Modeling optimal arousal by integrating basic cognitive components

Kazuma Nagashima (nagashima.kazuma.16@shizuoka.ac.jp),
Junpei Nishikawa (nishikawa.jumpei.16@shizuoka.ac.jp) ,
Ryo Yoneda (yoneda.ryo.17@shizuoka.ac.jp) ,
Junya Morita (j-morita@inf.shizuoka.ac.jp) ,
Department of Informatics, Graduate School of Integrated Science and Technology, Shizuoka University,
3-5-1 Johoku, Naka-ku, Hamamatsu-shi, Shizuoka-ken, 432-8011 Japan

Tetsuya Terada (terada.t@mazda.co.jp)
Mazda Motor Corporation
3-1 Shinchi, Fuchu-cho, Aki-gun, Hiroshima-ken, 730-8670, Japan

Abstract

Mind-wandering occurs as emotional arousal decreases, which is related to the level of mastery of the current task. As a worker becomes more proficient in a task, the cognitive resources required to perform the task decrease. Then, surplus resources emerge and are naturally directed to "default-mode thinking," which people usually engage in outside the task. As mind-wandering continues, this default-mode thinking becomes more active and affects the task performance. In this study, we describe this process by combining the basic functions of the cognitive architecture Adaptive Control of Thought-Rational (ACT-R). The chunk activation mechanism represents the on- and off-task thinking loops. Furthermore, we introduce stochastic fluctuation in the chunk activation to change the transition probability between these loops. This fluctuation is assumed to be driven by parasympathetic activity, which increases over time and is suppressed by novel stimuli. To develop this physiological change, this study uses the ACT-R temporal module. Simulations using these modules demonstrate the inverse U-shaped relations between task performance and task continuation. Such a process is consistent with theories of optimal levels of arousal.

Keywords: optimal level of arousal, homeostasis, mind-wandering, cognitive resource, ACT-R

Introduction

People often think and dream about things unrelated to the current task. This state is called mind-wandering and is reported to occur more than half the time humans are awake (Killingsworth & Gilbert, 2010). Therefore, mind-wandering can be considered the normal state (default mode) of humans. Although mind-wandering is assumed to promote creative thinking (Baird et al., 2012), it leads to a decline in task performance and triggers accidents caused by distraction from the task.

Mind-wandering is one phenomenon caused by decreased emotional arousal during a task. A similar process is sometimes expressed as mental fatigue, boredom, or habituation. These wide varieties of mental activities are related to an optimal level of arousal for better task performance (Yerkes & Dodson, 1908; Hebb, 1955; Easterbrook, 1959). Some researchers have proposed that the optimal level of arousal is influenced by the difficulty of the task (Oxendine, 1970; Csikszentmihalyi, 1990). Both excessive and insufficient arousal levels for the current task difficulty negatively affect performance. In other words, the task performance is related to arousal level by an inverse U-shaped function, the peak of which shifts depending on the task's difficulty. This inverted U-shaped curve is considered to apply to changes in task performance over time. As the task proficiency progresses, the task performance increases and becomes easier for the current workers. Simultaneously, the level of arousal (attention or cognitive resources) required to accomplish the task decreases. Then, surplus cognitive resources emerge, and they are naturally directed to "default-mode thinking," which workers prefer to use in their everyday life. As this process repeats, they lose motivation to continue the task, and their task performance gradually degrades. This transition eventually creates a inverse U-shaped curve relating the attention directed to the task (the arousal level required by the task) and the task continuation (similar mechanism is proposed by Shenhav et al. (2013)).

Many studies have been conducted concerning human cognitive functions related to the theory of the optimal level of arousal. However, detailed computational models describing the changes in performance and arousal level over time have not been fully developed. In this study, we represent this process using a cognitive architecture, ACT-R (Adaptive Control of Thought-Rational; Anderson, 2007). Like many other cognitive architectures (Kotseruba & Tsotsos, 2018 for a review), ACT-R provides modules corresponding to functions used repetitively across several tasks. ACT-R has multiple modules involved in learning tasks, and the combination of these modules can represent the complex nonlinear relationships between mastering the task and task motivation. Based on this idea, this study tries to describe these arousal changes by integrating the primitive cognitive modules provided in ACT-R.

In the following section, we will introduce related studies concerning the abovementioned goal of the study. Following this, the target human behaviors concerning the optimal level of arousal will be presented. Then, the ACT-R model integrating several primitive cognitive components to simulate these specific behavior patterns will be described. The simulation results will present a case of a U-shaped task performance change. In the final section, we will discuss the implications and limitations of this study.

Related Works

This study aims to model the optimal arousal level by combining primitive functions in ACT-R. This section presents two directions of previous studies: a human physiological mechanism and research on ACT-R.

Computational Models of Human Homeostasis

Physiological processes drive human arousal. Therefore, the optimal level of arousal described in the previous section can be interpreted as the maintenance of homeostasis in biological systems, which is a self-regulating process that fluctuates to maintain its optimal state (Billman, 2020; Cannon, 1929). Because of homeostasis, organisms can adapt to changing environments.

Computationally, homeostasis has been explained by the theory of predictive coding, also known as the free energy principle. Predictive coding is the concept that the brain minimizes the prediction error between sensory signals and internal prediction signals by which the brain perceives the environment (Friston, 2010). An organism is assumed to desire the minimization of long-term prediction errors caused by mismatches between predictions from experience and perceptions of current conditions. Mismatches also decrease as the organism masters the task. Thus, predictive coding describes human behavior in terms of a balance between minimizing the prediction error for the task and increasing the prediction accuracy. This relationship is also compatible with the exploration-exploitation relation discussed in the study of reinforcement learning (Sutton & Barto, 1998).

We consider that the above concepts of homeostasis and prediction errors explain the inverted U-shape of arousal level and task performance. Continuation of the same task leads to the saturation of prediction errors and increases the desire to explore new environments. However, the theory of homeostasis has difficulty describing the process of arousal changing over time. To solve this problem, we review the models developed using ACT-R.

ACT-R Models Regarding Arousal Change

Recently, some researchers have developed mind-wandering models using the activation mechanism of ACT-R. Van Vugt et al. (2015) implemented a model that recalls memories unrelated to the task while the task is being executed. Through simulations using this model, they represented how the task continuation induces mind-wandering and how it affects the task performance.

Other studies have focused on fatigue, which is also closely related to arousal changes over time. Gunzelmann et al. (2009) constructed a model representing the effects of fatigue on the execution of procedural memories. Specifically, they manipulated the parameters relating to the computations of utilities for production to represent the degree of fatigue. Gunzelmann et al. (2012) also constructed a mechanism for fatigue in memory activation, which affects the success of memory retrieval during the task. These changes in subsymbolic parameters over time affect the performance of the task and can define a inverse U-shaped curve representing the relation between the task continuation and reaction time (Atashfeshan & Razavi, 2017).

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

However, these studies have not explicitly discussed the correspondence of these parameter changes to human physiological mechanisms. Concerning the logic behind these models, Ritter (2009) defined emotion as physiological substrates affecting cognitive parameters, such as activation. This idea has been instantiated in ACT-R/Φ (Dancy et al., 2015), which combines cognitive processes in ACT-R with physiological mechanisms. Although this ACT-R extension successfully demonstrates the complex dynamics that emerge from interactions between physiology and cognitive components, it does not explain how those relations change over time.

As described in the first section, mind-wandering can be assumed to be a side effect of mastering a task. From this viewpoint, cognitive models of skill acquisition should be integrated with the models of arousal changes. Several computational models (Anderson et al., 2019; Kim & Ritter, 2015) has been proposed in ACT-R to represent a nonlinear theory of mastery (Fitts, 1964). Specifically, Anderson et al. (2019) recently proposed an ACT-R module enabling mastering primitive perceptual and motor coordination. We consider that an integrated account of optimal arousal theory can be developed using this module.

In summary, ACT-R has been used for various cognitive function models in different situations. By referring to these studies, we believe that it will be possible to construct a detailed model for the target of this study.

Human Data

Objective

Before presenting our model, this section presents data concerning changes in human arousal in a simple perceptual and motor task. To collect data from various individuals, we recruited participants from a crowdsourcing service (Lancers.jp).

Task

We set up a line-following task (Maehigashi et al., 2013) to examine fluctuations in arousal. Figure 1 shows the task interface. A polyline displayed on the screen automatically scrolls from top to bottom by one pixel every 40 ms (25-fps screen updates). The participants were required to follow the polyline (stay online) by moving the circular object left or right.

We chose this task because there is a publicly available ACT-R model (Morita et al., 2020). Moreover, it is relatively easy to modify the complexity of this task by manipulating parameters such as the ratio of vertical lines included in the polyline patterns. In this study, to induce arousal change in a short period, we set this parameter at 90%. The right panel of Figure 1 shows the overall pattern constructed. This pattern was repeated in a one-minute cycle in the following experiment and simulation.

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

Method

Eighty-one participants finished the experiment procedure, where they first accessed the online system and read the instructions for 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.

In this experiment, we set up three BGM conditions to examine environmental factors influencing the arousal changes during the task. The participants engaged in the task under the following conditions:

- No BGM: No music was presented ($n = 27$)
- Low BPM: The task environment included music at 80 beats per minute (BPM) ($n = 25$)
- High BPM: The task environment included music at 120 BPM ($n = 29$)

However, this paper did not focus on the difference between the conditions.

Results

Figure 2 shows the offline rate (the percentage of time that the circle did not follow the line). These results are shown for 30 segments of 1 min each of the 30-min task execution. In each condition, the offline rate decreased in the initial phase, suggesting that mastering the perceptual and motor coordination occurred during this early phase. Although the difference between conditions was not apparent, the average offline rate in the high-BPM condition (the thick red line) increased over time (after 18 segments), suggesting cases of U-shaped transitions [1]. The model presented in the following section tried to generate such a trend in task performance.

[1] Because the study uses an offline ratio as the performance index, the observed U-shaped curve corresponds to the inverse U-shape curve discussed in the introduction.

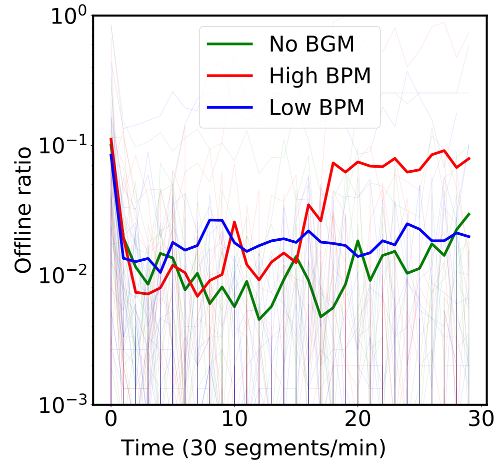

Figure 2: Participant performance in the line-following task. The thin line shows the cases per participant, and the thick lines show their mean. The vertical axis is on a logarithmic scale.

Model

We constructed a model following the four previous ACT-R models: the perceptual-motor process (Morita et al., 2020), the mind-wandering mechanism (van Vugt et al., 2015), time perception (Taatgen et al., 2007), and mastering the motor process (Anderson et al., 2019). By combining the first two, the current model represented the execution of the task and the deviation from the task. We also represented arousal changes by applying the temporal module representing subjective time, while the effects of mastering the task on mind-wandering were also modeled as motor skill acquisition.

Perceptual-Motor Process

The model's state transitions were constructed based on the previous study (Morita et al., 2020), which are represented in Figure 3. As seen in the figure, the model consists of cyclic behaviors of perceptual and motor processing. These processes are realized by the functions implemented in the following modules.

Visual Module This module simulates interaction with the external environment. The visual module reads the symbols (e.g., the position of a circle or a 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 in the task. In the line-following model, the module executes key presses corresponding to the movement of the circle and responding to a probe.

Declarative Module This module stores symbolic chunks, a unit of symbolic information in ACT-R. These chunks include 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 the model: the goal for the current task execution and the goal for default-mode thinking. In addition to these two goal chunks, the model has chunks corresponding to individual memories that are not relevant to the current task.

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

Production Module This module manipulates the 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 3. Importantly, each transition (corresponding to a single application of a production rule) requires a specific time cost (50 ms), following the default setting of ACT-R. By accumulating these time costs, the model can predict the line-following performance in time constraints that is compatible with the human experiment.

In this model, the modules shown so far are integrated in the following steps:

1. The model sees the state of the external environment in the visual module (Figure 3 ①),
2. It updates the current state of the goal module (Figure 3 ②),
3. 3. It requests a goal chunk for the declarative module (Figure 3 ③), and
4. It performs the necessary operations (key press) for the task through the motor module (Figure 3 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 recall of memories outside the task (mind-wandering). When the goal chunk about the current task is accidentally recalled in this process, the model returns to the task. The mechanism of switching between these two loops is further described in the next subsection.

Mind-Wandering Mechanism

As described above, the model loop related to the task competes with the loop related to mind-wandering. The conflicts

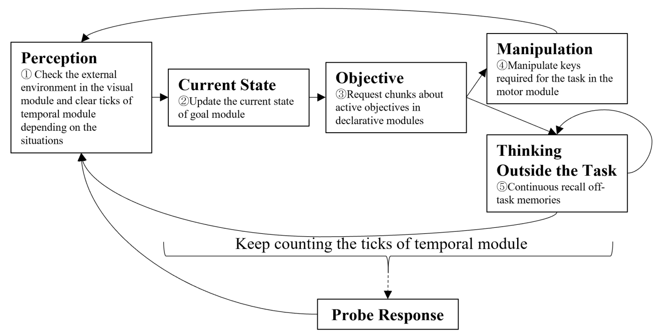

Figure 3: Block diagram showing the model processing.

between the loops are then resolved by the activation mechanism, following the previous mind-wandering model (van Vugt et al., 2015). In the ACT-R theory (Anderson, 2007), the activation of a memory depends on its recency and frequency of use. That is, memories that were most recently or frequently used are more likely to be recalled. Thus, when the goal for the current task is highly activated in the early stage of the task, the perceptual-motor loop (the upper part of Figure 3) continues to be strengthened.

However, when a memory involved in mind-wandering is accidentally introduced during mastering the task, and no penalty is imposed, the probability of selecting the goal for the default mode of thinking (an activity that was frequently engaged in outside the task) increases. When mind-wandering continues and the goal for the current task is no longer recalled, the model leaves the task.

Mastering Motor Control

The accuracy of the perceptual-motor loop (the upper part of Figure 3) is improved by learning through the task. This learning is controlled by a tracker module in ACT-R 7.27, initially proposed by Anderson et al. (2019), based on the simulated annealing algorithm (Kirkpatrick et al., 1983). This module adjusts the continuous conditions for selecting motor operations based on positive and negative feedback from the environment.

In the model presented in Figure 3, the motor operations include "stop" (release key), "go right" (press the key assigned to the right), "go left" (press the key assigned to the left), and "continue" (continue the previous operation). In this motor operation selection, the distances between the circle and the line (a continuous value) obtained from the perceptual processes in Figure 3 ① are used as conditions. The current model specifically observes two distances, which are visible as two lines drawn on the screen (see Figure 1)[2]: the magenta line showing the distance between the circle and the nearest point on the line and the blue line showing the distance between the circle and the next turn on the line.

The tracker module automatically adjusts the boundaries of these values to select one of the four motor operations ap-

[2]In the human experiment, these lines were removed.

propriately. If this adjustment is not appropriate, the model fails to follow the lines because the circle overshoots the line or executes the operation before it reaches the line. Appropriate coordination in this model is learned sequentially by receiving negative feedback for failing to follow the line. The tracker module has a subsymbolic parameter called temperature, which controls the fluctuations in the boundaries between motor operations. This parameter usually has a high value at the beginning of the task and decreases over time. In other words, the model engages in exploration in the early stages of the task, whereas it exploits the acquired coordination at the later stages. Therefore, it is assumed that the adjustment in boundaries between motor operations converges within a specific range at the appropriate temperature setting, leading to high perceptual-motor performance.

Homeostasis Through Time Perception

As discussed above, the mind-wandering mechanism previously presented (van Vugt et al., 2015) has limitations in connecting physiological mechanisms. To address this issue, ACT-R/Φ (Dancy et al., 2015) integrates ACT-R and physiological mechanisms. However, ACT-R/Φ uses an entirely independent simulator of physiological variables. Therefore, we consider this model to have a unification problem between cognitive and physiological components. Furthermore, because it uses two separate components developed for different purposes, it seems difficult to claim that ACT-R/Φ is a single consistent architecture. Therefore, this study attempts to construct the physiological mechanisms involved in mind-wandering using only the basic modules incorporated in the original ACT-R while basing the concept on ACT-R/Φ.

The concept of ACT-R/Φ is that physiological mechanisms such as homeostasis play the role of modulators adjusting cognitive processes (Ritter, 2009). This idea assumes a correspondence between various physiological indices and subsymbolic parameters in ACT-R. A typical relation is the correspondence between the amount of epinephrine released when the sympathetic nervous system is activated (aroused) and ANS (activation noise s), one of the ACT-R noise parameters. The ANS parameter is used to determine the degree of fluctuation in recalling chunks from the declarative module. When ANS is low, the model exploits highly activated chunks, whereas when ANS is high, the model explores the various chunks. This behavior allows us to understand the arousal level of the model relative to the ANS. In this study, we adjusted the ANS according to the above ideas (small and large ANS representing high and low arousal, respectively) and modeled the arousal changes as the task progressed.

To implement the above relation, this study used the temporal module (Taatgen et al., 2007) built in ACT-R. It is pointed out that temporal cognition is modified by the attention directed to the main task. When the task is performed at high arousal levels, people feel that time flows quickly. In contrast, when the task is performed at lower arousal levels, they perceive a slower time flow. Therefore, we considered that a more integrated architecture could be achieved by expressing the arousal changes with the time perception module (temporal module).

Time perception in ACT-R is controlled by a mental timer (pacemaker). This timer counts the number of ticks (t) that have elapsed since it started, using the equation

$$t_n = a \cdot t_{n-1} + \varepsilon, \qquad (1)$$

where a stochastic noise (ε) is added for each count (n). This equation represents the nonlinear time perception explaining why estimates of time intervals over long periods are less accurate than estimates of time intervals within short periods.

To use this equation for arousal change, this study assumed that n was reset ($n = 0$) when the model perceived new events. Specifically, the reset occurred when the circle fell away from the line or a probe appeared on the display. Thus, the interval between counts increased with the increase in counts until the model received the above events.

In addition, we assumed that the decrease in the accuracy of time perception corresponded to a decrease in arousal over time. Specifically, we introduced the equation

$$ans = k \times t \qquad (2)$$

where k is a coefficient to adjust the decrease in arousal level with respect to time. By manipulating this, we explored the conditions in the U-shaped curve observed in the human experiment.

Simulation

Objective

We proposed that the model could represent an inverted U-shaped curve for task performance according to the optimal level theory. To confirm this behavior, we used the following four indices.

(a) Concentration: Difference in activation between the goal chunks for the current task and default-mode thinking.

(b) Mind-wandering ratio: Percentage of time default-mode thinking occurs in the goal module.

(c) Offline ratio: Percentage of time where the circle does not follow the line.

(d) ANS: Value calculated by Equation 2.

Settings

The simulation conditions were set up by changing the value of k in Equation 2 in three steps (0.01, 0.03, 0.06). The model with a small k corresponded to a highly focused situation, while the model with a large k corresponded to a distracting situation.

Feedback for the tracker module was determined when the model perceived the environment (Figure 3 ①). The tracker module gave the model positive feedback of 10 when it was online and negative feedback of 10 at the moment it went offline.

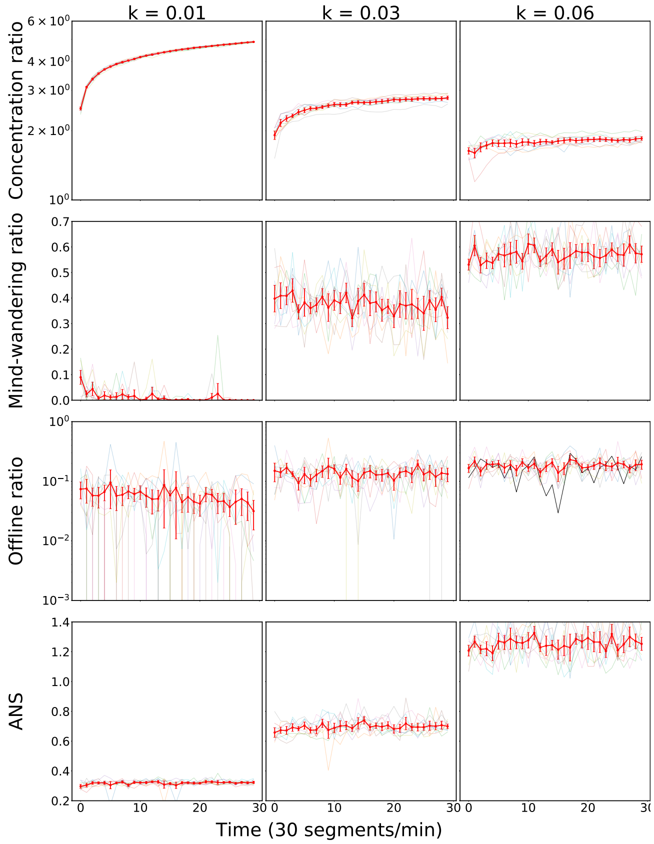

Figure 4: Simulation results. From the top, the concentration rate (logarithmic vertical axis), mind-wandering rate, offline rate (logarithmic vertical axis), and activation noise (logarithmic vertical axis) are shown. The red line is the mean of 10 runs; the error bars are the standard error multiplied by 0.5.

The simulation duration was set to 30 min to match that of the human experiment, and, as with the humans, 30 one-minute-long courses were used. In addition, at the beginning of the task, the goal for the current task was set to be more accessible to recall than the goal for default-mode thinking[3].

Results

Figure 4 shows the simulation results. These results show the effect of k on the four indices. The smaller-k conditions ($k = 0.01, 0.03$) are associated with a higher concentration ratio, corresponding to less mind-wandering, a lower offline ratio, and lower ANS. In addition, the concentration ratio increased over time in those conditions. This trend is also reflected in the decreasing trend of the offline ratio in the smallest-k condition ($k = 0.01$), indicating that a small ANS fluctuation strengthens the current task's goal and keeps the task execution stable.

[3]The activation was manipulated by parameters of "chunk creation time" in ACT-R. The chunk creation time for for the current task was set to 800, where as that for default-mode thinking was set to 300.

In contrast, the task performance did not increase over time in the high-k condition ($k = 0.06$), though the motor learning progressed. Although the average trend of offline ratio is almost flat in the higher-k conditions ($k = 0.03, 0.06$), some cases improved the task performance in the middle of the task. The thick black line highlights the typical case, showing such improvement in the middle of the task. As seen in this case, some cases show a U-shaped curve, which was also observed in the human experiment.

Conclusion

This study aimed to construct a model of arousal changes over time by integrating the primitive ACT-R modules. To achieve this goal, we first collected human behaviors in a simple perceptual-motor task and observed the U-shaped curves in some participants. We constructed a model of arousal change to reproduce such human behaviors by combining the perceptual-motor process, mind-wandering mechanism, time perception, and motor skill acquisition. These modules have different types of dynamics, and combining them is expected to reproduce the nonlinearity of arousal change, namely the theory of the optimal level of arousal. As a result, inverse U-shaped performance transitions over time in the task were observed in some cases.

The significance of this study is that physiological processes, which were previously considered independent modules, are represented in the ACT-R primitive modules. In contrast to previous studies (Gunzelmann et al., 2009, 2012) that used a computational physiological model, our model is original in that it integrates components that initially came from different backgrounds. We consider that to achieve a truly integrated understanding of the human mind, the approach of adding ad hoc parameters to the architecture is not exactly sufficient. This study can be viewed as an endeavor in refactoring complex cognitive architecture to be a unified theory of human cognition.

In the future, we need to proceed further with this approach. For example, we only manipulated the activation noise parameter reflecting the arousal level in this study. However, ACT-R includes several other noise parameters in the production, tracker, and temporal modules. Therefore, we need to explore methods of integrating such different noises. We also need to seek valid assumptions behind the correspondence between ACT-R's noise level and the physiological process through this process.

The experiment and model should also be improved. Although we manipulated environmental factors (background musics) in the human experiment, we did not find clear results. Revealing the robust factors leading to inverse U-shaped learning is critical for obtaining clear correspondence between human behavior and model simulation. By improving the experimental method and the model, we can explore a more plausible representation of the optimal arousal level.

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