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Full Length Article

Using sustainable technology to drive efficiency: Artificial intelligence as an information broker for advancing airline operations management

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A B S T R A C T

Airlines are frequently confronted with disruptions that interfere with their flight operations, resulting in revenue losses and unsustainable performance. While information sharing is an important approach to mitigate airline disruptions, the industry is still characterized by technology fragmentation and a lack of real-time information exchange between actors in the airline ecosystem. As a response, this study investigates how artificial intelligence (AI could be utilized as an information broker to enhance information sharing for collaborative decision-making in airline operations management. Adopting a qualitative research approach, we conducted 22 semi-structured interviews with managers and professionals from three critical airline functions - air, ground, and information technology - across multiple global airlines to examine how AI is used for coordination and information sharing in their operation and how it impacts operational processes and performances. The results show that AI in the airline industry is in its infancy with fragmented applications within the airline ecosystem, but managers highlight the need for implementation of context-aware, organizationally aligned, and carefully integrated AI into operational routines. Our findings also show that in order to use AI as an information broker, most participants prefer an agent-based model for operations management, however, integrating agent-based models require advanced data that need to be collected from process-based systems first. We further discuss theoretical and managerial implications and provide actionable recommendations for implementing AI in airline operations. This is one of the first studies to specifically examine cross-departmental information sharing through AI from an information brokerage perspective.

Introduction

Airlines are frequently confronted by disruptions that interfere with their flight operations, including technical and mechanical problems, congestion at airports, or simply bad weather conditions (Castro et al., 2014). Not only do these disruptions cause problems and delays from an operational perspective, but they often result in financial losses because delays and lower operational performance lead to higher fuel usage, increased flight crew overtime and potential compensation for passengers (Belobaba et al., 2015). In fact, Walker (2017) found that almost 24 % of European scheduled flights were delayed, which translated to approximately 6500 flights per day. Given the significant negative operational and financial implications of these disruptions, mitigation initiatives from airline managers have become increasingly important (Belobaba et al., 2015).

Existing research shows that despite the frequent occurrence of disruptions in the airline industry, the current operational management setup to solve these challenges is still characterized by a lack of collaboration and little automated information sharing among those involved and, thus, has limited ability to mitigate operational disruptions (Dube et al., 2021). Scholars point to a monolithic information system setup and a strictly sequential approach to dealing with problem situations by airlines, which "typically renders solutions from decision-support systems ineffectual within moments after they are generated" (Ogunsina & DeLaurentis, 2022, p. 2).

While existing research highlights the crucial role of technologies as information brokers for operational efficiency by enhancing collaboration and information sharing (Brooks et al., 2024), the current use of technologies seem to have only had a limited effect in the airline industry (Di Vaio & Varriale, 2020). Existing technologies in the industry often operate within fragmented infrastructures and have restricted integration capabilities, resulting in isolated data silos and subsequent

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delays in coordinating responses during airline disruptions (Geske et al., 2024b). Studies show also that information sharing techniques provide reactive rather than proactive data management, with minimal capacity for real-time updates or predictive insights (Weisz et al., 2025). As such, most recent research contributions fall short in addressing the dynamic complexity of airline disruptions. Research often treats information technologies as static tools rather than adaptive systems capable of learning and evolving in real time. Moreover, existing frameworks largely ignore the potential of artificial intelligence (AI) to unify fragmented data landscapes through intelligent integration and real-time analytics. As a result, there is a lack of empirical evidence on how AI-enabled information brokerage could support decision-making under operational uncertainty. This reveals a critical research gap at the intersection of AI and collaborative disruption management in the airline industry.

Against that backdrop and given the recent advances in, we argue that AI could be used as an information broker to enhance information sharing for collaborative decision-making in airline operations management. We specifically asked the question: "*How can AI act as an information broker for enhanced information sharing in collaborative decision-making in and for airline operations management?*"

To answer the research question, we adopted a qualitative approach, conducting 22 interviews with airline managers and professionals from multiple global airlines between June and November 2024. By doing so, we attempt to close the gap in the literature by shedding light on how AI as information broker can facilitate cross-functional information flows to support collaborative decisions in airline operations. By focusing on real-world practices, we provide context-rich and relevant insights on how AI can enhance information sharing and decision-making across departments. In particular, the contribution of this study is threefold: First, the findings presented in this study provide an insight into the current status of AI in airline operations management, thereby offering the current state of how AI and its applications are perceived by airline managers for information exchange. So far, the use of AI in the airline industry mainly consists of theoretical contributions or focuses on technical solutions, but only little empirical research exists that specifically investigates AI for information sharing or brokerage between departments. Second, we contribute to a better understanding of AI technology as an information broker, thereby not only providing a theoretical contribution on how AI has changed operational processes and practice in the airline industry but also extending the concept of information broker itself. Third, from a managerial viewpoint, we provide practical insights and highlight requirements, barriers and opportunities for the implementation AI in the airline industry, thereby providing actionable recommendations for managers in airline operations.

The remainder of the paper is structured as follows: In the next section, we discuss the role of information sharing and brokerage in the airline industry, in particular highlighting the concept of information brokerage and information through process-based models as well as agent-based models. This is followed by our methodology outlining our qualitative approach and providing details about the data collection and analysis of the semi-structured interviews. This is followed by the presentation of our findings which are structured around the common and recurring themes from the interviews. We then discuss the implications of our findings and conclude with a summary of results and suggest future research avenues for AI in the airline industry.

Information sharing and brokerage in the airline industry

The concept of information brokerage for enhanced information is an increasingly popular topic in organizational management research (Pawlowski & Robey, 2004). Managing and sharing large amounts of data and the associated information in complex ecosystem networks is often dependent on technology that acts as an information broker between systems (Wareham et al., 2014). As such, the role of the information broker, which can be defined as an actor "producing, interpreting, organizing, or communicating information to specific groups of people for a particular purpose" (Jorge et al., 2016, p. 516), is critical to exchanging information between other, as yet unconnected, actors in the ecosystem.

However, the current role of information brokers in the airline industry, facilitated by traditional systems and technologies, is characterised by several limitations that restrict the effective sharing of critical data, especially during disruptions (Ogunsina & DeLaurentis, 2022). Scholars point out that existing airline systems often operate within fragmented infrastructures, resulting in compartmentalized data silos where information is not easily accessible or transferable to actors across the ecosystem, leading to limited comprehensive situational awareness and to delayed coordinated responses (Di Vaio & Varriale, 2020). Airlines usually rely on static and rule-based systems, which limit adaptability and scalability, and on manual data inputs and legacy systems, which further exacerbate delays and errors (Bouarfa et al., 2018; Lee et al., 2020; Wen et al., 2024).

Moreover, existing scholarly frameworks investigating AI in organizations emphasize data-centric and predictive capabilities (Boone et al., 2025; Geske et al., 2024a; Herold et al., 2021a; Magliocca et al., 2023; Zong & Guan, 2024), but often overlook the contextual and organizational dynamics critical for effective application in complex environments. In fields such as information systems and knowledge management, AI is predominantly treated as a tool for automation and efficiency (Dobrovnik et al., 2025; Nemati et al., 2002; Spring et al., 2022), rather than as a socially embedded actor that shapes and is shaped by organizational routines. This framing limits its explanatory approach when applied to collaborative domains like airline operations, where information sharing is critical for on cross-departmental coordination and situational interpretation, in particular during disruptions in airline operations. In other words, existing AI models in these fields prioritize algorithmic performance over interpretability and adaptability, which constrains their utility as information broker. We argue that this conceptual misalignment reinforces the marginal integration of AI in airline operations, resulting in a gap between technological potential and organizational readiness.

To facilitate information sharing between actors, scholars focus on two prominent approaches, namely process-based models and agent-based models. Process-based models of information sharing are characterized by structured workflows and predefined sequences that guide data exchange among actors, often based on step-by-step protocols and decision trees that streamline communication channels (Bazan & Estevez, 2022; Wen et al., 2020). In other words, information brokers in process-based models act as coordinators that manage the flow of information across various stages, ensuring that data is delivered at the right time to facilitate transitions between operational processes, such as flight scheduling, ground handling and passenger management (Geske et al., 2024b). Scholars point out, however, that while process-based models are usually effective in routine operations, they may struggle in highly variable situations such disruptions or contingencies, where predefined pathways can become bottlenecks which limit flexibility and delay responses (Curley et al., 2020).

In contrast, agent-based models are decentralized and prioritize the autonomy of various entities or "agents" within the ecosystem, each acting based on its individual goals and constraints (Bouarfa et al., 2018). More specifically, an agent-based model in the airline industry allows different actors, such as airlines, ground handlers and regulatory bodies to exchange information dynamically *without* a rigid sequence. In these cases, information brokers act as facilitators that enable and manage connections between autonomous agents, helping them communicate and coordinate "on-the-fly" while respecting each agent's independent decision-making power (Karl et al., 2020). Existing literature suggests that agent-based models are particularly advantageous for handling airline disruptions, because agents can quickly adjust their strategies based on real-time information (Castro & Oliveira, 2010).

To address the lack of information sharing, academics and managers have suggested that AI could be used as an information broker for enhanced information exchange between actors in the ecosystem (Weisz et al., 2023). For the purpose of this study, we adopted the widely accepted definition provided by Marvin Minsky, the founder of MIT Artificial Intelligence Lab (Minsky, 1968), which defines AI as "the science of making machines do things that would require intelligence if done by men". In fact, numerous studies point out that AI has the potential to transform information sharing and collaboration (Zhang et al., 2022). However, the role of AI as an information broker is under-researched, in particular regarding its implications for airline operations management and the associated information sharing processes and practices. Therefore, we examined the role of AI as an information broker for enhanced information sharing among actors in the airline ecosystem. In methodology, we provide an overview of the methodology of our study.

Methodology

Research approach

The overall research aim was to examine how airlines could use AI as an information broker for better collaborative decision-making. To achieve that aim, we followed the interpretive research approach outlined by Darby et al. (2019). An interpretive approach focuses on a particular phenomenon in a particular place and, therefore, "particular motives, meanings and experiences are studied to provide 'thick descriptions' that are time- and context-bound" (Darby et al., 2019, p. 398). The interpretive approach allowed us to generate meaning and expand boundaries by analysing associations between constructs and focusing more on the process than on an explanation of the end product (Denzin, 1984). We used a part-to-whole process, represented by a hermeneutic cycle (Darby et al., 2019; Herold et al., 2021b). The beginning of the cycle included an orienting frame-of-reference that explained the self-relevance of the context (Thompson, 1997) and, thus, offered an overarching framework for the research methods and the analysis. Following Pagell and Wu (2009) the orienting frame-of-reference revolved around three themes that defined the context of this study, namely the information broker, AI and airline operations. First, the concept of the "information broker" provided a theoretical foundation to analyse how the social influences of environment became self-relevant. Second, the other themes consisted of the relationship between "AI" and "airlines" (or airline operations), which could be characterized as dialectic. On the one hand, AI is seen as a tool to improve airline operations; on the other hand, the adoption of AI presents new challenges for airlines with regard to existing practices and processes. In combination, the orienting frame-of-reference juxtaposed these themes to provide a framework to understand how AI as an information broker was influenced by the social aspects of the airline operations environment in which it was designed and implemented.

Selection of context and sample

Owing to the emphasis on an in-depth understanding of the context, the selected number of informant cases in interpretive research approaches is small, varying between 3 and 20 (Fournier, 1998). Therefore, based on the orienting frame-of-reference, in this study the informants were senior airline managers from low-cost carriers, full-service carriers and gulf carriers. Because the interpretive approach follows a judgment sample strategy, i.e. the samples are based on the opinion of an expert (Deming, 1990), interviewees were selected using the following criteria. First, the interviewees needed to work at airlines with a global presence (i.e. they were operating in an international/global market) with a hub-and-spoke system, thus they had an inherent complexity in their operations. Second, to understand the implications of AI on operations management, only informants within the airline operations department were interviewed. Third, to gather in-depth data, it was decided to interview informants from three different areas: a) operations management, b) strategy and c) IT/digital transformation. These three areas have been chosen as they reflect the core domains, i.e. AI adoption strongly intersects to and is influenced by operational performance, strategic alignment, and digital capabilities. These three areas allow to investigate holistically how AI as information broker can act as a cross-functional enabler in the complex airline environment.

For the interviews, 22 informants, from 13 different airlines, were purposefully selected (Yin, 2018) to ensure that the respondents possessed an in-depth understanding and rich experience of the operational impacts and their underlying processes from an AI viewpoint. The informants consisted of senior operations managers and professionals with strategic and operational management experience. Because the aim of the interpretive research was to gather in-depth knowledge and the information was received with a promise of confidentiality, we guaranteed anonymity to the informants. An overview of the informants can be found in Table 1.

Data collection

Based on data-gathering techniques in interpretive research, we collected primary data via semi-structured interviews, interviewing informants from the airlines described above. Semi-structured interviews were chosen because they ensured that the content of the interview was focused "on the issues that are central to the research question, but the type of questioning and discussion allow for greater flexibility than does the survey interview" (Minichiello et al., 1995, p. 65). Although we used the orienting frame-of-reference as a guide, our questions were not "strictly scripted" (Yin, 2018, p. 134) and we followed a conversational mode to encourage a two-way interaction to better understand the particular role of AI as an information broker and its implication for airline operations management. As such, the questions focused specifically on AI and addressed three main issues: a) AI information and transparency, b) collaborative decision-making, and c) AI as information broker and decision-maker.

The interview questions were short and open-ended with the goal of

Table 1
Description of informants.

No	Geographical Location of Airline	Function
1	Middle Eastern Airline	Operations Technology and Innovation Manager
2	European Airline	Hub Control Center
3	European Airline	Head of Operations
4	European Airline	Head of Operations Planning and Development
5	European Airline	Head Flight Operations & Training Captain
6	European Airline	Manager Performance Hub Operation Center
7	Asian Airline	Operation Control Center Manager
8	European Airline	Head of Operations Control Center
9	European Airline	Head Ground Operations
10	European Airline	Head of Flight Dispatch and Navigation Office
11	European Airline	Manager Operations Network
12	European Airline	Manager Operations Development and Optimization
13	European Airline	Head of the Crew Control
14	European Airline	Head Operation Strategy and Performance
15	European Airline	Head of Ramp Services
16	Middle Eastern Airline	Manager Network Operations
17	Asian Airline	Senior SpecialistPerformance Analysis and Reporting
18	European Airline	Senior Director Digital Operations
19	American Airline	Senior Manager Operations & Automation
20	Middle Eastern Airline	Business Analyst
21	Middle Eastern Airline	Operational Analysis Specialist
22	European Airline	Director Information Systems

creating a circular dialogue influenced by the recurring interaction between interviewee and researcher (Wimpenny & Gass, 2000). This allowed us to understand the informants "on their own terms and how they make meaning of their own lives, experiences and cognitive processes" (Brenner, 2006, p. 357). To keep the conversation going, we made use of probes and follow-up questions not only to stimulate the informant to expand upon their original comments (Yin, 2018), but also "to hear the meaning of what is being said" (Rubin & Rubin, 2011, p. 7). The interviews were conducted either face-to-face or virtually and all interviews were recorded and transcribed in August 2020.

Data analysis

In the data analysis stage, each case was analysed intratextually (Darby et al., 2019) using the orienting frame-of-reference for interpretation. By reading and rereading the transcripts individually, we interpreted the text in context for each of the informants (Murray, 2002). To support this process, we used NVivo 14 to assist in the coding and organization of the data. To minimise subjectivity and bias, the authors conducted the coding process collaboratively. Codes were assigned by evaluating how the data in each case related to the orienting frame-of-reference. Initially, each author independently reviewed and coded a subset of the data to capture individual insights. This was followed by consensus meetings where discrepancies were discussed, justifications for coding decisions were provided, and adjustments were made to reach agreement. The process was iterative, involving multiple rounds of discussion and cross-checking to validate the codes and ensure consistency. This intratextual analysis was concluded using a detailed summary including a list of the major findings for every informant to identify the reoccurring and main themes. In addition, we documented our analytical choices and remained critically aware of our own assumptions throughout the process. After completing the intratextual analysis, we analysed the findings intertextually (Darby et al., 2019) to identify common themes across the cases. In this step, we searched for shared storylines concerning the role of AI as an information broker for the purpose of achieving a higher level of abstraction (Prasad, 2017), allowing us to identify overarching themes. This analysis stage aimed to provide all information in contextual detail and produce "thick" descriptions (Geertz, 1973). Following the approach from Arnould and Wallendorf (1994), we repeated the process of thematic analysis until the orienting frame-of-reference was contextualized and no new themes emerged from the data, indicating that thematic saturation had been reached.

Findings

The interviews focused on three main areas: a) information sharing and transparency, b) collaborative decision-making, and c) the role of artificial intelligence as an information broker and decision-maker. For each of these sections, three common and recurring themes could be identified, which are elaborated in more detail below.

Information sharing and transparency

In the analysis of the interviews three main recurring themes in the area of information sharing were identified: progress towards digital information flows; reliance on manual data input and the lack of real-time date updates; and need for transparent tools for tailored output of relevant information.

Progress towards digital information flows

The interviews showed that airlines have made significant progress on digitizing and creating digital information flows, setting the basis for automated information brokerage. However, depending on the airline, a considerable amount of information is still exchanged on a verbal level in the form of meetings or phone calls, as well as in written form such as emails or chat messages. These unstandardized verbal and written forms may decrease the speed and reliability of information flows. They also hinder the integration of this communication into the source systems to allow it to be incorporated into the decision-making process of all stakeholders involved. This highlights the importance of and need to establish an information broker. To solve this issue, one interviewee suggested implementing large language models (LLMs).

Interviewees also named information sharing of resource availability and time stamps from external stakeholders involved in the turnaround process as a major burden in collaborative decision-making. Even if the generation of time stamps is widely done using a semi-manual process of turnaround apps, where employees initiate process starts by pressing a button, it is often believed to not fully represent the true time stamps. Although technical solutions such as virtual recognition exist, airlines managers widely consider a rapid implementation unrealistic due to security and labour union concerns as well as the need for infrastructure investment. Furthermore, experts saw the turnaround processes away from home base as another major hurdle in the digitalization process owing to low purchasing power at the suppliers. In addition, IT experts questioned the feasibility and integrability of system-wide turnaround data, owing to the lack of standardized data formats, and the multitude of different systems and interfaces. Despite advances in the progress towards digital information flows, seamlessness has yet to be established to streamline airline operations, increase transparency and accelerate the collaborative decision-making in the multi-agent system to ultimately improve performance and efficiency.

Reliance on manual data input and lack of real-time data updates

Despite progress in the digital transformation of airline operations, the interviewees indicated that airlines still relied on manual data entry, which resulted in time lags and which might potentially be more error prone. Especially in case of disruptive events, a significant share of inputs was still done manually. During the management of a disruption, critical information, e.g. about a potential diversion and the pilot's intention, was not shared with all relevant stakeholders, required some manual input or had a time lag. For instance, one interviewee stated: *"It's a mix… a lot of information is coming on an automatic way like weights for the flight path and will you the true at the beginning of the line there's someone sitting at the waiting balance office and he's doing the job manually […]"* (Interviewee #10). The absence of digitalization of early steps in the process chain and automated information brokerage may have cascading implications for this single process and may also represent a bottleneck for other downstream processes. This was supported by another interview from a different IOCC: *"Normally OPS control has to insert the delay in the in the OPS ++ system and then we would get almost an immediate information our cruise system that there is a delay and then there would be like a warning in our system that there is like maybe a rest time problem or duty time violation"* (Interviewee #13).

This combination of digital and manual data input exemplifies the gap in achieving full automation in situations when every minute is crucial and all stakeholders should have the same knowledge. High competition and cost pressure has reduced slack in the aviation system, making it even more vulnerable to knock-on effects. These conditions stress the importance of moving to an automated information brokage tool working with real-time data but they also hinder the implementation of AI in this area. In the airline industry, if information is not received correctly or in real time, there is a loss of time and money. Several interviewees emphasized that every manual input by human is less reliable than an automated data exchange. For example, Interviewee #10 stated: *"Of as you can imagine, it's a mix a lot of information is coming on an automatic way like waits for the flight uhm path and we er tell you er the to be tell you the true er, at the beginning of the line there's someone sitting at the waiting balance office and he's doing the job manually."*

Necessity for transparent tools for tailored output of relevant information

Airline operations rely heavily on standardized and streamlined processes, which involve many different stakeholders and agents, but which also provide the opportunity to collect many different data points. The interviewees supported these aspects and emphasized the need to have access to the right information at the right time. Many managers stressed that the challenge was often not the data availability, but rather the information sharing between stakeholders, the data quality and the amount of generated data in the sense of information overload. One interviewee pointed out: *"When I did my research in 2018, I saw it with other airlines as well. I think it make I made a comment somewhere that the average OCC and operation control team has to have a total of or average of 22 IT systems. That I have someone to have to come to this session that I have to go through all these systems. Just too much really"* (Interviewee #11). Because the work in an IOCC setup requires employees to make decisions under uncertainty in a short period of time and the most critical decisions must be made when dealing with disruptions, employees must be supported by the respective IT infrastructure rapidly providing all relevant information in one view: *"That flow of information has to happen very quickly. Not everything is relevant to everyone, so if you're customer-facing, information that you get should be tailored to help you deal with a customer. You don't need to know every single thing"* (Interviewee #1). This statement underlined the time-sensitivity of decision-making in airline operations. At the same time, airline managers pointed out the diversity of different departments involved in airline operations, leading to multiple requirements. Each department has different requirements for their tailored information displays. The deployment of tools serving as information brokers not only empowered individuals with situational awareness to make optimal decisions under time-pressure, but also fostered transparency and allowed for proactive collaborative decision-making.

Collaborative decision-making

Three main areas for collaborative decision-making were repeatedly mentioned by airline managers: centralized decision-making and operational delays; challenges in accessing real-time data for timely decisions and integration of ground handling; and the importance of cross-departmental coordination.

Centralized decision-making and operational delays

Airline managers emphasized that safety and security were the key attributes for all decisions and actions initiated. This led to the need for a clear definition of roles, responsibilities and especially of accountability in the decision-making process. Broadly, two phases can be distinguished in the airline operations: the pre-flight planning and turnaround phase; and flight operations. There is a clear distinction of responsibilities during those two phases: *"The final decision is still made by IOCC and by the pilot in command"* (Interviewee #5). The IOCC (and most prominently the operations control centre (OCC)) are involved in all decisions made. For the pre-flight planning phase, including the aircraft turnaround, the IOCC is accountable and responsible for decisions. As soon as the aircraft leaves the parking stand (off-block), the pilot in command takes over the ultimate accountability and responsibility, while IOCC officers play a supporting role. Consequently, collaborative decision-making narrows to one centralized actor who ultimately makes the decision.

The predominant goal of most airlines in the sample was to optimize punctuality and reliability. *"We know that the passenger is looking at the arrival punctuality more than the departure punctuality, but we are still very much as we are steering out of the hubs we are still very much focusing on the departure itself"* (Interviewee #6). While the customer experience and related costs, e.g. for missed flight connections or for mishandled bags, were slowly gaining more attention, only one airline primarily focused on passenger connectivity as a leading KPI.

One interviewee mentioned that the collaborative decision-making in its centralized form was working well. However, due to the lack of effective information brokerage, manual or verbal information sharing and slow communication to front-line works, measures might not be initiated in time to positively impact the process. While stakeholders had the common goal of working on an on-time departure, which was also aligned with overarching initiatives like A-Collaborative Decision Making (CDM) from Eurocontrol, this KPI was considered to be too high-level to effectively steer front-line processes, which resulted in inefficiencies. It was also advised by some managers that the focus on operational steering must reflect the return flights into the hub and other factors such as actual flight times as well. Therefore, a more holistic view of the system operations was required, which was currently not possible due to a lack of labour as well as to insufficient technical support.

Challenges in accessing real-time data for timely decisions and integration of ground handling

The prevailing opinion of airline managers identified the need to have access to real-time data to respond in a timely manner. The number of external stakeholders led also to the need to integrate different systems, with a risk of data inconsistencies which created another challenge before being able to access data in real-time. Yet, many decisions were based on fragmented information with different stakeholders struggling with varying sets of available data. This may lead to ambiguity and the information gap may hinder collaborative decision-making. As already mentioned, major obstacles in obtaining all relevant data persisted due to technological and security constraints.

IOCC setups for the interviewed airlines mostly focused on the OCC, which acted as a focal point and ultimately took the decision, the hub control centre, flight dispatch and crew control. However, the interviews showed that other relevant stakeholders such as ATC, ground handling service providers, passenger handling units (gate, check-in) or hub airports were not sufficiently represented by the typical actors and agents in the traditional IOCC setup. Interviewees indicated that collaboration with stakeholders in the aircraft turnaround process led to an under-achievement of efficiency gains. In contrast, fostering collaboration, advancing information sharing and increasing transparency could be a mutual benefit for both sides. Airlines may benefit from increased on-time performance and, therefore, reduced disruption and propagation effects, while service providers may better use their resources and may be able to reduce buffers. Some of the researched airlines tackled this issue by adding duty managers from passenger handling units or airport representatives into the IOCC round. The interviews showed that there were many attempts to obtain crucial information such as timestamps. One manager stated: *"[…] for us it would be important to get real time timestamps. Especially for the hub control centre so that they can optimize the steering"* (Interviewee #15). The investment into establishing integrated systems did not only ensure real-time data, but also could bridge the gap between relevant departments, which included internal and external stakeholders. According to the airline managers it would decrease reaction times and allow for more informed decisions in the dynamic and disruptive environment of airline operations.

Importance of cross-departmental coordination

For an efficient airline operations and effective disruption management, *"Everyone has to get behind it. And the rest of it, we know is going to take this much delay or this much operational impact and we're okay with it. We've mitigated, we've communicated early and that's how we need to make decisions […]"* (Interviewee #1). To achieve this, managers' emphasized interconnectedness in terms of communication and a high degree of synchronization among all stakeholders and their teams. Owing to the lack of operational buffers, as well as the high degree of interconnectedness within the system, small issues in one process quickly led to major operational disruption. As outlined before, the consistency, speed and accuracy of information flows towards all departments and internal/external stakeholders, was vital to avoid cascading delays which affected flights, resources and, ultimately, passengers.

In addition, access to data must be granted for all stakeholders, as one interviewee noted: *" […] everyone is able to access the data and can use* *it for their decision-making in the back end […]"* (Interviewee #9). To further foster cross-departmental coordination, an alignment of goals between all stakeholders was required to avoid conflicting actions that impacted the overall operational performance. It was also noted by one manager that the constant information exchange and update must not stop when the aircraft leaves the parking stand, but a constant feed and exchange of information was required also during the flight to support an efficient flight execution. *"You save* 10 min*, that costs 2 tons of fuel. I'm on time and then you find out. OK, the next connecting flight* is 2 h *away and it did not make any sense to fly high speed. So, speed control via cost index or speed control via estimated touchdown time would be a huge step forward for pilots, in order to fly more economic from the standpoint of total costs"* (Interviewee #5).

Artificial intelligence as information broker and decision-maker

The three core topics that were identified from the interviews of various airline representatives were AI as a tool to bridge information gaps and increase understanding of cause-effect relationships as well as correlations; AI's role in real-time operational adjustments and in predictability of decision consequences; and AI as a support tool rather than the sole decision-maker.

AI as a tool to bridge information gaps and increase understanding of cause-effect relationships as well as correlations

The great potential of AI in the context of airline operational steering and disruption management was widely acknowledged by all interviewees. The airline ecosystem has an inherent complexity stemming from the many stakeholders involved and numerous influencing factors and variables, which include weather conditions, passenger itineraries and resource situations such as staffing. Thus, AI may support an understanding of correlations, cause-effect relationships and the root cause of delays. Moreover, AI tools may also serve to bridge existing information gaps. Interviewee #1 commented: *"I want to see how artificial intelligence could be used as an information broker to have more information to make the right decisions."* However, the interviewees also identified that the application of AI in the context of airline operations and disruption management should go beyond automation and its functionality as an information broker, and also incorporate the capability to review and interpret data in a timely fashion.

Unlike human agents, AI tools can analyse data extremely fast, which enables decision-makers to reduce evaluation times and also to detect patterns and trends or incorporate historic data into the decision. Airline managers estimated that AI could also be applied to ensure that different stakeholders received only the information relevant for performing their tasks which would address the current issue of information overload. An AI system could act as a central point of information, ensuring real-time updates to all departments. Interviewee #2 also noted: *"Often, the processes can be lengthy and may have gaps, resulting in information not being received. This communication must occur seamlessly and that's one of our biggest challenges."*

However, in this context it was also emphasized that airline managers did not anticipate the implementation of AI to replace employees, but rather to shift labour intensive data gathering, interpretation and visualization tasks from employees to an AI tool to provide additional capacity for more critical or strategic decisions. AI was also seen to enhance decision-making through its ability to forecast different scenarios and their impact on the operational system.

AI's role in real-time operational adjustments and in predictability of decision consequences

Airline managers highlighted the variety of influencing factors and the high degree of dynamism as major challenges that IOCC officers must handle in daily operations and when dealing with disruptions. The ability to derive decisions faster and incorporate more influencing factors, as well as evaluate the impact of decisions on the remaining day of operations or the following day, were among the expectations that airline experts had for AI support tools. Such AI tools could help by tracking delays and identifying real-time adjustments to manage them. Besides this, AI applications were faster in real-time monitoring and the detection of patterns leading to delays. This would allow IOCC teams to move towards proactive operations guidance aimed at minimizing the occurrence of disruptions. Thereby, AI could assess the entire chain impact to ensure that decisions did not cascade into bigger issues.

Most airline operation experts expected real-time operational adjustments to be driven by two main factors: integrating the variety of different data sources into one system and predictions that combined historic and real-time data. One airline IT expert considered these were critical and saw a different path for the future. According to this expert, LLMs could solve a lot of existing problems and contribute to making more informed decisions. Using LLMs would allow challenges to be circumnavigated in terms of system integration and facilitate the use of free-text verbal and written data input: *"I think the ChatGPT or LLM is the future model of the IOCC"* (Interviewee #20). The same interviewee also had a more critical opinion on predictions of the underlying setup owing to the complexity of the operations system. For many events, predictions were more likely to be more educated guesses compared with the status. However, unlike many airlines managers, he suggested that it would be beneficial to start the implementation immediately because such systems would outperform humans, even with the current data availability. Other interviewees also supported an early implementation with continued development from a process level to full implementation in the system. The current absence of real-time information was often seen to lead to delayed or inadequate reactions.

AI as a support tool rather than sole decision-maker

While the capabilities of AI application were widely understood and acknowledged by the interviewed airline managers, these industry experts postulated that such tools should only support human decision-makers, but would not replace their ultimate judgement. It was commonly agreed that AI would definitely support human decision-making by gathering and combining data from various sources as well as processing and analysing data. This would allow a shift in responsibilities such as flight plan monitoring, delay predictions or resource allocation to AI support tools and would free up IOCC officers to focus on higher level decisions.

The managers also mentioned that airline operations were too complex and unpredictable for a full reliance on an AI system to be feasible. Nevertheless, it was widely believed among experts that AI would increase cross-departmental coordination and, thereby, foster collaboration, especially in stressful disruptive situations. As identified above, accountability was cited as a major reason for not only focusing on AI solutions: *"Because one still wants to have a human making the final decision."* (Interviewee #16)

Discussion and implications

The findings of this study extend existing knowledge in the field of AI-supported decision-making in operational environments, particularly in the context of information brokerage. With AI in its infancy in the airline industry, we particularly discuss how the concept of information brokerage has evolved compared with traditional technologies and how AI can be utilized for better operations from a theoretical and managerial viewpoint. In the following sections, we discuss our findings in the broader context of AI, information brokerage and operational efficiency, followed by theoretical implications on how AI has changed operational processes and practices in the airline industry and lastly, by a practical discussion about how managerial implications of AI in the current airline environment.

The role of AI as information broker in the airline industry

Existing research has framed AI as a rather technical solution for data processing and predictive analytics but has seem to have overlooked the systemic and operational challenges found in the airline industry (Burström et al., 2021; Geske et al., 2024b). Our findings, however, show that while digital infrastructures have evolved, manual processes and fragmented systems remain deeply embedded in airline operations, thereby limiting the performance of AI as a real-time information broker (Ogunsina & DeLaurentis, 2022). By grounding these limitations in empirical data, the study highlights the misalignment between technological capabilities and organizational readiness (Dobrovnik et al., 2025; Lu & Ramamurthy, 2011; Uren & Edwards, 2023; Webster & Gardner, 2019). The interviewees' emphasis on tailored outputs and context-specific data relevance speaks to a growing recognition of cognitive overload and the need for human-centric AI design, a theme underdeveloped in existing literature on AI in operational decision-making. The study therefore shifts the focus from abstract potential of AI to the situated conditions that shape its practical deployment, highlighting the collaborative elements and the complex networks of actors and processes (Anthony et al., 2023; Wen et al., 2024).

Building on these insights, we extend research in collaborative decision-making and organizational coordination by emphasizing the fragility of current models when faced with real-time demands. While frameworks such as CDM highlight the need for shared situational awareness (Vail et al., 2015), our findings suggest that airlines often remain at a procedural rather than integrated level of coordination, i.e. with IOCCs functioning as centralized silos rather than distributed decision environments. This operational centralization persists even in data-rich settings, reinforcing the paradox of information abundance and limited utility. We thereby confirm concerns raised by Di Vaio and Varriale (2020), such as the inability to integrate ground handling, external providers, and ATC into shared systems, thereby illustrating a structural barrier to collaborative efficiency. These findings also extend the literature by showing that collaborative decision-making is not only about information access, but also about timing, trust, and cross-functional alignment.

Our findings also position AI as an adaptive and context-aware support system, thereby shifting AI as a sole decision-maker to a more collaborative approach. In contrast to narratives promoting AI autonomy, our findings are in line with findings of Davenport (2018), who argues for AI as augmentation rather than replacement. The airline managers' insistence on human oversight, particularly during disruptions, reflects a wider organizational logic that prioritizes accountability and interpretive judgment over algorithmic determinism (Silverman, 2020). This also aligns with emerging calls in information systems research to reorient AI from a purely computational model to an embedded, participatory actor in decision environments (Dolata et al., 2022; Kane et al., 2021). The emphasis on scenario forecasting, selective information dissemination, and AI-driven modelling illustrates an evolving shift from reactive to anticipatory operational logic. As a consequence, our findings can also be considered as a roadmap for designing AI tools that enhance agency rather than constrain it.

Theoretical implications

Based on our findings, we were also able to draw three theoretical implications on how AI has changed operational processes and practices in the airline industry, namely: a) operational efficiency; b) data management and decision support; and c) safety and risk management.

AI as information broker for operational efficiency

Our findings indicated that the AI-supported systems were seen as risky because the environment had not yet established clear rules. For example, AI systems for airline operations were not yet fully standardized across the industry, leading to fragmented AI implementation and limited interoperability. Interviewees argued that the lack of standardization complicated communication between airlines and hindered collaborative data sharing, which reduced overall adaptability. Moreover, AI systems in airline operations relied heavily on external data sources, such as real-time weather reports and traffic flow data from air traffic control, but these sources were not always consistent or uniformly available, thereby potentially creating gaps in AI-driven decision-making.

Nevertheless, most interviewees agreed that AI as an information broker represented a major evolution for information sharing compared with current systems. In traditional airline operations management, the efficiency of information brokering was heavily dependent on the manual coordination between departments such as flight operations, maintenance and customer service. As such, existing models in traditional technological systems focus on workflow optimization and process standardization to improve efficiency, but these models are limited by the capacity of human operators and legacy infrastructure.

AI as information broker for data management and decision support

The role of AI as an information broker has clear implications for data management and its associated decision support. Similar to 5.1.1, information brokers in traditional airline operations usually act as intermediaries who collect, compile and distribute crucial operational data, such as flight schedules, weather reports, maintenance records and passenger information. This process involves manual input and human oversight to ensure data accuracy and timely dissemination, which is limited by the processing speed and the volume of data that can be managed by human operators. In contrast, AI as an information broker would be able to automate data collection, processing and distribution, thereby expanding the systems to utilize predictive analytics and machine learning models and integrate real-time data in decision-making processes. However, our findings also showed that AI as an information broker for better data management was dependent on accurate data and processing, which is still a challenge in the airline industry. For example, AI's reliance on high-quality, unbiased data mean that incomplete or skewed datasets could lead to inaccurate predictions and restricted adaptability. Moreover, it was mentioned that complex AI models, particularly deep learning models, often lacked transparency, which complicated their application in critical airline operations where explainability is essential. However, it can be argued that the shift to AI support systems enhances the information broker role, allowing airline operators to handle complex, multi-variable scenarios more effectively than traditional methods.

AI as information broker for scalability

Our findings showed that these systems, while robust for handling routine operations, were not designed to scale dynamically with fluctuating demand or to adapt quickly to unforeseen changes in the environment. The interviews revealed that AI has the potential to overcome many of these limitations through distributed architectures, real-time data processing and adaptive algorithms, thereby elevating the role of AI as an information broker.

However, the interviewees also noted that in an AI-supported airline system, scalability and adaptability may impose significant implementation challenges. For example, upgrading infrastructure is a primary hurdle, because transitioning from legacy systems to AI requires costly investments in cloud architectures, advanced storage and computational power. Integrating diverse data sources, such as weather feeds, maintenance logs and passenger data, also poses complexities, given differences in data formats, privacy laws and system interoperability. Moreover, studies show that many AI models trained on historical data may struggle to generalize unexpected events, such as unprecedented disruptions, reducing their predictive reliability.

Managerial implications

Our results also had managerial implications with interviewees highlighting the impact of AI for operational processes. In particular, participants pointed out how AI could help to migrate to an agent-based system and its implications for existing process-based models (see also Castro et al., 2014, who developed an agent-based system for airlines disruption management). Most interviewed airline managers argued that the data availability of agents was the major challenge in the implementation of such a support system. The interviewees favoured a process-based approach due to its structure and predictability in the workflow, which has been confirmed by literature in other disciplines. Practical examples showed that many airlines had already implemented single optimization tools for different process steps such as delay prediction or tail sign assignment optimization (Eurocontrol, 2023). Due to the number of different processes involved in airline operation and disruption management, such process-based approaches can handle routine scenarios, but rapidly increase in complexity because of the number of exceptions and the variability of influencing factors.

The airline managers acknowledged that an agent-based system was likely to become the eventual solution for supporting decision-making in airline operations, because such an approach could provide increased flexibility and adaptability for managing dynamic and disruptive situations as well as propagating effects. However, agent-based models require advanced data sets to provide sufficient data on agents' behaviour and their interactions (Ogunsina & DeLaurentis, 2022). Therefore, it was noted that a process-based approach was first required before gradually adopting an agent-based approach. It was also emphasized that the airline system's inherent complexity prevented a direct move from the current manual and experienced-based system to a fully integrated agent-based system. It was emphasized that process-based and agent-based systems might also play complementary roles in airline operations and disruption management. Process-based models handle predictable, rule-based tasks, while agent-based approaches are suitable for dealing with continuous and fluid decision-making in an environment with a high degree of variability (Wen et al., 2020).

The academic literature as well as practical insights showed that the implementation of AI-based decision support systems must be done gradually by solving single problems first rather than implementing a radical approach (Wu & Law, 2019). A recurrent challenge is obtaining all relevant data and the integration of different systems and different data formats into one application or core system (Roh et al., 2019). One interviewee argued that LLMs with functionalities comparable with ChatGPT could bridge these gaps and make information easily accessible for individual decision-makers in a tailored output to prevent information overload. This idea has been tested in other industries (Xiao & Xu, 2024). In this way, information particularly targeting one flight could be provided. This would also reduce barriers between stakeholders in the Integrated Operations Control Centre setup to foster collaboration. When transforming airline operations and disruption management towards data-driven and predictive approaches, airline experts did not only expect changes in the way of working and collaborating in the IT landscape, but also stated that such a transformation would radically affect the KPIs because the optimizations would be done on a cost level, which required an entirely new additional data set and the translation of operational KPIs into costs.

Conclusion

In this study, we set out to examine how AI can act as an information broker to enhance information sharing and collaborative decision-making in airline operations. To do so, we conducted 22 semi-structured interviews with senior airline managers. We found that while digitalization has progressed, many airlines still operate within fragmented information infrastructures that rely heavily on manual inputs, delayed data updates, and limited interoperability. These conditions are considered a barrier for real-time situational awareness and collaborative decision-making, particularly during disruptions. Despite these challenges, airline managers expressed strong confidence in the potential of AI to fill these systemic gaps but highlighted the need for implementation of context-aware, organizationally aligned, and carefully integrated AI into operational routines. More specifically, the findings revealed that while agent-based systems offer greater adaptability for managing disruptions, their implementation requires rich datasets and cannot replace the current manual or process-based systems immediately. Instead, a phased approach was recommended, where process-based and agent-based models coexist—each addressing different operational needs depending on task predictability and system complexity.

Drawing on these insights, this study offers four actionable recommendations for the implementation of AI in airline operations: First, the creation of a unified data layer across all operational units should be prioritised, particularly by integrating flight, crew, ground handling, and maintenance systems into a shared platform. This requires not only technical API development and standardized data formats, but also formal agreements with third-party stakeholders to enable data exchange in real time. Second, the development of AI-driven dashboards that can provide role-specific, time-sensitive, and action-relevant insights. For example, ground handlers should receive predictive insights on baggage delays or gate conflicts, while crew control teams require alerts on rest time violations or pairing conflicts. Third, the deployment of AI pilots in narrow use cases, such as delay root cause analysis, turnaround prediction, or disruption propagation modelling. These use cases offer high operational value, manageable complexity, and measurable outcomes, thus making them ideal for organizational learning and confidence-building. Fourth, embedding AI tools as information broker within existing IOCC decision routines and CDM frameworks, thereby ensuring that AI outputs are directly actionable within current workflows and communication channels. This may also involve creating mixed human-AI decision loops, where accountability and override mechanisms are clearly defined, and AI becomes part collaborative part rather than a parallel mechanism.

While the study offers critical insights, they need to be viewed in the light of its limitations. The qualitative design and judgment sampling approach, though well-suited for in-depth understanding, limit the generalizability of the results to broader airline segments, such as regional or low-cost carriers with different resource structures. The reliance on managerial perceptions also means that findings reflect expectations and challenges as understood by key decision-makers, but not necessarily the technical or behavioural realities of frontline users. In addition, we did neither examine the full implementation lifecycle of AI tools nor did we assess the role of vendor partnerships, regulatory compliance, or cybersecurity, which are likely to play critical roles in AI deployment. As such, future research should aim to expand and deepen our findings, in particular we encourage researcher to collect more in-depth data to develop a control model illustrating the role of AI as an information broker across the different functions and actors within airline operations. We also see a potential future research avenue in the assessment of performance gains of AI-enabled decision systems based on operational data, such as reductions in delay propagation, cost savings or improvement in on-time performance metrics. Moreover, organizational and behavioural research should explore employee trust in AI recommendations, resistance to automation, and the evolution of decision accountability structures. Another potential research opportunity is the exploration of emerging technologies such as large language models (LLMs, in particular their potential to process unstructured communications, interface with legacy systems through natural language, and support decision-makers in asset-driven environments. We hope that both the challenges and opportunities presented in this contribution will spark ideas, discussions and projects on how to fill this largely open canvas.

CRediT authorship contribution statement

Alexander M. Geske: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **David M. Herold:** Writing – review & editing, Writing – original draft, Supervision. **Sebastian Kummer:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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