Advancing Situation Awareness Systems:Evaluating Decision-Making Methods with UAV Applications

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Abstract

Situation awareness (SA) refers to the perception of environmental elements within a specific volume of time and space, understanding their meaning, and projecting their near future status. This model has three levels: perception of the current situation, comprehension of the current situation, and projection of future status. SA is a term used to describe an individual's level of awareness and understanding of "what is happening". Therefore, SA serves as the first step in decision-making, providing an understanding of "what is happening" and "what is likely to happen". In practice, safe decision-making depends on the continuous extraction of technical and environmental information, integrating knowledge, and forming a coherent mental picture to guide perception and predict future events. The use of this concept is essential for several reasons. First, situation awareness systems improve the accuracy of decisions by providing up-to-date and comprehensive information about the environment. These systems, by delivering precise data and analyses, reduce human errors and ensure that decision-makers consider all relevant factors and data, leading to more accurate decisions. Moreover, situation awareness increases decision-making speed. These systems quickly identify environmental changes and process large volumes of data in a short time, providing decision-makers with relevant information rapidly, which leads to timely and swift decisions.

In recent years, the application of SA has gained prominence in Unmanned Aerial Vehicles (UAVs), where continuous extraction of technical and environmental information is vital for safe and efficient operations. UAVs rely on real-time data integration to form coherent mental models that guide perception, enhance decision-making, and predict future events, thus improving operational safety and efficiency. The use of SA systems in UAVs is essential for several reasons. First, they enhance decision accuracy by providing comprehensive, up-to-date information about the environment, reducing human errors and ensuring that all relevant data are considered, and increases decision making speed. Hence, in this paper, we examine and evaluate various decision-making methods in situation awareness systems by focusing on UAV application.

Keywords: *Situation Awareness, Decision-making, Unmanned Aerial Vehicles (UAVs), Heuristic based methods, Model based methods, Data driven methods*.

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1. Introduction

Situation awareness (SA) is a critical factor in environments where timely and accurate decision-making is essential. Originally developed in aviation and military domains, SA refers to the perception of elements in an environment within a volume of time and space, the comprehension of their meaning, and the projection of their future status [1]. In today's data-driven world, SA systems have expanded to a variety of fields, including cybersecurity, healthcare, transportation, and autonomous systems. These systems aim to process complex data streams in real-time to aid human operators in making informed decisions [2017].

Decision-making is an integral part of SA systems as it directly influences the effectiveness of response actions in dynamic and unpredictable environments [2017]. In modern SA systems, the challenge lies not just in acquiring and interpreting vast amounts of data but in making decisions under uncertainty. Whether the application is managing cybersecurity threats or responding to emergencies, the quality of decisions made impacts overall system performance and the safety of human operators and systems involved. Over time, decision-making methodologies have evolved in line with advancements in artificial intelligence (AI), machine learning (ML), and computational models. Traditionally, SA systems relied heavily on rule-based and heuristic approaches, but these were often inadequate in highly dynamic environments. The evolution of AI and ML techniques has opened up new avenues for decision-making, enabling systems to adapt, learn from patterns, and predict future states of the environment more effectively.

The review of decision-making methods in SA systems can be broadly categorized into manual, automated, and hybrid approaches. Manual methods rely on human operators who use SA system outputs to make decisions, often supported by visual interfaces or dashboards. Automated approaches, typically powered by AI or algorithms, aim to eliminate human intervention in decision-making processes. Hybrid methods combine human judgment with AI-driven insights, striking a balance between automation and human oversight, which is crucial in highly sensitive or high-risk environments. Despite technological advancements, decision-making in SA systems faces several challenges. These include dealing with incomplete or noisy data, balancing real-time processing demands, mitigating the risks of automation bias, and ensuring the explainability of AI-driven decisions. Additionally, ethical concerns surrounding autonomous decision-making, particularly in safety-critical applications, need to be addressed. It is crucial that decision-making methods are not only efficient but also transparent and accountable [3].

In recent years, the application of SA has gained prominence in Unmanned Aerial Vehicles (UAVs), where continuous extraction of technical and environmental information is vital for safe and efficient operations. UAVs rely on real-time data integration to form coherent mental models that guide perception, enhance decision-making, and predict future events, thus improving operational safety and efficiency. The use of SA systems in UAVs is essential for several reasons. First, they enhance decision accuracy by providing comprehensive, up-to-date information about the environment, reducing human errors and ensuring that all relevant data are considered, and increases decision making speed [4].

This paper aims to provide a comprehensive review of decision-making methods employed in SA systems, highlighting key methodologies, their evolution, strengths, and limitations by focusing on UAV applications. It will explore both traditional and cutting-edge approaches, with a focus on AI-driven methods that enhance decision support in real-time environments. Furthermore, the paper will identify ongoing challenges and suggest future research directions to advance the role of decision-making in SA systems, particularly in the context of increased automation and complex operational environments.

1- Situation Awareness

1.1.1.

Situation awareness is a cognitive process that can perceive and comprehend the current situation and project the near future. Then, based on the obtained awareness, a plan, decision, and act can be performed [5]. There are different definitions for situation awareness. One of the most famous of which was provided by Mica Endsley [6]: "

Situational awareness or situation awareness (SA) is the perception of environmental elements and events with respect to time or space, the comprehension of their meaning, and the projection of their future status." This definition subtly distinguishes between three levels of situation awareness, i.e., perception (including observation), comprehension, and projection (including prediction). Its lowest level is observation and perception, and the highest level is projection of the near future, i.e., the projection of the current situation into the future to predict the evolution of the tactical situation. The highest level in Endsley's situation awareness model is called projection when the status of elements in the environment in the near future is predicted [5].
Figure 1 illustrates the role of situational awareness (SA) in the decision-making process. According to the model, an individual's perception of relevant environmental elements—derived from system representations or direct sensations—forms the basis of their SA. Action selection and execution emerge as distinct phases from SA. Several factors influence this process, starting with individual variations in the ability to achieve SA from the same data input, which depends on information processing mechanisms, innate abilities, experience, and training. Additionally, biases and goals can shape how individuals filter and interpret their environment. The system design also impacts SA by determining how effectively it provides necessary information and its alignment with human information processing capabilities. Furthermore, characteristics of the work environment, such as workload, stress, and complexity, may affect SA. The influence of these individual and system factors on SA has been discussed [7].

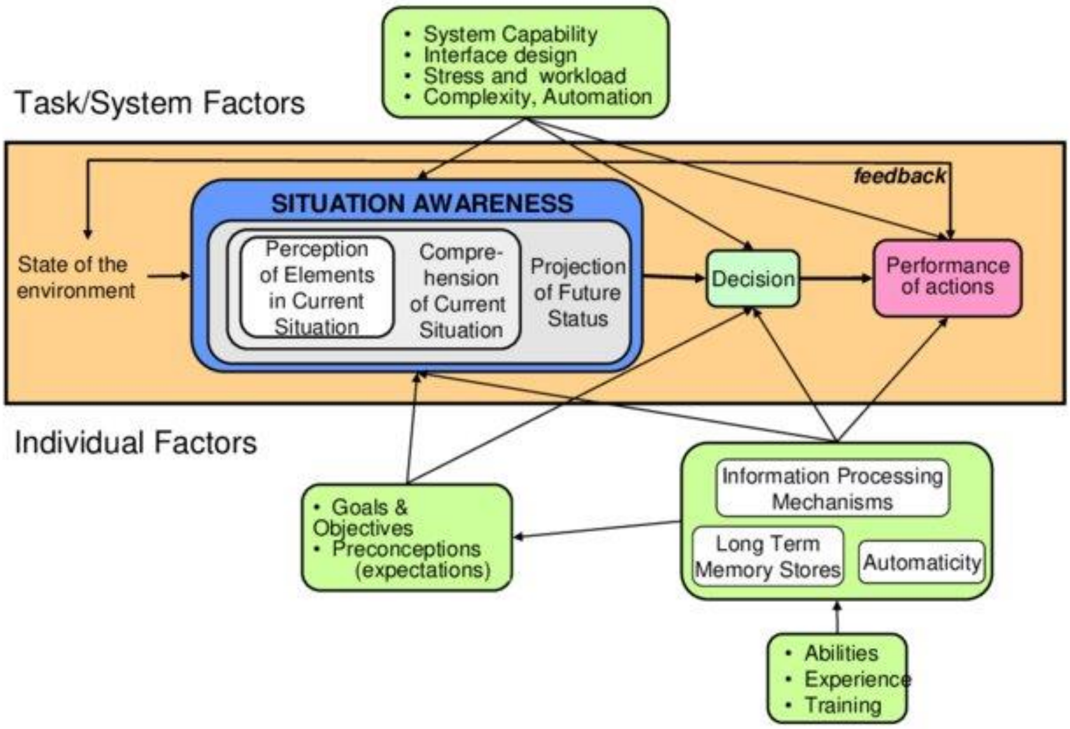

Figure 1- Model of Situation Awareness in Dynamic Decision-Making [1]

2- The Relationship between Situation Awareness and Decision-making

1.1.2.

Situation awareness (SA) forms the foundation upon which effective decision-making is built, particularly in dynamic, high-stakes environments such as aviation, military operations, and cybersecurity. SA is concerned with understanding the current state of an environment, predicting its future developments, and identifying potential risks or opportunities. Without a clear and accurate grasp of the surrounding context, decision-making becomes reactive rather than proactive, leading to suboptimal or erroneous choices. In this way, SA directly informs the decision-making process by providing essential information that helps to clarify possible options and their consequences. The decision-making process is typically broken down into three stages: recognizing the situation, selecting a course of action, and implementing the decision. SA is critical at every stage of this process [5]. At the recognition stage, SA ensures that decision-makers are fully aware of all relevant factors and their implications. In the selection phase, SA enables decision-makers to weigh various options based on their understanding of current and predicted conditions. Finally, during implementation, maintaining SA allows decision-makers to adjust their course of action in response to evolving conditions, ensuring that the decision remains appropriate as new information becomes available. In many complex environments, SA systems not only provide real-time insights but also predict future events, enabling decision-makers to anticipate potential developments before they occur. This predictive capability is especially important in domains like cybersecurity, where threats evolve rapidly, or in emergency response situations where conditions change dynamically. By forecasting how situations might unfold, SA enhances decision-making by offering proactive rather than reactive options, allowing for better-prepared and more strategic responses. The ability to predict outcomes based on the present situation helps decision-makers plan for contingencies and mitigate risks before they escalate. The integration of automated decision-making processes with SA systems further tightens the relationship between these two areas. In AI-driven SA systems, algorithms can analyze large volumes of data faster than humans, identifying patterns, anomalies, or emerging risks that would otherwise go unnoticed. These systems can then propose or even execute decisions autonomously based on the situational context. While human oversight remains critical in many scenarios, automated decision-making supported by SA can drastically improve response times and reduce the cognitive load on human operators, especially in environments where quick decisions are crucial [6].

The relationship between situation awareness (SA) and decision-making can be effectively understood through the lens of the OODA loop, a decision-making framework developed by military strategist John Boyd, as depicted in Figure 1. The OODA loop, which stands for Observe, Orient, Decide, and Act, describes a continuous process used to make fast, effective decisions in dynamic environments. Here's how SA integrates into each phase of the OODA loop [3]:

The first phase of the OODA loop, Observation, is directly aligned with the process of acquiring situation awareness. In this phase, the decision-maker gathers information from the environment—monitoring real-time data, sensing changes, and identifying relevant factors. SA comes into play as it ensures that this observation is comprehensive and accurate, forming a clear picture of the environment. High-quality SA in the observation phase leads to better data collection, allowing the decision-maker to perceive critical elements such as threats, opportunities, or system states that will influence the subsequent steps in the OODA cycle. In the Orient phase, the gathered information is processed and contextualized, which aligns with the deeper levels of SA—comprehension and projection. Here, the decision-maker evaluates the meaning of the observed data and integrates it with prior experiences, knowledge, and mental models. This is where situation awareness plays a crucial role in not just understanding the current state but also predicting future outcomes. A high level of SA enables the decision-maker to correctly interpret the implications of the observed information, foresee possible developments, and refine their mental model of the environment, which is essential for making informed and adaptive decisions. In the Decide phase, the decision-maker selects a course of action based on the orientation phase. The quality of decision-making at this point is directly influenced by the level of SA developed in the previous stages. Decision-makers with strong SA will have a better understanding of the possible consequences of their actions, allowing them to choose the option that best aligns with their goals and the evolving situation. In this way, SA ensures that decisions are not only reactive but also predictive, factoring in both immediate conditions and potential future states of the environment. The final phase of the OODA loop, Action, involves implementing the chosen decision. Once a decision is executed, the loop begins again with new observations as the environment reacts to the decision. Maintaining SA during and after the action phase is crucial, as it allows for real-time adjustments and the detection of any new developments that might require rethinking the strategy. Feedback from actions taken feeds back into the observe stage, and thus, the loop is continuous. This dynamic nature highlights the importance of SA in keeping the decision-maker aligned with the changing reality and being able to adjust actions accordingly [3].

3- Decision Making Techniques in Situation Awareness

In this section, we describe decision making techniques with a focus on their relevance to situation awareness systems, as illustrated in Figure 2. These decision-making techniques are widely applied in situation awareness systems, each offering different strengths depending on the complexity, uncertainty, and data availability in the environment. Modern SA systems often integrate multiple techniques to enhance the overall decision-making process, balancing speed, accuracy, and adaptability.

Heuristics are simplified, rule-of-thumb strategies used to make decisions when quick judgment is required. These techniques rely on experience and intuition rather than comprehensive data analysis. While heuristic approaches are often fast and effective in familiar or structured environments, they may be prone to errors in highly dynamic or novel situations. In situation awareness systems, heuristic methods are commonly used in early decision-making systems, especially when real-time decisions are needed under conditions of uncertainty. Rule-based decision-making relies on predefined sets of rules or logic that guide actions based on observed inputs. These systems are relatively simple to implement, as decisions are triggered when certain conditions are met. For example, in a cybersecurity system, a specific type of threat may automatically trigger a response based on preprogrammed rules. Although rule-based systems are straightforward and efficient, their rigidity makes them less adaptable to complex and evolving environments where dynamic decision-making is required. Multi-Criteria Decision Making (MCDM) techniques are used when decisions involve several competing objectives or criteria. These methods, including techniques like **Analytic Hierarchy Process (AHP)** and **Weighted Sum Models (WSM),** evaluate multiple factors and assign weights based on their importance. MCDM is widely used in SA systems to balance trade-offs between conflicting goals, such as cost vs. risk or efficiency vs. safety. This approach is particularly beneficial in complex systems like emergency management or autonomous systems, where decisions must consider multiple, often competing, factors. Bayesian decision-making techniques use probability distributions to make decisions under uncertainty. This approach is based on Bayes' theorem, where prior knowledge is updated with new evidence to make better-informed decisions. In SA systems, Bayesian methods are employed when decision-makers must work with incomplete or uncertain data, allowing them to continually refine their decisions as new information becomes available. This technique is often applied in fields like robotics, navigation systems, and medical diagnosis, where uncertainty is a common challenge. Machine learning (ML) algorithms have become increasingly important for decision-making in modern SA systems. These techniques allow systems to learn from historical data and identify patterns, making decisions without explicit programming of rules. Common ML approaches include **supervised learning**, where models are trained on labeled data, and **unsupervised learning**, where systems discover patterns in unlabeled data. **Reinforcement learning**, a subfield of ML, is particularly relevant in dynamic environments, where agents learn optimal actions by interacting with the environment. ML-driven decision-making is widely applied in areas such as autonomous systems, cybersecurity, and healthcare.

Game theory focuses on decision-making in competitive environments, where multiple actors with conflicting interests interact. This approach is valuable when decisions depend not only on an individual's strategy but also on predicting the actions of other agents. In SA systems, game theory is used in scenarios like cybersecurity, military strategy, or economic systems, where decision-makers must account for the strategies of adversaries or competitors. The focus is on finding optimal strategies based on the behaviors and likely responses of others. Fuzzy logic provides a framework for decision-making in environments where information is imprecise or ambiguous. Instead of relying on binary true/false decisions, fuzzy logic allows for reasoning based on degrees of truth, making it useful in systems that must handle uncertainty and vagueness. In SA systems, fuzzy logic is particularly effective in complex environments, such as robotics, weather forecasting, and traffic management, where precise data may be unavailable or subject to varying degrees of uncertainty.

In many complex systems, hybrid approaches that combine several decision-making techniques are used to optimize performance. For example, combining machine learning with rule-based systems allows for both adaptability and reliability. Hybrid models are particularly useful in situations where decisions require both automated processing (to handle large volumes of data) and human oversight (for judgment-based decisions), as seen in healthcare and autonomous driving systems.

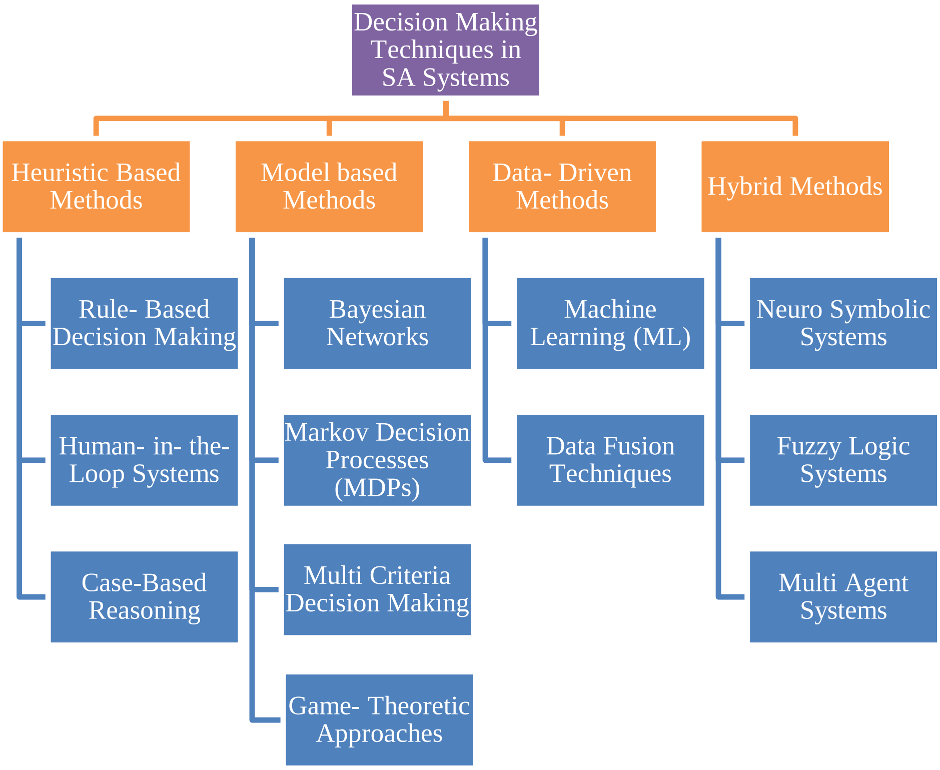

Figure 2- Decision Making Techniques in SA

4- Literature Review

1.1.3.

Decision-making is intricately linked to situation awareness (SA), particularly in dynamic environments. Effective decision-making relies on the ability to perceive, comprehend, and project the state of the environment, which is essential for anticipating outcomes and selecting appropriate actions. The Role of Situation Awareness in Decision-Making can be described as follows:

Perception and Interpretation: In maritime contexts, trainees demonstrated that while basic perception (Level 1 SA) is crucial, the interpretation of rules and anticipation of others' actions significantly influence decision-making outcomes [9].
Knowledge Processing: Autonomous systems utilize SA to process information from sensors, enabling informed decisions in changing environments. This involves formalized knowledge and information fusion, which enhances decision-making capabilities [16].
Case-Based Reasoning: Integrating context-aware case-based reasoning with SA improves problem-solving in complex scenarios, allowing for better predictions and handling of uncertain knowledge [12].
Team Dynamics: In team settings, generating consensus on SA through web-based systems enhances collective decision-making, especially when dealing with uncertainties [10].
While the integration of SA into decision-making processes is beneficial, challenges remain, particularly in predicting future states in highly dynamic environments. This highlights the need for ongoing research to refine these systems and improve their predictive capabilities.
In 2005, Stanners and French, employed Direct Questioning Technique (DQT) to assess SA and decision making relationship. In that research, SA linked to decision quality and planning [8].
In 2008, Chauvin et al. studied on situation awareness in young watch officers. Based on their study, decision-making influenced by rule interception and vessel intentions. Moreover, Trainee profiles based on course change decisions. Training needs to emphasize recognizing prototypical situations. They used two questionnaires on situation awareness and strategies, bridge simulators to simulate interaction situations [9]. In that year, Lu et al. proposed team situation awareness to support crisis decision making. They used web- based fuzzy system to aid distributed team collaboration [10]. In 2009, Brannon et al. combined humans with neural networks (Supervised, reinforcement, and unsupervised learning modes) for SA. They used adaptive resonance theory architecture for decision optimization [11]. In 2011, Nwaiabu et al. combined SA, context awareness, case-based reasoning and general knowledge. They improved similarity assessment and problem-solving prediction in decision support [12].
In 2015, Eräranta, S., & Staffans employed collaborative methods and knowledge management with face-to- face interaction. Their case study in Helsinki showed integrative, learning focused urban planning process [13]. In 2016, Moshin et al. used UAV carrying multiple sensors, and computer- based expert systems. Their proposed system enhances SA in complex disaster using UAV and expert systems. They proposed collaborative decision support system for first responders and incident commanders [14].
In 2017, Venayagamoorthy proposed a system for analyzing, monitoring, predicting, and controlling electric power systems. He utilized multi-dimensional, multi- layer cellular computational network for SA [15]. Moreover, Mykich and Burov [15], proposed algebraic model for information fusion in dynamic environments. Their research is on situation awareness in autonomous systems using formalized knowledge [16].
In 2019, Tower et al. used think-aloud research method and semi-structured interview. They investigated final-year nursing students' use of SA in clinical decision- making. In that research, students demonstrated varying levels of SA and inconsistent decision making [17]. In that year, Laugier, employed Bayesian and machine learning approaches for decision-making in autonomous vehicles [18].
In 2020, Patel et al. conducted interviews with eight General Practitioners. They used SA model for thematic classification. Their interviews reveal needs for better information visualization and SA [19]. Grigaliunas et al. employed Digital Evidence Object (DEO) model based on category theory and 5Ws integration. They used this model for SA and time- critical decision. Because, DEO model reduces false positives, aiding digital evidence investigation [20]. In that year, Jain and Patel, used non-monotonic logic framework and hybrid reasoning approach for decision support. They utilized top-down and bottom-up reasoning for decision support [21].

In 2022, Insaurralde and Blasch, used ontological reasoning for knowledge representation in SA. Moreover, they employed semantic reasoning incorporating uncertainty metrics [22]. In that year, Roman used integrated simulation systems in the management of military actions [23].

In 2023, D'Aniell and Gaeta, used computational methods and techniques for situation modeling, identification, prediction, reasoning, and control. Their feedback of study is that, SA is critical for decision making in complex environment. Moreover, Human- machine systems can support SA through computational methods and techniques [24]. In 2024, Molloy et al. Evaluated Clinical Decision Support tool in pediatric ICU. Their study demonstrated high usability scores, and positive feedback on learnability and information display [25].

A timeline and review of previous research for decision-making in situation awareness is depicted in Figure 3, and Table 1, respectively.

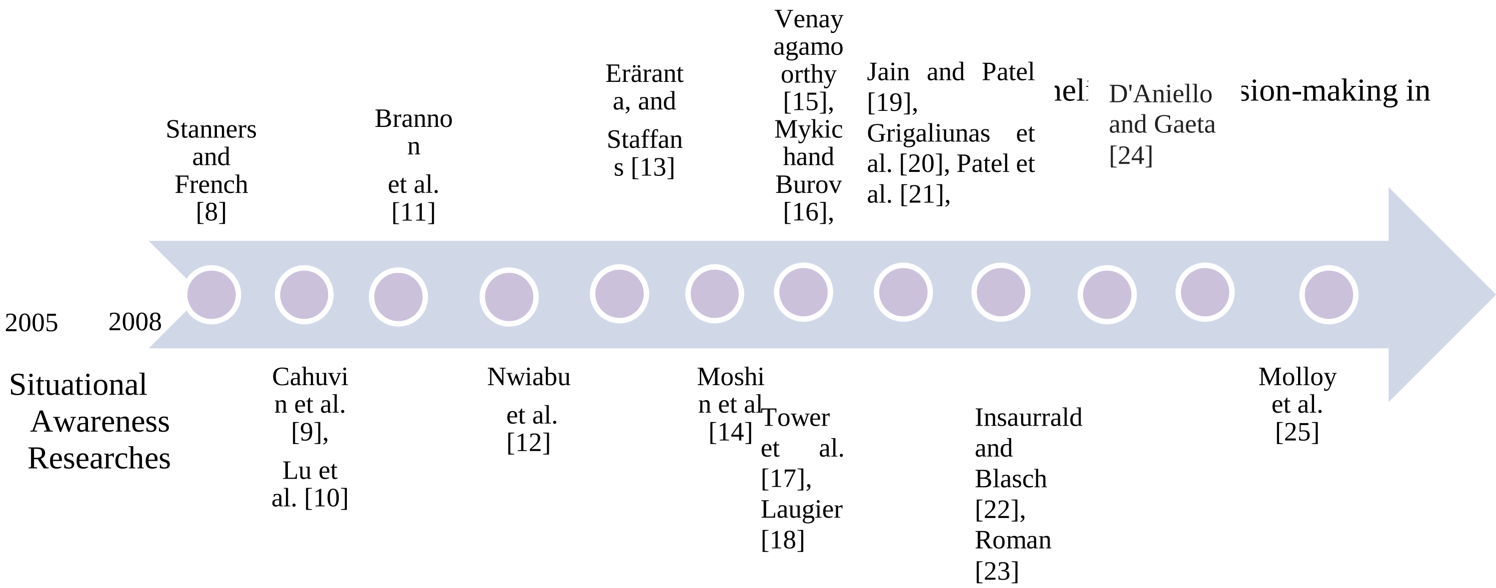

Table 1- A Review on Previous Researches

Paper	Contribution	Limitation
Stanners and French, 2005 [8]	- SA linked to decision quality and planning in study. - DQT used to assess SA and decision making relationship	- Other factors contribute significantly to decision quality - Little research has been undertaken to validate assumptions
Chauvin et al., 2008 [9]	- Study on situation awareness in young watch officers - Decision making influenced by rule interpretation and vessel intensions - Trainee profiles based on course change decisions - Simulation of interactions with bridge simulators	- Timing error in questionnaire administration affected decision-making - Some trainees may not have grasped necessary information
Lu et al., 2008 [10]	- Team SA supports crisis decision making	-

	- Web-based fuzzy system aids distributed team collaboration	
Brannon et al., 2009 [11]	- Proposed system which combines humans with neural networks for SA - Employed Adaptive Resonance Theory based architecture for decision optimization	-
Nwiabu et al., 2011 [12]	- Combines situation awareness, context awareness, case-based reasoning, general knowledge - Improves similarity assessment and problem- solving prediction in decision support	- Future situation- dependent problems cannot be anticipated - General gas model lacks required explanations
Eräranta and Staffans, 2015 [13]	- Employed collaborative methods, and knowledge management - Integrative, collaborative learning process with face to face interaction	- Smart city planning not solely data-driven super linear scaling practice - Integrative and collaborative learning process facilitated by face-to-face interaction
Mohsin et al., 2016 [14]	- Proposed system which enhances SA in complex disasters using UAV and expert systems - Collaborative decision support system for first responders and incident commanders	- Future research effort required in certain areas - Regulatory requirements and end user needs addressed
Venayagamoorthy, 2017 [15]	- Proposed system for analyzing, monitoring, predicting, and controlling electric power systems - Utilizes multi-dimentional, multi-layer cellular computational network for SA	-
Mykich and Burov, 2017 [16]	- Study on SA in autonomous systems using formalized knowledge - Proposed algebraic model for information fusion in dynamic environments	-
Tower et al., 2019 [17]	- Investigated final- year nursing students' use of SA in clinical decision- making - Students demonstrated varying levels of SA and inconsistent decision- making	- Students demonstrated inconsistent SA in decision making
Laugier, 2019 [18]	- Proposed decision making system for motion autonomy and safety in autonomous vehicles based on Bayesian and machine learning approaches	-
Patel et al., 2020 [19]	- Conducted interviews with eight general practitioners - Used SA model for thematic classification	- Interviews reveal needs for better information visualization and SA - Difficulty in locating and prioritizing patient data - Impaired SA affects decision making and care quality

Grigaliunas et al., 2020 [20]	- **Employed digital evidence object (DEO) model based on category theory and 5Ws integration** - **Real- life case study demonstrating DEO model application**	**Mission- driven autonomous perception and fusion. based on UAV swarm technology**
Jain and Patel, 2020 [21]	- Proposed non- monotonic logic framework for SA decision support during emergencies - Utilizes top- down and bottom-up reasoning for decision support	- Uncertainties influence advice and recommendations - Decision- makers focus on knowledge abstractions, not lower-level datails
Insaurralde and Blasch, 2022 [22]	- Employed ontological reasoning for knowledge representation in SA - Used semantic reasoning incorporating uncertainty metrics	-
Roman, 2022 [23]	- Used integrated simulation systems in the management of military actions	-
D'Aniello and Gaeta, 2023 [24]	- Used computational methods and techniques for situation modeling, identification, prediction, reasoning and control.	-
Molloy et al., 2024 [25]	- Evaluated usability of Clinical Decision Support tool in pediatric ICU	- Opportunities for improvement in tool integration noted - Limited qualitative feedback from think-aloud testing participants

5- Conclusion

In today's data-driven environments, situation awareness (SA) systems play a pivotal role in ensuring that decision-makers can process, understand, and act upon vast amounts of information in real time. The central problem addressed in this paper is the challenge of making accurate and timely decisions when faced with large, complex, and rapidly changing data. Effective decision-making in these contexts requires not only perceiving environmental elements but also comprehending their significance and projecting future states accurately to prevent errors and optimize outcomes.

To address this challenge, various decision-making methods within SA systems have been explored. Traditional rule-based systems provide structured, deterministic responses that are effective in stable environments, while heuristic methods offer more flexible solutions based on experiential knowledge. However, these approaches often fall short when rapid changes occur or when data are incomplete or ambiguous. In response, machine learning and AI-driven methods have emerged as powerful tools for enhancing decision-making in SA systems. These methods enable the processing of large volumes of data in real time, improving both the speed and accuracy of decisions through adaptive learning and predictive modeling.

Despite the advancements brought by AI and other adaptive methods, several limitations remain. AI models can be opaque, making it difficult for decision-makers to fully understand how certain conclusions are reached, which raises concerns about trust and accountability. Additionally, these models require large datasets for training, which may not always be available or of sufficient quality in all situations. Another potential issue is the risk of over-reliance on automated decision-making, which can reduce the role of human oversight and increase vulnerability in critical scenarios where nuanced judgment is required.

Looking to the future, hybrid approaches that integrate the strengths of traditional decision-making methods with the adaptability and power of AI-driven techniques offer a promising path forward. Developing systems that combine the interpretability and transparency of rule-based methods with the data-processing capabilities of

AI could help overcome the current limitations. Additionally, research should focus on enhancing the robustness of AI models, making them more resilient to incomplete or low-quality data. Another important area of future work involves improving the user interface and interaction with SA systems to ensure that decision-makers remain engaged and informed, even as automation increases.

In conclusion, while existing decision-making methods in SA systems offer significant benefits in terms of speed, accuracy, and efficiency, there are still important challenges to address. By refining these systems and focusing on human-AI collaboration, future SA systems will be better equipped to handle complex, dynamic environments, ensuring safer, more reliable, and more effective decision-making.

9- References

[1]. Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human factors*, *37*(1), 32-64.

[2]. Stanton, N. A., Salmon, P. M., Walker, G. H., Salas, E., & Hancock, P. A. (2017). State-of-science: situation awareness in individuals, teams and systems. *Ergonomics*, *60*(4), 449-466.

[3]. Munir, A., Aved, A., & Blasch, E. (2022). Situational awareness: techniques, challenges, and prospects. *AI*, *3*(1), 55-77.

[4]. Dehghan, M., Sadeghiyan, B., & Khosravian, E. (2021). Private trajectory intersection testing: Is garbled circuit better than custom protocols?. *International Journal of Engineering*, *34*(4), 863-872.

[5]. Dehghan, M., Sadeghiyan, B., Khosravian, E., Moghaddam, A. S., & Nooshi, F. (2022). Proapt: Projection of apt threats with deep reinforcement learning. *arXiv preprint arXiv:2209.07215*.

[6]. Endsley, M. R. (2018). Automation and situation awareness. In *Automation and human performance* (pp. 163-181). CRC Press.

[7]. Dehghan, M., Khosravian, E., (2024). A Review of Cognitive UAVs: AI-Driven Situation Awareness for Enhanced Operations. AI and Tech in Behavioral and Social Sciences, 2(4), 54-65. https://doi.org/10.61838/kman.aitech.2.4.6

[8]. Stanners, M., & French, H. T. (2005). *An empirical study of the relationship between situation awareness and decision making*.

[9]. Chauvin, C., Clostermann, J. P., & Hoc, J. M. (2008). Situation awareness and the decision-making process in a dynamic situation: avoiding collisions at sea. *Journal of cognitive engineering and decision making*, *2*(1), 1-23.

[10]. Lu, J., Zhang, G., & Wu, F. (2008). Team situation awareness using web-based fuzzy group decision support systems. *International Journal of Computational Intelligence Systems*, *1*(1), 50-59.

[11]. Brannon, N. G., Seiffertt, J. E., Draelos, T. J., & Wunsch II, D. C. (2009). Coordinated machine learning and decision support for situation awareness. *Neural Networks*, *22*(3), 316-325.

[12]. Nwiabu, N., Allison, I., Holt, P., Lowit, P., & Oyeneyin, B. (2011, February). Situation awareness in context-aware case-based decision support. In *2011 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)* (pp. 9-16). IEEE.

[13]. Eräranta, S., & Staffans, A. (2015, July). From situation awareness to smart city planning and decision making. In *14th International Conference on Computers in Urban Planning and Urban Management*.

[14]. Mohsin, B., Steinhäusler, F., Madl, P., & Kiefel, M. (2016). An innovative system to enhance situational awareness in disaster response. *Journal of Homeland Security and Emergency Management*, *13*(3), 301-327.

[15]. Venayagamoorthy, G. K. (2017). *U.S. Patent No. 9,778,629*. Washington, DC: U.S. Patent and Trademark Office.

[16]. Mykich, K., & Burov, Y. (2017). Algebraic framework for knowledge processing in systems with situational awareness. In *Advances in Intelligent Systems and Computing: Selected Papers from the International Conference on Computer Science and Information Technologies, CSIT 2016, September 6-10 Lviv, Ukraine* (pp. 217-227). Springer International Publishing.

[17]. Tower, M., Watson, B., Bourke, A., Tyers, E., & Tin, A. (2019). Situation awareness and the decision-making processes of final-year nursing students. *Journal of clinical nursing*, *28*(21-22), 3923-3934.

[18]. Laugier, C. (2019, November). Situation Awareness & Decision-making for Autonomous Driving. In *IROS 2019-IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 1-25). IEEE.

[19]. Patel, A. M., Porat, T., & Baxter, W. L. (2020, November). Enhancing Situation Awareness and Decision Making in Primary Care: Clinicians' Views. In *2020 IEEE International Conference on Healthcare Informatics (ICHI)* (pp. 1-9). IEEE.

[20]. Grigaliunas, S., Toldinas, J., Venckauskas, A., Morkevicius, N., & Damaševičius, R. (2020). Digital evidence object model for situation awareness and decision making in digital forensics investigation. *IEEE Intelligent Systems*, *36*(5), 39-48.

[21]. Jain, S., & Patel, A. (2020). Situation-aware decision-support during man-made emergencies. In *Proceedings of ICETIT 2019: Emerging Trends in Information Technology* (pp. 532-542). Springer International Publishing.

[22]. Insaurralde, C. C., & Blasch, E. (2022). Situation awareness decision support system for air traffic management using ontological reasoning. *Journal of Aerospace Information Systems*, *19*(3), 224-245.

[23]. Roman, D. (2022, December). SITUATIONAL AWARENESS IN THE MILITARY ACTIONS MANAGEMENT FOR INTEGRATED SIMULATION SYSTEMS. In *PROCEEDINGS OF THE INTERNATIONAL SCIENTIFIC CONFERENCE STRATEGIES XXI. VOLUME XVIII* (pp. 545-552). Carol I National Defence University Publishing House.

[24]. D'Aniello, G., & Gaeta, M. (2023). Situation Awareness in Human-Machine Systems. *Handbook of Human-Machine Systems*, 451-461.

[25]. Molloy, M. J., Zackoff, M., Gifford, A., Hagedorn, P., Tegtmeyer, K., Britto, M. T., & Dewan, M. (2024). Usability Testing of Situation Awareness Clinical Decision Support in the Intensive Care Unit. *Applied Clinical Informatics*, *15*(02), 327-334.