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# Frequency of Mind-Wandering in a Sustained Attention to Response Task: A Cognitive Model of Distraction

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**Abstract.** The present study examines how the frequency of mind wandering varies over time during a semantic sustained attention to response task. A model was built on the ACT-R cognitive architecture in order to replicate the study conducted by McVay & Kane (2009) on human participants, where subjects showed a notable increase in the frequency of mind- wandering over time. The model was able to replicate human behavior, showing a steady increase in the proportion of mind wandering with respect to attending over time. This increase was found to be statistically significant, thus supporting the hypothesis that mind wandering increases over time. Further research is proposed where more complexity is introduced in the model, so that it is able to better approach human behavior with respect to response times.

**Keywords:** Mind-Wandering, SART, ACT-R, Cognitive Model.

## 1 Introduction

The experience of getting distracted is common to all human beings. While performing a given task, we may suddenly find ourselves thinking of some other topic, with little or no relation to the task at hand. This experience of distraction is called mind wandering, defined as the process of task-unrelated thinking that is initiated by the mind itself, as opposed to external triggers (Van Vugt, Taatgen, Sackur, Bastian, Borst, & Mehlhorn, 2015). It is a mental state (or a sequence of mental states) that arise freely in the absence of strong constraints on the content of thought (Christoff, Irving, Fox, Spreng & Andrews-Hanna, 2016). Mind-wandering as a mental state is more constrained than dreaming–given that the subject is consciously awake–but less constrained than creative thinking and goal-directed thought, where executive control is fully activated.

In cognitive tasks–commonly measured in education–such as reading comprehension, aptitude tests, intelligence tests and sustained attention tasks, mind-wandering has been found to have negative effects on performance (Mooneyham & Schooler, 2013; Smallwood & Schooler, 2015). Mind-wandering has also been found to be correlated to increased error rates and variability in reaction times (Bastian & Sackur, 2013). Research on individual differences with respect to mind-wandering has shown a negative relationship between cognitive performance and the frequency of mind-wandering (Robison & Unsworth, 2018). Two theories have been posed in response to this. The control failure theory posits that mind-wandering arises spontaneously due to failure to maintain focus on the task (Mcvay & Kane, 2012). On the other hand, the lack of motivation theory argues that low-ability participants may feel disengaged from the task and therefore engage more in mind-wandering (Seli, Cheyne, Xu, Purdon & Smilek, 2015).

It has been observed that the rate of mind-wandering does not change linearly with time, so we may not engage in mind-wandering for equal amounts of time, the same number of times during a given cognitive task. Mind-wandering is also more frequent in attention tasks that require less vigilance (Mcvay & Kane, 2012; Robison & Unsworth, 2018). In an experiment looking at mind-wandering during lectures, it was observed that over time the frequency of mind-wandering increased and the amount of time subjects remained focused on the lecture decreased gradually (Risko, Anderson, Sarwal, Engelhardt, & Kingstone, 2011). This effect of fatigue has been replicated by Stawarczyk & D'Argembeau (2016), who found that greater sleepiness predicted a higher frequency of mind-wandering and lower task performance. In another study, drivers reported engaging more in mind-wandering when they felt tired as opposed to when they felt more alert (Burdett, Charlton & Starkey, 2016).

The present study will focus on mind-wandering during a sustained-attention-to-response-task (SART) based on semantic categories. The task presents the participant with a stream of visual stimuli that can be either a target or a non-target. When a target stimulus is presented, they are required to press a key as soon as possible. When a non-target stimulus is shown, they are required to withhold the key press (Cheyne, Carriere, & Smilek, 2009).

In the semantic SART implemented by McVay & Kane (2009), the participant sees a series of words on the screen. Target and non-target words differ in their semantic category—targets are fruits such as “apple” and non-targets are animals such as “dog”. During the task, the subjects are occasionally prompted by a thought probe asking them whether their recent thoughts were about task-related matters (on-task) or other matters (off-task). Responses to thought probes are considered as self-reports of mind-wandering: participants that report thinking of task-unrelated matters are taken to have been mind-wandering in the recent period.

This type of SART adds some interesting complexity to the simpler version where stimuli are only letters—O’s are targets and Q’s are non-targets, for example. The semantic SART imposes more cognitive demand on the subject, leading them to search in their memory for the appropriate categorisation of the words that are presented. Thus, the semantic SART typically shows higher mean response times compared to simpler types of SART (McVay & Kane, 2009). Furthermore, there is scarce literature looking into complex SART versions connected to mind-wandering with a computer modelling approach.

Hence, the aim of the study is to investigate how the frequency of mind-wandering varies over time during a semantic sustained-attention-to-response-task. This research question was tested on a computer model of McVay & Kane’s (2009) experiment, implemented in the Adaptive Control of Thought-Rational (ACT-R) cognitive architecture. This makes it possible to measure how the proportion of on-task and off-task thoughts varies across many consecutive SART trials, and to directly compare the model's performance to that of human participants. McVay & Kane (2009) found that, with increased repetition of SART trials, the proportion of task-unrelated thoughts increases while on-task thoughts decrease. Following their results, it is expected that the frequency of mind-wandering will increase over time during the semantic SART performed by the model.

## 2 Method

A computer model of the semantic SART was implemented in ACT-R, which is a powerful cognitive architecture where cognitive tasks can be modelled by programming a series of if-then statements—called production rules—describing how the cognitive elements interact (Van Vugt et al., 2015). The model for this study was built upon the SART model developed by Van Vugt et al. (2015), which was extended to incorporate the semantic SART that McVay & Kane (2009) conducted on human subjects. A detailed description of the model is offered below. The LISP code for the ACT-R model, as well as the dataset used for analysis, can be found in the following repository: https://github.com/renzo-cuadra/mind-wandering-model

### 2.1 Implementing Mind-Wandering

Mind-wandering was implemented following Van Vugt et al.'s (2015) ACT-R model, where task-unrelated thoughts during SART arise due to competition between two goals: attend and wander. When the activation of the attend goal is higher, the model focuses on performing the task. On the other hand, when the activation of wander is higher, the model starts retrieving memories repetitively from the declarative module, until it retrieves one memory, which reminds it to pay attention to the task. Only then does the mind-wandering process stop. If during mind-wandering the model sees any stimulus on the screen, it immediately presses the "w" key as a default response. This simulates how a distracted person would respond automatically, without evaluating the appropriate response. After giving this default response, the model may retrieve either the attend or wander goal, depending on activation. If the wander goal is activated, the memory retrieval process will start again. If the attend goal is activated, the model will get back to the task.

The production rules involved in this implementation of mind-wandering are shown below in pseudocode. The rule start-wandering begins the memory retrieval process as soon as the model detects that its current goal is wander. Then, the retrieve-memories rule checks that the memory retrieved is not the one that tells the model to pay attention and, if so, continues retrieving other memories. Meanwhile, the remember-to-attend rule activates when the pay-attention memory is retrieved, signaling the model to change its goal from wander to attend.

Finally, the default-response rule fires when the model is in the wander state and the screen changes (that is, a stimulus is shown), after which the model presses the "w" key and retrieves a new goal: either attend or wander, once again.

No individual differences were considered as part of the mind-wandering implementation in this model. The only source of variation in model performance across runs was the stochasticity introduced by model parameters and the randomness in stimuli display and memory retrieval during mind-wandering:

```
production start-wandering
       IF
              goal IS wander
       THEN
              retrieve memory
  production retrieve-memories
       IF
              memory retrieved
              AND
              memory NOT pay-attention
       THEN
              Retrieve memory
  production remember-to-attend
       IF
              memory retrieved
              AND
              memory IS pay-attention
       THEN
              set goal attend
  production default-response
       IF
              goal IS wander
              AND
              screen changed
       THEN
              press key w
              AND
              retrieve goal
```

### 2.2 Implementing Semantic SART

Semantic information was implemented by incorporating a vocabulary of fifteen animal words and fifteen fruit words in declarative memory, mimicking a subject with perfect knowledge of these words and their semantic categories, which is to be expected from an average adult, such as the participants in McVay & Kane's (2009) experiment. Fruit and animal words were obtained from Battig & Montague's (1969) list of the most common English words in these categories (see Table 1). The added chunks included mappings from strings to objects and from objects to categories.

These mappings provide the model with knowledge of how a string of characters (a word) represents an object, and how that object belongs to a particular semantic category. The below mappings were provided for all fifteen words used in the model's vocabulary:

```
  ;; Chunks for string-to-object mappings
```

**Table 1.** List of fifteen most common English words in the fruit and four-footed animal categories from Battig & Montague (1969).

| Nº | Fruits | Four-footed animals |
|---|---|---|
| 1 | Apple | Dog |
| 2 | Orange | Cat |
| 3 | Banana | Horse |
| 4 | Grape | Lion |
| 5 | Pear | Bear |
| 6 | Peach | Tiger |
| 7 | Strawberry | Cow |
| 8 | Kiwi | Elephant |
| 9 | Pineapple | Deer |
| 10 | Watermelon | Mouse |
| 11 | Tomato | Pig |
| 12 | Plum | Rat |
| 13 | Grapefruit | Giraffe |
| 14 | Mango | Squirrel |
| 15 | Cherry | Rabbit |

```
(map-apple isa word string "apple" meaning apple)
(map-dog isa word string "dog" meaning dog)
;; Chunks for object-to-category mappings
(apple isa object title apple category fruit)
(dog isa object title dog category animal)
```

The process for performing the semantic SART is as follows: when the attend goal is activated and a stimulus is presented, the model reads the text, maps that string onto an object by retrieving the corresponding string-to-object mapping in declarative memory and then categorizes the object by searching the object-to-category mapping.

After that, the model searches for the stimulus-response mapping to evaluate the appropriate response: it presses the “a” key if the object is a fruit and refrains from pressing any key if it is an animal. If, on the other hand, the model is in the wander state and it sees a new stimulus appear on the screen, it will press the “w” key as a default response. Figure 1 offers a graphical representation of this process.

## 2.3 Implementing Thought Probes

In McVay & Kane’s (2009) design, thought probes were presented as a menu where participants could select various options that represented how related their recent thoughts were to the task. In the model, however, thought probes are represented by an “X” on the screen. If a thought probe is shown and the attend state is active, the model will read it and map it to its proper response, which is to press the “x” key.

If the wander state is on, it will give the default mind-wandering response and press the “w” key. This makes it possible to detect when the model was paying attention or mind-wandering whenever a thought probe is presented. All responses to thought probes were recorded in order to determine the frequency of mind-wandering throughout the experiment.

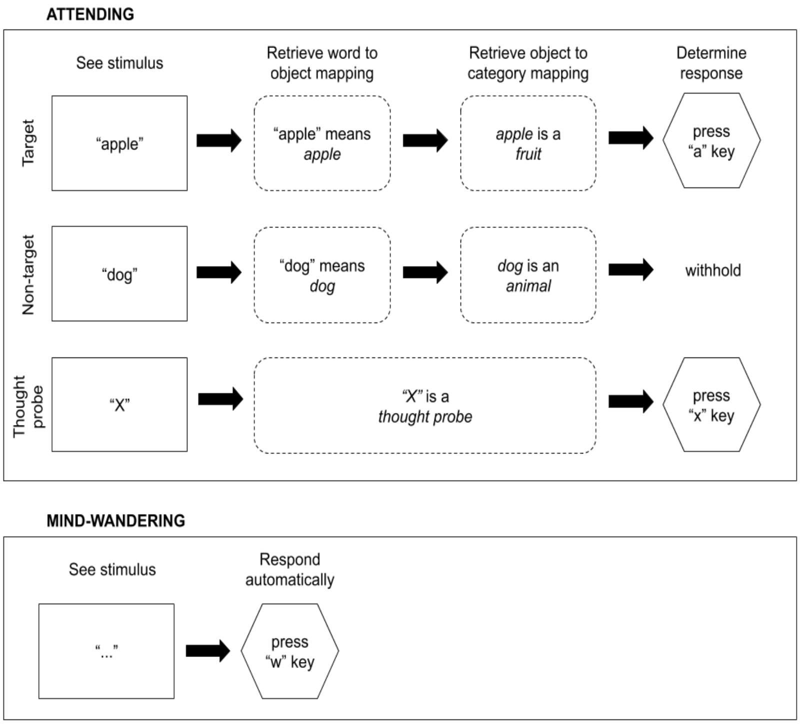


**Fig. 1.** Graphical depiction of the process followed by the model to respond to stimuli, both in the attending and mind-wandering states.

## 2.4 Procedure

The model was run 100 times in order to simulate 100 experiment participants. In each run, the model performed four blocks of the semantic SART, each one including 225 trials of one word, for a total of 900 trials per run. Targets (fruit words) were presented in 89% of trials and non-targets (animal words) were presented in 11% of trials, with a random distribution. In each block, a thought probe was presented 120 times (53% of trials), interspersed randomly throughout all trials.

The model's responses to all thought probes were recorded: "x" key presses counted as on-task thoughts and "w" key presses counted as off-task thoughts. In order to measure the frequency of mind-wandering over time, the mean proportion of on-task and off-task responses per block was computed across all participants. Furthermore, response times were recorded to evaluate the model's performance with respect to humans.

The independent variables in the study are the number of blocks of the semantic SART performed, the proportion of target vs. non-target words and the number of thought probes. All three were kept constant for all participants, as explained above. The dependent variable is the proportion of on-task and off-task responses and the response time in each block.

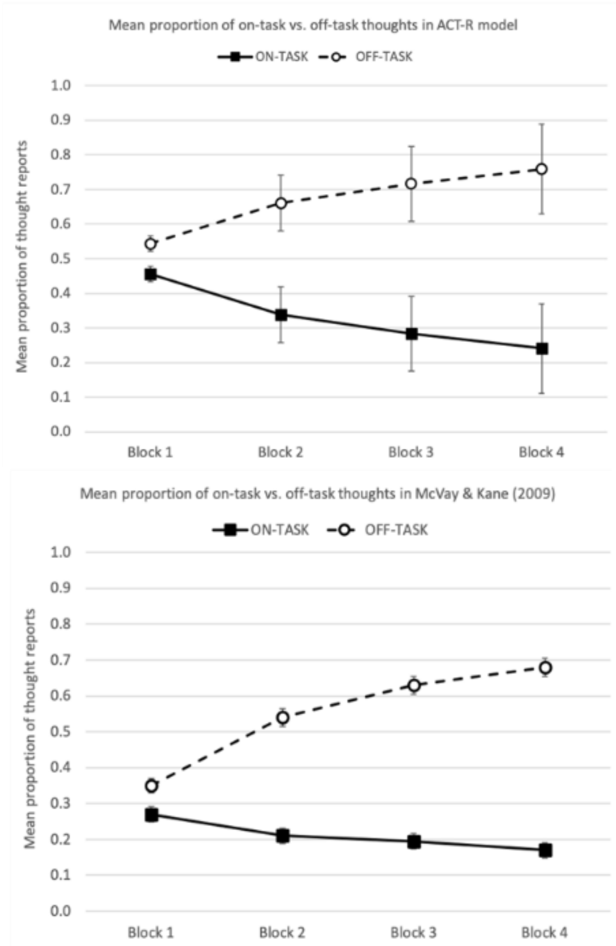


**Fig. 2.** Mean proportion of on-task vs. off-task thought reports by the model (N = 100) compared to human data (N= 243). Bars represent standard error. In McVay & Kane (2009), ratios do not add up to one in each block because a third intermediate option for thought probes was available. This was disregarded for purposes of this study.

## 2.5 Parameter Settings

McVay & Kane's (2009) results show a steep increase in the proportion of mind-wandering with respect to attending over time (see Figure 2). The model assumes that this increase is due to growing activation of the wander goal. In order to achieve this, base-level learning was used with a decay rate of 0.1, to ensure that chunks that were recently activated would be strengthened for a long time.

In addition, spreading activation was used with a value of 2.0 so that activation could be amply spread between associated chunks. The chunks that would bring the model into the attend state were given less activation than their peers. Lastly, all chunks were

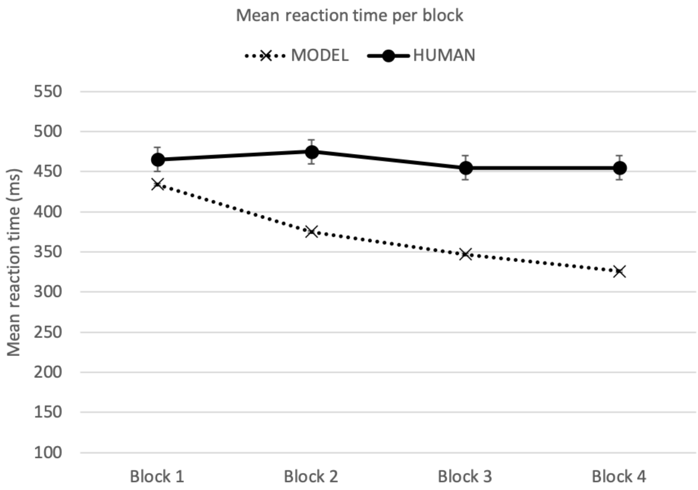


**Fig. 3.** Mean reaction time in the model compared to the data from McVay & Kane (2009).

initialized with a creation time of 10,000, except for the attend goal chunk, which was given a creation time of zero. In this way, the model starts the task with a similar proportion of mind-wandering versus attending, but then mind-wandering rapidly takes over due to growing activation.

## 3 Results

The frequency of mind-wandering over time was measured as the proportion of on-task versus off-task thought reports. These can be seen in Figure 2, which compares the ratios obtained by the model to the ratios obtained by McVay & Kane (2009) from human participants. The model visibly approaches the rate of mind-wandering found in human subjects. Off-task thoughts start at an even proportion with on-task thoughts (both near 0.5) in block 1, but then increase steadily up to around 0.75 in block 4. That is to say, the model engages more frequently in mind wandering as time goes by figure 2.

A one-way repeated measures ANOVA was conducted in order to assess the significance of the changes in the proportion of off-task thoughts over time. The proportion of off-task thoughts was found to be significantly different in every block, $F(3, 297) = 531.47$, $p < 0.05$, generalized $\eta^2 = 0.82$. Post-hoc analyses with a Bonferroni adjustment revealed that all the pairwise differences between blocks were significantly different ($p < 0.05$). This shows that the rate of mind-wandering increases significantly from one block to the next.

Response times (RT) were recorded as an indicator of the model's performance with respect to human participants' in McVay & Kane (2009). Model response times show a decrease from block 1 through block 4, unlike human response times, which remain stable (see Figure 3). While the model's performance improves over time in spite of the growing frequency of mind-wandering, humans do not show such a decisive improvement over time.

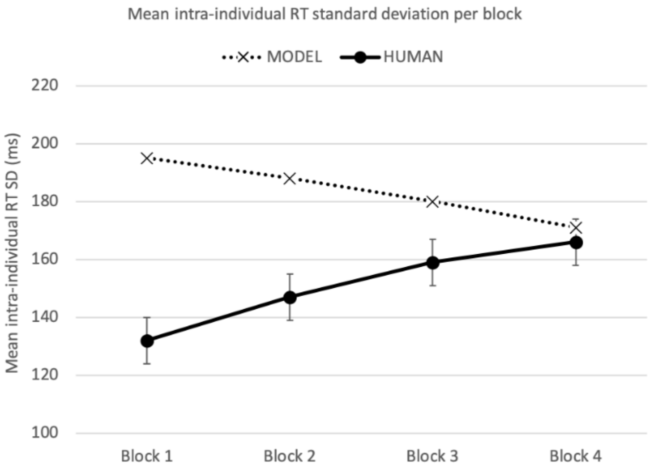


**Fig. 4.** Mean intra-individual reaction time standard deviation in the model compared to McVay & Kane's (2009) data.

Performance was further assessed by the mean standard deviation of intra-individual response time per block, which indicates the extent to which response times vary over time for the average participant. In this regard, the model's behavior differs notably from that of humans: while mean intra-participant SD of response times increases notably over time in humans, in the model it decreases (see Figure 4).

With respect to response time, humans behave much more erratically over time, whereas the model does just the opposite: it shows more consistent behavior from one block to the next.

# 4 Discussion

The present study examined how the frequency of mind-wandering varies over time during a semantic SART. An ACT-R model was built in order to replicate the study conducted by McVay & Kane (2009) on human participants. Following McVay & Kane's (2009) findings, it was hypothesized that the frequency of mind-wandering would increase over time.

The model was able to reflect successfully the performance of human participants with respect to the frequency of mind-wandering, showing a steady increase in the proportion of off-task thoughts and a decrease in the proportion of on-task thoughts throughout the experiment. The increase in the proportion of off-task thoughts was found to be statistically significant across all blocks. These results support the hypothesis that the frequency of mind-wandering increases over time during a semantic SART.

These findings provide additional evidence in support of the control failure theory of mind-wandering proposed by Mcvay & Kane (2012). Considering mind-wandering to be the product of a competition between the goal of attending and the goal of retrieving memories, following the model proposed by Van Vugt et al. (2015), renders a successful model of human performance in a cognitive task. Under this proposal, control failure arises from the memory retrieval goal taking over the attending goal, thus clouding executive control.

This model also provides a plausible mechanism for how attention may decrease over time due to the growing prevalence of mind-wandering, as the memories being retrieved in this process are strengthened by recurrent retrieval cycles. This is in line with the positive correlation of fatigue and mind-wandering frequency, as well as their negative effect on performance, as reported by Risko et al. (2011), Mcvay & Kane (2012), Burdett et al. (2016), Stawarczyk & D'Argembeau (2016) and Robison & Unsworth (2018).

Further assessment of the model was focused on response time. In the model, the reduction in response time is related to the increase in mind-wandering over time. When mind-wandering, the model does not take the time to find the correct response for the given stimulus and just responds automatically, thus reducing mean response time. In human participants, however, response times remain approximately stable across blocks. This implies that the decrease in response time in the model should not necessarily be regarded as a sign of learning, but rather a mere side-effect of the increase in mind-wandering, which is not present in humans.

The model also shows a notable difference with regard to response time variability. Humans tend to be more erratic in their response times as they do more trials—most likely due to fatigue and the growing rate of distraction. However, the model shows more consistent response times across trials. This is also due to the growing frequency of mind-wandering, which leads the model to give more automatic responses more often.

In humans, however, mind-wandering is associated with inconsistent performance, which indicates that the default responses implemented in the model are likely to be an oversimplification of the response mechanism used in human cognition.

These discrepancies indicate that the model is unable to capture the full complexity of human performance. Therefore, suggestions for future research involve developing the model further, while keeping the growing trend in mind-wandering over time. For instance, the default response mechanism in mind-wandering could be extended to accommodate a range of responses, some of which may involve some degree of cognitive processing—thus increasing response time. A more complex system of memory retrieval could be used for mind-wandering, where some memories may be more pervasive than others. The model's vocabulary can also be extended with a larger set of words and categories. Furthermore, thought probes could consider the option range given in McVay & Kane (2009). This would bring the model closer to humans' more variable performance.

Finally, this modelling approach of mind-wandering through competing goals should be applied to other cognitive tasks. It will then be possible to examine how the frequency of mind-wandering and response time vary in those tasks and to compare that performance to the semantic SART.

The utility of studying the mechanisms of mind-wandering is in deepening our understanding of how human cognition and executive control behave in task-oriented scenarios. Applications of this research are especially useful in educational and work environments, where enhancing learning and productivity by maximizing the time spent focusing on the task as opposed to mind-wandering is key to meeting performance goals. Building cognitive models of mind-wandering in various tasks may reveal which task attributes make participants more or less prone to off-task thoughts, which may aid teachers or managers in designing tasks that facilitate performance. Similarly, studying individual differences in mind-wandering may prove extremely useful in assisting low-performing individuals to improve performance by enhancing task focus. In sum, expanding our insight into mind-wandering could largely advance the way humans learn and work.

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