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AI Adoption in the Aviation Sector of Pakistan: A TAM based analysis of Air Traffic Control and Meteorology Domains

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Abstract

Artificial Intelligence and its related technologies in recent decade emerged as one of the most dominating transformative forces, restructuring economies, reshaping industries, and broadly influencing every other domain of life. This analysis, by deploying Technology Acceptance Model (TAM), attempted to analyze the adoption pattern of Artificial Intelligence (AI) based technologies for the Air Traffic Control (ATC) and Meteorology (MET) segments in the aviation sector of Pakistan. The study comprehensively analyzed the main constructs of technology acceptance model and their interaction towards adoption of artificial intelligence in the two critical domains of Pakistan's aviation sector. 180 professionals with varying roles associated with ATC and MET departments under the broader umbrella of Pakistan Civil Aviation Authority (PCAA) were surveyed using a standard questionnaire concerning usefulness, usability, behavioral attributes, and actual adoption of AI technologies. The survey responses obtained were then used to construct indices related to Perceived Usefulness(PU), Perceived Ease of Use(PEOU), Behavioral Intentions(BI), and AI Adoption, the key inputs for the further mediation analysis conducted in the light of Preacher and Hayes's bootstrapping method. Study findings reveal that mediated by BI, both PU and PEOU significantly affect AI adoption in the MET department. Whereas in the ATC segment the relationship is found to be less significant, depicting a likely prevalence of institutional resistance or contextual constraints. The outcomes obtained in this study emphasize the greater policy role of user centric strategies to facilitate acceptance and influence positive behavioral intention towards AI technologies, contributing both practically as well as theoretically towards policy and technology adoption discourse.

Keywords: Technology Adoption Model; Artificial Intelligence; Aviation Management; Air Traffic Control; Mediation Analysis; Pakistan Civil Aviation Authority.

1. Introduction

Artificial Intelligence and its related technologies in recent decade emerged as one of the most dominating transformative forces, restructuring economies, reshaping industries, and broadly influencing every other domain of life. Due to AI, the way different industries execute their business operations is massively changing and the global aviation industry, like others, is gradually embracing this change. Airlines, an important component of aviation industry, by using chatbots, predictive models, algorithms and robotics, are effectively dealing with their everyday operations such as maintenance, customer services, flight scheduling, baggage handling, security, and various others. Generally, through AI platforms, the airlines are not only making their business operations more efficient but also adding value to the passenger experience through smoother and more personalized customer services (Tafur et al., 2025). Technologically advanced nations such as USA, China, UAE, UK, and many others have quickly adopted AI beyond routine airline operations, to deal with the critical aviation sector functions such as air traffic control, weather forecasting, aviation construction, monitoring and safety, risk assessment, airport operation's planning, efficient utilization of aviation related resources, and to deal with technical breakdowns (Alketbi et al., 2024; Mgbachi, 2024). At a time when the whole world is embracing technological transformation, the adoption of artificial intelligence and its related technologies in Pakistan's aviation sector is massively lagging advance nations. This slow pace of AI adoption at one hand keeps Pakistan's aviation industry stuck in the traditional business operations, and on the other hand widening the efficiency gap in critical areas such as Air traffic operations, customer services, air traffic flow management and other aviation operations. Generally observed, scarce technical expertise, poor IT infrastructure, and negligible investment in AI technologies remains the dominant factors towards slow pace of adoption (Hussain & Rizwan, 2024). In addition to technical deficiencies, a general lack of awareness among key stakeholders such as policy makers, management, work force and others, when coupled with their efforts to preserve status quo, creates further resistance toward AI's broader adoption in the aviation sector of Pakistan. Furthermore, contrary to the technologically advanced nations having innovation conducive policies, Pakistan lacks concrete policies or comprehensive plan of action to facilitate the broader AI adoption in aviation industry. Similarly, the lack of organized efforts by the state towards developing technical capacity with transparency and ethical AI deployment, further undermines the pace of AI adoption, and thus global competitiveness of Pakistan's aviation sector. Thus, dealing with these complex challenges is the need of the time to put Pakistan's aviation sector at par with the rest of the world for providing safe, efficient, and resilient aviation operations in every domain. On academic fronts, despite a widespread scholarly acknowledgment of AI's usefulness and effectiveness in global aviation industry, an evident insufficiency of research on the AI adoption in the aviation sector of Pakistan, further highlights prioritization of AI based research. Most of past studies have focused on advanced regions like North America, Europe, and East Asia, where developed infrastructure and regulatory institutions ease the implementation of sophisticated AI. Contrarily, Pakistan's aviation sector struggling with economic constraints, old infrastructure, regulatory loopholes, and deficits of technical expertise is sorely under researched (Ahmed, 2025).

Although some scholarly work attempted to explore AI's application within general aviation activities, there remains a significant research gap in addressing AI wider adoption in some more critical aviation functions. Important aspects related to AI-Human interaction within the critical aviation operations, such as system awareness, financial viability, trust, dynamic decision support, safety assurance, and regulatory readiness as well as support, have not been examined systematically. No concrete scholarly work has been traced so far on the adoption of AI in the critical functions like Air Traffic Control (ATC), meteorological operations, and aviation safety management in the context of Pakistan. In addition, existing research largely overlooks the multidimensional and complex nature of AI based technologies in the aviation's operational environment. Consequently, some very important considerations, critical for building trust among involved stakeholders, are not addressed substantially. These significant research gaps thus highlight the urgent need for an evidence based and focused research efforts to lead AI based technologies integration into Pakistan's aviation domains of ATC and Meteorological operations, coherent with the global trends (Halawib et al., 2024). With these dynamics, present study attempted to develop a comprehensive understanding of how artificial intelligence (AI) technologies can be safely and effectively integrated into Pakistan's ATC systems as well as meteorological operations to ensure safe, efficient and sustainable aviation operations in Pakistan according to the global technological standards.

With these objectives, present study aimed to analyze three key aspects related to Ais adoption in Air Traffic Control(ATC) and Meteorology(MET) departments: First, how the professionals associated with the Air Traffic Control (ATC) and Meteorology (MET) departments perceive the broader usefulness as well as the convenience associated with the Artificial Intelligence (AI) technologies; Second, it analyzed that how these perceptions influence their behavioral intentions to adopt these technologies; and Third, it assessed how those intentions drive actual adoption of the technology.

Under earlier explained objectives, this study is organized as follows: Section 2 presents the relevant literature and outlines the theoretical framework underpinning the research related to technology adoption. Section 3 explains the data and methodology employed for analysis. Section 4 reports the estimation results and provides a comprehensive analysis. Finally, Section 5 offers the conclusion along with key recommendations, followed by bibliography and appendices.

2. Literature Review

As comprehensively explained by (Schwab, 2016) the world is currently experiencing the Fourth Industrial Revolution, three words which describe a technological revolution based on the fusion of physical, digital and biological domains. This revolution marked its concrete presence in the form of advancement of technologies, mainly information technology through the faces of Artificial Intelligence (AI), Robotics, and Internet of Things (IoT). Thus, ascribed to a range of advanced technologies, the fourth industrial revolution is greatly impacting and transforming every domain of life, and thus challenging the role of humans in contemporary world (Schwab, 2016). Thus, the fourth industrial revolution by redefining the contemporary economic and industrial landscapes through technological advancements, completely transforming the pattern as well as pace of global competitiveness. The business entities, under such demanding circumstances, face the dual challenge of embracing innovative technologies while ensuring its meaningful integration into the existing infrastructure. The rapid advancement of technologies amide fourth industrial revolution, has greatly transformed not only the operational models of contemporary business entities but also impacted the managerial thinking process and hence strategic the mechanism of strategic decision making (Venkatesh et al., 2003; Schwab, 2016; Marocco et al., 2024). Despite massive worldwide appreciation, there exist massive variation in the value perception and sustainable adoption of advanced technologies among varying contexts, economies and industries. Persistence of such a variation highlights a critical fact that the value of innovation is not inherently dependent on its technological design, but realized through the contextual parameters as well as cognitive, social, and organizational course of actions that facilitate its acceptance and support its alignment with the existing status quo by ensuring its effective use (Boe-Lillegraven & Monterde, 2015; Bankins et al., 2024; Lee et al., 2025; Rogers, 2003; Marangunić & Granić, 2015). Several studies addressing innovation and technology acceptance have long attempted to explore the fundamentals of these variations by means of different renowned frameworks, such as Diffusion of Innovations (DOI), Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), providing comprehensive insights regarding technology adoption (Rogers, 2003; Marangunić & Granić, 2015; Venkatesh et al., 2003). The subsequent empirical evidences thus exposes that technology adoption is not a simple and linear rational process; instead, it involves complex interactions of organizational infrastructure, individual behaviors, and broader institutional ecosystem (Chiesa et al., 1996; Lai, 2017; Baker, 2011; Meri, et al., 2023). When considered for the context of adoption of Artificial Intelligence technologies, this broader understanding has become highly important. This fact has been concretely identified in the prior research that contrary to the adoption of earlier generations of technology, acceptance of AI technologies and capabilities, is challenging the traditional assumptions of certainty, user control, and transparency (Dwivedi, et al., 2021; Romeo & Conti, 2025). Given this context, adoption of AI and its related technologies, therefore, cannot be reduced to an analysis of usability or perceived usefulness alone, it further relies on the trust in decision making process, efficient data governance, description of models, and above all a strong ethical framework to ensures accountability as well as operational fairness (Hassan et al., 2024)

In many instances, towards AI adoption, individual, institutional as well as societal apprehensions around regulatory compliance, data management, and fear of job displacement act as strong barriers that research related to adoption of traditional technologies fail to capture (Marocco et al., 2024). Consequently, contemporary research greatly emphasized the need for a reconceptualization of technology acceptance discourse for the analysis of AI based technologies and hence comes up with a comprehensive framework which integrates individual, institutional, social, and ethical dimensions with organizational and behavioral models (Ghosh, 2025). The proponent of this expanded perspective recognizes that the triumph of AI and other advanced technologies under the umbrella of fourth industrial revolution, depends not only on the readiness of physical and technological infrastructure but also on the willingness of individuals, societies, and governance mechanisms to realize, accept, absorb and sustain change (Wirtz et al., 2019; Granić, 2024). The following sections review the key theoretical foundations that have redefined the technology acceptance/adoption research and further highlighted how these extended frameworks have evolved to deal with the institutional, individual, ethical and societal challenges and complexities introduced by artificial intelligence.

3. Theoretical Foundations

3.1 Theory of Reasoned Action (TRA)

One of most fundamental models addressing the adoption of technology with behavioral dimensions is the Theory of Reasoned Action (TRA), a psychological model introduced by Fishbein (1979) that describes the way attitudes and subjective norms influence behavioral intentions, which in turn influence actual behavior of individual towards technology adoption. The model assumes that rational decisions are arrived at by beliefs and what other people would want the individual to do. TRA is applied widely across many fields, including finance, health, and technology adoption, to predict people's behavior from their intentions (Armitage & Christian, 2003). TRA is also most suitable to the study of AI adoption in aviation because it focuses on how specialists' beliefs and social forces control their openness to embracing AI. The scientific approach followed, makes TRA an effective tool towards assessing the intention to act and crafting methods for driving technology acceptance.

3.2 Diffusion of Innovation Model

While the theory of reasoned action (TRA) provides valuable insights related to individual behaviors towards AI adoption, it is equally important to look at another important question that how such technological advancements pierce through the broader social as well as institutional context, a perspective efficiently explained by the Theory of Diffusion of Innovation (DOI) proposed by Rogers (2003).

The Diffusion of Innovation (DOI) theory explains how new ideas, technologies, or practices diffuse through a social system over time. It explains innovation diffusion as a vital process of communication carried through adopted channels or messages within a social system (Rogers, 2003). The theory of DOI highlighted five important factors that significantly affect decision making process of technology adoption. According to Rogers (2003), relative advantages, compatibility, complexity, trialability, and observability, are the key factors which significantly influence the speed and extent to which an innovation is adopted by populations. The theory of DOI, to represent adoption levels, places technology users along a continuum, classified as, innovators, early adopters, early majority, late majority, and laggards, emphasizing that adoption varies across a continuum and is socially constructed (Rogers, 2003). Since, technologies like AI involves complexities and uncertainty that require high levels of knowledge sharing, leadership buy-in, and communication networks for successful diffusion (Lai, 2017). Given these fundamentals, while addressing the diffusion of Artificial Intelligence, DOI provides important insight into how organizational and individual perceptions contribute to the diffusion rate and its success integration (Marocco et al., 2024).

3.3 UTAUT Model

Though DOI model focuses on the social dynamics and communication patterns within the organizational environments which facilitate the diffusion of innovations, the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), provides a more rigorous and integrated framework of unleashing the fundamentals of individual technology adoption behavior.

The UTAUT model provides a unified approach defined through the combination of various perspectives on adoption of technology. It involves four dimensions of individual behavior related to technology adoption such as performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by gender, age, experience, and voluntariness of use (Venkatesh et al., 2003).

In recent years, this framework has developed a strong reputation due to efficient predictive capability of adoption behavior and associated empirical robustness across various industries. Such strengths are beneficial for assessment of AI adoption in a complex organizational context, such as aviation, because of the moderating factors it identifies for social influence, facilitating conditions, and the foundational determinants of perceived usefulness, perceived ease of use, and the user's experienced environment (Venkatesh et al., 2016). The comprehensive nature of the model provides insight in both individual behavioral intentions and on the factors that are associated with the adoption of a system. These qualities of UTAUT framework make it useful tool while assessing the user perceptions from the associated air traffic controllers and meteorologists regarding the perception of AI systems while engaging these systems in their daily operational workflow.

3.4 Technology Organization Environment model

UTAUT effectively captures user intentions and behavioral factors driving technology acceptance, it remains centered on individual perspectives and is less effective if analysis requires consideration of organizational and environmental contexts that significantly influence implementation decisions. Given this context, The Technology Organization Environment (TOE) framework developed by Chiesa et al., (1996) is an effective approach to deal with organizational and environmental considerations towards technology adoption.

The Technology Organization Environment (TOE) model provides a complete view of the adoption of technology at the organizational level. This approach states that adoption is driven by three contexts: the technological context which refers to the availability and characteristics of the technology; the organizational context explained by the organizational structure, size, resources, and management support for the adoption process; and the environmental context associated with the characteristics of the industry, rivals and competition, and regulations. While user-level models have generated psychological insights into technology acceptance, TOE is more directed towards institutional and contextual preparedness in determining adoption behaviors (Chiesa et al., 1996). As far as AI adoption in aviation is concerned, the TOE is particularly effective in understanding how regulatory constraints, organizational hierarchies, and infrastructural capacity traditionally shape adoption results. In the Pakistan ATC and MET cases, environmental context, driven by CAA regulations and organizational culture, and organizational expertise are just a few environmental factors that affect AI assistance implementation (Baker, 2011).TOE complements psychological models such as TAM and UTAUT, which focus largely on individual purpose factors or predictors, where the broader macro-context envelops enablers and barriers to support institutionalization of AI-enabled systems(Lai, 2017).

3.5 Technology Adoption Model (TAM):

After looking at the behavioral, social, and contextual frameworks of technology adoption through earlier mentioned models such as TRA, DOI, UTAUT, and TOE, the Technology Acceptance Model (TAM) emerges as a foundational framework that quantitatively measures user attitudes toward new technologies. Introduced by Davis (1989), TAM provides a parsimonious yet powerful explanation of how perceived usefulness and ease of use shape users' acceptance behavior. Thus, based on its appropriateness and relevance, the theoretical foundations of this study rely on Fred Davis's Technology Acceptance Model, which explains how individuals embrace and use technology(Davis, 1989).

According to the Theory of Reasoned Action and related to the Theory of Planned Behavior by (Ajzen, 1991). TAM recognizes two key perceptions i.e. Perceived Usefulness(PU) and Perceived Ease of Use(PEOU), associated with an individual's attitude towards adoption of technology. PU refers to the belief that the proposed technology enhances job performance and makes it things effective & PEOU the belief that technology brings ease of use in operations. These factors influence users' attitudes, which in turn determine their intention and actual use of technology (Marangunić & Granić, 2015). TAM is not only powerful because of its simplicity, but also its adaptability as an empirically reliable model, which has led to continued developments in the form of TAM2, TAM3 and UTAUT (Venkatesh & Davis, 2000). In the context of AI adoption in aviation, TAM can concisely capture the influence of professionals' perceptions of AI usefulness in making decisions, accuracy and safety, as well as usage perceptions, on their intention to adopt

(Yadav & Shrawankar, 2025). Thus, it serves as the central theoretical premise of this research due to its robustness as a behavioral and cognitive basis to explore AI adoption patterns in Pakistan's ATC and MET professionals.

TAM is used as the foundational framework for this research due to the convenience as well as effectiveness is associated with it while examining the individual perception towards AI adoption in Pakistan's aviation sector. Other models such as the theory of Diffusion & Innovations DOI of Rogers in 1995 and the Technology Organization Environment framework of Tornatzky and Fleischer 1990 consider wider organizational and environmental aspects but not personal attitudes (García-Avilés, 2020). Unified Theory of Acceptance and Use of Technology UTAUT can be used in similar context as explained by Venkatesh et al. (2016), but is broader in scope for the case of this study.

Application of Artificial Intelligence in Pakistan's aviation sector has not been analyzed comprehensively. Through the application of TAM, this research attempted to fill this gap successfully by identifying the psychological and behavioral factors of AI adoption, aligned with the broader objective of integration of AI technologies in Pakistan's aviation sector, specifically focused on the ATC and MET domains. Thus, within the scope of this research, the TAM model thus adopted facilitated the comprehensive assessment of the individual perceptions about the usefulness and ease of use associate with the AI technologies in the Air Traffic Control and Metrological Operations. Furthermore, driven by the two perceptions, it helps analyses the behavioral intentions of the individuals towards actual adoption of the technology.

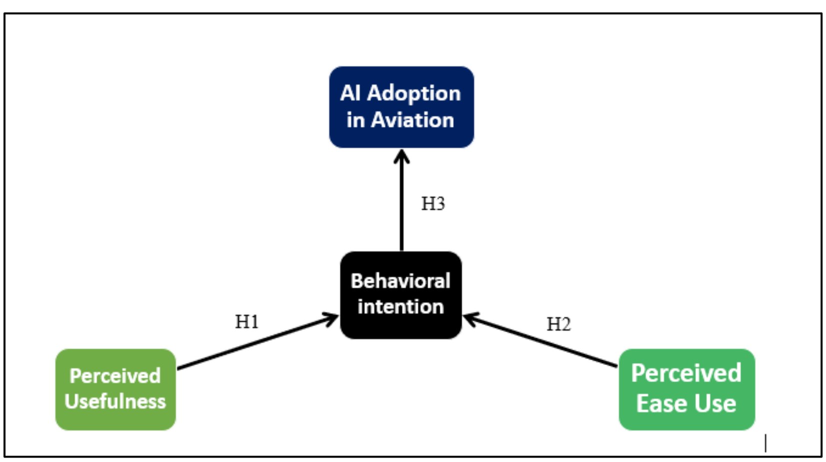

Figure 1: Theoretical Framework

Given these fundamentals, three key building blocks of technology acceptance model i.e. Perceived Usefulness, Perceived Ease of Use and Behavioral Intentions (BI) define the theoretical framework for this study. As depicted in Figure (1), the framework depicts the relationship between variables PU, PEOU, and BI as explained in the coming section.

3.6 Perceived Usefulness (PU)

Perceived Usefulness (PU) refers to the extent to which an individual believes that using a particular system will enhance their job performance. In most organizations, employees receive both tangible and intangible rewards to motivate them and improve performance outcomes. Several key factors directly influence PU, including the system's importance, relevance, usefulness, and value. These factors have been widely examined by researchers because of their strong association with an individual's belief in a system's capability to improve task performance. Furthermore, perceived usefulness is closely linked with attributes related to outcome expectations, performance anticipation, technology-task matching, job relevance, staff training and support, and a user experience and familiarity with the proposed technology (Marangunić & Granić, 2015).The interplay of these attributed collectively determine the user perceptions about the benefits of a system indicated through the dimensions of Efficiency, Decision Making and Productivity, Effectiveness, Task Management, and Overall Usefulness. These dimensions collectively reflect the proposed system's ability to save time and resources by enhancing quality and speed of decisions making processes towards achievement of organizational goals through better organization of workflows and task management. Thus, together, these dimensions provide a comprehensive understanding of how users anticipate a proposed system or technology's usefulness in enhancing their professional efficiency and performance (Marangunić & Granić, 2015). Based on the important role Perceived Usefulness plays towards the adoption of technology, the relevant hypothesis for this study is:

H1: Perceived Usefulness (PU) significantly impacts AI based technology adoption in Air Traffic Control and Metrological Operations in Pakistan's Aviation Sector.

3.7 Perceive Ease of Use(PEOU)

Perceived Ease of Use (PEOU) refers to the degree convenience associated with a particular technology as perceived by its users. It entails the user's perception about the simplicity, understandability, and manageability of the proposed system towards execution of operational tasks. Individuals generally prefer technologies or systems which are simple and easier to operate (Barron, 2003). The analysis of perceived ease of use involves assessment of five key dimensions related to ease of learning new technologies, the simplicity and convenience the technology offers towards performing routine operations; clarity and understanding associated with the interface of the technology; the extent to which technology offers skills as well as confidence enhancement of its users; and a general sense of simplicity, convenience and comfort while interacting with the proposed technology. Collectively, these dimensions of perceived ease of use provide a thorough understanding of how users generally evaluate a system's usability (Lia, 2017). The general behaviors, as examined by various studies, highlight a positive association between ease of use and likelihood of new technologies adoption (Yadav et al., 2025). To analyze this observation for the adoption of AI technologies in ATC and Metrological Operations in Pakistan Aviation Sector, this study analyzed the following hypothesis:

H2: Perceived Ease of Use (PEOU) has a significant influence towards AI Adoption in the ATC and Metrological Operations in Pakistan.

3.8 Behavioral Intention(BI)

As explained by Fishbein & Ajzen (1975), adoption of technology when infleunced by its usefullness and assocaited convenience, it heavily depends upon the degree to which an individual is willing to engage in a particular behavior towards adopting or using a technological system. As explained by the Theory of Reasoned action, the intention to use a particular technology depends on an individual's attitude toward performing this behavior and subjective norms surrounding it (Hagger, 2019). This broader individual attitude, known as Behavioral Intentions, to Use, generally implies that an individual is more likely to engage in a specific behavior towards adoption of a technology when they have a positive attitude toward that behavior and perceive that all other stakeholders and society will support them in doing so. Defined by four main dimensions related to a particular technology's future use, recommendation and exploration of different technology solutions, and Integration of future operations, the behavioral intention captures users' readiness, motivation, and proactive attitude toward the continued and expanded use of technology. Behavioral intention is an important and significant predictor of AI adoption in service industry. Affected by perceived usefulness and perceived ease of use, behavioral intentions to use, significantly influences actual adoption of AI based technologies. This indicates that encouraging positive intentions toward AI use is the prerequisite for its successful adoption and integration in professional settings (Chadaga et al., 2025). A lot of studies, while addressing the AI adoption in services industry, highlighted that A lot of studies highlighted that the actual adoption of AI technologies based on perceived usefulness and ease of use are mediated by behavioral intention to adopt (Liu, 2025). Given this context the relevant hypotheses for this study related to behavioral intentions are:

H3: Behavioral Intention (BI) mediates the relationship between Perceived Usefulness (PU) and AI Adoption.

H4: Behavioral Intention (BI) mediates the relationship between Perceived Ease of Use (PEOU) and AI Adoption.

4. Data and Methodology

4.1 Data:

Coherent with the objectives, this study analyzed the adoption of AI technologies in the Air Traffic Control and Meteorology department within the aviation sector of Pakistan by using the Technology Acceptance Model (TAM), with a quantitative, cross-sectional, research design. The data were collected over an estimated three-week period through a cross-sectional survey. The primary survey instrument for collecting data was a structured questionnaire developed based on the TAM model to analyze Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention to Use (BIU), and AI Adoption. A sample of 180 respondents was chosen using a purposive sampling technique from different airports throughout Pakistan. Professionals actively working in the aviation sector, especially those in Air Traffic Control, Metrological Department, and technical support, made up the sample. The study mainly focused on employees of the Pakistan Civil Aviation Authority (CAA), such as flight officers working in the aerodrome, area, and approach control units, meteorological staff (MET personnel), and air traffic control officers (ATCO's). Both individual workers, decision makers within organizational departments served as the unit of analysis for this study. This method made it easier to comprehend how departmental functions, job duties, and individual behavioral characteristics affect the adoption and integration of AI. For each of the four constructs, all the respondents were asked few questions related to their operational domain i.e. ATC or MET to be responded according to the Likert scale as shown in the **Appendices A and B**. The survey questionnaires were distributed to the Atco's and Met Personals online via LinkedIn, QR code, Links and other social media platforms at different airports and by physically visiting of the Islamabad airport and Pakistan Metrological Department Islamabad. The survey items, related to all the four constructions of this study i.e. Perceived Usefulness(PU),Perceived Ease of Use(PEOU), Behavioral Intentions (BI) and AI Adoption(AIA), for the Air Traffic Control and Metrological Department are listed in the **Appendices A and B.**

As mentioned earlier, a total of 180 valid responses were obtained from the professionals working in Air Traffic Control (ATC) and Meteorological (MET) departments at various airports in Pakistan. This sample size of 180 is considered statistically adequate for inferential analysis in behavioral and adoption research. According to Jobson (2012) and Kline, (2018), having a minimum of 100 to 200 observations is sufficient for reliable empirical analysis, particularly in a situation where the model involves less than ten latent constructs with as moderate item-to-construct ratios. It is further supported by the rule of thumb proposed by Tabachnick and Fidell (2013), which provides a simple numerical rule to determine the sample size. According to this rule if an analysis involves k regressors then the sample size N must be $N \geq 50 + 8k$.Tis thumb rule further supports adequacy of 180 observations in the context of present study. Apart from the technical justifications, the specific nature of the respondent population involved in this research, comprising trained professionals from the critical aviation operations of air traffic control and meteorological functions. Given this, every response obtained carries a higher domain relevance and a very high informational value, enhancing the robustness of the data and findings. Under these conditions, the sample of 180 respondents provides a solid empirical foundation for the subsequent quantitative analysis.

4.2 Data transformation and Index Construction

To facilitate a unified quantitative analysis, composite indices were constructed for each of the four constructs i.e. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), and AI Adoption (AIA). These indices were computed based on the180 responses obtained from the officials working in the Air Traffic Control (ATC) and Meteorological (MET) departments. Creating indices, thus enabled transformation of multi-item data into a standardized, continuous measures having values in the range of 0 and 1, thereby improve comparison across different constructs and respondents. These indices thus served as the primary variables in the empirical analysis. As shown in the Appendices A and B, each of the four-construct consisted of multiple observed items, assessed on a 5-point Likert scale ranging from 0 = Strongly Disagree to 4 = Strongly Agree. To compute an aggregate score, the total score obtained by an individual respondent across all items for a construct was divided by the maximum attainable score for that construct. The value of this ratio then represents an individual's aggregate perception for that construct. For example, the Perceived Usefulness (PU) construct consists of five items. Given a Likert scale with a highest value of 4, the maximum achievable total score has been 20 (5 items × 4 = 20). If a respondent responded with 2 for item 1, 3 for item2, 3 for item 3, 4 for item 4 and 2 for item 5, then a total obtained score would be 14 for all five items. The composite index value for PU would thus be calculated as a ratio of Total Obtained Score (14) to the maximum achievable score for 5 items (20) which is equal to 0.7.Using the similar approach, the index values for all individuals was calculated for all the four constructs, as summarized below:

Perceived Usefulness (PU):
$$PU_i = \frac{\sum_{j=1}^{5} PU_{ij}}{5 \times 4}$$

Perceived Ease of Use (PEOU):
$$PEOU_i = \frac{\sum_{j=1}^{5} PEOU_{ij}}{5 \times 4}$$

Behavioral Intention to Use (BI):
$$BI_i = \frac{\sum_{j=1}^{4} BI_{ij}}{4 \times 4}$$

AI Adoption (AIA):
$$AIA_i = \frac{\sum_{j=1}^{5} AIA_{ij}}{5 \times 4}$$

where:

$PU_{ij}, PEOU_{ij}, BI_{ij}, AIA_{ij}$ indicates ith respondent's score on the j^{th} item of the respective construct; n refers to the number of items in each construct with *n=5 for PU, n=5 for PEOU, n=4 for BI, and n=5 for AIA; and* 4 is the highest possible Likert-scale value.

This method of aggregating item wise responses into standardized composite measures aligns with established practices in behavioral research as well as studies related technology adoption. Davis (1989) in his original work pertaining *Technology Acceptance Model (TAM)* conceptualized Perceived Usefulness and Perceived Ease of Use as a multi-item measures that capture underlying behavioral tendencies. Later development in the discourse on technology acceptance such the work by Venkatesh and Davis (2000) and Venkatesh et al. (2003) under the umbrella of *Unified Theory of Acceptance and Use of Technology (UTAUT)* relied on the aggregation of multiple items to form composite construct scores. Furthermore, the approach of standardizing these aggregated scores within the range of 0-1 follows the aggregation conventions discussed in the literature (El Gibari et al., 2019; Booysen, 2002). This approach ensures both comparison and interpretation across constructs with different number of items and facilitates quantitative analysis while maintaining the theoretical validity of behavioral constructs. As a result of this computation, the aggregate values closer to zero indicate higher level of disagreement with the statement of given item pertaining to the construct under investigation (strong disagreement if the value is exactly zero) whereas a value closer to 1 indicates higher level of agreement with the statement (strong agreement if the value is exactly 1). If a value is closer to 0.5, it indicates the neutrality of respondent between disagreement and agreement. The method of standardization offers two technical advantages. First, it mitigates the impact of variation in the number of items across constructs, ensuring high level of comparability in subsequent analyses. Second, it provides normalized input measures for mediation analysis with much improved stability and interpretability of estimates. Thus, the outcome indices were subsequently used as composite variables representing PU, PEOU, BI, and AIA in the mediation analyses as explained in the coming section.

4.3 Mediation Analysis Approach

Given the conceptual structure of this study, mediation analysis was employed to analyze the impact of *Perceived Usefulness (PU)* and *Perceived Ease of Use (PEOU)* on *AI Adoption (AIA)*, by considering the intervening role of *Behavioral Intention to Use (BI)*. Rather than relying solely on traditional models, this analytical approach provides a more nuanced understanding of the phenomenon that involves interaction of individual perceptions and behavioral factors towards shaping the AI adoption decisions for ATC and MET. Thus, by recognizing the limitations of the traditional approach (Baron & Kenny, 1986), mainly its limited statistical power and core reliance on significance testing this study used a more robust mediation bootstrapping resampling framework of mediation proposed by Preacher and Hayes (2004). This framework allows for estimation of mediation effects based on the 5,000 bootstrap samples, ensuring the enhanced statistical robustness as well as the reliability of inference without considering the normality conditions. Thus, the use of this advance bootstrapping technique, strengthens the analytical rigor of this study.

5. Data Analysis and Results

The total sample(180) considered for this study consisted of 85 respondents from Air Traffic Control and 95 participants from the Metrology department. The gender profile of respondents for both the departments i.e. ATC and MET depict a dominance of males. Whereas with reference to the professional roles, the largest group of respondents comprised of Working Staff followed by line manager (Supervisors), Policymakers, Analysts and Instructors respectively. Overall, this composition reflects a diverse representation of individuals across hierarchical and functional levels, with a notable majority drawn from operational and supervisory roles. This mix of respondents offers a balanced perspective on AI related perceptions across various organizational positions.

5.1 Descriptive Statistics

The descriptive statistics of overall sample indicate a general positive tendency of respondents for all four constructs involved in this study. The mean values of indices related to Perceived Usefulness, Perceived Ease of Use, Behavioral Intentions and AI Adoption exceeds the midpoint (0.50), indicating favorable perceptions as well as attitude with respect to the adoption of AI. As shown in Table 1, Perceived Usefulness (PU) depicted the highest mean value (0.722) followed by BI(0.663), PEOU (0.641), and AIA (0.595). This observation suggests that participants from aviation industry not only acknowledge the usefulness of AI but also demonstrate a strong willingness to adopt AI based technologies. Furthermore, the negative skewness for all four constructs indicates that most of the participants selected higher values on the Likert scale of survey, thereby emphasizing a generally favorable opinion towards all four constructs.

Table 1: Descriptive Statistics

Construct	AIA	PU	PEOU	BIU
Minimum	0	0	0	0
Maximum	1	1	1	1
Mean	0.641	0.722	0.595	0.663
Std. Deviation	0.216	0.198	0.2	0.196
Skewness	-1.101	-1.807	-0.624	-1.237
Kurtosis	1.126	3.831	0.617	2.037

Moreover, the relatively high skewness observed for PU and BI indicates a strong consensus regarding the usefulness of AI and individual intentions to adopt. As far as kurtosis is concerned, the positive values indicate a leptokurtic nature of distributions with lower variance and clustering of responses around the mean values. This pattern of data further reinforces the idea that respondents from aviation industry of Pakistan holds a consistent and convergent point of view about the adoption of AI. Generally, the behavior of data illustrates a robust and homogeneous tendency toward effective evaluation of AI adoption within the ATC and MET functionalities in the light of technology acceptance model. These fundamentals of raw data highlight the stronger predictive validity of Technology Acceptance Model, which believes that individual perceptions of technology's usefulness and ease of use directly influence their intention to adopt it. From a practical perspective, the data's general behavior suggests that enhancing individual awareness regarding the usefulness and usability of AI based technologies can significantly improve individual behaviors towards its adoption within the ATC and MET.

5.2 Mediation Analysis

Coherent with the main objectives of this study, the mediation analysis has been conducted to test the direct as well as indirect relationships by using Preacher and Hayes's (2004) method with 1000 simulations. The method produced Average Causal Mediation Effects (ACME) and Average Direct Effects (ADE), with 95% confidence intervals for testing significance of mediation.

5.2.1 Full Sample Analysis

When data from both the ATC and Meteorology departments are pooled together (180 observations), the analysis, as presented in Table 2 shows that Perceived Usefulness (PU) has a significant influence on Actual Intention to Adopt (AIA), largely through the mediating role of Behavioral Intention (BI). The Average Causal Mediation Effect (ACME), an indicator of the indirect effect of PU on AIA through BI, is significant. This indicates that the perceived usefulness of AI systems results in greater adoption intentions through stronger behavioral intentions. The Average Direct Effect (ADE), which reflects the direct association between PU and AIA after adjusting for BI, is not statistically significant. It implies that after considering BI, PU does not contribute to AIA independently. The Total Effect, which combines both direct and indirect effects, is significant. In addition, 58% of the total impact is mediated by BI, again affirming the pivotal role played by behavioral intention in mediating perceived usefulness to adoption intention.

Table 2: Full Sample Results with PU

Effect Type	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (Indirect)	0.1297	0.0587	0.21	<2e-16 ***
ADE (Direct)	0.0937	-0.0736	0.26	0.270
Total Effect	0.2234	0.0666	0.38	0.002 **
Prop. Mediated	0.5802	0.2208	2.03	0.002 **
Signif. codes: * (0), ** (0.001), * (0.01), "." (0.05), " " (1)**				
Sample Size Used: 180				
Simulations: 1000				

Similarly, the Average Causal Mediation Effect (ACME) of PEOU on AIA through BI, as shown in the Table 3, is found to be significant statistically, indicating that PEOU has a significant impact on AIA through BI. The Average Direct Effect (ADE), which indicates the direct impact of PEU on AIA controlling for BIU, is on the margin of significance. Although this shows some proof of direct impact, marginal significance level lowers the confidence over this claim. The Total Effect, being a combination of both direct and indirect effects, is extremely significant, indicating that PEOU has a positive effect on AIA. As shown in the Table 3, about 54% of this total effect is mediated by BI. These findings emphasize that although PEOU has a strong overall effect on AIA, most of this effect is indirect through BI.

Table 3: Full Sample Results with PEOU

Effect Type	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-value**
ACME (Indirect)	0.2014	0.0997	0.31	<2e-16 ***
ADE (Direct)	0.1730	-0.0143	0.35	0.062 .
Total Effect	0.3744	0.2105	0.53	<2e-16 ***
Prop. Mediated	0.5377	0.2556	1.05	<2e-16 ***
Signif. codes: * (0), ** (0.001), * (0.01), "." (0.05), " " (1)**				
Sample Size Used: 180				
Simulations: 1000				

5.2.2 Departmental Analysis

The data from both the ATC and Meteorology departments has been analyzed separately with the same Hayes and Preacher (2004) method to assess the fundamentals variations regarding the AI adoption in ATC and MET departments.

5.2.2.1 Air Traffic Control

The findings related to association of PU, BI, and AIA for the ATC department, based on 85 observations, as presented in the following Table 4:

Table 4: ATC Results with PU

Effect	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-value**
ACME (Indirect)	0.0803	-0.0132	0.20	0.09
ADE (Direct)	-0.0297	-0.3124	0.27	0.85
Total Effect	0.0506	-0.2304	0.34	0.73
Prop. Mediated	0.2733	-7.4223	10.00	0.77
Signif. codes: * (0), ** (0.001), * (0.01), "." (0.05), " " (1)**				
Sample Size Used: 85				
Simulations: 1000				

The results presented in Table 4 portrays insignificance of direct and mediated paths, implying a lack of adequate evidence for both direct effect of PU on AIA as well through BI's mediating role in the relationship. The Total Effect is similarly estimated as negligible and insignificant. These outcomes indicate that the association between PU and AIA in the ATC department is weak and not mediated by BI, possibly due to organizational, cultural, or sample-size-related limitations.

For the association of PEOU on AIA within ATC, the analysis shows that there is a high and significant Total Effect of PEOU on AIA indicating that PEOU has a direct positive impact on AIA using both direct and indirect paths. The Average Direct Effect (ADE) is also significant indicating that PEOU has a direct effect on AIA even after accounting for the impact of BI. But the indirect effect via BI, is not significant, showing no evidence of mediation, also confirmed by the insignificance of proportion mediated, as shown in Table 5. These results, by indicating that in the ATC department, where only a direct impact of PEOU on AIA prevails, emphasizing the need of a direct improvement in the individual perceptions related to convenience and ease of use to encourage AI adoption without bothering for behavioral intention.

Table 5:ATC Results with PEOU

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (Indirect)	0.1784	-0.0420	0.43	0.12
ADE (Direct)	0.4215	0.0512	0.77	0.02 *
Total Effect	0.5999	0.3241	0.87	<2e-16 ***
Prop. Mediated	0.2886	-0.0686	0.87	0.12
Signif. codes: * (0), ** (0.001), * (0.01), "." (0.05), " " (1)**				
Sample Size Used: 85				
Simulations: 1000				

5.2.2.2 Meteorology Department

The findings for the department of Meteorology, based on 95 observations, as shown in the Table 6, indicate a significant mediation effect of BI in the relationship of PU and AIA. The significance of ACME reflects that BI significantly mediates the effect of PU on AIA. The ADE, measuring the direct effect of PU on AIA, is also significant, indicating that PU directly affects AIA regardless of BI. The Total Effect as well as proportion mediated both are statistically significant. These findings indicate that although PU has a significant direct impact on AIA, BI has an important mediating role to play in this relationship.

Table 6:MET Results with PU

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (Indirect)	0.1378	0.0588	0.23	<2e-16 ***
ADE (Direct)	0.2964	0.1494	0.45	<2e-16 ***
Total Effect	0.4343	0.2874	0.58	<2e-16 ***
Prop. Mediated	0.3173	0.1337	0.57	<2e-16 ***
Signif. codes: * (0), ** (0.001), * (0.01), "." (0.05), " " (1)**				
Sample Size Used: 95				
Simulations: 1000				

For the relationship of PEOU , BI and AIA within the Meteorology department, as shown in the Table 7, the model indicates a strong mediation effect with a significant indirect effect of PEU on AIA through BI, suggesting PEOU has a significantly affect AIA through its influence on BI. By contrast, the direct effect (ADE) of PEOU on AIA found to be insignificant, indicating absence of the direct effect of PEU on AIA. The Total Effect is significant, and proportion mediating is high as well as significant. These findings highlight that in the Meteorology department; BIU is the main channel by which PEU influences AIA. Strategies aiming to enhance adoption should focus on enhancing behavioral intentions, as the effect of PEU on AIA is nearly fully mediated by BIU.

Table 7: MET Results with PEOU

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (Indirect)	0.12703	0.05061	0.22	<2e-16 ***
ADE (Direct)	0.01268	-0.13368	0.15	0.864
Total Effect	0.13971	0.00346	0.28	0.046 *
Prop. Mediated	0.88473	0.19660	5.44	0.046 *
Signif. codes: * (0), ** (0.001), * (0.01), "." (0.05), " " (1)**				
Sample Size Used: 95				
Simulations: 1000				

Along with the Hayes and Preacher mediation analysis, the study also used the Baron and Kenny (1986) method, which also provided similar results.

6. Conclusion and Policy Recommendations

As discussed earlier, for full sample analysis, mediated by behavioral intentions, perceived usefulness has a strong impact on AIA. This mediating effect highlights the importance of looking at behavioral intentions as the driving force behind AI adoption. At departmental level, on the other hand, conflicting patterns persist: Within Meteorology department, both direct and mediating effects are significant. The ATC department, on the other hand, does not demonstrate any substantial direct, indirect, or overall effects, indicating the likely existence of contextual barriers or other unobserved factors influencing AI adoption. Similarly, the full sample analysis with respect to the interconnection of PEOU,BI and AIA, most of the relationship has been found to be mediated by BI, with a minor direct effect. While at departmental level, the results are contrasting, in the ATC department, there is a robust direct effect of PEOU on AIA, with no significant mediation through BIU. In the Meteorology department, almost the entire effect of PEU on AIA passes through BIU, with no significant direct effect. The results show that MET professionals in comparison to ATC depicts high behavioral intention and thus higher willingness to adopt AI based technologies. In comparison, ATC professionals depict low behavioral intention, and thus insignificant actual adoption, implying the existence of resistance or organizational barriers. With these results, this study supports the validity of TAM in the context of a developing nation and verifies the relevance of incorporating behavioral intention as a mediating factor in technology adoption studies. Moreover, the research provides an integrated approach of highlighting the key determinants of AI adoption in Pakistan's aviation sector. The existence of mediating role of BI explains that the technology should be not only efficient and easy to use but also be psychologically and behaviorally acceptable to its perspective users. The findings clearly establish that integrating AI into aviation operations predominantly requires a positive user willingness to adopt it. Furthermore, even when users are willing and technology is within reach as well as involves greater importance, but, still, it may go unused or unproductive if the perspective users are not confident or capable of using it. This fundamental fact emphasizes the need of user capability and trust building measures such as training, engagement in system design and deployment, and a stronger believe on the effectiveness of AI solutions. Given these necessary conditions, the adoption efforts must extend beyond technical rollout and emphasize convenience, transparency, effective communication, and realistic applicability. More specifically, in highly sensitive work settings such as air traffic control, where safety is paramount, it's particularly significant for individuals to be confident and empowered in their usage of AI technologies.

Concluding from the whole analysis, the effective adoption of artificial intelligence in Pakistan's aviation sector is not just about infrastructure and associated convenience only, it is more about shaping individual behaviors and mindset. Through investment in technology, user training, and policy framework that accelerates participation, the aviation sector can establish a conducive ecosystem for AI to flourish. Though professionals from meteorology department exhibit stronger willingness and capacity to apply AI, the ATC department exhibits lower willingness levels, highlighting a significant barrier to technological innovation in such a safety sensitive air traffic domain. Thus, with an equal emphasis on both technology and human beings, Pakistan can transition to a smarter, safer, and more efficient aviation future.

Despite the valuable information highlighted in this research, several constraints need to be mentioned: First, only Pakistan Civil Aviation Authority professionals associated with ATC and Meteorology departments employed at major Pakistani airports were considered for this analysis. With this sample structure, the perspectives of officials from private carriers ,regional stakeholders, and global aviation institutions, remained unaddressed. This data limitation thus making this study completely contextual and hence constrained its universal applicability. Second, the cross sectional nature of the research, constrained the ability to capture the variations in user perceptions, behavioral intentions, and adoption patterns over time. Thirdly, the use of self-reported measures may lead to threat of biases such as social desirability and overestimation of behavioral intention.

A few recommendations are put forward to facilitate future research and practice and address these limitations. First, to build consumers' familiarity with AI technologies, training programs need to be instituted. Such programs can strengthen behavioral intention to adopt as well as significantly enhance perceived utility and ease of use. Second, effective and fruitful policy support from the regulatory bodies and policy makers is essential to establish trust and providing an environment that smoothly facilitate the integration of AI in the aviation sector without any resistance and harm. Thirdly, in designing and implementing AI systems, the factors of user convenience, effective communication, and stakeholder engagement must be given highest level of priority to ensures trust, willingness and then higher rates of technological adoption. Finally, due to rapidly changing social, economic, and technological conditions, studies with longitudinal research design are recommended to monitor variations in the behavior and perceptions over time. The implementation and success of AI in Pakistan's aviation sector can be significantly enhanced by tackling these problems and listening to these recommendations.

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Appendices A: Scale and Survey Items Related to PU, PEOU, BI and AI Adoption for Air Traffic Control:

0 = Strongly Disagree	1 = Disagree	2 = Neutral	3 = Agree	4 = Strongly Agree

Construct	Sr #	Item
Perceived Usefulness	PU1	AI-powered ATC systems would improve my ability to identify potential airspace conflicts.
	PU2	AI would enhance the accuracy of ATC systems prediction compared to traditional methods.
	PU3	AI would help me make faster and more reliable decisions during high-traffic situations.
	PU4	AI would reduce the workload associated with manual monitoring for ATC.
	PU5	Overall, AI-powered ATC systems would be useful in my ATC operations.
Perceived Ease of Use	PEOU1	Learning to use AI-powered ATC systems would be easy for me.
	PEOU2	Interacting with AI for ATC system would be clear and understandable.
	PEOU3	I would find it easy to interpret the alerts and recommendations provided by AI systems.
	PEOU4	Integrating AI-powered ATC system into my current workflow would be straightforward.
	PEOU5	Overall, I would find AI-powered ATC systems easy to use.
Behavioral Intentions	BI1	I intend to use AI-powered ATC systems if they become available.
	BI2	I would recommend AI-powered ATC systems to other ATC professionals.
	BI3	I would prefer using AI over traditional methods for ATC systems
	BI4	Overall, I plan to use AI-powered systems in my ATC tasks.
AI Adoption	AIA1	We use AI for real-time decision-making in aviation operations.
	AIA2	AI adoption improves the efficiency of our ATC safety protocols.
	AIA3	AI helps in reducing operational costs and improving overall productivity in our ATC segment.
	AIA4	We are actively involved in AI research and development to improve aviation operations.
	AIA5	AI adoption is viewed positively by employees in our department.

Appendices B: Scale and Survey Items Related to PU, PEOU, BI and AI Adoption for Meteorology:

0 = Strongly Disagree	1 = Disagree	2 = Neutral	3 = Agree	4 = Strongly Agree

Construct	Sr #	Item
Perceived Usefulness	PU1	AI-powered weather forecasting tools improve the accuracy of aviation weather prediction.
	PU2	AI systems help in early detection of severe weather phenomena that could impact flight safety
	PU3	Using AI for weather analysis enhances the efficiency of operational decision making.
	PU4	AI integration in meteorology reduces manual workload and repetitive data interpretation.
	PU5	Overall, AI-based tools are useful for enhancing meteorological operations in Aviation.
Perceived Ease of Use	PEOU1	Learning to operate AI-driven weather forecasting tools would be easy for me.
	PEOU2	The interface of AI-based weather systems is user-friendly and understandable.
	PEOU3	I find it easy to interpret alerts and recommendations provided by AI weather systems.
	PEOU4	Integrating AI forecasting tools into existing meteorological workflows would be straightforward.
	PEOU5	Overall, I find AI-based meteorological tools easy to use.
Behavioral Intentions	BI1	I intend to use AI-powered meteorological systems if made available in my department.
	BI2	I would recommend AI meteorological systems to my colleagues in aviation operations.
	BI3	I prefer AI-based analysis over traditional methods for interpreting weather data.
	BI4	Overall, I plan to integrate AI tools into my meteorological decision-making processes.
AI Adoption	AIA1	AI is utilized in our meteorological operations to support real-time decision-making in aviation weather forecasting and alerts.
	AIA2	The adoption of AI has improved the efficiency and accuracy of weather prediction and climate data interpretation for aviation safety.
	AIA3	AI implementation helps reduce resource consumption and enhances overall productivity in meteorological services supporting aviation operations.
	AIA4	Our metrological unit is actively exploring or engaged in research and development related to AI for aviation weather solutions.
	AIA5	AI adoption is generally viewed positively by meteorology professionals working in aviation-related weather services.