

An ACT-R approach to investigating mechanisms of performance-related changes in an interrupted learning task

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Abstract

Learning constitutes an essential part of human experience over the life course. Independent of the domain, it is characterized by changes in performance. But what cognitive mechanisms are responsible for these changes and how do situational features affect the dynamics? To inspect that in more detail, this paper introduces a cognitive modeling approach that investigates performance-related changes in learning situations. It leverages the cognitive architecture ACT-R to model learner behavior in an interrupted learning task in two conditions of task complexity. Comparisons with the original human dataset indicate a good fit in terms of both accuracy and reaction times. Although interruption effects are more obvious in the human data, they are prevalent as well in the model. Furthermore, the model can map the learning effects, particularly in the easy task condition. Based on the existing mapping of ACT-R module activity with fMRI data, simulated neural activity is computed to investigate underlying cognitive mechanisms in more detail. The resulting evidence connects learning and interruption effects in both task conditions with activation-related patterns to explain changes in performance.

Keywords: Learning; Interruption; Cognitive performance; ACT-R; Simulated neural activity

Introduction

As an omnipresent requirement, learning happens throughout the entire life. From speaking the first words as a child to operating new technical devices as an elderly, the establishment of knowledge structures constitutes a core outcome of learning processes of all kind. Previous research indicated benefits in terms of performance, once already existing knowledge structures can be applied automatically (e.g., Wirzberger, Herms, Esmaeili Bijarsari, Eibl, & Rey, 2018). Besides these internally occurring process-related changes, externally induced situational characteristics such as interruptions also effect cognitive performance. Interruptions are highly prevalent across various contexts in

daily life, including learning situations (e.g., Scheiter, Gerjets, & Heise, 2014). They can be described as usually neither planned nor expected cognitive breaks in the task performed up to that time (Brixey et al., 2007). To avoid or at least minimize resulting impairments, the interplay of interruptions and learning effects needs to be inspected in more detail on a cognitive level. On this account, computational cognitive modeling approaches offer a promising way to gain insights into underlying dynamics.

Based on that, the current paper introduces an ACT-R model that performs an interrupted learning task and is inspected in terms of behavioral parameters and underlying neural processes. After briefly describing the modeled experimental task and core results from human data, the paper outlines characteristics of the cognitive architecture ACT-R (Anderson, 2007). Following an explanation of the underlying model concept, the behavioral results obtained from the model runs are presented and compared with the described human data. The subsequent chapter addresses model performance on a neural level by reporting results from simulated fMRI analyses.

In summary, the obtained evidence highlights the connection of observable changes in cognitive performance due to learning and interruption effects with the mechanism of activation.

Task outline

The task setting underneath the cognitive model is reported in more detail in Wirzberger, Esmaeili Bijarsari, and Rey (2017). Participants in this study had to learn four abstract geometric symbol combinations via trial and error by verifying feedback (Shute, 2008) over a total of 64 trials. As outlined in Figure 1, they were shown the first part of the combination at the beginning of a trial and had to select the appropriate response by mouse click. Afterward, they were informed about the correctness of their response as well as

the correct response in terms of errors. Task complexity was represented by the number of symbols in a defined order that formed a combination. In the easy task condition, symbol combinations consisted of two symbols (input-response), whereas in the difficult task condition three symbols (input-input-response) formed a combination.

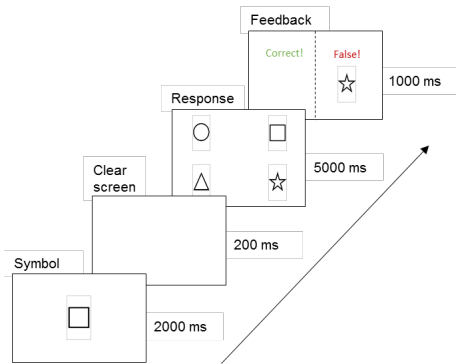


Figure 1: Sample learning trial in the easy task condition (adapted from Wirzberger et al., 2017).

At five pre-defined stages over the task (i.e., after trials 8, 24, 32, 40, and 56), an interrupting visual search task was induced. As displayed in Figure 2, it required participants to count the number of two out of four types of geometric symbols on a visual search screen and provide their responses afterward. The screens were accompanied by an instruction on the target symbols. A high similarity to the symbols used in the learning task (Gillie & Broadbent, 1989; Trick, 2008) and an appropriate task duration (Monk, Trafton, & Boehm-Davis, 2008) should ensure its interrupting potential.

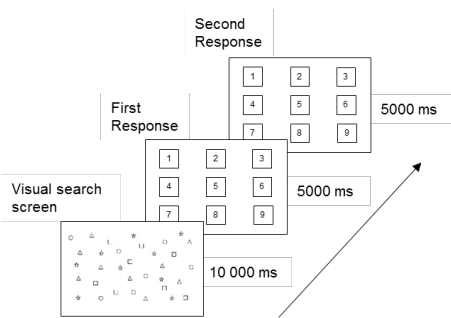


Figure 2: Sample interruption trial (adapted from Wirzberger et al., 2017).

Experimental results

In terms of reaction times in correctly solved trials, Figure 3 shows that participants speed up with increasing task progress in both conditions. Standard errors decrease over trials due to the increasing number of correct reactions. In addition, resumption effects are observable in both conditions, but are more distinctive in the easy task condition.

Approaching accuracy, Figure 4 indicates that participants in the difficult task condition learn slower, but in the end both conditions reach a comparable level. Again, resumption effects are more prevalent in the easy task condition. These effects raise the question which cognitive mechanisms underlie the observed learning- and interruption-related patterns.

Computational cognitive modeling

Building on vested psychological evidence on human information processing, computational cognitive modeling approaches offer the opportunity to derive well-founded explanations of behavioral phenomena. The idea of building models to explain cognitive phenomena has already been discussed by Wegener (1967), who outlined the indicative value of an electronic simulation of mental processes for deriving and validating the related hypotheses.

Constituting a prevalent and broadly used production-based approach, ACT-R (Anderson, 2007) is particularly characterized by its modular brain-inspired structure. The included *modules* represent goal planning (goal module), declarative memory (declarative module), intermediate problem states (imaginal module), action coordination (procedural module), the handling of visual and auditory inputs (visual and aural module), and motor and vocal outputs (motor and vocal module). The mapping of these modules on corresponding regions-of-interest (ROIs) in the human brain has been validated with fMRI data by Borst, Nijboer, Taatgen, van Rijn, and Anderson (2015). For instance, when a model retrieves content from declarative memory, increased activity in the declarative module corresponds to activity in the prefrontal cortex, which has proven to be sensitive to both retrieval and storage operations. Activity in the goal module corresponds to activity in the anterior cingulate cortex, which is involved in higher-level control functions such as attentional allocation or performance monitoring. *Buffers* with limited capacity serve as interface between modules and enable their communication. They can hold one information element at the same time, representing existing limitations in information processing resources.

ACT-R uses a hybrid approach of both symbolic and subsymbolic mechanisms: *chunks* of information from declarative memory are retrieved not only on the match of content but also based on their level of activation. Activation is calculated from the history and context of use of a chunk and has to exceed a defined threshold to be eligible for selection. The full equation for each chunk i involves the components displayed in the subsequent equation:

$$A_i = B_i + \sum_k \sum_j W_{kj} S_{ji} + \sum_l PM_{li} + \epsilon. \quad (1)$$

The recency and frequency of use of the chunk i is reflected by the *base-level activation* B_i . Each time a chunk is presented, its base-level activation is increased, which decays as a power function of the time since that presentation. These decay effects are summed up and then transformed

logarithmically. With the *spreading activation* mechanism (Anderson, 2007), ACT-R accounts for the fact that activation is distributed across related chunks that share information elements. It is represented in the equation by W_{kj} , the amount of activation from source j in buffer k , and S_{ji} , the strength of association from source j to chunk i . W_{kj} and S_{ji} are summed over all buffers that provide spreading activation and all chunks in the slot of the chunks in buffer k . As humans sometimes retrieve related but ultimately wrong information from memory, ACT-R further includes a partial matching mechanism. Based on initially defined similarities between chunks, a mismatch between request and actual retrieval is calculated. The higher the mismatch, the more the activity of the chunk is penalized (Lebiere, 1999). In the equation, P reflects the amount of weighting given to the similarity in slot l and M_{li} represents the similarity between the value l in the retrieval specification and the value in the corresponding slot of chunk i . M_{li} is summed over the slot values of the retrieval specification. The value of ϵ represents noise, which is computed at the time of a retrieval request for each chunk.

Model concept

Each model run starts with an initial set of the task goal to the symbol learning task, which is assumed to result from the previously read instruction. In the following, each learning trial builds upon three task-related steps: at first, the presented symbol is encoded, which is repeated for the second symbol in the case of the difficult condition. This procedure stores an intermediate representation of all encoded visual content in the problem state (Borst, Taatgen, & van Rijn, 2010, 2015; Nijboer, Borst, van Rijn, & Taatgen, 2016), for instance, the input symbols ‘square – circle’ in the difficult condition. Next, the model attempts to retrieve the associated response symbol from declarative memory. In the second step, a response is selected from the provided opportunities on the screen, either according to the retrieved chunk or by random choice in case of no successful retrieval. In the final step, the model searches for visual feedback on the given response and, in the case of a false response, an update of the existing intermediate representation. The final information contains both the input and the correct response parts of the symbol combinations, such as ‘square – circle – square’ in case of the previous example.

In the first trials, there is no sufficiently matching content or no content at all to retrieve, resulting in slower and less accurate responses. After being presented the input symbols several times and retrieving related content from declarative memory, the model performance gets increasingly faster and more accurate due to increasing chunk activation. In the current task, the above outlined spreading activation mechanism particularly effects the difficult task condition. In more detail, symbol combinations including the same input symbols, such as ‘square – circle’ and ‘circle – square’, obtain equal activation, independent of the correct symbol

order. Following the concept of element interactivity in instructional research (Sweller, 2010), task demands increase with more logically interrelated information elements that have to be processed simultaneously. In the current task, the symbols that form a combination can be regarded as information elements that are related to each other by order. Without considering the order information, a wrong input-response association is more likely to be retrieved, which is then penalized by the partial matching mechanism. In consequence, due to more potentially mismatching information, the chunks in the difficult condition receive less activation and are harder to retrieve.

Following a goal change due to the bottom-up triggered saliency of the interrupting task, the task procedure involves the steps of searching, counting, and responding to the indicated target symbols. Using a color to indicate the task switch followed the model implemented by Wirzberger and Russwinkel (2015) and represents the immediate attention to the related screen change. Tying in with evidence on pre-attentive and attentive processes in the visual module of ACT-R (Nyamsuren & Taatgen, 2013), the second visual-location request in the visual search is enhanced by additional information on stimulus color that relates to distinct characteristics of the presented symbols. After finishing the counting part that also employs the problem state (Borst et al., 2010, 2015; Nijboer et al., 2016), on each of the two response screens the model encodes the requested symbol and attempts to retrieve the potential answer. Again, the possibility to retrieve a wrong answer persists due to the partial matching mechanism. When resuming the learning task, in line with Altmann and Trafton (2002) the model attempts to retrieve the previous task goal and thus restores its representation. Emerging interruption effects can be attributed to a decay in the activation of chunks related to the learning task that slows down subsequent retrieval requests (Borst et al., 2010, 2015; Trafton, Altmann, Brock, & Minz, 2003).

Model comparison

The inspected model data based on $n = 100$ model runs in each condition to obtain robust conclusions from the average model performance. A further goal was to achieve a balanced fit pattern across both accuracy and reaction time in either condition. Compared to a base model¹ that includes neither spreading activation nor partial matching, the overall root mean squared scaled deviation (RMSSD) decreased by almost one standard error and fit indices were quite aligned.

Besides the shared prevalence of interruption effects, in both conditions the model speeds up in reaction time over trials. The visual inspection in Figure 3 indicates that it can map the decreasing progression particularly in the difficult task condition. However, the model performs slightly slower than human participants during most of the trials. On the level of numerical goodness-of-fit indices, the model achieved

¹ In addition to the base model and the reported model, models including either only spreading activation or partial matching were

inspected. Due to the superior fit, only the final model that applies both mechanisms is reported.

RMSSD = 2.16 and $R^2 = 0.58$ in the difficult task condition. Apart from a subtler decrease in the beginning, the mapping also fits quite well for later trials in the easy task condition. On a numerical level, RMSSD = 1.67 and $R^2 = 0.52$ resulted in this condition.

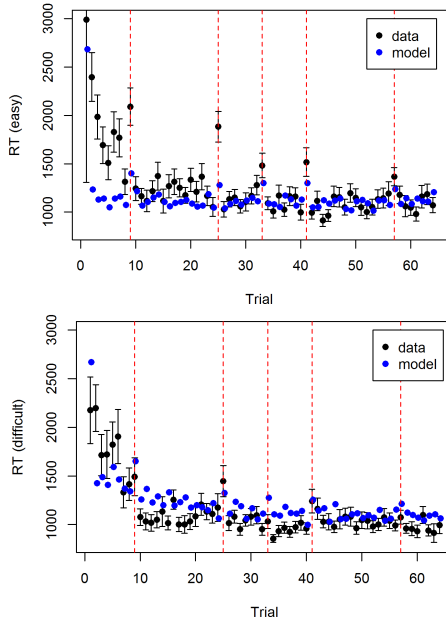


Figure 3: Comparison of human and model behavior in terms of reaction time. Red dashed lines indicate the first trial that immediately follows an interruption.

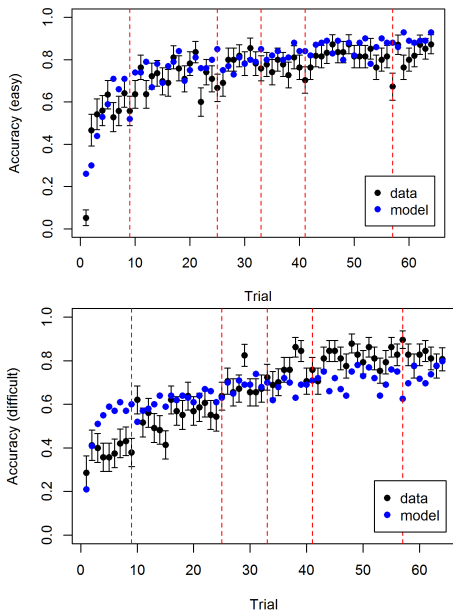


Figure 4: Comparison of human and model behavior in terms of accuracy. Red dashed lines indicate the first trial that immediately follows an interruption.

For accuracy, Figure 4 indicates that the model can map the progression in human behavior quite well in the easy task condition, although it achieves a higher performance in the end and shows a subtler reflection of interruption effects. On a numerical level, RMSSD = 1.51 and $R^2 = 0.69$ were achieved in this condition. The model in the difficult task condition learns slower compared to the easy task condition, but still faster than the human participants. However, apart from the nearly perfect location match in the last data points, it cannot fully map the final increase in the human data. The goodness-of-fit indices for the difficult task condition resulted in RMSSD = 2.07 and $R^2 = 0.57$.

Simulated fMRI data

Based upon the already mentioned mapping of activity in ACT-R modules on defined brain regions, simulated neural activity in predefined ROIs is computed to investigate underlying cognitive mechanisms in more detail (Borst & Anderson, 2017). This approach uses the recorded start and end times of module activity to simulate a signal comparable to the blood oxygenation level obtainable via fMRI, which shows peaks about 4-6 s after the occurrence of neural activity. In the first step, the activity of each inspected module is represented as 0-1 demand function and convolved afterward with the hemodynamic response function displayed in Figure 5. As an example, related to the task of the current model, longer retrieval times due to lower levels of chunk activation would result in increased activity in the declarative module. Such patterns are expectable in early stages of the task, with increased task difficulty, or caused by decay during an interruption, and would be observable by higher peaks in the resulting simulated signal.

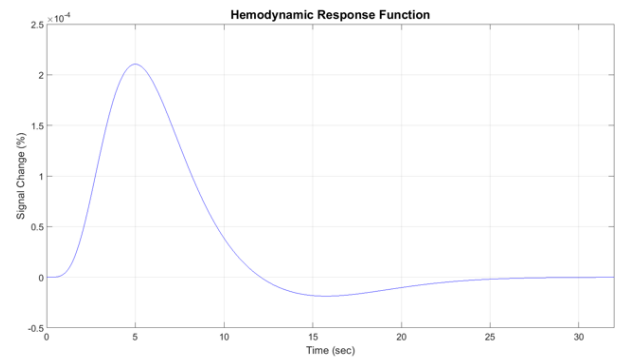


Figure 5: Hemodynamic response function (adapted from Borst & Anderson, 2017).

Prevalent changes in the declarative module activity across the learning task, which simulates activity in the prefrontal cortex, are displayed in Figure 6. Whereas blue lines represent the first third of the trials in the task, the red lines indicate the middle third of the trials, and the black lines refer to the last third of the trials. The curves predict a decrease in cognitive activity in later task stages in both conditions in the prefrontal cortex due to task-inherent learning processes. In the difficult task condition, represented by the dashed lines, a

higher level of activity is prevalent across all stages, with a particularly distinctive peak across early task stages. As already outlined, this relates to increased retrieval demands from lower levels of chunk activation.

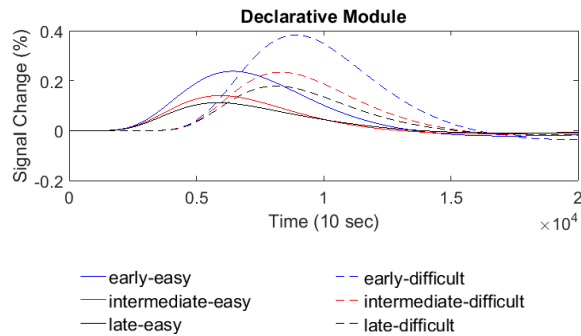


Figure 6: Simulated neural activity in the declarative module (corresponding to activity in the prefrontal cortex) across stages of the learning task.

Comparisons between the interrupting task and the learning task are depicted in Figure 7 and Figure 8. These include a separate visualization of the resumption phase (red lines), defined as the first trial that immediately follows the interrupting task. Across all inspected modules, activity levels in the interrupting task do not differ between both task conditions, since the solid and dashed blue lines overlap almost all the time. For both the declarative module, relating to the prefrontal cortex, and the goal module, relating to the anterior cingulate cortex, a higher activity across resumption trials compared to the remainder of trials in the learning task (black lines) is predicted for both conditions. In addition, differences between task conditions during the resumption phase are predicted for the anterior cingulate cortex and indicate higher levels of activity in the easy task condition. Even if these effects are less obvious in the behavioral model data, this also corresponds to the higher prevalence of resumption effects in the easy condition in the human data.

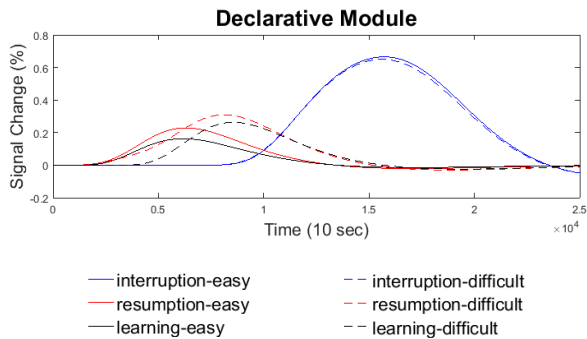


Figure 7: Simulated neural activity in the declarative module (corresponding to the prefrontal cortex) across interruption, resumption, and learning stages.

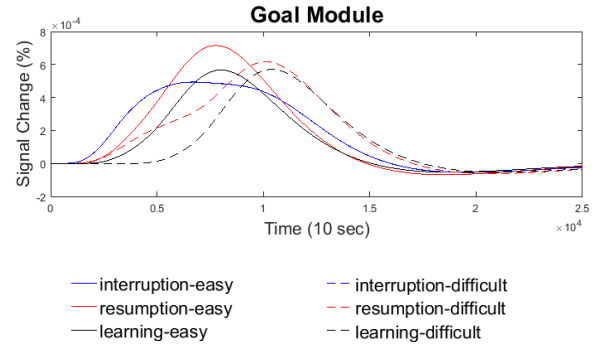


Figure 8: Simulated neural activity in the goal module (corresponding to the anterior cingulate cortex) across interruption, resumption, and learning stages.

Discussion

The current model explores cognitive mechanisms that underlie changes in performance due to the inserted interruptions and task-related learning processes. Comparing model performance across both conditions on a behavioral level, the obtained results indicate a good fit in terms of reaction times and accuracy. The model can map both the learning-related increase in performance and the decrease in performance due to experiencing an interruption. A potential improvement to increase the visibility of interruption effects in the model might involve adjusting when the model starts to retrieve information related to the correct response symbol. For the difficult task condition, the accuracy result pattern hints on a shift in task-related strategies. Due to the small number of learned symbol combinations, over time people in the difficult condition might have applied a more heuristic encoding strategy with focus on the first symbol, directly mapping task execution in the easy task condition. Taking this into account, the current modeling approach offers potential for future work by explaining such strategy shift with a more complex model on both the level of production rules and corresponding selection mechanisms.

The pattern observed in the simulated neural activity relates to the fact that the model needs to invest a higher amount of declarative memory resources upon each retrieval request in the early task stage due to the lack of suitable chunks and lower levels of chunk activation. The smaller level of cognitive activity with increasing task progress emphasizes the prevalence of learning effects in both conditions, as existing content in the declarative memory receives increasingly higher activation and thus can be retrieved faster and more accurately. In the difficult task condition, invested declarative resources are constantly higher across all stages, which by closer inspection relates to effects of spreading activation and the increased influence of partial matching that penalizes chunk activation and extends retrieval times. Increased levels of resumption-related activity in the declarative module arise from the activation decay in chunks related to the acquired symbol combinations. Observable differences in goal activity during the resumption stage align well with predictions stated by the memory-for-

goals model (Altmann & Trafton, 2002). They relate to the demand to rebuild the goal-representation of the learning task after each interruption. The obtained fMRI predictions will be compared with human data sets in the next step.

Conclusion

Taken together, the obtained results emphasize the importance of considering activation-related dynamics when approaching changes in performance in learning situations. The outlined cognitive modeling approach inspects the influence of both internal and external factors in these contexts and can be taken as promising step to investigating related patterns of cognitive resource investment. Since it extends beyond human experiments and model-based behavior on a neural level, it provides a more detailed understanding, which is crucial for developing adequate support and minimizing harmful effects.

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