# ACT-R model for cognitive assistance in handling flight deck alerts

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**Abstract**

The ability to respond to the needs of an individual operator is key for cognitive assistance in naturalistic settings. In order to keep track of changing operator demands in dynamic situations, a model-based approach for cognitive assistance is proposed. Based on model tracing with flight deck interactions and EEG recordings, the model is able to represent individual pilots' behavior in response to flight deck alerts. As a first application of the concept, an ACT-R cognitive model is created using data from an empirical flight simulator study on neurophysiological signals of missed acoustic alerts. Results show that uncertainty of individual behavior representation can be significantly reduced by the combination of cognitive modeling and EEG data. Implications for model-based cognitive assistance in flight deck operations are discussed.

**Keywords:** Cognitive modeling; flight deck alerts; model-based cognitive assistance; model-tracing; neuroadaptive technology;

## Introduction

### Individual user behavior

Representing individual user behavior is a challenge for cognitive modeling. Most models aim to simulate average user behavior under controlled conditions instead of individual performance in complex tasks (Rehling, Lovett, Lebiere, Reder, & Demiral, 2004). Representing individual behavior in naturalistic settings requires dealing with multiple sources of variation such as inter-individual differences (e.g., architectural and knowledge differences; Taatgen, 1999) and uncontrolled external factors of the situation. For example, when modeling pilot performance in commercial aviation, different levels of experience and changing weather conditions would need to be considered. A cognitive model that is able to keep track of the operational context and an individual users' cognitive dynamics can serve as the basis for cognitive assistance in operations (Zhang, Russwinkel, & Prezenski, 2018).

Cognitive assistance is about providing the right information at the right time. The quality of support that can be provided therefore depends on what is and can be known about the task environment and the operator's cognitive processes. In naturalistic situations, very extensive models would be needed to incorporate all sources of variation for explaining individual performance in a deterministic fashion. Regardless of the feasibility of such modeling, understandability of the model would be traded in for completeness, also known as "Bonini's paradox" (Dutton & Starbuck, 1971). Alternatively, leaner models would introduce epistemic uncertainty (Kiureghian & Ditlevsen, 2009), leaving specific aspects of behavior unexplained due to a model's lack of knowledge. A number of methods have been used to reduce epistemic uncertainty caused by individual differences, such as pre-test scores as predictors (Rehling et al., 2004), model tracing (Fu et al., 2006), inserting physiological data on user's workload into the model (Putze, Schultz, & Propper, 2015) and dynamic adjustment of parameters with pre-computed lookup tables (Fisher, Walsh, Blaha, Gunzelmann, & Veksler, 2016).

### Cognitive assistance in aviation

Inattentional deafness leads to performance drops in the cockpit (Dehais, Roy, & Scannella, 2019) that can benefit from cognitive assistance, e.g. in the form of verbal reminders (Estes et al., 2016). Causes and consequences of overheard messages for individual pilots' performance need to be considered to identify the right information to be provided and the right timing to provide it for cognitive assistance in operations.

Causes can be diverse and situation dependent (e.g., perceptual/attentional factors, see Dehais et al., 2019) and are likely too complex for deterministic modeling of single occurrences of missed alerts. Often, alerts are declared as missed when pilots fail to react. Knowing what made a pilot fail to react or what pieces of information he or she was unable to process gives diagnostic value and helps to identify adequate means of support. For cognitive assistance in handling flight deck alerts, information about a message's contents and whether it was processed by the pilot is a viable alternative to complex models required for deterministic prediction of user states.

Consequences of an overheard or ignored message for pilots' performance can be anticipated with the help of a cognitive pilot model. ACT-R (Anderson et al., 2004) is a comprehensive and scientifically substantiated cognitive architecture that has produced models representing processes e.g. involved in "manual" flight control of single engine aircraft (Somers & West, 2013), visual attention allocation in a glass cockpit (Byrne et al., 2004) and the use of and skill acquisition for the flight management system (Schoppek & Boehm-Davis, 2004; Taatgen, Huss, & Anderson, 2008). For model-based assistance such formal descriptions of flight related tasks and processes can describe what constitutes normative performance.

## Neuroadaptive cognitive model

In the present paper a modeling concept is proposed that is able to explain uncertainty in single instances of missed alerts by representing individual pilots' behavior. In the fashion of Putze et al. (2015) we extend the idea of model tracing (Fu et al., 2006) by incorporating physiological data. Whereas Putze et al. (2015) integrate physiological data to model architectural differences, i.e. occupying cognitive resources with a dummy model to model workload, the concept in this paper focuses on modeling knowledge differences (Taatgen, 1999) due to unprocessed auditory messages.

Model tracing based on monitoring pilot interactions with flight deck instruments enables the model to identify when performance deviates from normative behavior. Based on such deviations, the model can make inferences about the pilot's cognitive states. By treating instances of deviating behavior as situations it cannot explain due to lack of knowledge, the model consults external sources of information, i.e. event-related physiological data of the pilot it tries to represent.

Physiological measurements, e.g. electroencephalography (EEG) can provide information about cognitive operations. With a passive brain computer interface (Zander & Kothe, 2011) EEG can be recorded without interfering with the task and data can be processed in (almost) real-time. The integration of these data into the model allows for more refined representations of individual pilots. Such a neuroadaptive (Zander, Krol, Birbaumer, & Gramann, 2016) cognitive model would be able to adjust its generic or normative behavior to measurements of a pilot's current cognitive state and to identify current needs for assistance.

Physiological measures can be subject to errors that introduce intrinsic or aleatory uncertainty (Kiureghian & Ditlevsen, 2009). Whereas epistemic uncertainty represents defined model boundaries, aleatory uncertainty is hard to identify in single situations where there is no ground truth available. That is, the model is able to identify situations of deviating behavior, but it cannot say which of the physiological data are affected by measurement or classification error and which are not. In model-based cognitive assistance, thoughtful handling of the two types of uncertainty is required (see Figure 1 for an overview of type of uncertainty introduced by data source).

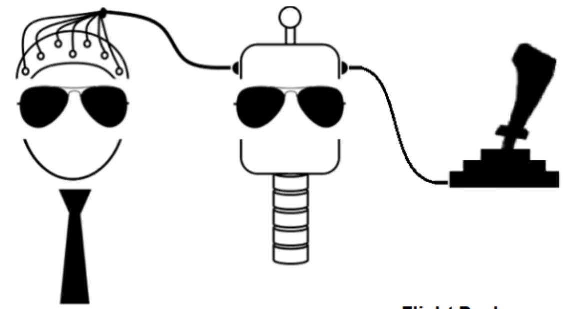


Figure 1: Sources of uncertainty in neuroadaptive concept

The objective of this study is to increase the effectiveness of modeling individual pilot behavior in response to flight deck alerts. For increased effectiveness, model tracing and EEG recordings are used to reduce uncertainty due to individual differences. Behavioral data from an empirical study on the neurophysiological reaction to auditory signals in simulated flight (Krol et al., 2018) are modeled to demonstrate how the proposed concept can be implemented. Accuracies of a neuroadaptive cognitive pilot model and normative model are compared to quantify the fraction of uncertainty reduced by inserting pilots' EEG data. Epistemic and aleatory uncertainty are quantified and examined regarding their implications for model-based cognitive assistance in flight operations.

# Methods

## Empirical study

21 air crew (one female) who were predominantly military pilots participated in the empirical flight simulator study. Participants had a mean age of 49.08 years (*SD* = 6.08) and an average experience of 3230 hours of flight (*SD* = 2330.71). All participating air crew had normal or corrected to normal vision, all but two were right-handed. Air crew were seated in a fixed base experimental flight simulator in single pilot setup that approximated Airbus A320 cockpit design. Participants were asked to perform an 18 minutes scenario that consisted of 9-14 events resembling flight deck alerts per participant, each preceded by auditory warnings or air traffic control (ATC) messages. The scenario had to be flown by selecting heading and altitude on the auto flight system according to ATC instructions. In addition, participants were asked to manage thrust manually and attend to alerts. Alerts included in the scenario could have low ("amber alert", e.g. fuel pump failure) or high priority ("red alert", e.g. engine fire) and ATC messages contained navigation or speed instructions. Speed warnings were issued dynamically whenever participants left a speed threshold area, which resulted in different numbers of acoustic events per participant. For the scenario, the open

source flight simulation software "FlightGear 3.4"[1] was used. Essential instrument properties and state changes in the scenario were recorded in log files with a sampling rate of 20 Hz.

Before the flight scenario, participants' EEG was recorded while performing an auditory oddball paradigm (frequent versus rare sounds). A classification algorithm was trained on the EEG data to recognize activity patterns for processing of target (i.e. processed alerts) and standard sounds (missed alerts). The algorithm was tuned to have equal chances for false alarms and misses in case of incorrect response classification. Due to the frequent use of standard compared to rare target sounds in the training paradigm, classifier accuracy needs to be higher than 0.78 to perform significantly better than chance. EEG was recorded during classifier training and scenario with a 32 channel BrainProducts LiveAmp system.

## Cognitive modeling

ACT-R was used to create a cognitive model to represent individual pilot's behavior. ACT-R consists of memory, perceptual and motor modules that interact with each other by exchanging chunks of information through buffers. The declarative memory module can hold and store information about the task state, whereas procedural memory allows for modeling productions (condition-action-statements) that apply depending on the state of the task or the environment. Perceptual and motor modules allow for modeling of basic sensory processes and enable a model to interact with the environment. When modeling pilot activities, the respective modules can be used to represent storing and updating flight information such as altitude and speed, procedures for how to react in case of alerts, and auditory and visual perception of messages in the cockpit.

For assistance in operations, a cognitive pilot model needs to be flexible, adaptive at runtime and knowledgeable of the operational context. Not only does it need to know what constitutes optimal or normative performance of a task, but also alternative means to meet the objective. In case of deviations from normative performance, it has to be able to adapt its functionality and adjust its representation of the pilot. Finally, the model needs to be able to anticipate the consequences of both normative and alternative performance in a task so it can offer support when needed.

A scenario specific hierarchical task analysis (HTA; Stanton, 2006) was conducted identifying seven main tasks of which one routine and six alert specific tasks. Main tasks were then split up iteratively until the lowest level of actions that can be observed in simulator log files. Based on this HTA, an ACT-R cognitive model was created that was able to memorize flight information by reading airspeed and altitude data, decide when to adjust the throttle, process and respond to auditory messages, and check if its own actions match pilot's actual behavior. This model will be referred to as the "normative" model.

[1] http://home.flightgear.org/

An extended version of ACT-CV (Halbrügge, 2013) was used to create an interface and FlightGear log files. ACT-R did not interface with FlightGear directly (see Somers & West, 2013), but through recordings of individual participants' performance The graphical interface of the flight simulator was represented textually, e.g., "on", "539", in ACT-R's visual representation of the environment, the visicon. As the study's focus was not on visual behavior, different parameters (e.g., airspeed, altitude, etc.) were presented at pre-defined locations independent of Airbus cockpit design. Parameter changes linked to events (e.g., engine1-on-fire from "0" to "1") triggered sounds in ACT-R, so messages from the cockpit were presented in the same modalities as in the empirical study. Processed EEG data were displayed as event-related Boolean variable ("1" for alerts processed as target sound, "0" for standard sounds). Contents of ATC messages in the controller-pilot datalink communications could not be communicated through FlightGear. As a workaround, an extra buffer was added that gives the model access to information not displayed in the visicon.

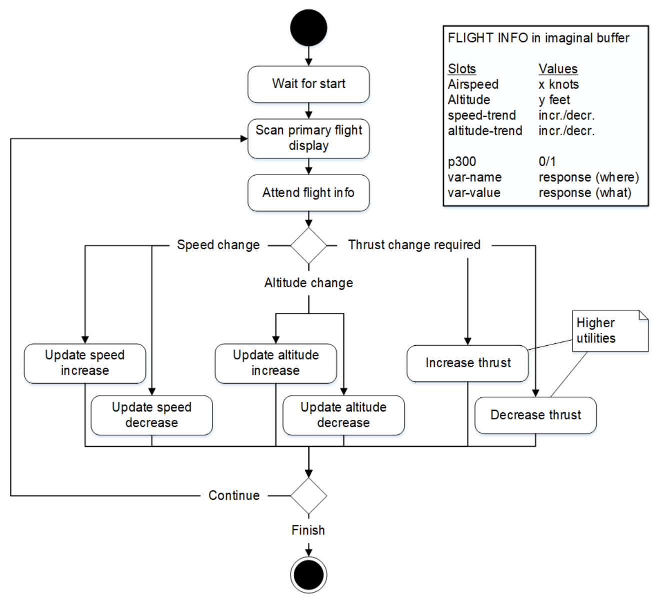


Figure 2: Routine loop in both models

For the routine task (see Figure 2), the model monitors variables of airspeed and altitude that were shown in the simulator's primary flight display. Based on these data, it computes trends for speed and altitude and updates its internal representation of the flight information that is stored as declarative knowledge in an imaginal buffer. If airspeed approaches threshold values, the model prepares to adjust the thrust accordingly. If speed trend is not increasing or decreasing considerably, the model returns to monitoring speed or altitude after updating its flight information.

In case of auditory signals, the model leaves this routine loop and processes the sound and the corresponding message. In case of ATC messages, it processes navigational instructions and stores them in the imaginal buffer. If the model hears an alert, it retrieves a checklist matching the alert type and puts the response required from the pilot in its imaginal buffer. For all acoustic events, the normative model assumes that pilots will respond adequately and, after each event, it checks the log data for the required pilot response to evaluate if its assumption is correct. Situations where pilots do not respond adequately are treated as epistemic uncertainty and marked as cases when some sort of assistance should be provided.

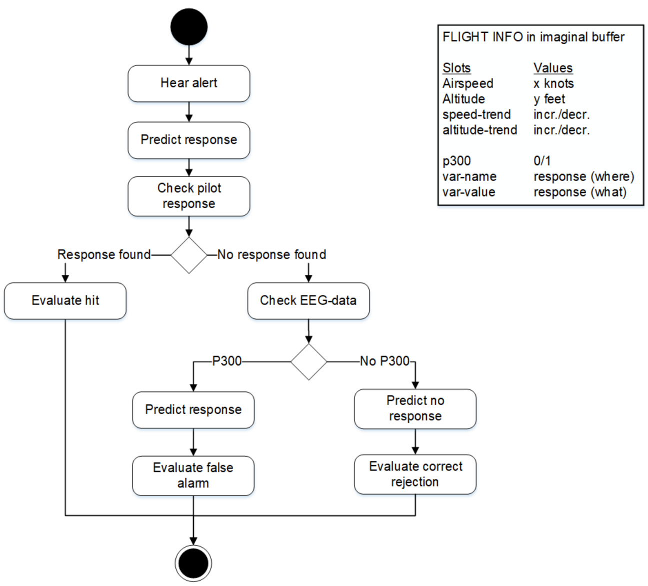


Figure 3: Alert procedure for neuroadaptive model

The neuroadaptive model forms an extension of the normative model. It follows the same courses of action for routine tasks and acoustic events that were followed by an adequate pilot response. If no adequate response is observed, the neuroadaptive model consults the EEG data to check if the pilot had paid attention to the sound (see Figure 3). If EEG data show the pilot has processed the alert or message like a standard stimulus, the neuroadaptive model updates its description of the situation to a missed alert. The model considers these cases as situations that require verbal reminders of the alert or message. Situations where no adequate response was observed but EEG-data show the preceding sound was processed are treated as epistemic uncertainty. For these situations, the model knows that assistance of some form other than a verbal reminder is needed.

## Analysis

For this study the first reaction to the auditory events was evaluated, i.e. adjusting selected altitude in response to ATC messages or opening a checklist in response to alerts. In both models epistemic uncertainty was scored as incorrect description of pilot behavior. Both the normative and the neuroadaptive model could correctly describe situations with adequate pilot reactions to acoustic events; in addition, the neuroadaptive model was able to classify lacking responses as correct descriptions, when EEG data showed no reaction to the sound.

Correctly described responses are scored with 1, incorrect response descriptions with 0. For each participant, both models divide the sum of correct descriptions by the total number of alerts and ATC messages to quantify model accuracy. For both models, mean accuracy is computed across pilots. As the number of auditory events was not the same for all participants due to ATC speed messages, median and interquartile range had to be used as measures of central tendency and dispersion. Wilcoxon signed rank tests for pairwise comparisons are used to quantify added value of EEG-data for the neuroadaptive model.

Aleatory uncertainty in the neuroadaptive model is equal to one minus EEG classifier accuracy. As the data give no information about which situations are concerned by classifier inaccuracies, aleatory uncertainty is accepted and scored as correct. Added value of neuroadaptivity to the normative model is quantified by subtracting normative from neuroadaptive model accuracy. By multiplying added value with EEG classifier accuracy, a mean accuracy of the neuroadaptive model corrected for aleatory uncertainty can be computed.

## Results

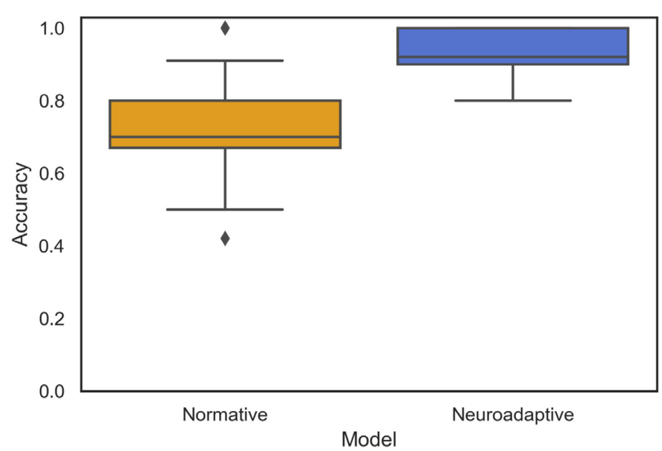


Figure 4: Median accuracy per model

In total, behavior descriptions for 225 events were generated by each model for all pilots with an average of 10.7 (*SD* = 0.9) per pilot. The normative model correctly described participant's behavior for 163 of these events ($Acc_{\text{Norm.}}$ = 0.72) with a Median model accuracy of $MDN_{\text{Norm.}}$ = 0.70 (*IQR* = 0.80 - 0.67; Figure 4). Thus, the total amount of uncertainty treated as epistemic is 0.30.

The neuroadaptive cognitive model generated correct descriptions in 213 of 225 cases ($Acc_{\text{Neuro.}}$ = 0.95) with a median accuracy of $Mdn_{\text{Neuro.}}$ = 0.92 (*IQR* = 1.0 - 0.9; Figure 4). The uncertainty treated as epistemic is therefore 0.05.

The signed rank test showed that neuroadaptive model accuracy is significantly higher compared to the normative model ($z$ = -4.01, $p$ < 0.01). Added value of the EEG-data is 0.23. Correcting the added value for the EEG classifier accuracy of 0.86 results in a corrected accuracy of the neuroadaptive model of 0.92 and aleatory uncertainty of 0.03.

Model accuracies per participant and model are shown in Figure 5.

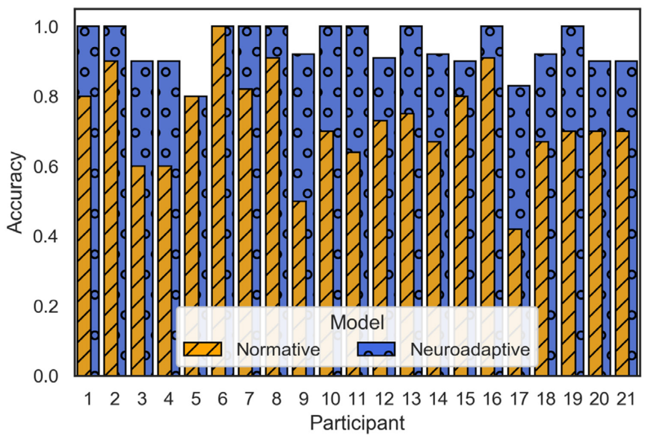


Figure 5: Mean accuracy per participant and model

## Discussion

The presented concept and its application demonstrate how pilot performance can be modeled in spite of individual differences using model tracing and physiological data. The distinction between aleatory and epistemic uncertainty (Kiureghian & Ditlevsen, 2009) and their quantification was decisive for the neuroadaptive model's design and implementation. Data show how model accuracy can be significantly increased by connecting model-tracing and EEG data in line. The specification of remaining fractions of epistemic and aleatory uncertainty provide starting points for further improvement of the concept.

Whereas flight deck instrument interactions can be observed directly, unprocessed alerts can only be detected by behavioral or physiological symptoms. Due to aleatory uncertainty introduced by the EEG classifier, model tracing with instrument and EEG data had to be connected in line to maximize effectiveness in reducing epistemic uncertainty. Compared to other studies using EEG data to model effects of individual differences, the integration of EEG data was quite straightforward for the neuroadaptive model and did not require a dual model approach (Putze et al., 2015). Model tracing based on the log files proved effective in detecting deviations from normative behavior due to an increased density of acoustic events in the scenario. Real flight however contains long periods of monitoring instruments without direct input required. Deriving mental states based on model tracing (Fu et al., 2006) in such highly automated or autonomous environments could therefore require other pilot behavior data sources, e.g. unobtrusive monitoring of neurophysiological activity, speech or gaze. Cognitive models are well suited for the interpretation of such data by linking physiological phenomena to context.

Apart from measurement and classification errors, the neuroadaptive model was able to explain ~81% of the normative model's epistemic uncertainty, leaving a total of 5% of cases when the model does not know what made participants fail to react adequately. These data suggest that cognitive assistance in form of verbal reminders would suffice to help with performance recovery in all other situations lacking responses from participants.

Normative model accuracy represents the effects of individual differences on performance given the scenario. By design, the neuroadaptive model improves on the normative model; the significance of improvement with the EEG data is moderated by the effect of individual differences. Nonetheless, increased accuracy of the neuroadaptive model shows how epistemic uncertainty can be reduced with the help of physiological data. For an empirical evaluation of the concept, a comparison with alternative designs for model-based assistance is required. E.g., a wizard-of-oz setup with a human co-pilot interpreting pilot behavior could be compared to the effectiveness of the neuroadaptive model.

The neuroadaptive model tracks pilots' perception of auditory events. The fact that a piece of information has been perceived and processed by a pilot does not mean that it has been understood. Measures of pilots' situation assessment and awareness (Endsley, 1995) may help to reduce epistemic uncertainty about why a pilot may fail to respond adequately. Physiological symptoms of cognitive conflict can be used to identify when information that was perceived could not be comprehended by the pilot.

Mean accuracy of the neuroadaptive model corrected for aleatory uncertainty is 92 %. Aleatory uncertainty may be reduced with other independent physiological measures, e.g. eye tracking. EEG classification could be supported with corresponding gaze data by connecting both methods in line. E.g., when the EEG data show that a pilot has processed an alert, saccades to the warning display after the alert can reduce the uncertainty by eye tracking classification accuracy.

Further research is required on how to model individual differences with the help of behavioral and physiological measures of operators' cognitive states. Model-based assistance in human machine interaction can provide machines with an implicit feedback loop that allows to check if the information they provide is perceived and understood by the user. Ideally, this will enable machines to form a more refined model of their users and to anticipate their behavior in much the same way that humans learn to interact with a machine.

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