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# Decision-Making Failures in the Boeing 737 MAX Crisis: A Cognitive and Bayesian Network Analysis

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**ABSTRACT**

This report analyses the Boeing 737 MAX crisis as a systemic decision-making failure within a safety-critical engineering environment rather than as the consequence of a single technical defect. It examines two interconnected decision situations: Boeing's attempt to preserve design and training continuity with previous 737 aircraft, and the subsequent reassessment of risks associated with the Manoeuvring Characteristics Augmentation System (MCAS). A cognition-driven model is first applied to evaluate how anchoring, overconfidence, bounded rationality and confirmation bias influenced the continuity decision. The findings indicate that commercial pressure to maintain the 737 platform's operational familiarity contributed to limited pilot training, insufficient disclosure of MCAS and the underestimation of automation-related risks. A Bayesian network model is then used to illustrate how emerging warning evidence should have altered the assessment of systemic MCAS risk. The estimated probability of high systemic risk increases from 30.0% to 66.7% following severe accident evidence and to 84.2% when low pilot awareness and weak regulatory scrutiny are also considered. The analysis demonstrates that the crisis resulted from the normalisation of unsafe assumptions and inadequate updating of risk assessments. It concludes that safety-critical engineering decisions require transparent assumptions, independent scrutiny and systematic reassessment when new evidence emerges.

## 1. Introduction

The Boeing 737 MAX crisis is an important case about decision making due to the demonstration that technical design, human judgment, commercial pressures and regulation can all interplay in an engineering context that is critical with regard to safety.Formal investigations revealed flaws in MCAS design-communication, pilot-response assumptions, subcontracted certification and post-incident reassessment [1]-[3].

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This report argues that the crash of the 737 MAX was not brought about by a single technical or human mistake. It was caused by a decision environment where unsafe assumptions were normalised, which was not tested in a manner that was hard and was not revised when warning information surfaced. This report through a synthesis of a cognition-based model and a Bayesian network technique, it shows that engineering decision-making is enhanced by making more definite assumptions, systematic challenge, and rigorous reassessment in the environment of uncertainty.

## 2. Case Context and Selected Decision-Making Situations

### 2.1 Case Overview

The case of the Boeing 737 MAX crisis is an example of a high-stakes case of engineering decision-making regarding the design of aircraft, certification regulation, training of pilots, commercial necessity, and safety of people. The most notable technical problem was the Manoeuvring Characteristics Augmentation System (MCAS), an automated flight-control system, an answer to handling characteristics added to the 737 MAX. And led to a significant re-examination of the design choices made by Boeing, along with the reporting of the risks involved with MCAS, the assumptions made by pilots to react and how certification was conducted [1]-[3].

This report treats the 737 MAX crisis not as a single technical malfunction, but as a socio-technical decision failure. The key issue was how risk moved across design, training, certification and post-warning reassessment without being sufficiently challenged.

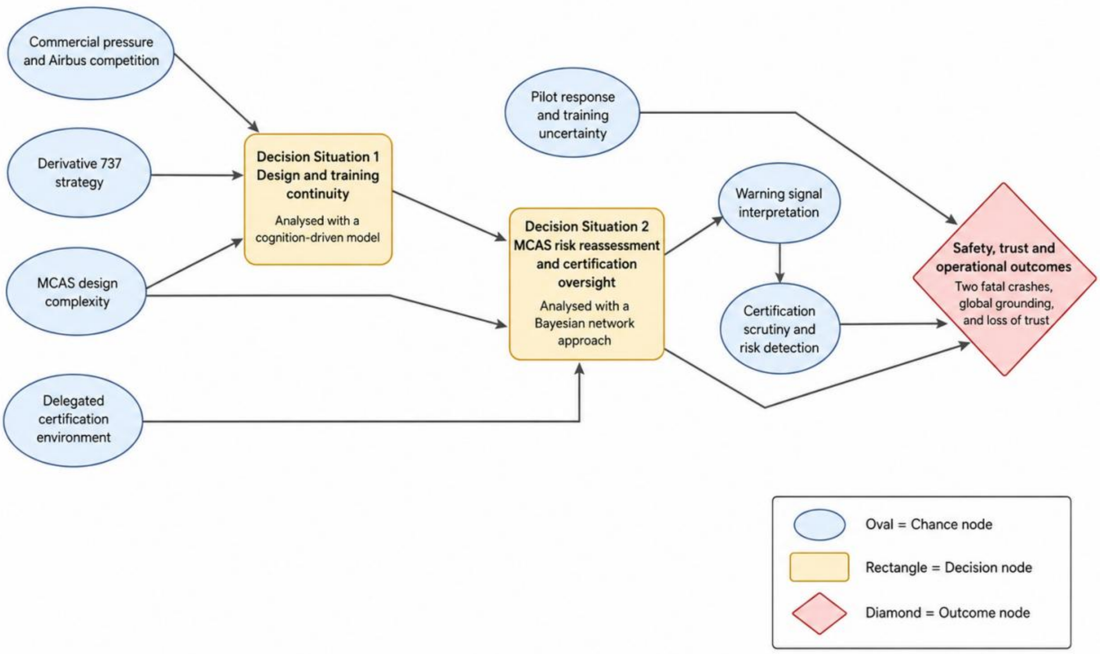


**Figure 1.** Influence Diagram of the Boeing 737 MAX Case and Selected Decision Situations

As is shown in Figure 1 The influence diagram clarifies the scope of this report. It does not represent every technical or regulatory factor in the 737 MAX crisis. Instead, it identifies the two decision situations , first, Boeing's decision to maintain design and training continuity; and second, the certification and post-warning reassessment of MCAS-related risk.

### 2.2 Decision Situation 1: Design and Training Continuity

The first decision situation concerns Boeing ' s pre-crash decision to maintain design, certification and pilot-training continuity between the 737 MAX and earlier 737 variants. This meant treating the MAX as a manageable derivative aircraft rather than as a platform requiring more conservative design review, fuller MCAS disclosure and more extensive simulator-based training.

A cognition-driven model is selected because the core issue was judgement under uncertainty. Boeing's decision was shaped not only by technical evidence, but also by how decision-makers framed the aircraft, interpreted incomplete information and relied on prior assumptions. Anchoring helps explain Boeing ' s attachment to 737 continuity; overconfidence explains the under-challenged assumptions about pilot response and system manageability; and bounded rationality explains how commercial, schedule and certification pressures simplified a complex safety problem into a narrower continuity decision.

### 2.3 Decision Situation 2: MCAS Risk Reassessment and Certification Oversight

The second decision situation concerns Boeing and regulators' certification and post-warning reassessment of MCAS-related risk, especially after the Lion Air crash. The key issue was whether the existing assumptions about MCAS design, pilot response, training adequacy and certification scrutiny should have been updated as new evidence emerged.

A model-driven Bayesian network is selected because this situation involved interacting risk variables rather than a single judgement problem. MCAS design complexity, AOA sensor dependency, pilot awareness, training adequacy, warning-signal interpretation and regulatory intervention were conditionally linked [1]–[3]. Bayesian reasoning is appropriate because it represents these factors as connected nodes and shows how new evidence should update risk judgement. Therefore, this model best explains how MCAS-related risk could have been reassessed more systematically before weak signals became catastrophic outcomes.

**Table 1.** Selected decision situations and models

| Element | Decision Situation 1 | Decision Situation 2 |
|---|---|---|
| Focus | Design and training continuity | MCAS risk reassessment |
| Core tension | Efficiency vs safety review | Certification confidence vs system reassessment |
| Key uncertainty | Pilot response to abnormal MCAS behaviour | MCAS design, AOA dependency, training and oversight |
| Model selected | Cognition-driven model | Bayesian network model |
| Rationale | Explains judgement, bias and bounded rationality | Represents interdependent risks and evidence updating |

Table 1 shows that the cognition-driven model is best suited to explaining how judgement and bias shaped Boeing's continuity decision, while the Bayesian network model is stronger for analysing interdependent MCAS risks and how new evidence should update risk judgement.

A data-driven approach is not selected as a primary model because the available public evidence is retrospective, incomplete and difficult to convert into a reliable dataset for predicting rare, high-consequence aviation failures.

## 3. Decision Situation 1: Cognition-Driven Decision-Making Model

### 3.1 Decision Context

Decision Situation 1 relates to the fact that Boeing pre-crash made the decision to continue the design and training process with the 737 MAX variants and the previous 737 products. This was a move that had commercial appeal since airlines would be able to implement the MAX with minimum disruption to operations as well as absence of high levels of simulator based transition training. But same continuity goal guided the interpretation of these matters of risk associated with MCAS, assumptions of pilot-response, and requirements of training.

A cognition-based model is appropriate in this case as the problem with the decisions was not purely technical. It entailed the way the decision-makers thought of the aircraft, the choice of evidence, simplification of uncertainty and confidence to hold onto assumptions of pilot behaviour. The crucial cognitive problem was that the 737 NG was considered close enough to the 737 MAX, which did not take into account new automation-related risk that was not entirely apparent to the pilots [1], [3].

### 3.2 Rationale for Selecting the Cognition-Driven Approach

The development of cognition-based approach is chosen due to its explanation of the human judgement process in the context of uncertainty, pressure and the scarcity of information. It was not just a question of technical alternatives in this case that Boeing was facing. It was passing judgment on alternative absorption of a new aircraft system within an existing design frame, certification and training frame.

This model was more appropriate than just using a purely numerical model to define Decision Situation 1 since simply not having data was not the main problem. It was the interpretation of available evidence. The implications of continuity and insufficient training seem not to impact the correctness of my judgment despite the fact that system-level safety margins were becoming smaller [4]–[6] due to anchoring, overconfidence and bounded rationality.

### 3.3 Model Application: Anchoring, Overconfidence and Bounded Rationality

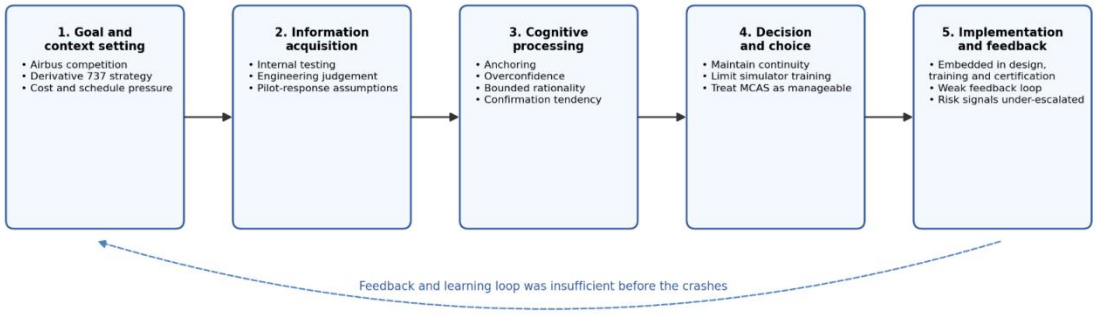


**Figure 2.** Cognition-Driven Decision-Making Model Process for Design and Training Continuity

Figure 2 depicts a process with five stages of cognition. The context of the decision was influenced, in the first place, by Airbus competition, derivative-aircraft strategy, and cost and schedule pressure. Second, Boeing depended on a internal testing, engineering judgement, certification expectations and assumptions of pilot-response. Third, anchoring, overconfidence, limited rationality and confirmation tendency influenced the cognitive processing. Fourth, the decision to continue was preferred, and lessen simulator training and treat MCAS as bearable. Ultimately, this choice became institutionalized to design, certification and training, and the feedback loop was too frail to turn the frame prior to the crashes.

**Table 2.** Cognitive bias, evidence and decision effect

| Cognitive factor | Case manifestation | Evidence basis | Decision effect |
| --- | --- | --- | --- |
| Anchoring | MAX framed as a derivative aircraft requiring limited pilot transition | Boeing emphasis on continuity and limited simulator training [3] | MCAS was less likely to be treated as a major training/disclosure issue |
| Overconfidence | Strong confidence in pilot response and controllability | JATR concerns about pilot response-time assumptions [1] | Cockpit workload and abnormal-event recognition were underestimated |
| Bounded rationality | Safety complexity simplified under commercial, schedule and certification pressure | Findings on production pressure, certification assumptions and oversight [2], [3] | Continuity became the default despite system complexity |
| Confirmation tendency | Evidence supporting limited training gained stronger organisational acceptance | Findings on communication and certification weaknesses [3] | Contrary risk signals were not escalated sufficiently |

Table 2 shows how anchoring, overconfidence and bounded rationality shaped Boeing's continuity-based decision. Anchoring kept the 737 MAX framed as a manageable derivative of earlier 737 models. Overconfidence then reinforced the belief that pilots could respond effectively to MCAS-related abnormal behaviour with limited additional training. Bounded rationality explains why, under commercial, schedule and certification pressure, Boeing simplified a complex safety issue into a narrower continuity decision. Together, these cognitive factors reduced the likelihood that MCAS would be treated as a major training, disclosure and system-safety issue.

## 3.4 Outcome Interpretation and Data-Based Analysis

The cognition-driven model shows that the continuity decision produced short-term commercial advantages but severe long-term safety, operational and financial consequences. Table 3 compares the decision assumptions with later outcomes.

**Table 3.** Decision assumptions and outcomes

| Indicator | Continuity assumption | Actual / later outcome | Implication |
|---|---|---|---|
| Pilot transition training | Limited extra training was sufficient | Return-to-service required revised training and procedures [7], [8] | Initial training assumption was too narrow |
| Pilot response | Pilots could manage abnormal trim behaviour quickly | JATR questioned simplified response-time assumptions [1] | Human-performance uncertainty was underweighted |
| Safety consequence | MCAS risk was manageable within derivative-aircraft frame | Two crashes caused 346 deaths [1], [3] | Catastrophic risk was not adequately stress-tested |
| Operational consequence | Continuity would support market entry and adoption | Global grounding lasted March 2019–November 2020 [7] | Short-term efficiency caused long-term disruption |
| Reputation and cost | Avoiding simulator training protected customer value | Boeing faced major reputational damage and crisis costs [3] | Convenient assumptions created larger downstream losses |

The juxtaposition in Table 3 reveals a discrepancy between the initial decision frame and the outcomes that occurred. Continuity, speed and customer convenience, took a high priority in the decision frame. The results indicated that that frame was not a proper representation of the actual system risk. It was not merely a technical error that Boeing committed. A more fundamental problem was that, the decision architecture made it hard to question an assumption that is commercially attractive before it was hard-coded into design, training and certification.

## 3.5 Strengths, Limitations and Applicability

The central advantage of the cognition-based model is that it describes why the continuity decision may seem to be plausible within the context of Boeing business and organisational-level and yet may be unsafe regarding the safety systemic-level. It links judgement, bias and human factors with tangible results of decisions instead of considering the crashes as individual technical incidents.

The model proposes feasible controls too. The effects of anchoring may be minimized with reference-class forecasting and independent design review. Areas of overconfidence might have been critiqued by premortem analysis and by human-factors testing using simulators. Structured dissent and obligatory escalation criteria and independent certification challenge may have dealt with bounded rationality.

The weakness lies in the fact that this model to some extent is a retrospective model and this means that, there is likelihood of hindsight bias attempting to trace cognitive failures following the incident. It also fails to measure the probability of each failure pathway. Thus, the cognition-based model proves to be most valuable in understanding how the unsafe decision frame was developed whereas the Bayesian network in Section 4 is required to create interdependent risk updating in a more systematic manner.

# 4. Decision Situation 2: Model-Driven Bayesian Network Approach

## 4.1 Decision Context

Decision Situation 2 involves the re-evaluation of MCAS risks and the management of certification. In contrast to Decision Situation 1 the mind based judgement evident in the continuity of the design and training processes of Boeing, the situation, in this case, is whether the Boeing and the regulators had an organized mechanism of updating risk involved in MCAS even after warning signs had been observed. The most significant choice was to keep the current design of the training and certification assumptions defensible following the Lion Air crash or to put a firmer footing, re-assessment, and design adjustments, updated pilot training and regulating controls.

In this case, a model-driven approach is suitable since it is not a single variable that has led to the MCAS risk. It arose as a result of interrelation between MCAS design complexity, the reliance of the angle-of-attack sensor, pilot awareness, the sufficiency of the training program, scrutiny by certifying authorities and decoding warning signals. Authority reviews revealed that there were concerns regarding the flight-control assumptions, pilot-response assumptions, and human-factors testing and certification control [1]–[3]. A Bayesian network is thus appropriate since it can model such factors as conditional dependencies and indicate how risk judgement should be revised based on new evidence.

## 4.2 Rationale for Selecting a Bayesian Network

A Bayesian Network is chosen, as it enables to make a decision in the presence of uncertainty, by interconnecting the previous assumptions with some new evidence and new estimates in terms of risks. In a Bayesian reasoning, a decision-maker starts with a prior belief after which he/she observes evidence then updates the probability of a hypothesis [9]. Concerning this case, the concerned hypothesis is that there was high systemic MCAS-related risk. The applicable evidence features an extreme MCAS-coherent accident, coupled with unfavorable system factors like insufficient pilot consciousness and poor certification oversight.

This is an enhanced method compared to a mere risk matrix since the likelihood and consequence are not likely to be very dynamic in a risk matrix. In comparison, in a Bayesian network, the position of decision can change upon the emergence of new evidence. This is essential in aviation safety since, infrequent but devastating events might lack large datasets prior to something being taken about them. A catastrophic incident is enough to warrant forceful intervention in case it questions fundamental assumptions regarding system behaviour, or the quality of training or certification.

Another desirable aspect of the model is that it exposes assumptions. The design of MCAS, pilot training and certification review, were not stand-alone problems in the case of the 737 MAX. The risk posed by one area could be exacerbated by a weak area. A Bayesian network is a disciplined means of demonstrating those dependencies.

## 4.3 Model Construction: Nodes, States and Dependencies

Figure 3 demonstrates the potential Bayesian network and Bayesian phase of risk reassessment of MCAS. It is important to read that the figure is an illustrative decision model and not an accurate model to predict accidents. It demonstrates the effect of five input risk factors on intermediate risk conditions and eventually, regulatory intervention.

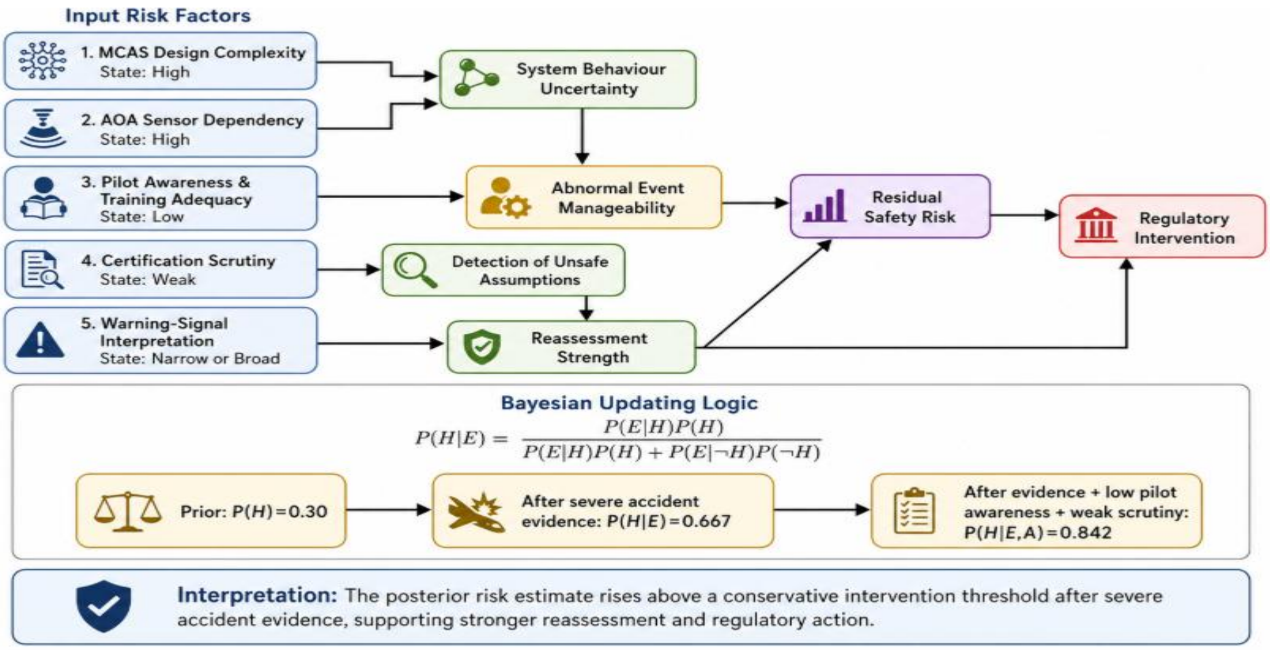


**Figure 3.** Bayesian Network Structure and Updating Process for MCAS Risk Reassessment

Figure 3 indicates that the model starts with five input factors, complex MCAS design, reliance on AOA sensor, sufficiency of pilot awareness and training, certification inspection, and interpretation of warning signals. The complicated nature of MCAS design and dependence on AOA sensors enhance uncertainty in system behaviour. The adequacy of training and pilot awareness has a direct impact on the manageability of abnormal events. The scrutiny of certification influences the detection of unsafe assumptions whereas the interpretation of warning signals influences the treatment of evidence, narrowly, as an incident or broadly as a system warning.

**Table 4.** Bayesian network nodes and decision relevance

| Node | State | Decision relevance |
|---|---|---|
| MCAS design complexity | High | Requires stronger design review and pilot support |
| AOA sensor dependency | High | Increases vulnerability to erroneous sensor input |
| Pilot awareness/training | Low | Reduces abnormal-event recognition and response |
| Certification scrutiny | Weak | Lowers chance of challenging unsafe assumptions |
| Warning-signal interpretation | Narrow / Broad | Determines limited review or systemic reassessment |
| Residual safety risk | Acceptable / Unacceptable | Indicates whether continued operation is defensible |
| Regulatory intervention | Limited / Strong | Determines limited response or escalation to grounding, redesign or revised training |

This framework is important in that it will not allow MCAS risk to be considered as a small technical problem. The model demonstrates that the risk of the system grows with accumulation of technical complexity, uncertainty of human-performance and poor oversight. That is, the question was not simply whether it was possible that MCAS failed in any way, but whether the surrounding design and training and certification system would reliably recognize and manage that failure.

## 4.4 Bayesian Updating and Decision Implications

The model can be made decision-useful, only when there is the updating logic. The important part of the main text is only the results, and all calculations are given in Appendix A.

**Table 5.** Bayesian update results

| Scenario | Risk probability | Decision meaning |
|---|---|---|
| Prior assumption before severe accident evidence | 30.0% | Risk treated as possible but manageable |
| After severe MCAS-consistent accident evidence | 66.7% | Strong technical and training reassessment justified |
| After accident evidence + low pilot awareness + weak scrutiny | 84.2% | Strong intervention justified, including design, training and regulatory action |

The illustrative prior probability of large systemic MCAS risk is fixed to 30.0% before the Lion Air crash. This is a decision position where MCAS risk was perceived as something that was likely to happen, but could be controlled. This results in an increase of the posterior probability to 66.7% once severe MCAS-consistent evidence of accidents has been introduced. Combining that evidence related to accidents with the insufficient awareness of pilots and ineffective certification checks, the posterior probability is further increased to 84.2%.

**Table 6.** Decision threshold interpretation

| Posterior probability | Suggested decision response |
|---|---|
| Below 40% | Continue monitoring and targeted review |
| 40%–60% | Require formal reassessment |
| 60%–75% | Require strong technical and training review |
| Above 75% | Trigger strong intervention, including grounding, redesign, training revision or additional certification action |

With this logic of threshold, the post-Lion Air evidence only passes through the strong reassessment domain. With low pilot awareness and poor scrutiny it is estimated that the risk will exceed the strong intervention threshold. The implication of the decision is obvious: the first crash could not be considered merely as an operational incident or a failure in isolation. It ought to have occasioned a wider review of the assumptions to MCAS design, pilot training necessities, and delegated certification controls.

Bayesian network also explains the role played by delegated certification. Delegation is not necessarily a problem but when scrutiny is at a low level then chances of spotting unsafe assumptions are less. This postpones re-evaluation and reduces the possibility of regulatory action. Thus, certification scrutiny is an administrative variable, not an administrative risk-control node.

### 4.5 Strengths, Limitations and Applicability

The key advantage of the Bayesian network method is that interdependencies are made explicit. It does not consider MCAS design and AOA sensor dependency as independent problems. This becomes significant since the issue of the 737 MAX caused by the crisis occurred as a result of interplay among technical design, human performance and oversight assumptions.

Dynamic updating is a second strength. Bayesian reasoning also demands the need to update past beliefs with newly-evolving evidence. As depicted in the results, there is a possibility of a probability of high systemic MCAS risk that on average is estimated as may fall by 30.0 to 66.7 and subsequently to 84.2 when evidence of severe accidents are considered. This provides the decision-makers with a better analytical premise of earlier intervention.

There are limitations to the model also. First, probability values are demonstrative since the public evidence is not giving conditional probability tables of all variables in its entirety. The calculation can then be interpreted as an illustration of decision-logic as opposed to an honest forecast of another crash. Second, analyst judgement is relied upon in selecting nodes. Failure to include organisational pressure, culture of communication or regulatory incentives could result in the model undervaluing the entire risk environment. Third, the answer is that Bayesian analysis can help make a decision and make better reasoning, but not what amount of residual uncertainty is morally admissible when the lives of many people are considered.

On the whole, the Bayesian network can be very much applied to Decision Situation 2 since the main concern was whether Boeing, along with regulators, had an organized approach to rendering assumptions and re-evaluating risk judgement and intervening before the weak signals transformed into devastating results.

## 5. Evidence and Supporting Inputs

### 5.1 Case Evidence and Research Inputs

The two chosen models can be justified in terms of official evidence of investigation, decision making theory and modelling assumptions created by the author. This section does not aim to restate the background of the case, but rather to explain what the evidence is behind cognition-driven and bayesian network analyses.

Best case evidence is provided by government reports on the design of the 737 max, certification and the process of returning to service. The JATR report assists in the analysis of pilot response assumptions, problems with MCAS-related flight-control and certification issues [1]. The report prepared by the U.S. Department of Transportation contributes to the discussion of delegated certification, FAA control and necessity of the better control of human-factors and system-level review [2]. Reports of the U.S. House Committee detail the evidence of the main organisational pressure at Boeing, communication in MCAS, trainings supposed, and weak certifications [3]. The documents of the FAA and EASA concerning returns to service are employed to demonstrate that subsequent corrective action involved redesigned training, design and operational considerations [7], [8].

Models also vary in terms of their theoretical inputs. A working model which supports the cognition based model is the heuristic work,anchoring, overconfidence and limited rationality [4]-[6]. Bayesian network model has its basis in probabilistic reasoning where past assumptions undergo a change when new evidence is presented [9].

### 5.2 Key Assumptions

Since there is no public evidence available with all the internal data of Boeing, the FAA or airline operators, the following report is based on transparent assumptions instead of stating numerical accuracy. The cognition-based model presupposes that the continuity frame Boeing went the first Boeing used affected the interpretation of decision-makers regarding MCAS-related risk and pilot training needs. This does not mean that they deliberately paid negligence. It is to say that some assumptions were more acceptable on the basis of commercial pressure than others and on the basis of familiarity and certification expectations of the previous platform.

The Bayesian network model makes the assumption that the risks of MCAS were conditional as opposed to independent. That is, high MCAS design complexity, high AOA sensor dependency, low pilot awareness and low certification scrutiny interacted in other words, to raise residual safety risk. The numerical change in Appendix A speaks volumes. It illustrates Bayesian decision logic and not a precise estimation of the likelihood of accidents.

**Table 7.** Evidence, inputs and use in the report

| Evidence / input | Source basis | Use in analysis | Reliability | Key limitation |
|---|---|---|---|---|
| MCAS design and certification findings | JATR, U.S. DOT and House reports [1]–[3] | Defines technical and oversight context | High | Retrospective evidence |
| Pilot response and training concerns | JATR and return-to-service reports [1], [7], [8] | Supports cognition-driven and Bayesian analysis | High | No full simulator dataset |
| Organisational and commercial pressure | House Committee report [3] | Supports continuity framing and bounded rationality | High | Internal decisions partly inferred |
| Cognitive bias theory | Tversky and Kahneman; Kahneman and Lovallo; Simon [4]–[6] | Explains anchoring, overconfidence and bounded rationality | High | Requires case-specific application |
| Bayesian update assumptions | Case evidence and Bayesian logic [1]–[3], [9] | Supports posterior risk estimate and Appendix A | Medium | Illustrative, not empirical |

### 5.3 Reliability, Relevance and Data Limitations

On the whole, the evidence is rather pertinent as it directly relates to the design of the 737 MAX, its certification, the risk of the MCAS, and post-crash evaluation procedure. Reports of authorities are particularly the most helpful as they detail case-specific findings of the aviation and government investigations. The evidence has its limitations, however, there are three as well.

To start with, the majority of the evidence that is made public is retrospective. This poses a likelihood of hindsight bias. In order to curb this risk, the report has not presented an argument that the second crash was exactly foreseeable. Rather, it holds that red flagging evidence ought to have evoked more vigorous re-examination of earlier assumptions.

Second, the evidence at hand is not a comprehensive dataset. Complete tables of conditional probability in pilot recognition, MCAS-activation cases, in-house certification choices or all simulator results are not available in the public. This is why the Bayesian model is employed as a structured decision-logic model, and not as an accurate predictive model.

Third, a range of key variables is qualitative. Organisational pressure, regulatory confidence, culture of communication and strength of independent challenge are hard to quantify but they are the key focus of decision quality. This limitation contributes towards the mixed modelling approach of the report: the cognition-driven model describes the judgement and organisation interpretation, whereas the Bayesian network describes the uncertainty and evidence revision.

Collectively the evidence base is adequate to a defensible AS2 decision-making analysis but only on the assumption that numerical results are to be treated as illustrative, and not definitive.

## 6. Comparative Reflection

### 6.1 Comparison of the Two Selected Approaches

The cognitive-motivated framework and the Bayesian network model consider various aspects of the Boeing 737 MAX decision fiasco. The most useful model is the cognition-based model that could offer insight into the formation process of the continuity-based judgement of Boeing prior to the crashes. It demonstrates the ways anchoring and overconfidence and limited rationality informed risk interpretation of MCAS-related risk, methods and assumptions of pilot reaction, and training need [4]–[6]. It contributes primarily in the field of diagnostics: why a commercially appealing decision frame might seem to be sound internally, yet not at all system-safely.

Applying the Bayesian network approach will be more appropriate to Decision Situation 2 due to the MCAS risk reassessment being in need of ordered interdependence of the dependent variables. It demonstrates the interaction of complexity of MCAS design, dependency of AOA sensors on pilots, pilot awareness, certification review and interpretation of warning signs on the residual safety risk [1]-[3], [9]. Its key contribution is procedural: it shows how risk judgement could have been updated at the time of the Lion Air crash by decision-makers rather than needing to consider evidence as isolated.

### 6.2 Critical Reflection on the Unused Data-Driven Approach

Decision Situation 1 required a cognition-driven model because Boeing's continuity-based judgement involved anchoring, overconfidence and bounded rationality, which a dataset alone cannot fully explain.

Decision Situation 2 also required a model that could represent uncertainty and evidence updating. A Bayesian network is more appropriate because it shows how MCAS design, pilot awareness, certification scrutiny and warning evidence interacted to change the level of risk [9]. By contrast, a data-driven model would mainly provide inputs, not the decision logic for when to redesign, retrain or intervene.

The data-driven approach also has reliability limits. Public evidence on the 737 MAX is retrospective and incomplete, and full datasets on Boeing's internal decisions, pilot recognition of MCAS activation, simulator performance and conditional failure probabilities are not publicly available [1]–[3]. A data-driven approach is not selected as a primary model because the available public evidence is retrospective, incomplete and difficult to convert into a reliable dataset for predicting rare, high-consequence aviation failures.

## 7. Conclusion

This report applied two decision-making approaches to two bounded decision situations in the Boeing 737 MAX crisis. The cognition-driven model showed that the decision to maintain design and training continuity was shaped by anchoring, overconfidence and bounded rationality. This explains how commercial pressure and prior platform assumptions reduced the visibility of MCAS-related human-performance risks.

The Bayesian network model showed that MCAS risk reassessment should have been treated as a conditional system-level problem. The illustrative update demonstrated that severe accident evidence should have shifted the estimated probability of high systemic MCAS risk from 30.0% to 66.7%, and to 84.2% when low pilot awareness and weak scrutiny were included. This supported stronger technical, training and regulatory intervention.

The unused data-driven approach remains valuable, but only as a supporting tool because the available public data are incomplete and retrospective. Overall, the case shows that high-stakes engineering decisions require both cognitive safeguards and structured uncertainty modelling. In safety-critical systems, decision quality depends not only on technical expertise, but also on transparent assumptions, independent challenge and disciplined reassessment when warning evidence emerges.

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**Conflicts of Interest**

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

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## Appendix A. Illustrative Bayesian Calculation

This appendix provides the calculation behind the Bayesian update reported in Section 4. The probabilities are illustrative and are used to demonstrate decision logic rather than exact accident prediction.

Let:

$H$ = systemic MCAS-related risk is high

$\neg H$ = systemic MCAS-related risk is not high

$E$ = severe MCAS-consistent accident evidence appears

$A$ = adverse system conditions are present, including low pilot awareness and weak certification scrutiny

A1. Prior assumption

Before severe accident evidence:

$$P(H) = 0.3$$

$$P(\neg H) = 0.7$$

A2. Update after severe accident evidence

Assume:

$$P(E \mid H) = 0.70$$

$$P(E \mid \neg H) = 0.15$$

Bayes' theorem:

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E \mid H)P(H) + P(E \mid \neg H)P(\neg H)}$$

Substitution:

$$P(H \mid E) = \frac{0.70 \times 0.30}{(0.70 \times 0.30) + (0.15 \times 0.70)} = 0.667$$

Therefore, after severe MCAS-consistent accident evidence, the probability of high systemic MCAS risk increases from 30.0% to 66.7%.

A3. Update after accident evidence and adverse system conditions

Assume:

$$P(A \mid H) = 0.80$$

$$P(A \mid \neg H) = 0.30$$

Bayesian update:

$$P(H|\ E,A)=\frac{P(H)(E|\ H)P(A|\ H)}{P(H)(E|\ H)P(A|\ H)+P(\neg H)P(E|\neg\ H)P(A|\neg\ H)}$$

Substitution:

$$P(H|\ E,A)=\frac{0.30\times 0.70\times 0.80}{(0.30\times 0.70\times 0.80)+(0.70\times 0.15\times 0.30)}=0.842$$

Therefore, after accident evidence plus adverse system conditions, the probability of high systemic MCAS risk increases to 84.2%.

A4. Interpretation

The calculation shows that severe accident evidence should materially increase concern about systemic MCAS-related risk. Under the threshold used in Section 4, 66.7% supports strong reassessment, while 84.2% supports strong intervention.