Identifying Human Failure Events (HFEs) in the Context of Aviation Incidents Using Cognitive-based Human Reliability Analysis (HRA) Methods

Farid Jafarli[a], Ahmad Al-Douri[a]
[a] School of Sustainable Chemical, Biological and Materials Engineering, University of Oklahoma,
Norman, OK, 73017, farid.jafarli-1@ou.edu, aaldouri1@ou.edu

Abstract: Nowadays, Artificial Intelligence (AI) is increasingly applied in many engineering systems to enhance automation and efficiency. AI-based systems enable monitoring of the overall system and automate basic tasks. However, adopting AI may create conflicts between the system and the human operator. A few studies are focusing on the interaction between AI and Human Intelligence (HI), but they don't analyze machine and crew failures separately in detail from a safety perspective. This work combines risk assessment of system failure due to human errors utilizing cognitive-based third-generation human reliability analysis (HRA) methods. We use the Information, Decision, and Action (IDA) phases of the crew context for qualitative human reliability analysis (HRA) to evaluate human failure mechanisms and performance influencing factors (PIFs) that lead to human failure events (HFEs). We evaluate the human error probability (HEP) for each crew failure mode (CFM) and calculate a total probability using Bayesian networks. The framework is demonstrated through an investigation of the Ethiopian Airlines Flight 302 Boeing MAX 737 crash as a case study, considering a research gap in exploring the development of HRA methods in the aviation field.

---

1. INTRODUCTION

The use of AI-based systems for autonomous operations is rapidly increasing as AI technology advances[1]. Aviation and process industries are also undergoing digital transformation to increase profits and reduce failures by automating control systems[2]. On the other hand, adopting AI may lead to conflicts between the system and the human operator due to system failures or human errors[3]. From a safety perspective, existing risk assessment methods struggle to account for human-machine interactions within the HRA frameworks[4].

The history of HRA dates back to 1983, with the introduction of the Technique for Human Error Rate Prediction (THERP), which was developed for nuclear power plant operations and is the ancestor of first-generation techniques[5]. It was followed by subsequent first-generation approaches, such as the Success Likelihood Index Method implemented through Multi-attribute Utility Decomposition (SLIM-MAUD)[6], the Human Error Assessment and Reduction Technique (HEART)[7], and other frameworks. However, these methods had some disadvantages in accounting for the interaction between the human operator and the system, treating the operator as a mechanical or electrical component. Second-generation HRA methods were published to overcome the issue by focusing on the factors influencing the operator's performance[8]. Some examples include Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H)[9], Cognitive Reliability and Error Analysis Method (CREAM)[10], Technique for Human Error Analysis (ATHEANA)[11], Information, Decision and Action in Crew context (IDAC)[12]. The methods still lack a model of causal mechanisms that illustrates the connection between human responses and PIFs. The limitations of both first- and second-generation methods led to the development of hybrid frameworks, or third-generation methods, to improve initial techniques[13]. For example, Kirawi et al. modified HEART to develop the Nuclear Action Reliability Assessment (NARA) in 2004[14], Abrishami et al. adopted the BN methodology for the SLIM technique[15], and Mosleh et al. introduced a model-based HRA framework called Phoenix[16]. In 2025, Levine proposed building a robust causal logic model by synthesizing various HRA resources[17].

In aviation, only a few studies have explored the development of HRA methods. The initial research focused on human error identification (HEI) in air traffic control (ATC) by presenting the Technique for Retrospective and Predictive Analysis of Cognitive Error (TRACEr) tool[18]. Following that, the European Organization for the Safety of Air Navigation published a report that highlighted the need for an HRA framework adopted in air traffic management in 2007 and introduced the Controller Action Reliability Assessment (CARA), which is based on HEART[19]. Burns et al. adapted SPAR-H to the aviation domain and estimated HEP for knowledge-based, rule-based, and skill-based types of pilot actions[20]. In another work, Guo et al. integrated the FTA into BN to identify and evaluate the human errors in flight for aviation safety[21]. The objective of this research is to combine and extend third-generation techniques for analyzing the interaction between the system and the operator by applying the framework to the Ethiopian Airlines Flight 302 crash as a case study.

2. METHODOLOGY

In this work, we use the Phoenix HRA framework to identify the major causes of pilot error in the Ethiopian Airlines Flight 302 accident as follows: (1) construction of crew response trees (CRTs), (2) identification of main crew failure modes (CFMs), and (3) construction of Bayesian networks (BNs) to identify causal pathways leading to pilot error. This approach will be integrated with the concept of human failure mechanisms[22] to enhance the causal basis of human error identification. This section explains the necessary steps to build a qualitative and quantitative analysis for the case study of the given accident.

Crew Response Tree

The purpose of the first step is to identify human failure events (HFEs) using Probabilistic Risk Assessment (PRA) models such as event tree analysis (ETA) or fault tree analysis (FTA). If these models exist and HFEs are already identified, the scenarios leading to these events are investigated, and further information is gathered by plant visits, report reviews, and other activities to develop the crew response tree (CRT). The CRT is a flowchart showing interaction scenarios between the crew and the system that lead to the failure. Crew response situations can be divided into three categories: procedure-driven, knowledge-driven, and hybrid. The CRT helps to identify the conditions that cause the crew to take failure pathways[23].

The starting point of the CRT construction is the specific safety function. A safety function is the desired state or intended function of a given system. In some cases, there may be several safety functions, each with its own CRT. These CRTs can be connected to form a more comprehensive structure that covers the accident timeline and all scenarios leading to the HFEs. Ekanem et al. describe the necessary flowchart questions for the branch points of the CRT and explain the success and failure paths for each. To sum up, the key components of the CRT are the HFE definition, the safety function, the context of the human operator and the system, and the procedures needed to maintain the safety function. The last step may be to simplify the flowchart by breaking out the paths into more detail if needed[13].

Crew Failure Modes

The Crew Failure Modes (CFMs) are introduced to determine crew failure forms for information, decision, and action phases. They represent modes of crew failure for human-machine interaction and are used to identify root causes of failure events. Ekanem defines 19 CFMs: 9 for the information phase, 7 for the decision phase, and 3 for the action phase[24]. The CFMs are integrated from the error modes described in the Scenario Authoring, Characterization, and Debriefing Application (SACADA) database of the Nuclear Regulatory Commission (NRC)[25]. The failure modes are theoretically relevant to the branch points of CRT. Still, only a subset will be relevant when the study is carried out in the context of the given scenario. Consequently, a set of fault trees (FTs) can be used to select relevant CFMs for each scenario[13].

Levine proposes a fourth CFM in the action phase to extend the Phoenix model: “No Action Taken”. The author highlights that, despite the first action phase CFM in the Phoenix model (“Incorrect Timing of

Action”), which covers scenarios where the operator doesn’t take the required action, the new mode is useful for distinguishing between delayed and non-taken actions. The failure mode can occur due to a lack of tools, attention, or team coordination. It refers to situations in which the necessary information is collected and the proper decision is made, but the action is not taken. Alternatively, the crew may forget to perform the assigned task due to high loads or a stressful work environment[17].

Human Failure Mechanisms and Performance Influencing Factors

The third layer of the framework is the human failure mechanisms. Failure mechanisms are developed to support a more detailed analysis of HFEs. The CFMs are linked to these mechanisms, which represent causes of failure modes. Levine et al. introduce modeling human failure mechanisms and their identification using BN structures[22].

The bottom layer is PIFs. PIFs are widely used in various HRA methods to analyze crew-system interactions. They are used to represent both negative and positive factors influencing crew performance and to predict the primary causes of human error. Groth et al. introduced a set of PIFs using four sources to expand the Information, Decision, and Action in crew Context (IDAC) cognitive model[26].

Bayesian Networks and Quantification

The linkage between the mentioned parameters is illustrated using Bayesian networks (BNs). BNs are directed acyclic graphs that describe interactions between nodes from root causes to final outputs[27]. PIFs constitute the bottom layer of the BNs in this study and represent the leading causes of the human failure mechanisms, which constitute the second layer of networks. Ekanem et al. extend their qualitative analysis and introduce quantitative analysis for the Phoenix framework[28]. However, we integrate the human failure mechanisms into the model and will refer to works that introduced these integration of these concepts[17], [22]. The work illustrates nominal and degraded probabilities, as well as conditional multipliers, for each node in Bayesian networks[17].

3. Case study

The primary focus of this study is the Ethiopian Airlines Flight 302 crash. The Boeing Company introduced the 737 MAX family to compete with Airbus's upgraded aircraft, featuring a larger, more efficient engine[29]. The Maneuvering Characteristics Augmentation System (MCAS) was added to the new series, designed to push the plane’s nose down automatically when a high angle of attack (AoA) was detected. However, the conflict between the software and the pilots led to two fatal disasters within several months: Lion Air Flight 610 and Ethiopian Airlines Flight 302[30].

The incident occurred on March 10, 2019, a few months after the Lion Air Flight JT610 crash. A short time after liftoff, the left Attack of Angle failed due to an intermittent electrical defect or vane separation after a bird strike[31], [32]. The value of the left AoA sensor erroneously reached 74.5, whereas the maximum value of the right sensor was 15.3. The erroneous data triggered the illumination of the "MASTER CAUTION" and "ANTI-ICE" lights and activated the left stick shaker in the flight deck, which remained active until the end of the accident. The failed data also corrupted the captain’s display and caused conflict in the reading of the captain’s and the first officer’s instruments. The “AOA DISAGREE” indicator didn’t appear in the flight deck, as it was an optional feature for the Boeing 737 MAX series, and Ethiopian Airlines didn’t purchase the alert[32].

The failure also caused erroneous data for the MCAS system, as it relied on only the faulty left sensor. At 400 ft, the captain tried to engage the autopilot to stabilize the plane. It was engaged in the third attempt after two unsuccessful attempts. During the auto flight, the system was still getting data from the left AoA sensor, so the autopilot failed to reach the desired altitude due to high speed[32]. The reason for the high speed was the autothrottle, which should be turned off upon stick shaker activation, according to the procedure; however, the crew failed to deactivate it[31]. According to the Cockpit Voice Recorder (CRV), the flight crew didn’t discuss the activation of the stick shaker. The airplane began to descend after reaching maximum altitude, and the autopilot disconnected automatically[32].

Disengagement of the autopilot and incorrect AoA data led to the first MCAS activation, lasting nine seconds, which trimmed the stabilizer and nosed it down. The captain applied a two-second electric trim up input, which was insufficient to counteract the software. It was reactivated after a few seconds; this time, the captain applied nine seconds of electric trim up and was able to deactivate the MCAS system. After the second activation, the first officer suggested "stab trim cut out"; the captain agreed, and the stabilizer trim cutout switches were moved to the “CUTOUT” position, cutting the electrical power to the trim system, as mentioned in the runaway stabilizer non-normal checklist. Therefore, there was no motion of the stabilizer after the third activation of the software[32].

Despite the successful deactivation of the MCAS, the airplane was already in an unstable flight, and there was too much aerodynamic pressure on the manual trim wheel to control it manually due to the high speed. The captain asked the first officer to try with him, but the first officer told him it wasn't working after a few seconds of effort. The crew moved the "CUTOUT" switches back to the normal position, and the captain applied two electric trim-up inputs for one second to control the stabilizer, but it activated the MCAS software for the fourth time and caused an unrecoverable descent by decreasing the stabilizer’s trim unit[32].

The pilots had very limited training on the MAX 737 series before their first flight, which didn't include MCAS or its functions[3]. On the other hand, the pilots failed to communicate effectively during the accident. For example, the flight officer neither acknowledged nor complied with the captain's request to maintain runway heading in return for the defined route by air traffic control (ATC). They also had no conversation regarding the activation of the stick shaker. This may be due to the noisy flight deck environment after the stick shaker activated, as well as the chattering from ATC[32]. The National Transportation Safety Board (NTSB) highlights that crew resource management (CRM) aspects also include the first officer's limited flight experience and division of duties[31].

4. Results

The results are derived following the process described in the methodology section using the accident reports and procedure manual. The CRT is designed to identify HFEs and CFMs, and BNs are developed to show the failure mechanisms and PIFs that lead to the failure modes. The detailed description for each step is provided in the section.

Crew Response Tree

The intended function of this case is to maintain a stable flight and to land the plane safely. To avoid any conflict between the pilot and the system, the crew had to deactivate MCAS and manually control the aircraft. Therefore, the crew should perform five tasks for five branch points, one for each. The branch points of the diagram are determined using the runaway stabilizer checklist[32]. The crew should hold the control column, disengage the autopilot and autothrottle, turn off the CUTOUT switches, and manually trim the stabilizer in an orderly manner. Also, there is an opportunity to recover from turning off the switches by applying the electric trim-up input, which delays the software's activation. The generated FTs contain 8 HFEs, which are caused by 13 occurrences of 7 unique CFMs. 9 of these CFMs are observed in the action-taking phase, 3 in the decision-making phase, and only 1 in the information-gathering phase. **Figure *1*** and **Figure *2*** demonstrate the CRT, the potential and observed failure events at each branch point, and the CFMs that cause these events. The branch points are described in light blue, the failure events for branch points in light grey, HFEs in red, and CFMs in light pink.

Figure 1: CRT Diagram for Runaway Stabilizer Checklist

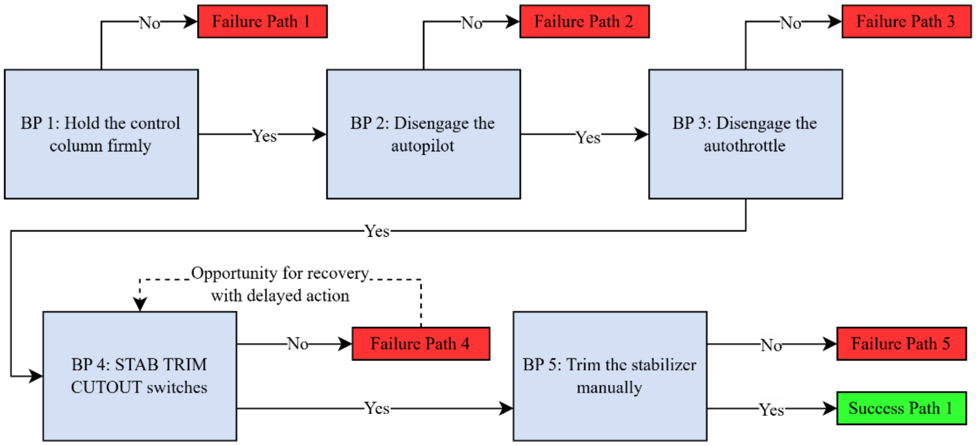
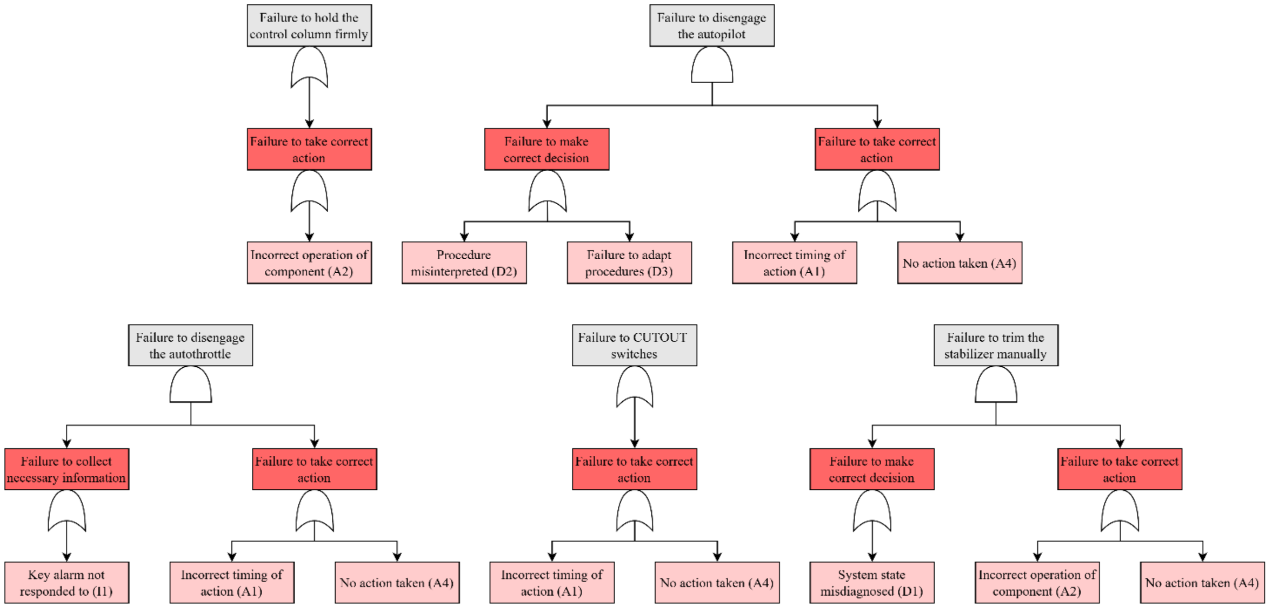


Figure 2: FT Diagrams for Runaway Stabilizer Checklist



Crew Failure Modes

This section explains the CFMs that led or could lead to human error. The first failure of the crew is to disengage the autopilot, in which the crew fails to correctly understand (D2) and adapt (D3) the checklist and take no action (A4). The CUTOUT switches were moved after the second activation of the MCAS software, indicating incorrect action timing (A1). Even though the crew had turned off the system, they couldn't control the airplane because the trim wheel was under high pressure. The main reason for this pressure was the autothrottle, which had to be disengaged after the stick shaker was activated. However, the crew didn't respond to the stick shaker (I1) and didn't take any action for the autothrottle (A4). Also, the first officer couldn't determine that the issue was due to high pressure and said the trim wheel wasn't working, making a wrong judgment (D1). This misdiagnosis of the system led the crew to incorrectly operate the trim by applying electric power (A2), which ultimately triggered the final and fatal reactivation of the MCAS. In addition to CFMs described above, there are other potential failure modes that may occur.

These include applying too much force to the control column (A2), spending too much time disengaging the autopilot and autothrottle (A1), and taking no action on the switches and trimming the stabilizer (A4).

Bayesian Networks and quantification

The failure mechanisms and their root causes (PIFs) are shown through BNs for information gathering (**Figure *3***), decision-making (**Figure *4***), and action-taking (**Figure *5***) phases.

Figure 3: BN for the Information Phase CFMs

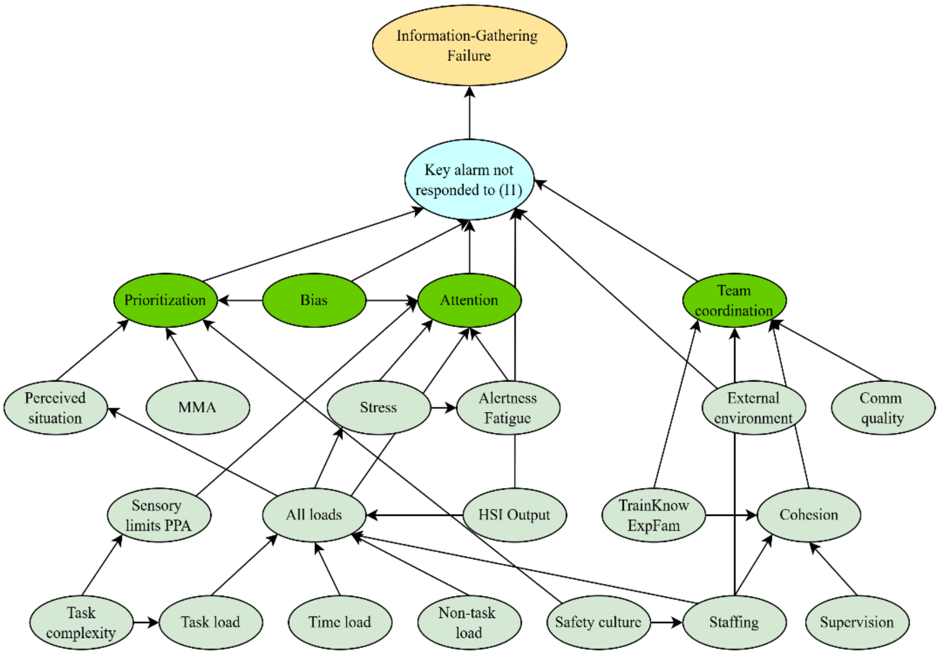


Figure 4: BN for the Decision Phase CFMs

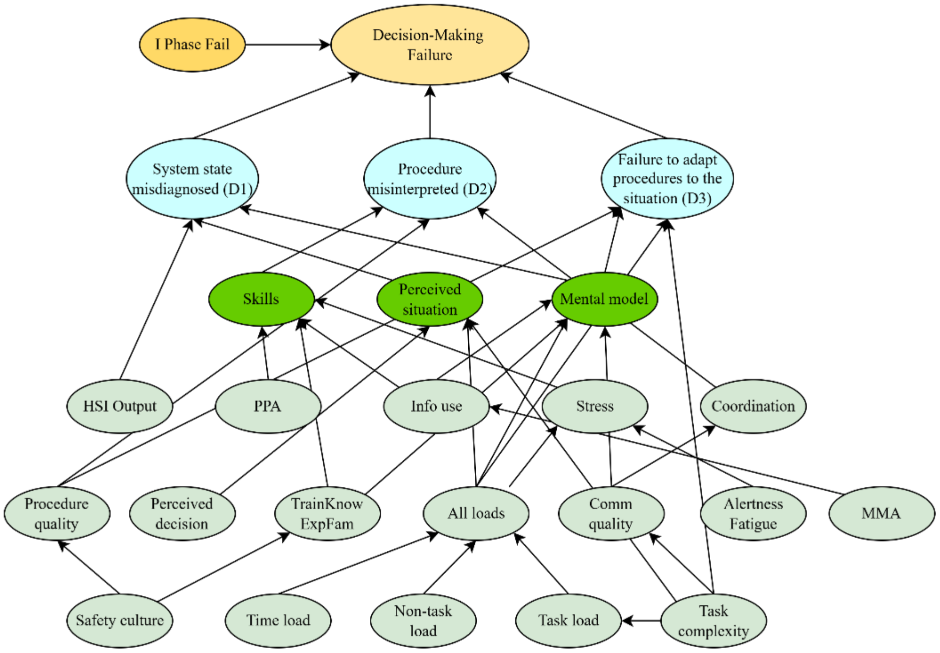
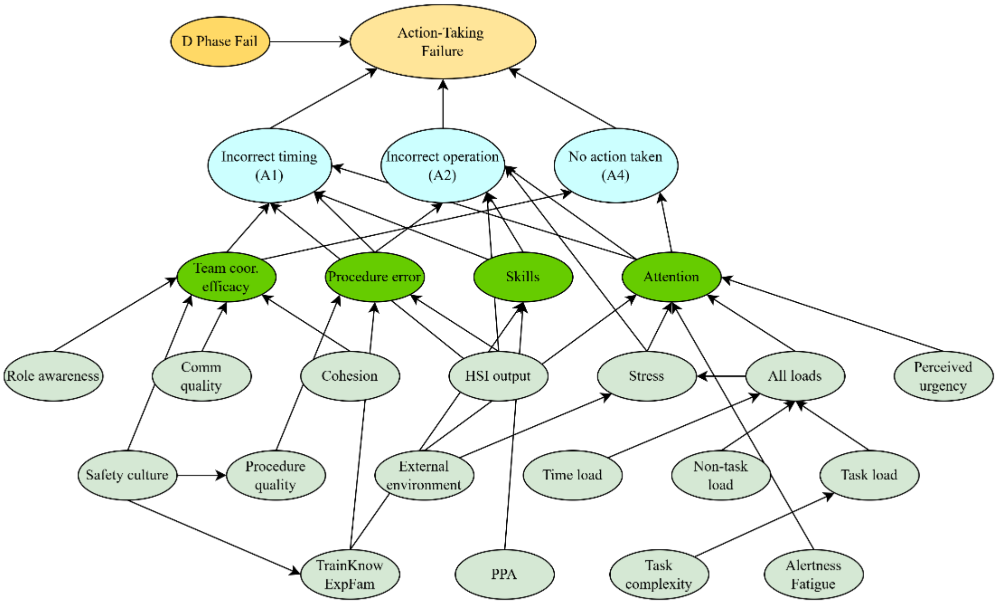


Figure 5: BN for the Action Phase CFMs



There are several failure mechanisms leading to failure modes. As mentioned before, the pilots lacked sufficient training on the system, which affected the crew's skills and led to procedural errors. The crew had poor communication in several areas and failed to coordinate as a team. The pilot and the officer's attention was also distracted by the noisy, stressful environment. All these aspects negatively affected the crew's mental model during the accident.

BNs are constructed based on relevant failure mechanisms and PIFs by excluding irrelevant ones for the aviation field. For example, Levine describes tool availability as a direct cause of "Incorrect timing (A1)" and "No action taken (A4)", and tool quality as a direct cause of "Incorrect operation (A2)" failure modes in the action phase[17]. The PIFs refer to the availability and quality of the physical tools provided by the organization to the crew[26]. However, the pilots interact with the yokes, sensors, throttles, buttons, screens, etc., in the cockpit environment, which are included under the HSI performance influencing factor. Therefore, the PIFs aren't considered separately for this study.

As mentioned above, Levine presents the base probability of each failure mode and the multiplier values for failure mechanisms and PIFs that lead to those CFMs. The HEP is computed for each CFM and used to calculate failure event and task failure probabilities at each branch point via the FTs. The probabilities are summed for the or gate and multiplied for the and gate.

Table 1: HFE Probabilities for each Phase and Total HEP for each Task

Task	HFE	Base Probability	HFE Probability	Task Failure Probability
1: Hold control column	A phase error	0.00029	0.0008	0.0008
2: Disengage autopilot	D phase error	0.0038	0.6546	0.2468
	A phase error	0.00111	0.3771	
3: Disengage autothrottle	I phase error	0.00107	0.9219	0.3476
	A phase error	0.00111	0.3771	
4: CUTOUT switches	A phase error	0.00111	0.0561	0.0561
5: Trim stabilizer manually	D phase error	0.00099	0.3754	0.3506
	A phase error	0.00073	0.9340	

Table 1 shows how the human failure mechanisms increase the HEP. For instance, the base probability of "Incorrect operation (A2)" CFM is 0.00029 for the task of holding the control column. However, the states of high stress and degraded attention boost the probability to 0.0008, which also affects the task failure probability. The highest HEP is calculated for the last task, due to an error in the action phase. The error probabilities are also high for disengaging autothrottle and autopilot tasks, due to information and decision phase errors, respectively. The lowest values are observed for holding the control column and moving the CUTOUT switches, which is reasonable given that the crew reached the success path in these steps.

5. Conclusion

In this paper, we extended and applied the Phoenix model to investigate the Ethiopian Airlines Flight 302 accident. The aim of this work is to show the applicability of the method to human actions in the aviation field in the context of human intelligence and (AI) collaboration.

The crew response tree (CRT) and fault trees (FTs) were developed to define relevant crew failure modes (CFMs) for the qualitative analysis. 13 occurrences were observed across 7 different CFMs, most of which occurred during the decision-making and action-taking phases. Also, we identified human failure mechanisms and performance influencing factors (PIFs) that contribute to CFMs. The linkage between root causes and failure modes was shown through the Bayesian networks (BNs). The error probability of failure events and overall tasks was calculated at each branch point of CRT for quantitative analysis. The highest HFE probability is observed in task 5, trimming the stabilizer manually, due to the high error probability in the action-taking phase. The case study results demonstrate the framework's suitability and robustness for the aviation industry.

Despite a comprehensive human reliability analysis (HRA), future work could focus on the AI system working in collaboration with the human operator. Failure modes should be defined for AI systems to identify causes of AI failures and quantify the probability of AI errors. Furthermore, the approach should be integrated with HRA methods to assess the entire process, leveraging AI-human intelligence (HI) collaboration.

References

[1] R. Arunthavanathan, Z. Sajid, M. T. Amin, Y. Tian, F. Khan, and E. Pistikopoulos, "Process safety 4.0: Artificial intelligence or intelligence augmentation for safer process operation?," *AIChE Journal*, vol. 70, no. 7, p. e18475, 2024.

[2] H. Wen, M. T. Amin, F. Khan, S. Ahmed, S. Imtiaz, and S. Pistikopoulos, "A methodology to assess human-automated system conflict from safety perspective," *Computers & Chemical Engineering*, vol. 165, p. 107939, 2022.

[3] R. Arunthavanathan, Z. Sajid, F. Khan, and E. Pistikopoulos, "Artificial intelligence–Human intelligence conflict and its impact on process system safety," *Digital Chemical Engineering*, vol. 11, p. 100151, 2024.

[4] D. Kaber and M. Zahabi, "Enhanced hazard analysis and risk assessment for human-in-the-loop systems," *Human factors*, vol. 59, no. 5, pp. 861–873, 2017.

[5] A. D. Swain and H. E. Guttmann, "Handbook of human-reliability analysis with emphasis on nuclear power plant applications. Final report," Sandia National Labs., Albuquerque, NM (USA), 1983.

[6] D. Embrey, P. Humphreys, E. Rosa, B. Kirwan, and K. Rea, "SLIM-MAUD: an approach to assessing human error probabilities using structured expert judgment. Volume I. Overview of SLIM-MAUD," Brookhaven National Lab., Upton, NY (USA), 1984.

[7] J. Williams, "A proposed method for assessing and reducing human error," presented at the Proc. 9th Advances in Reliability Technology Symp., Univ. of Bradford, 1986.

[8] L. Ciani, G. Guidi, and G. Patrizi, “Human reliability in railway engineering: Literature review and bibliometric analysis of the last two decades,” *Safety science*, vol. 151, p. 105755, 2022.

[9] D. Gertman, H. Blackman, J. Marble, J. Byers, and C. Smith, “The SPAR-H human reliability analysis method,” *US Nuclear Regulatory Commission*, vol. 230, no. 4, p. 35, 2005.

[10] E. Hollnagel, *Cognitive reliability and error analysis method (CREAM)*. Elsevier, 1998.

[11] S. E. Cooper, A. Ramey-Smith, J. Wreathall, G. Parry, and Nuclear Regulatory Commission, “A technique for human error analysis (ATHEANA),” Nuclear Regulatory Commission, Washington, DC (United States). Div. of …, 1996.

[12] Y. J. Chang and A. Mosleh, “Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents: Part 1: Overview of the IDAC Model,” *Reliability Engineering & System Safety*, vol. 92, no. 8, pp. 997–1013, 2007.

[13] N. J. Ekanem, A. Mosleh, and S.-H. Shen, “Phoenix–a model-based human reliability analysis methodology: qualitative analysis procedure,” *Reliability Engineering & System Safety*, vol. 145, pp. 301–315, 2016.

[14] B. Kirwan, H. Gibson, R. Kennedy, J. Edmunds, G. Cooksley, and I. Umbers, “Nuclear action reliability assessment (NARA): a data-based HRA tool,” in *Probabilistic Safety Assessment and Management: PSAM 7—ESREL’04 June 14–18, 2004, Berlin, Germany, Volume 6*, Springer, 2004, pp. 1206–1211.

[15] S. Abrishami, N. Khakzad, S. M. Hosseini, and P. van Gelder, “BN-SLIM: A Bayesian Network methodology for human reliability assessment based on Success Likelihood Index Method (SLIM),” *Reliability Engineering & System Safety*, vol. 193, p. 106647, 2020.

[16] A. Mosleh *et al.*, “A model-based human reliability analysis framework,” presented at the Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 2010), 2010.

[17] C. S. Levine, “Expanding the Causal Logic Foundations of Human Reliability Analysis,” 2025.

[18] S. T. Shorrock and B. Kirwan, “Development and application of a human error identification tool for air traffic control,” *Applied ergonomics*, vol. 33, no. 4, pp. 319–336, 2002.

[19] B. KIRWAN, “Technical basis for a human reliability assessment capability for air traffic safety management,” *Complexity (EPC)*, vol. 1, p. 7, 2007.

[20] K. Burns and C. Bonaceto, “An empirically benchmarked human reliability analysis of general aviation,” *Reliability Engineering & System Safety*, vol. 194, p. 106227, Feb. 2020, doi: 10.1016/j.ress.2018.07.028.

[21] G. Xinyao, M. Bin, L. Yawei, L. Na, F. Shuai, and S. Qingmin, “A human error mechanism for pilot based on fault tree analysis and Bayesian network,” *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 6, pp. 6863–6871, Jun. 2020, doi: 10.3233/JIFS-179764.

[22] V. P. Paglioni, C. S. Levine, A. Al-Douri, and K. M. Groth, “Why Do Human-Machine Teams Fail: Investigating Failure Mechanisms in Human Reliability Analysis,” Jul. 2023.

[23] N. J. Ekanem, A. Mosleh, S. H. Shen, and J. Oxstrand, “Model-based HRA methodology: International Topical Meeting on Probabilistic Safety Assessment and Analysis 2013, PSA 2013,” 2013, pp. 1779–1790.

[24] N. J. Ekanem, “A model-based human reliability analysis methodology (phoenix method),” Ph.D., University of Maryland, College Park, United States -- Maryland, 2013.

[25] Y. James Chang *et al.*, “The SACADA database for human reliability and human performance,” *Reliability Engineering & System Safety*, vol. 125, pp. 117–133, May 2014, doi: 10.1016/j.ress.2013.07.014.

[26] K. M. Groth and A. Mosleh, “A data-informed PIF hierarchy for model-based Human Reliability Analysis,” *Reliability Engineering & System Safety*, vol. 108, pp. 154–174, Dec. 2012, doi: 10.1016/j.ress.2012.08.006.

[27] N. Fenton and M. Neil, *Risk Assessment and Decision Analysis with Bayesian Networks*. CRC Press, 2018.

[28] N. Ekanem, A. Mosleh, S.-H. Shen, and M. Ramos, “Phoenix–A model-based human reliability analysis methodology: Data sources and quantitative analysis procedure,” *Reliability Engineering & System Safety*, vol. 248, p. 110123, Aug. 2024, doi: 10.1016/j.ress.2024.110123.

[29] J. Herkert, J. Borenstein, and K. Miller, “The Boeing 737 MAX: Lessons for Engineering Ethics,” *Sci Eng Ethics*, vol. 26, no. 6, pp. 2957–2974, Dec. 2020, doi: 10.1007/s11948-020-00252-y.

[30] J. Sterman and J. Quinn, “Boeing’s 737 MAX 8 Disasters.” MIT Management Case Studies, 2023.

[31] National Transportation Safety Board, “US Comments on Draft Aircraft Accident Investigation Report: Ethiopian Airlines Flight 302, Boeing 737-8 MAX, ET-AVJ,” National Transportation Safety Board (NTSB), Washington, D.C., Tech. Rep., Mar. 2022.

[32] Ethiopian Aircraft Accident Investigation Bureau (EAIB), “Aircraft Accident Investigation Report: Ethiopian Airlines Group B737-8 (MAX) Registered ET-AVJ,” EAIB, Addis Ababa, Ethiopia, Rep. AI-01/19, Dec. 2022.