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Intelligent Pilot Advisory System: The Journey From Ideation to an Early System Design of an AI-Based Decision Support System for Airline Flight Decks

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ABSTRACT

The availability of more and more data from commercial aircraft, opens up new development potential for artificial intelligence (AI)-based assistance systems on the flight deck. In this context, a number of research areas need to be addressed, including the interaction between AI and the cockpit crew. This concept paper discusses the need for an AI-based assistance system in the cockpit of commercial aircraft and provides an approach to realise it. To discuss the need for such a system, existing interviews with pilots were analysed and a subsequent ideation process is conducted to discuss possible applications for a new AI-based assistance system. The idea is then made more concrete by formulating use cases and a first proposal on how such a system could be implemented. The proposed assistance system will serve as a research platform to explore various aspects of human-system integration of AI-based applications in the cockpit of airliners. Two of these research topics, which are currently being worked on, are presented at the end of this paper.

Keywords: Human AI interaction, Human systems integration, Systems engineering, Artificial intelligence, Interpretable AI, Aviation

INTRODUCTION

In emergencies and time-critical situations, making decisions in the cockpit of commercial aircraft is one of the biggest challenges for pilots. Decision-making schemes such as FORDEC (Facts, Options, Risks, Decision, Execution, Control) (Hoermann 1994) or TDODAR (Time, Diagnosis, Options, Decide, Assign Task, Review) (Walters 2002) help pilots make decisions in a structured way. In such cases, the pilots have to make operational decisions: Is the aircraft able to finish the planned flight? Should the aircraft land as fast as possible? What is the best alternative airport for a safe landing?

Interviews with seven airline pilots conducted at the DLR (Deutsches Zentrum für Luft- und Raumfahrt e.V., engl. German Aerospace Center) indicate a need for development in the area of decision support systems in airline cockpits. Already in 1996, Mosier and Skitka calls for developing decision support systems because of the increasing amount of data available to pilots.

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In aviation, AI is increasingly being found and implemented. Intelligent assistance systems that support pilots in the cockpit will play a major role in the future (European Union Aviation Safety Agency 2020). This paper analyses interviews on the topic of new assistance systems, presents the most important results and outlines possible use cases. In addition, a preliminary system design of an Intelligent Pilot Advisory System (IPAS) is presented on the basis of the selected use cases. The goal is to expand the current body of work pertaining to AI decision support systems and address current research questions on aspects of human-system integration.

BACKGROUND

Cockpit systems have been constantly improving, and certain pilot tasks have become increasingly automated over the years with the help of new assistance systems. This have been done to both improve the safety and reduce the number of crew members needed (Coombs 2005). Expert systems, which have been developed for aviation applications since the 1960s, represent the beginning of the development of intelligent assistance systems (Walsdorf 2002). Examples for knowledge-based decision support systems are CASSY (Cockpit Assistant System) and CAMA (Crew Assistant Military Aircraft) which were developed in the 90s. The goal of the systems was to improve the pilots' situational awareness and to take over tasks in order to reduce the pilots' workload (Walsdorf 2002; Onken 1999). Both systems can be also seen as early cognitive assistant systems (Flemisch and Onken 1998).

Cognitive assistance systems are systems that automate mentally demanding tasks usually performed by humans, such as acquiring and analysing information, then generating and implementing decisions based on this information (Parasuraman et al. 2000). Shared control between humans and automation can be defined more detailed in three different levels: the strategic level, the tactical level and the operational level (Flemisch et al. 2019). While the first AI technologies, such as expert systems, still process data using rules defined "manually" by the developer, machine learning algorithms learn on the basis of data and create their own rules for solving a problem or optimize them. Thanks to self-learning algorithms such as Machine Learning or the more advanced Deep Learning, which process huge amounts of data, the field of AI is seeing a new boom (Paaß and Hecker 2020).

In 2020, the European Union Aviation Safety Agency (EASA) published a roadmap for the development of AI in the domain of aviation with a "human-centric approach" (European Union Aviation Safety Agency 2020). Special attention should be paid to the interaction between AI and the pilots, because its application opens up new challenges and opportunities with regard to human system integration aspects for cockpit systems. For example, Endsley (2015) and the EASA Roadmap (2020) provide a valuable overview of some aspects of human factors involved in developing effective human AI systems. These aspects include the need for calibrated trust, system transparency, and adequate explainability, as well as mitigating potential risks such as lack of situational awareness, the "irony of automation", and out-of-the-loop problems.

Thus, the DLR has projected the development of the IPAS in 2021. The IPAS should be developed as an experimental platform to explore suitable AI algorithms, but also to take a closer look at the aspects of human factors of AI-based systems. The IPAS is intended to assist pilots in decision making by identifying and assessing situations and generating options for action at the strategic flight management level (Programmdirektion Luftfahrt 2021).

ANALYSIS OF AN INTERVIEW STUDY AND IDEATION

As an approach for the research and development of the IPAS, an explorative design process is chosen, as presented in (Flemisch et al. 2022). The characteristic feature of this iterative development process called "Human System Exploration" is that users are involved in the development process at an early stage and thus new ideas and development hints are discovered with each development iteration, which seems very appropriate for exploring novel systems with a focus on human-AI interaction. The basic application and design ideas for the IPAS are identified in an ideation process that also involves the end users, airline pilots. At the beginning of the ideation process, it is only defined that the IPAS should be an AI-based decision support system on a strategic level.

Interview Analysis

The development of the IPAS started by evaluating an interview study conducted with seven active first officers holding flight licenses for various commercial aircraft types, ranging from short- to long-haul aircraft such as the Airbus A320 and the Boeing 747. All pilots reported between 3,000 and 10,000 flight hours. At the beginning of the semi-structured interviews, the need for support that is not covered by the existing cockpit systems was discussed. The pilots were not informed in advance of the interview about the considerations of the IPAS described above, nor about the planned implementation of the IPAS as an AI-based system, so they went into the interviews unbiased and with an open mind. The second part of the interview focused on AI-assisted decision support, wherein the IPAS concept was presented and discussed with the pilots using fictitious scenarios to gather insights on concerns, requirements, and functionalities. The goal of these sessions was to identify possible functionalities for the IPAS as well as ideas for the future of AI-based assistance systems and their possible realization. The statements of the interviewed pilots are summarized and grouped in the following main categories:

1. Problem areas and possible applications.
2. General concerns, comments and ideas about AI-based decision support.
3. Possible functionalities of an AI-based decision support system.

The first main topic deals with the question of what support is currently lacking in the cockpit from the pilot's point of view. This was discussed in an open-minded way and was not restricted to decision support systems. The collected statements show that today's cockpit lacks projection support to assist flight planning on a strategic level by providing a forecast of the status of the aircraft and environment in the future. The quote "We don't know anything beyond the next 10 minutes" is referring to the weather (5 mentions) as well as to the traffic situation (3 mentions) along the route or at the destination. The desire for early mapping and forecasting of the situation on the complete flight route was requested several times in all interviews. This is also shown by the fact that pilots inform themselves about the situation on the route and at the destination airport via flight tracking or weather apps on their personal mobile phones. Related to these strategic planning issues, all pilots interviewed mentioned the need for an assistance system that assists in finding and assessing operational options and supports strategic planning in emergencies, such as helping pilots find a suitable alternate airport. A suggestion showed that the system can also help with normal operations. By analysing weather and traffic data, pilots could be informed early about potential events at the destination so that planning for route changes could begin sooner. This would also allow the flight path to be adjusted - routing and speed corrections - in terms of sustainability. It is noteworthy that, without influencing the participants in advance, one of the most important demands is related to the original idea of the IPAS - support in decision making at a strategic level. The second major issue is the need for a technical error support system. 6 out of 7 pilots requested support in interpreting technical errors and assessing their impact on operations. The current provision of technical information by the cockpit systems is either too complex or the search for the required information in the available manuals takes too much time. In addition, according to participants, the combination of two errors and their operational impact are not taken into account in today's systems.

Under the second main topic, the pilot's concerns regarding AI-based systems are discussed. It is discussed which characteristics the participants expect from an AI-based assistance system and which problems they see regarding such systems. All participants mentioned in the interviews that the understandability of the system results is very important. For example, it is important for pilots to know how up-to-date the data is and what criteria the system uses to evaluate the options. In the case of self-collected information, the pilots know where the data comes from and how old it is. If the data is collected by an automated system, the pilots do not know anything about the origin of the data – this system transparency must be guaranteed. In addition, three pilots mentioned that besides the understandability of the data, good interpretability must also be ensured, as situations with high workloads do not allow much time to interpret the information on the display. It is also clear (4 out of 7 mentions) that a sufficient and well-designed familiarization period is necessary for a high level of acceptance of a new system. This is also specifically addressed by the pilots: Quotes "regular training in the simulator" or "understanding must be trained what the IPAS does and how". This desire for system transparency, to show what the system does, is also directly related to the topic "understandability of results" and is extremely important to the pilots for new unfamiliar systems. Last, some ideas for design and implementation, as well as worries about the IPAS were raised. The concerns mentioned are aimed at the pilot being overwhelmed by too much information, as well as the overloading of information channels and cockpit displays.

It was also mentioned that pilots might get used to the assistance over time and thus might have difficulties in making decisions on their own.

Lastly the information and relevant factors for the decision support system, pertaining to alternate airport selection, were discussed. Time, available fuel and the particular landing risk were named as main factors here. In addition, current and predicted weather, the traffic conditions, as well as up-to-date NOTAMS, were named as important decision factors. In particular, the expected weather conditions in combination with the runway infrastructure (technical equipment, approach procedures, runway length) contribute significantly to the evaluation of an alternate airport. Additional logistical and operational factors, such as passenger handling, and maintenance availability were mentioned as further factors.

Results of Ideation Process

Based on the gathered information and the accompanying ideation process, the following IPAS functions were determined, focusing decision support functionalities. The idea behind this is to describe what the system should roughly do so that it can be defined more specific in the following design phase.

1. Support in strategic in-flight planning during normal operations – The new system should assist the crew by analysing weather and traffic data in real time along the route and especially at the destination. The system should assist crews in projecting future status and predicting potential events by, for example, identifying possible route changes, predicting which approach direction is active at the destination, or whether holding patterns are required at the destination.
2. Find alternate airports and routing options in case of emergency and abnormal situations – The new assistance system should support the pilots in the decision-making process by collecting data, analysing the data and generating and assessing options for action. It will display the relevant information to the pilots, identify potential risks and the effects of technical errors on operational limitations, and finally provide decision options adapted to the situation. For example, it will find suitable alternative airports based on situational factors when the system detects that a continuation of the flight is no longer possible.

Given the intended use of the IPAS, valid concerns were raised, regarding the explainability and interpretability of an AI-based decision support system. To address these concerns, the research areas of Explainable AI (XAI) (Gunning et al. 2021; Rojat et al. 2021) and interpretable AI (Rudin 2019; Molnar 2022) should be take into account.

PROPOSED IPAS CONCEPT

At the beginning of the conceptual design phase, the basic system idea and requirements are defined using the ideation process outcome to obtain a basic understanding of the system. This forms the transition between the ideation and the development of the new system (Flemisch et al. 2022). The IPAS 1. is intended to be a decision support system whose recommendations are based on AI algorithms. 2. should assist pilots in workload-intensive situations. 3. should continuously monitor the status of the mission and the aircraft, highlight anomalies, and assist in decision-making if needed. 4. The resulting support should be easily interpretable by the pilots.

Use Cases

First, eight detailed use cases are formulated to specify the ideas of the functions and usage of the IPAS. All Use Cases are categorized in two main applications.

1. Information Support - In normal operation, the IPAS prepares and displays data regarding traffic conditions, weather, etc. along the route and at the destination airport. The crew will be informed if increased traffic is detected, a change in weather is likely, or any other situation that will affect the flight is identified. Possible effects on the mission are then calculated by the IPAS and advices are provided to the crew.

2. Decision Support – The IPAS detects a technical error that leads to operational limitations and risks. Based on the aircraft status and collected data from the environment (weather, airport, …) the IPAS calculates the criticality of the situation, if a diversion is necessary and if so, which airports are suitable for a landing with the given parameters and constraints.

Basic System Functions

To go deeper into the system design, some more detailed basic functions are developed, which the IPAS has to provide to fulfil the previously defined use cases. All functions are grouped into four pillars. First, the situation must be perceived and evaluated automatically by the system using AI. Depending on the situation, functions from pillar 2 - functions for assistance in normal operations - or pillar 3 - functions for assistance in abnormal or emergency situations - are used. The last pillar provides interaction functions between the crew and the IPAS. With the help of these functions, all use cases can be realized.

System Modell

After the required base functions are defined, a first system model of the IPAS is developed, which can be seen in Figure 1. On the right side you can see which process steps are performed in the different system modules. The classification of the described functionality is oriented by the model of shared situation awareness and the situation model of autonomy according to Endsley (2015). First, the "IPAS Data Collector" has to collect data from the aircraft, but also from outside the aircraft via satellite communication. Some examples are weather data, topographical data or traffic data. The "AI-Core-Module" (AICOM) continuously assesses the situation based on the collected date. If the situation assessment detects a situation like an emergency, the AICOM generates operational options to assist the pilot in decision making. Finally, the "AI Crew Interaction System" (AICIS) presents the AI results and relevant information to the pilots in an understandable way so

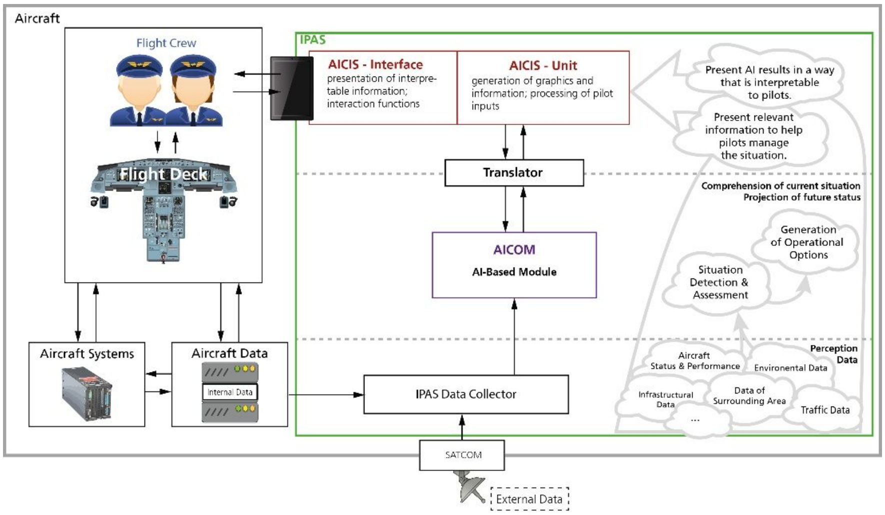

Figure 1: System model of the IPAS.

that the pilots can quickly interpret the information and recommendations even under time pressure.

OUTLOOK

This concept paper gives an overview of an AI-based Intelligent pilot decision support system, the IPAS. The concept for this system stems from the analysis of a pilot interview. The system consists of two key elements: The AICIS and the AICOM.

The AICIS is intended to present AI results to pilots in a way that allows pilots to quickly understand and interpret them, even under time pressure. This is one of the findings from the interviews and is also addressed in the baseline requirements. Since the end user is not in the focus of XAI and therefore the usability of XAI is neglected (Rudin 2019), the focus of the research of the AICIS will be placed on better interpretability for the end user. A domain-specific and end-user centered interface should be developed, which contains features that support interpretability. Finding these characteristics is the main research question of the AICIS development. The goal of the AICIS is to present the information provided by an AI model in a way that is understandable and interpretable, similar to what is described by Lipton (2018) and not to create new more interpretable models. In order to find the mentioned characteristics that should support interpretability, the explorative development approach is chosen. Through multiple iterative prototypes and immediate feedback from the pilots, the goal here is to find as many clues as possible for characteristics that support interpretability. These characteristics will then be evaluated in a final prototype.

The AICOM is tasked with the determination of the proper course of action. The AICOM should make use of models to provide the decision that will then be given to the AICIS. Given the requirements for explainable and interpretable AI along with the number of factors that should be considered simultaneously, the AICOM is currently envisioned to be based on multi-criteria decision making (MCDM) concepts (Aruldoss et al. 2013) with the main algorithm being a learning classifier system (LCS) (Urbanowicz and Moore 2009). MCDM allows decision makers to take into account multiple variables at once, while making a decision. On the other hand, the LCS has been shown to be a prudent approach when trying to tackle MCDM problems (Bernadó-Mansilla et al. 2006) and also is a more interpretable model as it is a rule-based model, where the rule follows a more simple if, then structure (Urbanowicz and Moore 2009). The LCS also allow both offline and online learning, which means new rules can be added dynamically with little hassle and it may acquire new rules on the fly (pun intended) (Urbanowicz and Moore 2009). Given limited data availability the plan is to train the AI model in a simulated environment which incorporates multitude of real world data, where many varying scenarios can be represented. The simulated environment enables the algorithm to be exposed to very extreme and niche situations, that although unlikely, can happen in the real world. Thus, the hope of our system is to truly be a helping hand even in the toughest and strangest of situations.

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