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LLM-Based Human-machine Teaming for Air Traffic Controllers

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Abstract

Nowadays, the air traffic control (ATC) system is much more complex, and the number of situations in which controllers have to make decisions that can be assisted by intelligent decision-support systems (IDSSs) has grown. Current ATC systems are mainly based on human skills and rule-driven automation, which may have challenges in coping with dynamic operations, unstructured communication, and the growing airspace density. The advent of Large Language Models (LLMs) has brought new opportunities for human–machine teaming, such as contextual reasoning, natural language understanding, and decision-support capabilities that adjust to the context. This paper explores the feasibility of human–machine teaming in air traffic control employing LLM. The study used a qualitative conceptual research approach using literature review and thematic analysis. Existing studies on human–machine teaming, aviation systems utilizing AI, explainable AI, and the field of air traffic management have been reviewed to explore the opportunities, challenges, and safety implications of implementing LLM in an ATC scenario. The results indicate that LLMs can assist air traffic controllers in various aspects, including communication management, procedural guidance, workload reduction, and situational awareness enhancement. The research also identified important problems of explainability, automation bias, reliability, risk of hallucination, cyber security and regulatory compliance. The study recommended a conceptual human-in-the-loop framework for LLM-assisted ATC operations that focuses on enhancing controller authority, introducing explainable AI mechanisms, ensuring system transparency, and designing systems for safety. The study contributes to the ongoing conversation regarding the impact of AI systems on aviation systems and provides a conceptual framework for integrating LLM with collaborative ATC decision-support systems. The results also indicate that human oversight, safety and reliability in system operation are critical considerations for future LLM-driven ATC systems, necessitating careful and transparent integration of AI capabilities to ensure reliable and safe ATC.

Keywords: Air Traffic Control; Large Language Models; Human–Machine Teaming; Artificial Intelligence in Aviation; Decision-Support Systems; Explainable AI; Aviation Safety.

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Introduction

Air traffic control (ATC) is among the most safety-critical and cognitively challenging environments in today's transportation system. Air traffic controllers ensure safe separation of aircraft, manage traffic flow, communicate with pilots and react to dynamic operational situations. Air traffic management has become more complex due to the steady expansion of air transportation and airspace congestion. This places a high cognitive demand upon controllers who are handling vast amounts of real-time data, maintaining situational awareness and making accurate decisions, amidst of high cognitive load. The old ATC systems are highly rule-based and expert-based to assist in operational decision-making. While these systems have made strides in enhancing safety and efficiency, they still struggle with addressing dynamic operations, understanding unstructured communication flows, and intelligently adapting to unexpected situations. Current decision-support systems are primarily data visualization and conflict detection and alert functions, but they may not have the ability to reason from context or to adaptively collaborate. Thus, the demand for intelligent systems that can assist controllers without infringing on their authority and accountability is growing. The new opportunities for human-machine collaboration in complex operational environments have been driven by recent developments in AI, specifically Large Language

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Models (LLMs). LLMs are sophisticated deep learning models that can comprehend, create, and reason about natural language. OpenAI GPT Models and Google Gemini have shown impressive performance in areas like information summarization, conversational abilities, and contextual reasoning. Unlike traditional automation systems, LLM-based solutions can handle both structured and unstructured data, allowing for more dynamic and context-aware interactions between people and intelligent systems. This new infusion of LLM technology into aviation systems brings about a paradigm shift: human–machine teaming, which sees intelligent systems supporting and augmenting human controllers rather than replacing them. For ATC environments, systems based on LLM can facilitate communication management, conflict interpretation, procedural guidance, workload reduction and decision support of operations. These can help increase efficiency and reduce cognitive load on controllers, while providing increased situational awareness and maintaining human oversight. But these are not without their concerns, as they also hold up for their reliability, explainability, trust, cybersecurity, and regulatory compliance in the field of safety-critical aviation. While there is increasing interest in the use of AI in aviation, there is a paucity of research that has focused on human–machine teaming with LLMs in an air traffic control setting. The current research on LLM applications in ATC is mainly concentrated on standard machine learning solutions, predictive analysis, and automated routing systems, with a few studies addressing the collaborative capabilities of LLMs. This study is therefore focused on the opportunities, challenges, and implications for operations of integrating LLMs into the ATC decision support system. The study also outlines a conceptual model for LLM-supported ATC, highlighting the importance of human-in-the-loop collaboration, explainable AI, operational safety, and reliability.

Literature Review

Human–Machine Teaming

Human–machine teaming is a form of teamwork between humans and intelligent systems, where both participate in the decision making process during operations. It is not the same as conventional automation, but focuses on human and intelligent system awareness, adaptability, and human-computer collaboration (Endsley, 2017). Human-in-the-loop systems, which are crucial in the aviation sector, enable human controllers to maintain the final say while AI systems provide context-specific and explainable assistance (Parasuraman et al., 2000).

AI can also be used in the field of air traffic control to help manage information, detect conflicts, summarize operational conditions, and reduce the workload of air traffic control staff. But, the level of confidence in automation remains a great concern. However, the absence of trust can result in the operators rejecting the valuable AI assistance, while too much trust can result in automation bias, when the controllers are too reliant on the output of AI (Lee & See, 2004). Situational awareness, cognitive workload and explainability are thus important themes in human–machine teaming studies. To enable safe operational decision-making, effective AI systems must offer transparent recommendations, levels of confidence, and explainable reasoning (Endsley, 2017).

Aviation Safety and Air Traffic Control Systems

Air traffic control systems are used to assure the safety and efficient operation of aircraft in controlled airspace. Controllers manage aircraft separation, monitor radar screens, communicate with pilots and coordinate aircraft movements in real-time. Several systems are needed for ATC workflows, such as surveillance technologies, flight plans, weather data, communication systems, and conflict detection systems (FAA, 2023).

Communication and surveillance systems are still vital to managing the position, speed, and altitude of aircraft, and radar is used to keep track of aircraft.Communication and surveillance systems are still crucial for issuing clearances and providing safety instructions to aircraft controllers, while radar is used to track the position, speed, and altitude of aircraft. Conflict detection devices help to avoid aircraft separation loss. Notwithstanding, most existing ATC systems are rule-based and are geared primarily towards structured data and can not interpret the contextual or unstructured operational information (ICAO, 2022). This is a problem that will allow for intelligent systems to offer adaptive, context-aware support, with the help of large language models.

Artificial Intelligence in Aviation

AI is used in various fields of aviation to enhance safety, forecasting, efficiency, and assistance with decision-making. Machine learning is widely used across the board in the field of maintenance prediction, flight delay forecasting, fuel optimization, trajectory prediction, and airport operations (Kopardekar et al., 2016). Other use cases of AI in air traffic management include traffic flow management, route planning, collision avoidance and scheduling.

Predictive analytics can process vast amounts of operating data to not only predict congestion or delays, but also to inform aviation systems how. AI-driven decision-support tools can aid controllers in assessing operational alternatives and risk better. Yet, in aviation, AI systems need to be used as support tools instead of decision-making tools (Shrestha et al., 2019). Recent research also shows that AI can enhance real-time collaboration in conflict detection, trajectory management, and anomaly monitoring, while ensuring that humans remain in control of operations.

Large Language Models

Large Language Models (LLMs) are complex AI tools able to comprehend, create, and think about human language. Most of the latest LLMs adopt transformer architecture for efficient reasoning within context and understanding of language (Vaswani et al., 2017). AI systems include those like OpenAI's GPT Models and Google Gemini Demonstrate a high level of understanding in summarising, dialogue and information retrieval.

In aviation, LLM can be used for communicating with others, provide guidance on procedures, reducing workload and explaining the decision. They are also multimodal, which means that they can process information from multiple modalities, including text, voice, visual, and operational information (OpenAI, 2024). Real-time language processing is essential in an ATC when controllers are required to communicate at a high speed and act promptly. However, before being implemented into safety-critical ATC applications, LLM applications will also require multiple tests on reliability, secure integration, explainability, and operational validation.

Research Gaps

Although the field of AI development for aviation is growing, studies focused on the application of LLM in human–machine teaming for air traffic control are still scarce. The literature on the topic of machine learning, predictive analysis, and automation systems is quite extensive, but not as much as collaborative LLM assistant support for controllers. But studies on human factors such as trust, workload, situational awareness, and automation bias with regard to the use of LLM integration are lacking.

One critical area of oversight and control that is missing is the governance of LLM deployment in safety-critical ATC environments. There remain a number of issues that need to be resolved: Explainability, Accountability, Certification, and System Reliability. The risk of generating erroneous outputs is especially problematic because it may negatively affect operational safety, causing hallucination (Ji et al., 2023). Future LLM based ATC systems thus require features such as validated aviation databases, human validation, confidence measure and fail-safe. To fill in these gaps, this study proposes an LLM-based air traffic control system with a human-in-the-loop concept, emphasizing the need for safety, explainability, operational reliability, and controller authority

Methodology

Research Approach

In this study, a conceptual and qualitative research method is used to explore the potential of incorporating Large Language Models (LLMs) into human–machine teaming for air traffic controllers. The methodology is centered on comprehending the impact of LLM-based systems on decision-making, communication management, workload, and situation awareness in air traffic control (ATC) contexts. The type of ATC systems supported by LLM are not fully matured and operational; therefore, a conceptual framework approach for this research is appropriate.

The study is a literature-based analysis, coupled with the development of a framework, to examine the potential for collaborative AI in safety-critical aviation contexts. The methodology focus is on human-in-the-loop operations, where the air traffic controller is the controller's ultimate decision-making tool and the LLM system should be viewed as an intelligent decision-support assistant.

Research Design

Research design is a qualitative review and the development of a framework. To understand the challenges, opportunities, and safety considerations for operational use of ATC in the context of existing research on human–machine teaming, AI in aviation, air traffic management, explainable AI, and large language models, a review and synthesis of existing research on these topics was conducted.

- The study design can be segmented into three big phases:
- Students will read literature and conduct data collection. Students will read literature and collect data.
- Thematic analysis based on operational and technical requirements.
- Design and development of a human–machine teaming framework using LLM technology for ATC.

This design enables the study to link the previous concepts with the proposed operational structure, which has been developed specifically for the air traffic control system.

Data Analysis

Thematic analysis was used to analyze the collected literature. Using this method, common themes, operational challenges, and technical needs for LLM integration within ATC environments were identified.

- The main analytical themes comprised:
- Situational awareness
- Cognitive workload management
- Human–machine collaboration
- Trust in automation
- Explainability and transparency

The potential for reliability and hallucination issues in AI.The potential for errors and hallucinations in AI. How to keep a site safe and effective.How to maintain a safe and effective site.

The thematic analysis provided a valuable framework for understanding how LLMs can be used alongside humans to support ATC operations, while keeping them in control and adhering to safety regulations.

Framework Development

The results of the literature review and thematic analysis were used to develop a conceptual framework for LLM–based human–machine teaming in ATC. The framework was intended to illustrate the potential interaction between LLM systems in a real operational context and the controllers, for the purposes of communication management, traffic monitoring, conflict interpretation and procedural assistance.

The framework incorporates four key sections

- Operational data acquisition
- LLM-based reasoning and decision support
- Human-controller interaction and validation.
- Mechanisms for safety and reliability

The proposed framework keeps the human-in-the-loop (HILo) structure, where the AI-generated outputs need to be assessed by the controller before they are implemented during operation.

Ethical and Safety Issues

Ethical and operational safety issues are of major importance in this study since ATC is considered a safety-critical domain. The methodology places a strong focus on augmenting rather than replacing the human controller in the use of LLM systems. Some of the key issues discussed are automation bias, explainability, accountability, data security, and risks of hallucination.

Aviation governance needs for transparency, reliability and regulatory compliance are also taken into consideration. Future implementation is emphasized as having a number of safety mechanisms, including fail-safe controls, audit logging, procedural verification and confidence scoring.

This Research offers a structured framework for comprehending the role that LLM-based human–machine teaming can play in future air traffic control operations without compromising safety, transparency, and human control.

Results

Overview of Findings

This study's results suggest that Large Language Models (LLMs) could facilitate human–machine teaming in Air Traffic Control (ATC) applications, when used in a human-in-the-loop setting. The literature review indicates that existing ATC systems are still largely dependent on human knowledge, rule-based automation, and formal operating procedures. While these systems have been instrumental in aviation safety, there are still challenges with processing unstructured communication, reasoning in context, and dealing with the evolving nature of flight situations.

The analysis also reveals that advances in artificial intelligence over the last few years, specifically the LLM and related tools, offer the promise of more adaptive and context-aware decision-support systems. The previous research indicates that LLMs can handle language comprehension, communication summarization, contextual interpretation, and information retrieval all of which could be beneficial in supporting controller tasks in ATC. The literature also points to the need to regard such systems as tools for assisting the operator and not as independent systems for control.

The proposed human–machine teaming framework is detailed in this section. This section details the proposed human–machine teaming framework.

A conceptual LLM-based human – machine teaming framework for ATC operations was developed, based on the thematic analysis performed in this study. The framework is intended to facilitate the interaction between the air traffic controller and the AI-based decision-support system, and retains human control over the operational decisions.

The framework has four key elements

- Operational data acquisition
- The ability to use LLM for reasoning and decision support. LLM reasoning and decision support.
- The interaction between the human and the controller and the validation process of the control action.
- Mechanisms for safety and reliability.

We propose a framework architecture for LLM-assisted human–machine teaming for ATC processes, as shown in Figure 1.

The figure shows an overview of the proposed human–machine teaming (HMT) architecture for air traffic control (ATC) operations, highlighting the role of the controller and the importance of decision support, explainability, and operational safety.

The operational data acquisition element collects data from radar systems, flight plans, communication systems, weather data and surveillance technologies. This information then goes through the LLM-based reasoning layer, where the LLM gives contextual support like summarization of the conversation, instructions on how to proceed, helping with workload, or recommendations on how to operate.

The framework is designed to include a human in the loop and all the things generated with the help of Artificial Intelligence will be evaluated by the controller before implementation. This will preserve operational control with the controller and have the LLM system act as a collaborative support tool.

Key Operational Themes Identified

Several key operational themes were identified in the study related to LLM-enabled ATC systems. There is one big theme: Situational awareness support. There is a strong potential for LLMs to assist controllers in organizing and interpreting operational information more efficiently, especially during heavy traffic or significant workloads. There is evidence in the literature that LLMs could be beneficial to controllers for organizing and interpreting operational information more efficiently, especially under heavy traffic and high workload situations.

The other important finding is with respect to cognitive workload management. Past research shows that AI-based tools can help streamline repetitive information processing tasks, such as managing communication, retrieval procedures, and summarizing operations. The results also highlight, however, that over-automation can create dangers that

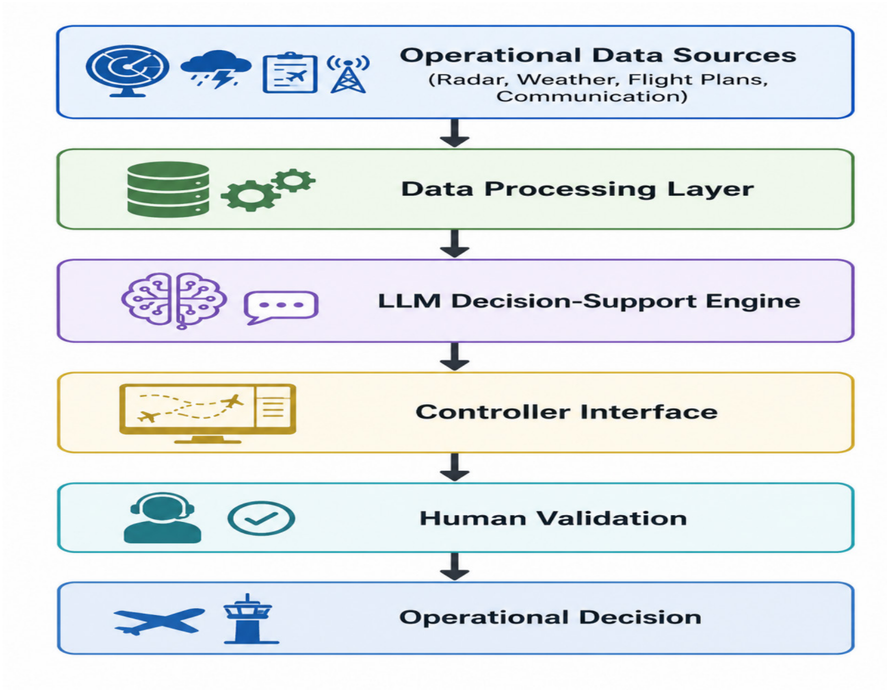

Figure 1: Proposed LLM-Based Human–Machine Teaming Framework for Air Traffic Controllers

include over-reliance and automation bias when measures are not taken to prevent these issues.

Explainability and transparency also became among the essential demands. The results indicated that the more systems can explain their recommendations, offer confidence metrics and trace their reasoning processes, the more controllers trust the AI-generated recommendations.

The findings on Safety and Reliability are presented below. Safety and Reliability Findings

The findings also show that safety continues to be the top priority in adopting LLMs for ATC use. Some issues raised in the literature have been the risk of hallucination, wrong output, cyber security issues, or reliability issues of the systems.

Table1: Proposed Safety and Reliability Mechanisms for LLM-Assisted ATC

Safety Concern	*Proposed Mitigation Mechanism*
Hallucination Risks	Human validation and procedural verification
Automation Bias	Human-in-the-loop operational control
Low Explainability	Confidence scoring and explainable outputs
System Failure	Fail-safe operational controls
Cybersecurity Risks	Secure data integration and monitoring
Accountability Issues	Audit logging and traceability

To mitigate these concerns, the proposed framework features a number of safety-enhancing mechanisms, such as human validation, confidence scoring, procedural verification, audit logging and fail-safe operational controls. They have been designed to minimize operational risks and to ensure transparency and accountability in the decision-support process.

Table 1 presents the major safety concerns identified in the literature and the corresponding mitigation mechanisms proposed in the framework.

Overall, the results are promising for the use of LLM-based human–machine teaming to offer valuable support capabilities for future ATC operations in carefully controlled, explainable and supervised environments. The results do, however, suggest that additional simulation testing, operational testing, and regulatory evaluation are required prior to real-world deployment.

Discussion

The results of this study suggest that ATC environments can be suitable for human–machine teaming with the help of Large Language Models (LLM) in human-in-the-loop (HITL) environments. The literature reviewed indicated that, in the current ATC practices, there is still a significant involvement of human resources, there is some degree of structured automation and there is real-time operational judgment required. These systems can still be very useful in the support of aviation safety, but they also have certain disadvantages in the area of workload management, contextual reasoning and unstructured communication in complex working contexts. This study reveals that there are significant possibilities to use LLMs in augmenting operational support, such as understanding the language in context and offering communication support. One of the benefits of LLM is that they can handle both structured and unstructured data, potentially helping controllers to better understand an operational scenario than traditional rule-based systems. This can be particularly beneficial when summarizing communications, capturing procedures or supporting workload in high traffic density or abnormal operations. The study does not imply that LLM should be used instead of air traffic controllers, however. Rather, the results suggest that AI systems should be used as assistive technologies to augment the human decision-making process without taking over control authority.

The situational awareness and cognitive workload management is highlighted in ATC environments as part of the study. Controllers operate in a very dynamic environment and require a very quick response to operational information to maintain safety. According to the literature, some repetitive information processing tasks could be reduced by introducing an AI system, which could allow the controllers to concentrate on more suitable decisions regarding operational management. But, relying too much on automation can also create risks in operation, such as automation bias, which involves operators relying too much on AI recommendations without proper checks.

Another aspect that emerged from this research and is equally important is called Explainability. In the safety critical case of an aviation system, the controller must be able to know why the control system is recommending a control action before he/she makes a decision on the control action for the system. The results demonstrate the need for explainable AI features, such as confidence scoring, clear reasoning, and audit logging, in systems that utilize LLMs to support ATC functions, to increase trust and accountability. The AI outputs may not be explainable, which may result in confusion, mistrust, or unsafe operations.

It also underscores the critical need for safety and reliability in the deployment of LLMs for ATC operations. The following risks were consistently identified from the literature reviewed: hallucination risk, inaccurate output risk, exposure to cyber security risks, and limited system reliability. ATC decisions are a critical driver in the separation and safety of operations, so any recommendation from the AI needs to be thoroughly tested before it can be executed. Thus, the proposed framework will be limited to human validation, fail-safe mechanisms, procedural verification, and limited operational authority as the most important safeguards.

This study also highlights some governance and regulatory issues with regard to the use of AI in aviation. The current aviation regulations are more geared towards traditional automation systems, which are designed to be used by people and not AI. Lack of guidance and standards for accountability and certification of LLM-based ATC systems and data governance and ethical oversight are the current limiting factors. This gives rise to the need for additional guidance on how ATC systems shall be certified, on who shall be accountable for the ATC system, on governance of data and on ethical oversight of the LLM-based ATC system. The results, therefore, indicate a need for future cooperation between aviation regulators, AI developers, and aviation operational stakeholders.

The proposed framework provides a glimpse of the capabilities of LLM-assisted human–machine teaming in ATC scenarios, but has some limitations. The research is conceptual with a primary reliance on the literature rather than actual and on going testing. There is a need to further validate the framework, however, using simulations, expert evaluation, workload analysis and human factor studies prior to deployment in operations.

In summary, the conversation suggests potential benefits for intelligent ATC systems in the future through human-machine teaming using LLM, such as better communication support, contextual reasoning, and better operational awareness. However, it will need to be effectively deployed through ongoing human control, explainability concerns, safety considerations and defining good rules for aviation AI systems.

Recommendations And Future Research Directions

The findings from this study indicate that the next steps for implementing an LLM system in air traffic control should be directed towards human-centric and safety issues in the system design. AI-driven ATC systems should be integrated within a human-in-the-loop system with the final say over the control decision. Explainability, transparency, confidence scoring, and procedural verification mechanisms are further steps toward improving the operational safety, trust, and accountability.

The study also suggests that aviation stakeholders, such as regulators, researchers, and AI developers, should work together to create governance frameworks and certification standards for AI-assisted ATC systems. However, before this can happen, the validity of the operation, reliability testing, cyber protection, and hallucination mitigation should be thoroughly discussed.

Future studies should be undertaken on simulation-based experiments, controller workload analysis, human factors evaluation and real-time operational testing of LLM-assisted ATC systems. Multi-modal integration of AI, adaptive communication support, and explainable AI methods for safety-critical applications in the context of aviation could be further areas of research.

Conclusion

The use of Large Language Models (LLMs) in human–machine teaming for air traffic controllers in aviation's safety-critical environments was explored in this study. Existing literature was reviewed to look into available studies on the human-machine collaboration in the aviation context, air traffic control systems, artificial intelligence in the aviation sector, and large language models, and identify potential for applications of these systems for operational decision making in ATC contexts.

The results suggest that LLMs can offer beneficial support functions, including communicating, reasoning about context, providing instructions, reducing workload, and situational awareness. The study also revealed some key operational issues of explainability, automation bias, reliability, cybersecurity, and hallucination risks. The results of this study show that LLM-based systems may be able to make some improvements in the support given to controllers, but must be used with the utmost care and supervision in an ATC environment.

The study recommended a conceptual human-in-the-loop framework that incorporates LLM into the air traffic control system, after doing the literature review and thematic analysis. The literature review and thematic analysis led to a conceptual human-in-the-loop framework for LLM-assisted ATC operations. The framework emphasizes the authority of the controller, AI mechanisms that are explainable to humans, transparency in operations, guarantees of safety and fail-safe operational controls. It is important to note that the proposed framework does not introduce AI with the aim of replacing human controllers, but rather leveraging LLMs as decision support systems for controllers when faced with complex scenarios.

Overall, the study contributes to the ongoing discussion on AI for aviation systems and highlights the potential and challenges of applying LLMs to ATC. It also provides a foundation for future investigations of human–machine teaming in aviation and a conceptual basis for creating explainable and safety-oriented AI support systems in the field of air traffic management.

The study is a conceptual study and not carried out in the field, but this has certain drawbacks. Future research should thus aim to validate simulationally, evaluate the human factors aspects, analyse the workload of the controllers and assess the regulatory aspects of LLM-based ATC systems to further explore their practical feasibility.

Overall, the study indicates that LLM-based human–machine teaming could be a viable option for the future of air traffic control if it can be embedded in human-centric, explainable, and transparent operational processes that maintain safety, accountability, and human oversight.

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