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Clustering to Determine Interconnected Activities in Supervisory Control Tasks of Pilots

Karl Tschurtschenthaler and Axel Schulte

University of the Bundeswehr München, Bavaria, Germany

ABSTRACT

We propose a method that allows pilot activity determination by clustering pilot actions. Such systems are of great interest for assistance systems that adapt to pilot performance. However, the determination of supervisory control tasks is non-trivial since they can only be observed indirectly through pilot actions. Therefore, our former approach of determining activities based on evidential reasoning resulted in a highly fragmented pattern of recognized tasks over time. To address this, we suggest clustering these scattered patterns into partitions. This better reflects the activities of the pilot. To evaluate the approach, we conducted an experiment in a fast-jet simulator with 11 participants. Using our former approach, we then determined the activities and applied k-Means clustering to find partitions of interconnected activities. Lastly, we evaluated whether these could be compared to the activities reported by the participants. The results show that clustering may not be an effective activity determination method for adaptive assistance systems. These systems represent a necessity in assisting pilots in aerial Manned-Unmanned Teaming applications.

Keywords: Activity recognition, Human factors, Human-machine interaction, Adaptive assistance, Agents, Human-autonomy-teaming, Manned-unmanned-teaming

INTRODUCTION

Aerial Manned-Unmanned Teaming (MUM-T) plays a key role in future military operations. In these missions, unmanned aerial vehicles (UAVs) are guided by manned aircraft. Accordingly, the pilots' tasks are broadened by a large number of supervisory control tasks in the cockpit. These tasks include planning, monitoring, and guidance of highly automated vehicles (Chen, Barnes and Harper-Sciarini, 2011). It is known that various problems related to human factors occur in such human-machine interactions (Parasuraman et al., 1992; Parasuraman and Riley, 1997). To resolve these problems, human-centered automation systems incorporate human factors in their design (Billings, 1991). These can also be referred to as adaptive assistance systems.

The working principle of adaptive assistance systems is based on the evaluation of the pilots' mental states (e.g. situation awareness or workload) (Feigh, Dorneich and Hayes, 2012). This is required since assistance agents are designed to sense a demand for assistance and then initiate an adequate intervention strategy. To do this adaptively, the agent must also be aware of the context (Colman et al., 2014).

One key context variable for an appropriate decision on the application of an intervention strategy: *what are pilots doing and what goals are they trying to achieve?* In the literature, this is often referred to as pilot activity (Schulte, Donath and Honecker, 2016). Moreover, the determination of the activity must be carried out in real-time. Therefore, assistance agents continuously estimate the task context of the pilot and utilize it as a decision criterion for assistance.

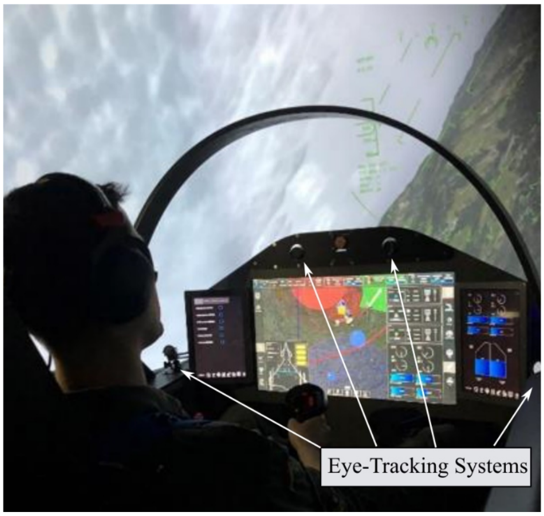


Figure 1: A Pilot operating UAVs interacts with the cockpit interface during an experiment. The touch-sensitive tactical map is used to task the UAVs. Each gaze interaction is tracked and passed by the eye-tracking system. Then, the observation generation in the aircraft interface uses the semantics of each gazed instrument to infer what information the pilot perceived at a given time, according to (Mund and Schulte, 2017).

There are several methods for generating observation data for activity recognition. However, activity recognition systems for adaptive assistance require context-rich observations. In this work, we capture manual interactions (e.g., button presses) with a touch-sensitive display and gaze interactions (e.g., looking at a cockpit instrument) with a gaze-tracker. From this, semantic observations are generated that contain information about which instrument was touched or looked at. This mechanism makes them context rich. Figure 1 shows our setup (cockpit of a fast-jet simulator) in which we apply this mechanism.

Evidential Reasoning Approach for Pilot Activity Determination

(Honecker and Schulte, 2017) developed a method that recognizes the tasks being performed by the pilot in real-time. They consider this set of tasks as the pilot activity. They used evidential reasoning for the determination of tasks. For the recognition, each context-rich observation is interpreted as evidence in the sense of the Dempster-Shafer theory. The degree of *belief*, *doubt*, and *ignorance* (Dempster-Shafer Triplet) for each evidence was evaluated experimentally or defined by expert knowledge. The recognition model considered task dependencies in a hierarchical task model.

Motivation for This Study

Figure 2 shows results using the described approach in a combat situation in form of a task-time plot. The vertical axis lists the performed tasks. The results were generated by the activity recognition in one of our fast-jet simulators. In the scenario, the task was to suppress a hostile SAM-Site (surface-to-air missile) using an unmanned vehicle. Therefore, the pilot delegates the UAV and monitors the automation task.

The pattern of recognized tasks in

Figure 2 appears heavily fragmented in a temporal representation. This mostly originates from the switching of visual attention during the supervisory control tasks. These tasks can hardly be performed concurrently and are therefore characterized by fast attention shifts.

Moreover, the approach by (Honecker and Schulte, 2017) can only determine tasks which are directly observable by human-machine interactions. Thus, the results solely show granular, low-level tasks (e.g., button-presses indicate the task *Start EO Stream*). However, mostly higher-level tasks can be associated with mission tasks and are thus relevant for pilot assistance. According to (Tschurtschenthaler and Schulte, 2023), they occur in the pilot's working memory and are therefore hidden from the observer. The importance of the determination of higher-level tasks from the evidential-reasoning data approach was also addressed in (Brand and Schulte, 2021).

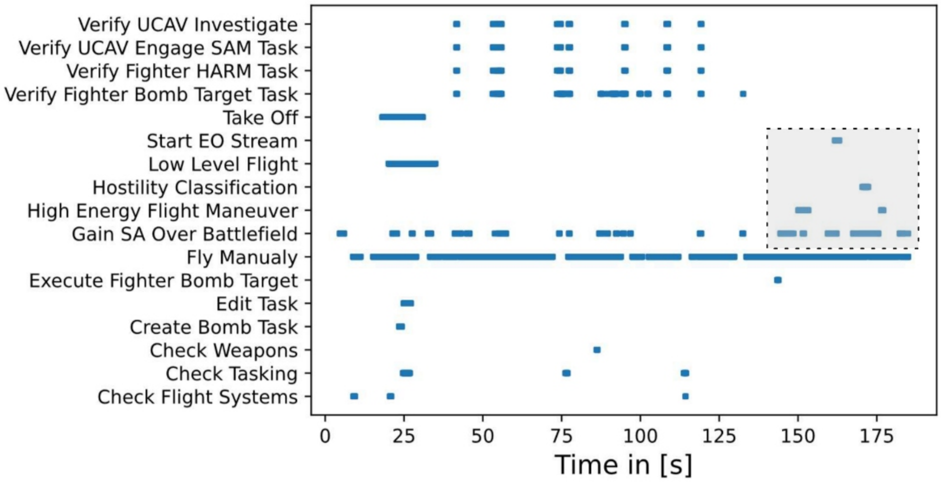
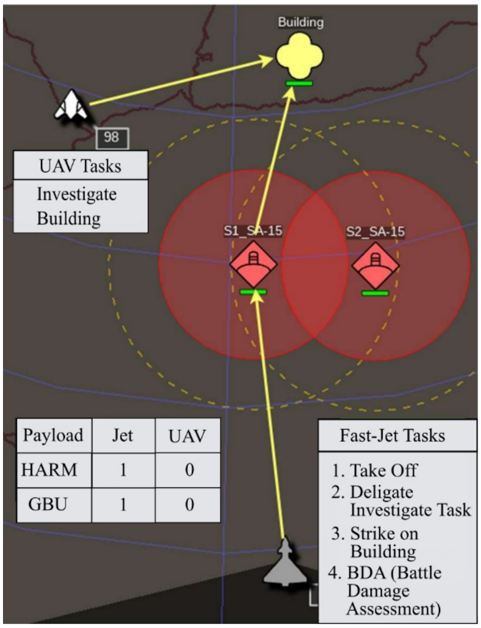


Figure 2: Activities recognized over time in form of a task-time plot. Data was generated using evidential reasoning. Degree of belief > 0.75 is colored blue. The data shows a typical multitasking situation in MUM-T: The pilot delegates a UAV to attack a SAM-Site and controls the aircraft in parallel (data was collected as part of this study). Tasks in the grey area occur in the context of a superordinate sensor classification task.

We observed that activity recognition results are fragmented, especially for supervisory control tasks. Due to their high number in MUM-T missions, the evidential-reasoning approach misses a higher-level reasoning of the output data. For an expert, some of the scattered tasks are interconnected and represent an occurring superordinate task. Partitioning the task-time plot could be a solution to overcome the issue with supervisory control tasks. For instance, the tasks in the grey section of Figure 2 represent a single classification task of the SAM-Site. This suggests that the scattered tasks share interconnectivity in context of a higher-level task.

This paper presents a method to tackle the determination of the interconnected partitions by unsupervised clustering. For this, we conducted a data collection experiment and used cluster methods on recognized tasks by (Honecker and Schulte, 2017). Lastly, we compared the resulting clusters with the reported activities of the participants.



UAV Tasks

Investigate Building

Payload	Jet	UAV
HARM	1	0
GBU	1	0

Fast-Jet Tasks

1. Take Off
2. Deligate Investigate Task
3. Strike on Building
4. BDA (Battle Damage Assessment)

Figure 3: Tactical situation of the experiment block 1a. The map shows the jet (bottom), the hostile SAM-Site (red), and the UAV (white). The tasks of the participant and automation are shown in the info boxes (added for this figure and not visible to the pilot).

EXPERIMENT

Experimental Setup

For the study, we used a fast-jet simulator as shown in Figure 1. It covers flight, UAV guidance and mission planning tasks within a MUM-T Scenario. It has an exterior view with a heads-up display and three touchscreens as main display elements. Manual interaction with the fighter cockpit is carried out by HOTAS (Hands on Throttle and Stick) for flight control. All other manual interaction with the system is done using touchscreens. A four-camera, 60 Hz eye-tracking system from SmartEye® was used for data acquisition. The system can capture gaze on the external view and touchscreens. For activity data generation, we used semantic observation generation and the activity recognition from (Honecker and Schulte, 2017).

Experimental Design

The experiment consisted of six experiment blocks. The duration of each block was around 5 minutes and included a main objective to be achieved. It was either the suppression of a hostile building or SAM-Site. The main objective demands execution of several tasks which are relevant in the context of MUM-T. Thus, task performance was kept as naturalistic as possible.

In addition, the difficulty of achieving the main goal increased with each block. The difficulty was intended to be mentally demanding through time and payload constraints rather than complexity. It was decided not to randomize the order of the blocks among participants, because we wanted to ensure that every participant experienced the same increase in difficulty. Figure 3 gives an overview of the goal, tasks, and the tactical situation of experiment block 1a.

While designing the experiment, a hierarchical task model for the activity recognition was created. It includes all directly observable and non-directly observable, superordinate tasks. These tasks were relevant for achieving the main objectives of the experimental blocks. Hereby, hierarchically 12 (first level), 4 (second level) and 1 (third level – root) superordinate tasks were created.

Participants

We conducted an experiment with 11 participants (male: 10; female: 1) aged between 20 and 34 (mean age 23.6 y; SD: 3.9y). All participants had a high level of experience either in video games (mean hours per week of video games: 6.9h; SD: 7.8h), flight simulators (mean total hours in a fight simulation: 42.9h; SD: 83.1h) or flight experience (mean hours of flight experience: 3.9h; SD: 3.1h). Questionnaires showed that all study participants demonstrated a high level of motivation during the study (mean motivation [0; 10]: 9.0; SD: 0.9). To further increase motivation, pilot performance was assessed with a score. Several factors were included in the score, such as resource consumption (payload, fuel, etc.), asset loss and total mission time. For gaze measurement, each participant was calibrated with the eye-tracker just before the start of the experiment. Two of the participants wore contact lenses for the experiments. Eye-tracking calibration data were found to be good (mean accuracy for left and right: 1.71°; SD: 0.35°). All participants provided written informed consent.

Procedure

Training for each participant took between two and three hours. Each training consisted of scenarios to train the basics of flying, UAV guidance, sensor- and mission-management. Each participant had to successfully complete each task (required in each block) at least once. This was to ensure that each participant was sufficiently familiar with the functions required for the experiment.

Before each experiment block, the participant received a short briefing about the mission objective and if constraints applied for the block. The participant was not able to see the tactical map of the block until the simulation started. We chose this approach to capture gaze during first sight of the tactical situation. After each block, the score was reported to the participant.

After the experiment, a debriefing was conducted with the participants to protocol what tasks were executed during the block experiments. For this, we asked them to set labels in a task-time plot. During the debriefing, the replay of the simulation was shown to the participants.

Data collection was followed by cluster analysis using the Python packages *Pandas* and *SciKit-Learn* (McKinney and others, 2010; Pedregosa et al., 2011).

CLUSTERING OF PILOT ACTIVITIES

There are different known methods in clustering for activity recognition, as reported in (Colpas *et al.*, 2020). We decided to use k-Means clustering (kMC) (centroid-based clustering method). It appears to be the most used method in unsupervised activity recognition and a good starting-point for this study. For the clustering itself, we used a two-staged clustering procedure: (1) Sorting the tasks on the vertical task scale (as in Figure 2), and (2) applying kMC.

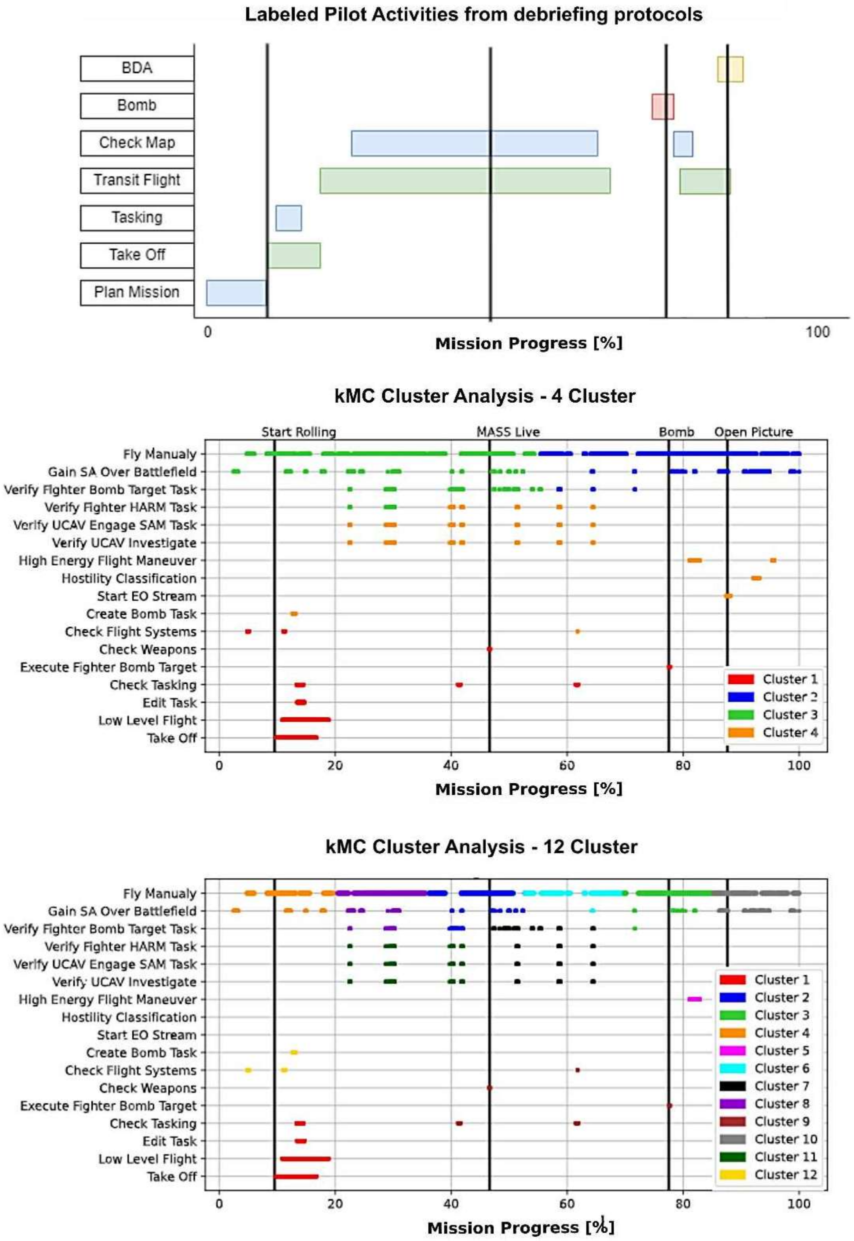
The preprocessing step of sorting is imperative: kMC groups data points together based on the minimized distance to the cluster centroids. However, this cannot be natively applied to nominal scales (see alphabetically sorted vertical task scale in Figure 2). For this, one needs a sorting and distance assumption for the tasks in the vertical scale. For the first stage, we chose two sorting strategies:

1. Model-based sorting (MBS): (Honecker and Schulte, 2017) used a task model to group tasks. Thus, it is plausible to use the task model structure as a basis for sorting the task scales. Sorting was done manually.
2. Connectivity-based sorting (CBS): Reordering of task scales can also be done by searching for connectivity using agglomerative clustering. Such approaches can be used without prior knowledge and reorder items on a scale based on the minimal distance to each other. Using this heuristic, tasks which occur simultaneously are grouped together. We used hierarchical clustering as an agglomerative clustering method. Thus, the sorting was done by computation.

kMC requires a predefined cluster number for clustering. We associated the clusters with superordinate tasks from the task model. Therefore, we decided to use 4 and 12 as number of clusters. The Elbow method suggested an optimal number of 4 clusters for most of the data plots.

After the preprocessing with MBS/CBS and clustering with kMC with the cluster number of 4 and 12, we inspected the quality of the cluster results.

Inspection was done by visually comparing the task-time plots of the debriefing protocols with the clustered plots. Subsequently, the quality was then scored.



Labeled Pilot Activities from debriefing protocols

kMC Cluster Analysis - 4 Cluster

kMC Cluster Analysis - 12 Cluster

Figure 4: Clustering results from a single participant in experiment block 1a: Task-time plot from the debriefings (top), results of the kMC task-time plot for 4 (mid) and 12 clusters (bottom). Prior to the kMC, CBS was applied to the activity recognition data. The black vertical lines are considered as events (e.g., *Start rolling*: Begin of Take Off). The long duration task *Check map* and *Transit Flight* are determined by the green and yellow clusters in the 4-cluster-plot.

We also wanted to see if the activity data of all participants led to comparable cluster results to assess reproducibility. To do this, we clustered each participant's cluster centroids of for each experiment block. Then we used the Cluster-Sum-of-Squares (SSE) to determine the scattering magnitude of all centroid points. We had the assumption that participants showed more similar results which a lower SSE.

RESULTS

Figure 4 demonstrates the clustering results for a single participant in the block experiment 1a as an example. Data was processed using CBS and kMC (4 and 12 clusters). Note that the tasks on the vertical axis are sorted by connectivity when CBS was used (compared to Figure 2).

Table 1. Scores of clustering results created by visual inspection. Score ranges from 0 to 10 (10 is the best, 0 is the worst).

Clustering Methods	Mean Score	Standard Deviation
CBS and 4 Clusters	6.8	1.9 (27.4 %)
MBS and 4 Clusters	9.4	0.9 (10.2 %)
CBS and 12 Clusters	6.9	1.8 (25.5 %)
MBS and 12 Clusters	9.0	1.2 (13.1 %)

By visual inspection, someone can see that long-duration-tasks (LDTs) show a better match using kMC with 4 clusters (e.g., LDTs like *Transit flight*). We found that this is mostly true for all participants and blocks. Short-duration-tasks (SDTs) in kMC with 12 clusters slightly better matched with the reported activities. However, SDTs are often grouped together in the plots using kMC. In addition, we found that larger clusters (e.g., in LDTs like *Transit flight* or *Check Map*) are often sliced into smaller clusters.

In all approaches, concurrent multitasking for SDTs is difficult to capture by clusters. This can also be seen in the *BDA*, *Bomb*, *Check Map* and *Transit Flight* tasks at the end of the experiment block in Figure 4.

The scoring of the results by visual inspection can be seen in Table 1. The MBS showed better agreement between the debriefing protocols and the cluster results. Also, the score standard deviation in MBS was much lower. The use of expert knowledge in form of a task model seems to be more reliable for grouping tasks than an agglomerative clustering approach. This originates mostly from the grouping assumption by CBS which is based on connectivity by time. However, this connectivity assumption is not fully satisfied in multitasking situations: In these situations, CBS groups tasks even though they may be different in contrast of the task context (see *Fly Manually* and *Gain SA Over Battlefield* in Figure 4).

Figure 5 shows the SSE values for all clustered centroids. The MBS with 4 clusters is much less dispersed than the CBS with 4 Clusters. This can be explained by the more reasonable task sorting using a task model. Both SSEs in terms of the 12 clusters are much less dispersed. This is mainly due to the reduction of data point outliers by increasing the number of clusters. Overall, it can be said that 12 clusters seem to show a high uniform quality of clusters among all participants.

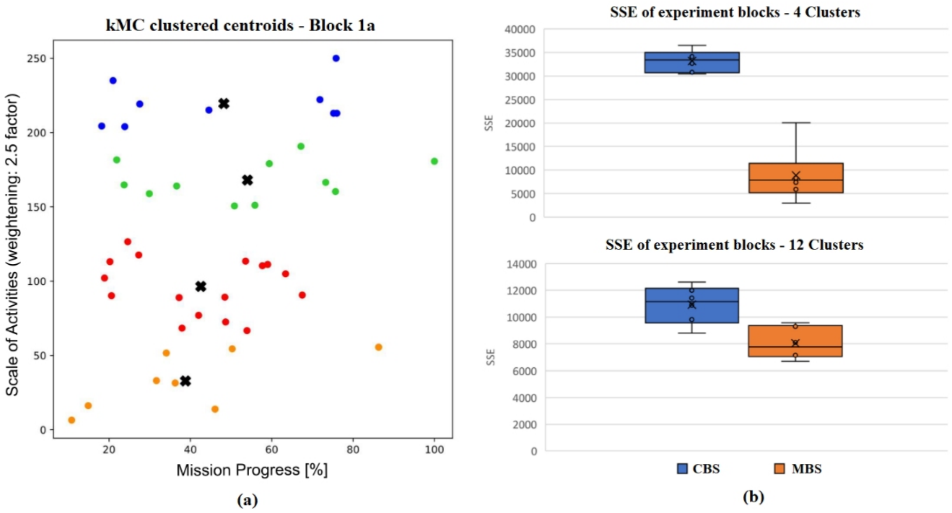


Figure 5: Comparison of clustering results between participants for each experiment block: (a) kMC of the clustered centroids of each participant and experiment block 1a. (b) SSE of all clustered centroids over all experiments for 4 and 12 clusters.

CONCLUSION

The kMC results show that the approach is not able to identify SDTs (e.g., tasks in the task context of *UAV guidance* or *mission planning*). This is especially true when two or more tasks are executed in parallel. Greater weaknesses are seen in tasks that exhibit a high degree of task switching (like supervisory control tasks). Also, kMC algorithms solely use data points to determine cluster boundaries. Therefore, time periods with multiple data points are preferred over partitions with fewer data points. LDTs, such as flight tasks (constant usage of HOTAS), are therefore much more represented in the cluster charts. Overall, results show that the clustering approach can provide plausible results but is not suitable to identify tasks as interconnected clusters with certain reliability. Moreover, interpretable results usually involve a very high modelling effort.

With the presented clustering approach, it is also very difficult to incorporate the method in a real-time activity recognition. The partition into clusters requires already completed task executions, which does not meet the requirements of an adaptive assistance system. However, this might be overcome by dynamic clustering. Another approach would be to apply supervised learning methods like support vector machines (SVMs) to the activity data. They can also be used for real-time classification. Labelled data from the debriefing protocols could then be applied as training data. SVMs can lead to reliable classification results even with small data sets. However, this still needs to be tested.

We see that CBS can provide meaningful grouping of tasks in cases where human performance in a human-machine interaction is not fully understood.

Therefore, it could be a viable method to support a hierarchical or cognitive task analysis based on experimental data.

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