Future Ability Requirements for Human Operators in Aviation

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Abstract. The present study addresses the optimal fit between technical innovations in aviation and aircraft operators. Because of the increase in computerization, an accurate and efficient monitoring of the automation poses a key challenge to future operators. As the German Aerospace Center's Department of Aviation and Space Psychology is responsible for personnel selection of pilots and air traffic controllers, our objective for the selection of future personnel is to distinguish good monitoring operators from bad operators. In order to identify good monitoring behavior we developed a simulation tool that represents tasks of pilots and controllers within a dynamic air traffic flow. Participants have either to monitor the automatic process or to control the dynamic traffic manually. Monitoring behavior is measured by recording eye movement parameters. The identification of accurate monitoring behavior enables us to adapt selection profiles to future ability requirements.

Keywords: automation, monitoring behavior, human performance, personnel selection, eye tracking, future ATM.

1 Introduction

Improvements in air traffic management (ATM) and aircraft systems as well as organizational structures have become one of the key challenges of aviation in the 21st century. This is especially important with regard to the considerable increase in air traffic. The key question of DLR`s research program Aviator 2030 deals with changes that will concern pilots and air traffic controllers: Which modifications of operators' tasks, responsibilities and ability requirements are to be expected?

1.1 Aviator 2030 – Ability-Relevant Aspects of Future ATM Systems

Research project Aviator 2030 (see Fig. 1) focuses on an optimal fit between ATM system design and human operators in future aviation. This will be carried out by adapting selection profiles to future ability requirements. In the first project phase, workshops with experienced pilots and air traffic controllers were conducted in order to

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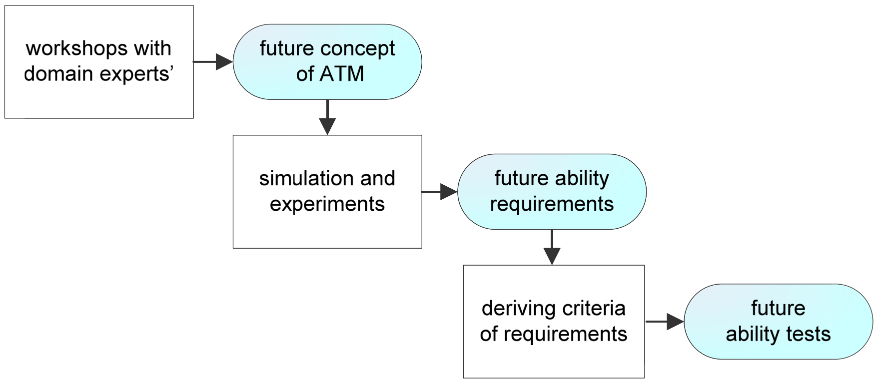

Fig. 1. Phases of the project Aviator 2030

develop a concept of future ATM. They were asked to tell their expectations regarding future tasks, roles and responsibilities. Summing up these workshop results, monitoring and teamwork in a highly automated workplace pose a challenge to future aircraft operators [1]. Thus, research should focus on the ability of monitoring as one major topic. The second project phase comprised the development of simulation tools that represent future workplaces in aviation. Experiments with humans operating in these simulated future workplaces serve as basis for identifying potential changes in ability requirements for pilots and air traffic controllers. Results allow for a timely adjustment of selection profiles and, thereby, for the development of future ability tests.

1.2 Monitoring Automated Systems

Technical developments make it possible to automate many aspects of a human-machine system. Automation is the allocation of functions to machines that would otherwise be allocated to humans. It is the human's job to monitor the automated system and assume control when the automation fails. There is considerable evidence that automation issues are involved in most accident reports [6]. Modern workplaces in aviation are often complex human-machine systems, in which humans and machines work closely together. The quality of human-machine interaction determines the reliability of the system. Generally, there are three approaches affecting the interaction between the operator and machine: system design, operator training and personnel selection. Our focus is on the third approach: Which ability requirements are important for future human-machine interaction if many functions and tasks are automated?

Concerning the requirements of humans interacting with automated systems, maintenance of situation awareness and adequate trust in automation pose a challenge. Sufficient situation awareness exists if the operator has a picture of the traffic situation, understands the situation and sees what happens in the future [5]. Human operators may lose their situation awareness when deficits in monitoring occur.

Monitoring an automated system includes rapidly processing a complex and dynamic scene on the display of an automatic system. Moreover, manual system handling, in case of a system failure, is an important requirement. Often processes of automated systems are based on complex rules that are difficult for human operators to understand. If operators monitor sub optimally, they do not consider important information in their traffic picture. Hence, operators cannot interpret perceived information of system behavior. The resulting gaps and misconceptions make it difficult to form proper expectations of system status and behavior. Analyses of pilots´ accidents and incidents suggest these monitoring failures are responsible for breakdowns in pilot-automation coordination [17].

Previous studies have focused on the monitoring behavior and performance of operators in view of system design and degree of automation. In this regard, Murmaw, Nikolic, Sarter and Wickens studied both performance and eye-tracking data from pilots [9]. Whereas they observed pilots` flying a challenging scenario in a simulator as for performance data, they took pilots´ fixations of relevant targets as indicators for monitoring. Pilots appear to monitor flight mode announcements to a much lesser extent and at a more superficial level than intended and expected by designers and training departments. Murmaw et al. concluded that pilots` monitoring performance should be enhanced through a more adequate system image and the design of more effective automation feedback [9].

In our study, we focus on human ability requirements instead of ergonomic and design aspects in highly automatic environments. Therefore, we are interested in individual differences in monitoring strategies. We assume that individual differences in monitoring lead to differences in learning the underlying principles of the automatic system.

1.3 Individual Differences in Monitoring

Models describing underlying cognitive processes of monitoring behavior provide first indicators for differences in monitoring behavior.

Operators differ in their mental representation of the traffic situation. Whitfield and Jackson introduced the term “picture” as the global mental representation of traffic situation in working memory, which air traffic controllers use to solve their task [14]. Whitfield and Jackson found that experienced and novice controllers differ in their picture: Experienced controllers generate it more easily and faster. Furthermore, they are more flexible in switching between aircrafts and areas of interest. Additionally, another study pointed out that experienced controllers monitor information about aircrafts in accordance with their importance for controlling the traffic [8].

Niessen and Eyferth developed a model of an experienced air traffic controllers’ mental representation of traffic situation. It is a domain-specific model of controllers’ cognitive abilities [10]. The assumptions about the model are based on comparing novice and experienced controllers. The monitoring cycle of the model differs between two phases: data selection to build up the picture of the current situation (phase 1) and update to refresh it (phase 2). An experiment showed that the representation of a current situation is built up under considerable reduction of information. Thus, controllers selected relevant features as codes, position and flight direction. The update frequency adjusts to the relevance of information just as well. Highly relevant objects are updated more often than less relevant objects. Additionally, the model includes an anticipation cycle that provides conflict resolutions [10].

Wickens, Helleberg, Goh, Xu and Horrey [15] developed a model called "SEEV" whose components are representative processes of pilots' allocation of attention to flight relevant information channels. Unique about this model is its linkage between visual attention and models of cockpit task management. The components of SEEV indicate that the allocation of attention in dynamic situations is driven by bottom up capture of salient (S) events, which is inhibited by the effort (E) required to move attention, and is also driven by the expectancy of seeing valuable events at certain locations in the traffic environment. Within aviation, there is a clearly established task priority hierarchy, which defines the importance of value (V) of areas of interest. In two cross validation experiments, the model fits increased with expertise, which accounts for 95 % of the variance. The results suggest that well trained pilots are indeed quite optimal in allocation of attention. Accordingly, the model can serve as a good standard for attention allocation in different complex environments [15].

Expert-novice comparisons provide additional indicators for differences in monitoring behavior as being responsible for differences in performance of human operators. In the field of driving psychology, there are studies that deal with the impact of skill and experience on visual search and hazard detection. Experienced drivers show increased horizontal variance in fixation locations and shorter gaze durations on dangerous objects compared to novice drivers [2]. Moreover, experienced drivers adjust scanning patterns to different processing demands, whereas the strategies of inexperienced drivers remained rather inflexible [3]. That is, novice drivers show more stereotypical fixation transitions [13].

Another important factor influencing human-automation interaction is the human's trust in automation [5]. Low levels of trust can lead to disuse, when automated systems generate many false alarms [11]. High levels of trust in automation, however, lead to complacency. Singh, Molloy and Parasuraman argue that human operators differ in their complacency potential [12]. Complacent behavior is defined as inaccuracy and delay in detecting changes or failure of an automated system. Furthermore, complacency reflects the strategy to allocate the attention to other concurrent tasks. Therefore, eye movement recordings should show that operators scan raw information sources less frequently when using automated systems [11].

Previous research focused on individual differences in monitoring behavior in view of expertise. It was assumed indirectly that an increase in experience accounts for accuracy in monitoring. However, in personnel selection it is often impossible and beyond undesirable to select completely trained and skilled experts. In fact, the German Aerospace Center's Department of Aviation and Space Psychology is responsible for the personnel selection of ready entries (ab-initio pilot or air traffic controller trainees) as they are called in aviation. Consequently, our scientific approach goes beyond differences in monitoring due to expertise. By contrast, we are interested in abilities that account for differences in monitoring behavior, independent of expertise.

1.4 Monitoring Performance in Future Personnel Selection

Wickens, Mavor, Parasuraman and McGee concluded that automation might affect system performance due to the new skills that may be required, but that controllers might not have been adequately selected and trained for [16]. Once automation is introduced, it is anticipated that the job of the controller shifts from a tactical one to an automation supported strategic job. Whereas tactical control refers to aircraft in one sector, strategic control refers to the flow of aircrafts across multiple sectors. Manning and Broach asked experienced controllers to assess the cognitive skills and abilities needed by controllers working with future automation [7]. Controllers agreed that coding (the ability to translate and interpret data) would be extremely important. Furthermore, verbal and spatial reasoning as well as selective attention would be needed in future aviation, particularly when control shifts from automation to the human operator. Numerical reasoning was rated as less relevant, because the automated system accomplishes numerical transactions. This was supported by a study with German air traffic controllers [4].

With the aim of adapting selection profiles to future ability requirements we focus on the ability of monitoring, which is of increasing importance to future aircraft operators. As our objective is to distinguish good performing operators from bad performing operators based on monitoring behavior, we firstly approach individual differences in monitoring strategies. Normative models of adequate and efficient monitoring behavior as well as differences between experts and novices serve as suggestions for critical monitoring behavior, on which we focus our study. Secondly, performance data after a monitoring phase serve as our criterion to evaluate the "goodness" of individual monitoring behavior. We zoom in on the link between monitoring and performance data, i.e. individual differences in monitoring behavior and differences in manual system handling. We assume that this link reflects differences in the ability to understand the underlying principles of the automatic system. On this note, we premise that monitoring automation predicts manual performing in case of automation failure. In view of all hypotheses, "good monitoring behavior" is associated with adequate and efficient system handling performance.

To summarize, we concluded some hypotheses from comparisons between novice and expert operators, and from models representing operators´ cognitive processes of attention allocation and visual scanning. Concerning expert-novice comparisons in section 1.3, we hypothesize that:

- Operators with "good monitoring behavior" do not differ much in their monitoring behavioral data as all these operators show a target-oriented scanning strategy that could be predicted by the demands of a given scenario. In contrast, operators with less understanding of the specific demands of a given scenario vary a lot in their scanning behavior, reflecting aimless and random monitoring behavior.
- Operators with good monitoring behavior adapt their scanning behavior to the situation. Therefore, their scanning behavior varies between different scenarios. Operators with inadequate monitoring behavior do not adapt their scanning behavior to the situation.

Furthermore, we derive hypotheses from the models of cognitive processes of operators (reported in section 1.3):

- Operators with good monitoring behavior start with a data selection phase, in which they scan the whole environment and categorize information as high or less relevant.
- After data selection, operators with good monitoring behavior update high relevant information more often than less relevant information. That means, high dynamic or critical situations are scanned more often.

- Good operators adapt their scanning behavior to situational demands while maintaining a robust mental representation of the whole system. Therefore, they switch faster between different tasks.
- Operators with good monitoring behavior have a less complacent potential than those with a bad monitoring behavior. Complacent behavior is associated with inaccuracy and delay in detecting changes or failure of an automated system.

As performance of manual control serves as the criterion for “good monitoring behavior”, i.e. “good monitoring” ensures an adequate and efficient performance in manual control in case of system failure, we premise for all hypotheses that “good monitoring” (as described above) is associated with an adequate and efficient manual system handling:

- “Good monitoring” operators show an accurate, quick and flexible system handling.

2 Simulation Tool

Research project Aviator 2030 targets the investigation of monitoring behavior and human performance in future ATM scenarios. We developed a simulation tool called “Self Separation Airspace” (SSAS) that represents future tasks of pilots and controllers. It is a dynamic simulation, which allows performance assessment. This tool consists of two workstations, which could be used separately and together. As our research focuses on general questions, the tool is a simplified and abstract simulation of basic requirements of future flight operators. In doing so, test subjects need no prior experience as a pilots or air traffic controller.

The simulation tool comprises a traffic flow simulation (Fig. 2) and a simple flight control simulation (Fig. 2). The operator’s task is to control the traffic flow between two airports. Both airports are connected by airways transporting the traffic between outbound and inbound of airports. Sometimes aircrafts are critical, i.e. they do not flight optimally in the airway. In this case, the operator should switch to the flight control screen navigating the critical aircraft on the optimal pathway.

The operator either monitors the automatic process or controls the dynamic traffic manually. In the automatic mode, the system controls the traffic flow automatically. In the manual mode, the human operator controls the traffic by using input devices. Both modes, automatic process and manual control, can be conducted in the same run. In doing so, we can research monitoring an automatic system and manual controlling the traffic separately.

Most parameters of the simulation are modifiable to configure traffic volume task, balance of system, system feedback and interruptions through dual task. We designed scenarios, which differ in their traffic volume at the beginning of the scenario and the variety of traffic in the traffic flow simulation. Concerning this, the traffic flow is balanced, if the traffic of the airports as well as airways is similar. It is not balanced, if the traffic flow is much different between airports and airways. Additionally, the variety of traffic flow could be modified by faster clocking of airways, different target and limit values of the airports and blocking of airways during runtime. This allows monitoring behaviour and performance to be researched under varying complexity.

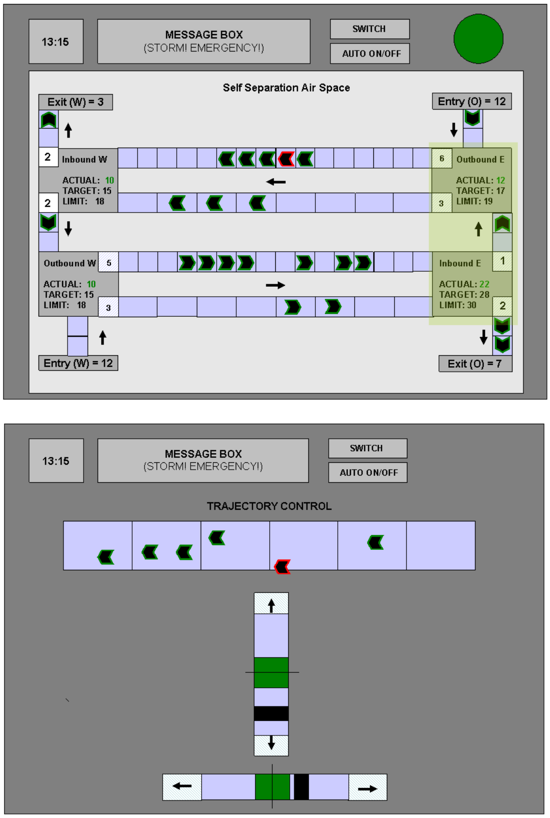

Fig. 2. Simulation tool “SSAS”: Traffic flow simulation (above) and trajectory control (below)

3 Method

In order to identify the core abilities of a future operator, our experimental paradigm focuses on interindividual differences in monitoring.

Experimental Paradigm: With the objective of varying complexity and dynamic of the automatic system, we vary the amount of traffic as well as the variety of traffic in the traffic flow simulation. Thus, we developed four scenarios reflecting four possible combinations of both traffic parameters: Limited amount of traffic with little variety (scenario 1), limited amount of traffic with a lot of variety (scen. 2), extended amount of traffic with little variety (scen. 3), and extended amount of traffic with a lot of variety (scen. 4). Within these scenarios, we test the quality of monitoring behavior as a substantial effect on handling the complex system in case of system failure.

Measurements: As for dependent variables, we focus on the establishment and maintenance of system understanding during the monitoring phase. We use eye movement parameters, which act as indicators for the perceptual and cognitive operations involved. As we assume the understanding of the system to be conditional for manual system handling in case of system failure, we combine both, eye movement parameters and performance data, as measurements. As for eye movement analyses, we include fixation durations, as an indicator of the time taken to assimilate fixated objects, and the variance of fixation co-ordinates to describe the spread of search in both the horizontal and vertical axes. Regarding the effect on system handling, we generate reaction times and performance parameters that identify the quality of individual manual control of the system. Based on individual differences in monitoring behavior and related individual differences in manual controlling parameters, we are able to identify the core competencies of future aviators.

Experimental device: Eye Movements are recorded by Eyegaze Analysis System manufactured by L. C. T.. Managing of raw data was conducted by NYAN software, developed by Interactive Minds. Subjects were seated in front of a 19-inch LCD computer display with a distance of approximately 60 cm.

Test subjects: Our experiments are conducted with candidates of DFS (Deutsche Flugsicherung GmbH) and DLH (Deutsche Lufthansa AG). This enables us to compare our experimental data about monitoring in future human-machine systems with abilities measured in personnel selection tests.

Procedure: Participants were tested individually. First, they were given a questionnaire measuring trust in automation, and the instruction for the following experiment. Participants were informed they would work on four scenarios, all consisting of two phases starting with an automation phase followed by a manual phase. Referring to the automation phase of each scenario, participants were instructed to monitor the automation with the objective of understanding the rule-based dynamics of the given scenario. Referring to the hand control phase (manual condition), participants were assigned to manually control the system in continuation of the automation. That is, participants should control the system in terms of the rules and dynamics that they have learned from monitoring the scenario in automation. After a short (15 s) calibration phase that ensures adjustment of Eyegaze Analysis System to individual gazes of the participants, the persons were then presented the four scenarios, each taking 5 minutes. There was a smooth transition between the automatic mode and manual mode within each scenario but pauses were placed between each scenario. The four scenarios were presented in a fixed order for every subject beginning with the easiest, scenario 1, finishing with the most complex, scenario 4.

4 Status Quo and Further Steps

At present, our simulation tool SSAS is developed and investigated in preliminary tests. SSAS represents future tasks of pilots and controllers. By varying the complexity and dynamics of SSAS, different degrees of task difficulty are realizable. Thus, the system allows for the investigation of human abilities required by future tasks and by varying task difficulties. As we are especially interested in the ability of monitoring an automated system, the simulation tool is connected with an eye movement tracker. We assume eye movement parameters to reflect perceptual and cognitive processes involved in monitoring, so that our approach is on identifying good monitoring operators on the basis of eye movement parameters. We further assume that “good monitoring” is associated with an accurate manual system handling in case of automation failure, and therefore, aimed at connecting monitoring behavior with manual control behavior. Hence, we implemented within SSAS both, an automated system that demands monitoring from a test subject, and a manual phase, that demands manual control from a subject. In this regard, performance parameters of manual control serve as criterion for “good monitoring” behavior. We suggest these performance data to reflect individual differences in the ability of learning underlying principles of an automatic system while monitoring.

Ability testing with dynamic simulation on the basis on eye movements is innovative and establishes new approaches assessing selection profiles. In this regard, SSAS is introduced as an appropriate basis tool to investigate human performance in future ATM Scenarios as well as the underlying ability requirements that allow for human performance in future aviation. Beyond this, fundamental research on other future core abilities is intended, e.g. attention and role shifting, diagnosing system control state as well as communicating with automatic functions. Accordingly, the simulation tool allows a smooth transition from research to future ability testing.

Further research is on failure detection while monitoring fully automated system. As Wickens mentioned the possibility that system reliability is less than perfect [16], the human operator must detect system failures and has to respond to them. In doing so, we plan a study, in which the human operator should be able to detect automation failures during the monitoring phase as well as switch to the manual control.

References

1. Bruder, C., Jörn, L., Eißfeldt, H.: Aviator 2030 - When pilots and air traffic controllers discuss their future. In: Proceedings of the EAAP conference, Valencia, Spain (2008) (in press)
2. Chapman, P., Underwood, G.: Visual Search of Dynamic Scenes: Event Types and the Role of Experience in Viewing Driving Situations. In: Underwood, G. (ed.) Eye guidance in reading and scene perception. Elsevier, Oxford (1998)
3. Crundall, D., Underwood, G., Chapman, P.: Driving experience and functional field of view. Perception 18, 1075–1087 (1999)
4. Eißfeldt, H., Heintz, A.: Ability Requirements for DFS Controllers – Current and Future. In: Eißfeldt, H., Heil, M.C., Broach, D. (eds.) Staffing the ATM System, Ashgate, Burlington (2002)
5. Endsley, M.R., Bolte, B., Jones, D.G.: Designing for situation awareness – An approach to user-centered design. Taylor & Francis, New York (2003)
6. Funk, K., Lyall, B., Wilson, J., Vint, R., Niemczyk, M., Suroteguh, C., Owen, G.: Flight deck automation issues. International Journal of Aviation Psychology 9, 109–123 (1999)
7. Manning, C.A., Broach, D.: Identifying ability requirements for operators of future automated air traffic control systems. DOT/FAA/AM-87/26. Federal Aviation Administration, Washington, DC (1992)
8. Mogford, R.H.: Mental models and situation awareness in air traffic control. International journal of aviation psychology 7, 331–341 (1997)
9. Murmaw, R.J., Nikolic, M.I., Sarter, N.B., Wickens, C.D.: A simulator study of pilots monitoring strategies and performance on modern glass cockpit aircraft. In: Proceedings of the 45^{th} Annual Meeting Human Factors and Ergonomics Society, Minneapolis, USA (2001)

10. Niessen, C., Eyferth, K.: A model of the air traffic controllers' picture. Safety Science 73, 187–202 (2001)
11. Parasuraman, R., Sheridan, T.B., Wickens, C.D.: Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs. Journal of Cognitive Engineering and Decision Making 2, 140–160 (2008)
12. Singh, I.L., Molloy, R., Parasuraman, R.: Automation-induced "complacency": Development of the complacency-potential rating scale. International Journal of Aviation Psychology 3, 111–122 (1993)
13. Underwood, G., Chapman, P., Brocklehurst, N., Underwood, J., Crundall, D.: Visual Attention while driving: Sequences of eye fixations made by experienced and novice drivers. Ergonomics 46, 629–646 (2003)
14. Whitfield, D., Jackson, A.: The air traffic controller's picture as an example of mental models. In: Johannsen, G., Rijnsdorp, J.E. (eds.) Proceedings of the IFAC Conference on Analysis, Design, and Evaluation of Man-Machine Systems (45–52). Pergamon Press, London (1982)
15. Wickens, C.D., Helleberg, J., Goh, J., Xu, X., Horrey, B.: Pilot task management: Testing an attentional expected value model of visual scanning (ARL-01-14/NASA-01-7). University of Illinois, Aviation Research Lab, Savoy (2001)
16. Wickens, C.D., Mavor, A.S., Parasuraman, R., McGee, J.P.: The future of air traffic control: Human operators and automation. National Academic Press, London (1998)
17. Woods, D.D., Sarter, N.B.: Learning from automation surprises and "going sour" accidents. In: Sarter, N.B., Amalberti, R. (eds.) Cognitive Engineering in the Aviation Domain, pp. 327–353. LEA, Hillsdale (2000)