchers have applied eye tracking to sustained applied attention tasks. Attention allocation aids have been developed to help with visual search by leveraging machine learning to predict the accuracy of a user's eye saccade patterns [36], which leverages the extensive work on the relationship between saccade patterns and covert attention [33]. By using similar techniques, attention-adaptive systems could be developed that can infer cover attention by observing eye saccades in reaction to novel stimuli.

What mouse, chat, and eye behaviors all have in common is that they are objective behavioral measures. An alternative approach which could be employed is subjective experience sampling. Similar to the Situation Awareness Global Assessment Technique employed in situation awareness research [10], experience sampling includes a range of approaches to collect a user's reported experience at a particular point in time [37].

Experience sampling is the most common method for identifying moments of mind wandering. Approaches have included probe-caught methods, which interrupt a user to collect an experience, self-caught methods, which ask users to spontaneously report their mind wandering experiences, and retrospective methods, which include post-hoc reports [14]. These techniques, particularly self-caught methods of experience sampling, might be incorporated into existing situation awareness paradigms to effectively measure mind wandering. While subjective techniques such as experience sampling can suffer from variance in individual perceptions, they have the advantage of reliably capturing a user's experience and can provide reliable labels for machine learning algorithms.

These subjective and objective approaches to the measurement of attentional constructs are not mutually exclusive. In the case of mind wandering specifically, eye tracking has been employed to complement experience sampling to make inferences about reading comprehension [38]. There are also relevant electroencephalography (EEG) measures which have been associated with both vigilance and mind wandering that could be adapted in a machine-readable context. EEG oscillatory activity are fluctuations in the brain's rhythmic patterns, and have been well-studied as a correlate of mental workload [40] and of mind wandering [9]. While these measures are most often observed in highly controlled environments and compared using statistical analysis, advances in machine learning have made it possible and accessible to develop brain-computer interfaces that leverage these signals to detect mind wandering [41]. An artificial agent could thus read these signals to provide interventions that change human behavior when it detects fluctuations that are typical of mind wandering.

EEG event related potentials (ERPs) can also be observed to infer a user's state. ERPs are brain responses brain to time-locked stimuli, such as a picture, or a security notification. Early onset ERPs have been associated with attentional vigilance [42] while later onset ERPs have been associated with attentiveness and mind wandering [8] and affective responses to notifications [43]. While ERPs are more difficult than brain oscillations to measure outside of a laboratory setting, they have also been adapted to brain computer interfaces which could contribute novel information for a situation aware AI. ERP-based brain-computer interfaces have been limited due to their requirements for large amounts of data, however, advances in the field have made it more feasible to detect differences in signals using fewer samples, and in real-time [44].

Recent developments in technology have also made the application of EEG to the workplace more feasible and affordable. For example, the Neurocatch EEG system has been clinically approved in Canada and the United States to measure ERPs for health purposes. It has been deployed to measure the impact of concussions, with a battery of ERP measures that can be employed in less than 10 minutes [45]. Alternatively the g.Tec Unicorn BI and Open BCI systems, with a total price tags of under USD $1500, are reliable devices regularly used in hackathons around the world [46]. Students have developed a range of novel BCI applications that can speak to the potential applicability of these techniques to the workplace. Finally, the Interaxon Muse system, which can be purchased at retail stores, has even been reported to detect both oscillatory activity [47] and event-related potentials [48] in ways that might be adapted to situation aware systems. As EEG hardware develops further, it will become more feasible to apply to improve situation awareness in human-AI teams using these techniques.

It is also important to highlight that many of these measures are not only relevant to mind wandering or sustained attention, but to varying attention-related functions such as distraction, executive control, task-switching, and overall mental workload. Task responses and physiological indicators can be adapted depending on the context and can be further developed to the situational context. Furthermore, it could be possible to design alternative interfaces that leverage these indicators beyond alerts. For example, a sustained attention interface could adapt to the rate of presentation of stimuli to reduce cognitive overload [49]. By considering the interface design, it could be possible to build a wide variety of attention-adaptive technologies.

Taken together, there are many ways that situation awareness can be expanded to include information about a user's attentional state. By collecting many subjective experience samples, it would be possible to train machine learning classifiers that integrate the various behavioral and psychophysiological measures as features by using these samples as data labels. The classifiers can then be trained to activate when the indicators exceed a relevant threshold. This suggested approach builds on past work on attention-adaptive interventions [36] and brain-computer interfaces, though at a much larger scale. Cognitive factors could thus be considered in conceptions of situation awareness. Given the proliferation of inexpensive sensors that are now performing comparably to research-grade tools, we may very well be on the horizon of artificial agents that are situation-aware of our cognition.

4 Conclusion: A pipe dream or imminent paradigm?

Imagine once again that you are sitting in a chair in the security office of a shopping mall, late at night, alone with SAM 2.0, your artificial "teammate". This time, as you find your attention fading from the room and towards breakfast, your brain rhythms become slower. However, the EEG channels that are in your over-ear headphones detect this change in your body rhythms. This was also corroborated by your slower mouse activity in the hour before. SAM, which detects these changes, can infer that you may not be attentive.

As the hour passes, SAM discovers the issues: an open door by the back exit and the presence of a cardboard box in the jewelry store. As it sends you notifications, it also sends you distraction cues to determine your sustained attention. It notices that you responded more slowly than normal and that your response speed is like when you have reported mind wandering in the past. It concludes that it should take a different action because your mind wandering is not deliberate. Instead of administering the standard notification, it decides to pop up on the screen with its virtual avatar. "How are you doing?" it asks, "are you able to check out the box in front of the jewelry store?" After taking a closer look, you realize that something is off; that the box had moved ever-so-slightly from where it was when you last checked. You decide to radio your human colleague, who quickly realizes the problem and calls the police.

We are currently at a point in time where this scenario is no longer science fiction. Rather than spurned by radical new developments, gradual advances in cognitive psychology, cognitive neuroscience, and artificial intelligence have not just made this scenario possible, but imminent. Consider some of the other contexts where human-AI teams can be adapted not just for new *interactions*, but also task or experience *enhancement*:

- Driving – While so much attention has been paid to self-driving cars, relatively little has been paid to human-AI teams. Can AI be used to create enhanced warnings, especially at high speeds or busy locations?
- Education – AI can be used to create attention-adaptive systems that can change a lesson depending on a learner's mental state. Could dynamic content contribute to improved learning outcomes?
- Cognitive and memory challenges – Individuals who face cognitive challenges, such as memory loss, may benefit from AI that can assist them when the situation requires it.

It is also worth noting that the approach of this chapter is formative and optimistic; it leaves out many details about exactly how to develop such machines and does not deeply discuss their downsides. There are many possible ethical concerns raised by situation-aware cognitive technologies. Surveillance studies scholars have long posited challenges to consent with big data, which apply in this context. When consent to use data is offered, it is often done so with limited knowledge of the ways that data can be integrated with other datasets, which can undermine someone's underlying right to privacy [51]. This criticism is not unique to psychophysiological data, though it presents new challenges due to its sensitivity [51]. For example, could this data be integrated with someone's driving history to determine their insurance policy? Would it be desirable to allow insurance companies to enforce policies that depend on a user's attentional capabilities? Furthermore, the resulting algorithms may be too complex for humans to interpret, and as a consequence provide informed consent to use. This is why some scholars have explored approaches for explainable artificial intelligence, which can help remedy concerns about consent [52].

The technology's use may also create larger moral hazards. Situation aware systems have the potential to radically improve the lives of their users, especially when it comes to their working lives. This technology can thus provide new capabilities which can advantage those who have the means to acquire them, which can lead to a gap in access and the reinforcement of power for the individuals with the means to purchase them [53]. Consider the implications of a situation aware tool which can provide a user with an advantage when studying for tests. New strategies and guidelines may yet be developed to help overcome these limitations, though these are still in their infancy. Nonetheless, to the optimistic, the opportunity remains clear: AI can enable humans to overcome not just environmental challenges, but also cognitive challenges that they may face in each situation. We can envision the situation awareness of cognition in future designs of systems that leverage human-AI teams—these technologies may yet even offer a new frontier for human advancement.

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