Attending to Attention: Detecting and Combating Mind Wandering during Computerized Reading

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Abstract
Mind wandering (MW) is a ubiquitous phenomenon that has a negative influence on performance and productivity in many contexts. We propose that intelligent interfaces should have some mechanism to detect and respond to MW in real-time. Towards this end, we developed an interface that automatically detects MW from eye-gaze during computerized reading. When MW is detected, the interface intervenes by asking just-in-time questions and encouraging re-reading as needed. After multiple rounds of iterative refinement, we summatively compared the interface to a yoked control condition in a randomized control trial with 104 participants. Preliminary results suggest that the system was successful in correcting comprehension deficits attributed to MW, thereby highlighting the potential for intelligent interfaces that improve performance by "attending to attention."

Author Keywords
Mind wandering; gaze tracking; user modeling; attention-aware interfaces

ACM Classification Keywords
Categories and subject descriptors: H.5.m [Information Interfaces and Presentation]: Miscellaneous

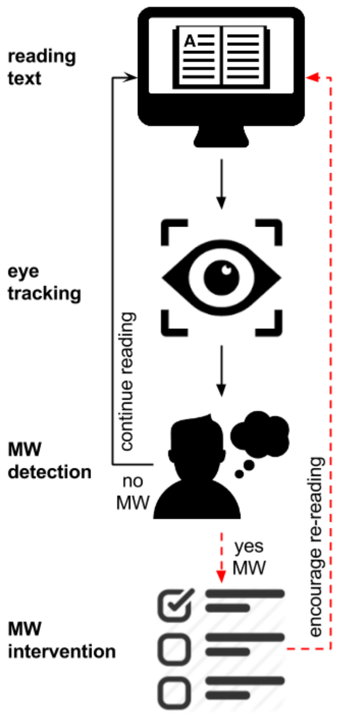

Figure 1: High-level overview of the interface that detects and responds to mind wandering (MW) during reading.

Introduction

Despite our best efforts to write a clear and engaging paper, chances are high that within the next six pages you might fall prey to what is referred to as zoning out, daydreaming, or mind wandering (MW) [1]. Despite your best intention to concentrate on our paper, at some point your attention might drift away to unrelated thoughts of lunch, childcare, or an upcoming trip. This prediction is not based on some negative or cynical opinion of the reader/reviewer (we read and review papers too), but on what is known about attentional control, vigilance, and concentration while individuals are engaged in complex comprehension activities.

One recent study tracked MW of 5,000 individuals from 83 countries with an app that prompted people with thought probes at random intervals [2]. People reported MW for 46.9% of the prompts, which confirmed lab studies on the pervasiveness of MW (see [1]). MW is also more than merely incidental; a recent meta-analysis of 88 samples indicated a negative correlation between MW and performance across a variety of tasks [3], a correlation which increases with task complexity. When compounded with its high frequency, MW can have serious consequences on performance and productivity. Therefore, our goal is to **develop intelligent interfaces that detect and combat MW in real-time.**

Related work. Automated detection of complex mental states is an active research area in HCI. This is an important step toward developing interfaces that adapt to users mental states. Different subfields focus on different aspects of the problem, such as social signal processing [4, 5], affective computing [6-11], attention-aware computing [12, 13], and augmented cognition [14, 15]. Interfaces that track and respond to attentional states have been explored in a number of domains, including monitoring driver fatigue and susceptibility to external distractions [16], selection of hints in educational games [17], adaptive information visualizations [18, 19], and others (e.g., [20, 21]).

Novelty. MW is an attentional shift away from the processing of external, task-related information to the processing of internal, task-irrelevant thoughts or ideas [22]. MW detection is related to attentional state estimation as both entail identifying the focus of a user's attention. However, MW is an inherently different phenomenon compared to other forms of attention (e.g., distractibility, object-of focus) because it involves more covert forms of involuntary attentional lapses spawned by self-generated internal thought [1]. Simply put, MW is a form of "looking without seeing" because the eyes might be fixated on the appropriate external stimulus, but very little is being processed as the mind is focused on stimulus-independent internal thoughts.

To date, MW has rarely been considered as an aspect of a user's state that warrants detection and corrective action, which is somewhat surprising given its frequency and negative consequences on performance. As such, automated approaches to detect MW in near real-time are in their infancy [23, 24]. With the exception of mindfulness training [25], to the best of our knowledge, computer-enabled automated interventions to detect and restore attentional focus when MW occurs have not yet been explored. We envision these gaps as opportunities for innovation that we will address in this research. By doing so, **we will enhance the field of HCI by building the first interface to automatically detect and combat MW.**

Figure 2: Reading setup with the Tobii TX 300 eye tracker

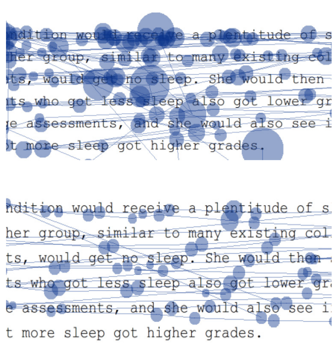

Figure 3: Gaze fixations during mind wandering (top) and normal reading (bottom)

Current research. We situate our work in the context of reading because reading is a common activity shared across multiple interfaces, thereby increasing the generalizability of our results. Further, students MW approximately 30% of the time during computerized reading [26-28]. Although MW can facilitate certain cognitive processes like future planning and divergent thinking [29, 30], it negatively correlates with learning tasks involving comprehension, such as reading or multimedia learning (reviewed in [1, 31]), suggesting that it is important to address MW during reading.

Our interface works as follows (see Figure 1). Users read a text on a computer screen on a page-by-page basis. We tracked eye-gaze during reading using a remote eye tracker that does not restrict head movements. We focused on eye-gaze for MW detection due to decades of research suggesting a tight coupling between attentional focus and eye movements during reading [32-34]. When MW was detected, the system intervened in an attempt to redirect attentional focus and correct comprehension deficits attributed to MW. The interventions consisted of asking a comprehension question on the page where MW was detected and providing opportunities to re-read. In this paper, we discuss the MW detector, intervention approach, and preliminary results of the summative evaluation study.

Mind Wandering Detection

Training Data. We obtained training data from a previous study [35] that involved 98 undergraduate students reading a 57-page text on the surface tension of liquids [36] on a computer screen for an average of 28 minutes. The text contained around 5700 words, with an average of 100 words per page displayed on a computer screen with Courier New typeface. We recorded eye-gaze with a Tobii TX300 set to a sampling frequency of 120 Hz (see Figure 2). Participants could read normally and were free to move or gesture.

Participants were instructed to report MW (during reading) by pressing a predetermined key when they found themselves “thinking about the task itself but not the actual content of the text” or when they were “thinking about anything else besides the task.” This is consistent with contemporary approaches (see [1]) that rely on self-reporting because MW it is an internal conscious phenomena. Further, self-reports of MW have been linked to predictable patterns in physiology [37], pupillometry [38], eye-gaze [39], and task performance [3], providing validity for this approach.

Supervised classification. The stream of eye-gaze data was filtered to produce a series of fixations, saccades, and blinks, from which *global* and *local* features were extracted (see Figure 3). Global features were independent of the words being read, such as fixation duration and pupil diameter. Local features were sensitive to the words being read, and included features such as the proportion of first pass fixations, re-fixations, etc. (see [40] for a full list of features). Features were calculated from only a certain amount of gaze data from each page, called the *window*. The end of the window was positioned 3 seconds before a self-report so as to not overlap with the key-press. The average amount of time between self-reports and the beginning of the page was 16 seconds. We used this as the end of the window for pages with no self-report. Pages that were shorter than the target window size were discarded, as were pages with windows that contained fewer than five gaze fixations. We experimented with a number of supervised classifiers

```
launch_intervention:
  if (current_page >=
  WAITPAGES and
  total_num_interventions <
  MAXINTERVENTIONS)
  then:
    if (gaze_likelihood >
    random(0,1))
    then:
      if (! has_intervened
      (previous_page)
      or
      0.5 < random (0,1))
      then:
        do_intervention()

do_intervention:
  answer = show_question();
  if answer is correct:
  then:
    show_positive_feedback()
    show_next_page()
  else:
    show_neg_feedback()
    suggest_rereading()
    if page advance detected:
    then
      show_question();
      show_next_page()
```

Table 1: Pseudocode for intervention strategy

on window sizes of 4, 8, and 12 seconds to discriminate positive instances of MW (pages with a self-report = 32%) from negative instances of MW (pages without a self-report) – see [40, 41].

Detector accuracy. A leave-one-participant-out validation approach was adopted where models were built on data from *n-1* participants and evaluated on the held-out participant. The process was repeated for all participants. Model validation was conducted in a way to simulate a real-time system by analyzing data from every page. When classification was not possible due to a lack of gaze data, we classified the page as a positive instance of MW. The best model was a support vector machine that used only global features and operated on a window size of 8-seconds. It had a precision of 69% and a recall of 67%, which we deemed to be sufficiently accurate for intervention.

Intervention to Address Mind Wandering

Our intervention approach is grounded in the basic idea that learning of conceptual information involves creating and maintaining an internal model (*mental model*). The model is constructed by integrating information from the learning environment (i.e., text in this case) with prior knowledge from memory [42, 43]. This integration process relies on attentional focus and breaks down during MW because information from the external environment is no longer being integrated into the internal mental model. This results in an impaired model which leads to less effective suppression of off-task thoughts. This increase in MW further impairs the mental model, resulting in a vicious cycle [44]. Our intervention targets this vicious cycle by redirecting attention to the primary task and attempting to correct for comprehension deficits attributed to MW. We proposed that asking users to answer questions on pages where MW is detected and encouraging re-reading in response to incorrect answers would aid in re-directing attention to the text and addressing knowledge deficits attributable to MW.

Intervention implementation. Our initial intervention was implemented for the same text used to create the MW detector (although it could be applied to any text), which was integrated into the computer reading interface (see Table 1 for pseudocode). MW detection occurred when the user navigated to the next page. In order to address ambiguity in MW detection, we used the detector's MW likelihood to probabilistically determine when to intervene. For example, if the MW likelihood was 70%, then there was a 70% chance that the system would intervene on any given page (all else being equal). We did not intervene for the first three pages in order to allow the user to become familiar with the reading. Additionally, the number of interventions was capped at 1/3 × the number of pages (19 for the present 57 page text) so as to not be overly disruptive. Further, there was a 50% reduced probability of intervening on adjacent pages.

The intervention itself relied on two multiple choice questions for each page of the text. When the system decided to intervene, one of the questions (randomly selected) was presented to the user. If the user answered this *online question* correctly, feedback was provided, and the user could advance to the next page. If the user answered incorrectly, the interface encouraged the user to re-read the page. The user was then provided with a second (randomly selected) online question, which could either be the same or the alternate question for that page. The user was allowed

MW Prob.		Posttest Perf.	
Int.	**Ctrl.**	**Int.**	**Ctrl.**
Low	Low	.604	.623
Low	**High**	**.643**	**.489**
High	Low	.535	.566
High	High	.546	.562

Table 2: Posttest performance (proportion of correct responses) as a function of mind wandering during reading. Cells in red represent a statistically significant difference. MW Prob= Mind wandering probability. Posttest Perf. = Proportion of correct responses on the posttest. Int. = Intervention condition. Ctrl. = Control condition.

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to advance to the next page regardless of whether the second question was answered correctly.

Iterative refinement. The intervention was refined through multiple rounds of formative testing with 67 participants. Specifically, participants were observed while interacting with the intervention, their responses were analyzed, and they were interviewed about their experience. We used the feedback gleaned from these tests to refine the intervention.

Evaluation Study

We conducted a randomized controlled trial to evaluate the intervention. The experiment had two conditions: an intervention condition and a yoked control condition (as described below). The yoked control was needed to verify that any learning benefits are attributed to the interventions being sensitive to MW and not merely to the added opportunities to answer questions and review afforded by the intervention.

Method. Participants (N = 104) were undergraduate students who participated to fulfill research credit requirements. Participants in the intervention condition received the intervention as described above. Each participant in the yoked control condition was *paired* with a participant in the intervention condition. He or she received an intervention question on the same pages as their paired intervention participant regardless of MW likelihood. For example, if participant A (i.e., intervention condition) received questions on pages 5, 7, 10, and 25 participant B (i.e., yoked control condition) would receive intervening questions on the same pages. However, if the yoked participant did not answer correctly, then (s)he had the opportunity to re-read and answer another question regardless of the outcome of their intervention-condition partner.

After reading, participants completed a 38-item multiple choice posttest to measure learning. The questions were randomly selected from the 57 pages (one per page) with the exception that a higher selection priority was given to pages that were re-read on account of the intervention. Participants in the yoked control condition received the same posttest questions as their intervention condition counterparts.

Results. Participants received an average of 16 (min of 7 and max of 19) interventions. MW likelihood was significantly negatively correlated with performance on the online questions (r = -.296, p = .033) as well as on the subsequent posttest (r = -.319, p = .021), which provides evidence for the validity of the MW detector.

There was some overlap between the online questions and the posttest questions. To obtain an unbiased estimate of learning, we only analyzed performance on previously unseen posttest questions. We compared each intervention participant to his/her yoked control with a two-tailed paired-samples t-test. There were no significant condition differences on overall posttest performance (p = .846). The intervention condition answered 39.4% of the questions correct while the yoked control condition answered 43.1% correctly. This finding was not surprising as both conditions received the same treatment except that the interventions were triggered based on detected MW in the intervention condition but not the control condition.

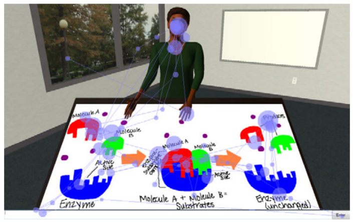

Figure 4: Guru Tutor interface overlaid with eye-gaze obtained via the EyeTribe commercial eye tracker.

Figure 5: Consumer-grade Eye Tribe gaze tracker.

Next, we examined posttest performance as a function of MW during reading. Each page was designated as a low or high MW page based on a median split of MW likelihoods (median = .35 and .36 on a 0 to 1 scale for intervention and control conditions, respectively). We then analyzed performance on posttest questions corresponding to pages with low vs. high likelihoods of MW (during reading). We found no significant posttest differences on pages where both the intervention and control participants had low (p = .759) or high (p = .922) MW likelihoods (first and last rows in Table 2, respectively). There was also no significant posttest difference (p = .630) for pages where the intervention condition had high MW likelihoods but the control condition had low MW likelihoods (row 3). However, the intervention condition significantly (p = .003) outperformed the control condition for pages where the intervention participants had low likelihoods of MW but control participants had high MW likelihoods (row 2). These last two finding suggests that the intervention had the intended effect of reducing comprehension deficits attributable to MW because it led to equitable performance when MW was high and improved performance when it was low.

A subset of participants were interviewed as to their experience with the intervention. The most consistent response was that participants adapted their reading strategies in anticipation of the online questions. They also felt that the questions were too easy and targeted factual knowledge rather than main ideas in the text, which increased the temptation to skim. Finally, participants reported difficulties with re-engaging with the text after answering an online question because they could not locate their previous position in the text. These are important items to attend to in future work.

Discussion

We developed the first intelligent interface capable of real-time MW detection and dynamic intervention during computerized reading. Our experimental evaluation suggested that the intervention was effective in combating the negative effects of MW. There is, however, considerable room for improvement. The intervention strategy, which required participants to answer online questions before proceeding with the reading, might have been perceived as limiting their sense of autonomy. To address this, we are exploring alternative strategies, such as tagging items for future re-study, highlighting certain portions of the text, or asking users to self-explain the content.

We are also developing MW interventions for more interactive interfaces, such as learning with an intelligent tutoring system called Guru Tutor [45] (see Figure 4). We are addressing scalability by replacing expensive research-grade eye tracking with cost-effective consumer-grade eye tracking (e.g., the Eye Tribe – see Figure 5) and real-world generalizability by conducting the next round of user tests in computer-enabled classrooms. By doing so, we hope to advance our foundational vision of developing next-generation technologies that enhance the process and products of learning by "attending to attention."

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