

Flight Delays at Navi Mumbai International Airport: Passenger Experience and Weather Impact

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Abstract - Navi Mumbai International Airport (NMIA) began commercial flights on 25 December 2025 to relieve the pressure on Mumbai's older airport, and its first monsoon as a working airport puts two questions on the table at once: how much of the region's heavy rain, low visibility and gusty wind turns into flight delay, and how passengers actually live through the waiting that follows. This paper proposes a mixed-methods study that connects the two. The quantitative strand matches flight-level punctuality records with aerodrome weather observations and uses logistic regression, random forest and gradient boosting to estimate both the probability and the length of a delay. The survey strand collects Likert-scale responses from NMIA passengers on information quality, facilities during the wait, staff conduct, ground access and overall satisfaction, and tests the relationships among them with correlation and regression. Models are judged by accuracy, precision, recall, F1-score, MAE and RMSE, and the questionnaire by Cronbach's alpha. No empirical findings are reported here. The paper sets out the full design, hypotheses, variables, instruments and analysis plan so that the study can be carried out and its results reported without redesign.

Key Words: Flight Delay, Navi Mumbai International Airport, Passenger Experience, Weather Impact, Passenger Satisfaction, Machine Learning, Aviation Operations

1. INTRODUCTION

Navi Mumbai International Airport (NMIA) was inaugurated on 8 October 2025 and handled its first commercial flights on 25 December 2025 [1], [2]. It was built as the second gateway for the Mumbai Metropolitan Region. Its first phase has one terminal, one runway and a planned capacity of 20 million passengers a year, and it opened cautiously, with twelve operating hours a day and 23 scheduled departures in the first month before moving towards round-the-clock service from February 2026 [1]. By April 2026, trade reporting put domestic activity at about 156 daily services and close to 20,000 passengers a day [7].

A new airport in this region meets the monsoon almost immediately. On 5 July 2026, gusts of up to 42 knots and

heavy rain forced the older Mumbai airport (CSMIA) to suspend runway operations for an hour; 13 flights were diverted and flight-tracking data counted 334 delayed flights, roughly 39% of that day's movements [3]. NMIA has not been exempt from the same weather. Its own opening ceremony was reportedly pushed back in September 2025 because heavy rain left loose soil and mud on the roads to the site [4], and one carrier cancelled flights to NMIA during the July 2026 spell [5].

Weather, however, explains only part of what a delayed passenger goes through. The same hour of waiting feels very different depending on whether the airline explains what is happening, whether water and food are offered, whether staff can be reached, and whether the passenger can find a cab or a bus afterwards. Early passenger accounts of NMIA mention patchy mobile coverage, trouble booking cabs, and weak lighting and signage [6]. These are small frictions that become large when a flight is late.

This paper therefore treats delay as two linked problems. One is a weather-and-operations problem that can be measured with flight and meteorological records. The other is an experience problem that can be measured only by asking passengers. The study proposed here ties them together for a single airport, inside and outside the monsoon. No results are claimed; the contribution is a complete and reproducible design.

2. LITERATURE REVIEW

Weather and delay. Work on weather as a driver of delay separates sudden events, such as a thunderstorm cell, from slow-onset ones, such as a long low-visibility spell, and treats both as capable of lengthening delays, though through different routes [8]. Schultz et al. proposed a way to quantify how weather erodes airport performance, an idea that matters most at an airport whose capacity rests on a single runway [9]. The cost side has been studied as well: the NEXTOR study for the United States estimated what delay costs airlines, passengers and the wider economy, which makes clear that passenger time is part of the bill [10].

Delay prediction. Sternberg et al. surveyed the many approaches to predicting flight delay, from statistical models to machine learning and network methods [11]. Rebollo and Balakrishnan used random forests on network-level features to predict delays at several look-ahead times [12]. Choi et al. combined flight records with weather observations and compared several classifiers [13], and Gui et al. applied random forest and LSTM models to large aviation datasets [14]. These studies agree that weather variables are useful inputs, but most concentrate on long-established airports with years of history.

Passenger experience. Oliver's expectancy-disconfirmation model describes satisfaction as the gap between what a customer expected and what happened [15]. SERVQUAL breaks service quality into measurable dimensions such as reliability, responsiveness and empathy [16]. Attribution theory adds that people react differently to a setback depending on whether they judge its cause to be controllable [17]. A weather delay and a crew-shortage delay may be equally long yet be judged very differently.

Regulatory context. In India, DGCA's Civil Aviation Requirement (CAR) Section 3, Series M, Part IV sets out what airlines must do for delayed passengers. According to a government reply in the Rajya Sabha, facilities are tiered by waiting time: drinking water for delays up to two hours, tea or coffee with snacks between two and four hours, and meals beyond four hours. Hotel accommodation with transfers applies to overnight delays, and an alternate flight or refund must be offered when the expected delay exceeds six hours. Airlines are not obliged to provide these where the delay arises from extraordinary circumstances beyond their control [18]. Adverse weather is the usual example of such a circumstance, so the passengers most affected by weather may also be the ones with the fewest entitlements.

3. RESEARCH GAP

Three gaps stand out in the literature surveyed for this paper. First, weather-delay studies draw mostly on established airports with long records, while a new airport in its first year of operation, with a short history and a changing airline mix, receives little attention. Second, delay models usually end at predicting a probability or a number of minutes, and passenger experience is handled separately, if at all. Third, in the Indian setting, where weather may relieve an airline of some duty-of-care obligations [18], the passenger side of a weather delay is a distinctive question in its own right. This paper responds with one design in which flight-level weather analysis and a passenger survey are gathered for the same airport and the same period, and then linked.

4. PROBLEM STATEMENT

NMIA is a single-runway airport in a region with an intense monsoon, and its traffic is growing quickly. When weather cuts visibility or raises crosswinds, arrivals and departures slow down and flights queue behind one another. What is not well understood is how strongly particular weather conditions at NMIA translate into delay, how passengers experience those delays, and whether the information and facilities offered during the wait shape that experience as much as the length of the delay itself. Without evidence, airports, airlines and regulators plan schedule buffers and passenger services on assumption.

5. OBJECTIVES

- To describe the pattern of flight delays at NMIA across monsoon and non-monsoon periods.
- To measure the association between weather variables and both the probability and the duration of delay.
- To build and compare predictive models of weather-related delay.
- To assess passengers' experience of delay with a structured, reliability-tested questionnaire.
- To test how information quality, facilities, delay length and perceived cause relate to satisfaction and reuse intention.
- To identify practical measures for the airport operator, airlines and regulators.

6. PROPOSED METHODOLOGY

The study uses a convergent mixed-methods design. Two strands are collected over the same period, analysed separately and then interpreted together.

Data Collection → Preprocessing → Feature Engineering → Modelling and Testing → Evaluation → Integrated Interpretation

- Data Collection: flight records and weather observations for the quantitative strand, and a passenger questionnaire for the survey strand.
- Preprocessing: timestamp alignment, weather matching, screening of survey responses.
- Feature Engineering: weather, operational and calendar variables derived for every flight.
- Modelling and Testing: classifiers and regressors for delay, and correlation and regression for satisfaction.
- Evaluation: held-out test performance for models and reliability checks for the instrument.

The research model in Fig -1 leads to five hypotheses.

- **H1:** Lower visibility, heavier rainfall, stronger gusts and crosswind, and thunderstorm activity are associated with a higher probability and a longer duration of delay.
- **H2:** Better perceived information quality during a delay is associated with higher satisfaction.
- **H3:** Better perceived facilities and staff support during a delay are associated with higher satisfaction.
- **H4:** Longer delays are associated with lower satisfaction, and the association is weaker when the passenger attributes the delay to weather rather than to the airline.
- **H5:** Higher satisfaction is associated with a stronger intention to use NMIA again.

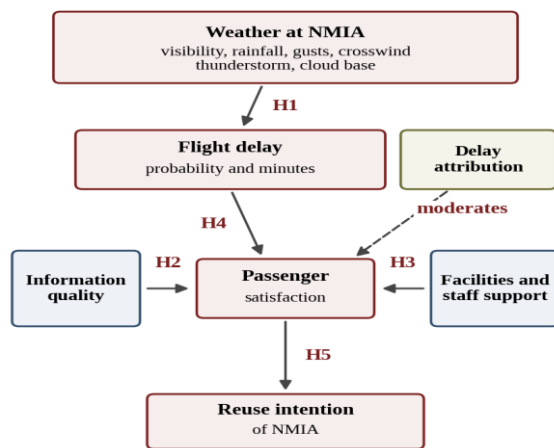


Fig -1: Proposed research model and hypotheses

7. STUDY AREA AND DATA DESCRIPTION

The study site is NMIA, in the Ulwe area of Navi Mumbai [4]. Because the airport is only months old, the observation window should run from the start of commercial operations in December 2025 to the end of the 2026 southwest monsoon in September, which allows dry-season and monsoon operations to be compared. Three data sources are proposed.

Flight records. Scheduled and actual times, flight number, airline, sector and status (on time, delayed, diverted or cancelled), taken from airline status pages, public flight-tracking archives and, where available, airport or DGCA statistics. The terms of use of each source should be checked before collection.

Weather data. METAR and SPECI reports for the aerodrome (visibility, wind direction, speed and gust, cloud base, present weather), supplemented by rainfall data and colour-coded warnings from the India Meteorological Department. Table -1 lists the variables and why each matters operationally.

Table -1: Weather variables used in the study

Variable	Source	Operational relevance
Visibility (m)	METAR	Low visibility slows arrivals and can trigger low-visibility procedures
Rainfall (mm/h)	IMD, rain gauge	Reduces visibility and braking action on a wet runway
Wind and gust (kt)	METAR	Gusts raise go-around and diversion risk
Crosswind component	Derived	Limits landings on the active runway
Thunderstorm flag	METAR	Arrivals held, departures paused
Cloud base (ft)	METAR	Sets approach minima

Passenger survey. The target population is adult passengers who have flown to or from NMIA and experienced at least one delay of more than 15 minutes. For a 95% confidence level, a 5% margin of error and maximum variability ($p = 0.5$), Cochran's formula [19] gives the required sample as follows.

$$n = z^2 \cdot p(1 - p) / e^2 = (1.96)^2 (0.5)(0.5) / (0.05)^2 \approx 384 \dots(1)$$

At least 384 valid responses should be targeted, with extra forms collected to allow for screening losses. Responses are gathered through a short questionnaire at the airport, with permission, and through an online link, using quotas across airlines and across monsoon and non-monsoon travel dates. Because this is non-probability sampling, findings should not be generalised beyond the sample without caution. Participation is voluntary and anonymous, informed consent is taken, and no personal identifiers are stored. Table -2 shows the planned constructs, each measured on a five-point Likert scale [20].

Table -2: Survey constructs

Construct	What it captures	Role
Information quality	Clarity, timeliness and channels of delay updates	Predictor (H2)
Facilities and staff support	Water, food, seating, assistance, staff courtesy	Predictor (H3)
Waiting-time perception	How long the delay felt, against the actual delay	Predictor (H4)
Ground access	Cab, bus and road access during rain	Control
Delay attribution	Whether the cause was seen as weather or airline	Moderator (H4)

Construct	What it captures	Role
Satisfaction	Overall judgement of the delay experience	Outcome
Reuse intention	Willingness to fly from NMIA again	Outcome (H5)

8. DATA PREPROCESSING

Flight and weather data need careful alignment before any modelling. The following steps are applied.

- Convert all timestamps to Indian Standard Time and reconcile them with METAR reports issued in UTC.
- Remove duplicate records, and keep cancelled and diverted flights in separate categories instead of mixing them with delay minutes.
- Define delay as actual minus scheduled time in minutes, and label a flight delayed when it exceeds 15 minutes [18].
- Attach to each flight the latest weather report issued before the scheduled time, so that the prediction task uses only information available in advance.
- Fill short gaps in weather series by carrying values forward, and drop flights that fall in long gaps.
- Keep extreme delays after confirming they are genuine, rather than deleting them.

Survey responses are cleaned separately.

- Remove incomplete forms, straight-lined answers and respondents with no delay experience.
- Reverse-code negatively worded items.
- Check reliability for each construct before averaging its items into a score.
- Retain free-text comments for later thematic coding.

9. FEATURE ENGINEERING

Each flight is described by three groups of variables. Weather features include visibility, hourly and trailing three-hour rainfall, wind speed, gust, cloud base, a thunderstorm flag and the crosswind component. With θ as the angle between the wind direction and the runway heading, the crosswind component is

$$\text{Crosswind} = \text{Wind speed} \times \sin(\theta) \quad \dots(2)$$

Operational features include hour of day, day of week, airline, sector, the number of scheduled movements in the same hour as a measure of congestion, and the delay of the aircraft's previous flight, since a late inbound aircraft often explains a late departure. Calendar features include a

monsoon flag and a flag for holiday and festival periods. Two targets are defined: a binary label (delayed or not) and delay in minutes.

10. ANALYTICAL MODELS

The delay models are chosen for a balance of interpretability and strength on tabular data, and the survey is analysed with standard statistical tests.

Table -3: Models and tests considered

Model	Used for	Role
Logistic Regression	Delay yes or no	Interpretable baseline
Random Forest [22]	Delay yes or no, minutes	Captures non-linear effects and interactions
Gradient Boosting (XGBoost) [23]	Delay yes or no, minutes	Strong benchmark for tabular data
Multiple Linear Regression	Satisfaction score	Tests H2 to H4
Spearman correlation, ordinal logistic regression	Likert outcomes	Robustness for ordinal data

Flights close in time share the same weather, so a random split would leak information from training into testing. A chronological split is therefore used: earlier months train the model and later months test it, with time-series cross-validation for tuning. Class weights address the imbalance between on-time and delayed flights. Implementation is planned in Python with scikit-learn [24].

11. SYSTEM ARCHITECTURE

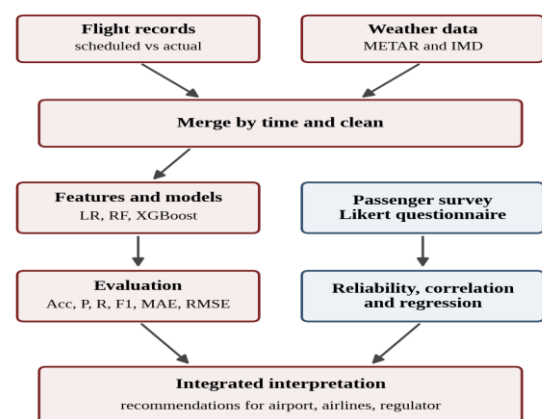


Fig -2: Workflow of the proposed study

The two strands run in parallel and meet only at the interpretation stage. Keeping the stages modular means a different classifier, a different weather source or a longer observation window can be substituted without redesigning the study. The same weather-matching module could later be fed live observations to support an operational dashboard.

12. EVALUATION FRAMEWORK

As this paper proposes a design and not a completed analysis, no performance figures are reported. Once data are collected, classification models are evaluated on the held-out period with the following metrics.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad \dots(3)$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad \dots(4)$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \quad \dots(5)$$

$$\text{F1} = 2 \times (\text{P} \times \text{R}) / (\text{P} + \text{R}) \quad \dots(6)$$

Delay-minute models are scored by mean absolute error and root mean squared error, where y is the observed delay and $\hat{y}$ the predicted delay over n flights.

$$\text{MAE} = (1/n) \sum |y - \hat{y}| \quad \dots(7)$$

$$\text{RMSE} = \sqrt{[(1/n) \sum (y - \hat{y})^2]} \quad \dots(8)$$

Because delayed flights are the minority, accuracy alone can mislead, so a confusion matrix and the recall for delayed flights should be reported, along with a simple baseline such as always predicting the majority class. Results should be given separately for monsoon and non-monsoon months. For the questionnaire, internal consistency of each construct is assessed with Cronbach's alpha [21], where k is the number of items, σ_i^2 the variance of item i and σ^2 the variance of the total score. A value of about 0.70 or higher is conventionally read as acceptable.

$$\alpha = [k / (k - 1)] \times [1 - \sum \sigma_i^2 / \sigma^2] \quad \dots(9)$$

Regression results for satisfaction should report standardised coefficients, R^2 and variance inflation factors to check multicollinearity.

13. EXPECTED RESULTS AND DISCUSSION

The expectations below come from earlier work and are not findings. Visibility and gusts are expected to rank among the stronger predictors of delay during the monsoon [8], [9], [13]. Tree-based ensembles are expected to outperform logistic regression where weather interacts with congestion, for example where the same rainfall does more damage in a peak hour than at midday [12], [14]. In

the survey, information quality and facilities are expected to matter at least as much as delay length for satisfaction [15], [16]. Attributing a delay to weather may soften dissatisfaction, yet the regulatory framework means fewer facilities may be owed in exactly those cases [18], so the experience of weather delays could be worse than attribution alone would suggest. That is a hypothesis worth testing and not a conclusion.

Any of these expectations may fail at NMIA, whose single runway, young operations and nearness to CSMIA differ from the airports in the cited studies. A result that contradicts them would be informative in its own right. Reporting should include model-comparison tables, feature-importance rankings, coefficient tables and the exact preprocessing choices, so that the work can be repeated and compared.

14. APPLICATIONS

For the airport operator, a tested link between weather and delay supports planning for low-visibility and high-gust periods, including staffing and passenger-service readiness. Airlines can use the findings to build realistic buffers into monsoon schedules and to decide when proactive messaging is worth the effort. Regulators and passenger-rights bodies gain evidence on whether current facility rules serve passengers well in weather-related delays. Passengers and local transport agencies benefit when delay forecasts and ground-access conditions are communicated together, since a late flight in heavy rain often means a difficult trip home as well.

15. CHALLENGES AND LIMITATIONS

NMIA is new, so the history available is short and covers at most one monsoon, which limits how far results can be generalised. A single weather station may not represent conditions across the whole approach path. Delay causes recorded by airlines are self-reported and may be assigned loosely. Because NMIA and CSMIA are close together, a restriction in the wider Mumbai airspace may produce a delay at NMIA that no local weather variable explains. The survey depends on passengers' memory of past delays and on non-probability sampling, both of which can bias responses. Finally, flight-tracking sources differ in coverage and definitions, so reconciling them takes care.

16. FUTURE SCOPE

Later work could extend the observation window across several years and seasons, add radar and short-term forecast data for nowcasting, and test sequence models such as LSTM on rolling weather series. A comparison between NMIA and CSMIA would show how two airports under one weather system differ in resilience. Passenger posts on social media offer another route, and emotion

and sentiment analysis of those posts could complement the survey with real-time reactions. Economic costing of delay at NMIA, and an operational dashboard that pairs live weather with delay risk, are further directions.

17. CONCLUSION

This paper has set out a complete and reproducible design for studying flight delays at Navi Mumbai International Airport, combining weather-linked delay modelling with a survey of how passengers experience the wait. By defining hypotheses, data sources, variables, models and evaluation measures in advance, it gives a practical starting point for a team that can collect the data. No empirical results are claimed. The aim is that, once the study is carried out, airports, airlines and regulators have evidence for treating weather delay as both an operational problem and a passenger-experience problem.

18. ACKNOWLEDGEMENT

The authors would like to thank the Department of MCA, D. Y. Patil Deemed to be University, School of Humanities & Sciences, Belapur, for its continued guidance and support throughout this work.

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