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A Systems Modeling Approach to Support Human-Agent Team Performance for Combat Identification

Clayton W. Couch

A SYSTEMS MODELING APPROACH TO SUPPORT HUMAN-AGENT TEAM PERFORMANCE FOR COMBAT IDENTIFICATION

THESIS

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Wright-Patterson Air Force Base, Ohio

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Abstract

Combat Identification (CID) in an air-to-air combat context is a highly complex cognitive task that requires the operator to make rapid, high consequence decisions. To accomplish CID, fighter aircrew must attend to and perceive a broad range of information while concurrently building situation awareness (SA) and conducting other tasks. While existing automated agents are available to help fighter aircrew with this CID task, they are designed for a very narrow subset of the overall task and are not well suited for human-agent teaming. An interdependence analysis of the human operator and supporting machine agents conducted for this task support the notion that the Orient step of the Observe-Orient-Decide-Act (OODA) loop is to the most consequential for improving reliability or efficiency of CID task performance. Modeling was performed to examine the CID task across existing system architectures to understand potential improvements that enhance human-agent team design for this task. More specifically, subjective logic was explored as a possible means of increasing the observability of a multi-agent interface that supports decision making in the CID use case. This approach was incorporated into the model to demonstrate potential utility. Initial findings suggest that further research on subjective logic should be conducted to understand the impact of this tool for improving multi-agent system performance in future Department of Defense systems.

Acknowledgments

I would like to express my sincere appreciation to my faculty advisors, Dr. Michael E. Miller and Dr. John M. McGuirl for their guidance and support throughout the duration of this thesis effort. Their insight and experience into human machine teaming and trust was certainly appreciated. I would also like to thank my wife for her constant devotion, encouragement, and support while I pursued this academic endeavor.

Lt Col Clayton W. Couch

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A SYSTEMS MODELING APPROACH TO SUPPORT HUMAN-AGENT TEAM PERFORMANCE FOR COMBAT IDENTIFICATION

I. Introduction

General Issue

Combat Identification (CID) of a target is a requisite step before weapons employment, bound by expected rules of engagement (ROE) and the Laws of Armed Conflict (LOAC). This research seeks to identify methods to further mitigate fratricide of friendly forces and also ensure the selected target is a valid military target. Today's technological enhancements, most notably automated agents comprising artificially intelligent (AI) agents, can extend CID capabilities well beyond the limits of human sensing and cognition. Optimizing such human-agent teams requires interface designs that afford trust building between human and automated agents while at the same time improving situational awareness (SA) for the human operator. Ultimately, any human-agent team must accomplish these goals within dynamic combat situations while accounting for the cognitive impacts caused by risk to self, risk to mission, time pressure, and fog of war. While this research focuses on CID in a military context, the more generalizable concept is human-agent teams (elsewhere the term human-machine team is often used) to accomplish differential diagnosis, which is extensible to other applications such as the medical community.

Problem Statement

Targeting doctrine used by the U.S. military requires any proposed target first establish a Combat Identification (CID) for a proposed target prior to proceeding with a weapons engagement. CID, sometimes referred to as Positive Identification (PID) or more generally just identification (ID), is a key task in the targeting process referred to as the Kill Chain. The steps in this kill chain are often referred to by the mnemonic F2T2EA, for Find, Fix, Track, Target, Engage, and Assess. Strictly speaking, CID could occur at any point across the Find or Fix step, but is located in the "Fix" step within joint targeting doctrine. Any target's CID must then be maintained through the Track and Target steps prior to engagement, otherwise the CID must be re-determined if an object's associated CID is lost. A diagram of this process is shown in Figure 1.

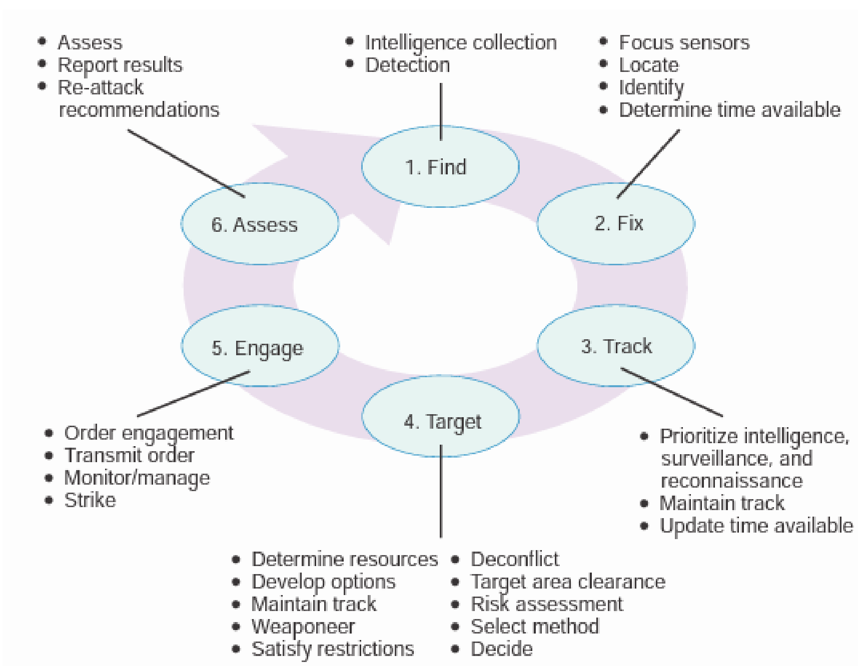

Figure 1. Joint Targeting Step 5 (Joint Publication 3-60, Joint Targeting, 2013)

As defined in the 1997 Joint Warfighting Science and Technology Plan, CID is "the process of attaining an accurate characterization of entities in a combatant's area of responsibility to the extent that high-confidence, real-time application of tactical options and weapon resources can occur." The objective of CID is "to maximize combat and mission effectiveness while reducing total casualties (due to enemy action and fratricide)." CID can be broken down into different levels of granularity, each of which can provide differing utility in any given scenario. The nomenclature typically used for technically (sensor and weapon system) derived CID are "class" identification and "type" identification (Joint Warfare Science and Technology Plan, 1997). Examples of these are "aircraft" (class), and "F-15" (type), although some technical solutions in use today use the term "platform identification" interchangeably with type identification. Additional CID denominations may include "nationality," which provides a further level of discrimination (e.g., a Russian Su-27 vs. a Ukrainian Su-27). However, a target's nationality often cannot be reliably ascertained using technical means onboard a friendly weapon system alone, unless that information is self-reported by the target. In many cases, these various levels of CID granularity are sufficient for inductively or deductively reasoning with sufficient confidence whether a given entity is a valid military target prior to weapons employment in compliance with established Rules of Engagement (ROE). Ease of achieving a sufficient level of CID depends on the context in which CID is conducted. For example, a human solider can at times identify enemies on the battlefield at short distances, sufficient for small arms fire. Such situations are not further considered in this research. However, for complex situations like air-to-air combat at long range, advanced sensors onboard weapon systems are necessary- the human cannot do it alone. For the purposes of this research, the primary objective of CID will be to establish and correlate the necessary association (or allegiance) of CID as either Friendly, Enemy, or Neutral for a given airborne entity. Doing so would affords real-time application of tactical options or weapon employment. A visual depiction of this ID association is shown in Figure 2 below, where any given target starts in the mutually inclusive region in the center. The Friend, Enemy, or Neutral association can then be ascertained as new CID information becomes available.

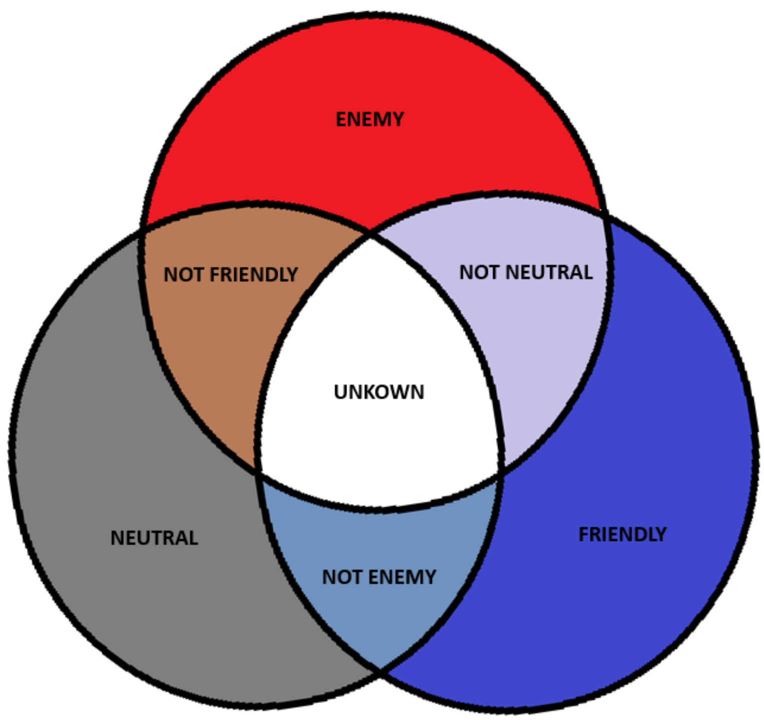

Figure 2. Conceptual Diagram of Friendly, Enemy, Neutral CID Association.

There are effectively two aspects for determining CID: 1) the use of system-sourced data, including sensors resident on a system accomplishing the identification (ID) (or from Command, Control, and Communication [C3] resources and associated communication architectures that provide this information from offboard systems), and 2) the human operator's mental model and current situational awareness derived from situated clues to target intent, origin, behavior, or visual identification. From a technical standpoint, many CID systems are designed for cooperative target recognition, such as Identify Friend or Foe (IFF) systems that are challenge and response, while others accomplish CID via non-cooperative target recognition (NCTR) methods. While cooperative target recognition is useful for avoiding fratricide, it imposes additional maintenance, logistical (e.g., may require cryptological keys or timing synchronization), and system of systems integration limitations that can preclude availability or reliability in some situations. Therefore, having a combination of cooperative and non-cooperative CID sensors at an operator's disposal is desirable because it allows decreased likelihood of CID misses and mitigates CID false alarms from use of a single system alone. However, concurrent use of multiple CID systems can create an overabundance of information for the human operator to observe and interpret prior to decision making. Worse, if their outputs conflict it can cause confusion for the operator.

Unfortunately, the onus is on human operator(s) to complete the CID task as they are the only entity capable of leveraging the context information and are ultimately responsible for any errors in CID. This requires using sensors and referencing automated CID "agents" that have low levels of autonomy, often with poor human-interface designs. Additionally, a majority of currently fielded CID systems are not designed to support teamwork (or task coordination) in dynamic environments. This can lead to suboptimal speed or accuracy for the CID task, which in turn increases the likelihood of derogatory mission impacts such as fratricide, failure to engage a valid target, or collateral damage.

The Congressional Office of Technology Assessment ascertained that 24% of coalition casualties in Operation Desert Storm were attributable to fratricide (OTA, 1993), while a study for the Joint Staff put that figure at 11-16% of total casualties. The latter further summarized that an overwhelming majority of casualties (97%) were ground-to-ground or air-to-ground, surmising that "the largest cause…is [target identification] error – misidentification of a friendly or neutral/noncombatant system as enemy." (Sparta, 2002). Unfortunately, the risk of loss due to fratricide is not the only consideration and mission execution must be balanced against time and other possible actions on the battlefield. For example, if an operator takes excessive time determining a proposed target is enemy prior to weapons employment, then ramifications due to enemy action (e.g., enemy weapons employment on friendly forces) may result in friendly loss, or the enemy may maneuver into an area with high likelihood of collateral damage, preventing weapons employment and allowing the enemy to fight another day. The outcome of biasing responses towards excessive delays are not easily determined or quantified. However, if the CID is incorrect and weapons are employed on a neutral (non-combatant) object or person, the outcome is apparent and U.S. Forces must then deal with the negative effects caused by collateral damage. Therefore, it is important to determine that a proposed target lacks any friendly indications, while having positive enemy indications. For all such potential scenarios, this dual aspect of CID (lack of friendly [LOF] and presence of enemy [PEI]) must be accomplished efficiently, as a combat situation may allow only time periods measured in seconds to accomplish the task, but also reliably so as to avoid fratricide and noncombatant casualty. Therefore, a basic understanding of reliability relating to signal detection theory is useful for this CID application, briefly mentioned below, but more thoroughly described later within the literature review (Hawley et al., 2017).

Regarding existing academic literature about identification aids and automated agent reliability, three things are worth noting: 1) highly reliable agents correlate positively to overall human-agent (used here interchangeably with human-machine) team performance; 2) False Alarm prone agents reduce operator compliance (strong negative correlation) and reduce operator reliance (weak negative correlation); and 3) Misses reduce operator reliance (strong negative correlation) and reduce operator compliance (weak negative correlation) (Rice et al., 2010). This is telling because human reliance on automation typically indicates willingness to trust the automation and provides a useful metric since trust cannot be directly measured. However, reliance may also indicate complacency on the part of the human or otherwise occurs when the human does not have the cognitive resources necessary to accomplish the task within expected time limits and chooses to blindly accept the automated agent's output. Additional factors such as time pressure or fear of negative repercussions resulting from poor task execution may result in misuse of automation. Misuse occurs when a human is over-reliant upon a system when in actuality the situation may warrant an elevated level of suspicion (or decreased trust) of the automated agent's output. Finally, some humans lack a willingness to trust a machine as a valuable contributor, leading to disuse of automation and subsequently lowering overall efficiency or reliability for the task. (Rice et al., 2009)

These automation considerations as they relate to signal detection theory describe the problem for designers of automated CID systems. Specifically, how to design automation to balance the differential effects of false alarms and misses on human decision behavior, while simultaneously eliciting an optimal pattern of human dependence (avoiding disuse or misuse) on the automated agent. Further, modern systems often employ multiple sensors and artificial agents, each of which provide either correlated or independent CID estimates. Unfortunately, the historical design approach that simply seeks to maximize system reliability of individual agents is not sufficient to accomplish all these goals. A different approach to system design that has merit would include both human operator and automated agents (i.e., the human-agent team) as complimentary elements of the solution rather than as separate entities. Similarly, users of an automated CID agent need to determine what specific training is required to optimize the human-agent team performance for a CID task. Unfortunately, due to inflexible designs inherent with many fielded DoD systems, it is the author's observation that military operators tend toward either strict misuse or disuse of that automation. The overarching objective of this research is guided by these system design and training tradeoff problems.

Research Hypotheses

The ultimate intent of this research is to provide insight into human-agent team performance improvement for a CID task. The hypotheses and objectives flow from identified pain points noted in the literature review as well as expert operator knowledge of the task. Assuming CID sensors can obtain and communicate the required data, the operator is expected to iteratively Observe, Orient, Decide, and Act (OODA) in a looping process before arriving at a final CID determination. The operator must rely upon the interface to the technical data sources to perform the Orient step of this OODA loop. When multiple interfaces, formats, and interpretations of CID are provided for this technical data, this step may become the most demanding and critical to accomplish reliably and efficiently. This is due to the need to interpret and fuse multiple streams of CID sensor data with the operator's own awareness of the situation to complete the Orient step.

An understanding of human-agent teaming across the entire CID process is needed to identify best design or training areas worth focusing on. This further requires knowledge of current CID system capabilities and limitations, including their impact on human cognitive processes as they relate to the levels of human control abstraction (LHCA). LHCA is a concept that defines the level of control a human has over an automated agent for a given task. This five level scale of human control requires less granularity of human control. These levels are 1) direct control, 2) augmented control, 3) parametric control, 4) goal-oriented capable agents, and 5) fully mission capable agents (Johnson et al., 2020). Upon pairing the CID problem with the author's knowledge of existing CID capabilities, three sequential hypotheses are proposed:

Hypothesis 1: Current CID agent utility and LHCA differs across steps of the overall CID task but is limited to parametric control at best during the Orient step. Since the human remains responsible for the team's overall CID task performance, <u>the area of greatest opportunity to improve human-agent team performance is the Orient step</u> of the OODA loop.

Hypothesis 2: Due to automation limitations, making sense of CID data for reliable and efficient fusion of multiple agent data streams with changing human situational awareness is the most difficult part for a human when accomplishing the overall CID task. This primarily occurs during the Orient step of the OODA loop.

Therefore, improving human-agent team efficiency and/or reliability is the best way to improve the Orient step of the CID OODA loop, and in turn the overall CID task.

Hypothesis 3: Use of summary metrics, for instance, subjective logic, during a CID task could improve human-multiagent team reliability or efficiency during the Orient stage of the CID OODA loop by increasing the agent's observability and predictability for the human user.

Research Objectives

The research focus has three multi-faceted objectives tied to the three hypotheses and are described here.

Objective 1: Demonstrate that a) varying level of CID autonomous agent capabilities and limitations for each CID subtask b) that greatest team opportunity lies in the Orient step, and c) that agents are not technologically capable enough to execute the task without a human teammate (i.e., limited to parametric LHCA for this use case).

Objective 2: Support the idea that the preponderance of difficulty and cognitive workload lies in the Orient step of the OODA loop, and identify touchpoints where training or system design may lessen this burden on the human operator through improved efficiency or reliability.

Objective 3: Demonstrate how subjective logic can aid reliability and/or efficiency of a human operator's decision to use automated agent's outputs to improve overall CID task execution.

Methodology

For objective one, the use of expert knowledge of currently fielded CID systems and their respective LHCA is used to model human-multiagent team interdependencies across an entire CID task according to Johnson's coactive design interdependence analysis (IA) modeling approach (Johnson, 2014), initially within MS Excel. This coactive design approach is described in detail in the literature review. Subsequently, adapt this CID task model into Model-Based Systems Engineering (MBSE) tools, specifically SysML to incorporate further context of the CID activity itself.

For objective two, (in addition to objective one outputs which support objective two) expert knowledge of the CID task is used to create cognitive maps of a) an air to air engagement as it relates to the CID process and b) differing human & automation information processing capabilities. These are done using openly available Florida Institute for Human & Machine Cognition's (IHMC) Cognitive Mapping (CMAP) tool. This objective demonstrates the difficulty and cognitive dependencies in the Orient step of the CID OODA loop, and helps identify likely limitations and opportunities for automated agent design, as well as areas for human-agent team training.

Objective three is accomplished in several parts. First, by modelling subjective logic in MS Excel and subsequently using MBSE tools, specifically a SysML parametric diagram and instance tables. Second, use cases to demonstrate model utility are created and outputs are adapted into a very basic graphical user interface (GUI) that adheres to the principle of observability, discussed later. The GUI seeks to demonstrate a graphical means of efficiently displaying multiple agent CID determinations and consensus resulting from the subjective logic.

Assumptions and Limitations

The F2T2EA kill chain can become very complex due to the multiple variables involved, so assumptions and limitations are needed to scope the problem into a digestible level. This research is intentionally limited to only the CID correlation and/or ID determination of a single target in an air-to-air scenario. This assumes that the "FIND" step (search, initial detection, and initial sensor allocation) is complete, and the initial "locate" subtask in the "FIX" step is complete. Secondly, it assumes that multiple automated agents and their human interface are available to aid in the CID task, and that each provides slightly different information (e.g., some can ascertain friendly status only, some provide "type" or "platform" ID, etc.). Third, it assumes that CID can be correlated to a target's geolocation in whole (angle and range to target is known) or in part (e.g., angle only). Next, there are other limitations that are not directly considered, but are variables that change from scenario to scenario. For example, target prioritization versus other targets in the battlespace or restrictions and deconfliction from other aircraft or their sensors. Finally, the majority of CID agents are not specifically discussed or modelled in detail based on security classification limitations. To further ensure releasability, any factual abilities and capabilities of agents were intentionally obfuscated or in some cases not even considered. However, this does not significantly limit the conceptual application or problem. When specifically named or described, any CID agent capabilities mentioned within this research is available through open-source references.

Implications

First, understanding the criticality of CID to mission execution applies to a multitude of physical domains, not just air-to-air. This research is intentionally applied to unclassified, tactical level of war scenarios focused on sensemaking (corollary to the Orient step of OODA). In addition to the assertions about the Orient step within this research, sensemaking is an area of interest to the Headquarters Air Force (HAF) Global Integrated Intelligence, Surveillance, and Reconnaissance (GIISR) panel, and based on ties to multiple Secretary of the Air Force (SECAF) Operational Imperatives (OI). Additionally, the CID processes involved in this research can scale to intermingle with, inform, or exist exclusively within the Operational level of war across multiple domains.

Second, at the system program office or operational unit level, understanding how to improve human-agent teaming informs future system design and upgrade considerations. It may also help identify worthwhile training or tactics, techniques, and procedures (TTP) that can improve human-agent teaming to aid mission execution.

Finally, the conceptual approaches used within this research may apply to other fields or not related to any CID problem. General areas of interest may include those related to the data sciences, human-agent teaming, or differential diagnosis tasks.

II. Literature Review

Chapter Overview

This chapter reviews research in three overlapping areas of interest: decision making in complex and dynamic environments, human-agent teaming and modeling concepts, and use of subjective logic for information fusion and decision-making support. Additionally, some literature reviewed here provides support for the hypotheses in this thesis and are pointed out appropriately. This paper also examines takeaways from previous research from a CID use case perspective, presents some noteworthy theoretical and proposed application constructs, and briefly describe how each applies to the stated research objectives.

Decision Making in Complex and Dynamic Environments

The military aviation CID use case in this thesis may ultimately be distilled into a complex decision-making problem. Perhaps more specifically, it is conducting a differential diagnosis – differentiating between two or more conditions which share similar indications – but with significant risk and time pressure. The first conceptual model is found in use across disciplines both inside and outside academia: the Observe, Orient, Decide, Act (OODA) loop. The conceptual groundwork for the OODA loop was originally laid out on Col (ret.) John Boyd's only written work, *Destruction and Creation* (Boyd, 1976), but he furthered the theoretical foundation of the OODA loop in a series of briefings beginning with *Patterns of Conflict* (Boyd, 1986, 1987a, 1987b, 1992, 1996). The OODA loop is typically applied as a closed-loop, four step information-processing model that has corollaries to both human decision-making as well as for use in automated agent design. It is often drawn most simply as a four step, continuous circular loop. For the purposes of applying to this paper's CID use case, the more detailed version drawn by one of Boyd's closest associates, Franklin C. Spinney, is shown in Figure 3. Though not a perfect application for CID, this version was chosen because it better depicts the numerous feedback loops, informational relationships, and outside influences present in a complex and dynamic environment. Many of these influences and relationships – or more importantly the output of the Orient step of the OODA loop itself – are elements key to situational awareness discussed next.

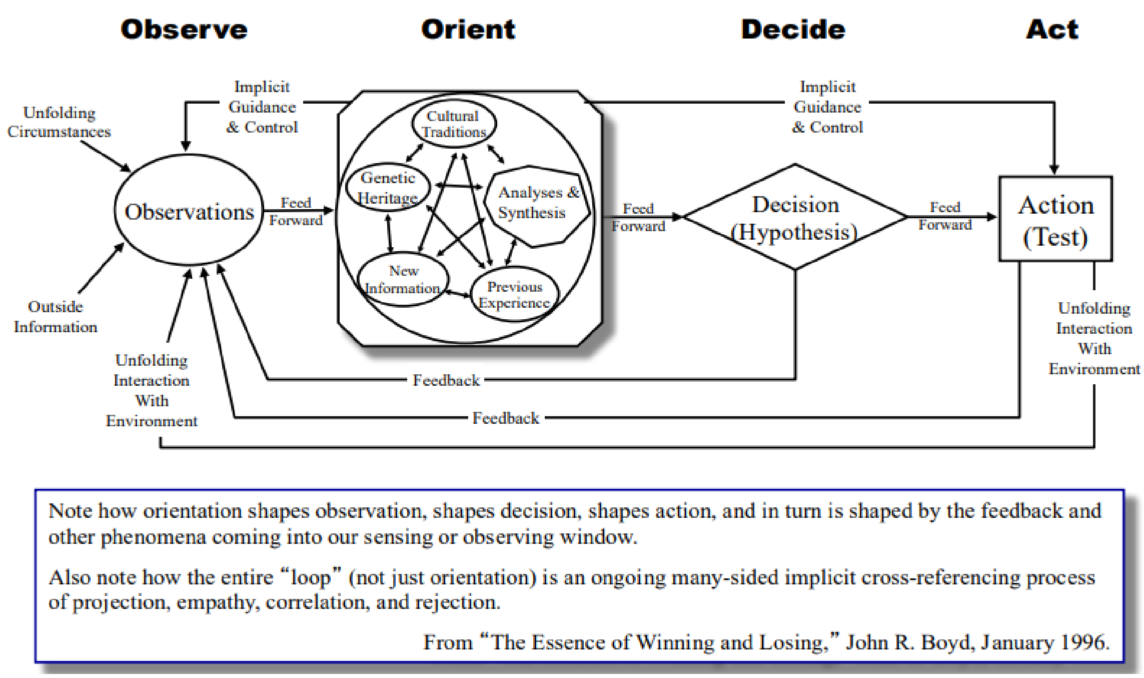

Figure 3. Franklin C. Spinney's graphic representation of Boyd's OODA loop (Rule, 2013)

Endsley defines the term situation awareness as "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" (Endsley, 1995). The military aviation community, and more broadly across aviation research in general, the term situation*al* awareness (SA) is often used. Anecdotally, the author is an experienced aircrew member and instructor in the fighter aircraft community where building and maintaining SA is readily acknowledged as key to acceptable mission performance. A commonly used model referenced within academic literature is shown in Figure 4. Though the term "situation awareness" is used by Endsley, it is used interchangeably with SA for the purposes of this paper.

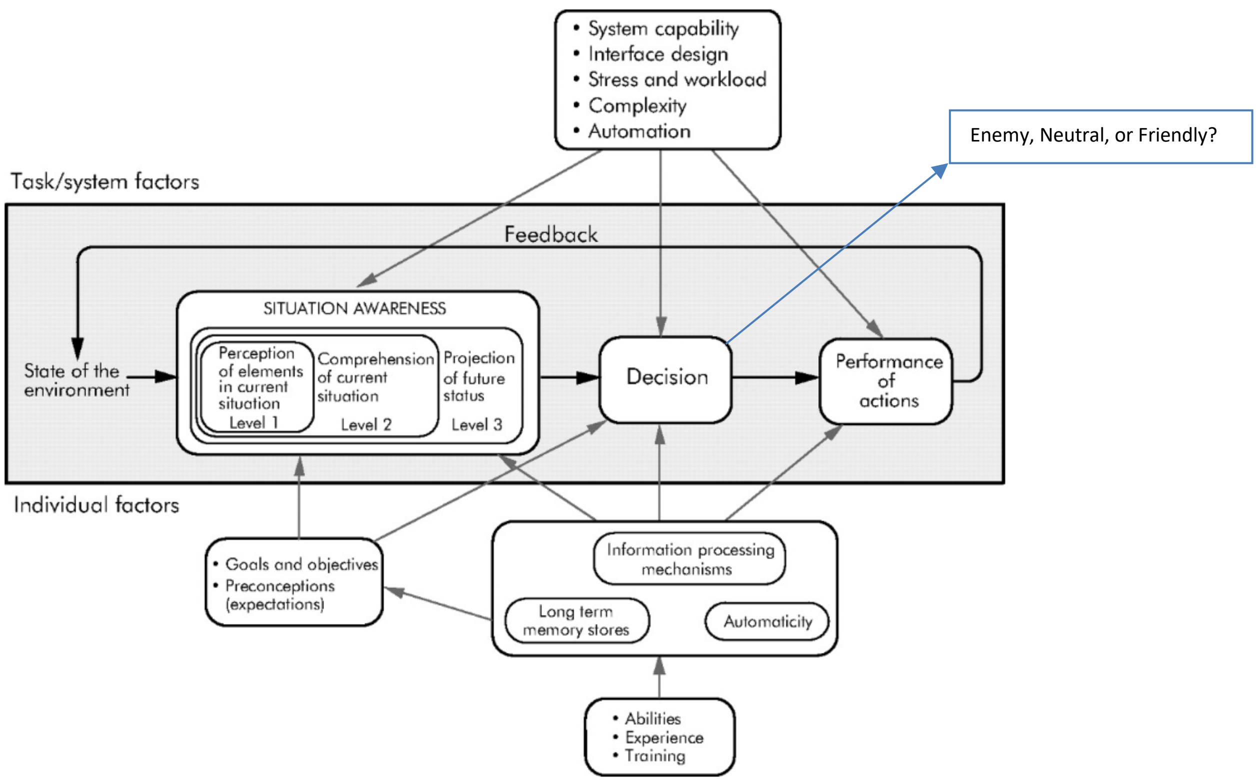

Figure 4. Situation awareness in dynamic decision making with CID context, adapted from (Endsley, 1995).

Note the similarities between Figure 3 and Figure 4, particularly how "Situation Awareness" appears to be a corollary to the Orient step of the OODA loop, feeding forward to "Decision" and "Performance of Action" which subsequently feed back into

SA. This observation highlights the importance of SA to decision making, and that in complex environments both processes can be cognitively demanding given the large number of variables, stimuli, and other influences which must be considered to make an informed decision. Additionally, while SA in this model occurs at the individual level affected by individual factors, SA can be extended to team or organizational levels. To apply to a CID use case, an ID can be accomplished by a single agent or actor in a system, but it can also be accomplished at the tactical level through human-agent team interactions or across multiple battlefield entities. However, it can also scale to occur at a more strategic level after it is observed alongside multiple ID sources across multiple targets by command and control (C2) echelons at an operational level of war. By extension, it may be asserted that as substantive reliability improvements occur in tactical level CID aids for beyond visual range engagements, improvements to operational level CID is needed to improve SA with target identification aids. (Hawley et al., 2017)

When applying Endsley's three levels of situation awareness model to the CID problem, in most cases only levels one and two apply to an entity's ID itself. Once CID has been ascertained, there is no need to project a future ID (level three situation awareness) because the CID itself (enemy, friendly, or neutral) is a static and unchanging state that merely needs to be maintained. That assumes a correct ID determination, as new information obtained during the feedback loop of the model could update or change the CID. From a more holistic perspective, SA of the entire context and projecting future states of the target is still important because the operator's overall task also includes projecting (level three situation awareness) the behavior of the identified target entity to understand how it affects mission objectives and forming appropriate plans that lead to mission success. Endsley extended this model into a taxonomy of SA errors shown in Figure 5. It was then applied to aviation mishaps through a quantified analysis of causal factors. Using four years of National Transportation Safety Board (NTSB) mishap investigation reports totaling 111 incidents, 88% of the mishaps were attributed to SA problems. Further decomposition indicates 72% of these SA errors were level one, and 22% involved a level two SA error. This implies only 6% of errors were due to incorrect projection or decision making alone (Endsley, 1999). These levels are depicted in Figure 6. The usefulness of this SA model and related error taxonomy is in their application to orienting to the available data and making sense of it. Relating this SA error taxonomy back to the OODA loop in Figure 3 suggests that SA tends to succeed or fail most commonly during the Observe or Orient step of the OODA. To demonstrate this, an assessment of which OODA step relates to the error taxonomy is shown in the figures.

	Assessed OODA Step
Level 1: Failure to correctly perceive information	
Data not available	Observe
Data hard to discriminate or detect	Observe
Failure to monitor or observe data	Observe
Misperception of data	Orient
Memory Loss	Orient
Level 2: Failure to correctly integrate or comprehend information	
Lack of or poor mental model	Orient
Use of incorrect mental model	Orient
Over-reliance on default values	Orient
Other	
Level 3: Failure to project future actions or state of the system	
Lack of or poor mental model	Orient/Decide
Over-projection of current trends	Orient/Decide
Other	

Figure 5. SA Error Taxonomy with OODA steps, adapted from (Endsley, 1999)

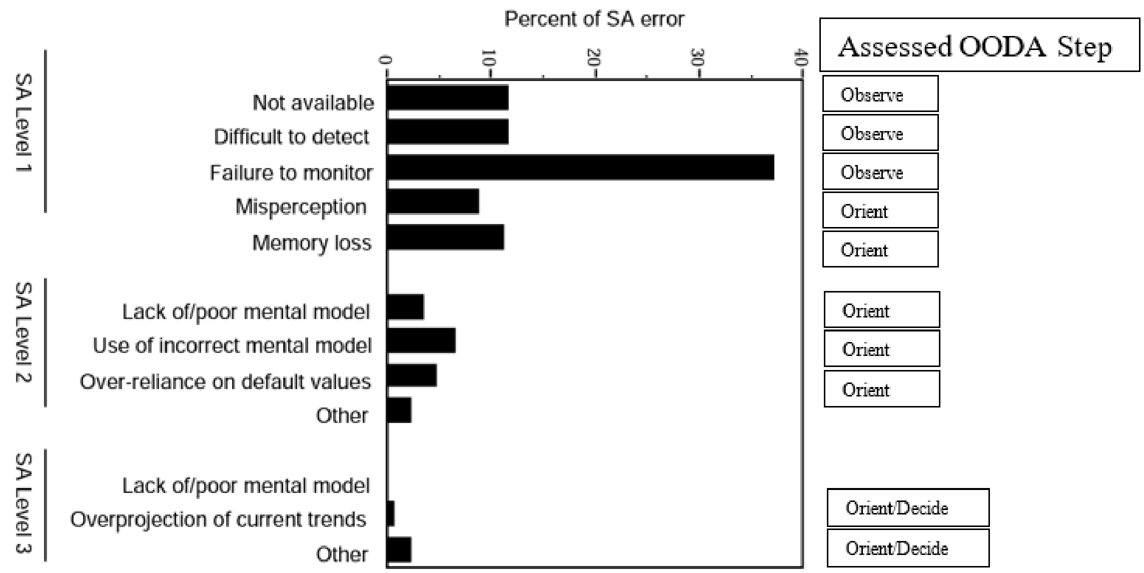

Figure 6. SA Errors in Aviation with OODA steps, adapted from (Endsley, 1999)

Unfortunately, there is not a direct connection between this statistical analysis of aviation SA errors and the difficulty presented by the CID problem. However, taken together they do lend support to hypothesis 1 and 2 of this thesis, namely that the Orient step of the OODA provides the greatest area of opportunity for improvement in the CID process. It may be easy to point to a poor decision as the cause for an incorrect CID determination, but a more likely case is the human makes an appropriate decision based on the data presented and resulting SA, but the operator SA is in error. Likewise, failure to observe applicable information (perhaps due to poor interface) has consequences in the Orient step of an OODA loop.

Given the above, when considering automation to aid SA building or executing an OODA loop, arguably the most important area to consider is diagnostic automation to aid information processing. Parasuraman, Sheridan, and Wickens (2000) posited four types or stages of automation corresponding to stages of human information processing: 1) information synthesis, 2) diagnosis, 3) selection, and 4) execution. (Rice, 2009) Semantically, this again roughly correlates to activities within both the OODA and SA models used above. To be clear, this is for diagnostic automation which infer and provide some level of diagnosis of the state of the world, and ultimately "work to augment the operator's situation awareness and situation assessment." (Rice, 2009). While stage 1 aids are more for alerting the operator to important information, stage 2 aids are diagnostic in nature (i.e., aid perception) and may help alleviate cognitive workload by allowing the human to spend less time diagnosing or collating data. Many of the studies discussed below reference these four stages of automation but focus their experimentation or data collection with diagnostic aids. Note, that while stage 2 automated aids may not provide insight into the raw data the aid is interpreting. When it comes to human SA errors, consider that potential root causes may span a lack of data, poor data communication, poor data perception, or poor comprehension of the data available. This leads into a discussion of what data is available, how it is presented to a user, and the cognitive demands needed to perceive and comprehend the data.

Data Driven Decision Making

Complex and dynamic environments range from data scarce to data rich, both of which present issues. In data scarce situations, the typical response is either to obtain more data if time and conditions permit or rely upon heuristics if they do not. Data rich scenarios typically present other issues and is more the subject of this section. Decision making in data rich situations presents multiple issues which can cause an SA error. A 2002 article discusses this data overload problem and poses the concept of the "*data availability paradox*": while more data is, in principle of benefit to the user, our limited ability to sort through and interpret data can be overwhelmed, posing the problem of finding the relevant information that is meaningful to user goals (Woods et al., 2002). In short, technology often provides more data collection potential, but often lacks support for orienting to and sensemaking for decision making.

The data overload issue can be characterized as having three interrelated causes: the clutter problem or too much data to sort through, a workload bottleneck problem where insufficient time or resources are available to synthesize and make sense of the data, and finally the problem of finding significance in the data. The article discusses certain system design strategies to account for each of these data overload issues and the limitations of these strategies. Furthermore, it describes the concept of *"context sensitivity"* where a given scenario can determine the utility of any given piece of data (Woods et al., 2002). This is particularly applicable to the CID use case when each scenario is uniquely different but tends to follow a typical pattern.

For the CID use case, often many data points are available, but fusing the data into information or correlating them to the same potential target presents a challenge. Several design solutions are intended to help this problem: "scale reduction" avoids providing too much information by not reporting it to the user unless a certain trigger or threshold for the data is met; a "prioritization" approach intends to only show what is important; an "intelligent agent" design intends for the machine to determine what is important for the human. For automated solutions, a key consideration is how "correct" the automation must be to be included in the process. In many cases, the system is designed with the assumption that an automated diagnostic aid's output must be highly reliable to be useful, leading to designs that focus on system reliability rather than optimizing for human-machine teaming. Many CID systems follow these design strategies. For example, some are designed to provide an outcome to the operator only once a certain threshold or criteria is met, or a static prioritization yields only the top results from a triaged list that may not fit the situational context. Unfortunately, *what is important can change over time*. This context sensitivity makes these designs brittle for two reasons: first, unreported data that is normally unimportant may be critical in a specific scenario, and second, a piece of information that is of minimal importance currently may become critical as the situation unfolds. In short, what isn't reported may be vitally important. Such situations are not accounted for in current CID systems and therefore a human is needed to team with the CID system to account for and mitigate brittle system design.

Lastly, some pertinent design considerations provided apply to this CID thesis. First, the concept of observability alludes to a user's ability to see and understand what a CID system is doing and how it is processing the data. Typically, what a system is doing is opaque to the user, particularly when the system is designed to only display an output when specific criteria are met. As defined in this article, observability refers to "cognitive work needed to extract meaning from available data," with the test for observability being that users should see more than they were expecting or looking for – if a user only sees what was expected, the system is only displaying data. The observability principle is discussed in more detail later but relates to the second design consideration: designs must consider context and data relationships to provide real meaning. It is proposed that data only provide real meaning and information based on its relationship to other data, relationships to other reference frames, and how the data relates to the expectations and interests of the user (Woods et al., 2002). Therefore, a proposed CID system design improvement should help the human operator put applicable target ID data into context by displaying it relative to other related data, then organizing it to answer meaningful questions – in short, model-based human interfaces. A CID system that only reports the probability that a target is an enemy is still useful. However, reporting the same information compared to alternatives (e.g., probability the target is friendly or neutral) provides additional context that may improve utility for the operator.

Ultimately, this article suggests that the data overload design problem is one of what data is useful to visualize and how to make automated and intelligent systems team players. For the system designer of any differential diagnosis or decision aid, it is important to understand what relationships, events, and contrasts provide relevant information for a given context (Woods et al., 2002). Perhaps this is simply reduced to involving the user early on in system design to obtain this understanding. For the CID use case, this context is not simply a target's ID data alone. The situation always includes a combination of elevated risk, consequences, and time pressure that do not afford complicated and drawn-out decision method.

Expert Decision Making Under Time Pressure

Complex and dynamic environments often involve significant risk, consequences, and time pressure. How experts handle stressful situations often differs from that of novice performers. This observation is very applicable to the typical CID situation where novice fighter pilots are still highly trained, but lack experience. A 1986 study of Fire Ground Controllers (FGCs) found that in 80% of decision-making cases, the strategy employed by the expert FGCs (average 23 years of experience) was to use their experience to identify a situation as fitting one or more prototypical models to determine a course of action for that prototype (Klein, 1986). In analyzing these FGCs' decisions, the study attempted to characterize and document the chronology of the FGCs' SA at each decision point, along with an assessment of time pressure at the time of decision, and an assessment of several risk factors (risk to structures, risk to civilians, and risk to the firefighters). Of 156 total decision points, 122 (78%) of them were made quickly, with the decision being made in less than one minute. Importantly, it was deemed likely that most of these decisions were made in a matter of seconds. Further, the study categorized the time metric above separate from time pressure, which included a second aspect to account for some measure of risk scaled from 1 (lowest) to 4 (highest). This is because in some cases, a quick decision is made because it can be, not because it must be. Of the 156 incidents analyzed, 95 (61%) were made under the higher end (3 or 4) of the time pressure scale. Only 13 decisions were made under low (1 on the scale) time pressure, which demonstrates the applicability to the CID situation where time pressure is typical, yet patience to obtain and analyze as much information as possible can be advantageous (Klein, 1986).

A couple of notable outcomes from this study are useful for the CID use case. First, these experts tended to use so-called "recognition primed decision making" (RPD) (Klein & Thordsen, 1989). RPD is a descriptive model of decision-making which shows that rather than attending to all available information and deliberating on courses of action, experts focus on critical cues and establish accurate expectations based on their rich mental models of representative situations. It was assessed that their recognition of the situation and their resulting SA at decision points afforded the experts the ability to identify solutions immediately, allowing them to efficiently select a course of action at every decision point. Secondly, the expert's recognition of a situation as being typical, or that "x situation applies to what they are observing" is dependent on their SA, or perhaps more importantly knowing when they need more information to have sufficient SA of the situation (Klein & Thordsen, 1989). This is very applicable to the air-to-air CID use case because a highly experienced fighter pilot uses multiple sensors and observations of the battlespace context to build SA of a target's potential identification apart from CID system aids themselves. In many cases, more information is needed just like in the case of the FGCs. Likewise, CID scenarios often follow a typical script or timeline of events. Experienced aviators in this situation usually know what their next course of action is based on this timeline, or a divergence from this expectation indicates that something needs attention. This results in aviators seeking more data to explain the deviation, or the aviator concedes that their mental model is incorrect and that this SA error must be addressed. Finally, the fact that decisions are made under significant time pressure is directly applicable to an air-to-air CID situation where the entire ID process must occur in a time space that can be measured in tens of seconds. A related concept presented next is the use of automation under time pressure, namely that in instances of intense time pressure an operator tends to rely more on automation.

Before continuing onto the next time-pressure related study, it is necessary to provide a brief overview of signal detection theory (SDT), how it relates to automation, and how it applies to the CID problem. SDT deals with binary processes – signals and noise – where what you are looking for is the "signal" and everything else is considered "noise". Four basic outcomes can be measured in SDT which is viewed here from a CID perspective that becomes more a question of a true or false assertion. In this example, consider when the signal of interest is determining if the target is an enemy: *False alarms*, or Type I errors, occur when an aid misdiagnoses a target as an enemy, when in fact it is not. A *miss*, or Type II error, is when the automation fails to ID an enemy target (e.g., the target is not reported as enemy when it is in fact enemy). Two correct outcomes are *hits* (i.e., the automated aid correctly determines the ID), and *correct rejections* (e.g., automated aid correctly reports that a friendly or neutral is a non-enemy). A notable excursion of SDT for this thesis is that SDT refers to a binary output, while the CID affiliation must determine one of three states: enemy, friendly, and neutral. Therefore, to properly apply SDT for determining the CID of a given entity, one must consider each affiliation as its own binary outcome or set of "signal" and "noise": enemy vs. non-enemy, friendly vs. non-friendly, neutral vs. non-neutral. However, most automated CID aids fail to adhere to principles of observability and effectively report a binary outcome based on a "true" or "false" state that meets some level of predetermined probability (e.g., report "enemy" when greater than 80% probability that a target is an enemy, otherwise do not provide an outcome). Further applying Boolean logic to show relationships between the three ID affiliations affords viewing them in a more holistic manner, and could prove particularly useful for CID (e.g., need to determine a target is enemy AND non-friendly AND non-neutral before firing). For example, at the outset of a given air-to-air engagement, an unidentified air target should be viewed from a collective state of "enemy OR friendly OR neutral," then after sufficient data are gathered and processed to derive a CID, the target may then resolve down to one single positive outcome and two negatives. Since in any given case a target can only have one positive determination, only certain combinations of outcomes are possible. It is not the intent of this thesis to explore the full set of probabilistic outcomes from a mathematical perspective. However, understanding the relationship between outcomes is worthwhile when considering quantitatively derived probabilistic outcomes for each of the three states, and is better for adhering to the principle of observability than a single "either-or" outcome alone. Such probabilistic outcomes are effectively the reliability of the automation's ability to derive the correct outcome. This approach is used to demonstrate the utility of applying SDT to CID in a later discussion on subjective logic. Further, knowing what output combinations are not possible may help a human to quickly ascertain there is a problem or arouse suspicion when automation derives a high probability of an impossible combination. Knowing when not to trust is also important, again particularly when considering time pressure situations.

A 2009 study investigated a model of causes for operator dependence in automation, which identifies multiple influences such as trust, stress, priorities, divided attention resources, extreme consequences (Rice et al., 2009). However, the primary purpose of the paper was to introduce time pressure as another influencer in that model. It also proposed that trust is a mediator between certain external factors like reliability or observability of the automation and operator dependence on automation. The study observed participants using a simulated UAV target detection task (by extension, a CID task) with the use of a diagnostic automated aid. The test apparatus captured both accuracy and agent-human agreement rates for 100 images, 50 of which had a target present. The aid had four different reliability ratings (100%, 95%, 85%, and 65%) which were randomly assigned to participants, along with a fifth control condition with no automation assistance to the participant. Furthermore, trust questionnaires were used as an additional measure to capture participant trust levels in the automation. Two variables were manipulated during the study: automated diagnostic aid reliability, and time pressure. The data obtained showed that while trust metrics remained relatively stable during the study, changes in time pressure had a direct effect on operator reliance on the automated CID aid. This suggests that time pressure as a factor for dependence on automation is not mediated by operator trust in automation. Another finding was that operator compliance – acting in accordance with the automation's alerts – was lower when the automation was prone to false alarms (FA). Likewise, when the automation was prone to missed detections, lower operator reliance on the automation – in this case still responding when the automation failed to report an event – is the typical result. A likely conclusion is that higher reliability systems in a time pressure situation should improve team performance due to higher reliance. However, the increased reliance on automation in this study was not specific to high-reliability situations alone. Two practical takeaways are provided by the authors: First, designers of automated aids must understand the environment that the aids will be used in. Second, in cases where automation is highly reliable, the authors propose that training users within time pressure situations may have the added benefit of increasing their dependence on automation in such situations. The counterpoint is that doing so could cause derogatory effects when the automation's reliability is in question. Finally, a related consideration that warrants discussion is level of human trust in automation (Rice et al., 2009).

Human-Machine Trust Considerations for Automated CID Aids

Research on the effects of automation bias on operator compliance and reliance, again utilizing an automated diagnostic, has suggested that trust is a mediator between automation errors and subsequent user compliance or reliance. Similar to the previous study, participants in a subsequent study were required to search an aerial image of Baghdad for an enemy tank, in which they were assisted by an imperfectly reliable (ranging from 50% to 95% reliable) automated diagnostic aid to assess if a target was present. Participants were informed of the aid's reliability and any response bias (FA or miss prone) before each search task. Participant agreement with the aid and response time (RT) were metrics used to correlate to a level of trust in the automation. Data captured through a state-trace analysis strongly supported the notion that both FA-prone and miss-prone automation appear to affect at least two different cognitive processes, and in turn differently affect the operator's behavior. Overall, the study provided further evidence and expanded upon findings of the previous study, specifically 1) that FA-prone automation strongly reduces operator compliance (but also has weakly correlated effects on operator reliance), while miss-prone automation strongly compromises reliance (but also reduced compliance). The practical implication was that automation designers must be aware of the differential effects of miss-prone or FA-prone automation on human dependence and behavior. More pointedly, which is more acceptable within the context of the aid's design: missing a target altogether or incorrectly identifying targets? By extension, the authors state that "the designer's goal should not be simply to optimize behavior of the aid itself, but to elicit an optimal pattern of dependence from the aid's user" (Rice et al., 2010). In other words, the goal should be a human user centered design optimized for human-agent team performance. While these last two studies focused on SDT and trust's effect on user compliance and reliance with automation, there are several other works related to trust in automation worth mentioning.

A 2017 paper proposed a model of human-agent trust that includes multiple factors influencing trust in automation. They build off Lee and See's (2004) definition of trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Rusnock et al., 2017) This paper indicates that trust research is difficult in academic study because it is difficult to simulate true vulnerability in a controlled laboratory setting. They argue that since trust cannot be directly measured, but merely calibrated to the automation's capabilities, the goal of system designers should not be one of building for "trust", but for team performance (Rusnock, et al., 2017). Another trust calibration study of human-robot teams found that while compliance is not significantly correlated with mission-success, trust is significantly correlated with the robot's capability (i.e., reliability). Perhaps more importantly, trust in a robot when the robot self-reported its ability was highly correlated to understanding the robot's decisions and the decision making process it used (Wang et al., 2016). This is further evidence for designing automated aids to provide user's sufficient observability, as previously noted.

A third paper considers how users would handle multiple automated aids of differing reliabilities. In this aviation monitoring, all aids were for the same task but with each monitoring a different system. In this instance, a simulation of four aircraft engines, each of which were monitored by its own automated aid. Each engine and associated aid could be monitored separately, but the aid's job was to alert when an undesirable engine state existed. However, three aids were perfectly reliable, and one was imperfectly reliable. Although data captured was for a monitoring task, this study demonstrated that participants tended to treat multiple aids as one entire unit rather than as separate aids, particularly for diagnostic help to alert the user to an abnormal situation. The biggest takeaway was one of multi-aid trust: when the imperfectly reliable aid failed, the other aids were treated similarly in-spite being perfectly reliable. Also, for instances where feedback was provided, performance improved. However, provision of feedback did not increase dependence on reliable aids when compared to the unreliable ones. The implication for multi-aid use is that of "system wide trust theory" which surmises that a pull-down effect occurs where multiple aids may be treated differently because of a single aid's failures. For training and design alike, the implication is one of trust: when one diagnostic aid fails, an operator may lose trust in others even if they are performing optimally (Geels et al., 2011). Another study investigated pilot use of an automated electronic warfare aid and supports this conclusion with its finding that, "pilots consider the performance of the entire suite, not just the automated agent" and further concluded that no matter "how well designed [the automated electronic warfare aid] is, how correct and quick its algorithms are, if it is basing its decision on wrong data, the outputs will inevitably be wrong" (Ramirez, 2021). Both studies are useful for this thesis' CID use case due to the use of multiple aids that have varying capabilities, or a suite of aids built to accomplish a function like CID.

Finally, a work by Johnson and Bradshaw, *The Role of Interdependence in Trust*, augments a trust model by Mayer et al. (1995), for application to a risk-taking trust relationship decision. Figure 7 presents a subsequently adapted model that also considers factors for this thesis, specifically the addition of training and experience, time pressure, and situations when a trustor compliance or reliance upon automation makes a risk-taking relationship the default (adaptations in red text on figure 7). The Johnson and Bradshaw trust model could help calibrate human trust in automation and is useful when analyzing "as is" CID systems for any potential "to be" human-agent team design for CID. Specifically, the consideration of the situational factors and assessment thereof is necessary considering the risk factors involved in combat (Johnson & Bradshaw, 2021).

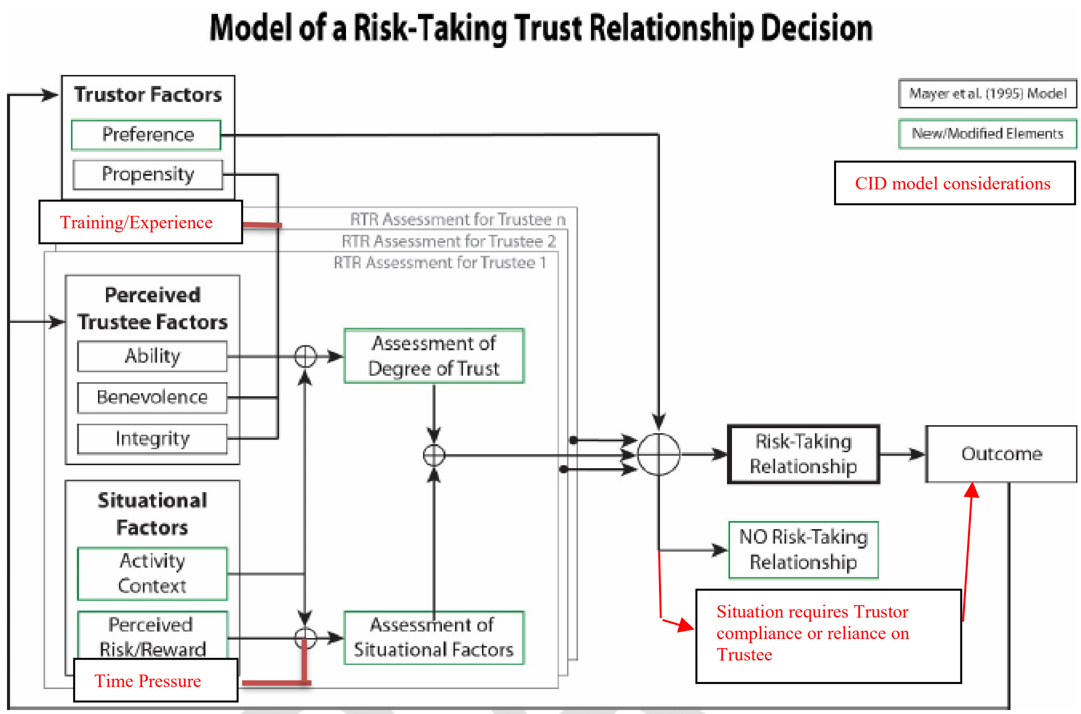

Figure 7. Risk-Trust Relationship Decisions, adapted from (Johnson & Bradshaw 2021).

Aside from those outlined above, a multitude of studies regarding trust in automation are available. However, some applicable themes and principles are perhaps best outlined in *A Taxonomy of Emergent Trusting in Human-Machine Relationships:* First, trust is dynamic, as the operational environment is dynamic. Second, trust does not necessarily develop over time, it morphs over time to account for both past performance and the current situation. Finally, trust as a concept may be alternatively termed by a lack of trust or "suspicion," which surmises a feeling of distrust, whether perceived as a state of uncertainty or one of malicious trust. (Hoffman, 2017).

Human Centered Design & Levels of Human Control for Automation

Before considering how to optimize "to be" or adapting "as is" human-agent design models, it is best to first understand the relationship between human and machine, and conceptually, how machine agent capabilities and limitations can affect that relationship. When considering automation design for human interaction, two general approaches apply- either the human accomplishes the entire task using automation only as an aid, or the task can be approached as an interdependent, human-machine (or human-agent) team. The former is most common but is rife with limitations and ironies. For example, McGarry and Parasuraman (2002) note that the more reliable the automation, the greater the detrimental effects when it fails. Regarding automation reliability, Dixon and Wickens (2006) assert that imperfect automation is manageable, as long as users are informed or trained to understand the nature of the imperfections, and even with this knowledge, once overall reliability drops below 75% – they caution that using the automation may be more problematic than beneficial (Hawley et al., 2017)

Meanwhile, when it comes to levels of automation, Norman (2007, p. 113) argued that perhaps the worst scenario is to leave operators somewhere between a fully manual and fully automated situation (Hawley et al., 2017). Current CID implementations are currently in that in-between region. To mitigate this, it is advised that operators should develop situation-specific trust in automation, while using improved SA to ascertain in which contexts to trust and which not to. The practical course of action is to couple higher operator expertise (by extension higher likelihood of high SA) with more reliable aids. How capable the automation is, and how best to use it to accomplish a given task depends on the task and level of control a human can trust it with (Hawley et al., 2017).

The concept of levels of automation (LOA) is not new. Numerous models have been proposed and applied to areas such as telerobotics, aviation, driving, and industrial processes, and most all use a similar "continuum of control" framework with multiple levels of human-machine interaction in which human control of the task decreases as the levels of automation increase (Sheridan, 1992; Parasuraman et al., 2000; Fong, 2001). In such cases, the models were primarily system-centric designs. A more recent model, LHCA, approached it from a human-centered view with the purpose of supporting human-agent teams and proposes five levels of control: Direct, Augmented, Parametric, Goal-Oriented, and Mission-Capable automation (Johnson et al., 2020). In systems with varying control levels, humans may elect to take a more active role in some situations, whereas in others the human may allow or direct the automated system to a higher level of task capability. This tradeoff between operator attention demands and an adaptable level of control is depicted in figure 8.

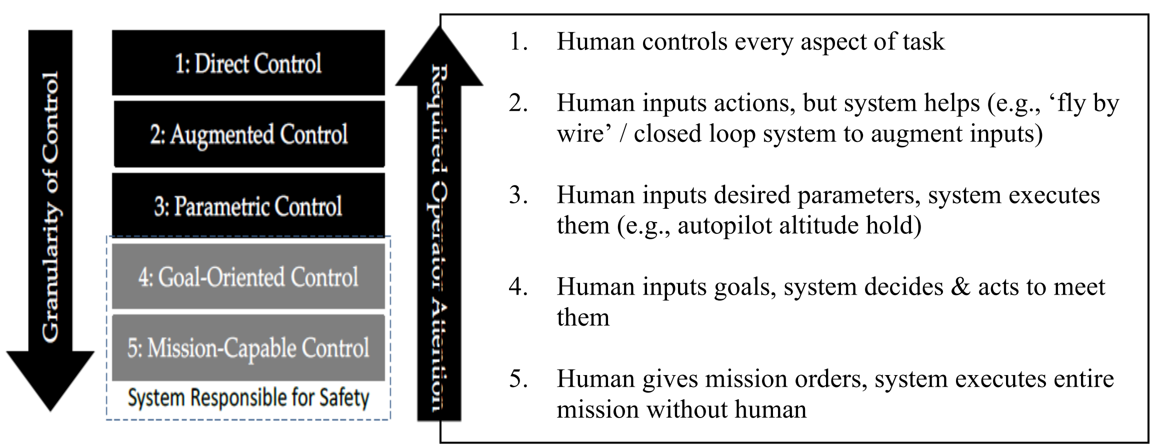

Figure 8. LHCA with aircraft use case examples, adapted from (Johnson et al, 2020)

In this paper, the LHCA model was applied to unmanned aerial systems (UAS). One notable takeaway was an assessment of nine air and ground-based vehicles' LHCA abilities, where only two were capable of a level four or five LHCA. However, a limitation was that this study's framework was for interaction with vehicle control systems, not a CID task. To demonstrate extension to a CID task, Figure 9 proposes how a vehicle control system and CID system have some parallels in LHCA. The study also notes that as LHCA increases, the decreased human attention allocated to that task may actually lower SA but affords greater attention to higher-level tasks. This may or may not be good for the CID use-case. Finally, this framework proposes that LHCA should be considered as single, instantaneous system states for a given task. What is not discussed is whether a given vehicle control system's LHCA should be applied to a single step of the OODA (or control) loop or across the entire OODA loop. This CID thesis asserts that certain CID systems are built to aid the user in completing a higher-level decision loop (what is the ID of a target?), but in practice only provide utility across certain steps of the OODA. For example, a system obtaining CID information (Observe) may in fact be capable of LHCA 4, but once that CID information has been obtained and reported, that system's task is done. A related CID system may be built to aid with making sense of the reported data (Orient), but in most cases those system designs are limited to only LHCA 3 at best. An unanswered question outside the scope of this thesis is whether the LHCA for any autonomous system-of-systems is limited to the lowest LHCA of any subsystem as suggested in the original publication, and whether or not that LHCA determination need apply across an entire OODA loop. Conversely, an autonomous system-of-systems could be designed as goal or mission oriented but be composed of multiple subsystems that are limited to parametric control or lower.

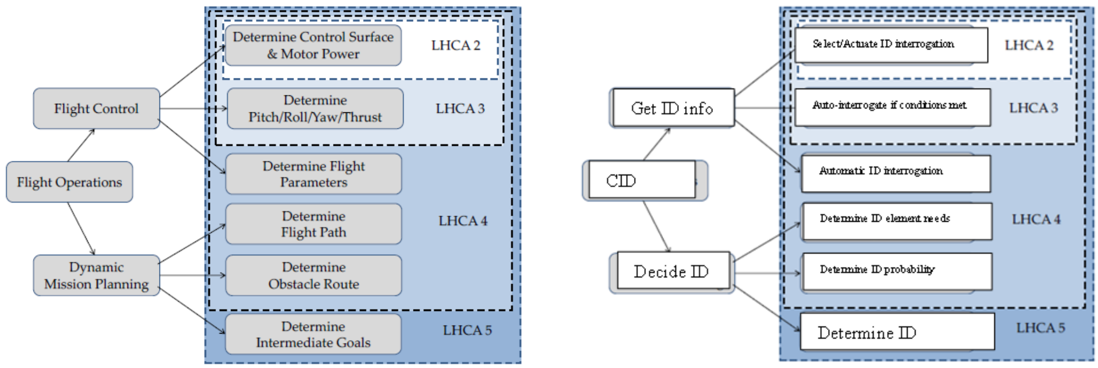

Figure 9. Vehicle Control LHCA Versus CID LHCA Comparison, adapted from (Johnson et al., 2020)

The limitations of the proposed LHCA paper are one area this CID thesis seeks to question. As mentioned in Chapter 1, it is hypothesized that certain CID systems are built to conduct tasks that aid the human with a higher-level decision (e.g., what is the ID of a target?) but are only capable of providing utility across certain steps of that OODA loop. For example, a system or automated aid that obtains CID info (Observe) may in fact be capable of performing its task at LHCA 4. Once that CID info has been obtained and reported, that aid's task is complete even though the human-automated team has yet to ascertain a consensus for the overall CID task. However, a different CID aid may be built to help with the subsequent part of the overall CID task by making sense (Orient) of the previous aid's reported data, but in most cases such system designs are limited to only LHCA 3 at best. What is the appropriate LHCA for this combination of automated agents? In any case, contemplating the answers to such questions may help designers of complex systems to develop a more human-centered, team design. What follows is discussion of some related works on that topic, as well as modeling to meet that intent.

Human Centered Design & Modelling

The first work reviewed in this section was a collaborative study by the Air Force Life Cycle Management Center (AFLCMC), Air Force Research Laboratory (AFRL), and AFIT that considered use of Model Based System Engineering (MBSE) to assess human-machine teams for Command and Control (C2) in military aviation. Its aim was to consider the problem for application to future system design. It begins with an overview of the OODA loop, then describes the area of technical development interest: C2 of UAVs and “autonomous” wingmen. It termed machine agents as MA’s, and MA’s intended for use as decision aids as knowledge-based agents (KA’s). Next, it utilized SysML designed mission area diagrams (MAD) and OODA diagrams to evaluate the physical and cognitive tasks the teams must achieve, then subsequently modeled the “as is” and “to be” systems. It assessed the tasks by mission phases for both human and automated actors for the MAD, but also did so across the OODA diagrams. Some interesting results occurred (LaMonica et al., 2022).

For the first of two tasks analyzed – analyze and evaluate workload capacity of candidate workload operator – three major human-machine teaming concerns were identified in the “as is” system: 1) “an excessive amount of cognitive activity is required from the human agent in the Orient stage,” 2) “a lack of machine agent assistance during the Orient, Decide, and Act phases of this task,” and 3) four potential points of error were highlighted, two falling in the Orient stage, and one each for Decide and Act (LaMonica et al., 2022).

The second task evaluated was to request transfer of a UAS. Very quickly, the authors realized that this task is actually composed of three distinct OODA loops. The finding, similar to the first task, was that "during the Orient and Decide phases, there is no KA assistance provided to the human agent" who is then prone to 11 potential points of error. The conclusion for this, and for task one, was assistance from additional KA's might improve OODA performance for both tasks. A visual depiction of the second task is shown in Figure 10, where the red box on the left side of the figure shows the dearth of automated help to the human and 11 points of potential error in blue boxes for the "as is" system, and the green boxes on the right side show a potential area for improved human-agent design in a "to be" system (LaMonica et al., 2022).

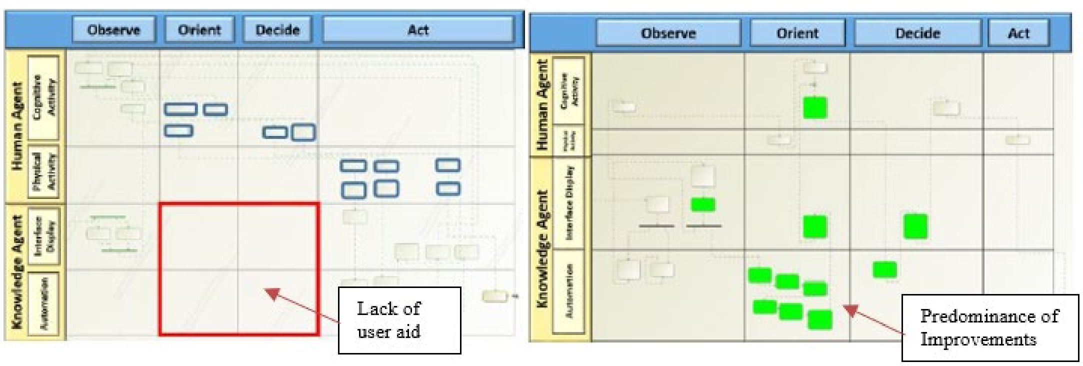

Figure 10. As-Is (left) and To-Be (right) UAS Transfer Task Model, adapted from (LaMonica et al., 2022)

While this research has yet to be field tested to show more authoritative results, simulation of the "to be" system yielded improvements in decision speed (total elapsed time for both tasks decreased from 10.22 seconds to 3.62 seconds), while identified potential error points decreased from 15 total in the "as is" system to only 2 in the "to be" system. A key overall conclusion was that the task breakdown across the individual

OODA stages allowed the researchers to highlight the excessive workload on the human agent in certain stages paired with the lack of KA help. Decomposing the tasks for both human and machine remained consistent to the four-stage information processing (or decision making) model that aligns with the OODA loop and supports the utility of using this approach for future research or system design evaluations. (LaMonica et al., 2022)

A 2013 research project by Idaho National Laboratory aimed at developing the Human Automation Collaboration (HAC) model for advanced small modular reactor (aSMR) control and monitoring tasks. It accomplished probably the most thorough academic review of existing literature reviewed for this thesis, including many of the sources already described above. From the existing literature considered, it recommends trying to keep the human in the loop for most functions by utilizing intermediate levels of automation. For their problem set, aSMRs employ human machine interfaces and advanced digital instrumentation and controls. For such complex systems and research of their operations, they note from observations that operator performance can become significantly degraded when working with highly automated systems due to loss of awareness at the system's state, increased workload required to regain awareness to recover from system failures, and also loss of skills to manually accomplish tasks that have been predominantly taken over by automation. While not directly related to CID systems, aSMRs employ a similar functional architecture of subsystems to accomplish the following tasks: sensing, monitoring, automation & control, communication, and human-system interface. Also of utility was the study's view that multi-agent teams are needed to accomplish the overall task, where the term agent may apply to a human, software, or hardware element that must work together in coordination. An example of this multi-agent setup is shown in Figure 11 but has been adapted to match the CID use case in this thesis. Note how the generic primary tasks follow an OODA loop, then requires correlating those agent interactions prior to interface with the human- this implies the importance of human-system interface design, particularly if automation is used as part of this process (Oxtrand, et al., 2013).

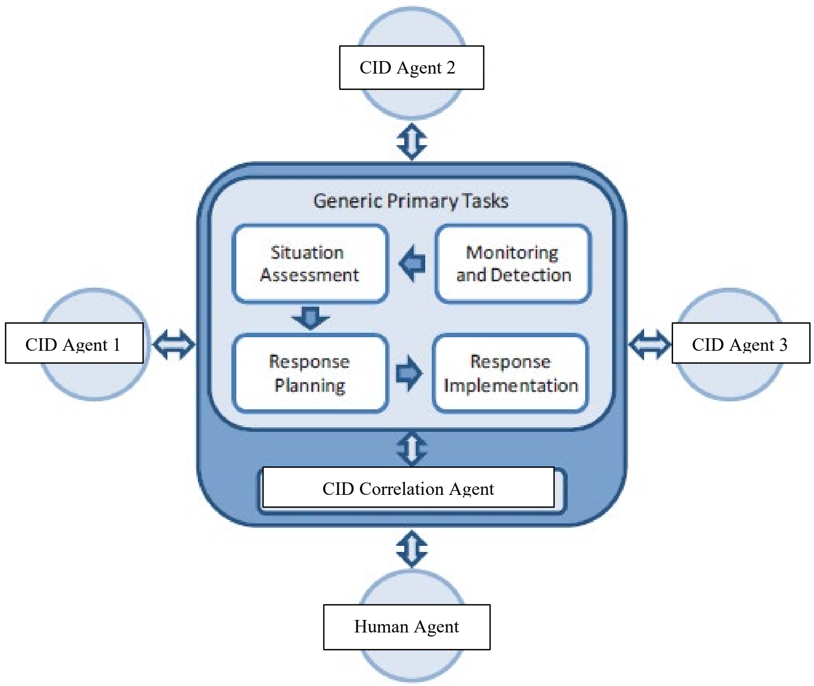

Figure 11. Human Automation Collaboration Model for CID, adapted from (Oxtrand et al., 2013)

Another useful takeaway noted by the Idaho National Lab team came from a study by O'Hara and Higgins (2010), which characterized automation as having six dimensions: level of automation, cognitive function, processes, modes, adaptability, and reliability. Level of automation, reliability, and cognitive function (i.e., information acquisition, diagnosis, selection, and execution, from Parasuraman, et al. 2000) have already been described, but an extremely worthwhile proposition is level of automation recommendations based on reliability across cognitive function as depicted in Figure 12 (Oxtrand, et al., 2013).

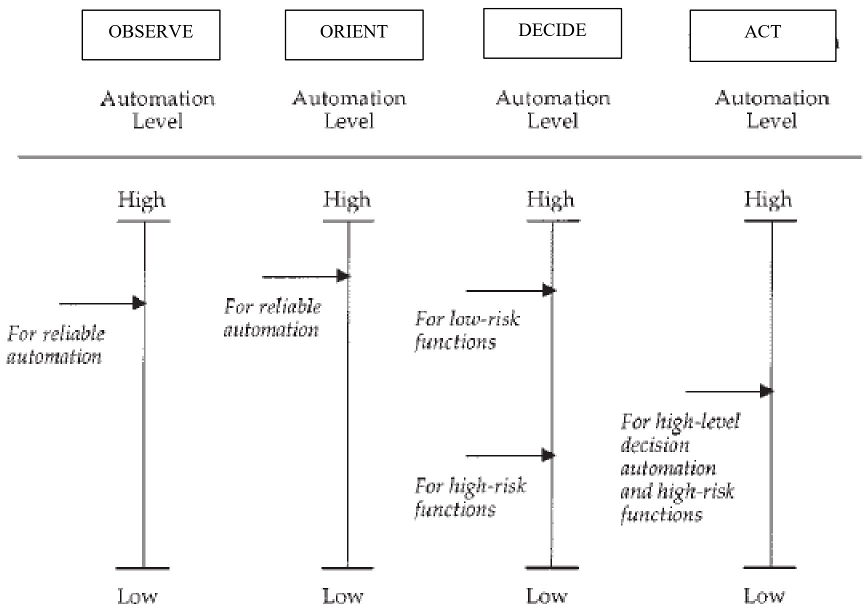

Figure 12. Recommended Levels of Automation Control, adapted from (Parasuraman et al. 2000)

The reason Figure 12 is useful for aSMRs is because of any risk level for failure in nuclear accidents is not tenable. This makes it an excellent corollary to the CID use case where risk levels can vary, but often result in high-risk situations. Perhaps one conclusion if following this recommendation is that for conducting CID, an ideal human-agent team is one that allows the human to adaptively direct the level of automation based on risk level and observed reliability for a given situation.

The remaining three dimensions of automation need definition. Process includes understanding of the process that is being automated such as control logic, decision logic (e.g., Boolean outcomes based on input), or other information processes. Modes describe mutually exclusive states or the systems focus to accomplish different tasks, though modes should not be confused with different levels of automation. An example provided was a navigation application that automates a route, but may be in a pedestrian mode for walking, or in a driving mode for vehicle use. Finally, adaptability considers an automation design that is not static in how the team of agents accomplishes the task (Oxtrand et al., 2013). Stated differently, the team may decide the best approach wherein the automated agent or the human agent may be the primary executor for a given task, based on available workload or task efficacy. Understanding the preconditions that trigger these adapted responses is a worthwhile consideration when designing a team. For example, what observed conditions will elicit a flag to the operator that recommends whether a machine or the human should take the lead for the task.

Ultimately this study's HAC model diagram is unnecessary to depict in detail, but its list of design considerations and mediators is worth sharing. For the design, it recommends considering the list of six characteristics from O'Hara and Higgins (2010), in addition to system degradation. For mediators, the study lists human-system integration, additional task load, and unexpected conditions as necessary considerations in a HAC system design for aSMRs (Oxtrand et al., 2013). The next set of research on co-active design and interdependence is perhaps one of the most important for the CID human-machine design approach. It incorporates many of the takeaways spanning the research described above, and the interdependence analysis was central to the methodology used for the use-cases in this CID thesis.

Interdependence Analysis and Co-active Design

A 2014 paper on Co-active design method (along with a related 2018 paper on interdependence analysis by the same primary author) by Johnson et al. argues for "a human-robot model that supports interdependence" by carefully attending to the observability, predictability, and directability (OPD) for automated agents teamed with humans. The study starts with the aim of supporting teamwork, and by extension the need for trust between agents on the team. It also states that any significant collaboration "cannot be fully addressed through mere task decomposition and allocation" (Johnson et al., 2014). Rather, at the center of collaborative activity is a joint human-machine team approach to critical tasks that is made possible by effectively managing interdependence. This concept of interdependence should not be reduced to simply mutual dependence. For the purposes of co-active design, the given definition for interdependence is "the set of complementary relationships that two or more parties rely on to manage required (hard) or opportunistic (soft) dependencies in joint activity" (Johnson et al., 2014). This set of dependencies is reliant upon capacity of a given agent (machine or human) capacity to accomplish a given task. The management of such relationships between humans and automation is then contingent upon the system design's OPD. The paper defines observability as the ability to observe and interpret pertinent signals, predictability as the ability to rely upon another agent's actions when considering their own, and directability as the ability to influence behavior by directing (or be directed by) others in a complimentary way (Johnson et al., 2014).

Notably, co-active design incorporates OPD as an extension of a model by Fong (2001), but also distinguishes itself by focusing on team functions to support interdependence rather than individual functions. To reduce the co-active design model to its simplest form is three interrelated processes: an identification process, a selection process, and an evaluation of change process (Johnson et al., 2014). Of these, this CID thesis implemented the identification process, more specifically by accomplishing an interdependence analysis (IA) of the hierarchical tasks and subtasks presented by the CID process. However, a better understanding of interdependence combinations and the associated color schemes is best explained with the following figure and table. Figure 13 depicts a color scheme for alternative performer and supporting team member role. Note that the performer and supporter could be either human or machine, and a full IA necessitates analyzing both in each role, respectively.

Color Key for Team Member Role Alternative Capability Assessment	
Performer	**Supporting Team Members**
I can do it all	My assistance could improve efficiency
I can do it all but my reliability is < 100%	My assistance could improve reliability
I can contribute but need assistance	My assistance is required
I cannot do it	I cannot provide assistance
Not applicable / Not significant	Not applicable / Not significant

Figure 13. Team Member Capability Assessment Key (Johnson et al., 2018)

While the color codes for performer and supporting team member are self-explanatory, the combinations when put together are not. For example, a green or yellow performer and an orange supporting team member is an invalid combination- since the performer can accomplish the whole task, assistance is not required. However, that does not mean that teaming should not occur if the supporting teammate may improve efficiency or reliability (green or yellow supporting team member). This is an example of employing interdependency to address a soft constraint or soft dependency. Use of the terms constraint and dependency here might be interpreted by some engineers as a required design consideration, but the intent is that an optional teaming opportunity exists which may improve performance efficacy under at least some circumstances. As such, the phrase “team opportunity” is perhaps the more appropriate, and is used interchangeably with soft constraint. In contrast, a “hard constraint” or dependency is more aligned to traditional engineering parlance where a design or process must consider teaming as a design requirement to enable successful task performance. This is for instances where the assessment for the performer is orange, or anytime the supporting team member’s assessment is orange- in short, the performer requires help, or the supporting team member’s assistance is required. Interestingly, it is possible for combinations where both hard and soft constraints exist simultaneously. Finally, tasks for which the performer is red cannot be accomplished. Table 1 below depicts these combinations using the color definitions from Figure 13 (Johnson 2018).

Table 1. Performer and Supporting Capability Assessment Combinations, adapted from (Johnson et al, 2018)

Performing Agent	Performer Notes	Supporting Agent	Teaming Notes
	Task can be achieved alone		Soft Constraint/Opportunity
			Performing agent must act alone
	Teaming recommended if available		Soft Constraint/Opportunity
			Performing agent must act alone
	Hard Constraint		Soft Constraint/Opportunity
			Hard Constraint
	Task unachievable		Task unachievable
	N/A		Teaming relationship is N/A or insignificant for task

With an understanding of the color key and teaming capability assessment combinations, an IA can be performed, a process depicted in Figure 14. The first step requires a larger task decomposition, which is represented by the number one, Model of Joint Activity in Figure 14. After decomposing into the specific tasks and subtasks of the activity, those tasks can then be given a capability assessment using the colors and combinations in Figure 13 and Table 1. This is represented by the number two, Assessment of Potential Interdependence. Finally, these are used to Analyze Potential Workflows, represented by the number three (Johnson et al, 2018).

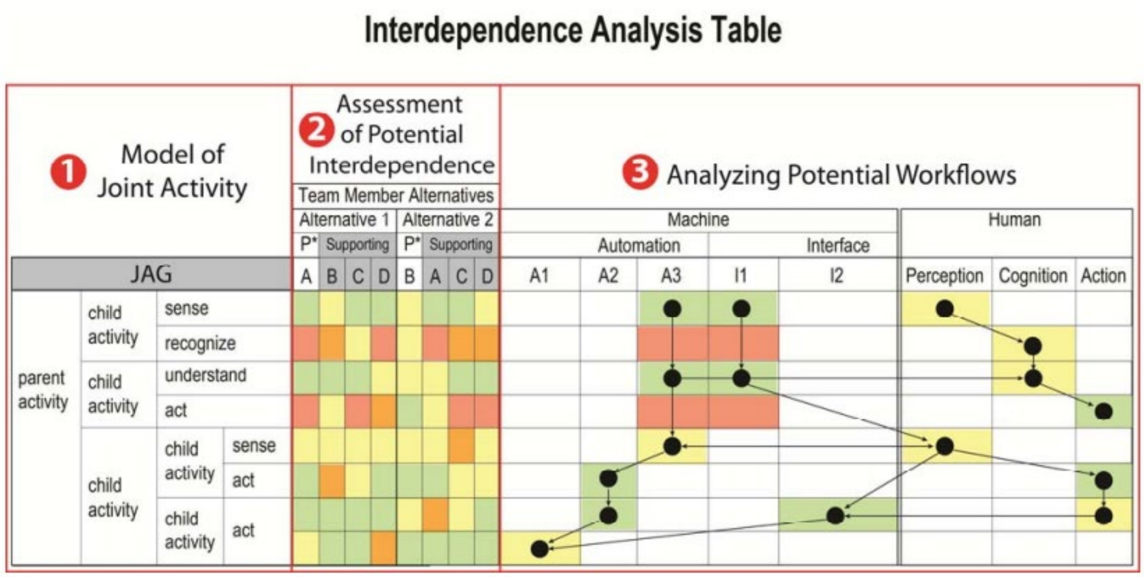

Figure 14. Interdependence Analysis Process Table (Johnson, et al., 2018)

Once again, recognize the congruence of terminology used within the IA table (e.g., sense, recognize, understand, act, perception, cognition, action) compared to observe, orient, decide, and act. Ultimately, the OODA terms are used within this thesis to maintain consistency of terminology. The OODA loop, situational awareness, trust, automation design and analysis of interdependence have now been addressed. The last section of the literature review is dedicated to a potential means of incorporating many previously discussed principles through a more quantitative means that retains context and affords improved observability for decision making: subjective logic.

Subjective Logic for Information Fusion

The final portion of literature review considers applying subjective logic to CID. The concept of subjective logic is over twenty years old and is described to a paper titled *Consensus Operator for Combining Beliefs* (Jøsang, 2002). This approach was extended to evaluate its use for trust modelling in information fusion. The original paper considers a mathematical approach to determining a consensus for a given hypothesis, where any single opinion of the hypothesis is necessarily composed of belief, disbelief, or uncertainty about any given hypothesis. In the realm of probability and statistics, a method commonly used is Bayesian theory for situations with a binary outcome. Subsequently, for information fusion purposes Dempster-Schafer theory for evidences builds upon the Bayesian approach, which affords modeling of situations that have more than two outcomes. However, this theory has been criticized as having a less-than-intuitive results (Håkansson, 2005). Jøsang's theory of subjective logic, as it is rooted in Bayesian theory, is tied to binary outcomes mathematically, and therefore results in a system of equations to incorporate the multiple outcomes.

For context of the problem behind information (or data) fusion for intelligence, Håkansson cites information fusion as a means "to perform assessments of identities, situations, and threat potential based on information derived from multiple electronic and intelligence sources" (Bisantz et al., 1999). Subsequently it is also noted that "current attempts to bring more information to commanders are doomed to failure due to cognitive overload" (Yu et al., 2004). Applying the subjective logic to trust modelling equates "trust" to "belief" for a given hypothesis, "mistrust" to "disbelief," and "ignorance" is then defined as a lack of knowledge whether to trust or distrust. Having introduced these three outcomes, the mathematical equation that considers subjective logic follows:

$$\omega_p = \{b_p, d_p, i_p\} where\ b_p + d_p + i_p = 1.0 \quad (1)$$

Where ω_p is a given agent's opinion, b_p is that agent's probability of belief, d_p is the probability of disbelief, and i_p is the probability of ignorance. This can then be applied to combine two beliefs using the following equation:

$$\omega_p^A \oplus \omega_p^B = \begin{cases} b_p^{A,\ B} = \frac{b_p^A i_p^B + b_p^B i_p^A}{k} \\ d_p^{A,\ B} = \frac{d_p^A i_p^B + d_p^B i_p^A}{k} \\ i_p^{A,\ B} = \frac{i_p^A i_p^B}{k} \end{cases}$$
$$where\ k = i_p^A + i_p^B - i_p^A i_p^B\ such\ that\ k \neq 0. \quad (2)$$

Where ω_p^A is the opinion of agent A, and ω_p^B is the opinion of agent B. These opinions through this set of equations then may be used to combine the two opinions for each of the outcomes b_p, d_p, and i_p respectively (Håkansson, 2005). For the purposes of this study, it was assumed that k would always be greater than zero, as a zero k assumes an agent with 100% reliability, and a perfectly reliably system is unrealistic for current technology levels. In summary, this allows combining multiple opinions (or levels of trust, or reliability) for multiple agents, and can be used in sequence (e.g., agent A+B, then C+D for a composite of the four). However, one diagram that could be adapted to provide a graphical output for CID purposes is shown in figure 15, and shows the subjective logic output for a hypothesis graphically. For this hypothesis the three outputs of belief, disbelief, and ignorance are shown each with their own axis, making a triangle. Conceptually, as these elements for a consensus ω_p, that consensus (here represented by a red dot) will begin to shift toward the consensus direction. In the case of figure 15, this is belief in the hypothesis. Such a graphical depiction may provide a more convenient or easy to process means of displaying the consensus outcome for some human users.

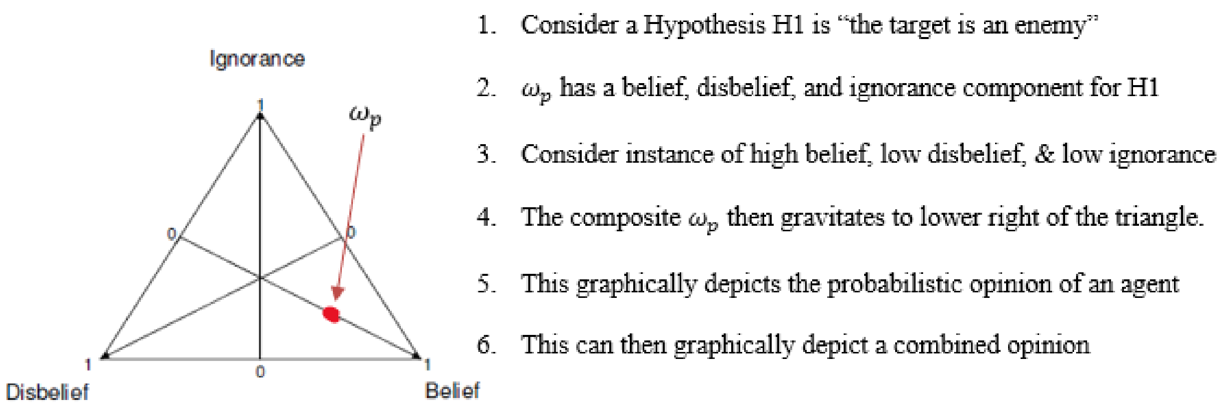

Figure 15. Graphical Subjective Logic Output for Notional Enemy CID Use Case, Adapted from (Håkansson, 2005)

Summary

Even when simplified, the CID problem set is a complex, interdisciplinary problem set. It considers decision making, large data sets, external pressures of time and risk, human-machine teaming, trust in automation, multiple automated agents, and human-machine interface design. How best to tackle and model this interdisciplinary problem for CID is the purpose of this thesis and is described in the methodology chapter below.

III. Methodology

Chapter Overview

This research required a multi-faceted, multi-step process to accomplish all three objectives. The first objective required two steps: 1) an IA of the CID process to model human-multiagent team, and 2) the CID process was then modeled in SysML as an activity diagram and other supporting views. Objective one results also supported objective two. The second objective of this research accomplished two things 1) it utilized objective one outputs, and 2) creation of two "cognitive maps" (CMAP) to better understand a) the interaction of events and data sources in the CID process, and b) explore parallels between human and machine information processing. Finally, the third research objective sought to incorporate subjective logic into the CID process, resulting in four deliverables: 1) a MS Excel subjective logic model, 2) recreating the MS Excel model within SysML using parametric diagram and instance tables, 3) creation of several scenarios to demonstrate application of subjective logic for the CID problem set, and 4) a notional human-machine interface to graphically depict the outputs while also adhering to the principle of observability. Assumptions and limitations are discussed within each objective's section below. Due to the multi-faceted, multi-step approach of this methodology a CMAP was created to depict how the hypotheses tie to the objectives and deliverables. It is shown in figure 16 below.

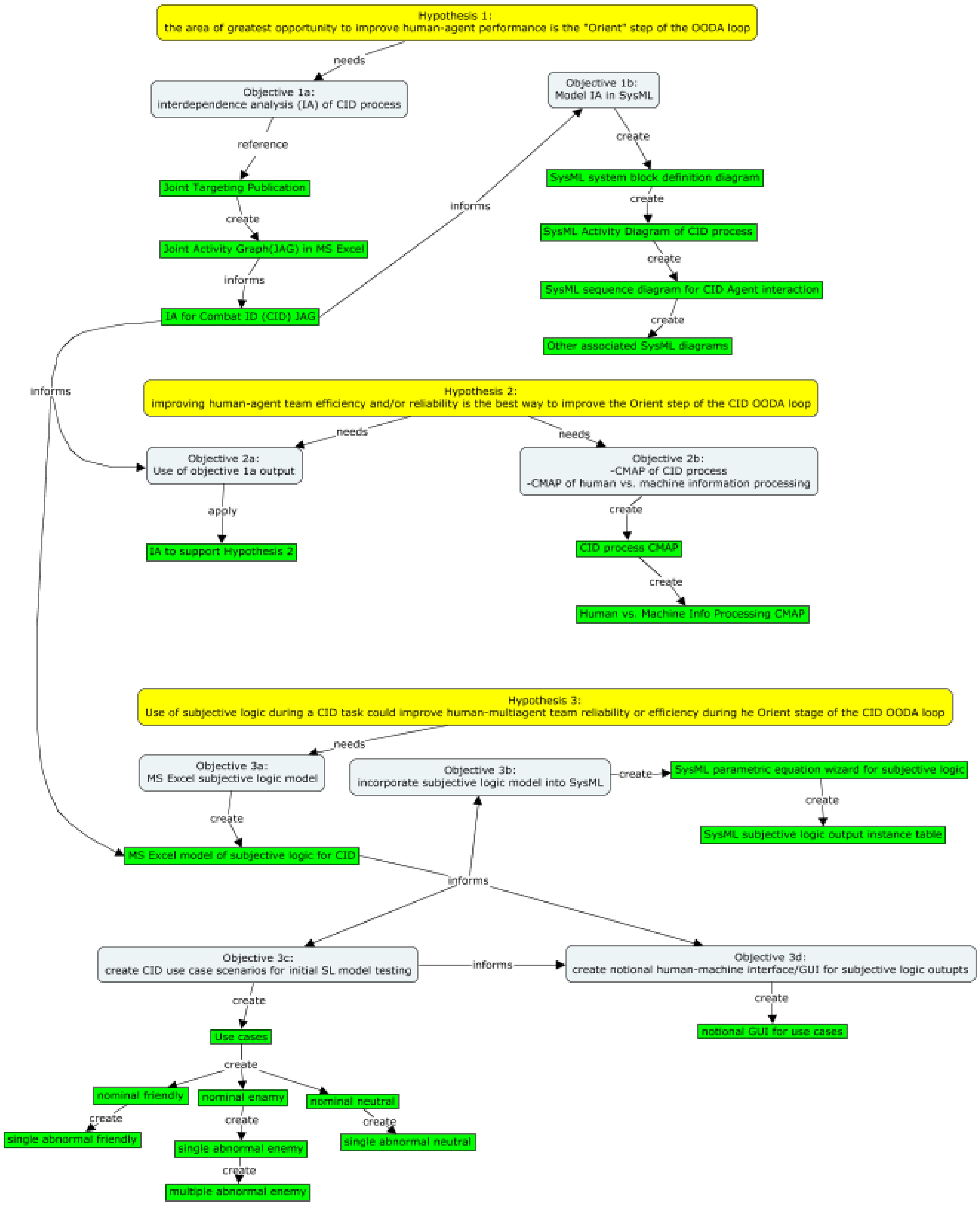

Figure 16. CMAP of Methodology process and deliverable flow diagram.

Overview of Objective One Methodology

Accomplishing the IA for objective one began by referencing the Joint Publication 3-60, Joint Targeting (2013), Chapter 2 which describes the task and subtask needed for the CID process- specifically, phase 5's mission execution, and the "Fix" and "Track" steps of the F2T2EA process. This doctrinal reference was then combined with expert domain knowledge of air-to-air targeting steps to further identify capacities needed for each subtask. This provided the framework for Joint Activity Graph (JAG) step of the interdependence analysis and was developed using MS Excel. The resulting list of task, subtask, and required capacities is depicted in the analysis and results chapter.

Following this, the JAG process was continued by adding columns for the performing and supporting agents. For the purposes of a supporting agent, all CID "sub-agents" were considered as a single composite. However, to capture their unique capabilities and limitations, each CID sub-agent is accounted for to depict IA for each of the OODA loop steps across the CID process. Performance capabilities for performing and supporting roles were then assessed. This aligns to the second step of the JAG process. Of note, one change made to the JAG for the purposes of this thesis was to align terminology to the OODA loop: perception was replaced with "observe," cognition was replaced with "orient" and action was replaced by "decide/act" since the action of note in the CID process is itself the determination or decision of the target's ID. Next, the roles for performing and supporting agent were swapped (i.e., CID agent composite as the performer, human agent fulfilling supporting team member role). Visual depictions of these outcomes are shown in the analysis and results chapter.

Limitations imposed for this study include conducting the IA only for an "as is" system based on expert knowledge of certain fighter aircraft, fighter aircrew performance capabilities and limitations, and the technical CID capabilities available for certain CID tasks. Also of note, for security classification reasons these CID agents are simply labeled A, B, C, D, and a correlating CID agent. Specific aircraft or ID agents are specified within this thesis aside from that of identify friend-or-foe (IFF) whose conceptual use is discussed at length in unclassified, open-source literature. Furthermore, assessed performance capabilities for the CID agents in this IA are generalized across a nominal CID situation, but is sufficient to demonstrate their use for teaming. Further assumptions and limitations for the IA in objective one is depicted in Table 2.

Table 2. Assumptions and Limitations for CID Interdependence Analysis

ASSUMPTIONS	
	the "FIND" task (search, initial detection, sensor allocations) is complete and we are now in the "FIX" stage
	initial "locate" part of the "FIX" step is complete, only correlation of ID with the location is needed
	multiple agents are available for the ID task, all with varying levels of efficacy for different aspects of ID determination
	an interface exists between agents and human so that human observations can use the agent output/display
	ID can be correlated to location or some geometric relationship (e.g., angle to target only, but no range)
	Capability to ID a given friendly vs. enemy vs. neutral varies across CID agent
LIMITATIONS	
	limit agent/sensor use to ID functions only (e.g., not location fixes)
	limit this to an air-to-air task only
	target prioritization not accounted for directly
	time pressure not accounted for directly
	restrictions/deconfliction not accounted for directly
	riks/consequences of decision not accounted for directly
	reward of decision/success not accounted for directly

For the second deliverable of objective one, JAG task and subtask breakdown was used as a baseline to develop a SysML activity diagram of the CID process. This required a more thorough system model of the activity, which includes embedded sequence and activity diagrams at a more detailed system or subsystem level. The intent of this was to portray certain agent interactions, interfaces, or data flows. Depictions of the SysML diagrams are included in the analysis and results chapter.

Overview of Objective Two Methodology

Objective two sought to investigate support for the hypothesis that the preponderance of difficulty and cognitive workload occurs during the "orient" step of the OODA loop and was done in two ways. First, the IA made in objective one already provided an analytical review of the process that breaks down steps of the CID OODA loop at the level of subtask and required capacity and is discussed in the analysis and results chapter. Secondly, expert domain knowledge was used to create a cognitive map of the CID process separate from the IA JAG. The intent was to reproduce the process from expert operator experience rather than direct from doctrinal processes to note if any significant differences exist while also capturing the process flow and inter-relationships to compare to the the SysML activity diagram. This CMAP was created using the Florida Institute for Human and Machine Cognition (IHMC)'s CMAP software tool, and shown in the results and analysis chapter. One limitation for this aspect of the study is that the expert knowledge of the process is subjective in nature and informed by experience, meaning it could differ slightly from one expert operator to another, although the expected the result is that each should be relatively similar. In both cases, the results should support the hypothesis that the preponderance of cognitive workload is tied to the "orient" step of the OODA and occurs before final CID determination.

The second part of objective two was to identify potential limitations or opportunities of a human-machine team conducting CID. Identifying these touchpoints should either inform "to be" system designs, or areas where focused training may help optimize team performance. automation capabilities. More specifically, this part of objective two helps to identify likely limitations and opportunities for automated agent design, as well as areas for human-agent team training. Once again, this used the IHMC CMAP tool to depict human and machine information processing side-by-side and is shown in the analysis and results chapter. For each part of the information processing OODA, required capacities, supporting elements, and human or machine limitations were considered.

For both objective two CMAPs, a significant limitation is that this was informed by the author's own experience, literature review, and research within this thesis. Therefore, these CMAPs may not be all inclusive and could also harbor some level of bias, even if unintended. A more thorough approach would include a multitude of experts from related domains of cognitive science, computer science, human factors, and military aviation or command and control who have insight into the CID process. However, as this cognitive mapping was only one non-critical consideration for this overall thesis, capturing similar CMAPs from a multitude of experts was deemed out of scope due to time limitations and perceived return on investment.

Overview of Objective Three Methodology

The intent of objective three is to support the hypothesis that using subjective logic with CID agent outputs could improve reliability or efficiency of the human-agent team, and thus improving overall CID task execution. This necessitated four sequential steps to meet this intent.

First, the subjective logic equations discussed in the literature review chapter were input into MS Excel and adapted to align with the CID agents assessed in the IA for later comparison. This consisted of three hypotheses (H1, H2, and H3), one per row, about the CID of a given target: H1 is "friendly," H2 is "enemy," and H3 is "neutral." Next, each

CID agent was given a column for “belief,” (B) “disbelief,” (D) and “ignorance” (I) to apply to each identity hypothesis. This requires nine total inputs for each CID agent. Additionally, the concept of atomicity was applied and utilized in the subjective logic equations. In this instance, an atomicity of 1/3 is used given only three possible CID outcomes (friend, enemy, neutral). The CID agents’ subjective logic inputs were then mathematically combined two at a time. This gave an agent A+B consensus, and a C+D consensus. These two consensuses were then combined for an overall quantitative consensus belief, disbelief, and ignorance across all four agents, for each of the three hypotheses. The resulting MS Excel model now allows for changing B, D, and I (henceforth BDI) for H1, H2, and H3 for a given use case. A noted limitation is that ignorance was always assumed as a non-zero quantity in order to maintain the same system of equations, and also because it is rarely the case that any automated agent has 100% reliability (belief or disbelief) for a given scenario. Additionally, to avoid skewing results when simulating an ID agent having no data or opinion for a given hypothesis, BDI were all given the same value of 1/3: 0.33 for B, 0.33 for D, and 0.34 for I. This also ensures all BDI inputs consistently add up to 1.0 for each hypothesis. For convenience, a depiction of this subjective logic table for a nominal friendly use case is shown in Figure 17 below, but further discussion is reserved for the analysis and results chapter.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.900	0.000	0.100	0.333	0.600	0.100	0.300	0.333	0.8919	0.0270	0.0811	0.333	k =	0.37
H2	Enemy	0.000	0.900	0.100	0.333	0.100	0.800	0.100	0.333	0.0526	0.8947	0.0526	0.333	k =	0.19
H3	Neutral	0.000	0.900	0.100	0.333	0.200	0.700	0.100	0.333	0.1053	0.8421	0.0526	0.333	k =	0.19

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.330	0.340	0.333	0.800	0.000	0.200	0.333	0.7161	0.1398	0.1441	0.333	k =	0.472
H2	Enemy	0.330	0.330	0.340	0.333	0.100	0.500	0.400	0.333	0.2748	0.5000	0.2252	0.333	k =	0.604
H3	Neutral	0.330	0.330	0.340	0.333	0.100	0.400	0.500	0.333	0.2970	0.4493	0.2537	0.333	k =	0.67

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity		
	belief	disbelief	ignorance					belief	disbelief
Friend	0.874	0.071	0.055	0.333	k =	0.21347	Friend	89.2%	9.0%
Enemy	0.099	0.856	0.045	0.333	k =	0.26595	Enemy	11.4%	87.1%
Neutral	0.145	0.810	0.046	0.333	k =	0.29301	Neutral	16.0%	82.5%

Figure 17. Instance of Subjective Logic Model for CID in MS Excel

The second deliverable for objective three was replicated the subjective logic equations in SysML. The parametric equation wizard was used and in turn an output of this parametric equation wizard is created an instance table. Due to the nature of the parametric equation wizard within SysML, a specific variable for each hypothesis (H1 through H3), each agent, and each consensus was required. While more elegant solutions may exist, optimizing this aspect of the model within SysML was not needed.

The third part of objective three intended to provide a limited validation and verification of subjective logic outputs for the CID use case. To do so, seven CID scenarios were developed: 1) nominal friendly, 2) nominal enemy, 3) nominal neutral, 4) enemy with a single abnormal agent output, 5) friendly with a single abnormal agent output, 6) neutral with a single abnormal agent output, and 7) enemy with multiple abnormal agent outputs. The term "abnormal" may include a system malfunction (e.g., the sensor that provides the data to the agent has failed), instances where the ID agent has ambiguous results (e.g., quantitative outcome supports belief in more than one hypothesis), or instances where fog of war or enemy action confuse an agent (e.g., the enemy is jamming or spoofing an ID agent's sensor). For each of these seven instances, multiple chronological subjective logic inputs were created. For example, early in the CID process only one CID agent may have a valid result. This progresses to more than one CID agent having a valid result, and finally terminates at a point where all CID agents have valid results. Such a progression was chosen to demonstrate how the consensus belief and/or disbelief progresses as additional agents provide input. Several limitations are noteworthy. First, since the data to demonstrate these are manually created combined with large number of inputs across all enemy, friendly, and neutral hypotheses (36 inputs in total), only enough use cases were made to demonstrate the utility. Second, the progression of these use cases is static in nature, while the CID process and agent outputs can often change more dynamically over time. Therefore, the full spectrum of validation and verification was limited in scope. Next, the agent inputs were not informed by real sensor or CID agent data. However, this was also a necessary limitation for security reasons- since CID agents are only labeled A, B, C, and D, care was taken to avoid using actual CID system performance by using notional values. However, values used are still representative of the scenarios chosen, and enable demonstrating the utility of subjective logic. Depictions of these CID use cases are provided and discussed in the analysis and results chapter.

Finally, the fourth deliverable was creation of a potential human-machine interface to quickly communicate subjective logic outputs. Because use of subjective logic does not exist in current "as is" systems, there is likewise no existing pilot-vehicle interface (PVI). The intent of this deliverable is to capture the quantitative subjective logic outputs across all hypotheses while adhering to the observability principle, and allowing an operator to note relationships, agreements, and disagreements between the

CID data. Such an interface would afford more rapid orientation to the data and subsequent decision making. However, development of an optimal GUI is not a primary goal or deliverable of the thesis. Therefore, what was created is an initial, rudimentary proposal intended only to demonstrate utility and feasibility, as well as improve the reader's ability to more efficiently understand the subjective logic results.

Summary

In summary, the methodology attempted to incorporate procedures and methods used for previous research into the CID process. A sequential approach to the objectives was used, as they necessarily build upon one another to answer the given hypotheses. The outcomes included several models across several software applications, as well as multiple scenarios for initial model test a validation. Further, these scenarios not only provide support to the identified thesis hypotheses but may also have utility for informing future system design or training foci.

IV. Analysis and Results

Chapter Overview

This chapter follows the same flow as the methodology chapter, covering each of the three objectives sequentially. As the results from each objective build upon one another, subsequent discussion of the results are discussed after each objective's results.

Objective One – Interdependence Analysis

The IA JAG has three main components. First, the task breakdown and required capacities are each allocated a row indicating a performer or supporting team member for the task. Second, As described in the methodology chapter, an "overall" composite of all supporting CID agents was chosen to represent the supporting team member role. These two components of the IA are depicted in Figure 18. However, each CID agent was given an assessment in accordance with Johnson's Color Key for team member role, which is embedded within Figure 18 for convenience. The third component is switching the performer and supporting team member roles. The results of this swap are depicted in Figure 19 but is shown next to the human performer for comparison.

Figure 18. Interdependence Analysis for CID, Human Performer

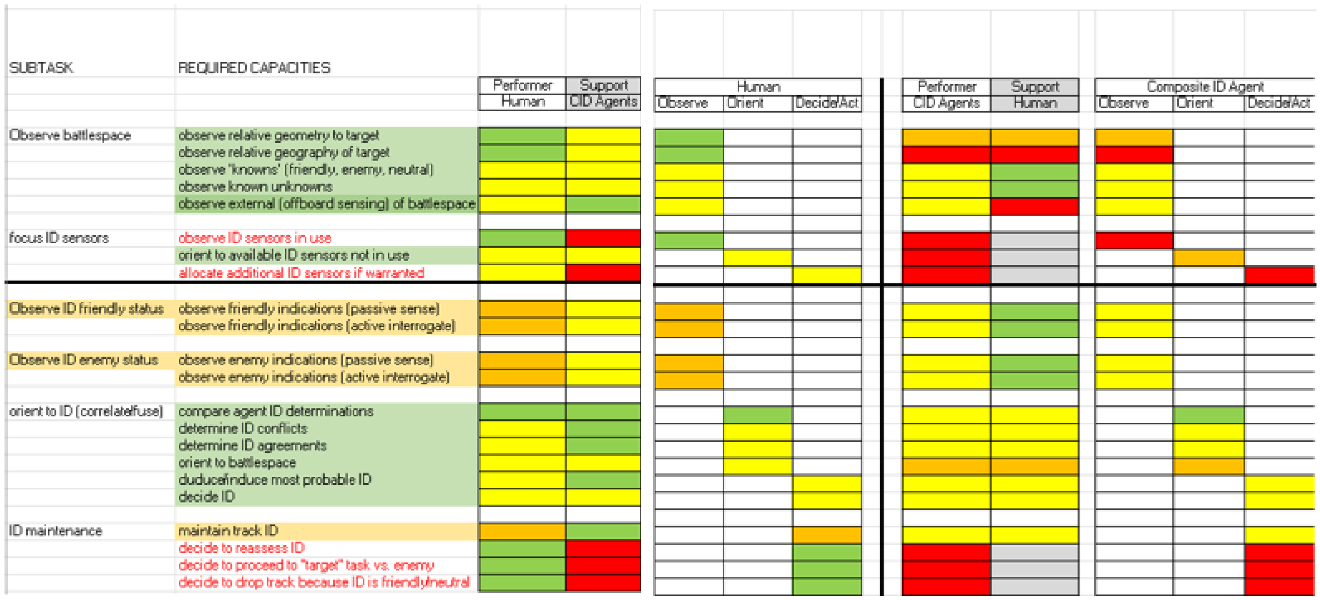

Figure 19. Comparison of Human vs. Agents as primary CID task performer

These assessments are for an "as is" system/aircraft and human operator conducting the air-to-air CID task. There are now several aspects of this analysis to highlight or discuss. First, the required capacities/tasks depict team opportunity (soft constraints) and team requirements (hard constraints) are highlighted in green and orange, respectively. The figures also note tasks for which the human is required highlighted in red text. Some of these are further discussed below. Looking at these highlights, one can see that the human is solely responsible for most tasks in the ID maintenance and focus ID sensors subtasks while the soft constraints occur primarily for the Observe ID friendly and enemy status subtasks.

Second, it became apparent that there are two OODA loops, separated by the bold black horizontal line in the figures. The first occurs when the human is building SA by observing the battlespace, relative geometries, and ID data elements available for referencing. This aids the human in understanding what information is available, to include and which CID sensors may or may not be available to further ascertain the CID of a given target. The human orients to this information and can then decide to take the action of focusing additional CID sensors to obtain additional CID information. This is the first OODA loop, the results of which help to inform the second OODA loop. The second OODA loop starts with observing and then orienting to the new CID information obtained. While the tasks, subtasks, and required capacities are depicted sequentially, they are in fact OODA loops because the performer must necessarily revisit these tasks as time progresses to account for changes in information. For example, although a human performer may be accomplishing the "orient to ID" subtask, the human must also constantly observe the battlespace. This explains the required capacity of "orient to battlespace" that is part of the "orient to ID" subtask.

The third thing to discuss is the human hard constraints. For a human performing an air-to-air CID use case, sensing of the environment must be done by the sensors that the CID agents use to make their assessment of the target's CID. This sensing extends well beyond the limits of a human's organic senses, making this a teaming hard constraint for the "observe" portion of the OODA loop. Similarly, a human's ability to observe (e.g., the battlespace) are necessarily accomplished primarily through a pilot-vehicle interface (PVI) that shows sensor and CID agent results. However, this interface is an assumed part of the system design, affording the ability to assess these as soft constraints rather than hard constraints.

Next, discussion of varying CID agent's capacity for task performance is noteworthy. In Figure 18, it is easy to note the varying ability to aid the human performer, indicated by a significant amount of red, indicating "I cannot provide assistance", in this portion of the Figure. However, it is only for the decide or act tasks which no CID agent can aid the human. In these cases, the human is the only agent capable of accomplishing those subtasks, and therefore ultimately the human is a required team member to accomplish the CID process as a whole. The other thing to note is the importance of a correlation or fusion function for the CID agents. While in many cases more than one CID agent is capable of providing information that improves overall system reliability, it is the correlation of this information across all agents that may ultimately improve human task performance efficiency. This assumes a PVI is in place to communicate this information to the human teammate. Therefore, it may be argued that this interface is a critical piece for optimizing the human-machine team, either through an optimal interface design or through sufficient training to improve the human's ability to process the agent's information output.

Fifth, reference the composite CID agent as the performer on the right side of Figure 19, compared to the human as the performer. There are many observe and orient tasks that cannot be accomplished, reflecting the reality that it is the aircrew member in a fighter aircraft who can obtain SA from the environment that the CID agents are not designed to assess. Ultimately for this "as is" system design, this observation reflects the reality that there are data elements that cannot be accounted for by a machine. Since there is no means for the human to communicate this SA to the CID agents for consideration, the ultimate fusion of all available CID context must be accomplished by a human operator.

Finally, comparing the composite CID agent performer vs. human performer in Figure 19, the "orient to ID" tasks in the second OODA loop gives the preponderance of teaming opportunity. This provides support for the first hypothesis the area of greatest opportunity to improve human-agent team performance is the Orient step.

Objective One – IA incorporation into SysML

The IA task decomposition aided development of a SysML model of a notional "as is" CID system of systems. Depictions of certain elements of this overall CID system model are not noteworthy for discussion purposes, but are documented in Appendix 1, SysML Model Diagrams. These Appendix 1 diagrams include a system Block Definition Diagram (BDD), a CID agent sequence diagram, and a subjective logic BDD, parametric equation diagrams, and associated instance tables. Additionally, an activity diagram was made that references the MS Excel IA and is reserved for discussion in objective two. However, depicted here is the CID agent sequence diagram that demonstrates how a correlating CID agent may obtain data from the various CID agents for compiling and subsequent display to the human user via interface. That is shown in Figure 20.

Additionally, the activity diagram shown in Figure 21 was created to account for aspects that affect the cognitive abilities and decision-making process for the human operator, such as time pressure and mission risk. It also shows how SA can be gained from the PVI and how SA (or known lack of SA) can be updated as the situation progresses. This activity diagram has a number of decision nodes to account for a number of variables and situation context that only the human operator can account for in "as is" systems in operation today.

These two diagrams model activities that are nested within the larger CID process IA activity diagram discussed later. Note that these are iteratively updating processes that feed into the larger activity and are considered OODA loops in their own right.

Secondly, they are both contingent upon human-machine interfaces, which is discussed more later.

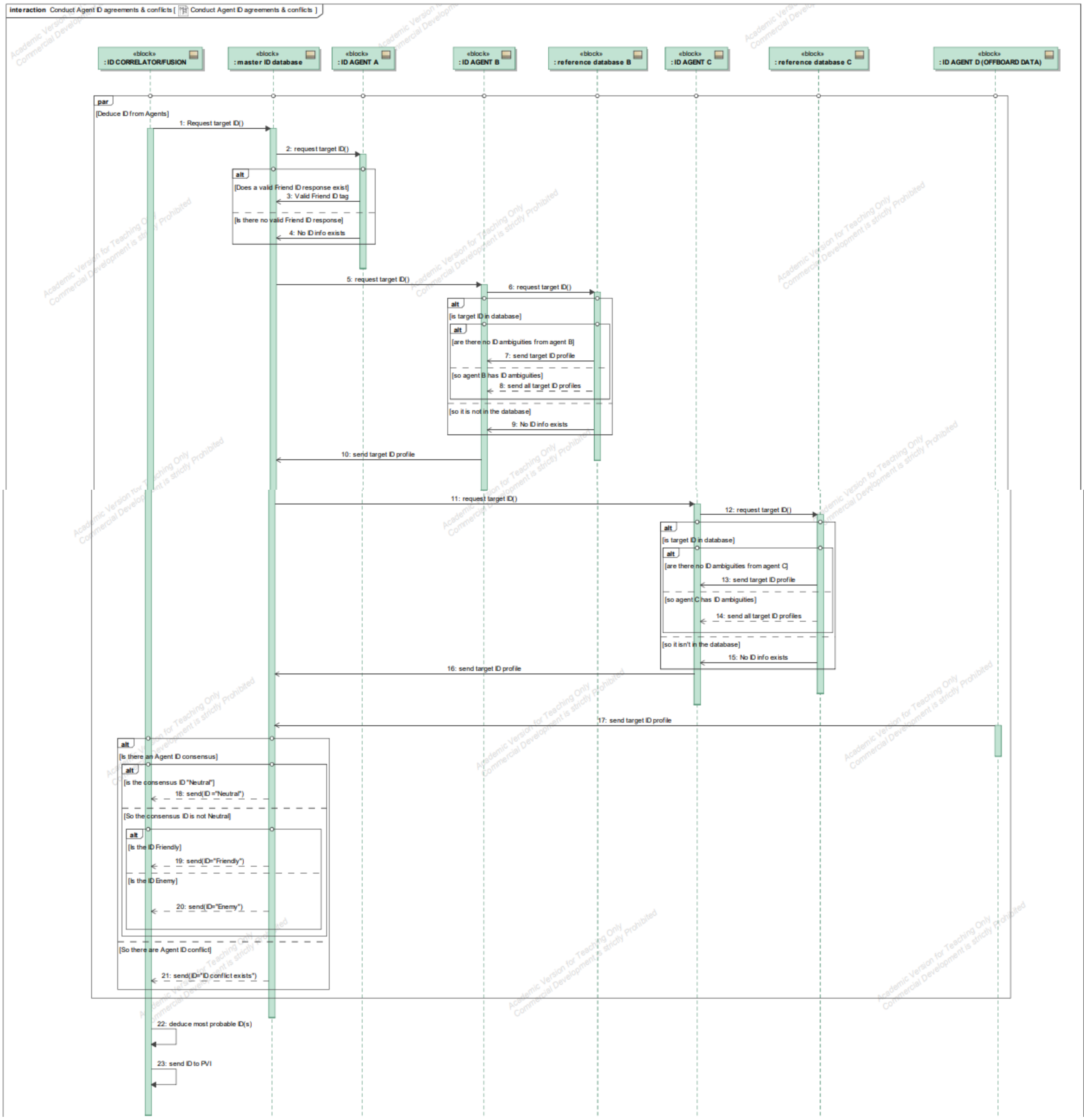

Figure 20. CID Agent Agreement SysML Sequence Diagram

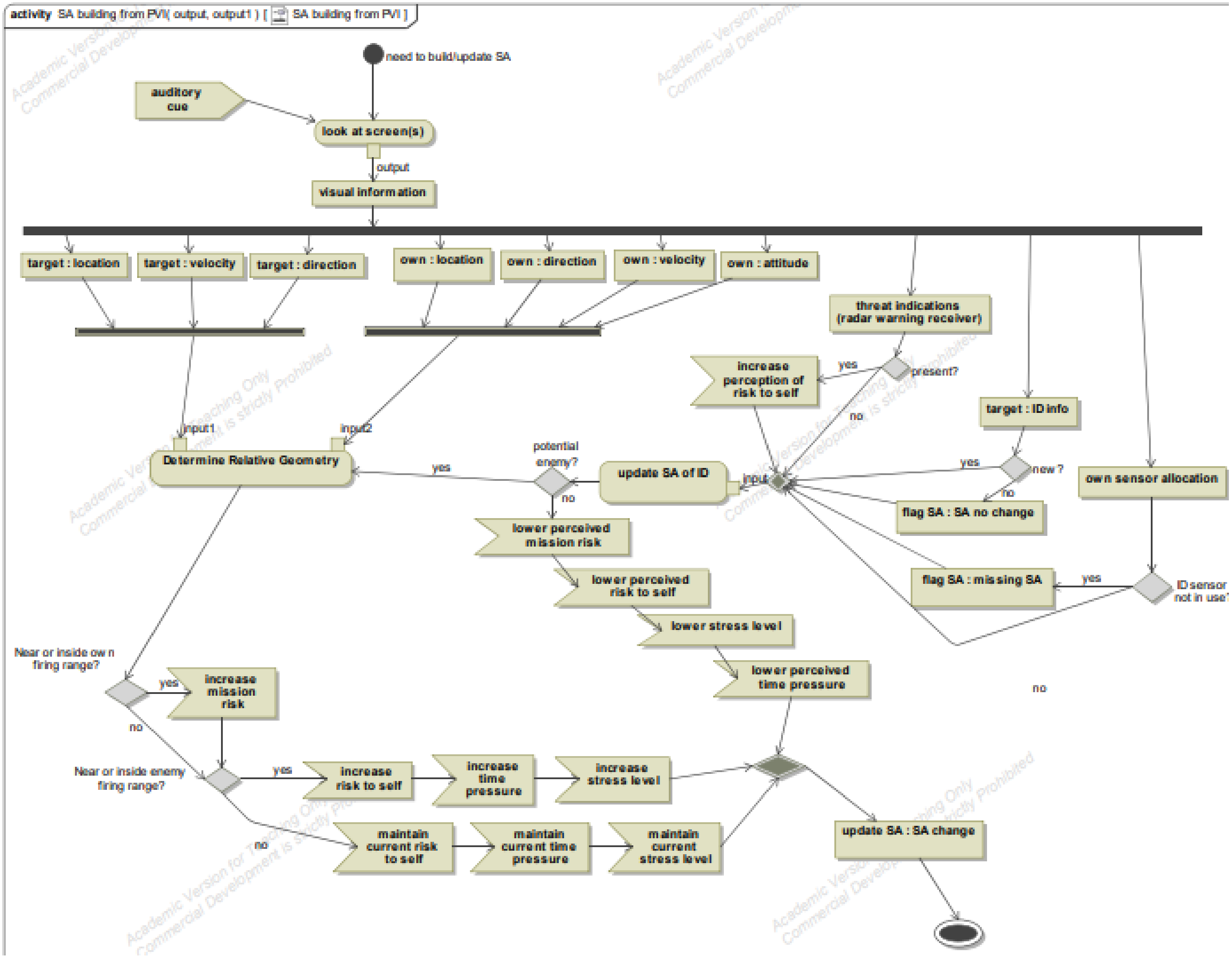

Figure 21. Human SA building from Pilot-Vehicle Interface SysML activity diagram

Objective Two – Air Engagement CMAP comparison to IA and SysML Model

The first aspect of objective two considered the MS Excel IA presented above, which was then was adapted into an activity diagram in SysML. That activity diagram is shown below in Figure 22.

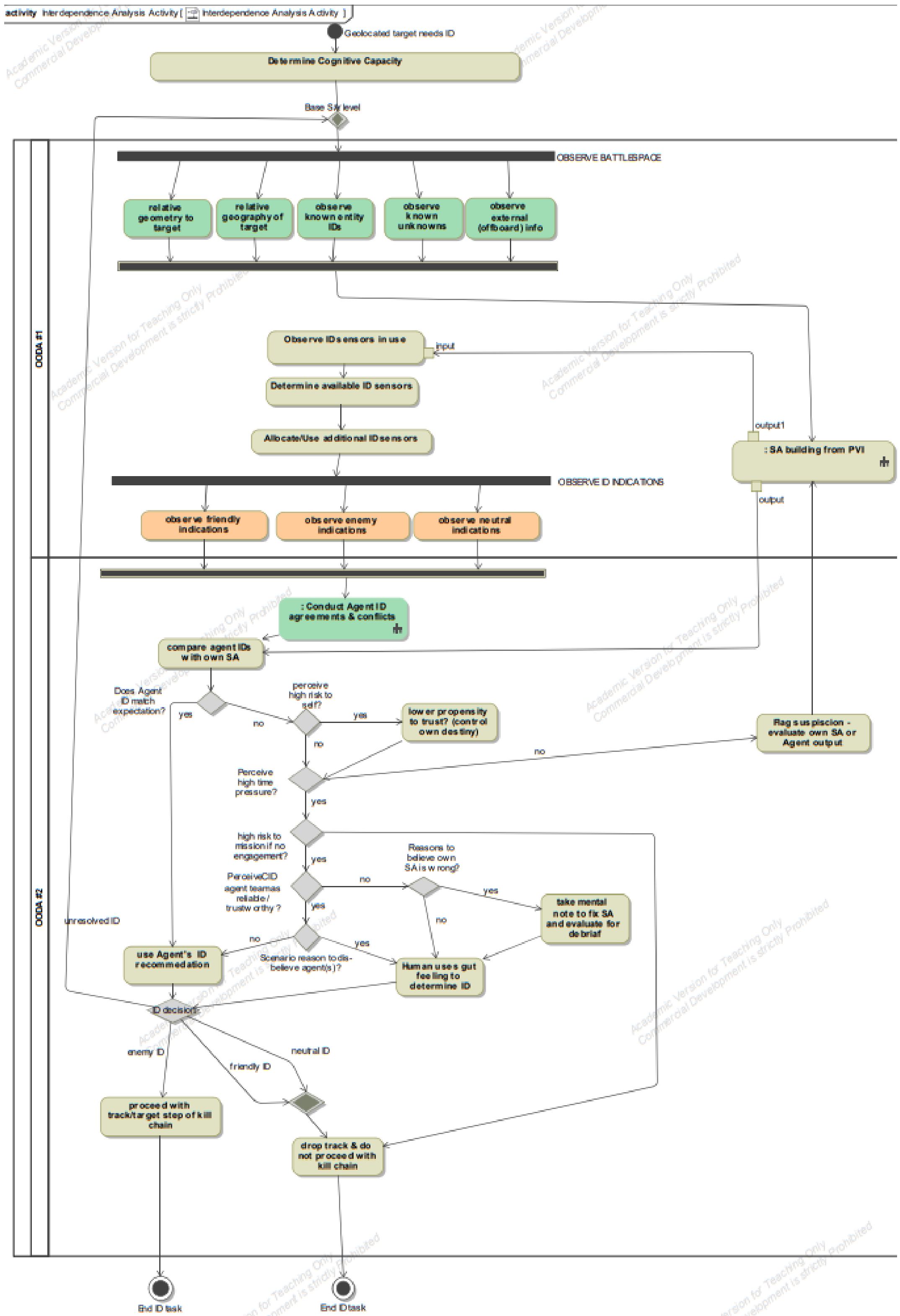

Figure 22. SysML Interdependence Analysis Activity Diagram of CID process

There are several noteworthy points to discuss in this activity diagram. First is the nested “SA building from PVI” activity and the “Conduct Agent agreement and conflicts” sequence diagram, as discussed above. The former is critical to building and updating human operator SA, while the latter is a CID agent only system process whose output is then presented to the human via interface. Second, this activity diagram is a more realistic representation of the process than the IA built in MS Excel. It accounts for the iterative nature of the CID process as more information becomes available, and the situation affords either additional observation and orientation, or dictates progressing to a decision. Furthermore, it accounts for higher-level cognitive considerations that requires the human operator’s SA, which by extension implies only the human can truly accomplish these tasks. This agrees with the IA’s assessment that automated agents cannot accomplish certain tasks, primarily in the decision portion of the OODA loop. Finally, human-machine interfaces (in this case referred to as PVI) enable the human machine teaming prior to these decision points. This process could be viewed strictly as the human observing the agent outputs then orienting to that information. However, what the human is observing from these interfaces is not raw sensor observations, but rather data that has been “oriented” to by the machine agents.

From the cognitive information processing perspective, this human-machine teaming is analogous to human only team where one human accomplishes an OODA loop for a lower-level subtask then communicates the results to another human who holds the decision authority for the higher level task. This typically requires consideration of additional SA of the situation that the human performing the subtask lacks. In such a human only team, communication is a critical enabler and is corollary to the human-machine interface (or PVI) for a human-machine team.

Objective two also resulted in a cognitive map of an air-to-air engagement with various objects, actions, and outcomes involved as shown in Figure 23. This is then compared to the IA activity diagram. Several elements between the two models are apparent. The first is the preponderance of elements which have some relationship to the human's situation awareness. Some elements are actions, some are material or object in nature such as sensors or CID agents, and others are non-material things perhaps best labeled as human factor elements or human states, including training, experience, risk tolerance, stress, time pressure, etc. Additionally, note how information is shown looping back to update or inform SA earlier in the air engagement.

While not conclusive proof, these diagrams taken together support hypothesis two. Specifically, the most difficult aspect of accomplishing a CID task is making sense of multiple CID data streams and pairing that insight with constantly updating human SA. These two models depict a large number of variables, situation context, and information that must be observed and synthesized to accomplish the orient step. For any of these, inefficiently arriving at a correct conclusion in a time constrained environment has significant consequences. Likewise, an incorrect or otherwise unreliable conclusion also has significant consequences. These models also support this hypothesis by showing that data elements primarily merge or feed the Orient step of the overall CID process OODA. Therefore, improvements in efficiency or reliability for these tasks are likely to improve performance for the overall CID task.

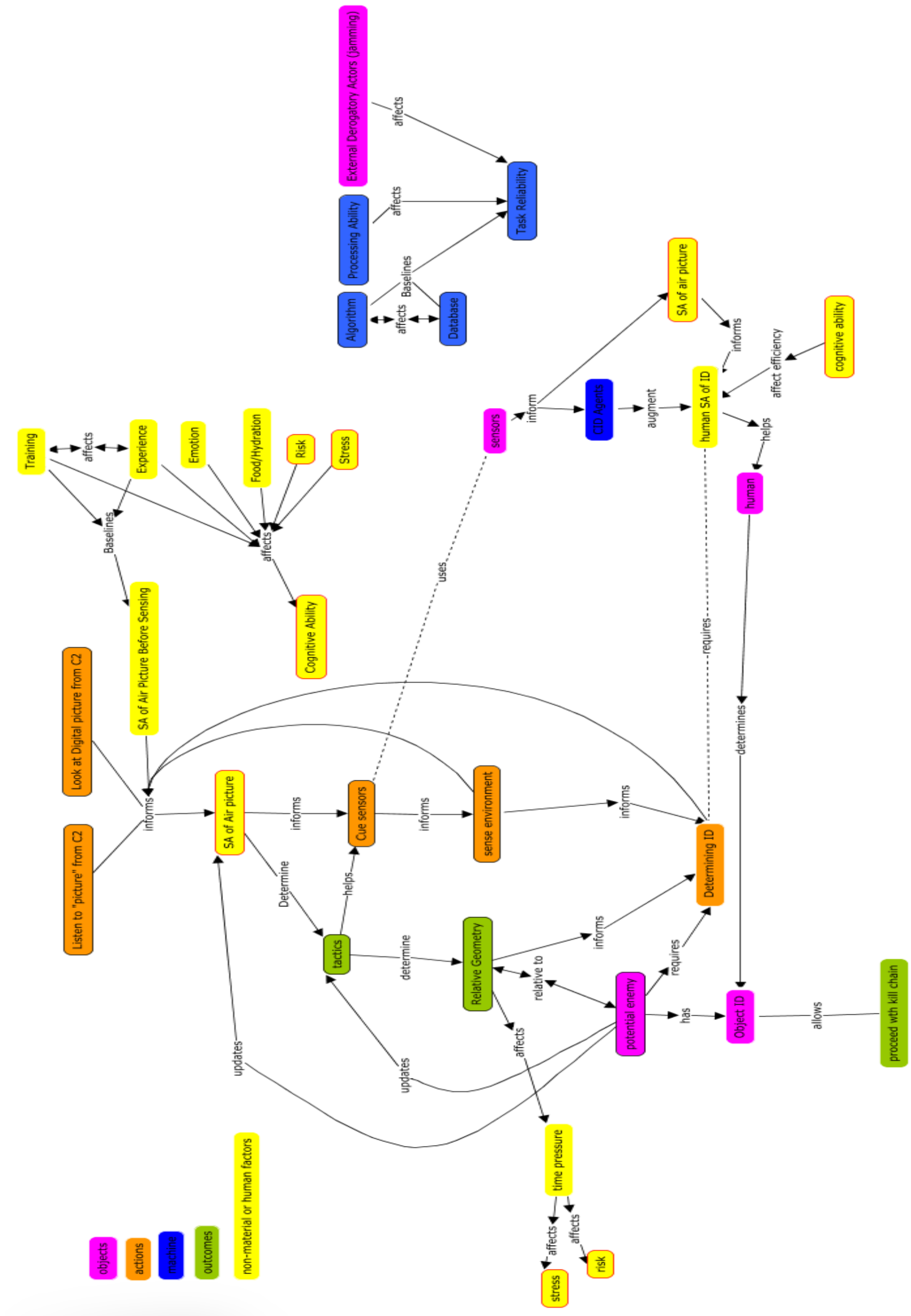

Figure 23. CMAP of Air Engagement

Objective Two – Human vs. Machine Cognition

This result from objective two compared information processing in a human to a machine for a given task. The resulting CMAP is shown in Figure 24.

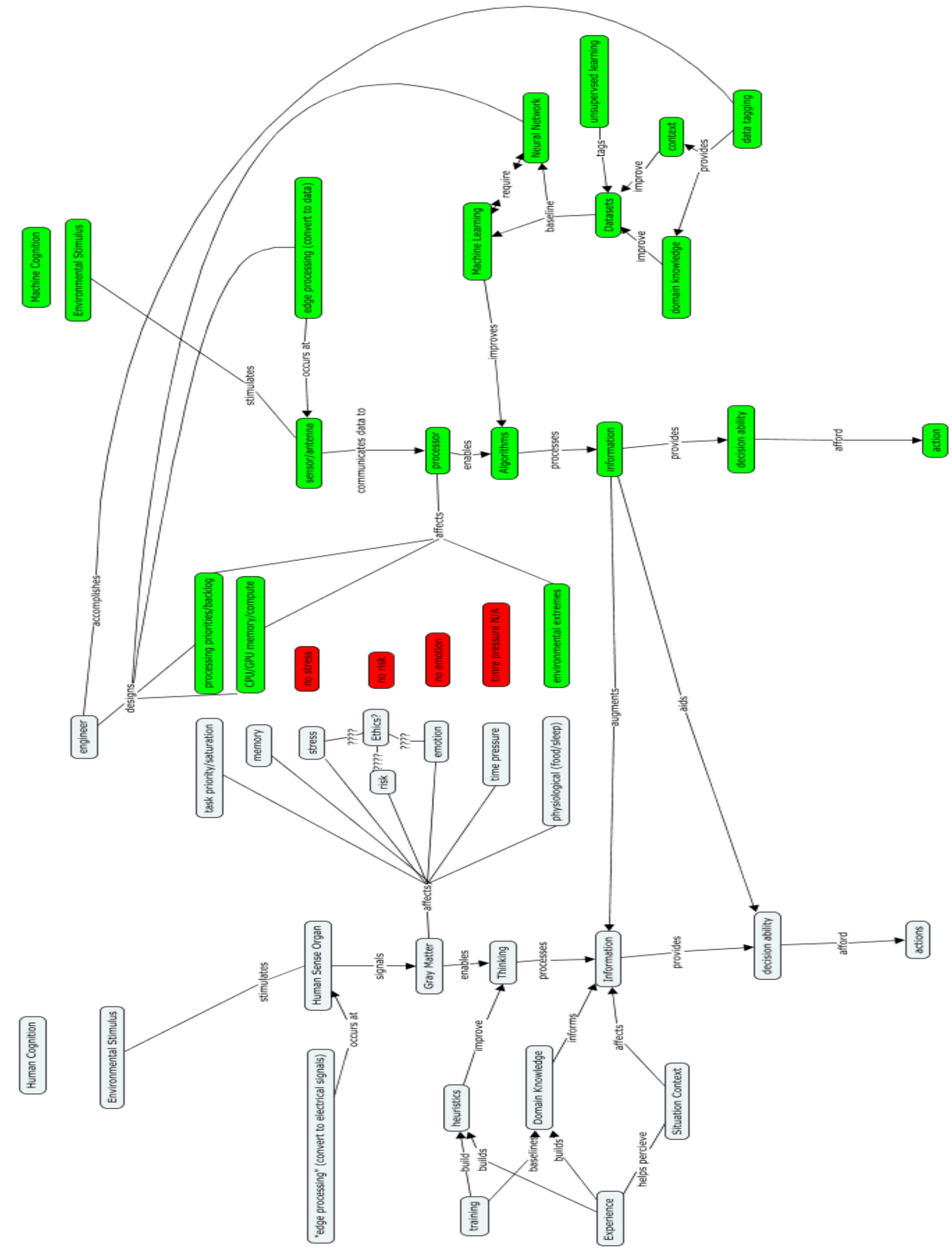

Figure 24. Human versus Machine Agent Information Processing CMAP

This CMAP is very limited in scope, as it was developed by the author's understanding of both human and machine information processing, primarily informed by existing academic models on information processing. The intent behind developing this CMAP was to compare human and machine information processing agnostic of a CID task. Secondly, it intended to identify any areas where training or system design might improve overall performance for one or the other. This CMAP assumes that although a machine is capable of decisions and actions based on designed algorithms, the machine's processed information may instead augment or aid a human's process prior to decision or action. Many elements are visually parallel between the human and machine, but some differences between these processes are apparent and described next.

First, human training and experience have parallels to machine learning, neural networks, and datasets that inform algorithmic processes used by artificially intelligent machines. However, one nuance to this according to this CMAP is that these elements can flow both into a human's thought process that derives information, but also these elements may simply change how the resulting information is perceived based on the situation's context. This ability to adapt outcomes based on situation context is only apparent on the human side. In the machine's case, these elements all flow into the algorithms and processing that provides information as an output, rather than feeding the ability to adapt and orient to the information that results.

Second, this CMAP depicts the machine's ability to augment the human's "Information," or aid a subsequent decision. Although it is conceivable that an interface design could allow a human to provide the same to a machine, for application to the "as is" CID process this is not the case. If the "information" step in this model is assumed as congruent to the orient step, there is again a significant augmenting of data from the machine agent that must be oriented to, and the human's ability to re-orient to this additional data stream depends on a sufficient human-machine interface design.

Third, the human's "gray matter" brain acts like a machine's processor. However, many external factors affect this node of the model, some of which may help or hinder a human. For example, it may be argued that physiological variables are more likely to affect a human's cognitive ability than environmental extremes are to affect a computer processor that has been designed to operate within these extremes. Additionally, human emotion, perceived risk, stress, time pressure, or morals and ethics are more likely to have a derogatory effect on a human's ability to process information efficiently, or reliably. However, these are not elements that affect a machine. When considered for speed and accuracy, a machine is superior to a human because of this difference. However, when it comes to making a decision about a given situation, these may be desired impediments that humanity desires as it may result in desirable behaviors such as not shooting a missile when the risk of civilian casualty is too high. This ability to consider moral and ethical outcomes to any action make the human the desired performer for such tasks. Although the CID process itself does not have moral implications, actions taken due to incorrect CID may absolutely have derogatory outcomes, including fratricide or civilian casualty.

In summary, there are obvious touchpoints where system design affects machine information processing ability. Additionally, to compare, fuse, or correlate information derived by a machine with that of a human, a human-machine interface is a requirement.

This interface design is critical for efficiently and reliably orienting both the human and machine information processing outputs for subsequent decision and action.

Objective Three- Subjective Logic Model for CID

Objective three began with the MS Excel model for subjective logic, which is described within the methodology section alongside an example instance provided in Figure 17. Although this was re-created in SysML using the parametric equation wizard and its outputs are displayed in an instance table, for the purposes of this thesis all subsequent use cases and model validation was accomplished via MS Excel. Screenshots of the SysML subjective logic model are in Appendix 1. For the purposes of discussion, recreation in SysML required 81 unique variables, which made incorporation of the subjective logic equations syntactically complex. Furthermore, changing each input with this syntax was very user unfriendly, although the outputs were verified to match the MS Excel model. This aspect of objective three was to prove that if further SysML model development for CID was desired, it is possible to accomplish but realistically requires an alternative design approach to improve the user interface with the model.

What follows here are each of the use cases created using MS Excel, in addition to a subjective logic GUI that reorganizes the graphical/chart data into a layout that is intended to improve the reader's ability to orient to and visually identify relationships or comparisons between the data.

Nominal Use Cases

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.900	0.000	0.100	0.333	0.330	0.330	0.340	0.333	0.8350	0.0813	0.0837	0.333	k =	0.406
H2	Enemy	0.000	0.900	0.100	0.333	0.330	0.330	0.340	0.333	0.0813	0.8350	0.0837	0.333	k =	0.406
H3	Neutral	0.000	0.900	0.100	0.333	0.330	0.330	0.340	0.333	0.0813	0.8350	0.0837	0.333	k =	0.406

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.340	0.330	0.333	0.330	0.330	0.340	0.333	0.3964	0.4025	0.2011	0.333	k =	0.5578
H2	Enemy	0.330	0.340	0.330	0.333	0.330	0.330	0.340	0.333	0.3964	0.4025	0.2011	0.333	k =	0.5578
H3	Neutral	0.330	0.340	0.330	0.333	0.330	0.330	0.340	0.333	0.3964	0.4025	0.2011	0.333	k =	0.5578

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity		
	belief	disbelief	ignorance					belief	disbelief
Friend	0.750	0.187	0.063	0.333	k =	0.26805	Friend	77.1%	20.8%
Enemy	0.185	0.752	0.063	0.333	k =	0.26805	Enemy	20.6%	77.3%
Neutral	0.185	0.752	0.063	0.333	k =	0.26805	Neutral	20.6%	77.3%

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.900	0.000	0.100	0.333	0.600	0.100	0.300	0.333	0.8919	0.0270	0.0811	0.333	k =	0.37
H2	Enemy	0.000	0.900	0.100	0.333	0.100	0.800	0.100	0.333	0.0526	0.8947	0.0526	0.333	k =	0.19
H3	Neutral	0.000	0.900	0.100	0.333	0.200	0.700	0.100	0.333	0.1053	0.8421	0.0526	0.333	k =	0.19

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.330	0.340	0.333	0.800	0.000	0.200	0.333	0.7161	0.1398	0.1441	0.333	k =	0.472
H2	Enemy	0.330	0.330	0.340	0.333	0.100	0.500	0.400	0.333	0.2748	0.5000	0.2252	0.333	k =	0.604
H3	Neutral	0.330	0.330	0.340	0.333	0.100	0.400	0.500	0.333	0.2970	0.4493	0.2537	0.333	k =	0.67

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity		
	belief	disbelief	ignorance					belief	disbelief
Friend	0.874	0.071	0.055	0.333	k =	0.21347	Friend	89.2%	9.0%
Enemy	0.099	0.856	0.045	0.333	k =	0.26595	Enemy	11.4%	87.1%
Neutral	0.145	0.810	0.046	0.333	k =	0.29301	Neutral	16.0%	82.5%

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.900	0.000	0.100	0.333	0.800	0.100	0.100	0.333	0.8947	0.0526	0.0526	0.333	k =	0.19
H2	Enemy	0.000	0.900	0.100	0.333	0.100	0.800	0.100	0.333	0.0526	0.8947	0.0526	0.333	k =	0.19
H3	Neutral	0.000	0.900	0.100	0.333	0.200	0.700	0.100	0.333	0.1053	0.8421	0.0526	0.333	k =	0.19

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.700	0.100	0.200	0.333	0.900	0.000	0.100	0.333	0.8929	0.0357	0.0714	0.333	k =	0.28
H2	Enemy	0.100	0.600	0.300	0.333	0.100	0.500	0.400	0.333	0.1207	0.6724	0.2069	0.333	k =	0.58
H3	Neutral	0.200	0.400	0.400	0.333	0.100	0.400	0.500	0.333	0.2000	0.5143	0.2857	0.333	k =	0.7

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity		
	belief	disbelief	ignorance					belief	disbelief
Friend	0.922	0.047	0.031	0.333	k =	0.1203	Friend	93.2%	5.7%
Enemy	0.069	0.887	0.044	0.333	k =	0.24864	Enemy	8.4%	90.1%
Neutral	0.126	0.828	0.047	0.333	k =	0.32331	Neutral	14.1%	84.3%

Figure 25. Subjective Logic Outputs for Nominal Friendly Use Case

For the nominal Friendly use case, the first progression (top of Figure 25) starts with only Agent A giving a CID result of 90% belief that the target is friendly. This simulates a scenario where only one CID agent has provided a result. Note that even with this single agent, the consensus belief of 77.1% and disbelief in enemy and neutral of ~77% each. This simulates when a human operator observes which CID agents are providing information and may decide to allocate additional sensors and CID agents to provide additional ID information. In the second progression, Agent B and Agent D are now providing inputs to the consensus, whose belief that the target is friendly has increased and disbelief has decreased, while also increasing disbelief that it is enemy or neutral and decreasing their belief values. Finally, the third instance of the progression has all four agents providing input and further sways the quantified consensus to very high belief that the target is friendly and very low belief that the target is enemy or neutral. For the opposite opinion, disbelief that the target is friendly is very low, while disbelief that the target is enemy or neutral is very high. Taken together, the consensus across the three hypotheses strongly supports the notion that this is a friendly and not enemy or neutral. By using conditional formatting in the Excel outputs, referencing the "consensus w/atomicity" in the bottom right of the figures, a very basic graphical output shows a blue "friendly" bar almost fully filled-in left (belief) and empty to the right (disbelief), while both the enemy and neutral belief are almost empty and their disbelief is mostly full. While simple to read with both a graphical (bar) and quantified (percentage) output consensus, if this one consensus output was the only graphical interface design available it would not adhere to the principle of observability because the consensus alone obscures each of the four CID agent's inputs. By using MS Excel to put these values into columns to maintain each CID agent's input for observability, the resulting bar chart is shown in the top half of Figure 26. At the bottom of Figure 26 these same bar chart columns were rearranged and colored to match their associated outputs: blue for friendly, red for enemy, and gray for neutral. This is referred to as the GUI henceforth for simplicity. The arrangement was put into a semi-circle where the disbelief measurements are located at the center of the semi-circle, while the belief measurements are on the outside of the semi-circle. The author's intent for using this shape was based on ease of making it, but also to provide a symmetrical design that allowed like information to be grouped (disbelief toward the middle, belief toward the outside), while the color coding provides an additional layer of associating similar shapes (bars from the graph) into the right group (friend, neutral, enemy). This is the closest to a proposed GUI that this thesis provides, as a desired aspect for objective three of this study. It is not an ideal interface from a design perspective since an actual CID interface would understandably update much more often with new information, and additional data elements to aid the operator might be warranted. Accounting for such considerations while also adhering to generally accepted human factors interface design principles is a worthwhile thesis topic in itself. Unfortunately, optimization of the interface was not in scope for this study and critiques should be reserved for future research toward a more optimal interface design.

Further addressing the GUI design itself, maintaining observability of all CID agent outputs as well as their subjective logic consensus was an important primary factor in choosing the layout. However, finding an alternative means of displaying the consensus (since it is not itself a CID agent) is perhaps a better design option that provides the operator a better means of discrimination between the two. In this instance, the lighter colors for the CID agent and darker color for consensus was used to provide this differentiation, but may or may not be sufficiently salient for a reader to properly attend to the importance of the consensus over other CID agents. Similarly, the agents' bar graph elements are shown sequentially from left to right (A, B, C, D, then consensus).

As a result, when comparing between friendly, enemy, and neutral, this may not provide an operator the easiest or most intuitive means of interpolating between a given agent's enemy, friendly, and neutral result without sufficient training.

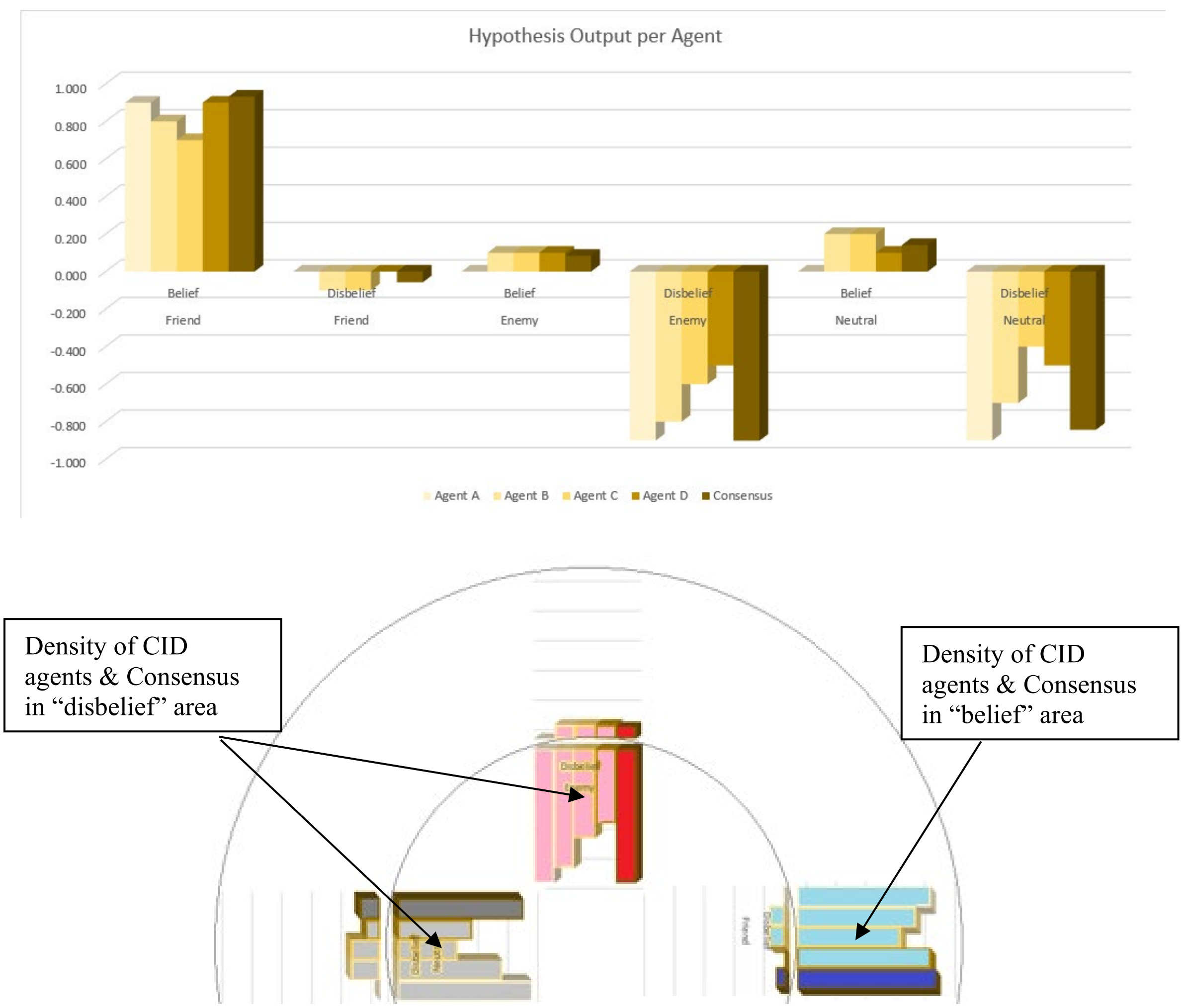

Figure 26. Nominal Friendly Use Case Final Output Bar Graph and GUI

The Figure 26 charts accomplish two things each case of friendly, neutral, and enemy. First, the quantified belief and disbelief of each CID agent is shown. Second, the derived CID consensus belief and disbelief is shown next to the agents that provided input to that consensus. This allows observability for comparison if an agent does not match the consensus. For each of the three nominal use cases, the Agents should generally agree with the consensus. For the colored semi-circle GUI, note how the enemy and neutral are weighted (the term density is also used within the figures) toward the center “disbelief” area, while the friendly agents are weighted toward the outside “belief” area of the semicircle. For all subsequent use cases, this GUI is used in lieu of the bar chart since the graphical information is the same. At a glance, if the consensus output or agents it is composed of are generally weighted toward the center, an operator should sense there is a disbelief that the target in question has that identification, while the opposite (weighted toward the outside) indicates belief in the identification. For more complicated combinations as seen later, having bars weighted in both directions should give a reader the sense that the situation has not yet been fully resolved by the CID agents. For simplicity to the reader, this semi-circle GUI is used hereafter, with comments embedded within the figures themselves further pointing out important takeaways.

For instances where there is disagreement between agents as in an abnormal use case, the disagreement should become more readily apparent, as demonstrated in the next use case. The nominal enemy and nominal neutral use cases did not provide additional discussion points, as their subjective logic simply supports their use case and were therefore not included.

Abnormal Use Cases – Single Abnormal CID Agent

Another type of use case is when one or more agents have an abnormal use case. As described earlier this could simply be a system malfunction, a system limitation, or due to something more nefarious such as enemy jamming, which simply masks true data, or enemy spoofing, which provides false information. One of these system limitations is called an ambiguity, an instance where the output shows some level of disagreement across multiple hypotheses. In the following use case, agent B has an ambiguity where there is a moderate belief that the target is enemy and equally moderate belief that the target is neutral. Note how the consensus output progresses as additional CID agents provide results. The bar graph for each progressive step is provided.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.330	0.340	0.333	0.100	0.600	0.300	0.333	0.2472	0.5632	0.1896	0.333	k =	0.538
H2	Enemy	0.330	0.330	0.340	0.333	0.600	0.100	0.300	0.333	0.5632	0.2472	0.1896	0.333	k =	0.538
H3	Neutral	0.330	0.330	0.340	0.333	0.600	0.100	0.300	0.333	0.5632	0.2472	0.1896	0.333	k =	0.538

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644
H2	Enemy	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644
H3	Neutral	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity		
	belief	disbelief	ignorance					**belief**	**disbelief**
Friend	0.354	0.536	0.109	0.333	k =	0.35558	**Friend**	**39.1%**	**57.3%**
Enemy	0.536	0.354	0.109	0.333	k =	0.35558	**Enemy**	**57.3%**	**39.1%**
Neutral	0.536	0.354	0.109	0.333	k =	0.35558	**Neutral**	**57.3%**	**39.1%**

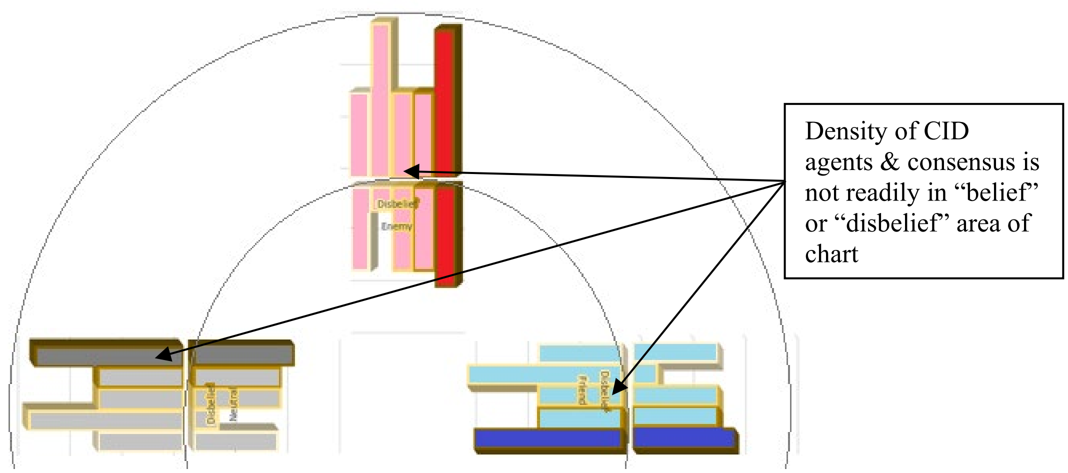

Figure 27. Single Agent Abnormality Use Case, First Progression

The first step in the progression shown in Figure 27 has only Agent B providing information towards the CID agent consensus. Unfortunately, Agent B thinks there is equally moderate (0.6) belief for the enemy and neutral use case. Referencing the bar chart, and the consensus there is insufficient information here to make a reliable decision on the target’s CID. The next progression follows.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.000	0.900	0.100	0.333	0.100	0.600	0.300	0.333	0.0270	0.8919	0.0811	0.333	k =	0.37
H2	Enemy	0.200	0.200	0.600	0.333	0.600	0.100	0.300	0.333	0.5833	0.1667	0.2500	0.333	k =	0.72
H3	Neutral	0.200	0.200	0.600	0.333	0.600	0.100	0.300	0.333	0.5833	0.1667	0.2500	0.333	k =	0.72

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644
H2	Enemy	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644
H3	Neutral	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644

	(A+B) + (C+D) consensus					
	belief	disbelief	ignorance			
Friend	0.140	0.798	0.062	0.333	k =	0.26929
Enemy	0.542	0.331	0.127	0.333	k =	0.40361
Neutral	0.542	0.331	0.127	0.333	k =	0.40361

Consesnsus w/Atomicity		
	belief	disbelief
Friend	16.1%	81.9%
Enemy	58.5%	37.3%
Neutral	58.5%	37.3%

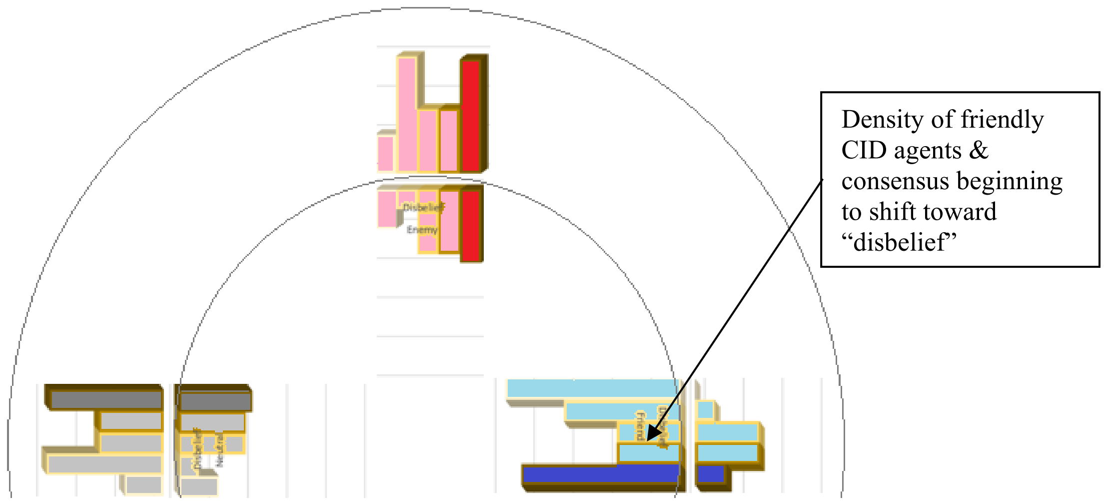

Figure 28. Single Agent Abnormality Use Case, Second Progression

Figure 28 shows now that Agent A is providing an input. However, in this instance Agent A has only provided information that supports disbelief in the hypothesis that the target is friendly. While Agent B’s situation has not changed, the addition of Agent A’s inputs toward consensus has ultimately helped to ascertain with relatively high certainty that the target is not friendly. While this helps to avoid fratricide, there is not yet sufficient quantified support that this target is in fact an enemy. From here the use case can progress.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.000	0.900	0.100	0.333	0.100	0.600	0.300	0.333	0.0270	0.8919	0.0811	0.333	k =	0.37
H2	Enemy	0.200	0.200	0.600	0.333	0.600	0.100	0.300	0.333	0.5833	0.1667	0.2500	0.333	k =	0.72
H3	Neutral	0.200	0.200	0.600	0.333	0.600	0.100	0.300	0.333	0.5833	0.1667	0.2500	0.333	k =	0.72

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.000	0.900	0.100	0.333	0.330	0.330	0.340	0.333	0.0813	0.8350	0.0837	0.333	k =	0.406
H2	Enemy	0.900	0.000	0.100	0.333	0.330	0.330	0.340	0.333	0.8350	0.0813	0.0837	0.333	k =	0.406
H3	Neutral	0.000	0.900	0.100	0.333	0.330	0.330	0.340	0.333	0.0813	0.8350	0.0837	0.333	k =	0.406

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity		
	belief	disbelief	ignorance					belief	disbelief
Friend	0.056	0.901	0.043	0.333	k =	0.15803	Friend	7.0%	91.5%
Enemy	0.823	0.110	0.067	0.333	k =	0.31281	Enemy	84.6%	13.2%
Neutral	0.221	0.712	0.067	0.333	k =	0.31281	Neutral	24.3%	73.4%

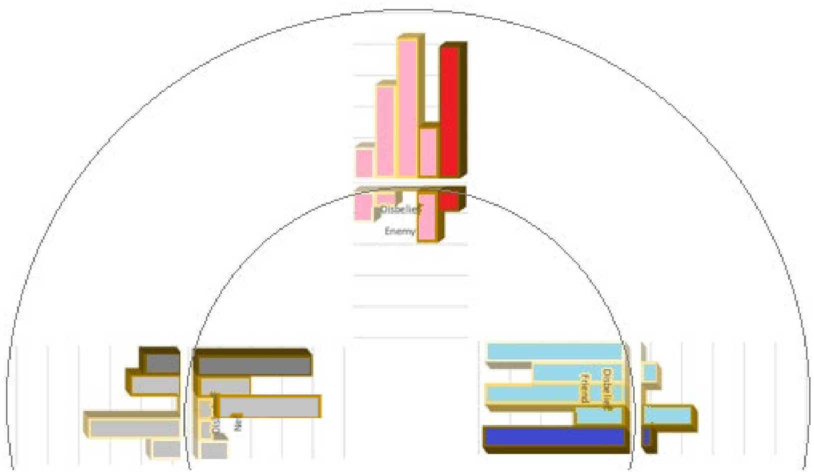

Figure 29. Single Agent Abnormality Use Case, Third Progression

Figure 29 provides some clarity to the target's CID based on the addition of CID Agent C's inputs. Compared to before, the confidence that the target is not friendly has improved. However, the enemy and neutral consensus values no longer match, and in fact they provide strong support for the belief that the target is enemy, and high disbelief that the target is friendly or neutral. If viewing the bar chart and only looking at the darker consensus bar, this becomes apparent. However, by retaining each of the four agent's beliefs together, it is easy to see that Agent B still has a relatively high belief that the target is neutral, and complies with the principle of observability. This affords a human operator information to investigate Agent B to see if perhaps there is a malfunction or some other appropriate explanation for the discrepancy. This use case continues with a progression.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.000	0.900	0.100	0.333	0.100	0.600	0.300	0.333	0.0270	0.8919	0.0811	0.333	k =	0.37
H2	Enemy	0.200	0.200	0.600	0.333	0.600	0.100	0.300	0.333	0.5833	0.1667	0.2500	0.333	k =	0.72
H3	Neutral	0.200	0.200	0.600	0.333	0.600	0.100	0.300	0.333	0.5833	0.1667	0.2500	0.333	k =	0.72

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.000	0.900	0.100	0.333	0.000	0.700	0.300	0.333	0.0000	0.9189	0.0811	0.333	k =	0.37
H2	Enemy	0.900	0.000	0.100	0.333	0.700	0.000	0.300	0.333	0.9189	0.0000	0.0811	0.333	k =	0.37
H3	Neutral	0.000	0.900	0.100	0.333	0.100	0.600	0.300	0.333	0.0270	0.8919	0.0811	0.333	k =	0.37

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity	
	belief	disbelief	ignorance				belief	disbelief
Friend	0.014	0.944	0.042	0.333	k =	0.15559	2.8%	95.8%
Enemy	0.891	0.043	0.065	0.333	k =	0.31081	91.3%	6.5%
Neutral	0.174	0.761	0.065	0.333	k =	0.31081	19.6%	78.3%

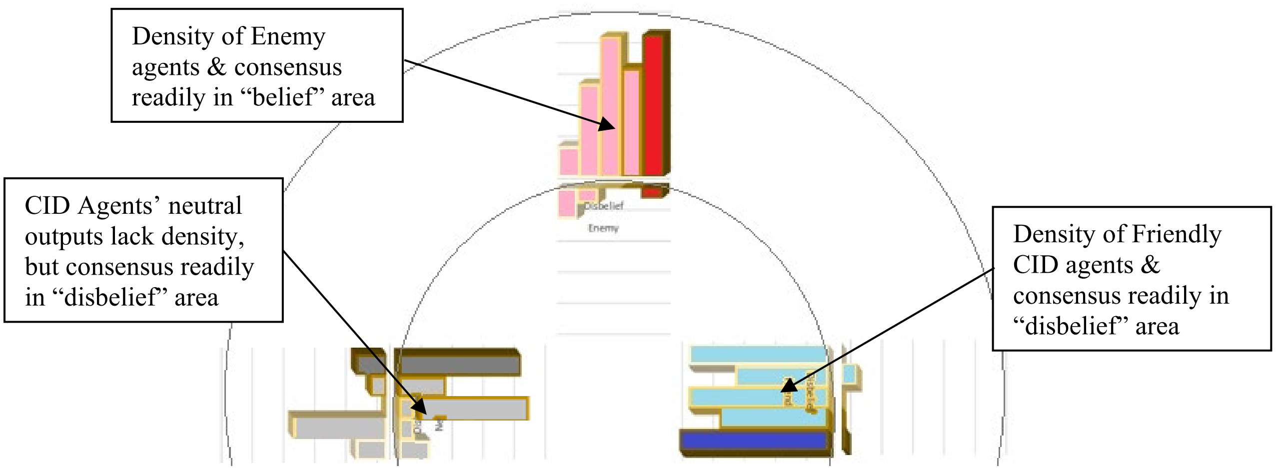

Figure 30. Single Agent Abnormality Use Case, Final Progression

Here in the final progression, the consensus progresses to provide strong support that the target is in fact enemy, and further support for the case that the target is not friendly or neutral. This progression takes into account the addition of CID Agent D's inputs toward consensus. Two things are worth noting. First, the agent B ambiguity (equal belief that the target is enemy and neutral) has remained since the beginning, and is fairly salient in the bar chart. Secondly, in spite of this the consensus belief that the target is neutral is very low, while the consensus disbelief that the target is neutral is very high.

For discussion, taken holistically this use case with a single ambiguity easily supports the notion that the target is an enemy, and not friendly or neutral. However, also consider that this is only taking into account the CID agent's inputs for the CID task. For the purposes of human machine teaming, a human combining his or her own SA of the battlespace may apply additional contextual information, or an understanding of system limitations that explain why the ambiguity has occurred. By ensuring observability, paired with the subjective logic, this ambiguity is not significant enough to sway the consensus, but is salient to the operator who can then interpret this information in the context of other situation factors. Ultimately, this use case is an example where other elements of SA likely agree with the consensus. A final use case is worth discussion, and that is an instance where there are multiple disagreeing agents.

Abnormal Use Case – Multiple ambiguous or disagreeing CID Agents

The final use case begins like the others with a single CID agent and is depicted in Figure 31.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644
H2	Enemy	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644
H3	Neutral	0.330	0.330	0.340	0.333	0.330	0.330	0.340	0.333	0.3976	0.3976	0.2048	0.333	k =	0.5644

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.100	0.700	0.200	0.333	0.330	0.330	0.340	0.333	0.2119	0.6441	0.1441	0.333	k =	0.472
H2	Enemy	0.800	0.000	0.200	0.333	0.330	0.330	0.340	0.333	0.7161	0.1398	0.1441	0.333	k =	0.472
H3	Neutral	0.100	0.700	0.200	0.333	0.330	0.330	0.340	0.333	0.2119	0.6441	0.1441	0.333	k =	0.472

	(A+B) + (C+D) consensus					
	belief	disbelief	ignorance			
Friend	0.315	0.592	0.092	0.333	k =	0.31938
Enemy	0.639	0.269	0.092	0.333	k =	0.31938
Neutral	0.315	0.592	0.092	0.333	k =	0.31938

Consesnsus w/Atomicity		
	belief	**disbelief**
Friend	34.6%	62.3%
Enemy	66.9%	30.0%
Neutral	34.6%	62.3%

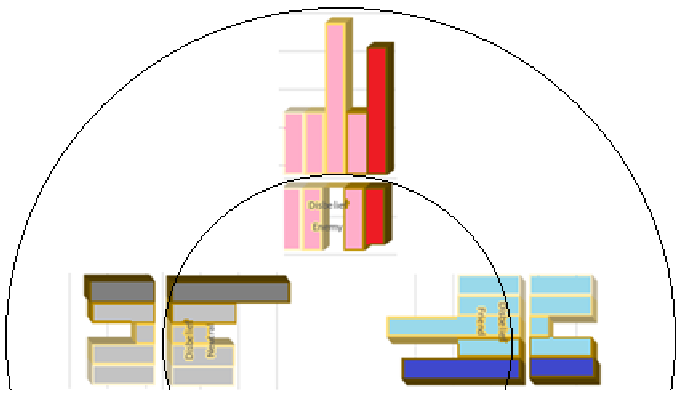

Figure 31. Multiple Agent Abnormality Use Case, First Progression

In Figure 31, one agent provides moderately strong evidence that the target is enemy, and not friendly or neutral. For discussion purposes, it may be feasible that this single agent's CID input alone, paired with human SA of the battlespace is sufficient. However, since that is situation dependent, this use case should not support the notion that a single CID agent is all that is needed before meeting rules of engagement to avoid fratricide or civilian casualties. Equally possible is a situation where a human operator's SA of the battlespace is in disagreement with a lone CID Agent. This use case now progresses to the next phase.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.330	0.330	0.340	0.333	0.100	0.800	0.100	0.333	0.1650	0.7512	0.0837	0.333	k =	0.406
H2	Enemy	0.330	0.330	0.340	0.333	0.100	0.800	0.100	0.333	0.1650	0.7512	0.0837	0.333	k =	0.406
H3	Neutral	0.330	0.330	0.340	0.333	0.100	0.800	0.100	0.333	0.1650	0.7512	0.0837	0.333	k =	0.406

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.100	0.700	0.200	0.333	0.330	0.330	0.340	0.333	0.2119	0.6441	0.1441	0.333	k =	0.472
H2	Enemy	0.800	0.000	0.200	0.333	0.330	0.330	0.340	0.333	0.7161	0.1398	0.1441	0.333	k =	0.472
H3	Neutral	0.100	0.700	0.200	0.333	0.330	0.330	0.340	0.333	0.2119	0.6441	0.1441	0.333	k =	0.472

	(A+B) + (C+D) consensus						Consesnsus w/Atomicity		
	belief	disbelief	ignorance					**belief**	**disbelief**
Friend	0.192	0.752	0.056	0.333	k =	0.21575	**Friend**	**21.1%**	**77.0%**
Enemy	0.388	0.556	0.056	0.333	k =	0.21575	**Enemy**	**40.7%**	**57.5%**
Neutral	0.192	0.752	0.056	0.333	k =	0.21575	**Neutral**	**21.1%**	**77.0%**

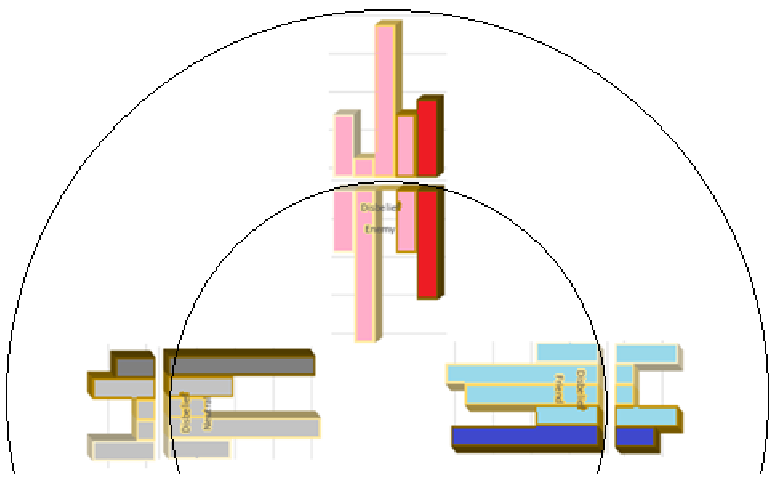

Figure 32. Multiple Agent Abnormality Use Case, Second Progression

For this next progression, a situation is proposed where enemy actions are spoofing CID agent B, namely to make agent B believe the target is not enemy. This result now stands in opposition to agent C's results. However, the impact on the consensus in this case is to simply lower belief that the target is friendly or neutral. For discussion, consider the effect on the consensus if the agent B spoof was capable of increasing belief that the target is friendly or neutral, and not just making agent B agree across all three hypotheses. This use case now moves on to a third progression.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.000	0.900	0.100	0.333	0.100	0.800	0.100	0.333	0.0526	0.8947	0.0526	0.333	k =	0.19
H2	Enemy	0.200	0.200	0.600	0.333	0.100	0.800	0.100	0.333	0.1250	0.7813	0.0938	0.333	k =	0.64
H3	Neutral	0.200	0.200	0.600	0.333	0.100	0.800	0.100	0.333	0.1250	0.7813	0.0938	0.333	k =	0.64

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.100	0.700	0.200	0.333	0.330	0.330	0.340	0.333	0.2119	0.6441	0.1441	0.333	k =	0.472
H2	Enemy	0.100	0.700	0.200	0.333	0.330	0.330	0.340	0.333	0.2119	0.6441	0.1441	0.333	k =	0.472
H3	Neutral	0.100	0.700	0.200	0.333	0.330	0.330	0.340	0.333	0.2119	0.6441	0.1441	0.333	k =	0.472

	(A+B) + (C+D) consensus					
	belief	disbelief	ignorance			
Friend	0.099	0.861	0.040	0.333	k =	0.18912
Enemy	0.169	0.771	0.060	0.333	k =	0.22431
Neutral	0.169	0.771	0.060	0.333	k =	0.22431

Consesnsus w/Atomicity		
	belief	disbelief
Friend	11.2%	87.4%
Enemy	18.9%	79.1%
Neutral	18.9%	79.1%

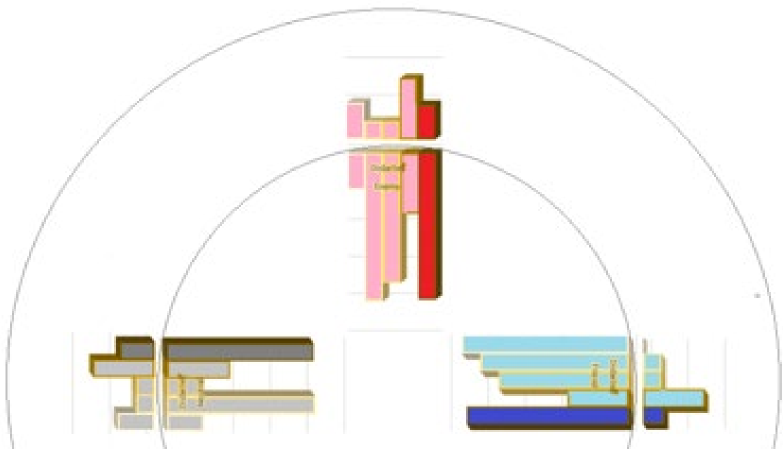

Figure 33. Multiple Agent Abnormality Use Case, Third Progression

In this third progression shown in Figure 33, a situation is postulated where agent A is now providing support that the target is not friendly. However, agent C's input has changed as well. This simulates additional enemy actions which are now spoofing agent C into believing that the target is not enemy, not friendly, and not neutral much like agent B. This is now a highly ambiguous situation for a human operator considering this information, and shows the potential effect that enemy jamming or spoofing of sensors can have on the CID process. In this situation, it is unlikely that any ROE can be complied with unless sufficient battlespace SA can trump the shown consensus.

		ID Agent A				ID Agent B				A+B consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.000	0.900	0.100	0.333	0.100	0.800	0.100	0.333	0.0526	0.8947	0.0526	0.333	k =	0.19
H2	Enemy	0.200	0.200	0.600	0.333	0.100	0.800	0.100	0.333	0.1250	0.7813	0.0938	0.333	k =	0.64
H3	Neutral	0.200	0.200	0.600	0.333	0.100	0.800	0.100	0.333	0.1250	0.7813	0.0938	0.333	k =	0.64

Note: For simplicity, it was ALWAYS assumed to be a non-zero ignorance to simplify required equations and maintain consistency for modelling purposes. It also considers "fog of war" and assumption that systems are less than 100-percent reliable

Note: if any ignorance = 0, then compute γ

		ID Agent C				ID Agent D				C+D consensus					
		belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity	belief	disbelief	ignorance	atomicity		
H1	Friend	0.100	0.700	0.200	0.333	0.000	0.900	0.100	0.333	0.0357	0.8929	0.0714	0.333	k =	0.28
H2	Enemy	0.100	0.700	0.200	0.333	0.900	0.000	0.100	0.333	0.6786	0.2500	0.0714	0.333	k =	0.28
H3	Neutral	0.100	0.700	0.200	0.333	0.000	0.900	0.100	0.333	0.0357	0.8929	0.0714	0.333	k =	0.28

	(A+B) + (C+D) consensus					
	belief	disbelief	ignorance			
Friend	0.047	0.922	0.031	0.333	k =	0.1203
Enemy	0.458	0.500	0.042	0.333	k =	0.15848
Neutral	0.077	0.880	0.042	0.333	k =	0.15848

Consesnsus w/Atomicity		
	belief	**disbelief**
Friend	**5.7%**	**93.2%**
Enemy	**47.2%**	**51.4%**
Neutral	**9.2%**	**89.4%**

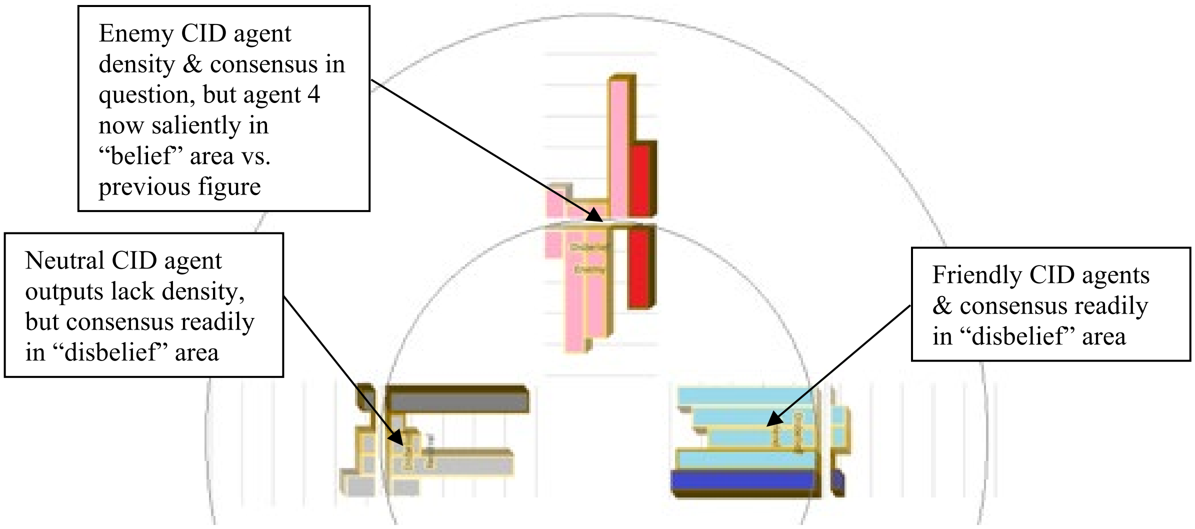

Figure 34. Multiple Agent Abnormality Use Case, Final Progression

The final progression of this use case is the addition of agent D to the overall CID consensus. Referencing the GUI in Figure 34, the compliance with the observability principle makes very salient agent D's strong belief that the target is enemy. However, the effects of spoofing on agent B and C are also apparent. Although there is strong consensus that the target is not friendly or neutral, consensus on whether the target is or is not enemy remains ambiguous. Using deductive logic, the operator may choose to utilize this information to assess that the target is enemy, because the CID agent consensus shows strong quantitative support that the target is not neutral or friendly. However, doing so is perhaps without sufficient presence of enemy (PEI) indication, unless agent D is known to be highly reliable in this scenario. This is a scenario where giving authority to a team of agents to accomplish the CID task alone is a precarious venture. However, this scenario is not insurmountable when paired with a human's SA, ability to see patterns and relationships in data, and adaptability to account for ambiguous or abnormal readings. If the human's battlespace SA supports the hypothesis that the target is enemy and not friendly or neutral, this could be sufficient to meet ROE. Additionally, if the human has insight into enemy abilities to spoof or jam certain sensors and affect a CID agent's output, that can also be considered. This adaptability supports the idea that human-machine teaming is preferrable to either human or autonomous agent(s) acting alone.

For subjective logic's use in the orient step of the OODA, this third thesis objective supports the hypothesis that subjective logic could improve human-multiagent team reliability or efficiency. This is accomplished via the subjective logic consensus outputs themselves, and through presenting them via a GUI that conveys the pertinent information while still adhering to observability of its constituent data elements.

Summary

This section reviewed results of this multi-faceted research approach to human-multiagent teaming for CID. The implications of these results are provided in the next chapter.

V. Conclusions and Recommendations

Chapter Overview

Human-Machine teaming for any context is decidedly a multi-disciplinary problem that includes human factors, multi-agent teaming, and trust. It can also include more quantitative and engineering fields like data and computer sciences. Specific to the CID problem set and air-to-air military application, a multitude of takeaways can be made.

Conclusions of Research

Speaking to the hypotheses of this thesis, they are progressive in nature from one to the next. Regarding the first, it was hypothesized that the area of greatest opportunity to improve human-agent team performance is the Orient step of the OODA loop. In addition to support shown in the literature review, by following the coactive design and IA process proposed by Johnson et al. (2014), a model was created which supports this hypothesis. One noteworthy finding from breaking this CID use case down into its multitude of subtasks is that executing this step of the kill chain requires multiple OODA loops. However, because these models were largely based upon qualitative expert opinion for their design which is grounded in a SME's assessment, additional quantitative means to support this hypothesis are a useful area for future research.

For the second hypothesis, it was proposed that for the CID OODA loop the best way to improve the Orient step of this process is through improving human-agent team efficiency and/or reliability. During the modelling phase of this study, it became apparent that the first two hypotheses are closely linked in terms of how they were answered. Since the IA conducted for the first hypothesis was specific to the air-to-air CID use case, and because the IA provided potential means of improving both reliability and efficiency, the outcomes from attempting to address hypothesis one easily transfer to support hypothesis two. Again, the same limitation of qualitative expert opinion in the model applies, making this another area for future research. Three insights are worth mentioning. First, although assessment of all subtasks in the Orient step supports the hypothesis, it was also noted that this was not the only step of the CID OODA where human-agent efficiency and/or reliability improvements are possible. Second, for this application there are several hard constraints for which a human-machine team are necessary, namely for observing the battlespace beyond human sensing and perception. Third, for the "as is" system design, it is required that the human operator be the primary owner of the overall CID task, as the non-human agents lack fully mission capable or even goal-oriented execution of CID across all tasks. This third finding is noteworthy for consideration when designing automated agents for complex decision loop tasks in future systems while automation may be more efficient or reliable than a human for more narrowly defined sub-tasks, they fall short for higher level application to the problem set.

For the third hypothesis, it was proposed that applying subjective logic could provide a quantitative means of improving efficiency and/or reliability for the human-agent team during the orient stage of the CID OODA loop. Notably, for any output created for this hypothesis, an appropriate interface that also adheres to the principle of observability is necessary. By applying subjective logic equations as described by Håkansson (2005) to the CID process, such a model was created. This was the most quantitative aspect of this research, as it uses a mathematical modeling approach to account for each automated agent's quantified assessment for a given situation. Although scenarios were created to accomplish very basic validation and verification of the model, it was very limited in scope due to time as well as the inability to utilize real sensor or agent output data for an unclassified thesis. However, by utilizing several use case scenarios, the utility of subjective logic to quantify outputs provides promise. Three findings are of note. First, to best utilize the quantitative outputs, a more elegant GUI is necessary, a matured design and testing of such an interface was out of scope for this study, but a worthwhile area for future research. Second, adapting this very rudimentary model had some limitations when developed using only MS Excel, or extending it into SysML. Any future iterations or application of subjective logic needs an improved design to ensure certain agent opinions are not unfairly weighted toward a consensus during periods when no data is available to form an opinion. Alongside that, for any "as is" system to use subjective logic a means of translating existing CID agents' outputs into a compatible format is a required design task. Finally, there exists no readily apparent way to capture and quantify a human's SA and opinion during a CID task and insert it into the subjective logic equation in a time-efficient manner under situations of high time pressure. For situations in which time-pressure is less of an issue, it might be accomplished using questionnaires or other data gathering techniques. However, this air-to-air CID context presents an elusive data fusion and orientation design problem. For now, system designs should focus on optimizing the agent outputs and PVI that allow automation to present an operator information. This approach would effectively seek to improve reliability or efficiency of human decision, rather than replace it.

Significance of Research

This research has presented several ideas for human-agent teaming, namely within the CID military context. As the Department of Defense pursues technological advances in automation in the coming years, some of the findings of this research may inform system architects, human factors engineers, and data scientists who hope to optimize their designs for the military user. Likewise, as new systems with increased automation are presented to military operators, methods for training toward optimized teaming or simply building operator trust in automation are needed. These training program designers must consider how best to build trust or develop tactics, techniques, and procedures for automation teaming to ensure the best results.

In a broader context, the problem set used for this research can apply to other fields. Ultimately, the CID problem as presented here is one of differential diagnosis, a phrase more commonly used in the medical profession. For example, engineers working on systems in the medical field could utilize subjective logic for automated agents which reference data composed of patient vitals, patient history, patient questionnaires or chief patient complaint to inform automated diagnostic aids. In turn, these agents could generate a list of diagnostic differentials along with proposed further points of investigation (e.g., labs or x-rays) that help a human medical provider further solidify the likelihood of correct diagnosis. If designed correctly and if given the necessary data, a team of such diagnostic agents could improve efficiency or even reliability, which could correlate to improved patient throughput or patient safety metrics. However, as in the case of this CID thesis which concludes that automation should augment the fighter pilot rather than replace them, a medical provider would ultimately remain responsible for diagnosis given that their expertise and adaptability can account for things a diagnostic aid cannot (e.g., perhaps the patient is lying about their complaint because they hope to get a particular prescription for medication). This aspect of medical diagnosis may be regarded as corollary to having situation awareness in the military CID context. Other fields may have similar such applications, but the utility that a well designed human-agent team can provide is apparent.

Recommendations for Action

As the Department of Defense continues to pursue automation, its approach should prioritize human-agent teaming rather than designing automation to replace human operators for tasks like decision making that require more complex cognitive reasoning. Likewise, as automated agents become more commonplace to augment military missions, operators must develop the required training to optimize human-agent teams, while tacticians and testers must identify areas for best operational use and tactics development. Some examples are already ongoing, for example the Air Force Research Laboratory's Autonomous Attritable Aircraft Experimentations (AAAx). Such testing pursuits should continue in parallel with technological development.

Subjective Logic has proven useful for this application and could be a worthwhile investment for other data-driven automation and decision-making tools in development. However, when significant amounts, types, or layers of information must be sorted through or made sense of, a combination of automation and human-machine interface design is necessary, and that interface design is best suited when it includes agent observability. Designs which fail to address these areas have significant limitations that must typically be accounted for by additional user training/expertise, or by accepting decreased performance of the task. The importance of these design aspects increases as mission risk and time pressure increase. However, if subjective logic is indeed chosen to augment existing systems, then additional engineering design to enable this added capability is necessary. Specifically, any CID or data outputs must either be compliant with the subjective logic system of equations, or otherwise those outputs must be adapted to comply. For certain existing CID capabilities, this requires an enabling design task.

Recommendations for Future Research

The following areas were identified as potential candidates for future research. Some were identified as natural extensions to this thesis research, while others were considered during literature review as worthy research to support improved human-agent teaming.

1. An optimized interface design for CID subjective logic/multi-agent outputs. This was a desired aspect of this study, but insufficient time and expertise was available.
2. Improvements to the subjective logic model. This is better suited by adapting the mathematical computations and their outputs using more powerful software capable of handling computations for multiple types of streaming data while also providing a more tailored output that can match with recommendation 1 above.
3. System wide trust theory and the pull-down effect is worth further investigation in the following ways, though may be largely dependent upon the use case, context, system design, and user base.

a. If multiple automated agents are available to aid a human operator for a multiple-step task, a human may employ a system-wide trust strategy across all steps of the task. When a human becomes suspicious of one agent, does it cause a pull-down effect wherein the human becomes suspicious of all automated agents in the system?
b. If a pull-down effect occurs as described in the paragraph above, does this cause a derogatory human-machine team performance, and if so, how great is the impact on team performance?
c. If the above hypotheses are correct and a human does in fact have a pull-down effect due to use of a system-wide trust strategy, is there a way to avoid this for an automated multi-agent team?

4. What is the utility or negative impact on mission performance when an automated agent is designed to give human operators the ability to control the output bias of the system? For example, the operator's mission may lead the human to choose to have minimum false alarms or alternatively the human may desire minimal misses from the automated agent. This provides a system design that conforms to the principles of predictability and directability, as discussed in the literature review.

Summary

This research gives additional weight to some DoD initiatives, but also provides some more specific research areas for further investigation.

Appendix 1. SysML Diagrams

Shown here are several elements of the overall SysML model which were not presented or discussed in the body of the paper. They are here for reference.

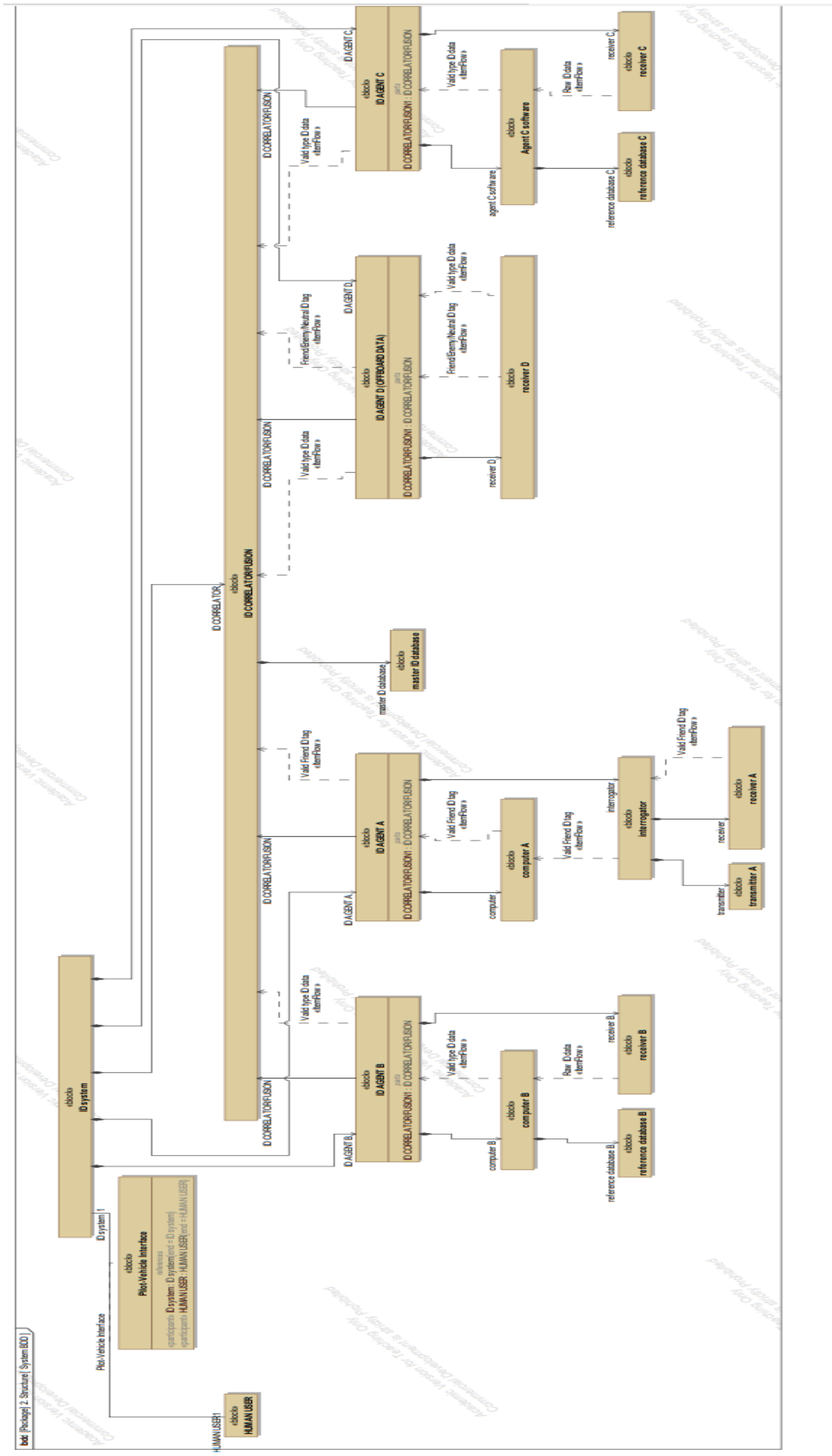

Figure A1. CID System Block Definition Diagram

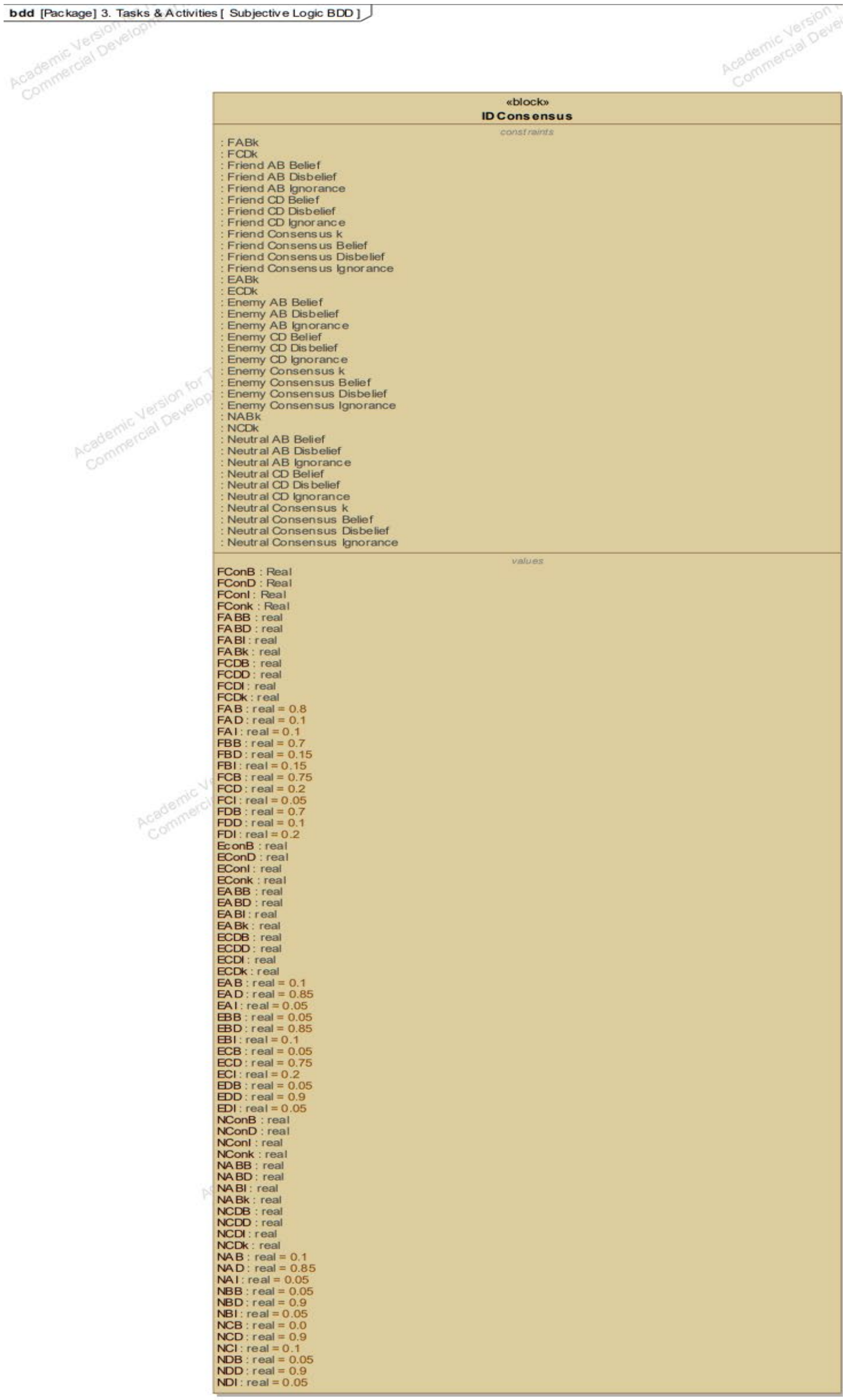

Figure A2. Subjective Logic Block Definition Diagram

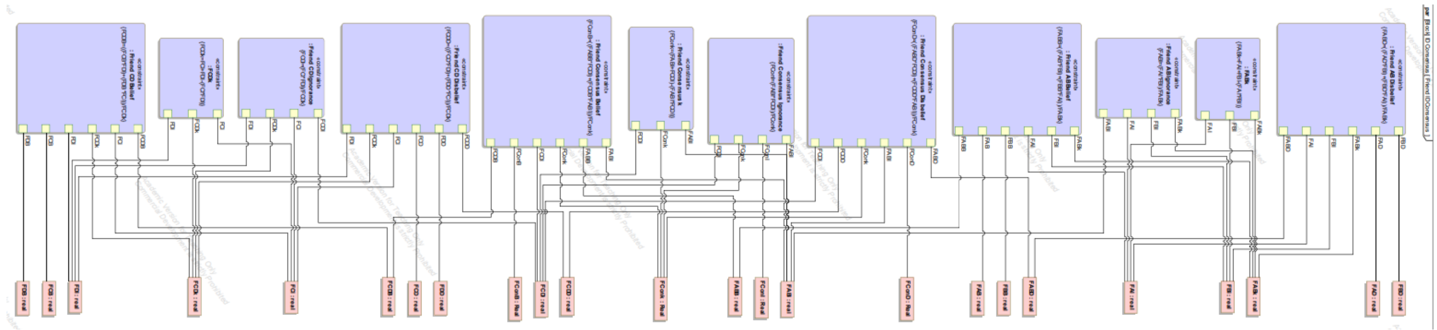

Figure A3. Friendly Consensus Subjective Logic Parametric Equation Diagram

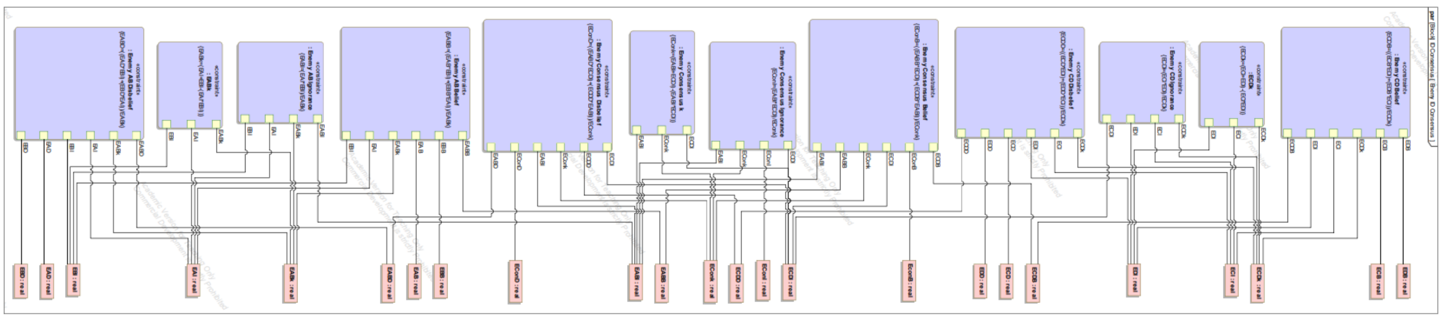

Figure A4. Enemy Consensus Subjective Logic Parametric Equation Diagram

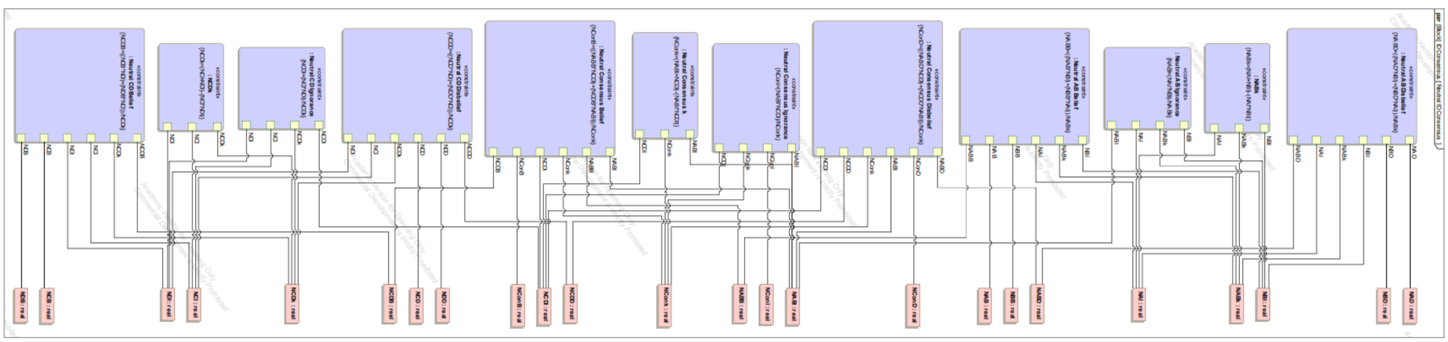

Figure A5. Neutral Consensus Subjective Logic Parametric Equation Diagram

Criteria

Classifier: ID Consensus ... Scope (optional): Subjective Logic BDD

#	Name	FConB : Real	FConD : Real	FConI : Real	EconB : real	EConD : real	EConI : real
1	id consensus	0.806	0.1681	0.0259	0.0721	0.9087	0.0192

Figure A6. Subjective Logic Instance Table. Note: This depiction only accounts for Friendly and Enemy Consensus Belief (FConB, EConB), Disbelief (FCondD, EConD), and Ignorance (FConI, EConI). The outputs are for the given scenario inputs made to the BDD that are then computed by the parametric equation wizard diagrams. Neutral was not included in this particular instance table, but could be incorporated if desired.

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14. ABSTRACT
Combat Identification (CID) in an air-to-air combat context is a highly complex cognitive task that requires the operator to make rapid, high consequence decisions. To accomplish CID, fighter aircrew must attend to and perceive a broad range of information while concurrently building situation awareness (SA) and conducting other tasks. While existing automated agents are available to help fighter aircrew with this CID task, they are designed for a very narrow subset of the overall task and are not well suited for human-agent teaming. An interdependence analysis of the human operator and supporting machine agents conducted for this task support the notion that the Orient step of the Observe-Orient-Decide-Act (OODA) loop is to the most consequential for improving reliability or efficiency of CID task performance. Modeling was performed to examine the CID task across existing system architectures to understand potential improvements that enhance human-agent team design for this task. More specifically, subjective logic was explored as a possible means of increasing the observability of a multi-agent interface that supports decision making in the CID use case. This approach was incorporated into the model to demonstrate potential utility. Initial findings suggest that further research on subjective logic should be conducted to understand the impact of this tool for improving multi-agent system performance in future Department of Defense systems.

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