Is Our Ability to Detect Errors an Indicator of Mind Wandering? An Experiment Proposal

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Abstract Mind wandering could have a variety of impacts on information systems phenomena, not least long monotonous tasks. Unfortunately, mind wandering states are difficult to measure objectively. In this paper, we describe work-in-progress to address this problem in a novel way. We describe two studies that will observe participants' ability to detect errors in a task as a correlate of mind wandering. Demonstrating the technique using a lecture paradigm, the studies employ previously investigated methods of measuring mind wandering as a baseline for the new technique. If successful, we will demonstrate a new method for measuring mind wandering that can be applicable to a broad range of information systems and psychological studies.

Keywords Mind wandering · Cognition · Attention · Vigilance · EEG

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1 Introduction

COVID-19 brought about a major shift in working environments and day to day life. In-person activities such as schooling, large gatherings, travelling, and work were all halted for months at a time, resulting in a need to radically change how they operate [1]. Prior to the pandemic, only 7.9% of the global population held a position where they worked from home [2]. Today, between 35 and 50% of workers in the United States and western European countries worked from home in some capacity [3]. As the importance of work from home has increased, so too has the need for making an individual's home environment productive [4].

However, the work-from-home environment comes with new challenges, both social and environmental. Individuals who work from home are likely to feel social isolation, which may negatively impact their performance. A study conducted by Toscano and Zappalà [5] found that there is a negative relationship between social isolation and remote work satisfaction, and a negative association between such isolation and stressful working conditions. Similarly, cognitive factors such as information overload [6] and work environment distraction [7] have been found to negatively impact productivity. We might wonder whether the persistence of self-generated thoughts or wandering minds throughout the workday could thus impact productive work-from-home spaces. This has motivated us to pursue research into the role that the presence of mind wandering can play in home workspace productivity and effective home workspace technology use.

It is currently difficult to measure mind wandering states in an ecologically valid for from home setting with objective measures. While questionnaires can give insight into the presence of mind wandering, even during technology use [8], they can tell us little about when mind wandering episodes occur. Alternatively, researchers have employed experience sampling probes [9] or electroencephalography [10] to measure mind wandering states. However, these are either distracting, as repeatedly prompting subjects to report on their mental state can be intrusive and take away from the task at hand, which is undesirable, or are difficult to employ remotely (i.e., EEG).

One approach that could overcome these limitations is to embed behavioural indicators of mind-wandering within the task itself. Instead of interrupting a person with questions about their mental state, we seek to infer their mental state by looking at how they perform the task with which they are engaged. Specifically, in this study we propose a method for detecting mind wandering episodes that relies on one of the most frequent tasks that anyone can encounter at work, regardless of their profession: attending to video-lecture wherein someone discusses a given topic. The only manipulation that we introduce is to insert, throughout the lecture's script, errors that render a given sentence meaningless relative to the preceding context. Our theory is that when mind wandering occurs, people would tune out the video stimuli and become less vigilant and will generate more errors. When attention drifts away from the main task people miss more task-related information than when focusing on the task, which has been corroborated in studies related to reading which showed that indeed episodes of mind-wandering increase the likelihood of missing errors [11, 12].

To further assess the validity of this approach and evaluate its generalizability, we employed a paradigm wherein subjects will be asked to listen to a video-lecture and indicate, by pressing a button, whenever they come across a sentence that contradicts the preceding ones. Using this paradigm we will conduct two studies: a proof-of-concept study employing only a behavioral task; and a more comprehensive EEG study. In the proof-of-concept study we will cross-validate the failure to detect errors with other well-established behavioral measures of mind wandering, such as experience sampling probes [9]. For this first study our research question and associated hypotheses are:

RQ1—How strongly is performance at detecting contradictory information in the video-lecture associated with mind wandering as recorded by sampling probes?

H1—There is a strong correlation between the extent to which subjects identify contradictory information and the extent to which they experience mind-wandering.

If H1 is supported by results of Study 1, we will further validate our approach using only EEG measures and no experience samples in Study 2. A second study will allow us to cross-validate these findings with past studies in the absence of confounding factors created by experience sample probes, would replicate our results, and would provide evidence for a truly passive measure of mind wandering [10, 13, 14]. Our main research question and associated hypotheses are:

RQ2—How strongly is performance at detecting contradictory information in the video-lecture associated with EEG correlates of mind wandering?

H2—There is a strong correlation between the extent to which subjects identify contradictory information and EEG markers of mind wandering (i.e. modulation of the amplitude of the P300 component elicited by auditory tones).

In the reminder of this paper we will describe our research methods for the studies before describing the potential contribution of the work.

2 Methods

2.1 Participants

For each of the two studies we are aiming to recruit 40 participants among the pool of undergraduate students. As the studies we are proposing are exploratory in nature—especially as there is little to no background literature documenting the size of the effects that we are aiming to detect—the sample size was not defined based on the result of an analysis of statistical power, rather on a number that is considered appropriate to conduct exploratory research involving the analysis of correlations [15]. To ensure a consistent sample, subjects from both studies will be excluded if they report uncorrected vision problems or physical impairments that would prevent them from using a computer keyboard or mouse or neurological conditions that could affect EEG (e.g., epilepsy or a recent concussion). For the second study the same criteria apply with subjects who have not taken part in Study 1.

2.2 Stimuli

We selected a lecture on machine learning based on freely available online courses through LinkedIn Learning as the material to be presented to participants. We first modified the transcript of the lecture to include 24 coherency errors. Then, one member of the research team recorded the lecture again based on the edited script. The following is an example of one of the errors that were inserted in the script of the lecture:

- Original text: "A machine might have an algorithm that says two types of data should be treated the same way. The machine will then use the algorithm to look for patterns."
- Edited text: "A machine might have an algorithm that says two types of data should be treated the same way. The machine will then use the algorithm to look for patterns, *based on a rule that states that two distinct types of data should be treated differently.*"

All participants will receive the same script including all 24 errors. Experience sampling probes [9] will be used to determine the extent to which participants were on-task or mind-wandering. To this end, each participant will receive 10 probes throughout the course of the entire lecture. Each probe will occur 5 s after the appearance of a coherency error. Three versions of the paradigm were created to ensure that, across participants, each coherency error was followed by a mind-wandering probe. Thus, each version of the paradigm contains 5 unique sampling probes (i.e., occur after coherency errors not probed in another version).

2.3 Procedure

Study 1. Upon the beginning of the experiment participants will be asked to enter a closed room equipped with only a computer and speakers. All participants will complete a quick questionnaire about their demographic information, and a multiple-choice test to assess their knowledge about the topic of the video-lecture. The latter test will be used to identify and exclude participants' with prior knowledge on machine learning, which will likely be a confounding factor in our analysis. Indeed, studies suggest that, while prior knowledge might have no effects on the extent to which people do experience mind-wandering, it does nonetheless facilitate information processing (i.e. text comprehension [16, 17]). Therefore, we expect that prior knowledge on the topic of machine learning will affect subjects' ability to detect incongruency errors independently from the extent to which their attention is on task. To prevent this from confounding our results, data from subjects scoring above chance level (25%) in the multiple-choice task will be excluded from data analysis.

The PsychoPy framework will be configured to record study start times, as well as the timing and response from the participants regarding embedded errors, and responses to the sampling probes. All participants will then be asked to sit through the 1-h pre-recorded lecture. Participants will be instructed to indicate with a button-press when they notice coherency errors within the lecture. To determine if missed-errors correspond to periods of self-identified mind wandering, participants will receive a mind-wandering probe 5 s after the onset of the coherency error. Participants' comprehension of the video-lecture will be tested before being debriefed on the nature of the contradictions that they encountered in the lecture. They will then be asked to leave upon completion of the task.

Study 2. Upon the beginning of the experiment participants will be asked to enter a closed room equipped with a computer, speakers and EEG device. Before being fitted with an EEG cap, participants will be asked to complete a quick questionnaire about their demographic information, and a multiple-choice test to assess their knowledge about the topic of the video-lecture. Participants will be fitted with horizontal and vertical electrooculograms (EoG) and 32 scalp electrodes (ActiCap, BrainProducts GmbH, Munich, Germany) positioned at standard locations according to the international 10–10 system and referenced to the midline frontal location (FCz). Electrode impedances will be kept below 15 kOhm at all channel locations throughout the experiment. EEG data will be recorded using a Refa8 amplifier (ANT, Enschende, The Netherlands) at a sampling rate of 512 Hz, bandpass filtered between 0.01 and 170 Hz, and saved using ANT ASAlab. While subjects are watching the pre-recorded lecture, single auditory tones will be presented in the background. Tone-presentation will occur 5 s after the onset of errors in the video-lecture. This is to ensure that, even if subjects infer the association between the presence of an error and the auditory tone, the tones cannot function as cues to the presence of an error. Button presses occurring after the onset of the auditory tones will be treated as missed errors, as they are likely attributable to the cueing effect, rather than on genuine error-detection. In total, 24 tones will be presented. Following the presentation of the lecture, the EEG will be removed.

2.4 Data Processing and Analysis

Behavioral Data. In both studies, subjects' responses will be of two types: *detected* or *undetected* error. Each of such responses will be assigned to one of two groups based on the mental state reported in the behavioral prompt that subjects receive 5 s after the onset of the error (i.e., *on-task* or *mind wandering*). To assess whether mental state predicts whether an error is detected or not, we will conduct a two-tailed t-test contrasting the *on-task* and *mind wandering* groups to test whether the difference in the type of response between them is statistically significant.

Neurophysiological Data. If results from Study 1 show a strong correlation between reported mental state and the ability to detect coherency errors in text, in Study 2 we will infer subjects' mental state based on their performance in the error detection task. Whenever participants will correctly detect an error in the lecture's script, we will assume that they were focused on the task at-hand.

To investigate the neural correlates of mind wandering, we will contrast these two categories of neural responses by looking at two distinct features: (1) neural oscillatory activity; and (2) event-related potentials (ERPs) elicited by auditory tones. The analysis of oscillatory activity will be carried out by selecting only the 10 s preceding the onset of an error. This way we parse out any potential confounding effect due to neural activity associated with the preparation and execution of a motor response that occurs when subjects detect an error. Instead, to analyze ERP responses we will look at changes in the amplitude of the P300 component associated with the two different mental states of interest. We will select neural activity occurring from −0.2 to 1 s after the onset of the auditory tone. The 200 ms preceding the onset of the auditory tone will be considered as the signal baseline.

EEG Statistical Modeling. Statistical analysis will be conducted through Generalized Additive Mixed Effects Modeling (GAMM), which extends the traditional Generalized Linear Mixed Model (GLMM) by modeling non-linear relationships between the dependent variable and the predictors [18]. Specifically, we will test three models that will differ only for the dependent variable: amplitude of the P300 component, defined as the mean amplitude in the time window going from 200 to 400 ms after the onset of the auditory tone; power in the Theta band of the neural oscillatory activity; power in the Delta band of the neural oscillatory activity. All models will include the following fixed and random effects. The only fixed effect that will be included is Mental State (2 levels: on-task, mind-wandering). Random effects will include the following variables: subject ID, electrode, age, gender.

3 Limitations, Contribution and Future Work

We anticipate some limitations to these findings. As a novel paradigm, it is entirely possible that we will find no relationship between the relevant measures. Furthermore, even if we find a relationship, it is possible that the correlation would be caused by a latent factor that underdetermines the observed relationships between mind wandering. It would also be important to replicate the findings, even if the relationships are observed in both versions of the study with both known behavioral and EEG correlates of mind wandering.

If successful however, we will identify a new measure of mind wandering which could be employed in future studies in a wide range of contexts. Again, we want to stress the importance of employing measures of mind wandering that can be obtained without interfering with a person's main task at-hand, which is the primary reason for us proposing this study. Nonetheless, this study is part of a wider initiative related to the impact of mind wandering in remote work and the applications of these findings could be wide-reaching, extending to domains such as human–computer interaction, ergonomics, education, and design science. The techniques might further complement the experience sample probe method that is frequently employed in psychological research [9] and may play a role in the fast-changing literature related to varieties of mind wandering and their family resemblances [8, 19]. Ultimately, this work is positioned to help bridge the gap between NeuroIS and the many interesting and similar ongoing conversations in its reference disciplines.

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