Journal of the Air Transport Research Society 3 (2024) 100026

Contents lists available at ScienceDirect

Journal of the Air Transport Research Society

journal homepage: www.elsevier.com/locate/jatrs

Integrating AI support into a framework for collaborative decision-making (CDM) for airline disruption management

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ARTICLE INFO

Keywords:
Aviation
Airlines
Artificial intelligence
CDM
Disruption management

ABSTRACT

Airlines are regularly confronted with disruptions that interfere with their flight operations, resulting in financial losses and lower operational performance. While collaborative decision-making (CDM) is a commonly used approach to mitigate these airline disruptions, it is unclear how artificial intelligence (AI) can support CDM to manage airline disruption. This study's purpose is to identify how the adoption of AI can support CDM to mitigate operational flight disruptions. Using a theory building approach, this conceptual paper advances the literature in aviation management by delineating the relationship between AI and CDM in the context of airline disruption management. First, we propose an AI–CDM framework illustrating the factors that influence disruption management in airlines. Second, we highlight the implications of AI-supported CDM for disruption management in and for airlines. We found that to effectively use AI-supported CDM for disruption management, airlines need to a) introduce data-driven CDM, b) enable AI management of complex systems, and c) transform disruption management into AI-supported performance management. As one of the first studies linking AI and CDM, the framework provides a structured recognition of the role of AI in CDM and its implications for airline disruption management.

1. Introduction

Airlines are regularly 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; Hassan et al., 2021). 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; Sun et al., 2020). In fact, Eurcontrol (2024) found that 23% of European scheduled flights were delayed and statistics show that these delays can lead to significant additional operational costs for airlines. According to the Federal Aviation Administration (FAA), the estimated the annual costs of delays (direct cost to airlines and passengers, lost demand, and indirect costs) sum up to US$28 billion for 2018 (Airlines for America, 2020). Reducing the impact of disruptions on the airline schedule could considerably reduce these costs.

One prominent approach to mitigate or reduce these airline disruptions is the use of collaborative decision-making (CDM) (Carlson, 2000; Rosenow et al., 2022; Sikirda et al., 2020). CDM focuses on the application of networked coordination, collaboration, and partnerships in a disruptive setting and emphasizes a decentralized and flexible structure along with relevant administrative and service delivery adjustments. In an airline disruption context, CDM is “a combination and utilization of resources and management tools by several entities“ (Kapucu and Garayev, 2011, p. 367) to achieve the common goal of mitigating the disruption. However, although the concept of CDM has been widely addressed by scholars in an airline context, the application of CDM and the implications for airline disruption management is limited. In particular, it is unclear how artificial intelligence (AI) can support CDM for airline disruption management, despite the rise of AI applications in organizations, including the aviation sector.

Current research shows that AI can support decision-making in organizations (Mikl et al., 2021; Pournader et al., 2021; Sun et al., 2023; Weisz et al., 2023) and has the potential to optimize airline communication networks, maintenance diagnosis systems, flight control, crew scheduling, and flight operations staff (Khalil, 2023; Pérez-Campuzano et al., 2021; Wandelt et al., 2024; Wandelt et al., 2023). However, the topic of AI and its potential for CDM support for disruption management has so far received little attention. In response, this study focused on how AI could support CDM to mitigate operational flight disruptions. Specifically, we asked the following two research questions:

RQ1: What are the CDM factors that influence airline disruption management?

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https://doi.org/10.1016/j.jatrs.2024.100026

RQ2: How can AI support CDM in and for airline disruption management?

To answer the research questions, we looked at the implications for airline disruption management in theory, based on the relationship between AI and CDM. Theory building through conceptual research is a prominent approach among management researchers (Meredith, 1993; Wacker, 1998). In fact, studies suggest that conceptual research is a helpful tool to better understand relationships among constructs and concepts and, thus, to build theories (Corley and Gioia, 2011). To answer RQ1, we identify and discuss the key factors behind CDM, thereby providing not only a theoretical foundation for further analysis, but also providing insights into CDM for aviation in general and for airlines in particular. To answer RQ2, this study built a framework incorporating the key factors behind CDM and how they could be used by AI to mitigate the airline disruptions. We thereby provide a more structured recognition of the role of AI for CDM and its implications on airline disruptions management.

The remainder of the paper is structured as follows: In Section 2, we elaborate on the link between CDM and disruption management in the context of airlines. This is followed by the introduction of our framework in Section 3, where we present the key factors of CDM. We also outline the implications of AI for airline disruption management that can drive AI-supported decisions. In Section 4, we provide a detailed insight into the implications of AI–CDM and provide airline-specific cases. We conclude, in Section 5, with an overview of the main results of the study along with the limitations and avenues for future research.

2. The role of CDM for disruption management in and for airlines

The role of CDM has received substantial attention in academia and in practice. Not only are complex ecosystem networks increasingly difficult to manage, but the unprecedented amount of data and the associated layered information exchange increase the need for enhanced collaboration (Ball et al., 2001; Magliocca et al., 2023; Mikl et al., 2020). The original role of CDM, in this respect, is not to reach an optimum or a comprise. In CDM, the goal is to produce "results in a significantly more valuable choice than the alternatives envisioned by any of the decision-makers through a process of aggregating their understandings" (Owen, 2015, p. 30). In other words, scholars emphasize the role of 'consensus-building' in CDM research (Filip, 2022), such that each decision-maker feels ownership in the decision-making and explicitly agrees to implement the decision.

In the context of airline disruption management, CDM usually focuses on operations control (Castro et al., 2014). In other words, disruption management deals with unexpected and unpredictable events that impact flight operations. Crew absenteeism, poor weather conditions, or aircraft malfunction can lead to arrival and departure delays, thereby disrupting existing operational plans (Clausen et al., 2010). Given the significant negative operational and financial implications of these disruptions, mitigation initiatives from airline managers have become increasingly important (Belobaba et al., 2015; Schoenfelder et al., 2021; Sun et al., 2020). Studies show that although disruptions in the airline industry frequently occur, the reaction to these disruptions is often still characterized by inadequate organizational capacity planning and lack of coordination among those involved during the disruption, in particular in crisis situations such as the COVID-19 pandemic (Dube et al., 2021). As a response, scholars and practitioners have called for more collaboration and CDM among internal and external airline partners as a solution (Di Vaio and Varriale, 2020).

One of the main challenges in CDM is to navigate and balance the needs and agendas of the parties involved. The scope of collaboration consists of different levels of commitment between partners and networks, ranging from coordination to cooperation (Todeva and Knoke, 2005). For example, complex projects may require a high level of commitment to exchange information and share resources through cooperation, while smaller projects only involve coordination activities (Du et al., 2012). The level of collaboration can thus be attributed to the capacity and the agendas of the parties involved, but often collaboration through inter-organizational and intra-organizational networks is required for effective decision-making (Gulati et al., 2012).

However, although studies show that CDM is capable of providing decision-support for airline disruption management, its monolithic information system setup and its strictly sequential approach to dealing with problem situations "typically renders solutions from decision-support systems ineffectual within moments after they are generated" (Ogunsina and DeLaurentis, 2022, p. 2). More specifically, the current airline disruptions management setup seems limited to mitigate operational disruptions, thereby neglecting new evolving technologies (Amadeus IT Group, 2016). As such, scholars argue that the rapid evolution of AI with more sophisticated information systems has the potential to provide decision-support for flight operations in form of decentralized platforms, which will lead to reduced complexity and real-time tracking of disruption resolutions during operational disruptions and recovery (Garrow et al., 2022; Xu et al., 2023). In particular, scholars point out that AI can help in disruption management process with evolving reinforcement learning (Ding et al., 2023), thereby providing faster decisions and solutions for e.g. crew recovery (Herekoğlu and Kabak, 2023) or airline recovery (Eikelenboom and Santos, 2023; Evler et al., 2022; Hizir, 2024; Xu et al., 2023). However, so far it is unclear how AI can support CDM to increase the proficiency of existing airline disruption management. This shows the need for frameworks that illustrate the role of AI as support for CDM to mitigate airline disruptions. In the following section, we provide a novel framework that addresses this gap and highlights how AI-supported CDM can improve airline disruption management.

3. The AI–CDM Framework

In order to achieve collaborative decision-making in an airline environment, a framework is required that will provide an answer to RQ1 ("*What are the CDM factors that influence airline disruption management?"*). The framework will comprise the key factors of CDM, namely the organizational system in which it operates, its environment, stakeholders, and resources. Owing to the organizational system's complexity, the great variety of influences and generated data, as well as the high degree of standardization, we suggest incorporating AI in the CDM process. We applied the conceptual framework developed by Kapucu and Garayev (2011) in the context of emergency and disaster management to the airline disruption management context (see the AI–CDM framework in Fig. 1).

The following subsections introduce the aviation system and its stakeholders, the external influences constituting the system's environment, and the resources. These factors contribute to the cognitive and operational base, and facilitate collaborative decision-making during disruptive events.

3.1. System

AI can enhance the aviation system's organizational structure and culture by streamlining complex interactions and fostering better coordination among diverse stakeholders. The aviation industry operates within a multifaceted network of airlines, airports, ground handling services, and air traffic control, each with distinct roles and competitive dynamics that shape the system's culture. Despite aiming for common goals such as cost minimization and on-time performance, stakeholders often operate independently, with limited collaboration and a focus on individual objectives. In the subsections, we describe the current influences of organizational structure, culture and goals.

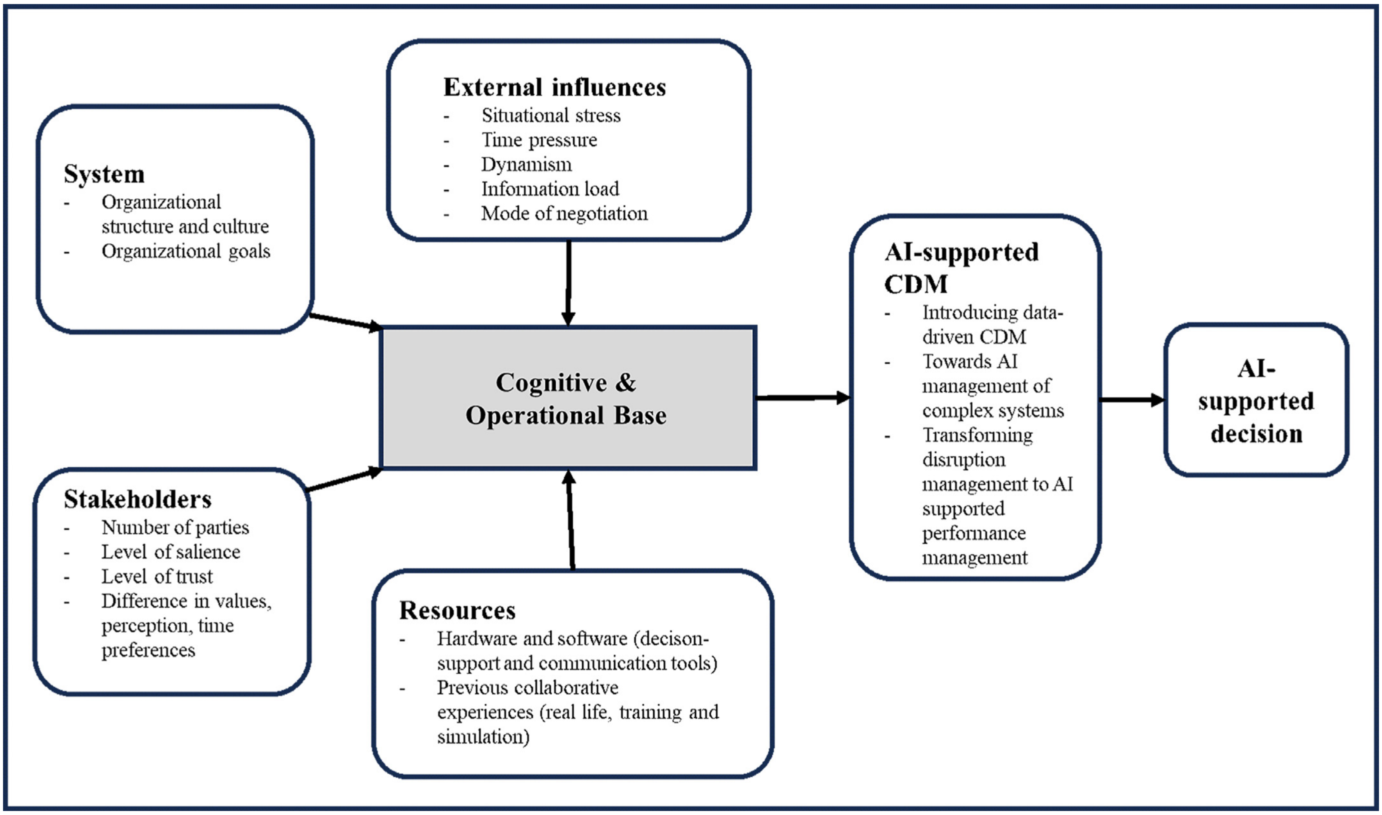

Fig. 1. The AI–CDM framework (adapted from Kapucu & Garayev, 2011, p. 370).

3.1.1. Organizational structure and culture

Airlines operate within a complex system, which Saurin and Gonzalez (2013) characterized as having many elements that interact dynamically, a great diversity of components, and a variability which cannot be anticipated and which is triggered by the system's interaction with its environment. However, the system is also built upon standardized procedures and processes. The aviation industry produces their services within networks (Tretheway and Markhvida, 2014). Thereby, it operates a global network with different actors in each node – airports, ground handling service providers, air traffic control (ATC), and airlines (Wittmer and Bieger, 2011). Thus, airlines connect the different nodes, while airports and ground handling service providers are usually present in only one (a few) nodes. Consequently, the aviation sector is characterized by a variety of different stakeholders (Niewiadomski, 2017). The different actors have individual competitive positions in the market, which not only shape the system's structure, but also the system's culture.

Airports offer the infrastructural prerequisites on the ground (like terminals or runways) to operate out of one node (Wandelt and Wang, 2024; Wittmer and Bieger, 2011). Within a catchment area, there is often only a single airport, or a few airports in larger metropolitan areas, to serve demand (O'Connor and Fuellhart, 2016). Therefore, airports constitute regional monopolies or oligopolies (Wittmer and Bieger, 2021). Airports in places that generate demand for full-service carriers have a substantially higher bargaining power (Niewiadomski, 2017). ATC is responsible for the safety and coordination of flight operations as part of the air traffic flow management. The European Union, for instance, has 32 national providers, which all have a national monopoly over their respective territory (Adler et al., 2022). The competition between ground handling and other service providers in airports is usually limited to only a few companies, which creates an oligopoly (Meersman et al., 2011).

Nearly all modelling approaches for airline disruption (schedule recovery) management neglect the ground operations unit, as well as the impact of turnaround processes on the recovery of the schedules (Evler et al., 2022). Only papers by Stojković et al. (2002) and Santos et al. (2017) partially consider ground operations (Evler et al., 2022). Owing to the impact of disrupted flight operations on ground handling resources and the recovery opportunities provided by ground handling, we incorporated ground handling into the framework.

The traffic volume of airlines at airports is indirectly proportional to the level of airport charges (Choo et al., 2018). Traditional full-service network carriers, operating on a hub-and-spoke system (hub airlines, see also Reynolds-Feighan, 2001), have a significant share of their operations concentrated in one airport, while the rest is fragmented across the network (Pels, 2008). Because hub airlines have only a limited choice of airports and mostly low traffic volumes, they have little negotiating power over airports and ground handling providers. Hub airlines may face a 'locked-in' effect at their hub owing to insufficient opportunities to switch airports (Thelle and Sonne, 2018). Besides this, airlines compete, especially when it comes to transfer passengers, with multiple carriers having different environmental circumstances and business models (Tu et al., 2020). Therefore, owing to the different nature of the parties involved, there is no common culture in the airline system.

3.1.2. Organizational goals

Even though all actors pursue similar objectives, they do not collaborate in the aviation system, but instead focus on their own goals. Basically, all stakeholders strive for cost minimization (Tsikriktsis, 2007), on-time performance (Hajko and Badánik, 2020), and, most importantly, safe and reliable operation (Stolzer et al., 2023). In addition, airlines and ground handling service providers usually agree upon certain service levels with regards to costs, scope, and quality. Overall, however, there is only a minor amount of coordination. The CDM process is a first initiative towards working on a common goal and setting common priorities (Corrigan et al., 2015; Eurocontrol, 2017). It focuses on sequencing aircraft and aligning stakeholders/processes. Nevertheless, this concept is more airport-centric (Schultz et al., 2022). While it may support the sequencing of aircraft and their turnaround processes, it still fails to incorporate detailed information. Here, it is vital to focus on variable process times, based on information like seat-load factor, fuel quantity or cargo volume.

3.2. Stakeholders

AI can enhance coordination and decision-making among aviation stakeholders by leveraging data and improving communication across different parties. The aviation industry involves various stakeholders, each contributing to a complex network that requires efficient coordination. Trust among these parties is essential for collaboration and data sharing, while effective communication improves operational efficiency and reliability across the system. In the subsections, we describe the current influences of different parties, trust and salience.

3.2.1. Number of parties

Although there are different airlines at airports, the focus of this paper was to develop a CDM framework for hub airlines, i.e. airlines that operate in a hub and spoke system (contrary to point-to-point carriers, see Ryerson and Kim, 2013). Castro et al. (2014) developed a disruption management approach for operations control of airlines. The authors focused on the coordination of operating units for flight dispatch, the passenger services/hub control center (HCC), the aircraft control/operations control center (OCC), maintenance services, and crew control. Flight dispatch organizes the flight plans and coordinates slots with ATC, while OCC deals with the management of aircraft resources. Even though these units use computer systems, which may include some kind of decision-support, many decisions are experience-based (Castro et al., 2014). For example, crew control manages of crew resources. Therefore, it usually exchanges crew members in case of disruption or sickness. Decisions on crew control are mostly based on previous experience and rule of thumb (Clarke, 1998). Maintenance services take responsibility for unscheduled, short-term maintenance events, while HCC handles passenger flows between flights (Castro et al., 2014).

Airports provide the terminal and apron infrastructure. In the context of our proposed CDM framework, we only focused on the apron side, which involves gates and parking positions (Dijk et al., 2019), as well as taxiways and runways. Ground handling includes catering, refueling, baggage handling, water, and lavatory services (Chen et al., 2023). In addition there are services such as cleaning (Schultz et al., 2020), pushback (Du et al., 2014), aircraft deicing (Norin et al., 2012), and (de-)boarding (Padrón et al., 2016). There are usually only a few different companies offering these services.

Pei et al. (2021) developed a decision-support system, which also mainly focuses on airlines' internal processes. However, the authors suggested including other factors such as airport capacity, weather conditions, and also implications for the flight network. Zou and Hansen (2012) argued that the relationship between costs and operational performance is not linear because longer delays propagate to other flights and impact ground operations, passenger itineraries, or the assignment of gates. Consequently, we extended the scope of Castro et al. (2014) and Pei et al. (2021) by incorporating other stakeholders like airports, ground handling service providers, and partially ATC. The importance of considering turnaround processes like the assignment of ground handling services and staff, as well as flight prioritization or stand allocation, was also raised by Evler et al. (2021).

3.2.2. Level of trust

In the context of the aviation industry, trust must be considered on three levels: trust for collaboration (Han et al., 2021); trust of customers in pilots, safety, and reliability (Winter et al., 2014); and trust on an organizational level for safety operation behavior (Li et al., 2021). While all stakeholders work towards a common goal of operating safely and reliably, the level of trust in terms of collaboration to achieve a smooth, efficient operation creating a global optimum rather than local optima for each stakeholder still requires improvement.

Trust is an important contributor to cross-organizational collaboration and data sharing (Müller et al., 2020). In order to develop trust on a collaborative basis, shared objectives, communication, and transparency are essential (Müller et al., 2020), especially for data sharing. There are different priorities as well as environmental, economic, and operational conditions leading to reduced levels of collaboration. A step towards better collaboration is the development and implementation of shared performance goals as well as metrics.

3.2.3. Level of salience

In the system of air transportation, airlines and airports are the actors most visible to customers. Moreover, airlines have interfaces with all stakeholders and their operational efficiency and reliability greatly depends on effective coordination among them. Because airlines have the most interfaces and data, they should lead collaboration among stakeholders to improve customer experience in the case of disruptions. Airports, in contrast, often take the role of facilitators between airlines and ground handling companies such as loading, or cleaning (Lee et al., 2020). Decisions from ATC, impact the operation of airport and airlines as well as ground handling providers in terms of capacity management. In contrast to airlines, airports, and ATC, ground handling service providers are highly dependent on decisions taken by other stakeholders. Owing to the low level of self-determination, all these stakeholders require a high degree of flexibility and responsiveness. As a result of the high level of interdependencies among stakeholders, continuous exchange, open communication, and effective coordination are required to optimize the system's output (Pereira et al., 2021).

3.3. External influences

AI can enhance the management of external influences in the aviation system by enabling real-time data analysis and predictive modeling to anticipate and mitigate disruptions. The aviation industry faces dynamic external influences ranging from operational disruptions to adverse weather conditions and unforeseen events like financial crises and natural disasters, necessitating a robust system to manage these impacts and prevent cascading delays. High situational stress and tight schedules emphasize the need for effective collaboration and real-time data sharing to manage disruptions proactively, while substantial information loads require efficient integration and dissemination of data among all stakeholders. In the subsections, we describe the current influences of dynamism, situational stress and time pressure, information load and mode of negotiation.

3.3.1. Dynamism

All stakeholders in the aviation systems are exposed to external and internal influences, which characterize the dynamism of the system. Such influences range from operational disruptions over technical issues to adverse weather conditions but also include uncertainty shocks like a financial crisis, natural disasters, or events related to terror (Danner and Geske, 2022). Even though not all actors may be directly exposed to each influence, the interdependencies within the system cause a transfer of the impact to other parties. For example, a disruption to a single flight or at a single airport may also spread to other flights and cause delays to propagate (Pyrgiotis et al., 2013).

3.3.2. Situational stress and time pressure

Danner and Geske (2022) state that the aviation system is characterized by disruptions and volatility; however, disruption handling has a strong short-term focus. Airlines, as core actors in the production process of flights, are confronted by low profit margins, requiring them to increase resource and asset utilization to improve profitability (van Schilt et al., 2024). Therefore, buffers have been removed making flight schedules tight, although several publication have proved the importance of buffers (e.g. Brueckner et al., 2021; Xu et al., 2024). Wu and Caves (2000) showed the relationship between scheduled buffer times and punctuality. Consequently, the turnaround processes are efficient without any slack to recover from disruptions, which poses the risk of propagating or cascading effects on customers, air crews, and resources. These circumstances directly affect ground handling providers and may increase complexity in the operation in case of delays. Likewise, airports are exposed to stress when facing delays due to capacity constraints in infrastructure. This emphasizes the importance of collaboration, communication, coordination and, most importantly, data-sharing to create awareness of disruptions and proactively manage them.

3.3.3. Information load

There are substantial information loads generated in aviation systems. However, to effectively manage disruptions and move to proactive performance management, it is vital that all information is shared in real-time with the involvement of every stakeholder (Holland et al., 2020). Airlines require information on flight plans, gate availability, and departure/arrival slots as well as details on congestion, weather, or runways in use (Olivares et al., 2023). ATC and airports may provide this information. For ground handlers, airlines are the best data source when it comes to arrival times of aircraft as well as passenger, cargo, or baggage loads, while airports should receive information on connecting passengers. In the first step towards effective and proactive disruption management, an airport should exchange real-time data with local ATC, ground handlers, and the major hub carrier. In subsequent steps, automated data links and shared systems should be integrated before the scope is widened to not only cover turnarounds at a single airport, but rather to integrate the flight operations of an entire airline. This may include information on flight times or time buffers at other airports to evaluate decisions based on the complete system and account for potential propagation effects, to optimize the system over an entire day of operations (Cook and Billig, 2023).

3.3.4. Mode of negotiation

Typical negations between airlines and other stakeholders include tactical and operational decisions, which involve access to gates, terminals, or check-in areas on the airport side, as well as the type of parking position (pier vs. apron) (De Neufville, 2020). The positioning of aircraft has a direct impact on the operation, capacity management, and performance of ground handling services. Operational decisions between airlines and ATC involve coordination and prioritization of aircraft movements, as well as capacity management to avoid delays, handle congestion, and maintain efficient flight operations.

3.4. Resources

AI can enhance resource management in the aviation industry by integrating decision-support tools across hardware and software systems, facilitating real-time, data-driven decisions. Numerous decision-support tools assist airlines in recovering from flight disruptions, focusing on areas like flight rescheduling, crew management, and passenger reaccommodation. However, these tools often address isolated problems, necessitating a more integrated approach that considers the entire airline ecosystem. In the subsections, we describe the current influences of hardware and software and the role of previous collaborative experience.

3.4.1. Hardware and software

There are many different decision-support tools for an airline ecosystem, to support recovering from flight disruptions. There are programs as well as research (e.g. Woo and Moon, 2021) looking at flight rescheduling. Other studies focus on crew management or rescheduling problems, which have been discussed in academia for nearly half a century (e.g. Arabeyre et al., 1969; or Stojković et al., 1998). McCarty and Cohn (2018) looked at proactively reaccommodating passengers on other flights in case of disruption, rather than waiting for passengers to miss their connecting flight. Similarly, aircraft swapping and resource allocation have been examined to achieve a better match between capacity and demand or to address needs for maintenance work (e.g. Wang and Regan (2006), Talluri (1996) and Gopalan and Talluri (1998)).

However, most research conducted so far only considers isolated problems for one stakeholder, and does not integrate other system components. Brunner (2014) presents an example of a more integrated approach, where crew and passenger connections were incorporated in the model. Castro et al. (2014) went further and developed a tool that considered an integrated decision among all operational departments of an airline. However, their approach did not review or examine other stakeholders in the aviation system.

3.4.2. Previous collaborative experience

A high degree of improvisation and flexibility is required as short-term disruptions occur regularly (Danner and Geske, 2022). Even though fully integrated decision-support tools have not been developed and implemented yet, there are settings that aim to make mutually coordinated decisions. Bilateral meetings among stakeholders are targeted to develop more integrated decisions relying on collaborative experiences and expert knowledge rather than on underlying data (Ball et al., 2007; Castro and Oliveira, 2011). Airport operations center meetings have been introduced in an attempt to improve the communication among stakeholders; however, the decisions about the actions taken to recover flights from a disturbance remain with the Airline Operations Control Center (AOCC) (Eurocontrol, 2018). Such meetings take place on a weekly (sometimes daily) basis. Owing to the system's volatility, however, even daily exchanges may not be sufficient to react to recent impacts on the system.

4. Implications for AI–CDM

Our framework demonstrated not only the key factors behind CDM, but also the inherent relationships within a factor and between the factors. The adoption of AI and data-driven mechanisms offers a promising approach to connect the CDM factors and derive near-optimal solutions for airlines in their embedded ecosystems (Hassan et al., 2021).

The following section outlines the initiatives that need to be taken to effectively utilize AI-supported CDM for airline disruption management, which also answers RQ2 ("*How can AI support CDM in and for airline disruption management?"*). The three key initiatives for adopting AI for CDM revolve around: a) introducing data-driven CDM, b) enabling AI management of complex systems, and c) transforming disruption management to AI-supported performance management. We elaborate on each of these steps below in detail.

4.1. Introducing data-driven CDM

Existing collaboration mechanisms often rely on expert knowledge and experience, and the associated human decision-making in often non-trivial environments. Human or experience-based decision-making, in particular during contingencies such as airline disruptions, are subject to time pressure, situational stress, and information overload (Geva and Saar-Tsechansky, 2021). In this context, the integration of AI into collaborative decision-making (CDM) for airline disruption management may introduce a paradigm shift from traditional, intuition-based methods to a more sophisticated, data-driven approach, particularly through big data analytics, which offers unprecedented opportunities to improve decision accuracy and efficiency. Provost and Fawcett (2013) claim that the exploitation of vast amounts of data is seen as a crucial competitive edge in various industries, including aviation. Airlines, facing frequent operational disruptions (Danner and Geske, 2022), can significantly benefit from AI by leveraging predictive analytics to foresee potential issues and proactive strategies to mitigate their effects (Okwechime et al., 2021). Baardman et al. (2023) highlight that the integration of machine learning and computational statistics into CDM enables airlines to process real-time data swiftly, fostering quicker, more personalized, and granular decision-making.

As such, we argue that an adoption of a data-driven CDM framework facilitates a more dynamic response to disruptions. AI's capability to analyze large datasets quickly and accurately allows for the simulation and evaluation of multiple disruption management scenarios in a fraction of the time required by human operators (Herold et al., 2021). Cheung et al. (2023) noted that AI systems are particularly effective in handling complex, multi-variable situations where various potential outcomes must be analyzed to find the optimal path forward. This is critical in airline operations where decisions not only need to be made quickly but must also consider the cascading effects on the schedule, cost, and passenger satisfaction. For instance, AI can provide decision-makers with multiple scenario analyses that balance different organizational goals such as minimizing delays, reducing operational costs, and maximizing route profitability (Sun et al., 2023). For example, AI could present a weighed analysis which would provide decision-makers with the opportunity to steer the system based on different organizational goals (i.e. on-time performance, cost minimization, or schedule reliability).

Human decision-makers are often confronted with situational stress, especially during disruptions, leading to decision fatigue and potential errors (Danner and Geske, 2022). As Geva and Saar-Tsechansky (2021) argue, AI can alleviate much of this situational stress by automating routine decision processes and presenting human operators with optimized choices based on robust, data-driven insights. This not only enhances decision quality but also helps in maintaining operational consistency and reliability during disruptions. Furthermore, AI can also play a critical role in training and supporting human decision-makers by providing them with simulations and real-time decision aids, which can improve their situational awareness and decision-making skills over time.

To implement a successful data-driven CDM strategy, it is crucial to consider stakeholder interests and enable changes to an organizational culture that supports data-driven decision-making. In particular, fostering a culture that values data literacy and continuous improvement, airlines can better manage disruptions and turn challenging situations into opportunities (Wandelt et al., 2023). Supporting that claim, Corrigan et al. (2015) emphasize the importance of developing AI tools that are inclusive and equitable, ensuring that the benefits of AI integration are distributed fairly across all stakeholders. More specifically, the successful and reliable implementation of data-driven decision-making include approaches that consider each stakeholder's circumstances and lead to mutual benefits for all parties involved.

Overall, we suggest that the integration of a data-driven CDM for airline disruption management improves decision-making when confronted with unexpected events, but can also significantly enhance the operational agility and resilience of airlines. By moving towards data-driven approaches, airlines can achieve more accurate, timely, and effective decision-making, leading to improved operational outcomes and higher levels of passenger satisfaction – and eventually to a better disruption management.

4.2. Towards AI management of complex systems

Existing management systems face challenges when dealing with complexity. Complexity in management can be attributed to the number of stakeholders with different demands, values, and organizational goals, which increases interdependency. Traditional management frameworks often struggle under the weight of complex, multi-stakeholder environments, where the diverse demands and goals can overwhelm human decision-makers (Sun and Wandelt, 2021). AI, with its capacity to handle large volumes of data and uncover insights through sophisticated modelling and simulation, offers a solution to these challenges (Pérez-Campuzano et al., 2021). Wang (2008) argues that AI can construct comprehensive models of complex systems, facilitating a deeper understanding of system dynamics and interactions. This capability is further enhanced by AI's ability to integrate and synthesize data from various sources, both internal and external, such as passenger feedback, operational data, and market trends, thus providing a holistic view of the operational environment (Wang et al., 2022).

In the context of airline operations, the relationships between airlines, ground handlers, service providers, and regulatory bodies form a web of interactions that are often too intricate for traditional data management tools to handle effectively (Wandelt et al., 2024). This complexity not only impedes swift decision-making but also hampers the ability to anticipate and react to disruptions efficiently. AI technologies, through advanced data analytics and machine learning, can mitigate these issues by providing decision-makers with integrated data insights, revealing hidden patterns and correlations (Pérez-Campuzano et al., 2021). Schultz et al. (2022) found that AI can significantly reduce complexity by automating the integration and analysis of disparate data streams, thus facilitating more informed and timely decisions. For instance, AI can deliver enhanced simulations and what-if scenarios that extend beyond linear predictions, offering insights into potential ripple effects of decisions across the entire network.

Research also found that the application of AI in managing complex systems within airline disruption management extends to improving situational awareness and decision-making quality (Minh et al., 2022). AI's ability to continuously analyze data from various touchpoints allows for the generation of predictive insights, which can prevent potential disruptions. Cheung et al. (2023) suggest that AI's role in enhancing situational awareness involves not only tracking current system states but also predicting future states, thereby enabling airlines to implement more strategic responses. This shift can significantly enhance operational resilience and agility, ensuring that airlines can maintain high levels of service quality even in the face of unforeseen disruptions (Ogunsina and DeLaurentis, 2022).

Overall, we suggest that the integration of AI in CDM can transform complex system management for disruption management by enhancing operational and decision-making processes. As current decision-making is rather focused on single events and neglects to consider the interdependencies in the immediate business environment, which may degrade the entire system's performance, AI in the form of data analytics and machine learning has the capability to reduce or eliminate this complexity by integrating data and identifying hidden correlations.

4.3. Transforming disruption management into AI supported performance management

Existing disruption management approaches rely heavily on reactive measures, i.e., a correctional action will only be initiated after the occurrence to recover from disruptions. Rather than focusing on the management of disruptive events, managers now have the opportunity to focus on long-term performance by the proactive protection of value chains and production processes (Herold et al., 2023; Pavlov et al., 2022). While we addressed above how AI could help to make better decisions, here we suggest that AI could help to prevent the disruption in the first place, that is, AI has the capability to predict certain events that allows for proactive measures to avoid or minimize disruptions. It also enhances resilience along value chains by creating transparency and thereby fosters performance management (Gupta et al., 2022). Performance management benefits from the incorporation of AI by using more recent data, having less bias, and becoming proactive (Stroet, 2020). Studies show that companies are already using predictive AI to optimize collaboration and coordination with stakeholders (Wamba-Taguimdje et al., 2020; Ziakkas and Pechlivanis, 2023).

In practice, AI-supported performance management in airlines can dramatically alter how operational challenges are addressed

(Heiets et al., 2022). Ogunsina and Okolo (2022) highlight AI's capability in analyzing vast datasets to uncover patterns and correlations that predict disruption exposure, thereby enabling airlines to adjust operations proactively. For example, AI systems can analyze historical data on flight loads and turnaround times to predict which flights might face delays due to increased passenger or cargo loads. As detailed by Chen et al. (2023), this capability allows for dynamic reallocation of resources such as loading staff, optimizing both efficiency and customer satisfaction by reducing wait times and preventing potential delays. This level of detailed, proactive management ensures that resources are not merely allocated based on existing demands but are strategically deployed where they will be most effective in maintaining or enhancing performance (La et al., 2021). AI tools may also simulate various operational scenarios, assessing the potential impacts of different decisions on the airline's overall performance (Pérez-Campuzano et al., 2021; Pournader et al., 2021). This is particularly valuable in an ecosystem as complex as that of an airline, where multiple stakeholders—including passengers, crew, airport authorities, and service providers—must coordinate seamlessly (Serrano and Kazda, 2020).

Overall, we suggest that AI-supported CDM can transform traditional reactive disruption management methods more into proactive and data-informed performance management. AI-supported systems enable managers to evaluate how changes in one area, such as scheduling or resource allocation, will affect other areas, thereby avoiding unintended negative consequences and ensuring that all actions contribute positively to the airline's overall objectives.

5. Conclusion

The aim of this paper was to identify how AI can support CDM in and for airline disruption management. We provided an AI–CDM framework illustrating the factors that influence disruption management in airlines, and also highlighted the implications of AI-supported CDM for disruption management in and for airlines. Our contribution through this study is to explore the relationship between AI and CDM, and provide a first conceptual framework summarizing the key factors and implications in an airline disruption context. Based on the literature, we identified four key factors, namely a) the aviation system and b) its stakeholders, c) the external influences constituting the system's environment, and d) the resources, which contribute to the cognitive and operational base, and facilitate CDM during disruptive events. We also identified three main steps to effectively utilize AI-supported CDM for disruption management. Airlines need to a) introduce data-driven CDM, b) enable AI management of complex systems, and c) transform disruption management into AI-supported performance management. We thereby provide a more structured recognition of the role of AI for CDM and its implications for airline disruption management.

However, the study's findings and implications must be viewed in the light of the research limitations. Because our AI–CDM framework and the associated implications for airline disruption management are exploratory in nature, we invite future researchers to expand on our framework by integrating other more-airline related CDM factors. Moreover, we restricted our focus on how to use AI in and for disruption management to the concept of CDM, but there are other concepts that mitigate and reduce disruption. We encourage future researchers to extend our framework by integrating other concepts, beyond that of CDM. Overall, it seems that research examining the relationship between AI and CDM is still in its infancy, particularly in an aviation context. Future research will help to understand how AI and CDM impact disruption management and how airlines can mitigate or prevent airlines disruptions.

Declaration of competing interest

The authors declare that there are no potential competing interests.

CRediT authorship contribution statement

David M. Herold: Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Sebastian Kummer:** Writing – review & editing, Validation, Supervision.

Data availability

Data will be made available on request.

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