FLEXIBLE AIR TRAFFIC CONTROLLER DEPLOYMENT WITH ARTIFICIAL INTELLIGENCE BASED DECISION SUPPORT: LITERATURE SURVEY AND EVALUATION FRAMEWORK

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Abstract

The current shortage of air traffic controllers (ATCO) and expected growth of air traffic in Europe requires new approaches to further ensure efficient and safe air traffic. One solution could be to increase the deployment possibilities of ATCOs to different airspaces or aerodromes. While concepts for such flexible endorsements in the upper airspace (centre) already exist, the development of similar concepts in the remote tower domain is not as advanced.

Flexible endorsements can be empowered by increasing standardisation and offering more comprehensive technical support for ATCOs. This approach helps ATCOs to adapt more easily to new environments, such as Remote Tower Centres (RTC). In this context, the use of Artificial Intelligence (AI) technology as a tool to support ATCOs is of increasing interest. Despite its potential to complement traditional support tools and facilitate adjustments to future employment models, AI's role in this area has not yet been thoroughly investigated. AI-powered decision making enables ATCOs to quickly adapt to different tasks and environments by performing rapid analyses of real-time data, improving their overall flexibility, and responsiveness.

To address this gap in research, this paper conducts a systematic literature review to identify the current state of research, trends, and challenges in the field of AI-supported decision-making for ATCOs. The review is carried out using Google Scholar and focusses on publications from the years 2020 to 2024. "Artificial Intelligence", "Decision Support", and "Air Traffic Controller" were used as keywords. 294 papers have been found and analysed. The findings were then iteratively filtered based on title, abstract, and content. Remaining hits were clustered according to thematic areas to provide an overview of key thematic focuses.

Subsequently, experts were consulted to examine the extent to which the literature review outcomes support the concept of flexible ATCO deployment. The research outcomes show, that AI technologies offer significant advantages when it comes to supporting ATCOs in real-time decision-making, route optimisation, conflict detection, and situational awareness. However, much of the focus is on applications in the upper airspace. There is an absence of research directly addressing tower or RTC environments. The research presented in this paper has been conducted in the frame of the European IFAV3 project.

1. INTRODUCTION

Current regulations and practices in air traffic control (ATC) require ATCOs to obtain specific endorsements for the particular sectors or aerodromes they manage [1]. This endorsement process is stringent, reflecting the complex and unique demands of each controlled area. An ATCO must undergo thorough training on local procedures and airspace structure, ensuring they are fully equipped to handle the specific challenges of their designated environment.

These regulations introduce significant inflexibility. An ATCO can only work in a specific sector or at a particular aerodrome if they hold the required endorsement, which applies exclusively to that sector or aerodrome. To work in additional sectors or at other aerodromes, they must obtain separate endorsements. For example, an ATCO certified at one aerodrome cannot be reassigned to another, even during staff shortages, without undergoing additional, time-consuming training that can take several months to complete according to ICAO [2] and EASA [3] regulations. The rationale behind such strict regulations is grounded in safety. ATCOs must possess an in-depth understanding of each environment to manage traffic effectively. This knowledge is vital, especially in complex or high-traffic environments. The current system's inability to adapt quickly to staffing shortages or shifts in traffic demand leads to operational inefficiencies. Although designed to maintain safety by ensuring deep familiarity with specific environments, this inflexibility limits the overall responsiveness of the air traffic management (ATM) system.

To address these challenges, there is a growing interest in developing new strategies that would enable ATCOs to obtain and manage multiple endorsements or extend their existing endorsements. This could be achieved by increasing the level of standardisation and automation in ATC processes, as well as by providing more comprehensive technical tool support.

In this context, this paper seeks to explore how AI might be integrated as part of the broader strategy to enhance ATCO flexibility. The focus is on evaluating whether AI can offer effective decision support and help ATCOs quickly adapt to various airspaces, aerodromes, and operational scenarios.

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1.1. Project Background

The IFAV3 project (Increased Flexibility of ATCO Validations - V3) started in summer 2023 as fourth of a series of SESAR projects conducting research on a more flexible ATCO deployment. The key approach is either to enable ATCOs to obtain and hold more unit endorsements in parallel than today at reasonable costs and with reasonable effort, or to extend existing unit endorsements to a larger airspace, or respectively more sectors and aerodromes. This shall be realized with various concepts and strategies, involving new technical means and ATCO assistance systems supporting him or her specifically in handling a less familiar airspace, nevertheless complying with all local procedures and ensuring a safe, orderly and efficient flow of traffic. The IFAV3 project is organized in two Solutions:

Solution 1 aims at developing and validating flexible ATCO deployment enablers for an application in the upper airspace area control, with the goal to reach Technology Readiness Level (TRL) 6;

Solution 2 aims to transfer the know-how about flexible ATCO deployment from previous projects to a new air traffic control environment that has not yet been considered as a use case: the application in RTCs. RTCs are facilities where ATCOs manage multiple aerodromes remotely, rather than being physically located at each site, offering a more flexible and efficient approach to ATM. Due to the very similar organization and nature of RTCs compared to area control centres (ACC), the same constraints and challenges are to be solved. Flexible ATCO deployments could be an appropriate answer here as well. In more detail, Solution 2 conducted a literature review as well as a review of previous project outcomes, performed an applicability analysis and a gap analysis, followed by development of assistance tools to specifically support flexible deployment of ATCOs to different aerodromes.

Previous SESAR projects PJ.33-W3-01a, PJ.10-W2-73 IFAV and PJ.05-W2-35 did not yet investigate in detail the use of AI-based technical means to support a more flexible ATCO deployment. The first two projects define the IFAV framework, and the last project defines the functions of a remote tower solution and provides a requirement specification for those functions. As a result, a study was launched specifically to explore the potential of AI-based technologies in enabling more flexible ATCO deployment.

1.2. IFAV3 categories of tool support

The IFAV3 project categorises technical support tools into several key types, each serving a specific function in enhancing ATCO operations. These categories include:

1) Pre-Shift / Learning Tools: Provide essential information and self-training opportunities to prepare ATCOs before their shift.
2) Real-time Learning Tools: Offer real-time information to support learning during shifts, aligning with the 'learning-by-doing' approach.
3) Post-Shift Learning Tools: Help ATCOs to reflect on their performance and improve for future shifts.
4) (Adaptive) Information Tools: Deliver relevant, real-time information during shifts to aid decision-making without giving direct advisories.
5) Advisory Tools: Provide direct handling recommendations for specific flights.
6) Auto-Control Tools: Automate routine tasks using predefined settings, similar to an 'auto-pilot'.
7) Other Tools: Include any tools that do not fit the above categories or are intended for non-executive roles, such as supervisors.

By examining the alignment between the literature's results and these predefined categories, the paper aims to identify which AI-based decision support tools are most relevant and beneficial for enhancing ATCO flexibility.

1.3. Artificial Intelligence – A Short Overview

AI is a field of computer science that focuses on developing computer systems capable of performing tasks normally requiring human intelligence. Human intelligence refers to the cognitive abilities and processes that enable humans to perform complex tasks. These tasks include learning, reasoning, problem-solving, understanding natural language, recognizing patterns, and making decisions. EASA has defined AI in its AI Roadmap 2.0 [4] as,

“Technology that can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with.”

AI systems were designed for specific tasks, such as speech recognition or image classification. However, the advent of transformer models has significantly broadened the scope of AI capabilities. These models have enabled the development of more general AI systems capable of solving a wide range of tasks. Generative pre-trained transformer (GPT) exemplify this advancement, demonstrating the ability to perform tasks such as text generation, reasoning, programming, and content creation, approaching the notion of general intelligence [5]. The field of AI includes a variety of techniques, such as traditional AI, evolutionary algorithms, and machine learning. Traditional AI involves the explicit programming of rules and logic, making these systems deterministic and highly interpretable. However, they often struggle with adaptability and generalization. In contrast, evolutionary algorithms, inspired by natural selection, are used for optimizing complex search spaces [6]. Techniques like genetic programming and evolutionary strategies are scalable and can model highly intricate problems, though they typically lack generalization and interpretability. Machine learning, another key area within AI, focuses on systems that improve their performance with experience and data. Within machine learning, deep learning stands out as a powerful subset, utilizing multi-layered neural networks to model complex patterns in large datasets, further pushing the boundaries of what AI can achieve. Similar to evolutionary algorithm, machine learning is scalable, generalizable and can model complex problems, but they usually lack of interpretability. These AI techniques and the challenges they pose are also present in ATC. AI research in ATC aims to improve decision-making, traffic flow, and safety, but challenges in generalisation, interpretability, and scalability persist.

1.4. Objectives of this study

This study aims to explore the potential of AI as a tool to support flexible ATCO deployment. Specifically, the study seeks to:

1) Conduct a systematic literature review to identify the current state of research, trends, and challenges in AI-supported decision-making for ATCOs.
2) Assess the alignment between the literature's findings and predefined tool categories to identify which AI-based decision support tools are most relevant and beneficial for enhancing flexible ATCO deployment.
3) Provide conclusions about the potential benefits and limitations of integrating AI technologies into ATC systems according to the literature review.

The research focuses on literature published between 2020 and 2024. While various applications of AI in ATC are examined, particular emphasis is placed on deployment challenges and opportunities within tower and RTC environments.

Section 2 explains the literature review methodology and provides the relevant literature. Section 3 summarises the main findings of the literature review. Section 4 links the literature findings to the concept of flexible ATCO deployment. Section 5 summarises the findings and suggests future research directions. Section 6 contains the references, including the entire literature overview mentioned throughout the paper.

2. LITERATURE REVIEW METHODOLOGY

The literature review methodology outlines the systematic approach undertaken to collect, analyse, and synthesize existing research on AI-supported decision-making for ATCOs. This section provides a detailed description of the processes and criteria used to ensure a comprehensive and unbiased review of relevant literature.

2.1. Research Questions

The literature review was guided by the following research questions:

RQ1: What is the current state of research on AI-supported decision-making for ATCOs?
RQ2: What are the emerging trends and key thematic areas in this field?
RQ3: What challenges and gaps exist in the application of AI technologies in ATC, specifically for flexible ATCO deployment?

2.2. Search Strategy

The search strategy involved a systematic approach, utilising Google Scholar as the sole database for identifying relevant publications. While relying solely on Google Scholar has its limitations, its broader coverage of academic literature compared to other databases ensures a more comprehensive search. This necessitates careful filtering but offers a wider range of relevant material. As keywords, 'Artificial Intelligence,' 'Decision Support,' 'Air Traffic Controller,' and 'Flexible ATCO Deployment' were used to ensure a broad yet focused search.

Following initial searches with various approaches, a combination of 'OR' and 'AND' operators was applied to allow greater flexibility in the inclusion of results containing at least two of the four specified keywords. This approach ensured a broader yet relevant search outcome, avoiding the premature exclusion of potentially relevant literature and ensuring a wider range of publications could be considered. The search was limited to publications from the years 2020 to 2024 to capture the most recent advancements and trends in the field.

2.3. Inclusion and Exclusion Criteria

To refine the search results, specific inclusion and exclusion criteria were established to select those papers that are more appropriate to answer the research questions:

Inclusion Criteria (all of these criteria must be fulfilled to be further considered in this study)**:**

- Publications must be peer-reviewed journal articles, conference papers, or reputable technical reports.
- Studies must focus on AI-supported decision-making in the context of ATM.
- Research must be published between 2020 and 2024.
- Articles must be written in English (dominant language of scientific communication)

Exclusion Criteria (if any of these criteria is not fulfilled the paper will be excluded from further consideration in this study)**:**

- Research that lacks a clear methodology or validation (e.g., papers that do not provide enough details on data sources, algorithms, or evaluation criteria).
- Studies where AI is used as a minor or incidental tool rather than a central part of the decision-making process.

2.4. Data Collection and Analysis Process

The data collection and analysis process followed a structured approach to ensure the quality and relevance of the selected literature. The process is illustrated in Figure 1 and described in detail below.

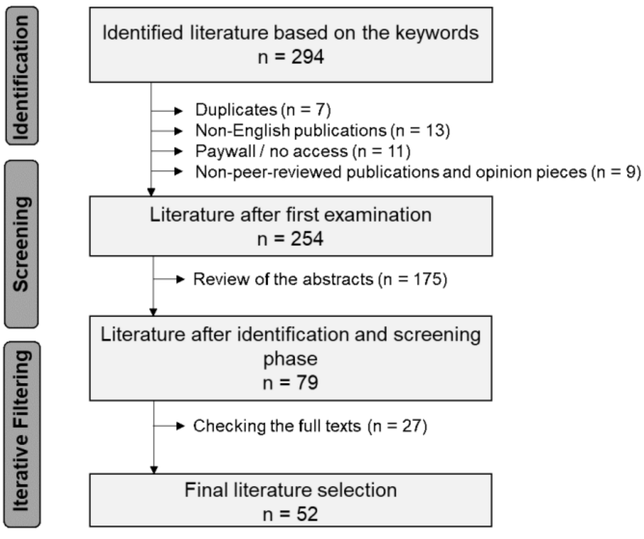

FIGURE 1. Data collection and analysis process

The initial search using the keywords described in Section 2.2 yielded 294 matching papers. The following steps were then taken to collect and analyse the results further:

1) First Examination (see upper third of Figure 1): The initial screening removed duplicates (7 papers), non-English publications (13 papers), articles behind paywalls or without access (11 papers), non-peer-reviewed publications, and opinion pieces (9 papers). This reduced the pool to 254 papers.
2) Titles and Abstracts Review (see mid third of Figure 1): The titles and abstracts of the remaining 254 papers were reviewed to assess their relevance to the research questions. This step excluded papers that were not relevant to the topic or belonged to the wrong target group. This left 79 papers for full-text review.
3) Full-Text Review (see lower third of Figure 1): The 79 remaining papers underwent a detailed full-text review. This iterative filtering process involved multiple rounds of review and discussion among the research team to ensure alignment with the study's objectives. Papers that did not meet the inclusion criteria were further excluded, resulting in a final selection of 52 papers.

2.5. Clustering of Thematic Areas

In order to provide a comprehensive understanding of the current state of research on AI-supported decision-making for ATCOs, the selected literature was clustered into thematic areas. This process involved categorising the final selection of 52 papers based on their primary focus and contributions. It is important to note that not every paper was assigned to a single cluster, because some papers address multiple thematic areas, reflecting the interdisciplinary nature of the research. The numbers in parentheses indicate the number of papers classified within each thematic area. The following thematic areas were identified:

1) AI in air traffic management and control (7): This theme focuses on the integration of AI technologies into overall air traffic management and control systems, exploring how AI can enhance efficiency and safety.
2) Decision support systems (15): This is one of the largest thematic areas and includes papers that not only explore AI-supported decision-making conceptually, but also present concrete AI tools and systems designed to assist ATCOs. These systems analyse real-time data and provide actionable insights, directly supporting ATCOs in making informed decisions during air traffic operations.
3) Trust in AI: Transparency and Explainability (11): This area addresses the importance of transparency and explainability in AI systems to build trust among ATCOs and other stakeholders.
4) Human-AI interaction (7): Studies in this cluster explore the dynamics between human operators and AI systems, focusing on improving interaction and collaboration.
5) Collaborative decision making (CDM) (5): Research under this theme investigates how AI can facilitate CDM processes among ATCOs and between different ATC units.
6) Personalised AI-systems and behaviour learning (8): This thematic area examines AI systems that can adapt to the individual behaviours and preferences of ATCOs, enhancing personalised support.
7) Conflict detection and resolution (CD&R) (15): Another major theme, it includes studies on AI techniques for detecting potential conflicts in air traffic and providing solutions to resolve them.
8) Trajectory and path planning (8): This area focuses on AI-driven methods for planning optimal trajectories and paths for aircraft to ensure safe and efficient navigation.
9) Separation and sequencing (approach phase) (4): Research here looks into AI applications for maintaining safe separation distances between aircraft during the approach phase and sequencing arrivals.
10) Urban air mobility (UAM) and unmanned aircraft systems (UAS) (3): This emerging area explores AI's role in managing UAM and integrating UAS into controlled airspace.
11) Ground operations and taxiing (5): Studies in this theme investigate AI applications in managing ground operations and taxiing procedures to improve efficiency and safety on the ground.
12) Meteorological and environmental factors (5): This thematic area covers research on how AI can assist in managing the impacts of meteorological and environmental factors on air traffic.

FIGURE 2. Thematic cluster co-occurrence in research papers

To further illustrate the distribution and relationships between the identified thematic areas, Figure 2 provides a visual representation of the strongest connections between the clusters. This chord diagram highlights the degree of overlap between thematic areas, showing how frequently two clusters are addressed together within the same papers. The diagram is particularly useful for identifying which thematic areas are frequently co-addressed.

The strongest connections in the chord diagram can be explained by several factors. Cluster 2 (Decision support systems) and Cluster 7 (CD&R) are the largest clusters, meaning more papers explore these areas, leading to frequent overlaps. Additionally, CD&R is a well-developed field, increasing the likelihood of developed decision support systems. The links between Cluster 3 (Trust in AI) and Cluster 4 (Human-AI interaction), as well as between Cluster 7 (CD&R) and Cluster 8 (Trajectory and path planning), are logically connected, as these themes naturally complement each other.

Having established the thematic clusters that categorise the current research, the next step involves leveraging these clusters to systematically extract insights relevant to the research questions. Specifically, these clusters will serve as the foundation for a detailed literature survey, guiding the identification of the current state of research, emerging trends, and key thematic areas within this field.

3. KEY FINDINGS ON AI-SUPPORTED DECISION-MAKING FOR ATCOS

3.1. State of the Art (RQ1)

This section provides an overview of the 52 papers selected for the detailed review, categorised into the thematic areas described in Section 2.5 based on their primary focus and contributions. Each thematic area includes a summary of the key contributions and references to the paper IDs in the references.

AI in air traffic management and control: [11], [12], [13], [14], [32], [41], [54].

The reviewed papers highlight AI's transformative potential in ATM and ATC. AI is transforming ATM by enhancing situational awareness, optimising traffic flow, and predicting potential conflicts. By processing real-time data, AI allows ATCOs to move from reactive to proactive decision-making, reducing workload and improving efficiency. Machine learning models offer predictive insights that help mitigate risks before they escalate. Additionally, AI enhances network resilience by detecting anomalies and safeguarding against cyber threats. Its integration not only ensures smoother and more efficient operations, but also enables ATCOs to handle higher traffic volumes, reduce delays, and improve overall safety. The scalability and adaptability of AI systems provide critical support for the future of ATM, allowing airspace to be managed more dynamically and sustainably as air traffic continues to grow.

Decision support systems: [7], [8], [14], [17], [19], [26], [28], [29], [34], [35], [36], [37], [40], [52], [58].

Numerous AI-based tools have been developed to assist ATCOs during various flight phases, particularly in managing emergency situations and handling complex traffic scenarios. These systems frequently utilise advanced machine learning algorithms and neural networks to deliver real-time risk assessments and support dynamic decision-making processes. By continuously processing live data, they offer precise risk evaluations and provide actionable recommendations, significantly enhancing situational awareness and improving coordination in critical, high-pressure situations. One of the key advantages these AI-driven systems hold over traditional approaches lies in their ability to automate repetitive tasks that typically consume time and cognitive resource. For instance, many of these tools efficiently manage conflict detection, trajectory planning, and communication, thereby reducing the workload of ATCOs. This allows human operators to focus more effectively on complex, unpredictable challenges that demand higher-level decision-making skills. In addition to conventional user interfaces, some of these tools incorporate innovative mixed-reality technologies. These interfaces offer a shared and immersive view of air traffic situations in real time, optimising collaboration between various human operators by providing a unified visualisation of traffic data. Such innovations are designed to further enhance coordination and decision-making among ATCOs, especially in high-density traffic scenarios. The specific functionalities of these AI-based tools are detailed further in the subsequent clusters.

Trust in AI: Transparency and Explainability: [8], [9], [10], [13], [16], [18], [19], [22], [24], [26], [31].

Key findings focus on Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), which are designed to make AI decisions more transparent and interpretable for human operators. These methods help bridge the gap between complex AI models and the need for understandable outputs that ATCOs can trust. Research also emphasizes the importance of balancing transparency with strategic conformance to improve the acceptance and effectiveness of AI tools. Experimental studies, including human-in-the-loop simulations, have shown that while higher transparency can increase trust and situational awareness, it may also lead to increased cognitive load and potential complacency if not managed properly. Additionally, the development of frameworks like the Multisource AI Scorecard Table (MAST) aims to provide a standardised approach to ensuring transparency and building trust across various aviation stakeholders. Surveys and user studies with ATCOs and drone operators further explore the specific transparency needs of different user groups, highlighting the necessity of tailoring explainability features to their distinct requirements.

Human-AI interaction: [9], [16], [18], [19], [23], [36], [53].

The papers in this cluster highlight the need for effective communication and teamwork between ATCOs and AI tools to ensure safety and efficiency in increasingly automated environments. Research focuses on developing advanced Human-Machine Interfaces and Interactions (HMI2) designed to improve usability and facilitate effective human-AI teamwork. Additionally, the concept of Human-Autonomy Teaming (HAT) is explored, aiming to balance human intuition with AI capabilities through interfaces that support different levels of human and autonomous control.

Collaborative decision making: [6], [17], [35], [38], [40].

Research focuses on developing systems like the Intelligent System for Supporting Collaborative Decision Making (ISSCDM), which aids in real-time decision-making during emergencies. Mixed reality (MR) is also used to provide shared visualisations of airport traffic, improving teamwork and collective decisions. Additionally, training systems incorporating AI are designed to build collaborative decision-making skills among aviation professionals, ensuring effective teamwork in both routine and emergency situations.

Personalised AI-systems and behaviour learning: [9], [15], [20], [21], [22], [40], [47], [56].

Key findings highlight the concept of strategic conformance, where AI tools align with each ATCO's unique decision-making strategies, thereby increasing acceptance and trust in automation. Studies focus on individual-sensitive automation, using techniques like convolutional neural networks (CNNs) to tailor AI-generated advisories to match the cognitive styles of different ATCOs. Additionally, behaviour learning models analyse real-world data to predict ATCO actions during conflict scenarios, ensuring that AI systems provide contextually relevant support.

Conflict detection and resolution: [10], [14], [20], [22], [27], [30], [33], [34], [36], [38], [43], [44], [45], [50], [58].

AI and machine learning methods are extensively employed to model ATCOs conflict resolution actions which enhances automation in CD&R tasks. These methods ensure that AI systems not only detect potential conflicts, but also generate resolutions that align with ATCOs' typical strategies. Examples of these applications include the development of tools like the Interactive Conflict Solver (iCS), which involves ATCOs in the process by generating conflict scenarios and learning from their resolution strategies. Similarly, AI agents are designed to solve conflicts in en-route traffic scenarios by predicting potential conflicts and suggesting appropriate resolutions. These systems aim to increase the acceptance and trust in AI-generated solutions by aligning them with the decision-making preferences of individual ATCOs.

Trajectory and path planning: [33], [34], [36], [43], [47], [51], [55], [56].

Key findings include AI-driven, decentralised systems that allow aircraft to autonomously adjust paths in real time, improving scalability compared to traditional centralised methods. CDR integrates with arrival sequencing, optimising paths through reinforcement learning. Tools like the Trajectory Generation and Advisory Tool (TraGAT) use evolutionary algorithms for conflict-free, efficient routes. AI enhances 4D trajectory planning by enabling real-time, dynamic re-planning during flight, responding to traffic, weather, or airspace restrictions without manual intervention. Unlike traditional methods, AI systems continuously optimise routes based on live data, balancing fuel efficiency, flight time, and safety. AI also clusters trajectories using Hidden Markov Models (HMMs), detecting anomalies in real time, further enhancing the safety and adaptability of ATM.

Separation and sequencing (approach phase): [34], [46], [48], [49].

Key developments include AI-driven tools that tackle the Arrival Sequencing and Scheduling Problem (ASSP), using techniques like time-based separation (TBS) and particle swarm optimisation (PSO) to optimise arrival order and timing, reducing delays at busy airports. In parallel, probabilistic models, such as those predicting separation buffers and the Tunnel Gaussian Process (TGP) model, help maintain safe distances between aircraft. These models provide ATCOs with tools to manage aircraft spacing effectively, even under uncertainty, while offering insights into flight dynamics during the final approach.

Urban air mobility and unmanned aircraft systems: [8], [23], [26].

This emerging area examines AI's role in managing UAM and integrating UAS into controlled airspace. As these technologies challenge traditional ATM methods, research focuses on leveraging AI to predict incidents and assess risks in low-level air traffic using algorithms like XGBoost. Studies also explore the transparency needs in unmanned traffic management (UTM) systems, revealing a preference among ATCOs and drone operators for operational transparency to enhance trust and usability.

Ground operations and taxiing: [24], [27], [35], [37], [51].

Key developments include AI-driven decision support systems and improved Q-Learning algorithms for optimising taxiing routes, reducing delays, fuel consumption, and emissions. Tools like the Runway Utilization Boosting Interface (RUBI) assist ATCOs by predicting runway exits and providing explanations, improving decision-making in complex scenarios. Additionally, machine learning models, such as Random Forest, help replicate ATCOs' conflict resolution strategies during taxiing. The integration of MR technology provides ATCOs with an interactive, immersive way to manage ground control, allowing them to use a tangible digital twin that projects a 3D view of airport traffic onto a physical model for intuitive, hands-on interaction.

Meteorological and environmental factors: [34], [48], [53], [54], [55].

Key developments include prediction systems that combine radar and weather data, aiding in route planning and reducing weather-related delays. Advanced visualisation techniques, such as five-dimensional displays, provide ATCOs with real-time views of weather conditions alongside trajectory data, improving situational awareness. These five-dimensional displays offer a three-dimensional visualisation of the flight route, combined with two additional dimensions representing time and meteorological data, such as wind fields and temperature. This allows ATCOs to monitor the current weather and forecast future conditions along the aircraft’s path in real time. Additionally, it is noted that the use of AI in decision support contributes to minimising the environmental impact of aviation by optimising flight paths and improving fuel efficiency.

3.2. Emerging Trends and Technologies (RQ2)

The trend towards greater transparency and explainability in AI tools is crucial. As AI becomes more embedded in critical decision-making, it's essential that ATCOs understand how recommendations are generated to build trust in these systems. While this need not be on a technical level, it is important to know what inputs the AI is using and the specific goals it is optimising for.

In this context, the personalisation of AI tools plays a significant role. By tailoring AI systems to align with the specific decision-making strategies and preferences of individual ATCOs, the process by which AI arrives at its recommendations becomes more intuitive and aligned with human thinking patterns. This personalised and adaptive approach helps to bridge the gap between human and machine, making AI a more reliable and transparent partner in ATC.

Although still in its early stages, the integration of AI in training is emerging. By familiarising ATCOs with AI tools during training, they gain confidence in the system's recommendations. Additionally, AI can personalise training to each ATCO's needs, supporting a skill-based approach that enhances their abilities. As this trend develops, it has the potential to significantly improve the deployment of ATCOs by equipping them with the necessary skills and confidence to adapt to diverse and complex operational environments.

3.3. AI in Tower and RTC Environments

This section presents the identified distribution and focus of AI-based decision support research papers within different ATC environments, with particular emphasis on Tower and RTC environments. The literature review is categorised into four distinct groups based on their primary focus areas, as illustrated in the accompanying bar chart (Figure 3).

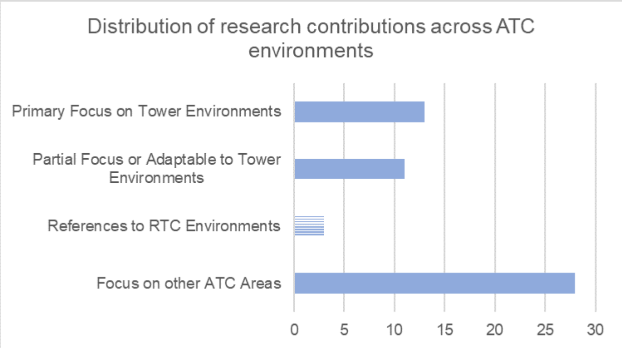

FIGURE 3. Distribution of literature contributions to ATC environments

The first category in Figure 3 includes papers that primarily discuss AI-based decision support specifically designed for airport control towers. Out of the final 52 papers selected, 13 belong to this category. These papers thoroughly explore the application of AI technologies to enhance decision-making processes within the control tower environment. The following key interpretations and applications of how AI can assist tower ATCOs in their decision-making were extracted from the literature:

1) Trustworthiness and explainability: By providing explainable AI systems, ATCOs can better understand how decisions are made, which enhances their trust in these technologies [8], [24].
2) Processing and analysing large data sets: AI-based systems can assist ATCOs in processing and analysing the vast amounts of multimodal data from various surveillance systems, helping them to quickly extract relevant information and stay up to date [19], [27].
3) Advanced support and automation: Concepts such as highly automated single controller operations (SCO) and the digital co-controller (DC) provide significant support by automating time-consuming tasks, thereby reducing the workload of ATCOs [29].
4) Immersive and interactive visualisations: Mixed reality (MR)-based systems, such as the digital twin, allow for interactive and immersive visualisation of ground control tasks, which can improve situational awareness and decision-making [35].
5) Efficient route planning: AI-driven decision support systems can allocate efficient and conflict-free taxiing routes, minimising taxi time, reducing fuel consumption, and mitigating emissions [37], [51].
6) Training and real-time monitoring: Frameworks for modelling and characterising aircraft trajectories near airports support the training of ATCOs and ensure safety through real-time monitoring of operations [47].
7) Optimising aircraft separation: Probabilistic models for predicting separation buffers can improve the safety and efficiency of landing operations by helping ATCOs to calculate optimal separations and account for uncertainties in aircraft movement [48], [49].

The second category in Figure 3 covers papers that partly focus on tower environments or discuss AI-based decision support that could be adapted for use in tower environments. There are 11 papers in this category. These findings may not be exclusively dedicated to tower operations, but contain significant insights or methodologies that could be beneficial when applied to tower environments.

For the third category in Figure 3, 3 papers reference (multiple) RTC environments. It is important to note that this third category overlaps with the first two, meaning that these 3 papers are already included in the counts for categories 1 and 2. To reflect this overlap, the bar for the third category is visually toned down in colour. The relatively low number of papers referencing RTCs suggests that this is a nascent field with significant potential for future research and development. Outstanding is the following application:

1) Smart Digital Tower (SDT) prototype: The SDT at Changi Airport provides real-time surveillance of Changi Airport's aerodrome operations. The AI systems in the SDT analyse large volumes of data in real-time, providing predictive insights and recommendations and enables the automation of routine tasks. By processing data from multiple sensors, AI enhances situational awareness and offers a consolidated airspace view, facilitating rapid, informed decision-making [52].

The fourth category in Figure 3 encompasses papers that address AI applications in various other areas of air traffic control, not specifically related to tower or RTC environments. This is the largest category, with 28 out of the 52 papers falling under it. However, as these contributions are already thoroughly discussed in Section 3.1, they are not detailed here again, as this section focuses specifically on applications in Tower and RTC environments.

3.4. Identified Gaps and Research Opportunities (RQ3)

Despite the considerable advancements in applying AI for decision support in ATC, several gaps remain. These gaps not only highlight the current limitations in the existing body of research, but also present valuable opportunities for future research. Areas requiring attention include:

1) Focus on tower and RTC: Research on AI applications in tower and RTCs is limited, with most studies focusing on upper airspace. Future work should target these environments, considering their unique demands.
2) Integration of AI with human factors: The successful deployment of AI in decision support requires a seamless integration with human operators. However, research on human-AI interaction in this field is still in its nascent stages. There is a critical need to understand how AI can be designed to complement human decision-making processes rather than replace them. This involves studying how AI systems can adapt to the cognitive and behavioural patterns of individual

ATCOs and how these systems can be designed to support rather than disrupt existing human workflows.

3) Skill fading and dependence on AI: There is a risk of ATCOs' skills fading due to over-reliance on AI. Research should focus on how AI can be used to support and retain essential skills. This is especially important given the emerging concepts for skill-based endorsements.
4) Ethical and regulatory considerations: Issues such as data privacy, job displacement, and ethical implications of AI-driven decisions are increasingly important. Research in this area should not only address the technical aspects of AI deployment, but also consider the broader societal impacts. Additionally, the development of regulatory frameworks, including certification processes that govern the use of AI, is vital to ensure that these technologies are deployed in a safe and responsible manner.

In conclusion, while AI offers immense potential in decision support, addressing these gaps is essential to ensuring its successful integration and long-term viability.

4. APPLICATION OF RESEARCH RESULTS TO FLEXIBLE ATCO DEPLOYMENT

In evaluating the alignment of literature findings with the tool categories (Section 1.2), it becomes evident that AI has the potential to play a significant role in supporting flexible ATCO deployment. The literature review reveals varying degrees of support for each tool type, as summarised in the following table. The ID column represents the respective category. “Other Tools” from category 7 are not considered in this evaluation.

ID	Fit	Explanation
1	M	The literature does discuss the potential of AI in training, specifically noting the importance of familiarising ATCOs with AI tools during their training phases. This aligns with the concept of pre-shift learning tools, as AI can be used to personalise training to each ATCO's needs and enhance their abilities before they take on operational responsibilities. However, the focus is more on real-time applications and the development of AI for situational awareness and decision-making rather than pre-shift training specifically.
2	H	The literature highlights AI's role in real-time decision-making, conflict detection, and route optimization, which aligns well with the concept of real-time learning tools that support ATCOs during their shifts. The emphasis on AI systems that provide non-disruptive support when ATCOs have spare capacity fits perfectly with this tool category.
3	L / M	While the primary focus of the literature is on real-time support, the mention of AI in training could be expanded to include post-shift learning scenarios. However, the literature does not extensively cover tools specifically designed for post-shift reflection and self-assessment, suggesting that this is an area where further development and research are needed.
4	H	The literature strongly supports the development of adaptive information tools, particularly through the discussion of AI systems that enhance situational awareness and provide tailored information based on current operational needs.
5	H	AI's role in providing direct advisories, especially in CD&R, is well-covered in the literature. The discussion around decision support systems and collaborative decision-making tools indicates strong research backing for tools that offer direct, actionable advices to ATCOs.
6	M	The literature discusses the automation of routine tasks and the development of AI systems that can perform certain control tasks autonomously, aligning with the concept of auto-control tools. However, while these concepts are discussed, full automation of ATCO tasks remains a topic of ongoing research and development.

TABLE 1. Alignment of literature findings with IFAV3 tool categories (L: Low, M: Moderate, H: High; for column Fit)

This table highlights that while AI integration is promising across most categories, the degree of support varies. Real-time learning tools, adaptive information tools, and advisory tools are particularly well-supported by current literature, reflecting a strong alignment between AI capabilities and the needs identified in the IFAV3 project.

5. SUMMARY

In the context of increased flexibility of ATCO endorsements, AI-powered ATCO decision support tools can foster the flexibility of ATCO deployment. The flexible endorsement concept has already been investigated for upper airspace. Furthermore, an applicability analysis explored which elements from upper airspace can be transferred to the tower environment. However, there must be further research that can support more flexible ATCO endorsements in tower and remote tower environments.

This paper presents a literature survey to investigate potential benefits and limitations of research topics from other applications than the IFAV3 project. Systematic methodology was applied to answer the questions about current state of research, emerging trends as well as gaps and challenges of AI-supported decision-making for ATCOs. 294 Google Scholar listed papers that match relevant keywords and were published in year 2020 or later, were filtered down to 52 papers after scanning titles and abstracts as well as a full-text review for a subset of the initial number of papers. The final selection of papers was clustered into twelve thematic areas (Section 2.5). The core topics, activities, and conclusions of these areas are compiled and presented.

While the potential of AI in ATC is recognized, the human factor of trust and human-AI interaction is often highlighted to play a critical role that deems more investigation. One application of interest is the prediction of ATCO actions to provide contextually relevant support. Furthermore, emerging trends of AI application in training and decision-making are described.

However, current AI research for tower applications is very limited. A deeper analysis revealed that just 24 papers can be attributed to the tower domain. Only three of those papers make a direct link to remote tower centres which are of key interest for applying IFAV3 concepts for flexible tower ATCO endorsements.

Finally, the studied literature has been analysed how the relevant ideas can be applied to seven different categories of tools for flexible ATCO deployment. For IFAV3 application, AI potential according to the literature analysis is highest for adaptive information tools, advisory tools, and real-time learning tools. The tool ideas to be developed for IFAV3 RTC support will undergo a TRL 2 validation as workshop with operational experts planned for 2025.

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