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Representing Motivation in a Simple Perceptual and Motor Coordination Task based on a Goal Activation Mechanism

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Abstract

An important topic in the field of cognitive systems is modeling a user's internal state. A computational representation of human internal states (i.e., emotion or feeling) is beneficial for exploring the conditions of optimally regulating levels of motivation, which is assumed to be a central factor leading to well-being in our life. To construct such models, cognitive architectures, which are collections of detailed specifications of mental functions, have sometimes been used as tools to achieve an understandable design of information systems. However, previous models of motivational change using cognitive architecture have treated motivation as an independent module and have not thoroughly examined its relationship with other internal processes. By contrast, this study represents motivation based on a general knowledge activation mechanism. Throughout the task, current goal activation was assumed to be fluctuate. When this fluctuation leads to the activation of another activity, mind-wandering or task-switching occurs. Thus, the fluctuation range of activation corresponded to the degree of concentration (motivation) in the current task. In particular, motivation in our model decreased with time and increased with the occurrence of startling or novel stimuli. We applied this model to a simple perceptual-motor task and attempted to replicate the results obtained in the experiments with human participants. Furthermore, simulations exploring intervention methods that maintain optimal motivation levels were presented. Based on these studies, we discuss the model's effectiveness in representing the emotional process of humans and obtain suggestions on interventions that inhibit motivation decline.

1. Introduction

To realize truly intelligent and natural support for daily human activities, machines must monitor the internal processes of humans to perform timely interventions. Computational models that represent the process of human emotion are essential for developing intelligent interactive systems. This study focuses on the motivation process as a critical emotional factor that leads to psychological well-being. Maintaining workers' intrinsic motivation is harder in simple routine tasks than in self-determined challenging tasks (Csikszentmihalyi, 1990; Pink, 2009; Ryan & Deci, 2000). Moreover, motivation loss induced by passive routine tasks degrades subjective well-being. Therefore, if intelligent machines can understand the symptoms of such motivation loss and prevent it by presenting attractive stimuli at the apropriate time, the quality of life of the worker will improve.

We believe that a computational model of human motivation will foster the development of such intelligent systems. To date, many emotion models have been developed. Among them, models developed based on cognitive architecture, a collection of specifications of independent mental processes (Anderson, 2007; Kotseruba & Tsotsos, 2020; Laird et al., 2017), have the potential to provide detailed descriptions of the motivational process (Sun et al., 2022; Juvina et al., 2018; Yang & Stocco, 2022).

However, past models of motivation have not fully described the process of motivation loss in an integrative form. While following the trend of cognitive architecture, our model focuses on arousal processes based on the general activation mechanism of knowledge representation (Anderson, 2007; Anderson & Schooler, 1991; Hebb, 1949). Many psychologists use this mechanism to explain human memory and learning as a function of brain regions such as the hippocampus (Anderson, 2007; Kelso et al., 1986). Using this mechanism, our model demonstrates that motivation loss is caused by the fluctuation in activation for the current goal and by the goal being supplanted by other goals outside the task. More specifically, our model was developed based on the model of mind wandering, which is defined as task-unrelated thought during the main task (van Vugt et al., 2015). We will combine the proposed model with one that executes a simple perceptual-motor task (Morita et al., 2020) and use it to simulate behavioral data obtained from human participants and propose homeostatic regulation based on external stimulation. Before presenting our model, the next section presents previous studies related to our model and the simulation.

2. Related Research

2.1 Task Performance and Motivation Mediated by Arousal

There have long been discussions on the relationship between emotional arousal, motivation, and task performance. In classical literature, the terms arousal and task motivation are used interchangeably. For example, according to Hebb (1955), arousal is a synonym of drive, which refers to the physiological component of motivation that energizes a target behavior. Following this concept, this study uses “arousal” as a physiological factor driving human activity, whereas “motivation” is a psychological effort influencing the continuation of the current task.

Psychologists have also discussed the inverted U-shaped theory of the relationship between arousal and task performance (Yerkes & Dodson, 1908). In this theory, there is an optimal level of human arousal to accomplish the target task. It has also been posited that the optimal level of arousal depends on task difficulty (challenge) and human skills (Csikszentmihalyi, 1990). Novel and difficult tasks require high arousal, whereas simple and well-practiced tasks tend to result in boredom. Thus, arousal level serves as a kind of attentional resource (Landers, 1980). Redundant arousal for the current task tends to be used for a mental activity that is usually engaged outside the task (default mode thinking) (Buckner et al., 2008). This off-task mental activity associated with decreased task motivation, is called mind-wandering (Brosowsky et al., 2020). Although mind-wandering can foster creative thinking (Baird et al., 2012), it usually diminishes task performance.

Researchers have explored the external factors affecting arousal levels during monotonous tasks (Obayashi et al., 2019; Yoneda & Morita, 2021). Such studies, which manipulated task environments such as airflow, lighting, and music, confirmed the effects of external stimuli to recover arousal in the task.

2.2 Cognitive Architecture and Cognitive Modeling

As noted in the Introduction, there are tools known as cognitive architectures for constructing computational models of the human mind. Among several cognitive architectures, adaptive control of thought-rational (ACT-R) (Anderson, 2007) is most commonly used to simulate various psychological experiments (Kotseruba & Tsotsos, 2020). ACT-R has a modular structure, where basic cognitive functions such as vision, speech, thinking, and memory are administered with each corresponding module. Such modules in ACT-R are also combined and controlled by a central production module (functioning as rule engine), which triggers production rules according to the current states of each module. To control the modules, ACT-R uses a symbolic representation called a *chunk*. In each step, the active ACT-R modules hold a chunk to represent a state. Chunks are also stored in a *declarative module* (functioning as a database) and retrieved when production rules request them.

This study focuses on ACT-R because it has a well-developed mechanism for the general activation theory presented in Section 1. Recently, Yang & Stocco (2022) claimed that motivation in ACT-R is considered a scalar value held in the goal module to continue the task. The present study extends this idea by replacing the scalar value with activation, which is attached to the chunks in ACT-R. In the ACT-R retrieval process, highly activated chunks are more likely to be selected. Using this mechanism, a model of mind wandering was developed using the ACT-R (van Vugt et al., 2015). In this model, mind-wandering is represented as taking over a goal state (defined as a chunk held by a *goal module*) through highly activated off-task chunks. The model continuously refocuses on the state of the goal (retrieving a goal chunk from the declarative module) during a simple, monotonous task. Chunks representing off-task activities sometimes become mixed in this refocus process. Thus, this model of mind wandering defines task motivation as the activation of chunks that represent the task goal.

However, this mind-wandering model does not explain how task motivation (or arousal) fluctuates over time. Several researchers have modeled emotional processes such as fatigue (Atashfeshan & Razavi, 2017; Gunzelmann et al., 2009) and stress (Dancy et al., 2015) within the ACT-R. These models treat emotion as a physiological substrate that affects cognitive parameters, such as activation (Ritter, 2009). In particular, an extension of ACT-R called ACT-R/Φ (Dancy et al., 2015) connects the arousal level (corresponding to the activity in the sympathetic nervous system) with random fluctuations of the activation, which are represented as probabilistic noise added to the activation. Thus, referring to this model, we can predict that a relaxed state (low arousal) leads to a large random fluctuation of activation, leading to frequent mind-wandering. However, previous studies on ACT-R have not developed a model combining motivation loss and mind-wandering. Therefore, this study constructs a model of motivation loss based on the fluctuation of activation noise (arousal level) over time.

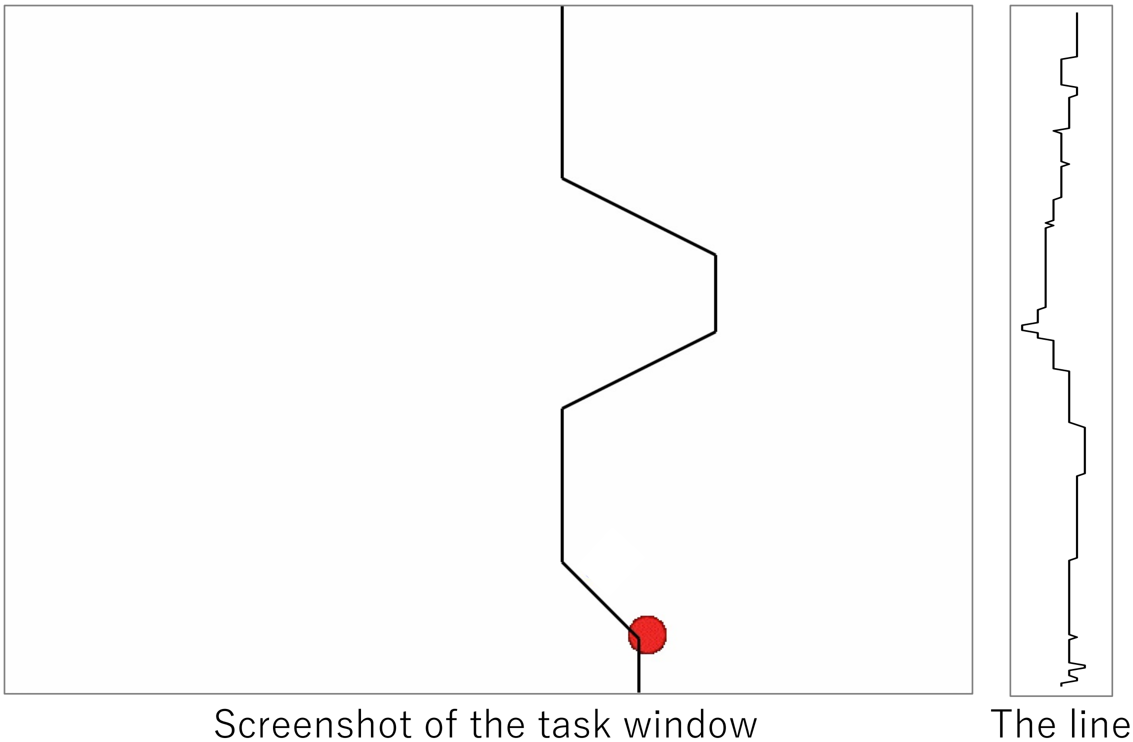


Figure 1: Task interface. Screenshot of the task window (left) and overall view of the line (right)

3. Task and Data

3.1 Line-Following Task

We set up a line-following task (Maehigashi et al., 2013) as a simple monotonous task to examine the effects of motivational change (habituation and boredom) and external stimuli. Figure 1 shows the task interface. In the line-following task, a polyline displayed on the screen automatically scrolls from top to bottom by one pixel every 40 ms (25-fps screen updates). Participants were required to follow the polyline (stay online) by moving the circular object to the left or right.

We chose this task because there is a publicly available ACT-R model for this task (Morita et al., 2020)[1]. In addition, it is relatively easy to modify complexities or challenges (Csikszentmihalyi, 1990) in this task by manipulating parameters, such as the ratio of vertical lines included in the polyline patterns. In this study, to induce boredom over a short period of time, we set this parameter at 90%. An illustration of the constructed pattern is shown in the right panel of Figure 1. In the following experiment/simulation, this line pattern was repeated in a 1-minute cycle for 30-minutes.

1. https://github.com/j-morita-shizuoka/line-following-tak

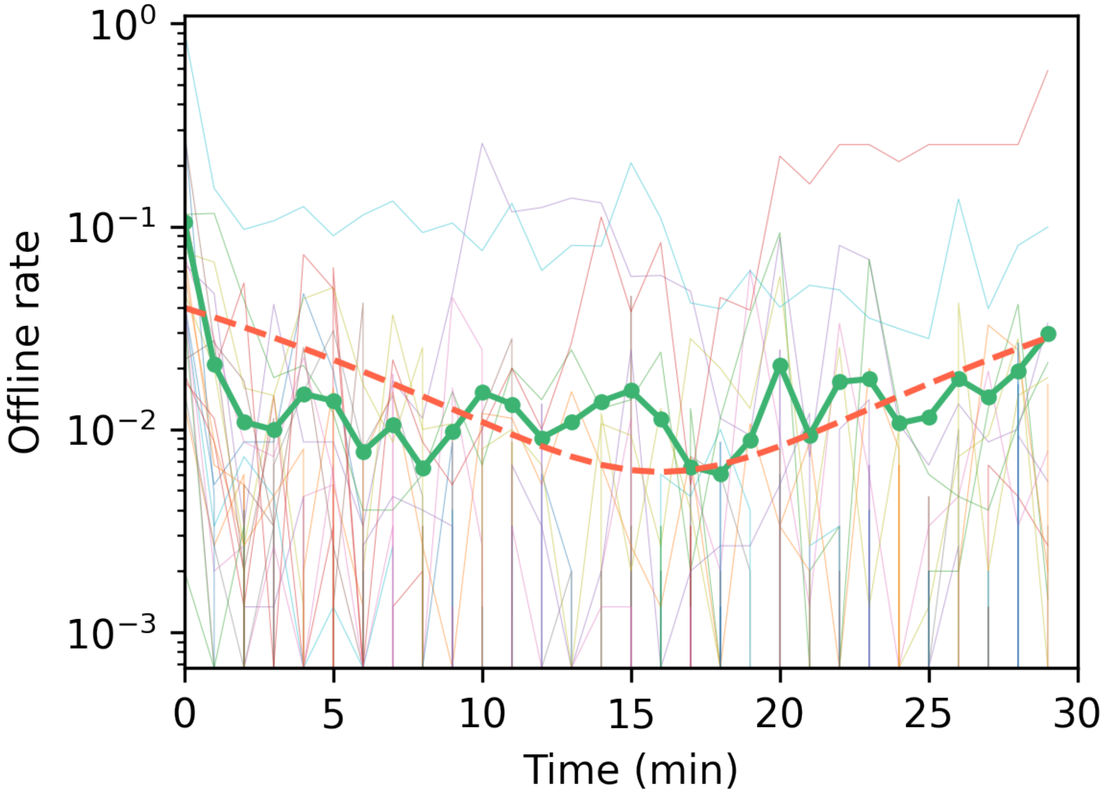


Figure 2: Participant performance in the line-following task. The thin lines represent each participant. The thick green line indicates the mean. The dotted red line indicates the result of a polynomial regression (degree = 2). The vertical axis is a logarithmic scale.

In addition, to examine changes in arousal level during the task, we designed a pop-up window asking participants to respond to the degree to which they focused on the task (probe). The probe was presented at an interval of approximately 50 s (randomized noise was added to this interval).

3.2 Average Human Behavioral Data

In this section, we present two types of human data obtained from line-following tasks. The first concerns changes in human motivation from various individuals. To collect data, we recruited participants from a crowdsourcing website (Lancers.jp). Twenty-seven participants completed the experimental procedure, in which they first accessed the online system and read the instructions on the task at their own pace. After completing a test to confirm their understanding of the task, they engaged in the line-following task for 30 min.

Figure 2 shows the transition of the offline rate (the percentage of time the circle did not follow the line in the total time of the segments) for each participant. These results are shown for 30

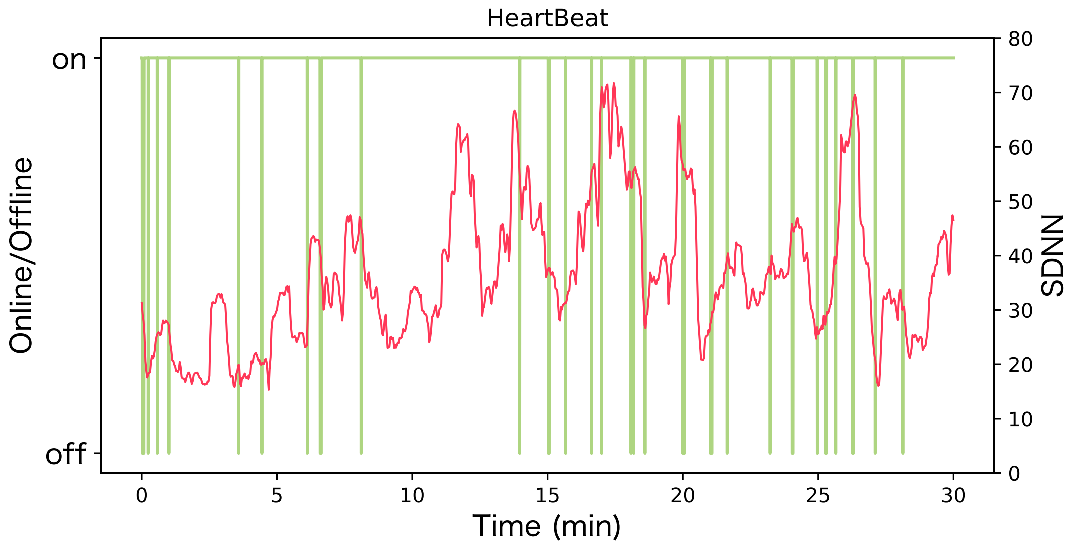


Figure 3: Results of case study

1-minute segments of a 30-minute task execution. The offline rate decreases in the initial three phases. However, from the midpoint (approximately 15 min), the value gradually increased over time, suggesting the occurrence of motivation loss in this task. The model presented in this paper aims to simulate the later part of this graph, focusing on process motivation loss.

3.3 A Case of Physiological Process

Although the online experiment provided behavioral data showing motivation loss in the line-following task, the participants' arousal levels could not be directly observed. Thus, the relationship between task performance and the physiological state remains unclear. For this reason, we collected a case from a male participant in the laboratory wearing a wireless heart rate monitor (MyBeat, Union tool).

Figure 3 shows physiological and behavioral data during this task execution. The former data is presented as the SDNN (Standard Deviation of NN, red line), which is the variance of RRI (R–R interval) usually corresponding to the dominant parasympathetic nervous activity. In this figure, we calculated this index with a sliding window of 60 beats width. The latter behavioral data (green line) is presented as binary values of on/off states of the scrolling line. Whenever the green line is at the bottom, it indicates when the circle is not following the line (Offline). A green vertical line is drawn when online and offline are switched.

In this case, SDNN increased from the middle to the end of the task, and the frequency of the offline periods also increased. These results illustrate the physiological processes that are accompanied by a decrease in arousal. As shown in Figure 3, the arousal level gradually decreased with large fluctuations.

4. Model

This section describes a model that represents the internal processes of the participants related to the decline in performance during the task owing to loss of motivation.

4.1 Basic Concept

We constructed a model that followed two previous ACT-R models: the perceptual-motor task (Morita et al., 2020) and mind-wandering (van Vugt et al., 2015) models. Combining these, the current model represents the execution of the task and the deviation from the task caused by thinking outside the task. The model performs a line-following task, as in the human experiment, and responds to the probes presented during the task.

Figure 4 shows an overview of the model by dividing it into symbolic (Figure 4 (a)) and subsymbolic parts (Figure 4 (b)). These two parts are conventionally divided into ACT-R modeling. Each part is described in the following subsections.

4.2 Symbolic and Subsymbolic Processes of the Model

This section illustrates the behavior of the models. Section 4.2.1, shows a symbolic process governed by chunks and production rules. Section 4.2.2 describes a subsymbolic process related to chunk activation.

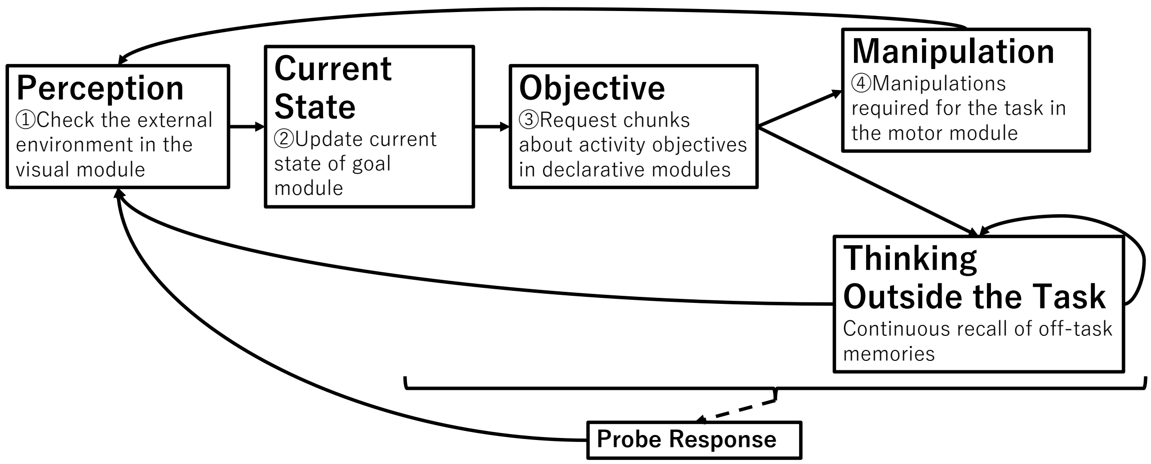
4.2.1 Symbolic Process

The internal state transit of the model is shown in Figure 4 (a). As seen in the figure, the model consists of cyclic behaviors of perceptual and motor processing. Because individual cognitive functions support this process, this section explains the model according to the ACT-R modules. Among several modules implemented in ACT-R, the most important in the line-following model are the visual, motor, goal, declarative, and production modules. These modules function as follows.

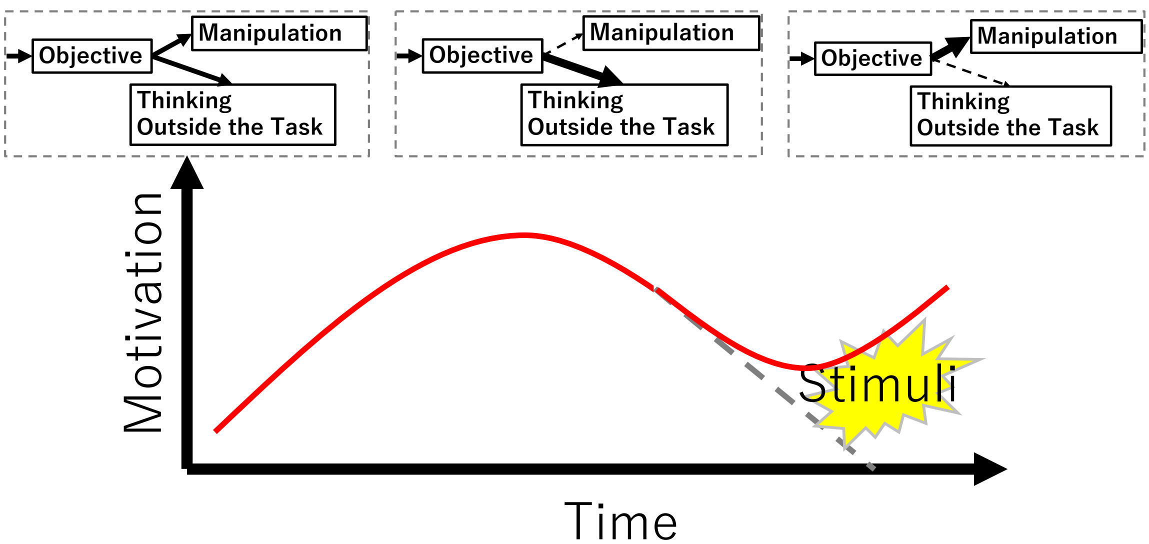
Visual Module: This module simulates interactions with the external environment. It reads the symbols (e.g., the position of a circle or turn in the line) necessary to perform the task from the external environment (in the model, a display on a virtually created window).

Motor Module: This module simulates the operations required for the task. In the line-following model, the module executes key-presses corresponding to the movements of the circle and responses to a probe.

Declarative Module: As noted earlier, this module stores symbolic chunks, including episodic memories, semantic knowledge, and the model's goals. The last chunk is important for representing mind wandering in the line-following task. As in the previous mind-wandering model (van Vugt et al., 2015), two types of goals are available in this model: the goal for current task execution and the goal for default-mode thinking. In addition to these two goal chunks, the model also has chunks corresponding to individual memories that are not relevant to the current task.



(a) Block diagram showing basic model processing



(b) Conceptual diagram of the change in motivation over time as shown in the model. Motivation decreases over time and increases with stimulation.

Figure 4: Model concept

Goal Module: This module holds one of the two goal chunks retrieved from the declarative module. In addition, the module stores the current state of the task required to control the flow of the line-following task. These states include those obtained from the visual module, such as the circle position and next turn position.

Production Module: This module manipulates other modules by selecting and applying production rules using chunks held by the other modules. In the current model, the application of this module results in the flow shown in Figure 4 (a). Importantly, each transition (corresponding to a single application of a production rule) requires a certain time cost (50 ms), which is the default setting of ACT-R for simulating the human cognitive process in various tasks. By accumulating these time costs the model can predict the overall execution time of a human line-following task.

This model integrates each of the modules shown thus far in the following steps.

1. When the model observes the state of the external environment in the visual module (Figure 4 (a) ①),
2. It updates the current state of the goal module (Figure 4 (a) ②),
3. requests a goal chunk from the declarative module (Figure 4 (a) ③),
4. and performs the necessary operations (key-presses) for the task through the motor module (Figure 4 (a) ④).

After the above steps, the visual module checks for a new state in the external environment and returns to step 1. If the declarative module retrieves the goal chunk that directs attention to default-mode thinking, it does not perform the operations required for the task (key-presses). Instead, it enters a state of continued memory recall outside the task (mind-wandering). When the goal chunk of the current task is accidentally recalled in this process, the model returns to the task.

4.2.2 Subsymbolic Process

In the above process, the task execution varies depending on the recalled goal chunk. In ACT-R, the availability of chunks in the declarative module is controlled by a value called *activation* assigned to each chunk. The activation in the current model is expressed as,

$$A_i = \ln(\sum_{j=1}^{n} t_j^{-d}) + \varepsilon_i \tag{1}$$

where n is the number of occurrences of memory item i, t_j is the time elapsed since the jth occurrence, d is the decay factor (the default value is 0.5), and ε_i is the transient noise. Applying this equation and setting, recently obtained and frequently visited memories are highly activated.

As Eq. 1 is constructed to represent concentration on the currently important task (Anderson & Schooler, 1991), the subsymbolic computation in ACT-R enables the model to perform tasks under the current goal stably. However, if a goal chunk other than the current task is accidentally recalled during the task (mind-wandering) and this recall is repeated, A_i for that chunk will increase, causing a task shift (quitting the current task and starting the next task).

The probability of such accidental recall is determined by ε_i. This parameter (activation noise) is generated using a Gaussian distribution with a mean of zero, and variance as follows:

$$\sigma^2 = (\pi^2/3) \times s^2 \tag{2}$$

where s is a parameter that determines the size of noise variance. Thus, this parameter represents the stochastic fluctuation added to the activation value for each retrieval. Under conditions with large fluctuations, chunks with a small activation can be retrieved. In other words, the increase in activation noise also increases the probability of mind wandering caused by retrieving the goal chunk for the default mode activity.

Based on this relationship, in this study, we considered noise (ε_i) as a parameter that changes depending on the autonomic nervous system (Dancy et al., 2015) during the task. As the parasympathetic nervous system becomes more dominant over time, the activation noise increases, and it decreases when an event directs attention to the task (e.g., falling off the line).

Such a physiological process is supposed to drive a change in motivation, as shown in Figure 4 (b), where the activation of the goal chunk for the task represents motivation. In the initial phase, the task goal is repeatedly retrieved and the activation of the goal chunk increases. However, as activation noise increases over time, mind-wandering becomes mixed. This repetitive mind wandering resulted in participants quitting the task. It can also be considered that giving external stimuli intervenes in such loss of motivation. The following simulations confirm this process.

5. Simulations

We first tried to replicate the behavioral results obtained in the human experiments (Simulation 1). Following this, we explored designs of interventions for motivation loss by manipulating the model parameters (Simulations 2 and 3).

5.1 Simulation 1: Task Motivation as the Fluctuation of Activation Noise

5.1.1 Objective

This simulation was conducted to confirm the occurrence of mind wandering owing to the aforementioned noise changes. Here, the activation noise increased by 0.0004 at each screen update (25 fps), which corresponds to increments of one per minute. We also set three conditions for noise reduction (small: 0.02, medium: 0.04, and large: 0.06), which decrease the activation noise when the model perceives that a circular object has fallen off the line. Because the activation noise corresponds to the physiological state (i.e., autonomic nervous activity), the noise reduction range is considered to correspond to psychological concentration, which is assumed to vary by environment or individual differences. Ten independent runs of a 30-minute line-following task were conducted for each noise-reduction condition.

5.1.2 Result

Figure 5 shows examples of change in the activation noise during the line-following task. The horizontal axis corresponds to the time of screen updates (25 fps $\times$ 60 sec $\times$ 30 min). The three graphs can be described as follows:

- Small decrease condition (0.02): The activation noise kept increasing.

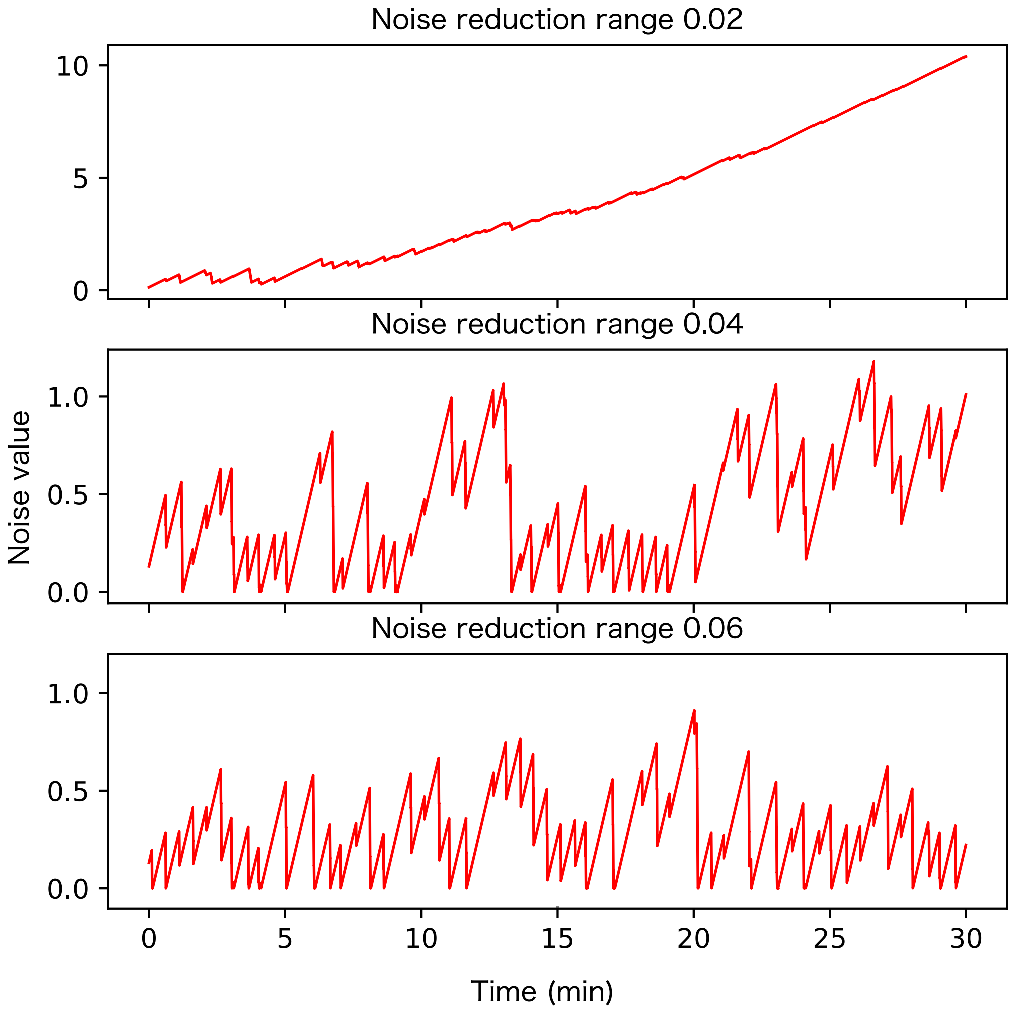


Figure 5: Examples of activation noise fluctuation from each simulation condition. Horizontal axis represents the screen update (every 40 ms). Note that only the top panel has a different range on the vertical axis.

- Medium decrease condition (0.04): The activation noise gradually increases with repeated ascending and descending fluctuations.
- Large decrease condition (0.06): The activation noise repeatedly moved up and down within a certain range.

From these descriptions, we can see a commonality between the medium decrease condition and the human heart rate fluctuation presented in Figure 3. This suggests the validity of our assumptions regarding the correspondence between activation noise and the autonomous nervous system. In ad-

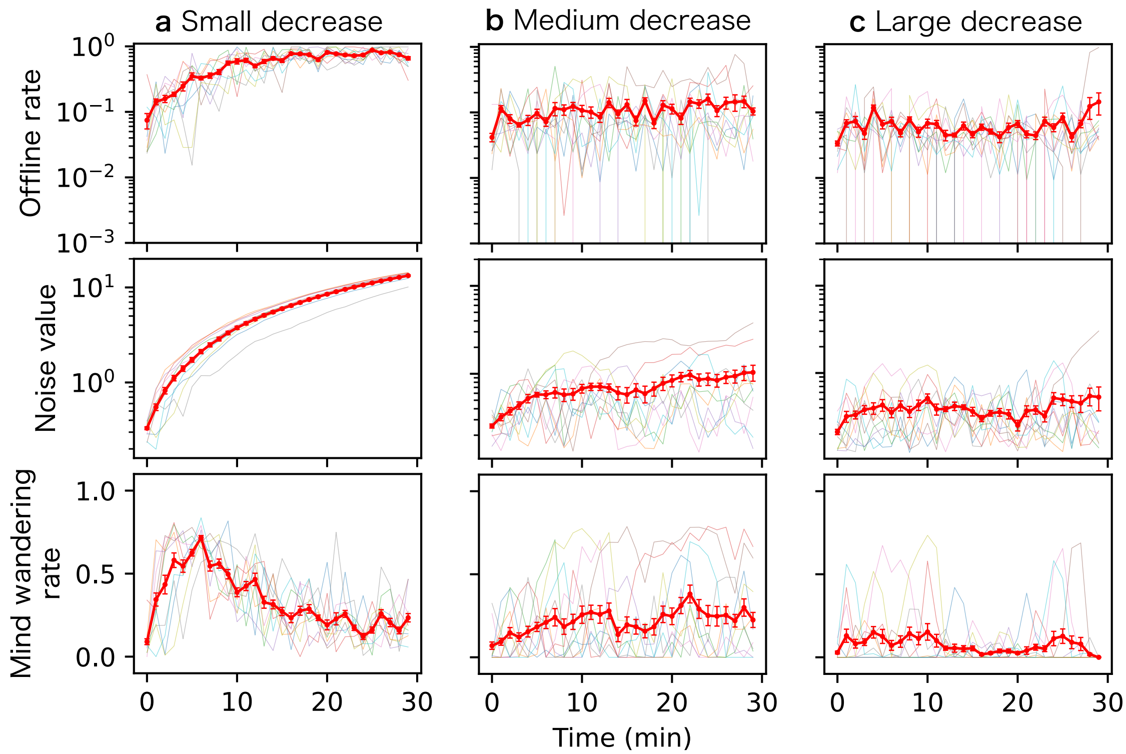


Figure 6: Simulation results. Each column corresponds to a condition (a: small decrease (0.02), b: medium decrease (0.06), c: large decrease (0.08)).From the top, the offline rate (logarithmic vertical axis), the activation noise (logarithmic vertical axis) and the mind-wandering rate are shown. The red line is the mean of 10 runs; error bars are standard errors.

dition, the description for the large decrease condition suggests that the noise reduction range must be larger than a certain value (the state in which it is easier to concentrate on the task) to maintain appropriate activation noise (arousal level) during the task. With regard to the small decrease condition, the behavior was significantly different from the other conditions. We discuss this issue at the end of this paper.

To confirm such trends and to explore how the activation noise relates to the performance of the task, Figure 6 summarizes the results obtained from all cases. The horizontal axes in Figure 6 correspond to the 30-minute simulation time divided into 30 segments of one minute each. Each column in the figure ((a)–(c)) corresponds to the conditions for the noise reduction range. The top, middle, and bottom panels show the ratio in which the circle was offline (offline rate), the activation noise, and the ratio in which the model had the goal outside of the task (mind-wandering rate), respectively. In particular, Figure 6 (b) shows that the mind-wandering rate (bottom panel) increased as the activation noise (middle panel) increased. This eventually degrades the task performance (top panel). These qualitative characteristics of the model are also observed in the human experiments (increase in offline rate from the middle point in Figure 2).

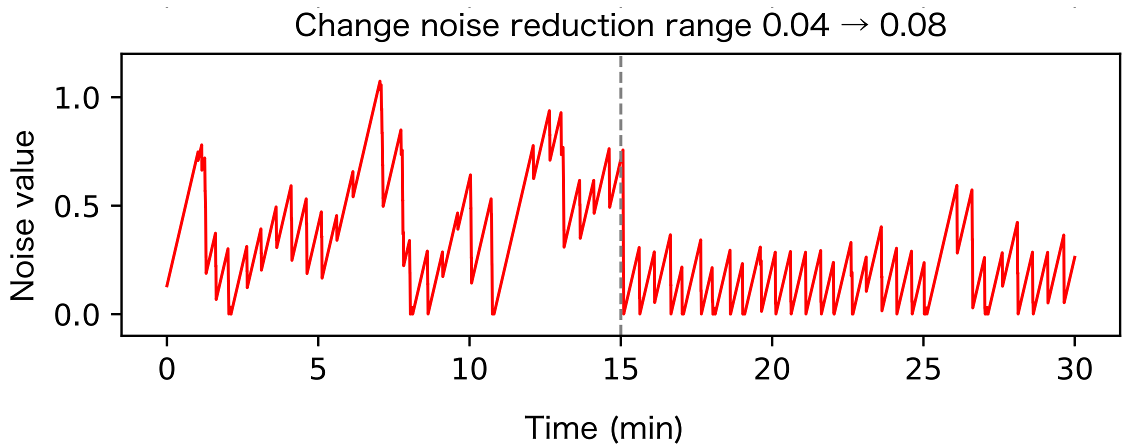


Figure 7: Examples of activation noise fluctuation from explicit event (modify noise reduction) conditions. Horizontal axis represents the screen update (every 40 ms).The gray dotted vertical lines indicate the timing of stimulus presentation (change in the noise reduction range).

5.2 Simulation 2: Stimulation for Motivation

5.2.1 Objective

The previous simulation showed the process of motivation loss due to the occurrence of mind wandering. Simulation 2 explored the conditions for preventing loss of motivation. To achieve this, we assume that the optimal level of arousal is maintained by giving participants explicit events (stimuli) at a certain time point in the task. To represent such stimuli, the range of decrease in activation noise was altered during the task. Specifically, the noise reduction was set to 0.04 at the beginning of the task, and was modified to 0.08 after half of the task (15 min). We assumed that the participants were presented with a stimulus, such as a startle sound, at this point (Dancy et al., 2015). The other settings were the same as those in Simulation 1.

5.2.2 Result

The results are shown in the Figure 7 and Figure 8, respectively. The gray dotted vertical lines indicate the timing of stimulus presentation (change in the noise reduction range). The activation noise gradually increases in the first half (0.04 noise reduction), whereas it tends to decrease after the noise reduction range is increased. The mind-wandering rate (bottom panel) also fluctuates with activation noise, showing a similar trend. Thus, the noise reduction setting worked as expected (i.e., to represent external stimuli for recovering mind-wandering).

5.3 Simulation 3: Adaptive Stimulation for Motivation

5.3.1 Objective

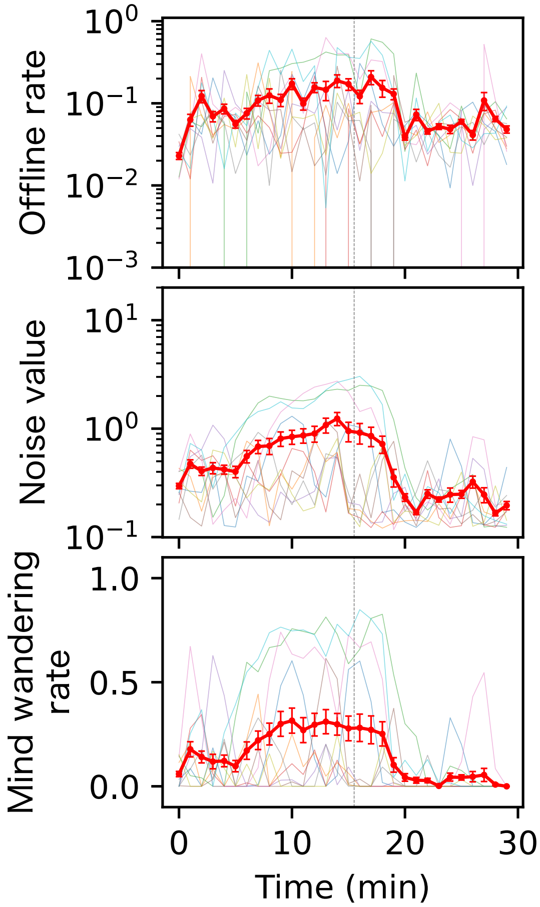


Figure 8: Results of explicit event (modify noise reduction) condition. The gray dotted vertical lines indicate the timing of stimulus presentation (change in the noise reduction range). From the left, the offline rate (logarithmic vertical axis), the activation noise (logarithmic vertical axis) and the mind-wandering rate are shown. The red line is the mean of 10 runs; error bars are standard errors.

The final simulation explored the theoretical plausibility of the adaptive stimulus presentation to maintain motivation. In this simulation, we assumed that participants' mind-wandering can be recognized by utilizing sensing devices such as eye trackers or heart rate monitors. Based on this assumption, we explored the effectiveness of stimulus presentation with proper timing for suppressing mind-wandering (motivation loss). This mechanism is considered to be a type of homeostasis, which is a physiological process, maintaining an organism's internal state under steady conditions (Cannon, 1929; Billman, 2020). However, unlike natural homeostasis, the method described herein can artificially set a steady condition.

To build such an artificial homeostasis mechanism, the mind-wandering rate, an internal variable of the model, was monitored, and the model was presented with a stimulus to focus on the task when the mind-wandering rate exceeded a certain level. Similar to the previous simulation, the stimulus to the model was represented by changing the range of decrease in noise.

To determine the timing of the stimulus presentation, the baseline of the mind-wandering rate was obtained by an independent run of the model (the setting was the same as the medium decrease condition in Section 5.1). From this procedure, the baseline is 0.441, which is $a+3\varsigma$ calculated from the mean a and standard deviation ς of the mind-wandering rate.

Simulations were performed using the obtained baseline to verify the artificial homeostasis mechanism. When the mind-wandering rate exceeded the baseline (0.441), the noise reduction range changed from a normal value (0.04) to a concentration value (0.08). The other settings were the same as those described in Section 5.2.

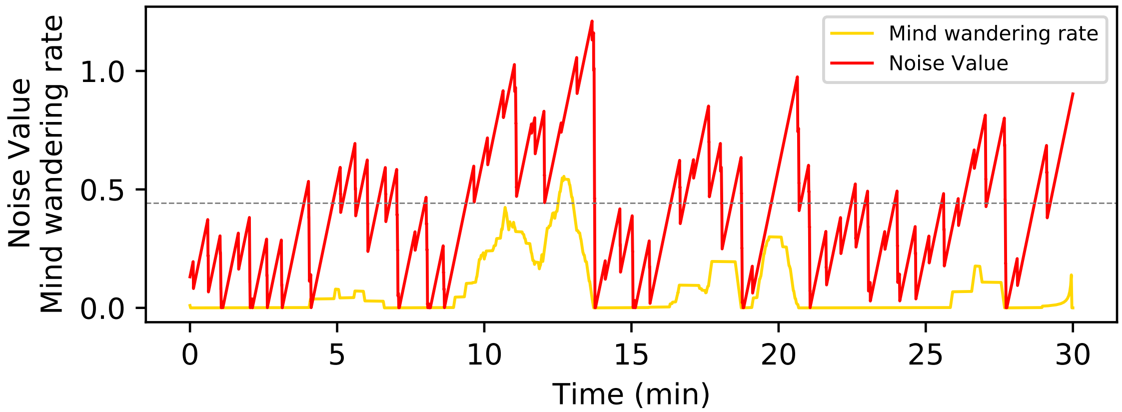


Figure 9: Example of activation noise change (red) and mind-wandering rate (yellow)

5.3.2 Result

Figure 9 shows an example of the evolution of activation noise in the simulation of a homeostasis-maintenance model. In Figure 9, the red, yellow, and gray lines indicate the activation noise, mind-wandering rate computed for the last minute, and baseline for triggering a stimulus, respectively. This figure shows that the activation noise and mind-wandering rate gradually increased until approximately 20,000 frames. Around this point, the mind-wandering rate exceeds the baseline and causes a stimulus presentation, leading to a rapid decrease in the activation noise.

The graphs presented in Figure 10 indicate that all indices maintained a low stable value, suggesting that the increase in the activation noise was suppressed and that mind-wandering was reduced by the stimuli (increase in noise reduction). Such effects of the adaptive stimuli can be characterized by comparing them with the results of Simulation 2 (Figure 8). In Simulation 2, although the overall trend shows a reduction in mind-wandering with the stimuli, some cases (see thin lines in the figure) show large fluctuations in the indices just before the stimulus presentation. In contrast, the adaptive stimulus presentation in Simulation 3 suppressed such large fluctuations in each run, suggesting that the method is effective in controlling the differences that emerged in each case (such as individual differences).

6. Conclusion

This study constructed a motivation model using ACT-R to implement adaptive interventions for simple routine tasks. The model was developed based on previous ACT-R studies on mind-wandering and perceptual-motor tasks. In addition, the model in this study stochastically switched the activated goal (task-focused or off-task thinking) during the task. By mapping the activation noise of knowledge to changes in the autonomic nervous system, we represented the mind-wandering that occurred over time. The model was used to simulate the basic behaviors of human participants and to explore methods of stimulating concentration on the task.

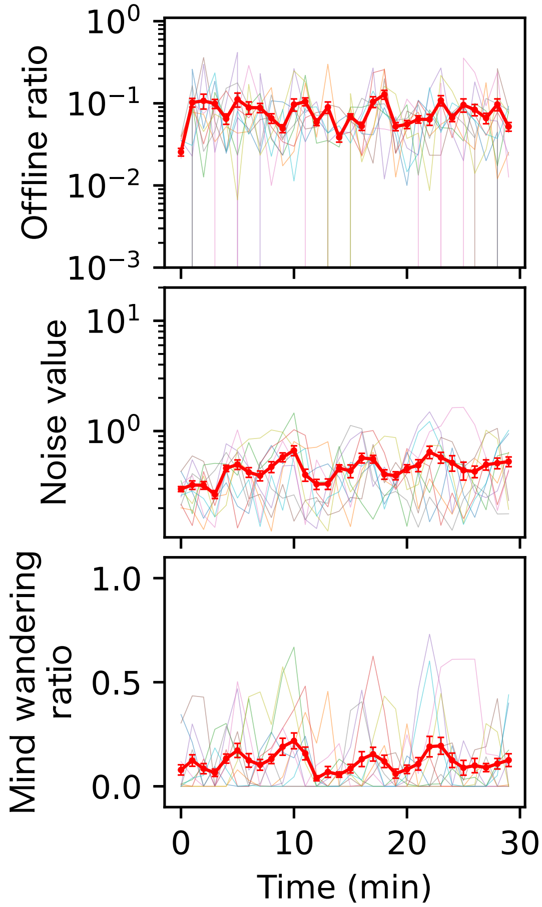


Figure 10: Results of proper timing stimulus conditions. From the left, the offline rate (logarithmic vertical axis), the activation noise (logarithmic vertical axis) and the mind-wandering rate are shown. The red line is the mean of 10 runs; error bars are standard errors.

This study contributes to the advancement of the field of cognitive systems by presenting a computational representation of physiological (arousal) and psychological (motivation) changes over time. Referring to such concrete representations, we can design future interactive systems that promote well-being. As the next step in this study, we will develop a system for suppressing mind-wandering during the task, as presented in Simulation 3. Although there are several technical problems to be solved, such as sensing accuracy or choice of stimulation, the computational model presented here will guide exploration to solve such issues.

The proposed model has several limitations that need to be refined or validated. For example, in the small decrease condition of Simulation 1, the mind-wandering rate was reduced despite the high offline rate and the failure of the task (Figure 6 (a), top and bottom panels). This is caused by the increase in memory retrieval time accompanied by a low activation level (in ACT-R, retrieval time is calculated from chunk activation). Thus, during the long retrieval of the goal chunk, the activity of following the line was stopped. Such behavior is not included in the assumptions of the model and needs to be validated. We will revise the setting and definitions of the indices in the model in the future and conduct an analysis that will allow us to fully examine the optimal level of motivation.

Moreover, future models need to include factors of initial learning, which are observed in the initial phase of the human data (Figure 2). We emphasize this factor because motivation is considered to interact with task learning (Csikszentmihalyi, 1990). Regarding this factor, we have already constructed a pilot model that includes motor learning in this task (Nagashima et al., 2022). Compared to the pilot model, we assume that the model presented in this paper is a simplified version that focuses on the factors of motivation loss caused by mind-wandering and recovering by homeostatic regulation. In the future, we will integrate these two models to fully explain the phenomenon related to motivation.

The final limitation of the study is the generality of the proposed mechanism. We selected ACT-R as the platform to implement the proposed mechanism. However, we believe that the proposed mechanism is not specific to the ACT-R architecture because the core of the mechanism is general memory activation, which has long been discussed since the classical literature by Hebb (1955). In the future, we hope to connect the proposed mechanism with a general cognitive modeling framework such as the common cognitive model (Laird et al., 2017).

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