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Operational Value of Information

A Reward-Function for Sensor Management Applications

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Foreword

The research described in this thesis is part of a cross-disciplinary research project that we, Patrick Langheim and Benedikt Petermeier, conducted jointly to support the design of automated sensor management systems by providing an objective function, which rewards sensor management actions considering the users' needs. This endeavor is challenging for several reasons: It requires a thorough understanding of the technical systems, the operators' needs, and the operational context. Further, the value of specific information to a user is highly context-dependent and challenging to quantify. Finally, development demands expert knowledge, but access to it is often limited and difficult to achieve – a problem commonly referred to as the "knowledge acquisition bottleneck." These challenges required extensive expertise in engineering and psychology and called for a multi-disciplinary approach.

Two dissertations resulted from our cooperation, each emphasizing a different perspective on the same challenge and answering separate research questions. Our collaborative approach helped us to achieve results that would not be reachable through mere engineering-centric or psychology-centric research approaches. The highly interactive process incorporated a tight coupling of each subject area's contributions. Consequently, some developed content, such as the human-machine interfaces for collecting expert knowledge, cannot be explicitly attributed to a single author. Further, each dissertation contains contents and results assigned to the other thesis to tell a coherent and complete solution process that is understandable to the reader.

The present thesis documents the engineering perspective and focuses on modeling and assessing the objective function for assessing sensor activity. The psychological view is documented in Petermeier's dissertation and concentrates on developing and evaluating methods for eliciting the expert knowledge required for the modeling and assessment activities. These contributions are explicitly attributed to Benedikt Petermeier in the present thesis. Section 3.3 features a more detailed explanation of the collaborative approach.

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Abstract

Sensor management systems control the sensing resources to maximize the expected reward. Developing objective functions for these systems is challenging because of the required thorough understanding of the avionics systems, the operators' needs, and the operational context. Further, it is difficult for experts to describe these functions explicitly.

The research aims to model the operational value of the information carried by sensed data, defined as the information's ability to fulfill the pilots' prioritized information needs. Elicited expert knowledge is evaluated and incorporated into a prototypical information valuation model. The model's reasoning is assessed against expert preferences in pairwise comparisons of information sets.

The joint study captures three sets of expert knowledge: task-specific data accuracy demands, prioritized tasks associated with objects, and expert preferences in comparisons. The review of the literature and the conclusions drawn from the knowledge elicitation studies lead to the capture of requirements for an information value model applied in the research use case. The model's architecture comprises three modules that process information sets at the parameter, task, and overall scenario. The prototypical implementation of the information value model matches expert preferences to 93% for all information set comparisons. This hit rate increases to 100% for comparisons with a low uncertainty in the experts' preferences.

Modeling the operational value of information addresses the identified gap in the literature by providing an explicit reward function for sensor management applications based on the operators' mission-specific needs. The research advances the knowledge of specifying the right optimization objective for complex systems and integrates the human component in the development process.

Keywords Sensor Management, Expected Reward, Optimization Objective, Utility, Information Value

Zusammenfassung

Sensormanagementsysteme steuern Sensorressourcen, um den erwarteten Nutzen zu maximieren. Die Entwicklung von Zielfunktionen für diese Systeme ist eine Herausforderung aufgrund des benötigten Verständnisses von Sensorsystemen, Nutzeranforderungen und des operativen Kontextes. Darüber hinaus ist es für Experten schwierig, diese Zielfunktionen explizit zu beschreiben.

Das Ziel dieser Forschung ist die Modellierung des operativen Wertes von Sensordaten, welcher die Fähigkeit der Information widerspiegelt, den priorisierten Informationsbedarf der Piloten zu erfüllen. Erfasstes Expertenwissen wird ausgewertet und in ein prototypisches Informationswertmodell aufgenommen. Die Ergebnisse dieses Prototyps werden im Verhältnis zu Präferenzen von Experten in Paarvergleichen von Informationsgrundlagen bewertet.

In gemeinsamen Studien werden folgendes Expertenwissen gesammelt: Datengenauigkeitsanforderungen, priorisierte objektbezogene Aufgabenliste, und Expertenpräferenzen in Paarvergleichen. Die Literaturrecherche und die Auswertung des erfassten Expertenwissens führen zur Formulierung von Anforderungen an ein Model des Informationswerts. Das entwickelte Modell besteht aus drei Modulen, welche die Informationen auf der Parameter-, Aufgaben- und Szenarioebene verarbeiten. Die prototypische Implementierung des Informationswertmodells trifft die Wahl der Experten in 93% der Paarvergleiche. Bei Vergleichen mit einer geringen Unsicherheit bzgl. der Expertenwahl erhöht sich die Trefferquote auf 100%.

Die Modellierung des operativen Informationswertes füllt die identifizierte Lücke in der Forschung und stellt eine Nutzenfunktion für Sensorsteuerungssysteme bereit, die auf den Bedürfnissen der Piloten beruht. Die durchgeführte Forschung erweitert den Stand der Wissenschaft bzgl. der Formulierung einer korrekten Zielfunktion für komplexe Systeme und unterstützt die Betrachtung der menschlichen Komponente.

Schlüsselwörter Sensorsteuerung, Erwartungswert, Zielfunktion, Nutzwert, Informationswert

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List of Abbreviations

ABS Antilock Brake System

AC Aircraft

ADM Aeronautical Decision Making

AESA Active Electronically Scanned Array

AI Artificial Intelligence

ATC Air Traffic Control

AWC Airborne Weapon Controller

BAI Battlefield Air Interdiction

BVR Beyond-Visual-Range

CAP Combat Air Patrol

COMAO Composite Air Operations

DAG Directed Acyclic Graphs

DCA Defensive Counter Air

DIKW Data, Information, Knowledge, and Wisdom

DOA Direction of Arrival

ECM Electronic Countermeasures

EO Electrooptic

ESM Electronic Support Measures

EW Electronic Warfare

EWS Electronic Warning System

F2T2EA Find, Fix, Track, Target, Engage, and Assess

FAA Federal Aviation Administration

FLOT Forward Line of Own Troops

HCD Human-Centered Design

HFE Human Factors Engineering

HMI Human-Machine Interface

ID Identification

IFF Identification Friend or Foe

IR Infrared

MAUT Multi-attribute utility theory

MDP Markov Decision Process

OA Operational Activity

OCA Offensive Counter Air

OE Operational Exchange

OGUPSA Online, Greedy, Urgency-driven, Preemptive Scheduling Algorithms

OODA Observe, Orient, Decide, and Act

POMDP Partially Observable Markov Decision Process

PSSUQ Post-Study System Usability Questionnaire

QRA Quick Reaction Alert

RADAR Radio Detection And Ranging

RMSE Root Mean Square Error

RWR Radar Warning Receiver

SA Situation Awareness

SAM Surface-to-Air Missile

SDT Signal Detection Theory

SEAD Suppression of Enemy Air Defenses

SEU Subjective Expected Utility

SJT Social Judgment Theory

SNR Signal-to-Noise Ratio

TCAS Traffic Collision and Avoidance System

TDL Tactical Data Link

UAF Unified Architecture Framework

UAV Unmanned Aerial Vehicle

US United States of America

UV Ultraviolet

V&V Verification and Validation

WSO Weapon System Officer

1. Introduction

The value of information in warfare, as in business, resides in its ability to affect decisions in one's favor [1]. Information superiority, a key aspect in modern warfare, is gained through the careful management of available information provided by advanced sensor systems and offers the potential to offset a numerical, technological, or positional disadvantage [2].

Success in missions flown by these aircraft is correlated to the pilots' situational awareness (SA) [3], a fundamental construct driving human decision-making that Endsley [4, p. 792] defined as "the perception of elements in the environment (...), the comprehension of their meaning, and the projection of their status in the near future." Acquiring and upholding SA in complex and dynamic environments is critical due to the potentially fatal consequences of minor inaccuracies in SA for the pilot [5], e.g., low SA played a significant role in the friendly fire of two US aircraft against a British convoy in March 2003 [6]. Good SA requires detecting, identifying, and tracking objects in the environment and estimating the threat posed by these objects [7].

Pilots primarily rely on their aircraft's RADAR to monitor the environment [8]. State-of-the-art radar systems can perform multiple tasks concurrently [9, 10] and enable complex mechanisms for the efficient use of the constrained RADAR resources [11]. Managing these resources becomes challenging when the available resources are insufficient to perform every sensor task [11].

Sophisticated management systems control modern sensor suits to take advantage of their flexibility [12]. These systems are called *sensor managers* and support the pilot's planning and scheduling of activities performed by the sensors [13]. Figure 1.1 illustrates the systems involved in the sensor management loop, from the environment to displaying information on the human-machine interface.

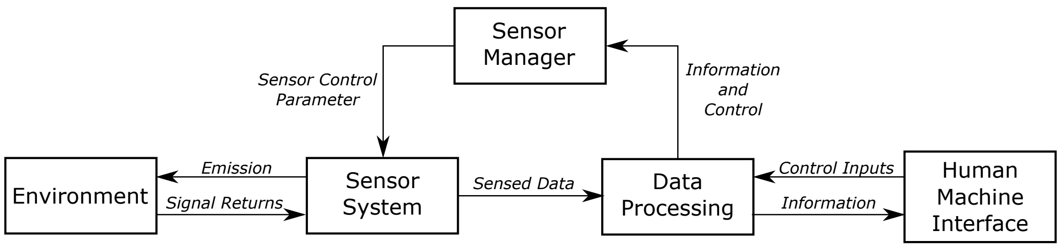


Figure 1.1.: *High-level abstraction of the sensor management loop.*

Hero et al. [14, p. 3064] defined *sensor management* as the "control of the degrees of freedom in an agile sensor system to satisfy operational constraints and achieve operational objectives". Therefore, sensor management systems should manage sensor tasks and parameters to provide the data required for the pilots' decision-making and dynamically adapt to changing environments [13]. Developing sensor management systems is challenging and best described as the design of decision processes to maximize the reward associated with performing a sensing task [14]. The sensor management's function defining the expected reward must reflect the user's information needs to support their ability to acquire and maintain an accurate mental picture of the environment [15].

1.1. Focus and Scope

The research focuses on designing reward functions for sensor management systems that are context-specific and independent of specific sensor implementations. The latter is achieved by evaluating the collected information irrespectively of the utilized sensor resources. Context-specificity is achieved by basing the evaluation metric on the tasks performed by operators.

This research aims to model the quality-dependent value of information for fighter pilots based on their task-specific information needs. The model is limited to the valuation of aircraft detections and aircraft state estimates' accuracies in static snapshots of a dynamic situation. Further, the operational context is limited to a single mission context to reduce the complexity and limit the number of model variables. The model does not determine the context-dependent information needs and receives these as input.

1.2. Relevance and Importance

Sensor management systems found in the literature use surrogate functions to assess the value of the information expected to be gathered by performing sensing tasks and do not consider the expected data quality as a trade-off criterion. The reviewed approaches have the following shortcomings:

1. Using mission-independent objectives, e.g., maximizing the expected information gain for the management of sensor systems, cannot ensure gathering the most valuable information for the operators since the value of sensed data usually depends on the current mission goal.

2. Bolderheij's [16] and Katsilieris's [17] approaches use a risk assessment to select the sensor tasks that is specified for naval radar operations and is challenging to transfer to airborne radar systems due to the diversity of missions conducted by swing-role aircraft.

3. De Groot's [18] use of "the optimality for the mission" as decision criteria is more general. It eliminates the need for heuristically defined task qualities, priorities, and expert opinions, but this criterion requires designers to define a metric to measure the "optimality for the mission."

4. Designing a sensor management system based on operator-defined priorities is complex and requires a thorough understanding of the of the avionics systems, the operators' needs, and the operational context [19, 20]. For example, the goal lattice approach by McIntyre [21] requires system designers to enumerate all the system's goals and quantify the interrelationship among them. The same issue arises in the approach by Molina et al. [22, 23, 24]. Using expert opinion is relatively complex [16], and reward functions are only sometimes explicitly given [25].

The research performed for this study will advance the knowledge on how to specify the right reward function for complex systems, which is a significant challenge in artificial intelligence (AI) [26, 27]. Further, involving human domain experts in the development process of complex automated systems has shown that these experts can learn from their interaction with artificial intelligence, as demonstrated by Lee Sedol in his fourth game against Google's AlphaGo [28].

1.3. Research Objectives

The study aims to model the operational value of information based on the pilot's task-specific information demands to answer the following research question:

> How can the operational value of information be specified for airborne sensor management systems?

The following objectives are addressed to investigate the research question:

Information Value Definition The research's first objective is to define the concept of information value and its relationships with the pilot's mission objectives and the data provided by the aircraft's sensors.

Expert Knowledge Exploitation The second research objective is to analyze and interpret collected expert knowledge linked to the value of information, which includes captured activities performed by the pilot, the data accuracy required to perform these tasks, and their priority.

Operational Information Value Modeling The research's third objective is to design a model of the operational value of the information provided to pilots.

Prototypical Model Performance Assessment The final research objective is to assess the ability of a prototypical information value model to reflect the pilots' information needs and their trade-offs based on a collection of information sets.

1.4. Thesis Outline

Chapter 2 provides a summary of the relevant literature and scientific concepts that highlight the research gap in operator task-based evaluation functions for sensor management applications and underpin the information value model. The theoretical concept of information value is described in Chapter 3, together with the description of the methodology selected for the four studies described in Chapters 4 to 7. Operator tasks considered within the study's scope and the related information needs are identified in Chapter 4. The collection of the prioritized tasks associated with objects in the environment is described in Chapter 5. Chapter 6 presents the study conducted to collect expert preferences concerning sets of information for various situations. These preferences are used to validate the information value model detailed in Chapter 7. The results of the four research blocks are discussed in Chapter 8. Finally, Chapter 9 concludes the research and suggests avenues for future research.

2. Theoretical and Technical Background

This chapter summarizes the relevant human factors and technical background. The first section describes the link between fighter aircraft operations and radar measurements. The second section outlines the sensor management domain and reviews management reward functions. The third section reviews human information processing theories linked to sensor management applications. The fourth section covers the automation issues arising from introducing sensor management systems and mitigation approaches. Approaches to the valuation of information are reviewed in the fifth section. Finally, the last section summarizes the primary literature review findings.

2.1. Airborne Sensor Operations

The Commission on Roles and Missions of the Armed Forces defined achieving air superiority, performing strikes, and enabling air mobility as the core missions of the US Air Force [29]. Air superiority is the "degree of dominance in the air battle by one force that permits the conduct of operations at a given time and place without prohibitive interference from air and missile threats" [30, p. 10]. Missions performed to achieve the desired degree of air superiority are classed as counterair operations and can either have an offensive (OCA) or defensive (DCA) nature [30, 31]. Achieving air superiority is critical, and as stated by Warden [32, p. 169], air superiority "alone can win a war" in many circumstances. Besides OCA and DCA roles, combat aircraft can perform close air support, air interdiction, battlefield air interdiction, or suppression of enemy air defenses [33].

Developments in the network capabilities and flexible weapons have contributed to the development of aircraft able to perform air-to-air and air-to-ground roles and switch roles multiple times mid-flight [34]. These aircraft are commonly called swing-role aircraft. Swing-role fighter aircraft roles may include reconnaissance and strike tasks besides the traditional air superiority enforcement [35]. The key to success in military operations is to collect data (Observe), process information (Orient), select actions (Decide), and perform these actions (Act) faster than the opponent [36].

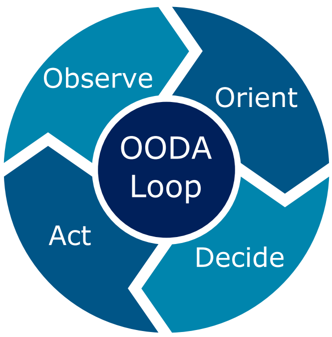


Figure 2.1.: *Boyd's observe, orient, decide, and act (OODA) loop.*

2.1.1. Fighter Aircraft Missions

The main missions flown by fighter aircraft are called Battlefield Air Interdiction (BAI), Electronic Warfare (EW), Fighter Escort, Fighter Sweep, and Suppression of Enemy Air Defenses (SEAD). Modern operations employing large aircraft fleets with dedicated tasks are called composite air operations (COMAO) [37]. Figure 2.2 exemplifies an operation with the main fighter aircraft missions listed below.

Fighter Sweep is defined as an "offensive mission by fighter aircraft to seek out and destroy enemy aircraft or targets of opportunity in a designated area" [30, p. 86]. It is generally conducted over hostile territory to establish air superiority and protect friendly forces by suppressing enemy fighters and other airborne targets [38]. This aim is achieved by neutralizing hostile airborne aircraft, attacking airfields with hit-and-run tactics, and engaging reconnaissance and transport aircraft over surface battles [38].

Fighter Escort is a mission flown to protect other air assets "over enemy territory, or in a defensive counterair role to protect high-value airborne assets" [30, p. 85].

Battlefield Air Interdiction (BAI) is an "air operation conducted to divert, disrupt, delay, or destroy the enemy's military surface capabilities before it can be brought to bear effectively against friendly forces" [30, p. 7].

Suppression of Enemy Air Defenses (SEAD) encompasses any activity "that neutralizes, destroys, or temporarily degrades surface-based enemy air defenses" [30, p. 229]. Preplanned SEAD suppresses permanent or semi-permanent threats, e.g., strategic surface-to-air missiles (SAMs) [39]. Reactive SEAD suppresses time-sensitive "pop-up" threats [39].

Combat Air Patrol (CAP) missions aim to intercept and neutralize hostile missiles and aircraft before they can reach their intended targets [40, p. 36].

Quick Reaction Alert (QRA) is an operation performed by an air force that aims to protect a country's air space from threats [41]. Usually, this air policing operation involves a ground-based radar station, air superiority fighter aircraft, and personnel [41]. A Master Controller gets alerted when a potentially threatening aircraft is spotted by the controller operating a ground-based radar. This information gets relayed to the pilots on QRA duty.

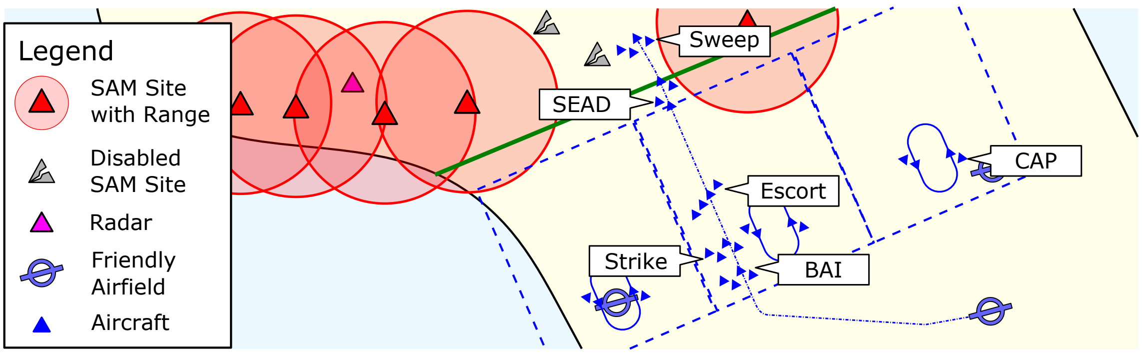


Figure 2.2.: *Exemplified OCA operation.*

2.1.2. Mission Phases

Missions are usually performed by flight groups of at least two aircraft [42, 43], with the smallest group composed of a flight leader and a wingman. The flight leader is responsible for planning and performing the mission [44]. The wingman monitors the environment and supports and cross-checks the flight leader's actions [44]. Missions can be divided into three main phases [44]: (1) mission preparation, (2) mission execution, and (3) mission debriefing.

Mission Preparation: Mission success demands a thorough preparation that consists of the mission planning and briefing phases [44]. Missions are planned jointly by the aircraft operators, operations organization, and intelligence organization to reach a set of specified mission objectives [45]. These objectives comprise a concrete list of actions to be performed by the flight members, the conditions that apply to these actions, and standardized metrics to measure the flight members' performances [44]. The mission planning is completed with the preparation of a concise and comprehensive briefing [44].

The mission briefing is conducted one and a half hours before takeoff and aims to ensure a safe mission accomplishment [45]. The mission objectives, events, and performance metrics are reviewed. In addition to the mission data, ground procedures, takeoff procedures, departure/en route, and recovery are discussed during the briefing [45].

Mission Execution: A generic air-to-air mission can be abstracted as the succession of 10 phases [46, 47, 38]. At the beginning of the mission, the aircraft (1) takes off and (2) proceeds to climb to altitude climb. Depending on the mission settings, the aircraft performs an air-to-air refueling (3) before establishing the flight package (4). The package then (5) cruises to the zone of operations and (6) ingresses into the hostile airspace when flying over the *forward line of own troops* (FLOT). After (7) performing the air-to-air mission tasks, package (8) egresses the hostile airspace. The aircraft (9) cruises back and ends the mission by (10) landing at the airbase. The various phases of the mission are illustrated in figure 2.3.

Debriefing: A debriefing is conducted post-mission to summarize the mission and assess its success. Additionally, the individual flight groups' strengths and weaknesses are assessed, and the required training needs are identified [44].

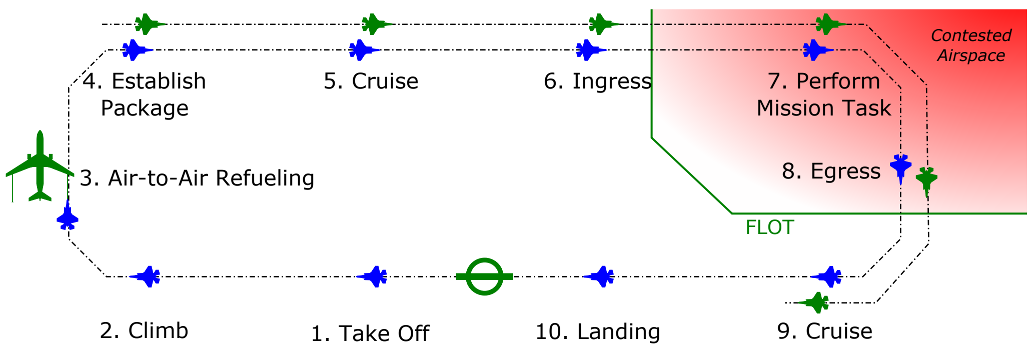


Figure 2.3.: *Generic air-to-air mission timeline.*

2.1.3. Fighter Pilot Goals

Two types of fighter pilot goals can be found in the literature: (1) operational and (2) tactical.

Operational Goals Operational goals are defined for a specific mission. The US 1998 Air Force counterair operations doctrine [40, p. 1] sets the objective of fighter aircraft operations "to facilitate friendly operations against the enemy and protect friendly forces and vital assets through control of the air." OCA missions are conducted to minimize the risk posed by hostile forces and enable friendly forces to focus on their mission achievement [40]. DCA operations are conducted to defend friendly forces from offensive operations by hostile forces [40].

Tactical Goals Tactical goals are specific to a situation in a mission. Endsley [7] conducted a goal-directed task analysis and established the following high-level pilot goals in air-to-air missions: kill the enemy, avoid harm and detection, reach a geographic point, defend a geographic area, and defend a friendly aircraft.

Goal Lattice McIntyre [21] extracted 91 goals from the US Air Force documents and structured these goals in a lattice shown in figure 2.4. The highest goal in the lattice is "to achieve control of the air" (1). At the lowest level, fighter pilots aim "to track all detected targets" (88), "to id targets" (89), and "to search for enemy targets" (90). The uppermost goal is connected to the lowest objectives by a series of sub-goals, e.g., "to avoid threats" (36) and "to detect threats" (79). McIntyre designed the lattice to calculate the importance of low-level tasks based on the weights associated with higher-level tasks. The complete list of goals is found in section A.1 of the appendix.

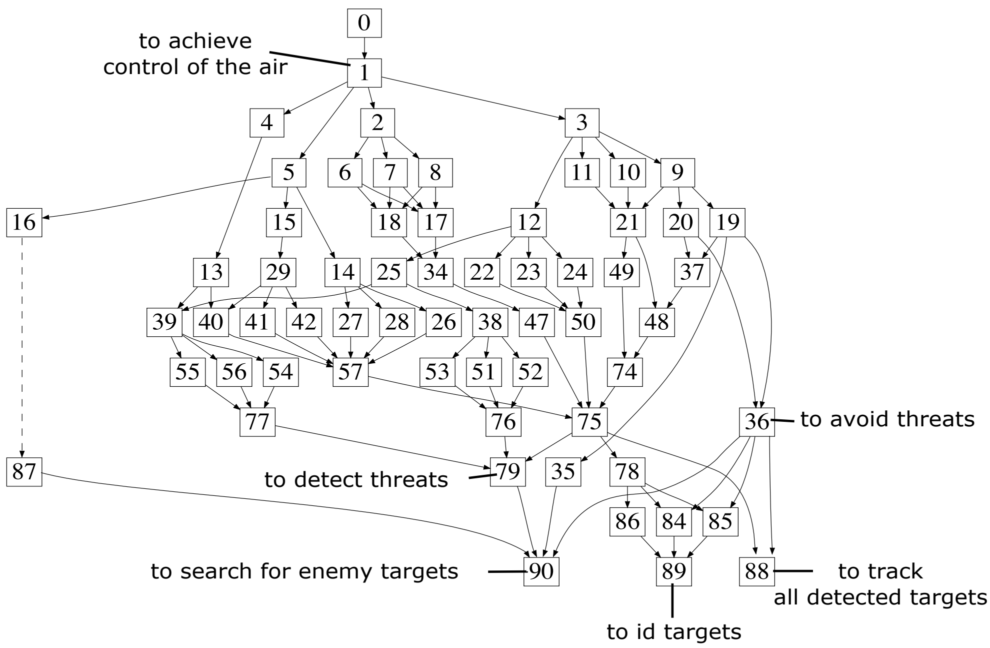


Figure 2.4.: *Lattice of Air Force Goals, adapted from McIntyre [21]. The dashed line abstracts the goals leading from goal 16 to 87.*

2.1.4. Fighter Pilot Tasks

Pilots perform several tasks to fulfill their mission goals [48]. Hollnagel [49, p. 385] defined a *task* as "one or more functions or activities that must be carried out to achieve a specific goal." These activities depend on the role of the pilot in the mission and within the flight group. Flight leaders handle tasks linked to organizing, planning, and controlling a mission while their wingman supports and monitors the environment [44]. Schulte [50] defined the following three principal kinds of motivation for pilot tasks[1]:

1. flight safety,
2. combat survival, and
3. mission accomplishment.

2.1.4.1. Flight Safety Tasks

Flight safety tasks are performed to ensure and maintain a safe flight, e.g., to avoid terrain by keeping the aircraft at least 250 ft. above ground level [50]. Ausink et al. [51] stated that flying the aircraft should be second nature for fighter pilots. The US Air Force handbook on F-16 combat fundamentals [44] lists the following high-priority tasks to be performed by pilots: to maintain control of the aircraft, to avoid terrain, to avoid midair collisions, and to manage fuel. The US 1996 Air Force Handbook for F-15 Aircrew operational procedures [45] lists the following routine operating procedures: check systems, manage formation, perform flight path deconfliction, and manage radios.

2.1.4.2. Combat Survival

Combat survival tasks are performed to minimize the threat posed by hostile actors, e.g., to maneuver to avoid getting hit [52]. Combat survival can be achieved by denying enemies to fulfill their engagement conditions. These conditions require the aircraft to be tracked with sufficient accuracy, be identified as hostile, be within range, and be considered a valuable target [52]. Avoiding enemy engagement can thus be achieved through a range of means, e.g., avoiding detection. Erlandsson and Niklasson [52] listed the following tasks to be performed to ensure combat survival:

- to analyze the situation,
- to predict the enemy's actions,
- to assess the risk associated with the mission,
- to plan the mission to avoid unnecessary risk,
- to trigger mission replanning if the risk is too high,
- to assess the risk of getting hit,
- to assess the threat posed by the enemy against the aircraft,
- to analyze enemy intentions, and
- to analyze enemy capabilities.

[1]The order of these pilot task types does not reflect their priority and Schulte's taxonomy is used to structure this subsection despite the overlap and interdependencies observed between the task types.

2.1.4.3. Mission Accomplishment

Pilots perform several tasks to accomplish the mission's objectives. The process of managing targets and threats follows the *Find-Fix-Track-Target-Engage-Assess* (F2T2EA) cycle [53]. The US Department of Defence [30, p. 235] defines a *target* as "an entity or object that performs a function for the adversary considered for possible engagement or other action."

F2T2EA Cycle The targeting process starts with the *find* step in which objects are detected, characterized, and nominated for further steps if they meet the criteria defined in the briefing. The *fix* step confirms the identification and refines the detected object's position to reach the desired level. The object's location is maintained at the desired accuracy level, and the object's actions are monitored during the tracking phase. Tracking is defined as recording successive positions of a moving object [30]. The decision to engage a target to create the desired effect occurs during the *target* step, and the action is performed during the engage phase. Finally, the action's results are assessed in the last phase of the F2T2EA cycle.

Pilot Tasks Houck et al. [48] determined the following pilot activities for the ingress phase of a DCA mission:

1. Operate onboard sensors,
2. React to electronic countermeasures (ECM),
3. Communicate with a wingman,
4. Communicate with airborne weapon controller (AWC),
5. Correlate onboard with off-board sources,
6. Fly offensive profile,
7. Fly defensive profile,
8. Radar warning receiver (RWR) interpretation,
9. Adjust the mission plan, and
10. Fly attack formation and navigation.

Information Management Houck et al. [48] determined that integrating onboard data and correlating information from various sources are some of the most demanding tasks for fighter pilots. Endsley and Jones [54] described three steps to achieve information superiority: (1) information collection, (2) information understanding, and (3) action projection. Superior information collection is based on real-time sensors and information fusion. Understanding the information requires the information to be integrated and compared against the pilot's goals and the environment's desired states. Finally, projecting actions is based on mental models that project information into the future. Ceborwski and Garstka [2] and Stillion [55] identified superior information collection as a key enabler for information superiority. Ausink et al. [51] predicted the ability to take information cues from sensors to be essential to successful operations. Trépant et al. [56, p. 3] defined *information superiority* as "the ability to meet the information requirements of supported forces with superior timeliness, relevance, accuracy, and comprehensiveness than can be achieved by an adversary." The processing of information by humans is reviewed in detail in section 2.3.

2.1.5. Fighter Pilot Informational Needs

Fighter pilots base their actions on information provided by the aircraft and presented on their cockpit displays. Several studies have investigated the pilots' informational needs. Endsley [7] used unstructured interviews followed by a goal-directed task analysis to identify the informational requirements for situation awareness in air-to-air combat listed in Table 2.1.

Table 2.1.: *Fighter pilot information requirements, adapted from Endsley [7].*

Flight	**Flight Path**	**Sensor**	**Emissions**	**Other**
ID[2]	Intercept time	Search mode	EWS[3] mode	Maneuver
AC type	Closing velocity	Search volume	IFF[4] code	Activity
Envelope	Acceleration	Limitations	IFF[4] reply	Energy State
Location	Vertical Velocity	Detections	Jamming	Tactics
Range		Lock-ons		Threat
Azimuth		Sorting		Info. source
Altitude				Info. confidence
Attitude				Weapon envelope
Heading				Missile p_k[5]
Aspect				
Acceleration				

Houck et al. [48] investigated the information demanded by pilots to perform critical tasks of an air intercept mission. Figure 2.2 lists the information demand by mission phase.

Table 2.2.: *Threat-related information demanded by pilots in phases of an air intercept mission based on Houck et al. [48].*

Information	**Mission Phase**			
	CAP	**Ingress**	**Attack**	**Merge**
Formations	Number	Number	Targeting Status	Targeting Status
Identification	Category	Type	ID[2]	
Geographic Location	Rough	Precise		
Geometric Relationship		Precise		
Altitude	Category	Precise	Precise	Precise
Azimuth		Precise	Precise	Precise
Range		Closest target	All targets	Closest target
Movement	Rough	Precise		
Observed tactics		Yes	Yes	
Reactions to actions			Yes	Yes

[2]The Identification (ID) of an aircraft expresses if it is friendly, hostile, neutral, or unknown.
[3]Electronic Warning System (EWS)
[4]Identification Friend or Foe (IFF)
[5]p_k represents the probability of a missile hitting its intended target.

2.1.6. Mission Information Sources

The information needed by fighter aircraft operators linked to mission tasks is provided either by on-board sources or provided to them by off-board sources, e.g., air traffic control.

Onboard Sources Modern fighter aircraft enhances the pilot's situational awareness by sensing the environment with various sensor systems and making this data available to the pilot.

Visual Fighter pilots primarily rely on their eyes to collect information about the state of the environment and their aircraft [8].[6]

RADAR RADAR systems use electromagnetic waves to gain information about objects in the environment, e.g., range, position, and velocity [58]. Subsection 2.1.7 provides an overview of RADAR information exploitation.

Electronic Support Measures (ESM) ESM systems comprise several passive sensors that collect signals in different frequency bands and determine their *direction of arrival* (DOA). The signal's characteristics, e.g., frequency, are further analyzed to classify and identify the emitter and assess the threat level posed by this emitter [59].

Electrooptic (EO) EO sensors monitor the environment in the visible, *infrared* (IR), and laser spectra of the electromagnetic spectrum [59]. Sensors operating in the visible spectrum capture light visible to the human eye and produce imagery subjected to further analysis, e.g., to detect threats. IR sensors sense the heat radiated by objects in the environment and produce either imagery or determine the direction of a radiation source. Specialized EO sensors monitor the IR or *ultraviolet* (UV) signature of launched missiles and active laser systems [59]. Drawbacks of EO sensors include the obscuration and scattering caused by gases or terrain [59].

Off-Board Sources Additional information is provided to fighter aircraft by external systems.

Radio Pilots can receive information from external players over the radio, e.g., *Air Traffic Control* (ATC). On request, ATC can support pilots with additional information, e.g., weather conditions at the aircraft's destination. Additionally, ATC monitors the aircraft's position by primary surveillance radar or transponder-based secondary radar.

Transponder The aircraft's transponder can send messages to aircraft in its proximity (interrogation) and process their response to determine their location and identity [59]. The interrogation can be omnidirectional or directional. Omnidirectional interrogations are used for collision avoidance systems, e.g., the *traffic collision and avoidance system* (TCAS). The directional interrogation, coupled with the primary radar, is used for *identification friend or foe* (IFF) operations.

Tactical Data Link (TDL) Communication links enable fighter pilots to exchange data between the aircraft [43]. Aircraft and other assets can exchange data and information via dedicated communication channels [59]. The most commonly used data link is Link 16, which has a throughput of up to 238 kilobits per second [59].

[6] More than 90% of the information processed by pilots acquired visually according to [57]. The share of information obtained through the cockpit instrumentation varies by type of operations, e.g. pilots need to rely on their displays for beyond-visual-range operations.

2.1.7. RADAR Systems

The onboard **Ra**dio **D**etection **A**nd **R**anging (RADAR) system is considered the primary sensor [8]. RADAR systems send electromagnetic waves, which are reflected toward the emitter by objects in the environment [60], as illustrated by figure 2.5. This return is analyzed to gain information about the source of the reflection, e.g., range, position, and velocity [58]. This section summarizes the theoretical background necessary to understand the modeled sensor system.

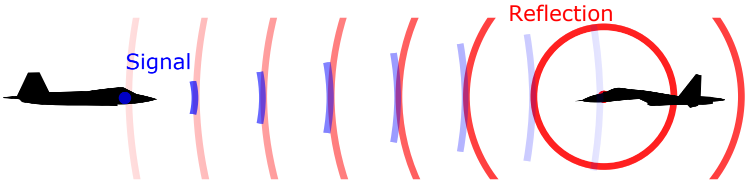


Figure 2.5.: *RADAR signal propagation.*

2.1.7.1. Signal-to-Noise Ratio

Two object parameters affect the intensity of the signal it reflects, its range R, and its RADAR cross-section σ. The cross-section measures the size of an object as seen by the sensor. It is described as the cross-section of a sphere having the same reflectivity as the object. Table 2.3 lists the cross-section of selected aircraft in the X-band.

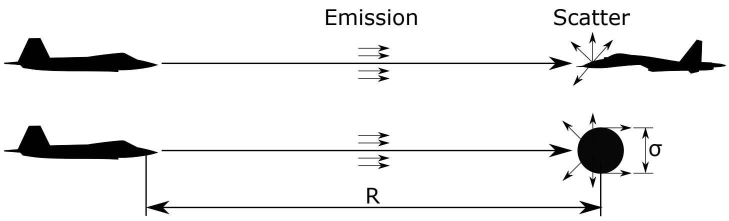


Figure 2.6.: *Object RADAR cross-section modeling.*

Table 2.3.: *Radar cross-section σ of selected aircraft, adapted from [61].*

Aircraft	B-52	F-15	Su-27	F-16	F/A-18	F-35	F-22
σ $[m^2]$	100	25	15	1.2	1	0.005	0.0001

The signal-to-noise ratio (SNR) between the signal and the noise floor can be described in terms of pulse, target, and system parameters [58]. The SNR of a pulse with a peak power P_t reflected by a target at range R is calculated using equation 2.1 [62]. The Boltzmann constant k, antenna temperature T_0, noise figure F, and losses L are assumed to be constant.

$$SNR = \frac{P_t \cdot G^2 \cdot \lambda^2 \cdot \sigma \cdot \tau}{(4\pi)^3 \cdot k \cdot T_0 \cdot F \cdot L \cdot R^4} \tag{2.1}$$

2.1.7.2. Detection Probability

The radar returns a detection when it receives a signal which exceeds a threshold value. This threshold is necessary due to random noise, and it is selected to meet a specified probability of false alarm P_{fa} [63]. These false alarms occur when random noise assumes large values [64, 65], as illustrated in figure 2.7.

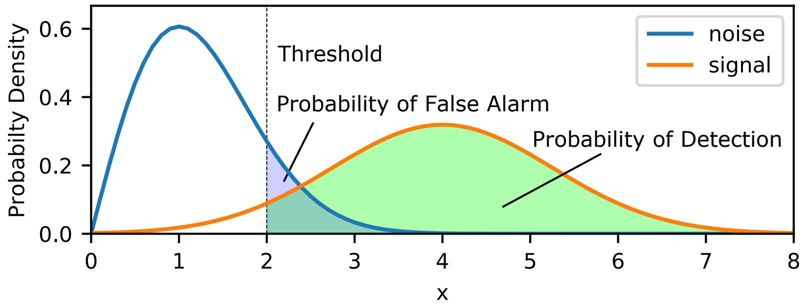


Figure 2.7.: *Detection and false alarm probability for a threshold set at $x = 2$.*

The detection probability P_D can be approximated with North's approximation (eq. 2.2) using the probability of false alarm P_{fa} and the signal-to-noise ratio SNR [58].

$$P_D \approx 0.5 \cdot \operatorname{erfc}\left(\sqrt{-\ln P_{fa}} - \sqrt{SNR + 0.5}\right) \tag{2.2}$$

2.1.7.3. RADAR Measurement

RADAR measurements Z contain four distinct values: the measured range $R_{m,tgt}$, azimuth angle $\theta_{A,m,tgt}$, elevation angle $\theta_{E,m,tgt}$, and Doppler velocity $V_{R,m,tgt}$.

$$Z = \begin{Bmatrix} R \\ \theta_A \\ \theta_E \\ V_R \end{Bmatrix}_{m,tgt} \tag{2.3}$$

Electromagnetic signals travel at the speed of light c. Thus, the range $R_{m,tgt}$ from RADAR to an object can be calculated by measuring the signal's round-trip propagation time t [58] and solving equation 2.4.

$$R_{m,tgt} = \frac{c \cdot t}{2} \tag{2.4}$$

The azimuth $\theta_{A,m,tgt}$ and elevation angles $\theta_{E,m,tgt}$ from the RADAR to the object can be determined by measuring the antenna's position $\theta_{A,antenna}$, $\theta_{E,antenna}$ at the time when the return is received.

$$\theta_{i,m,tgt} \coloneqq \theta_{i,antenna} \tag{2.5}$$

The radial velocity $V_{R,m,tgt}$ relative to the RADAR can be determined by measuring the Doppler frequency shift f_D. As can be seen in equation 2.6, the frequency shift is influenced by the signal carrier frequency f_0 [58].

$$V_{R,m,tgt} = \frac{c \cdot f_D}{2 \cdot f_0} \tag{2.6}$$

2.1.7.4. Measurement Accuracies

The radiated signal's time and frequency affect the accuracy of the information obtained from the return [66]. Additionally, returning signals are subject to noise generated by interfering signals from external and internal sources [58].

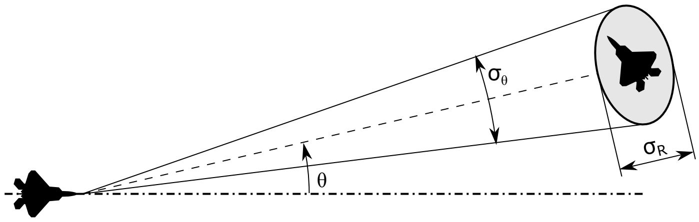


Figure 2.8.: *RADAR measurement range σ_R accuracy and angle σ_ϕ accuracy.*

Range Accuracy As discussed previously, the range of an object is determined by measuring the round-trip propagation time t. The duration of the returning pulse is unknown due to the effects of the reflecting object's velocity. The timing must thus be measured via the leading edge of the returning signal. The signal is distorted by noise, which leads to uncertainty regarding the round trip time t. The standard deviation of the range uncertainty σ_{R_m} is calculated using equation 2.7 [58].

$$\sigma_{R_m} = \frac{c \cdot \tau}{2 \cdot \sqrt{2 \cdot SNR}} \tag{2.7}$$

Angle Accuracy While the measured angles' accuracy is also subject to random errors, systematic errors due to internal sources are more frequent. The signal strength of the return varies with the object's position relative to the beam centerline [58]. The standard deviation of the angle error σ_ϕ is determined via equation 2.8 [62], where Θ_{3dB} represents the antenna's directivity.

$$\sigma_\phi = \frac{\Theta_{3dB}}{1.6 \cdot \sqrt{2 \cdot SNR}} \tag{2.8}$$

Velocity Accuracy The closing velocity V_r of an object is measured by calculating the Doppler frequency shift f_D. This frequency shift is obtained by comparing the signal's pulse duration τ_r against the pulse duration of the returning signal. The velocity estimation accuracy is thus proportional to the accuracy of the measured pulse duration. The standard deviation of the measurement error $\sigma_{V_{r,m}}$is calculated with equation 2.9 [62].

$$\sigma_{V_{r,m}} = \frac{\lambda}{2 \cdot \tau \cdot \sqrt{2 \cdot SNR}} \tag{2.9}$$

2.1.7.5. Object Tracking

RADAR systems are typically used to track multiple objects [10]. Object tracking estimates the trajectories of a moving object [67]. Tracking is accomplished by processing a sequence of measurements $\mathbf{Z}$ and their inaccuracies $\vec{\sigma}$ [60]. The tracking algorithm computes a state vector X for the object based on the measurements [60]. This state vector usually estimates an object's position, velocity, and acceleration. The Kalman Filter is commonly used for sensor tracking.

$$\mathbf{Z} = \left[\begin{Bmatrix} R \\ \theta_A \\ \theta_E \\ v \end{Bmatrix}_0 \cdots \begin{Bmatrix} R \\ \theta_A \\ \theta_E \\ v \end{Bmatrix}_n \right] \tag{2.10}$$

$$\vec{\sigma} = \left[\begin{Bmatrix} \sigma_R \\ \sigma_{\theta_A} \\ \sigma_{\theta_E} \\ \sigma_v \end{Bmatrix}_0 \cdots \begin{Bmatrix} \sigma_R \\ \sigma_{\theta_A} \\ \sigma_{\theta_E} \\ \sigma_v \end{Bmatrix}_n \right] \tag{2.11}$$

$$X = \begin{Bmatrix} x & y & z & \dot{x} & \dot{y} & \dot{z} & \ddot{x} & \ddot{y} & \ddot{z} \end{Bmatrix}^T \tag{2.12}$$

Tracking is a continuous process to iteratively determine a detected object's current position, e.g., an aircraft. The iteration begins after collecting a set of new detections with the prediction of the position of previously detected tracks [68]. A detection-to-track association is then performed to determine the plausibility of the detection being caused by a particular track [68, 69]. Detections associated with tracks are used to update the track position estimation. If measurements cannot be associated with any track, a new track is initiated and stored for future use. The track prediction and update steps are part of the track maintenance performed for every track stored by the tracking system. Tracks that do not receive an update after a defined number of iteration loops are considered to be lost, and the system terminates the track to free up system resources. Figure 2.9 illustrates the steps of the tracking process.

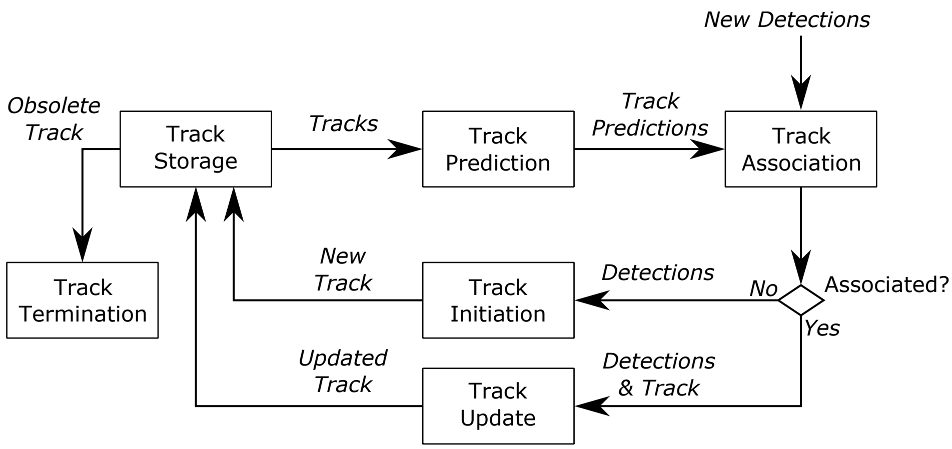


Figure 2.9.: *Tracking process steps.*

2.2. Sensor Management

The sensor resources, e.g., time, radiation energy, and processing capability, are typically constrained [11]. Sophisticated management systems control modern sensor suits to take advantage of their flexibility [12]. These systems are called *sensor managers* and support the pilot in planning and scheduling activities performed by the sensors [13]. Figure 2.10 illustrates the sensor management loop systems, from the environment to displaying information on the human-machine interface.

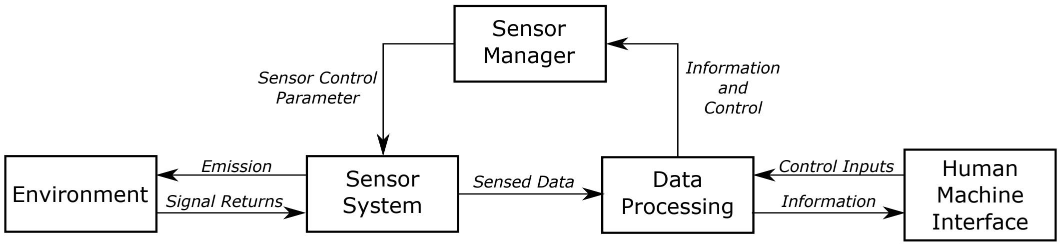


Figure 2.10.: *High-level abstraction of the sensor management loop.*

Systems Requirements Musick and Malhorta reviewed the Air Force Research Laboratory's research between 1992 and 2004 on sensor management for fighter applications and derived requirements for sensor managers [13]. A sensor manager should provide early detection, accurate tracking, and clear identification of objects of interest while dynamically adapting to changing environments. The system should identify the data required for the pilots' decision-making and assign tasks to the sensors with the highest information gain considering the system's constraints [13]. The system should be able to handle uncertainty since the number or existence of threats is assumed to be unknown for any mission [70].

High-level sensor management system At a high-level, sensor management systems are composed of the following elements: a utility function, a global objective, a coordination architecture, and a problem-solving strategy [71]. The coordination architecture manages available sensing resources of multiple sensing platforms and optimizes their resource allocation. The problem-solving strategy selects sensing activities to maximize a global objective, e.g., total utility. Figure 2.11 illustrates an overview of the high-level sensor management process.

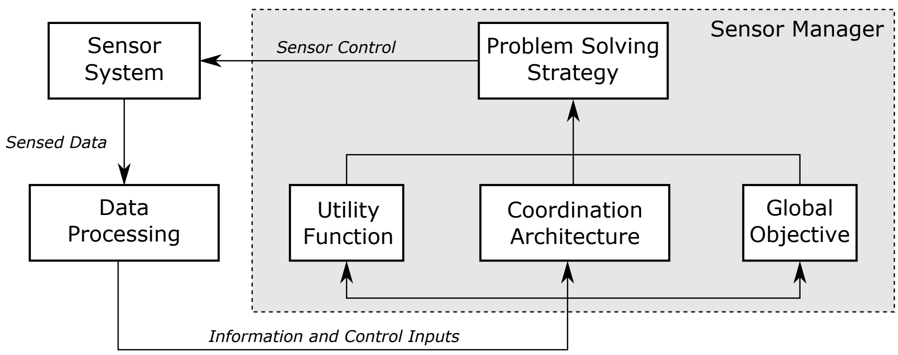


Figure 2.11.: *High-level diagram of the sensor management processes, adapted from Hilal [71].*

2.2.1. Sensor Management Domains

The sensor management domain covers several topics that can be clustered into the eight subdomains described below. This taxonomy is based on an adaptation of Hilal's work [71]. Additional information on the sensor management domain taxonomy is provided in section A.2.1 of the appendix.

Activities The sensor management field covers several activities. At the lowest level, sensor managers directly control the sensor systems' control parameters, e.g., pulse width. The five sensor management activities identified by Xiong and Svensson [72] are described in subsection 2.2.2.

Problem-Solving Strategies Sensor management can be viewed as a process performed to solve a problem that is made difficult by many degrees of freedom and constraints [71]. Researchers have developed combinatorial strategies, heuristics, artificial intelligence, expert systems, and other approaches to find solutions for the sensor management problem. The most popular approaches are explored in subsection 2.2.3.

Objectives Selecting the goal pursued by the system is a critical part of the sensor manager design process [73]. Usually, task-related metrics, information-based metrics, or application-specific metrics drive the sensor management objectives [71, 73].

Evaluation Metrics Multiple metrics have been defined to measure the performance of sensor management systems. Commonly used metrics are listed in section A.2.2 of the appendix for the problem-solving strategies reviewed in subsection2.2.3.

Environment Representation Automated sensor management requires systems with the ability to model the state of the environment [71]. Driven by the stochastic, noisy, and partially-viewed nature of the sensor management environment, probabilistic approaches are widely used to represent the environment.

Coordination Architecture Sensor management systems can manage one or more sensor systems. Centralized architectures, where a single agent performs the coordination, are typically used to manage small sensor networks [71]. Other approaches with multiple decision nodes, e.g., decentralized architectures, have been used in research to overcome the centralized architecture's drawbacks. This study focuses on the control of a single sensor; therefore, this domain is not further explored in this section.

System Setup Sensor management systems rely on target and sensor models to extrapolate the targets' trajectories and sensor performance to determine their control strategy. The impact of target and sensor model characteristics on the performance of sensor management systems has been the topic of several studies [71]. This domain is not further reviewed in this section due to the thesis's focus on a system-independent reward function.

Application Context Sensor management systems have been investigated for several applications. The context of these applications defines the sensor manager's characteristics [71]. This domain is not reviewed due to the focus on the fighter aircraft domain.

2.2.2. Sensor Management Activities

Xiong and Svensson [72] described the activities involved in managing sensor systems as levels of a top-down decision process, with the highest level being mission planning. Processes at this level are responsible for selecting system-level tasks and assigning priorities and the desired task execution quality based on the context of operation and requests made by the user [72]. The second-highest level, resource deployment, is responsible for selecting the number and location of sensors required to perform the system's mission objective [72]. The resource planning level allocates sensor tasks to individual sensors. A timeline of the tasks assigned to sensor systems is set up at the sensor scheduling level [72]. The lowest sensor management level, sensor control, controls the sensor system's degrees of freedom to carry out the scheduled sensing tasks [72]. Figure 2.12 illustrates the top-down decision process.

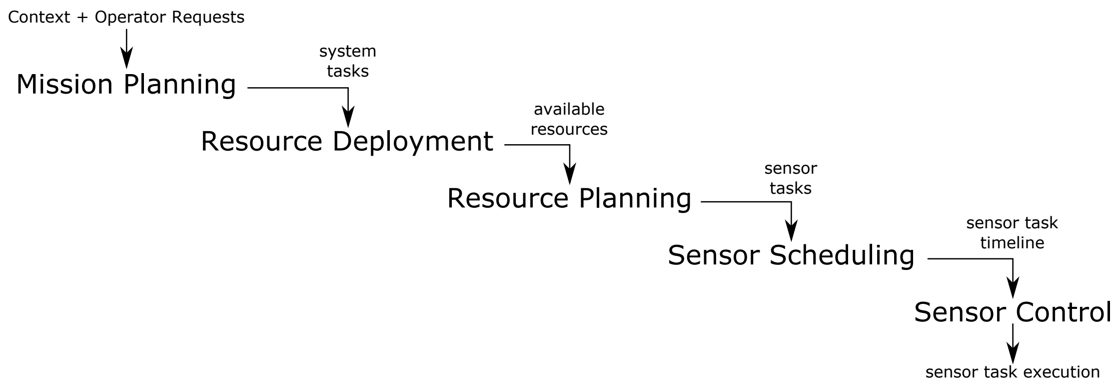


Figure 2.12.: *Top-down sensor manager activities, adapted from Xiong and Svensson [72].*

2.2.2.1. Sensor Control

The control of modern sensor systems, e.g., Active Electronically Scanned Array (AESA) radar systems, can be optimized for specific radar tasks, significantly improving their ability to collect information about the environment [74]. RADAR systems use electromagnetic waves to detect the presence and measure the position of objects in the environment [60]. These transmitted signals, or waveforms, have multiple degrees of freedom and can be optimized for the sensor system's task, e.g., the pulse repetition frequency f, dwell time T_{dwell}, and beam shape can be tuned to achieve a high detection sensitivity [75, 76]. Figure 2.13 exemplifies the waveform adaptation of an AESA Radar performing a search and a tracking task. Other tasks performed by modern sensor systems include threat identification, missile guidance, jamming, and imaging [10, 77].

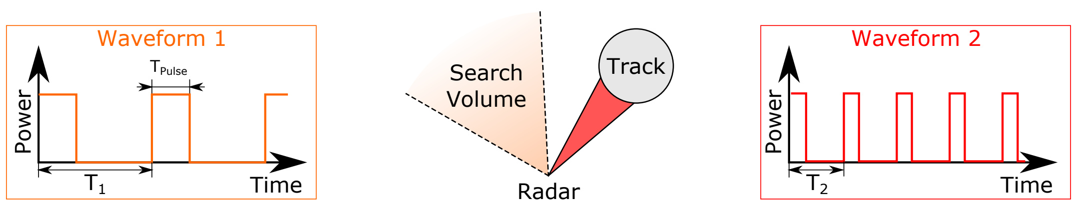


Figure 2.13.: *RADAR waveforms optimized for search (1) and tracking tasks (2). The waveform used to monitor a volume has a higher pulse duration T_{Pulse} and a longer pulse repetition interval T_1 than the waveform optimized for tracking.*

2.2.2.2. Sensor Scheduling

Sensor scheduling coordinates the use of sensor resources through resources by defining a sequence of concurrent and non-concurrent tasks [11]. This schedule accounts for many factors, e.g., available resources and waveform parameters [11]. Figure 2.14 shows a fictive timeline performed by a sensor system. Sensor scheduling is NP-hard[7], a computational complexity class for which algorithms cannot provide an optimum solution [78]. Therefore, the solution must be approximated using brick packing, genetic search, or Online, Greedy, Urgency-driven, Preemptive Scheduling Algorithms (OGUPSA) [72].

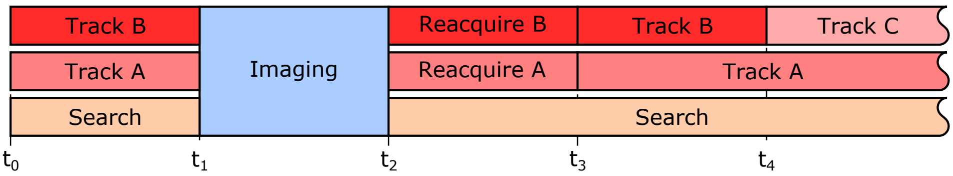


Figure 2.14.: *Exemplified sensor timeline. Between the t_0 and t_1, the sensor performs a search task and tracks two objects, A and B, concurrently. At t_1, the sensor starts a non-concurrent imaging task that lasts until t_2. After completing the imaging, the sensor returns to the previously executed tasks and reacquires tracks A and B. At t_4, the tracking of B is replaced by a task to track a new object C.*

2.2.2.3. Sensor Resource Planning

The available resources typically limit the sensors' sensing capabilities. Sensor management systems must, therefore, manage these finite resources when the resources needed to achieve the desired execution qualities exceed the available resources [11]. Resource planning assigns sensing tasks to individual sensor systems and allocates sensor resources based on task priorities and desired execution qualities [72]. Figure 2.15 exemplifies the resource planning for a single radar performing a search task and three tracking tasks.

2.2.2.4. Sensor Resource Deployment

The deployment of sensor resources is a high-level activity that manages assets' location, deployment time, and movement to achieve a given mission objective [72]. A simple resource deployment scenario is illustrated in figure 2.16. This aspect of sensor management is out of the scope of this research study.

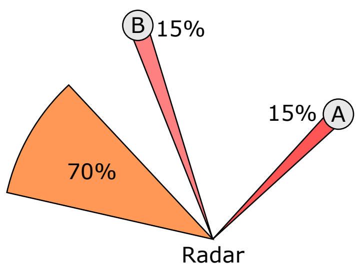


Figure 2.15.: *Illustrated resource planning with a search task and two tracks, A and B.*

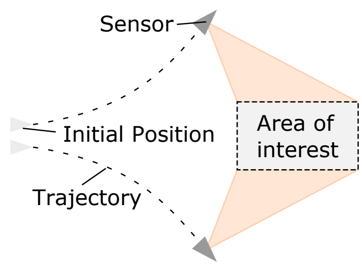


Figure 2.16.: *Illustrated resource deployment, where two sensor platforms optimize their trajectories to collect data from multiple angles.*

[7]The computational complexity NP-hard describes a class of problems for which non-deterministic Turing machines cannot provide an optimum solution in polynomial time [78].

2.2.2.5. Sensor Mission Planning

The highest level of sensor management activities involves selecting sensing tasks to be performed and defining task priorities and desired task execution qualities [72], e.g., tracking accuracy. The most challenging sensor management aspect is the generation and prioritization of sensing options due to the complexity and uncertainties associated with sensing operations and the changing context-dependent operator goals [79]. Sensor management systems will decide to degrade the execution quality of lower-priority tasks or delay their execution to cope with insufficient sensing resources [11]. Previous research studies inferred the priority of sensor tasks based on tasks fuzzy decision trees [11], the threat posed by tracked objects [16, 17], as well as the amount of information expected to be gained [80].

Figure 2.17 shows a simple scenario in which a sensor management system is required to make a trade-off decision between the quality of tracking tasks and the search task's detection performance. The radar resources are initially allocated sequentially to tracking an object and searching for new targets in a search volume. To accommodate the new tracking task, the sensor manager could double the revisit time of object A, which would halve the tracking accuracy and increase the probability of losing the track. Another option could be to reduce the sensor resources allocated to the search, reducing the search performance. A large number of other trade-off option exists, and deciding which of these should be preferred is highly context-dependent.

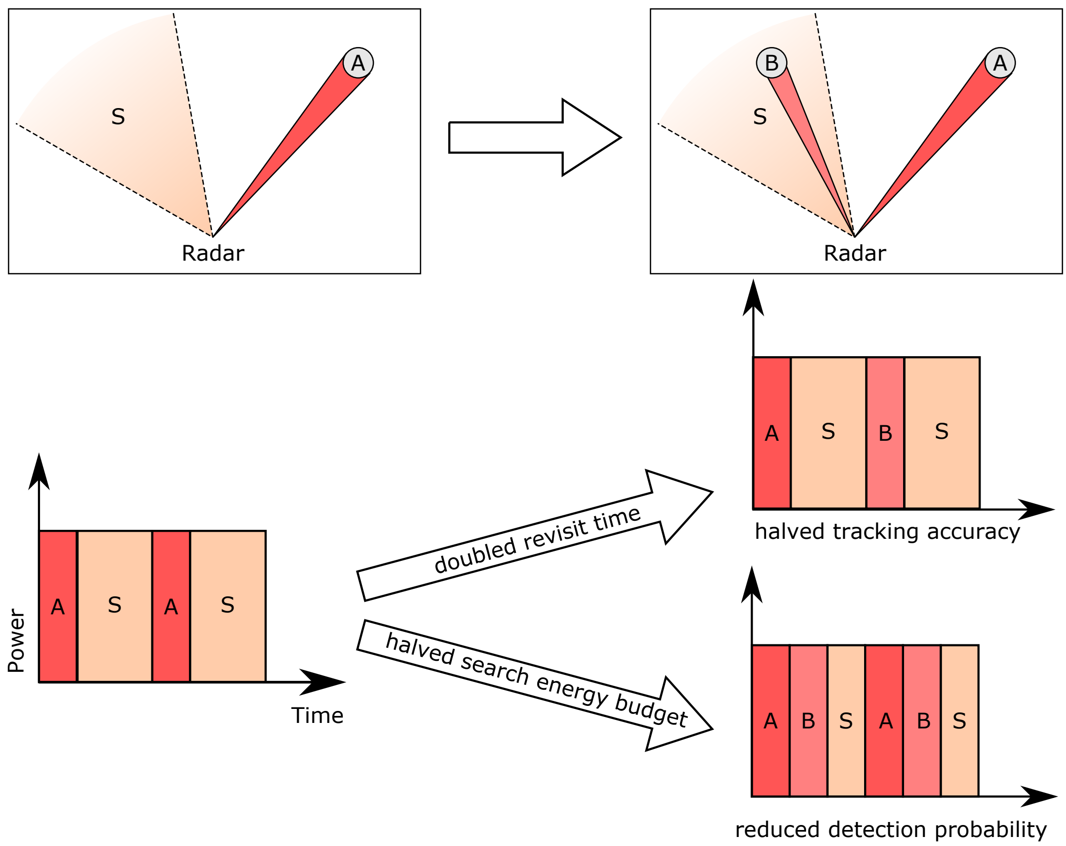


Figure 2.17.: *Sensor management system trade-off decision example due to creating a task to track object B.*

2.2.3. Problem-Solving Strategies

Designing sensor management systems is complicated due to many degrees of freedom and constraints that need to be controlled [71]. Multiple approaches have been put forward to determine solutions for this problem that Hilal [71] clustered into six categories: combinatorial strategies, heuristic optimization techniques, artificial intelligence approaches, expert systems, control-based approaches, and other strategies. Section A.2.2 of the appendix provides additional details for problem strategies and reviews implemented approaches found in the literature.

2.2.3.1. Expert Systems

Systems mimicking human reasoning are called expert systems and represent the transfer of task-specific expertise from a human expert to an automated system [81]. Rule-based expert systems use *if-then rules* [82] for their decision-making and have shown to be a viable approach to sensor management [83, 84]. The following authors described implementations of expert system sensor management applications: Bier et al. [85], McBryan et al. [86], and Stromberg et al. [87, 88].

2.2.3.2. Fuzzy Logic

The knowledge base of expert systems is based on human expertise and is often subjective [89]. This subjectivity makes the simplicity and similarity to human reasoning of fuzzy logic interesting for sensor management applications [90]. Zadeh [91] introduced fuzzy sets as objects assigned a degree of membership between zero and one, representing a generalization of the classical set [92]. Fuzzy decision trees have shown to be particularly good rankers and consistently outperformed non-fuzzy decision trees [93]. These characteristics make fuzzy decision systems well-suited for managing the information in prioritization and scheduling sensor tasks [94, 22]. Fuzzy sensor management system implementations are described in publications by Popoli and Blackman [95], Ng et al. [96], and Molina López et al. [22, 23, 24].

2.2.3.3. Bayesian Methods

Bayesian networks provide a framework for dealing with uncertainty using an underlying graphical structure [97] and are the most popular probabilistic sensor management approaches [71]. Bayesian networks combine prior knowledge and statistical data [98] and are based on prior beliefs that are updated based on collected data using Bayes' Theorem [99]. Bayes' Theorem, published posthumously in 1763 [100], relates the conditional probability $P(H \mid E)$ of a hypothesis H given the evidence E to the likelihood $P(E \mid H)$, the probability of the evidence $P(E)$, and the hypothesis's probability $P(H)$ [101], as shown in equation 2.13.

$$P(H \mid E) = \frac{P(E|H)P(H)}{P(E)} \quad , P(E) \neq 0 \tag{2.13}$$

Bayesian networks are probabilistic directed acyclic graphs (DAG) that are composed of nodes and directed edges [97]. Nodes have mutually exclusive states with a given prior probability or likelihood. The edges represent causal relationships between the nodes of the network. Examples of Bayesian sensor management approaches are found in Ye et al. [102], Kreucher et al. [103], and Demircioglu and Osadciw [104].

2.2.3.4. Decision Theoretic Approaches

The management of sensor systems can be modeled as a stochastic decision process, for which the most popular approach is the Markov Decision Process (MDP) [71]. The decision-maker in MDPs observes the system, selects actions from available options, and receives rewards for taking actions [105].

The noise in real-world sensing operations limits the observability of the environment's states and requires decisions to be made under uncertainty [106]. The partially observable Markov decision process (POMDP) extends MDPs to model the limited observability by hiding state features from the decision-making agent [106].

Decision-theoretic sensor management approaches are described in literature published by Krishnamurthy and Djonin [107, 108, 109], Miller [110], Chong et al. [111], Lauri and Ritaka [112], Lauri [113], and Gostar et. al. [114, 115, 116].

2.2.3.5. Information-Theoretic Approaches

Information-theoretic approaches estimate the future increase in information expected to be gained from taking a measurement [71], which is suited to a more considerable amount of objectives [14]. The theory underlying these approaches is a branch of the mathematical theory of probabilities and statistics that is based on the technical definition of information by Fisher [117]. *Shannon entropy* is the most popular metric used for information-theoretic approaches [118] and was first defined by Shannon [119] to describe the uncertainty of an outcome. Other metrics are the *mutual information* [120], the *Kullback-Leibler divergence* [121], and the *Rényi divergence* [122]. Implemented information-theoretic sensor management approaches are described in publications by Manyika [123], McIntyre and Hintz [124], and Kreucher et al. [125, 126]. Other information-theoretic sensor management concepts are described in [118, 127, 128, 129, 130, 131].

2.2.3.6. Other Problem-Solving Approaches

Other approaches to decision-making in sensor management operations are listed below:

Goal Lattices Goal lattices were used by McIntyre [21] to implement strategic and tactical goals explicitly into a metric used for the optimization. For this approach, designers describe the system's goals, e.g., the air superiority goals of a fighter aircraft, and define a weight for the relationship between these goals [33]. This weighted lattice is then used to calculate the relative importance of detecting, tracking, and identifying targets.

Risk-Based This risk-based approach followed by Katsilieris [17] aimed to allocate sensor resources such that the uncertainty in the threat posed by all targets is minimized. Kastilieris demonstrated that a risk-based approach delivers a Bayes-optimal resource allocation and can adapt to the operational context.

Mission-Driven De Groot [18] developed a mission-driven sensor management approach and defined the system's objective as maximizing the mission's success probability. This approach reframes the management of sensing activities as a system-independent decision-making process on an operational level. It determines sensing actions using the OODA loop.

2.3. Human Information Processing

Sensor management systems control the sensors' degrees of freedom to provide decision-makers with relevant information about their environment. Proctor and Vu [132] described the fundamental character of interactions between humans and computers as an information-processing task. The computer "must provide adequate information for the user" [132, p. 20] that the human operator identifies and on which he bases his actions. The large quantity of data that modern sensor suites can collect can overwhelm users and hamper their decision-making abilities [133] due to constraints in human information processing. Knowledge about the mechanisms involved in human information processing is thus required to design sensor management systems that support the operators' ability to acquire and maintain an accurate mental picture of the environment [15].

As described by Wickens et al. [134], the human information processing model comprises four processing steps, a memory model, attention resources, and a feedback mechanism. Information processing starts with capturing stimuli by various senses that are stored temporarily in a sensory buffer. A subset of the collected sensory information is selected for processing in the second step, perception, which derives meaning from the sensations. The filtering of sensory information is driven by the allocated attentional resources and past experiences that are stored in long-term memory. According to Wickens et al. [134], perceptions either trigger an immediate response or are stored in working memory. Responses are selected in the third step and executed in the model's fourth step. Performing actions often lead to changes in the environment that are picked up through new and changed stimuli patterns, completing a feedback loop.

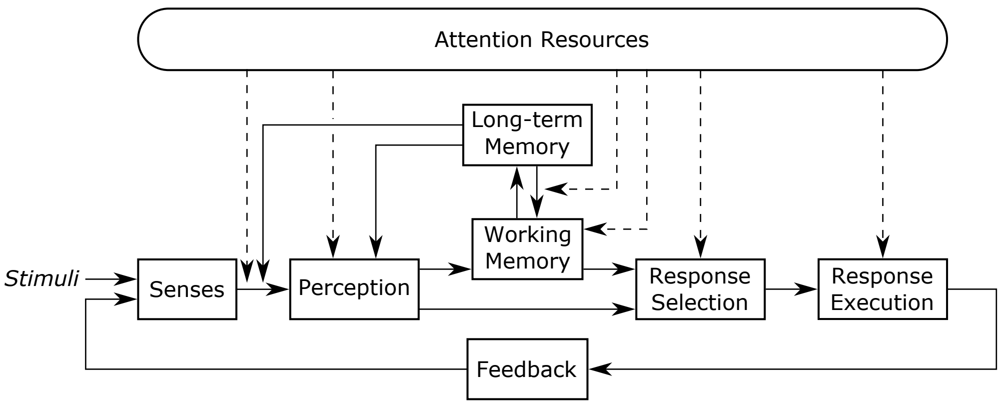


Figure 2.18.: *Model of human information processing stages, adapted from Wickens et al. [134].*

This section reviews the key elements of the human information processing model and covers literature about human sensation, perception, attention, memory, and decision-making. Additionally, this section reviews the concept of situation awareness. The appendix's section A.3 provides additional background on human information processing theories and models.

2.3.1. Human Sensation and Perception

Humans perceive their environment through six senses: vision, audition, olfaction, gustation, balance, and somaesthesia [135]. Vision is one of the essential senses in human-computer interactions [136], as pilots rely heavily on their displays to acquire and uphold their mental picture of the environment [7]. All six senses convey basic information about a stimulus: modality, location, intensity, and timing [135]. Table 2.4 lists the six human senses, their modalities, and stimulus type.

Table 2.4.: *Human senses and sense modalities, adapted from [135].*

Senses	Modality	Stimulus
Visual	Vision	Light
Auditory	Hearing	Sound
Vestibular	Balance	Gravity
Somatosensory[8]	Touch	Pressure
	Proprioception[9]	Displacement
	Temperature	Thermal
	Pain	Chemical, thermal, or mechanical
	Itch	Chemical
Gustatory	Taste	Chemical
Olfactory	Smell	Chemical

2.3.1.1. Perception Theories

Theories of perceptions can be divided into bottom-up and top-down theories based on the direction of the information flow [139], as illustrated in figure 2.19. In bottom-up theories, percepts [10] are suggested to correspond to external objects first perceived at the lowest sensory levels, e.g., points and lines [139]. These low-level sensory percepts are gradually processed into more complex constructs, e.g., trees [139]. Gibson's theory of direct cognition is the most prominent bottom-up theory [139]. The involvement of higher cognitive functions in perception is the main feature that differentiates top-down theories from bottom-up theories [139]. Top-down perception theories can be organized into three classes based on the method used to interpret the stimuli [139]: constructivist, computational, and synthesizing theories thart are summarized in section A.3.2.

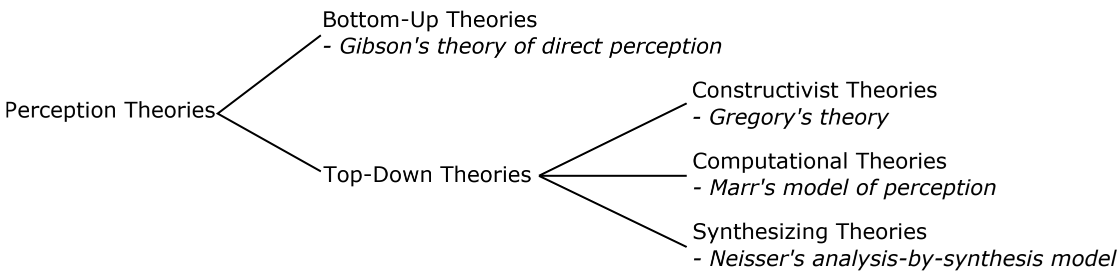


Figure 2.19.: *Taxonomy of perception theories and their most prominent examples.*

[8] The somatosensory system is a part of the nervous system that responds to changes inside or on the surface of the body [137].

[9] Proprioception is the sense of one's body position and motion [138].

[10] The Merriam-Webster dictionary [140] defines a *percept* as "an impression of an object obtained by use of the senses."

2.3.2. Human Attention

Proctor and Vu [132, p. 30] defined *attention* as the "increased awareness directed at a particular event or action to select it for increased processing" that enables humans to prioritize information. Attention has been the topic of numerous research studies in philosophy, psychology, neuroscience, and computer science [141]. Mancas [141] reviewed attention research and concluded that a single definition of attention is not feasible, but instead that attention relates to four distinct aspects:

- Sensory receptor tuning to prioritize the capture of specific outside information,
- Cognitive resource allocation to prioritize the processing of critical information,
- Memory and emotion influencing to pass information to a conscious state, and
- Behavior adaptation based on the received information.

2.3.2.1. Dimensions of Attention

Mancas [141] lists three dimensions of human attention: (1) overt vs. covert attention; (2) serial vs. parallel attention; and (3) bottom-up vs. top-down attention.

Overt vs. Covert Attention Overt attention prepares sensory receptors for expected stimuli through changes in posture or eye movements [141]. The movements of the eyes are usually categorized based on qualitative descriptions, e.g., fixations, saccades, and smooth pursuits [142]. Fixations occur when the gaze location is maintained in a single position. Saccades describe the fast movement of the eye between fixations during which visual stimuli are not processed [142]. Smooth pursuit describes the movement performed to follow a moving object with the gaze [143]. Contrastingly, covert attention does not involve visible changes [141].

Serial vs. Parallel Attention Human brains can process multiple tasks sequentially and concurrently [141]. Attention directs the degree of focus with which cognitive resources are allocated to these tasks, ranging from focusing on one task (serial) to a division between multiple tasks (parallel). Mancas [141] lists the following five types of attention by decreasing order of cognitive focus: focused attention, sustained attention, selective attention, alternating attention, and divided attention.

Bottom-Up vs. Top-Down Attention Mancas [141] describes the involvement of two hierarchical dimensions in attention: reflex-based bottom-up attention and conscious top-down attention. The bottom-up attention is driven by the external stimulus and is thus often referred to as exogenous attention. Top-down attention involves aspects internal to the individual, e.g., memories and emotions. It is often referred to as endogenous attention that can be further divided into two sub-classes: goal related-attention and memory-related attention. The goal-related attention modifies the weight of stimuli and information to adapt cognitive processes to pursue a specified goal. Memory-related attention is driven by experience and prior knowledge.

2.3.3. Human Memory

The information must be retainable and retrievable to be remembered and used for future actions [144]. Broadbent [145] proposed that information can be retained through repeated transition through the limited capacity channel. Norman [144] theorized the existence of two types of storage, transient short-term and permanent long-term memory, used by the attention process to process sensory inputs efficiently. Research [146] on the working memory capacity of athletes showed the importance of working memory for tactical decision-making, as athletes with a high working memory capacity were better able to focus on tactical decisions and suppress distractors.

2.3.3.1. Baddeley's model of working memory

Baddeley and Hitch proposed a modification of Atkinson and Shiffrin's model, described in section A.3.3, to account for the model's shortcomings. The original model was published in 1974 [147] and replaced the short-term store with a memory structure containing three elements: a central executive, a phonological loop, and a visuospatial sketchpad. Baddeley [148] added the episodic buffer as the fourth element in 2000.

Central Executive: The central executive is an attentional control system that directs the three other memory components.

Phonological Loop: The loop is composed of a rehearsal system and a temporary store for verbal and acoustic information suited to storing sequential information [148]. Information in the store is assumed to decay within a few seconds if the loop's rehearsal system does not revitalize it.

Visuospatial Sketchpad: The sketchpad stores visual and spatial information, e.g., the memory of a person's face.

Episodic Buffer: Baddeley [148, p. 421] describes the episodic buffer as a "limited-capacity temporary storage system that is capable of integrating information from a variety of sources." This buffer facilitates problem-solving tasks by providing a mechanism to model the environment and create new cognitive representations.

Figure 2.20 illustrates Baddeley and Hitch's model of human working memory containing the four key components.

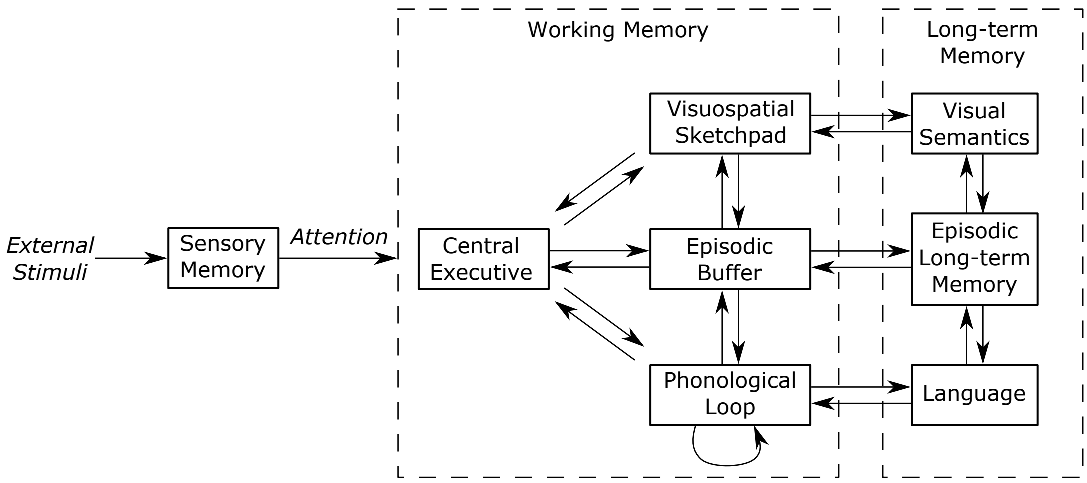


Figure 2.20.: *Baddeley and Hitch's model of human working memory [149].*

2.3.4. Decision-Making

The decision-making process occurs after the perception of stimuli and prior to executing a selected response [150]. Decision-making theories are either based on the observation of decision-making processes (descriptive paradigm) or based on the assumption of rational choice that is driven by well-defined rules (normative paradigm) [151]. The comparison of both types of theories by Tang et al. [152] is listed in table 2.5. This section outlines normative decision-making theories, descriptive decision-making approaches, and decision-making models. Further, research on the decision-making by fighter pilots is reviewed.

Table 2.5.: *Summary of normative and descriptive theories, based on Tang et al. [152].*

	Normative	Descriptive
Focus	How should people decide with logical consistency?	How and why do people decide the way they do?
Criterion	Theoretical consistency	Empirical validity
Scope	All decisions	Classes of decisions tested and reported
Theoretical Foundations	Utility theory axioms, subjective probability	Cognitive sciences, psychology of beliefs and preferences
Operational Focus	Analysis of alternatives, order rank, and preferences	Prevent systematic errors in inference and decision-making

2.3.4.1. Normative Decision-Making Theories

Classical decision-making problems are represented through a set of actions, a set of events, a set of consequences, and a set of probabilities for every action and event [150]. Normative theories specify the norms and rules underlying the choices made by rational agents [150], e.g., "do whatever yields the best consequence in the future" [153, p. 20]. The yield is either a measure of value, the objective worth of an item, or subjective utility [154]. Barron [153] defined *utility* as the degree to which an alternative lets decision-makers achieve their overall goals. The action's expected value is the sum of the consequences' yield multiplied by the probability of the outcome. The probabilities used in this calculation are either objective probabilities determined from observation or subjective probabilities [154]. Subjective probability expresses a degree of belief or expectation that is more or less rational [155, 156]. Table 2.6 shows the four variants of expected value models.

Table 2.6.: *Variants of expected value model, adapted from Bahill and Madni[154].*

	Objective Probability	Subjective Probability
Objective Value	Expected Value	Subjective Expected Value
Subjective Utility	Expected Utility	Subjective Expected Utility

Subjective Expected Utility (SEU) The subjective expected utility (SEU) of available alternatives, first postulated by Savage in 1954 [157], is the most influential explanatory concept in the analysis of decision-making under uncertainty [158]. SEU is a version of expected utility theory according to which decision-makers select alternatives by comparing their expected utility values based on subjective probabilities [159]. The SEU of an alternative A_i is the sum of all probability-weighted utilities $U(\cdot)$ of the alternatives' consequences C_{ik}. The subjective probability p_{ik} is used for the weighing.

$$SEU[A_i] = \sum_k p_{ik} U(C_{ik}) \tag{2.14}$$

Multi-attribute utility theory (MAUT) The multi-attribute utility theory (MAUT) is an extension of SEU, first developed by Keeney and Raiffa [160], to include more than one objective [150]. Hwang and Yoon [161, p. 16] defined *attributes* as elements providing "a means of evaluating the levels of an objective." Keeney and Raiffa [160] stated that attributes must be comprehensive and measurable for a decision-maker. Comprehensible attributes have a clear connection to an objective's achievement level. A measurable attribute provides a probability distribution of the attribute's level and the decision maker's preferences for these levels for all alternatives. Further, Keeney and Raiffa [160] called for the following five properties for sets of attributes used in MAUT:

1. Completeness, to cover all the important aspects of the decision problem.

2. Operationally, to be used meaningfully in the analysis.

3. Decomposability, breaking the decision problem into smaller, simpler parts.

4. Non-redundancy, to avoid double counting of impacts.

5. Minimalism, to keep the problem's dimensionality as small as possible.

The basic approach to designing a multi-attribute utility function is a two-step process [160]. First, the assumptions on the decision maker's preferences are postulated, and then the functional form of the multi-attribute utility function is derived from these assumptions. Torrance et al. [162] list the following independence assumptions, of which at least one must exist for MAUT to be used:

- First-order utility independence: There is "no interaction between preferences for levels on any one attribute and the fixed levels for the other attributes" [162, p. 507].

- Mutual utility independence: There is "no interaction between preferences for levels on some attributes and the fixed levels for other attributes" [162, p. 508].

- Additive utility independence: There is "no interaction for preferences among attributes" [162, p. 508].

Section A.3.4 of the appendix provides a taxonomy by Hwang and Yoon [161] of multi-attribute decision-making approaches.

2.3.4.2. Descriptive Decision-Making Theories

Descriptive decision theories attempt to describe how people make decisions, accounting for imperfect non-normative behaviors [152], e.g. the coginitive biases listed in section A.3.5. The most prominent descriptive decision-making theories are described in this section.

Social Judgment Theory (SJT) Social Judgment Theory (SJT) is a perspective and research methodology for the judgment of human decision-makers within the environmental context [163]. Two main themes govern SJT, according to Doherty and Kurz [164]: functionalism and probabilism. They defined *functionalism* as the need "to understand aspects of the environment that the organism is perceiving and to which it is responding to attain its goals" [164, p. 122]. Probabilism is the principle that "the organism cannot know the environment with certainty" due to the inherent uncertainty in the environment [164, p. 124]. The relations between the environment criterion Y_e, the set of cues $\mathbf{X}$, and the decision maker's judgments Y_S are usually represented using Brunswik's lens model illustrated in figure 2.21 [163]. The correlation w_{ei} between a cue X_i and the criterion is referred to as "ecological validity," and the correlation w_{Si} between a cue X_i and the subject's judgment is named "cue utilization validity" [163]. The correlation r_{ij} represents the correlation between cue states. The achievement r_a is defined as "the correlation between the values of some distal criterion (...) and the person's judgments of those values based on available cue information" [163, p. 142]. Zones of ambiguity represent the uncertainty between the three planes of the model.

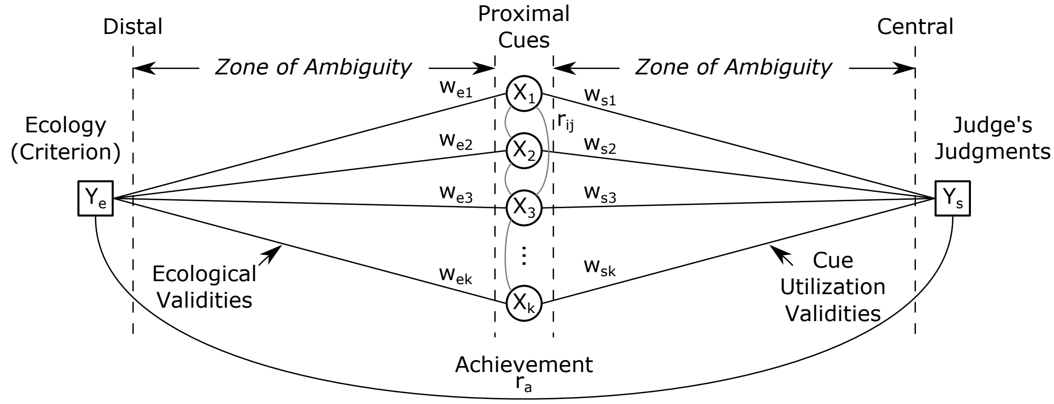


Figure 2.21.: *Brunswik's lens model as adapted by Cooksey [163] to study human judgment.*

Prospect Theory Kahneman and Tversky [165] put forward prospect theory as an alternative to expected utility theory for decision-making under risk. Their theory distinguishes two phases. The choice process begins with the editing phase in which a preliminary analysis of prospects is performed that often returns a simplification of the prospects. These edited prospects are evaluated in the second phase, and the prospect with the highest value is selected. Prospect theory values alternatives are based on gains or losses rather than the outcome and rely on decision weights π that are dependent on the probability p_i of the associated outcome x_i and determined using a weighting function that often overweighs low probabilities. The overall value V of a prospect with the outcomes $\mathbf{x}$ and outcome probabilities $\mathbf{p}$ is defined as the sum of the outcomes decision weights and the associated outcome's value $v(x)$.

$$V(\mathbf{x}, \mathbf{p}) = \sum_{i=1}^{n} \pi(p_i)\, v(x_i) \tag{2.15}$$

Ecological Rational Theory The theory of ecological rationality refutes the idea that maximizing utility is the only driver in human decision-making processes [152]. Ecological Rational Theory postulates that decisions are made quickly without necessitating probabilistic models [152], e.g., through the use of heuristics.

Heuristics The most popular theory for cognitive biases is the use of heuristics by decision-makers to manage their limited cognitive resources [166]. Gigerenzer and Gaissmaier [167, p. 454] defined a *heuristic* as "a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods." These heuristics are applied both consciously and subconsciously [167]. The accuracy of these rules of thumb depends on the environment's structure and the decision-makers' experience [167].

Gigerenzer and Gaissmaier [167] provide two reasons for using heuristics. First, heuristics reduce the cognitive effort for decisions that do not warrant the use of extensive decision-making processes and for decisions for which finding the optimal alternative would require more cognitive resources than available. Secondly, heuristics are tools for adapting decision-making to the environment and account for the number of observations, the distribution of cue weights, and uncertain or redundant cues [167].

Shah and Oppenheimer [168] proposed that heuristics rely on one or more of the following approaches to reduce cognitive effort:

1. Examining fewer cues,
2. Reducing the difficulty associated with retrieving and storing cue values,
3. Simplifying the weighting principles for cues,
4. Integrating less information, and
5. Examining fewer alternatives.

Gigerenzer and Gaissmaier [167] reviewed the following eight heuristics used by decision-makers:

- Recognition: "If one of two alternatives is recognized and the other is not, then infer that the recognized alternative has the higher value with respect to the criterion" [167, p. 460].
- Fluency: "If both alternatives are recognized but one is recognized faster, then infer that this alternative has the higher value with respect to the criterion" [167, p. 462].
- One-clever-cue: Select the alternative based on a single specific cue.
- Take the best action: Compare cues for their validity and select the alternative based on the first discriminatory cue.
- Fast and frugal binary decision trees: Select the alternative through a series of binary decisions.
- Tallying: Count the number of cues favoring one alternative compared to others and select the alternative with the highest count.
- Mapping model: Count the number of positive, relevant cues, weigh these by their importance, and select the alternative with the highest value.
- 1/N Rule: "Allocate resources equally to each of N alternatives" [167, p. 470].

2.3.4.3. Dual-process theory of reasoning

A possible interpretation of the divide between normative and non-normative decision-making is the two-process theory of reasoning [169], which postulates that two systems are involved in human decision-making. Stanovich and West [169] put forward the most popular labels for these systems: "System 1" and "System 2". The mapping of their notation to other terms used in the literature is listed in table 2.7.

Table 2.7.: *The terms used for the two systems of reasoning, adapted from Stanovich and West [169].*

System 1	**System 2**
Associative system	Rule-based system
Heuristic processing	Analytic processing
Tacit thought processes	Explicit thought processes
Implicit cognition	Explicit learning
Interactional intelligence	Analytic intelligence
Experimental system	Rational system
Quick and inflexible modules	Intellection
Intuitive cognition	Analytical cognition
Recognition-primed decisions	Rational choice strategy
Implicit inferences	Explicit inferences
Automatic processing	Controlled processing
Automatic activation	Conscious processing system

Stanovich and West [169, p. 658] described System 1 as “automatic, largely unconscious, and relatively undemanding of computational capacity.” Due to the low effort, most decisions are made by System 1. System 2, on the other hand, is slower, controlled, and effortful [170]. It processes more complex computations and monitors the actions of System 1, overriding responses if required. Figure 2.22 compares the characteristics of the processes performed by the two systems and the perception processes described in section 2.3.1. Further, the graphic shows the type of content processed by the systems.

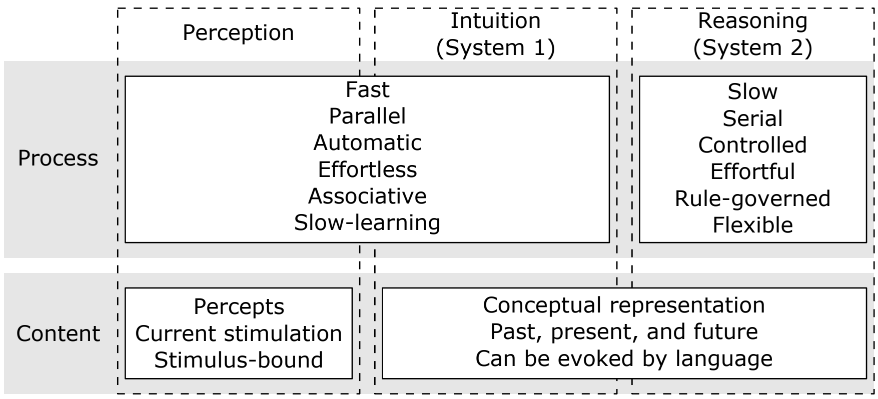


Figure 2.22.: *Process and content characteristics of perception, intuition, and reasoning, adapted from Kahneman [170].*

2.3.4.4. Decision Making in Aviation

Houck et al. [48] investigated the information processing of fighter pilots flying beyond-visual-range (BVR) intercept missions and noted that the complexity of the information processing demands "requires extensive cognitive resource management and decision-making abilities" [48, p. 1]. Task saturation, time compression, and incomplete data strain the pilots' cognitive abilities [48]. The competing demands can overwhelm the pilots' cognitive resources and push the pilots to reduce the cognitive load, e.g., via heuristics that only integrate a subset of the available data and ignore sources that are likely redundant or unreliable [48]. The time-sensitive nature of the decisions requires pilots to rely on streamlined decision-making strategies that they acquired through training and experience [48]. The main activities driving cognitive demand are the following, according to Houck et al. [48]:

- Integrating and interpreting information derived from multiple sources
- Maintaining situation awareness
- Adjusting the mission plan in response to changes in the environment

Endsley and Smith [171] researched the decision-making of fighter pilots in target replacement tasks, where subjects had the task of recalling the position of a set of targets shown on a tactical display. They found a high degree of variability in the decision-making, which they attributed to the planning ahead of pilots with combat experience [171]. Further, Endsley and Smith [171] observed that participants rarely considered multiple alternatives, supporting the theory of naturalistic decision-making.

Endsley and Jones [54] put forward the following characteristics of the military environment that complicate decision-making:

- Ill-structured problems with high stakes,
- Continually changing, incomplete, and ambiguous information,
- Fluid, competing, and time-dependent goals, and
- Severe time constraints.
- A series of decisions are required to achieve the desired outcome

O'Hare [172] reviewed the descriptive studies of pilot decision-making and summarized the studies' findings in the following six conclusions:

- Information-acquisition strategies followed by pilots are moderately poorer than the ideal strategy,
- Stress reduces the decision-making performance of pilots,
- Pilots simplify decision problems and focus on a subset of the available information,
- Pilots exhibit qualitative reasoning rather than probabilistic reasoning,
- The principal activity of operators is the monitoring and interpretation of information, and
- Flight tasks have a goal-oriented nature.

2.3.4.5. Aeronautical Decision Making

This prevalence of In-flight planning errors led the Federal Aviation Administration (FAA) to develop the concept of aeronautical decision-making (ADM) that is defined as “a systematic approach to the mental process used by pilots to consistently determine the best course of action in response to a given set of circumstances” [173, p. ii]. Figure 2.23 shows the ADM process in which recognized changes or events caused by the pilot, the aircraft, the environment, or external factors trigger the decision-making process. The responses are executed automatically using skills and procedures or solved using mental labor.

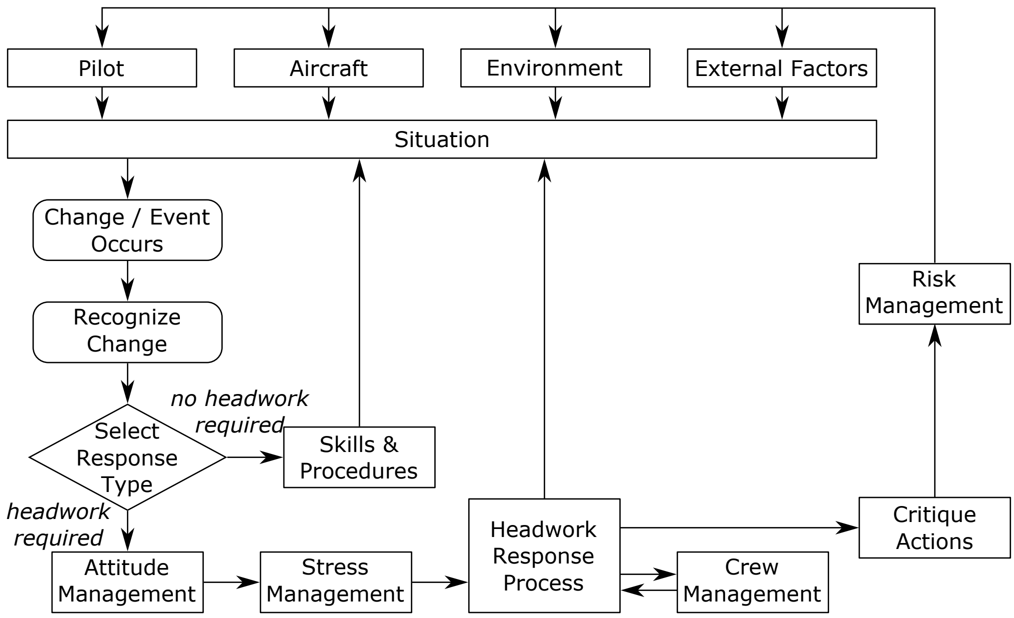


Figure 2.23.: *Aeronautic decision making-process, adapted from [173].*

2.3.4.6. Signal Detection Theory

The *signal detection theory* (SDT) framework measures an observer's ability to distinguish between two stimulus types, signal and noise [174]. The underlying mathematics was first derived for pulsed radar systems by Marcum [64] and later generalized for any signal by Peterson et al. [175]. Tanner and Swets [176] quickly adapted SDT into a psychological theory for "yes-no" and "forced-choice" experiments. In these experiments, subjects are forced to choose between two alternatives, usually between "signal present" and "no signal present." This forced choice leads to the four possible results listed in table 2.8. More information on SDT is provided in section A.3.1.

Table 2.8.: *SDT event classification, adapted from Fisher et al. [177].*

		Truth	
		Signal present	**No signal present**
Decision	**Signal present**	Hit	False alarm
	No signal present	Miss	Correct rejection

2.3.5. Situation Awareness

Endsley [5] defines situation awareness (SA) as a person's state of knowledge about a dynamic environment, separate from decision-making and performance. As illustrated by Endley's model shown in figure 2.24, SA is more than the mere perception of elements in the environment. The following general definition of SA by Endsley [4, p. 792] will be used:

> *Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.*

A good situational assessment is primordial in aviation, as 88% of all human errors in general aviation are attributed to poor SA [178]. For adequate SA, a pilot needs to detect, identify and track objects in his environment and estimate the threat they pose to his aircraft or friendly assets [7]. Small failures in situation assessment can have fatal consequences for the pilot and the people in his environment [5]. This criticality is especially true in the heat of combat operations where low situational awareness can lead to friendly fire, e.g., a US Navy ship shot down a civilian airliner in 1988 [179]. Endsley defined the following three levels of SA:

Level 1: Perception of the elements in the environment The first step of SA is perceiving relevant data about elements in the environment, e.g., location, altitude, and heading of ownship and other aircraft [5].

Level 2: Comprehension of the current situation To reach the second SA level, pilots form a holistic picture of the environment and assess its significance for their goals and objectives, e.g., the location and proximity of aircraft to friendly forces [5].

Level 3: Projection of future status The third level of SA is linked to the ability to project the actions of objects in the short-term future. This step requires knowledge and comprehension of the situation, e.g., projected aircraft tactics and maneuvers [5].

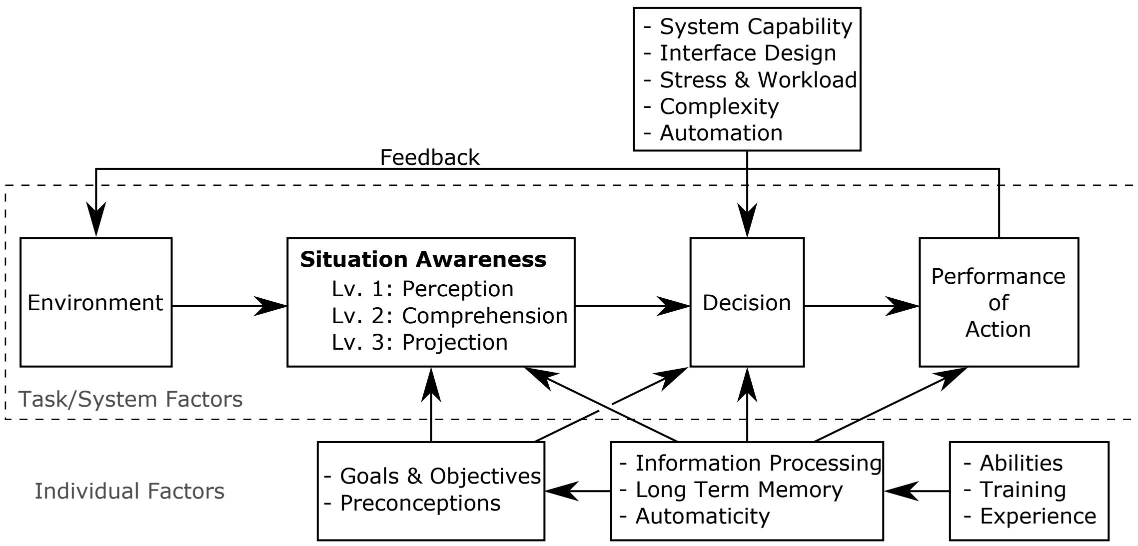


Figure 2.24.: *Model of SA in dynamic decision making, adapted from Endsley [5].*

2.3.5.1. Relationship of SA to Goals and Mental Models

SA can be viewed as a situation model built and maintained through actively seeking information related to desired goals [5]. The link between SA and an operator's goal is formalized through a set of complex cognitive schemata, commonly called mental models, that model the behavior of systems as understood by the operator [5].

Figure 2.25 illustrates the relationships between SA, mental models, and goals discussed by Endsley [5]. Mental models are selected based on the operator's goals and current SA. In turn, the mental models influence the SA by directing the attention to features of the environment deemed of interest in pursuing the desired goals and, therefore, influence the perceived information. The mental models are revised if deviations are observed between the model and the real world. SA is further reliant on mental models for comprehending and projecting perceived information. Mental models are a key element in decision-making since they direct plans to fulfill the operator's role and derive the necessary implementation actions. Further, mental models store the default values used by operators in their decision-making [5].

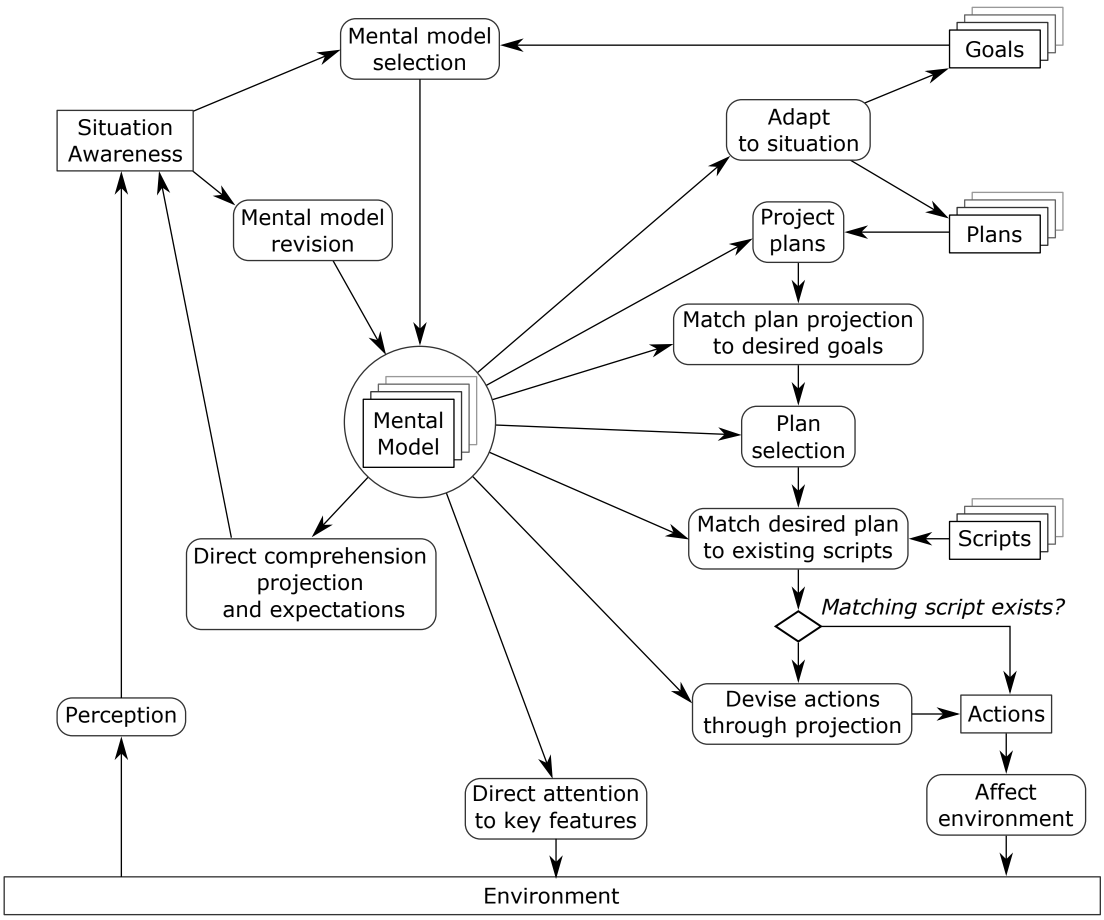


Figure 2.25.: *Relationship of goals and mental models to SA, adapted from Endsley [5].*

2.4. Human-Centered Automation

Sensor management systems are developed to reduce the pilot workload by automating complex sensor control operations [180]. Ironically, introducing automation does not decrease the contribution of human operators to the reliability and performance of complex systems [181], as operator tasks transition from direct control to monitoring and supervisory tasks with increasing levels of automation [182]. Enabling the synergy between humans and artificial intelligence (AI) has shown the potential to surpass the performance of either one, e.g., reducing the number of erroneous cancer diagnoses by up to 85% [183], as illustrated in figure 2.26.

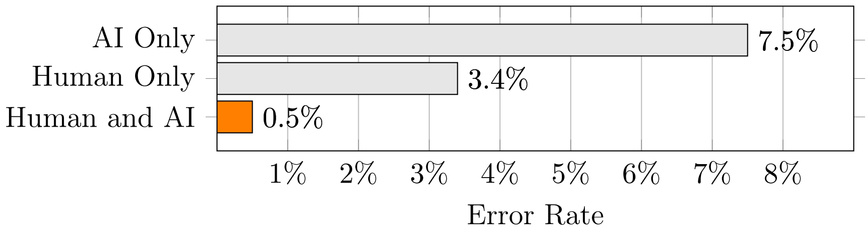


Figure 2.26.: *Error rate of a human pathologist, a deep learning algorithm, and an AI-augmented pathologist tasked with identifying metastatic breast cancer, based on Wang et al. [183].*

The scientific discipline that focuses on the understanding and design of technical systems interacting with persons is termed human factors and aims to optimize the interaction between humans and other system components, e.g., maximize system efficiency [184]. Czaja and Nair [184] defined three core elements of a human-machine system: the human involved in the operations, the tasks to be completed, and the technology at the disposal of the human operator. These elements have been reviewed individually in the previous sections of the theoretical and technical background chapter. This section reviews the interaction between the three core elements. It summarizes the analysis, design, and validation of automated information processing systems following the structure given by the V-model illustrated in figure 2.27.

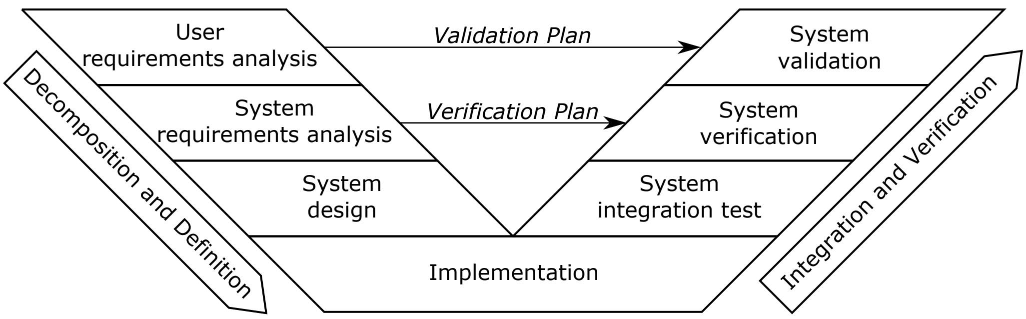


Figure 2.27.: *Systems engineering V-model, adapted from Forsberg and Mooz [185].*

The first part of this section describes automation and reviews automation issues faced by human-centered automation. Secondly, HFE aspects of system design are reviewed. The section ends with a summary of verification and validation methods for automation and interfaces.

2.4.1. Automation Characteristics and Issues

Automation, "the execution by a machine agent of a function that was previously carried out by a human" [186, p. 231], promises superior reliability and performance [187]. Recent developments in computer technologies and AI enable the automation of any task performed by humans [188]. Ironically, introducing automation does not decrease the contribution of human operators to the reliability and performance of complex systems [181, 189]. Minimizing the risk of automation-induced errors requires systems designers to understand the automated system's characteristics and be aware of the leading automation issues. This subsection addresses these aspects.

2.4.1.1. Dimensions of Automation

Automation encompasses a wide variety of systems with different characteristics, e.g., a simple thermostat and a complex AI-based system are both described as automated systems. Understanding the main dimensions of automation can support system design decisions [190]. This subsection addresses the following dimensions:

- Functions allocation,
- Automation level,
- Automation adaptiveness, and
- Underlying decision problem characteristics.

Function allocation Automation is introduced for many reasons, e.g., to reduce the workload of human operators and improve the overall system performance [191]. Tasks initially performed by humans are assigned to automated systems to reach these aims. The introduction of automation creates additional monitoring tasks that must be performed by both the human and the automated system [192]. Functional allocation is the step of the system design process in which the division of tasks between the human and the automation system is defined [192]. Pritchett et al. [192] defined the following requirements for an effective function allocation:

1. Each agent must be allocated functions that it is capable of performing.
2. Each agent must be capable of performing its collective set of functions.
3. The function allocation must be realizable with reasonable teamwork.
4. The function allocation must support the dynamics of the work.
5. The function allocation should be the result of deliberate design decisions.

Automation level The degree to which a system automatically performs an allocated task falls on a continuum from none (full manual control) to complete (no human intervention) [193]. Sheridan and Verplank [193] developed a nominal scale for this continuum of automation levels from low (level 1) to high (level 10). The levels of the scale are listed in table 2.9. Section A.4.1 of the appendix lists further automation level taxonomies.

Table 2.9.: *Tasks performed by the computer and the human at various levels of automation, adapted from Sheridan and Verplank [193].*

Level	Computer	Human
1	No tasks	Takes all decisions and actions
2	Helps determine options	Requests options, selects one, and implements the action
3	Helps determine options and suggests one	Requests options, selects one, and implements the action
4	Determines options and selects one	Requests option selection, approves action and implements the approved action.
5	Determines options, selects one, and implements the action if approved	Requests option selection, and approves action.
6	Determines options, selects one, and implements the action if it is not disapproved within a specified time	Requests option selection, and approves or disapproves action
7	Selects and implements action, then informs the human	Requests action selection and receives information
8	Selects and implements action, then informs the human if requested	Requests action selection and receives information if requested
9	Selects and implements action, then decides if the human is informed	Requests action selection and can receive information
10	Takes all decisions and actions	No tasks

Automation Adaptivity The potential of automation is greatest when applied to complex systems operating in highly dynamic and critical environments where a human operator is exposed to various stressors, such as noise, physical and psychological threats, and time pressure [194]. Software systems must adapt to changes in their context to maintain their value [195, 196]. Adaptive automation adapts the level of automation in real-time based on an adaptive scheme to fulfill operator needs better and mitigate the shortcomings of static automation levels [197]. These adaptation processes can be initiated by automation and the human operator [197]. Parasuraman et al. [198] list the following three categories of adaptive automation schemes:

Critical-event logic activates adaptation processes only upon the occurrence of an event that is critical from a tactical or doctrinal point of view [198].

Dynamic pilot mental workload assessment measures the operator's mental workload and implements adaptation measures to regulate this workload [198].

Pilot performance modeling triggers adaptive processes based on models of the human-automation system performance [198].

2.4.1.2. Automation Issues

With increasing levels of automation, operator tasks transition from direct control to monitoring and supervisory tasks [182], which might induce new issues impacting the overall system performance, e.g., reduced situational awareness [199]. Sarter et al. [200] mapped the expected benefits of introducing automation to their real-world observations, as listed in table 2.10.

Table 2.10.: *Presumed benefits of automation versus the real complexity, adapted from Sarter et al. [200].*

Presumed Benefit	**Real Complexity**
Increased performance	Automation transforms the practice and changes the human roles.
Reduced operator workload	Automation creates new cognitive work and is capitalized on to require human operators to perform more tasks.
Freed up attentional resources	Automation requires operators to track more aspects.
Reduced operator knowledge requirements	Automation demands new knowledge and skills from operators that are often kept out of the loop.
Autonomous functioning	Automation interacts with people and other automated systems.
No feedback changes required	Automation requires new levels and types of feedback.
Increased system flexibility	Increasing the flexibility of automated systems leads to a higher risk of failure.
Reduced human errors	Automation leads to new issues in human-machine cooperation.

The biggest potential loss of control risk factor for future aircraft operations is the increase of automation without adequate feedback for the pilots [201]. The issues surrounding advanced automation in the cockpit are complex [202], and the growing complexity of automation makes systems more and more difficult to handle for operators [203, 204]. The design and use of automation account for over 58% of flight deck automation issues, as illustrated in figure 2.28.

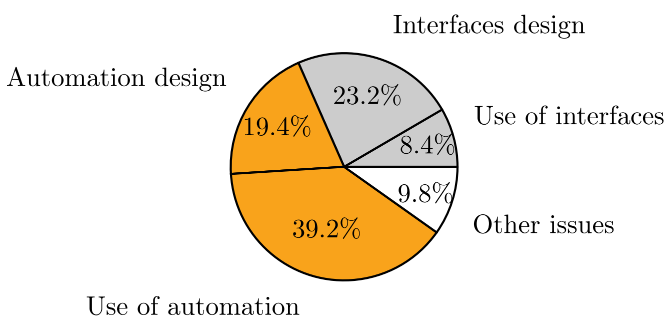


Figure 2.28.: *Distribution of perceived flight deck automation issues identified by Funk et al. [205] and listed on the Flight Deck Automation Issues website [206].*

Lee and Seppelt [190] link the issues arising from the interaction between humans and automation to the following three types of changes:

Feedback changes Automation often reduces the feedback received by the human operators, e.g., sounds and vibrations of a manufacturing plant. The main automation issues linked to feedback changes are the following:

Out-of-the-loop unfamiliarity: The reduced feedback can lead to erroneous mental models of the environment [189] and diminish the operators' ability to detect automation failures and apply manual control [190].

Skill loss: The reliance on automation makes operator interventions less likely and reduces their manual control skills, e.g., reliance on autopilot diminishes the pilots' manual control skills [190].

Task structure changes Bainbridge [181] noticed that automation designers often set out to replace the human operator but fail to achieve this goal, leaving the operator with arbitrary tasks. This task allocation can lead to the following issues:

Clumsy automation: The arbitrary task allocation between automation and humans often automates the easy tasks and leaves complex tasks to be performed by humans [190].

Behavior adaptation: Human operators show a tendency to adapt their behavior in ways that can reduce the potential gain provided by automated systems, e.g., car drivers adopted higher speeds after the introduction of the antilock brake system (ABS) [190].

Automation-induced errors: The introduction of automation can lead to new human errors that often go undetected for longer and cause more damage [190].

Relationship changes The introduction of automation leads to changes that propagate beyond the automated system's boundaries. It affects the relationship between the system and the operator and the relationship of humans to their work [190]. The main automation issues linked to relationship changes are the following:

Inappropriate trust: Operators tend to rely too much on automation they trust and underutilize automation they mistrust, which leads to sub-optimal performance [190].

Job satisfaction: Improperly implemented automation reduces the operators' decision latitude, leading to operators disengaging with the operations and not achieving the full potential of the introduced automation [190].

Automation issues interaction Disregarding the human component of automated systems often leads to the issues mentioned earlier, which often cause additional issues and negative feedback loops [190], as shown in figure 2.29.

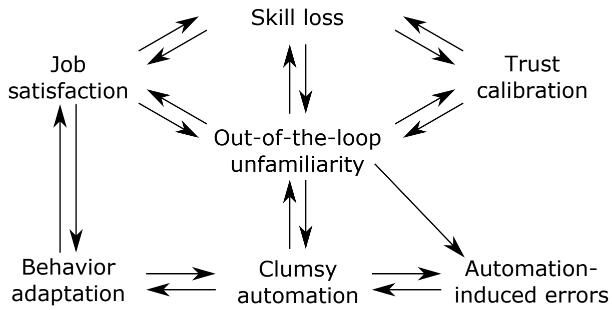


Figure 2.29.: *Interactions between automation issues, adapted from Lee and Seppelt [190].*

2.4.2. Human-Centered Automation Design

Automation issues are often caused by a failure to consider human factors in the early phases of the system development process, which is partly linked to the lack of effective methods and tools to assess the impact in the early phases of the design process [207]. The involvement of human factors in early development phases is essential since the cost of resolving issues grows exponentially with the development progress; e.g., figure 2.30 illustrates that fixing an issue when the system entered operations costs up to 1615 times as much as fixing the issue in the requirement phase. Further, considering human factors in the system design promises to deliver significant performance gains [208].

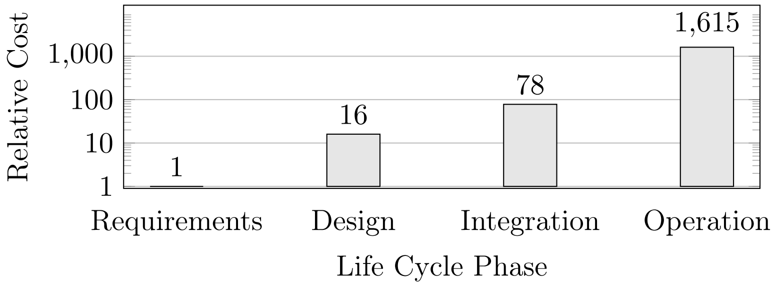


Figure 2.30.: *Relative cost to fix software errors per life cycle phase, based on Haskins et al. [209].*

The requirements analysis and system design are part of the left side of the V Model shown in figure 2.31. The steps performed aim to collect and understand user requirements, develop performance specifications, derive "design-to" specifications, and derive "build-to" documentation [185].

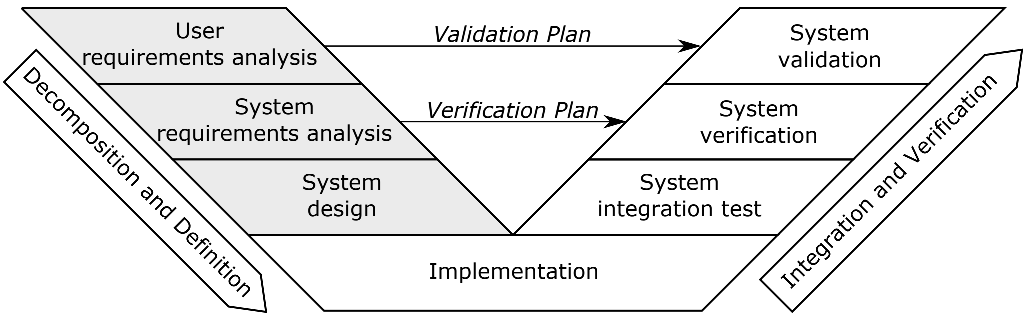


Figure 2.31.: *Left side of the systems engineering V-model, adapted from Forsberg and Mooz[185].*

This section reviews human-centered design. Further, the main system design aspects linked to human-automation issues are reviewed and derived into guidelines. Finally, methods supporting human-centered automation are discussed.

2.4.2.1. Human-Centered Design Philosophy

Human-centered design (HCD) is an approach to system design that incorporates human factor perspectives to deliver a usable system [210]. Maguire [210] provides the following fundamental principles of HCD:

- Actively involve users in the system development process,
- Allocate functions appropriately between the user and the system,
- Design the system iteratively and incorporate evaluation feedback, and
- Utilize multi-disciplinary system design teams.

Human-Centered Design Cycle Maguire [210] described the following 5 HCD phases.

Planning Successful system development requires careful planning of the entire process and strategic involvement of users and HCD expertise in specific parts [210]. The failure risk should be reduced by providing information to all project team members and integrating HCD into the overall development strategy [210]. The benefits and costs of HCD should be assessed, and the usability work should be prioritized [210].

Context analysis Systems are used in a specific context by a distinct set of users performing tasks to reach a list of goals [210]. Understanding this context of use is critical for the capture of user requirements and for ensuring the quality of the designed system [210].

Requirements capture As discussed earlier, the requirements capture is a pivotal step in system development. It is crucial to capture the users' needs and specify them so they can be easily considered in the design [210].

System design The system design is an iterative process that begins with the generation of new system designs that are iteratively developed based on user feedback [210]. Several tools are usually developed to visualize the future system throughout the design process, ranging from simple simulations to full-scale prototypes [210].

Design evaluation Evaluating designs against the specified user and system requirements delivers valuable information for the refinement of these designs [210]. This step requires the careful selection of evaluation metrics and is further detailed in section 2.4.3.

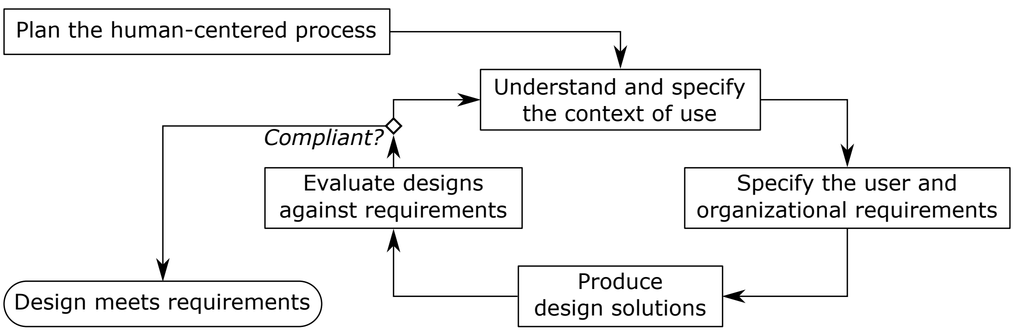


Figure 2.32.: *Human-centered design cycle, adapted from Maguire [210]*

2.4.2.2. HFE System Design Guidelines

The automation issues are mainly caused by changes in the feedback received by operators, tasks performed by operators, and the relationship between operators and automation (c.f. subsection 2.4.1.2). The following guidelines that are derived from a review of the HFE literature found in section A.4.2 of the appendix should be followed to mitigate automation issues:

- Allocate tasks and functions carefully and consciously,
- Keep the human operator in-the-loop,
- Design for an adequate operator workload,
- Avoid information overload,
- Calibrate trust in automation, and
- Align the automation's and operators' goals.

2.4.2.3. Human-Centered Design (HCD) Methods

This subsection reviews HCD methods. Maguire [210] reviewed and described HCD methods. Methods listed in the context, requirements, and design categories can be associated with the left side of the V-model and are listed in table 2.11. Section A.4.3 of the appendix features a detailed description of the listed methods.

Table 2.11.: *Methods for human-centered design Maguire [210].*

Context	Requirements	Design
• Identify stakeholder • Context of use analysis • Survey of existing users • Field study • Diary keeping • Task analysis	• Stakeholder analysis • User cost-benefit analysis • User requirements interview • Focus groups • Scenarios of use • Personas • Existing system analysis • Task mapping • Function allocation • User, usability, and organizational requirements	• Brainstorming • Parallel design • Design guidelines and standards • Storyboarding • Affinity diagram • Card sorting • Paper prototyping • Software prototyping • Wizard-of-Oz prototyping • Organizational prototyping

2.4.3. System Verification and Validation

Verifying and validating developed systems is critical in the system development process to avoid costly errors or subpar performance [211]. Verification and validation (V&V) steps should be performed throughout the development process with measures increasing sophistication along with design maturation [210]. O'Keffe and O'Leary [211] defined the following hierarchical view of system quality V&V steps:

1. Evaluation (high level)
2. Assessment
3. Credibility
4. Validation
5. Verification (low level)

This section first discusses the terms verification and validation, then reviews V&V methods, and ends with a brief discussion of V&V aspects for artificial intelligence systems. System validation and verification are part of the right side of the V Model shown in figure 2.33.

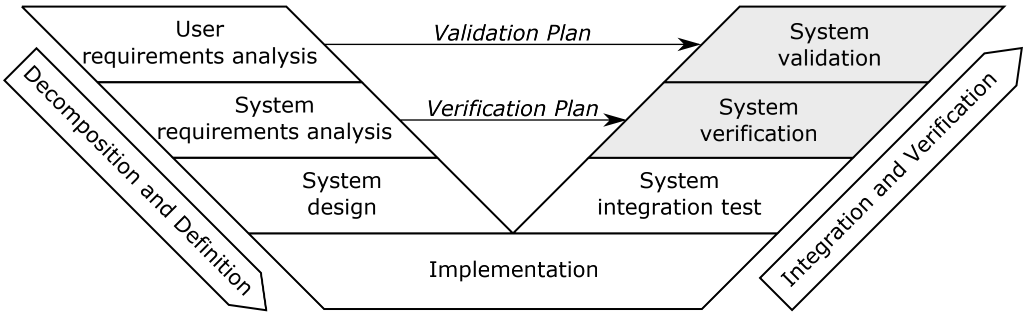


Figure 2.33.: *Systems engineering V-model, adapted from Forsberg and Mooz [185].*

System Verification The system verification step checks the developed system's consistency, completeness, and correctness concerning system requirements [212].

System Validation The validation step determines the correctness of the system with respect to the user needs and requirements [212]. Laundry et al. [213] distinguish five types of validity:

1. Conceptual validity: type of validity determines the relevance of the conceptual model's assumptions and theories.
2. Logical validity: This type of validity determines the formal model's capacity to correctly and accurately describe the problem (as defined by the conceptual model).
3. Experimental validity: This type of validity determines the quality and efficiency of the solution mechanism.
4. Operational validity: This type of validity determines the quality and applicability of the solutions and recommendations.
5. Data validity: This type of validity determines the sufficiency, accuracy, appropriateness, and availability of data.

2.4.3.1. Human-Centered Automation Verification & Validation Methods

The system's usability and other human-centered aspects should be evaluated throughout the development cycle to ensure an effective, efficient, and satisfactory design [210].

Table 2.12.: *Evaluation methods for human-centered design, based on Maguire [210].*

Method	When to apply	Output
Participatory evaluation	To identify user problems and misunderstandings about the system	Usability problems
Assisted evaluation	To assess how well users can operate a system with minimal help	User performance
Heuristic or expert evaluation	To detect major issues early in the development process.	Usability problems
Controlled user testing	To collect real-world system performance.	User performance
Satisfaction questionnaires	To quick and inexpensively measure user satisfaction	User satisfaction
Evaluation workshop	To quickly collect user feedback.	User feedback
Evaluation walkthrough	To collect detailed feedback.	Detailed user feedback
Assessing cognitive workload	To determine the user performance under stress.	User performance
Critical incidents	To record critical events that result in errors.	System errors
Post-experience interviews	To obtain subjective user feedback quickly and inexpensively.	User satisfaction & design inputs

Laundry et al. [213] listed the following frequently used model validation techniques:

- Face validation: Collect expert opinions.
- Tracing: Follow input through all the system's calculations.
- Internal validation: Analyze the system variability.
- Sensitivity analysis: Analyze the variation of input variables.
- Historical validation: Validation using historical data as input.
- Predictive validation: Compare system behavior and model predictions.
- Event validation: Compare the distribution of events for the system and the model.
- Turing tests: Test if an expert can differentiate between the system and the real world.
- Spectral analysis: Assess the system's responses in the frequency spectrum.
- Experimentation: Compare real-world systems to models.
- Convergent validation: Compare system predictions to expert predictions.

2.4.3.2. Artificial Intelligence Verification & Validation

Automated systems are introduced to perform various tasks and therefore vary greatly in complexity. With increasing complexity, automation cannot be considered a simple replacement for human information processing functions [190]. Advances in computer and information sciences, e.g., deep learning [214] and generative adversarial networks [215], have ushered in a new era of artificial intelligence (AI) [216]. The term AI, as used here, does not refer to systems able to simulate every aspect of human intelligence but rather to *narrow AI* able to outperform humans in specific tasks [217], e.g., image recognition. With *general AI* not expected to come of age in the next decades [218], humans will continue to play a role in automated processes, and no system will function completely autonomously [219, 220]. The increased system complexity and the interdependence between humans and machines might lead to an increased probability of latent errors [219].

Verifying and validating the behavior of intelligent systems, one of the major challenges in modern AI research [221, 222, 223, 196], is difficult, if at all possible [221]. Extensive testing might not be sufficient to verify and validate AI-based systems since it cannot guarantee adequate system behavior in situations not covered by test cases [224]. Additionally, extensive testing would need to be performed for every software revision [225], severely limiting the potential application of machine learning to improve machines automatically through experience [226]. Most proposed V&V strategies either ignore the uncertainties associated with linking logical thinking to real-world perceptions or are limited to simple systems operating in simple environments [225], e.g., formal verification does not scale well with the number of inputs to an AI-based system [227].

Simplex Architecture A promising approach to tackle the challenge of AI-system verification is the combination of design-time verification, run-time verification, and recovery techniques [221, 223, 196], since correcting occasional issues is easier than ensuring a fault-free system [228]. The *Simplex architecture* is an example of an architecture enabling run-time verification. It combines an error-prone high-performance system with a formally verified assurance system [228]. The decision logic switches the control to the assurance system when an undesired behavior of the high-performance systems is detected. Systems based on the *Simplex architecture* are either designed with the human out-of-the-loop, e.g., malware protection [229], or with humans acting as the high-performance subsystem, whose actions are verified by the automated system, e.g., to secure the manual control of robot motion [230]. While the *Simplex architecture* enables the verification of complex systems against a set of requirements, this only ensures a consistent and correct behavior for a set of specifications.

Adaptive Automation Validation In complex and dynamic environments, user needs and requirements may change over time [223, 231], requiring software systems to adapt to keep their goals aligned with users' objectives [196, 232]. The ability to adapt to contextual and environmental changes at run-time is a challenge for traditional validation methods [196]. Thus, novel methods are needed to determine the appropriateness of a system with respect to dynamically changing user needs and requirements [223, 212].

2.5. Data and Information Valuation

The value of information in warfare, as in business, resides in its ability to affect decisions in one's favor [1]. Information superiority, a key aspect in modern warfare, is gained through the careful management of available information provided by advanced sensor systems and offers the potential to offset a numerical, technological, or positional disadvantage [2]. The attention of expert operators is driven by the value of the information sources and their expectations [233].

The generation and capture of data are projected to grow exponentially and reach over 181 zettabytes by 2025 [234], as shown in figure 2.34. Silver [235] labeled most data as noise rather than useful data. This viewpoint is reflected by the low storage rate, with only 2% of the produced data saved in 2020 [234].

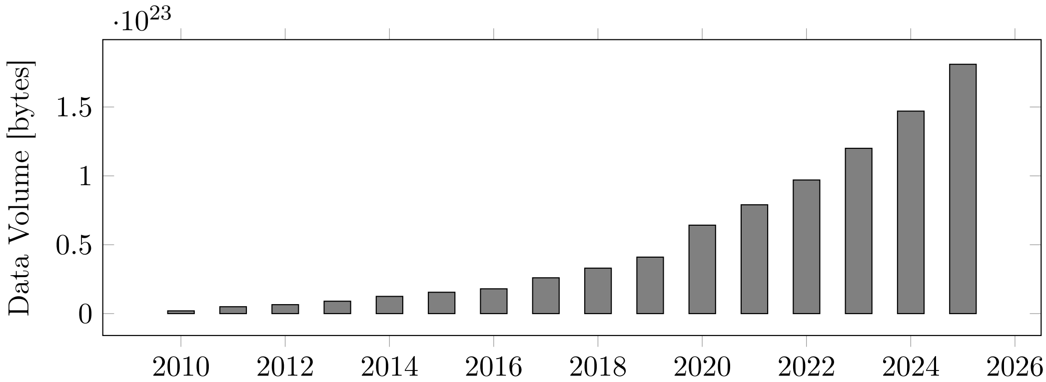


Figure 2.34.: *Yearly volume of data created worldwide according to Holst [234].*

> "The world's most valuable resource is no longer oil, but data."
> David Parker, The Economist, 2017.

The analogy between oil and data as a commodity is disputed, e.g., due to non-tangible nature of data [237], but the fact that data has value is undeniable, e.g., an accurate product demand forecast is very valuable to the wholesaler deciding on the optimum ordering amount of the product [238]. Bellin [239] described the three definitions for the value of information: use, traffic, and commodity. Sathananthan [240] gave the following reasons for the importance of data valuation:

- It enables businesses to manage large volumes of data and derivatives more efficiently, thus maximizing the return on investment.

- It makes the benefit of sharing data/information transparent.

While the prices on exchanges determine the value of a barrel of oil, the value of data can not be as easily determined. There is no widely adopted approach for the valuation of data [241]. This section first defines the terms data and information, then discusses the theory of value. The third subsection lists information metrics. Finally, information valuation approaches are reviewed.

2.5.1. Data and Information

The definition of the term *information* is the subject of an ongoing debate among scientists due to its use to denote several concepts [219]. Data and information are often described using the data-information-knowledge-wisdom (DIKW) pyramid [242], shown in figure 2.35. The pyramid suggests that more data is present in the world than information. The appropriateness of the DIKW pyramid is disputed in the literature, as it suggests that knowledge can be obtained by filtering information [242].

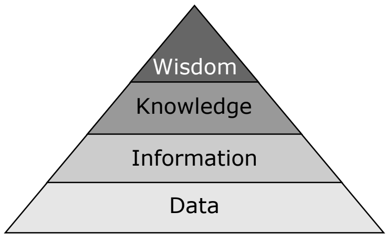


Figure 2.35.: *DIKW pyramid, adapted from Frické [242].*

Data *Data* can be defined as anything stored in a database through symbolic representation [242]. *Data* is often defined as unprocessed chunks of information on objects and context gathered through observations [243]. Frické [242] described data as being more than the measurement itself since it is never isolated from context, conventions, and pragmatics that are implicitly part of the measurement. The US Department of Defense defines *data* as “a basic unit of information built on standard structures having a unique meaning and distinct units or values” [30, p. 59].

Information Most definitions for the term *information* listed in the overview by Zins [243] describe information as something meaningful for humans, obtained from analyzing and interpreting data and putting it into context. Buckland [244] identified the following three uses as the principal uses of the term *information:*

- *Information-as-process*: The act of communicating knowledge.
- *Information-as-knowledge*: The knowledge about a specific subject that resides in a person’s mind and cannot be measured directly
- *Information-as-thing*: An object able to transmit knowledge, e.g., written documents.

The latter is the only type of information that can be processed by systems [244]. From the perspective of the information life cycle theory, the data itself carries no value, but the information provided by the data is valuable [241]. Data without context nor use has no value of its own [240].

2.5.2. Value Theory

The meaning of the term value varies depending on the scientific field [245]. The Merriam-Webster dictionary [246] lists the following main definitions for the term *value*:

1. the monetary worth of something,
2. a fair return or equivalent in goods, services, or money for something exchanged,
3. the relative worth, utility, or importance,
4. something intrinsically valuable or desirable, and
5. a numerical quantity that is assigned or is determined by calculation or measurement.

This section aims to review valuation theories that apply to *Information-as-thing.* This subsection thus focuses on the definitions of value derived from economic theory that can be applied to an object.

2.5.2.1. Types of value in economics

The definition of value has been a core topic of economic sciences, and several types of value have been defined over the past centuries [247]. Porter [247] summarized the following three types of value used in economic studies: value-in-use, value-in-exchange, and value-in-money.

Value-in-Use Value can reflect the utility provided by a specific object [248]. This type of value is defined by the end users' needs and wants and is not limited to economic aspects [247]. The users' psychology drives this type of value [247].

Value-in-Exchange Value can express the ability of an object to be exchanged for another [248]. This value is regulated by the quantity of available objects and the demand for these commodities [248]. The exchange is a social process that involves multiple individuals. This type of value is thus not driven by individual needs and wants but rather by the aggregated social system [247].

Value-in-Money The third type of value, value-in-money or price, is often seen as a sub-type of value-in-exchange [247]. Porter [247] views this type of value as a different order than value-in-exchange that deals with the psychology of decision-making with money as a criterion.

2.5.2.2. Economical theories of value

While there is a broad agreement on the types of values, what makes up these values divides the different schools of economic thought. The theory of value is necessary for the conception of economic theories, and several value theories have been conceived by economists [249].

Smith's adding-up theory of value Adam Smith [248] labels the value-in-exchange of a commodity as its "natural price." It postulates that this price is determined by the quantity of labor that a commodity can purchase. The natural price $p^*$of an object is defined as the sum of three elements used to produce it: the natural wage w^*multiplied by the amount of labor L, the natural rate of profit r^* multiplied by the amount of capital K, and the natural rent rate ρ^* multiplied by the amount of land T (eq. 2.16).

$$p^* = w^* \cdot L + r^* \cdot K + \rho^* \cdot T \tag{2.16}$$

Ricardo's labor theory of value David Ricardo [250, p. 1] stipulated that the value of a commodity is determined by "the relative quantity of labor which is necessary for its production." The main difference to Smith's theory of value is that there is no direct dependency between objects' prices and labor effort, but rather a relation between the change in relative prices $\Delta\left(\frac{p_A}{p_B}\right)$ and the change in relative labor effort $\Delta\left(\frac{L_A}{L_B}\right)$ [251].

$$\Delta\left(\frac{p_A}{p_B}\right) = f\left[\Delta\left(\frac{L_A}{L_B}\right)\right] \tag{2.17}$$

Marx's theory of value Karl Marx [252] followed Smith and Ricardo in rejecting the value-in-use approach to study value due to the subjective nature of utility. It introduced the concept of socially necessary labor as an abstract measure of the labor incorporated into a product. According to Marx [252], this intrinsic property of the product is the nature of its value. Figure 2.36 by Hagendorf [253] illustrates the relationship between the price of an object and the socially necessary labor required to produce the product.

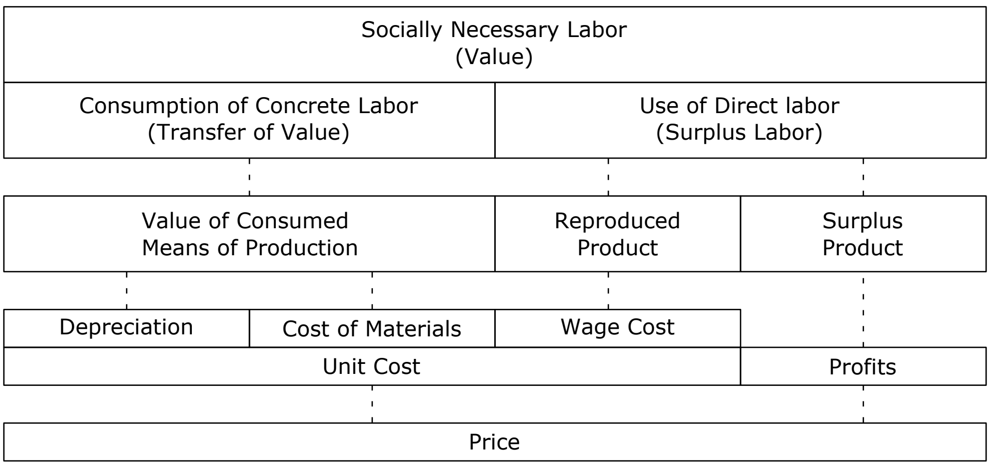
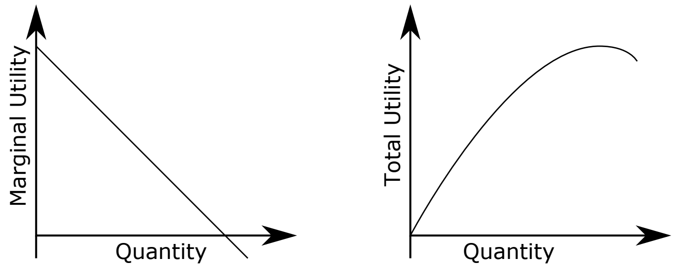


Figure 2.36.: *The commodity's value structure, adapted from Hagendorf [253].*

Subjective theory of value William S. Jevon [254] rejected the labor theory of value and theorized that labor only indirectly affects the value of a commodity through changes in supply. For Jevon, the value of a commodity stems wholly from its utility, which depends on its supply and demand. The law of diminishing marginal utility and the law of supply and demand are the main components of the neoclassical view of value.

Marginal utility The neoclassical school defines *utility* as "the satisfaction that an individual derives from the consumption of a good or the use of a service" [249, p. 157]. The utility of a commodity is thus subjective [249]. The marginal utility is defined as the context-dependent gain in satisfaction obtained by consuming an additional unit of the commodity [255]. Consuming an additional unit does not always provide a gain in satisfaction. It can sometimes even provide a negative utility (cf. fig. 2.37a), which can lead to a decrease in overall utility (cf. fig. 2.37b) [249].



(a) *Marginal utility* **(b)** *Total utility*

Figure 2.37.: *Utility as a function of the quantity of a specific commodity.*

Supply and Demand The demand for a commodity depends on the utility people associate with this item and the purchasers' characteristics [256]. Uncertainty in the provided utility discount the satisfaction expected by consumers and reduce the price these are willing to pay to acquire the commodity [256]. The diminishing marginal utility leads to a negative correlation between the number of purchased units and their price, expressed by the demand curve. Like the law of demand, the commodity's supply is correlated to its price, with higher prices increasing the benefit for producers to provide more units of a commodity to capitalize on these prices. A commodity's stable market price p^* is found at the equilibrium point, defined as the intersection of the demand curve and the supply curve [256], as shown in figure 2.38.

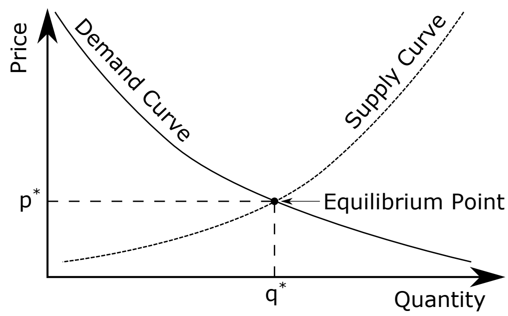


Figure 2.38.: *Relationship between the demand, supply, quantity, and price of a commodity, adapted from Marshall [256].*

2.5.3. Information Metrics

The value of information can be linked to several performance metrics that can be clustered into the following two categories: information quality metrics and utility measurements. Information-theoretic metrics are reviewed in section 2.2.3.5.

2.5.3.1. Utility Measurements

Hull et al. [257] reviewed utility measurement methods and distinguished the four following categories: (1) unidimensional utility functions, (2) multidimensional utility functions, (3) group utility functions, and(4) behavior-based utility functions.

Unidimensional utility functions Utility functions with a single variable can be divided into assumption-free methods and methods that assume a specific utility function form [257]. Common assumption-free methods are the direct rating method and the standard gamble method. The direct rating method asks users to rate their preferences on a discrete scale. The standard gamble method lets participants choose between a risk-free amount x_i and a gamble that returns the amount x_A with a probability p_i (eq. 2.18) [257]. Several variations of the two methods have been developed, e.g., midpoint methods and ordered metric methods [257].

$$u\left(x_i\right) = p_i u\left(x_A\right) + \left(1 - p_i\right) u\left(0\right) \tag{2.18}$$

The most prevalent assumption made for unidimensional utility functions is a quadratic form with the constant values a, b, and c (eq. 2.19) [257]. The expected utility $E\left[u\left(x\right)\right]$of a quadratic utility function is given by equation 2.20 with the mean μ and the standard deviation σ of x [257].

$$u\left(x\right) = ax^2 + bx + c \tag{2.19}$$

$$E\left[u\left(x\right)\right] = a\mu^2 + b\mu + c + a\sigma^2 \tag{2.20}$$

Multidimensional utility functions Decisions are often based on multiple criteria; therefore, the utility function for these types of decisions has multiple dimensions. The most straightforward approach is the linear utility function (eq. 2.21) that adds the attributes x_i multiplied by the constant a_i [257]. Another approach is the additive utility that sum up the utility functions provided by the individual attributes (eq. 2.22). Alternatively, the lexicographic approach can be employed if an attribute is more important than the remaining attributes.

$$u\left(x_1, \ldots, x_n\right) = \sum_{i=1}^{N} a_i x_i \tag{2.21}$$

$$u\left(x_1, \ldots, x_n\right) = \sum_{i=1}^{N} u\left(x_i\right) \tag{2.22}$$

Group utility functions Decisions can be made by more than one decision-maker. Hull et al. [257] described the utility function of a group that acts rationally as a whole through equation 2.23. This function is based on the subjective probability distribution $f_i(\xi)$ of the individual i and his utility function u_i for the outcome O that depends on the actions α and the external conditions ξ. The weights λ_i are selected prior to the maximization.

$$u(\alpha) = \sum_{i=1}^{N} \lambda_i \int_{\xi} u_i(O(\alpha, \xi)) f_i(\xi) d\xi \tag{2.23}$$

Behavior-based utility functions Friedman and Savage [258] postulated that the utility function of humans could be described by a curve composed of two convex sections that are joined by a concave section. The first inflection point p_1, where the curve transitions from a concave to a concave section, is located at the present worth of the individual making the decision. The two concave sections are theorized by Friedman and Savage [258] to represent two different socioeconomic levels. Markowitz [259] stipulated the existence of a third inflection point p_3 and an additional concave section in the negative wealth region. Figure 2.39 illustrates the theorized utility curve with three inflection points p_1, p_2, and p_3.

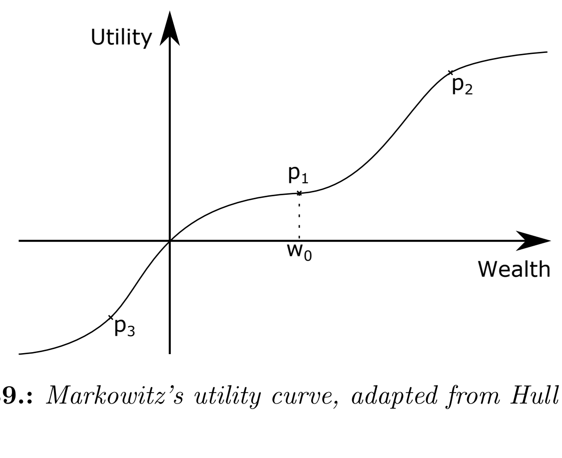


Figure 2.39.: *Markowitz's utility curve, adapted from Hull et al. [257].*

2.5.4. Information Valuation Approaches

The ability to determine the value of information facilitates the management of large volumes of data and the exchange of information between businesses [240]. Sathananthan [240] stated that the subjective and time-consuming nature of data valuation hapers the development of a standardized valuation approach. This subsection reviews information valuation approaches, divided into the following categories: commodity-based, entropy-based, and utility-based approaches.

2.5.4.1. Commodity-based Information Value

Bellin [239] argued that information value should only be described using the commodity approach. Information can be turned into a commodity if the information can be owned and assigned a value [260]. These information commodities allow users to perform decision and control actions [260]. Mowshowitz [261] listed the following five value-adding dimensions of information commodities:

1. The commodity's kernel represents the information provided by the commodity,
2. The commodity's storage medium,
3. The commodity's ability to process and reconfigure the information,
4. The commodity's distribution that makes the information available to users, and
5. The commodity's presentation of information to the user appropriately.

Glazer [262] defined the value of information as the sum of the profits P_e from the sale of the information and the additional profits gained from the information through lower costs C or higher revenues R. The value of information can be expressed through equation 2.24.

$$V = P_e - \Delta C + \Delta R \tag{2.24}$$

The value of information in the commodity form can be examined through the concept of demand and supply [263]. The supply component of the analysis is based on the costs of acquiring, processing, distributing, and presenting the information to a user. The demand side of the analysis is driven by the cost reduction or profit increase obtained by the user through the buying of the information commodity [263]. Mowshowitz [263] analyzed the value of information commodities by analyzing and modeling the users' production process.

2.5.4.2. Entropy-based Information Value

In his information value theory, Howard [264] defined the value of information as the expected gain due to clairvoyance C_b about a random variable b (eq.2.25). The information value is thus defined as the difference between the expected gain with clairvoyance $E\left[C_{b},x_i\right]$ and the expected gain without clairvoyance $E\left[x_i\right]$ (eq.2.26).

$$V = E\left[C_b, x_i\right] - E\left[x_i\right] \tag{2.25}$$

$$E\left[C_{b},x_i\right] = \int_x E\left[b, x_i\right] \cdot p\left(b \mid x_i\right) \tag{2.26}$$

Sheridan [265] modeled the value of information based on the reward $R\left(a_j \mid x_i\right)$ for taking action a_j when an event x is in state i. If x is known exactly, the value of information is calculated using equation 2.27. If x is known as a probability density, equation 2.28 is used to determine the value of information. Sheridan acknowledged that "assessing $R\left(a_j \mid x_i\right)$ is probably the most difficult aspect of applying this theory."

$$V_{avg} = \sum_i p(x_i) \left\{ \max_j \left[R\left(a_j \mid x_i\right)\right] \right\} \tag{2.27}$$

$$V'_{avg} = \max_j \left\{ \sum_i p(x_i) \cdot R\left(a_j \mid x_i\right) \right\} \tag{2.28}$$

Pitre et al. [266] modeled the value of the information collected by an unmanned aerial vehicle (UAV) during a mission with equation 2.29. The value of information is defined as the expectation $E\left[\cdot\right]$ with respect to all uncertainty. This uncertainty is summed up for every discrete time step k and target n and based on the importance $\alpha_{n,k}$ of target n, the time factor $\lambda_{n,k}$ for tracking target n and the trace $\mathrm{tr}\left(I_{n.k}\right)$ of the information matrix $I_{n,k}$ for target n at time k. $I_{n,k}$ quantifies the data accuracies [266].

$$V = E\left[\sum_{k=1}^{K} \sum_{n=1}^{N} \alpha_{n,k} \cdot \lambda_{n,k} \cdot \mathrm{tr}\left(I_{n.k}\right)\right] \tag{2.29}$$

2.5.4.3. Utility-based Information Value

Dongge [267, p. 580] stated that "the value of information should be measured by the human's satisfaction" and defined *information utility* as "the degree of satisfaction of information users" [267, p. 581]. For Dongge, the utility of information is driven by two aspects: (1) the amount of information and (2) the responding time. Equation 2.30 models the normed information utility U over time t based on the lasting period T_L and responding time T_0 needed to consume the information [267].

$$U(t) = (\frac{T_L - t}{T_0})^{T_0} \cdot e^{t-(T_L - T_0)} \tag{2.30}$$

Morrison and Cohen [268] modeled the value of information as the difference between the maximum expected utility E_{max} of a decision made after obtaining the information and one made without the information.

$$E_{max}\left(T\right) = \max_{a \in A} \sum_{t \in T} P\left(t\right) \cdot U\left(a, t\right) \tag{2.31}$$

$$E_{max}\left(T \mid I\right) = \sum_{i \in I} P\left(i\right) \cdot \max_{a \in A} \sum_{t \in T} P\left(t \mid i\right) \cdot U\left(a, t\right) \tag{2.32}$$

$$V\left(T \mid I\right) = E_{max}\left(T \mid I\right) - E_{max}\left(T\right) \tag{2.33}$$

Xianliang et al. [269] based the value of information on two factors, the information's utility U and the cost C to realize the utility. The utility of the information is calculated through a linear combination of 5 values u_i with the weights λ_{ui} for the (1) reliability, (2) increment, (3) timeliness, and (4) availability of information, as well as, (5) the ability of information users [269]. The cost of information is composed of 4 weighted values for the cost of (1) creation, (2) service, (3) usage, and (4) opportunity. To bring the range of the information value within a finite range, the researchers normalized the values and formulated equation 2.35 to quantify the value of information in supply chains.

$$V = \frac{U}{C} = \frac{\sum\limits_{i=1}^{5} \lambda_{ui} \cdot u_i}{\sum\limits_{i=1}^{4} \lambda_{ci} c_i} \tag{2.34}$$

$$V' = \frac{1 + \sum\limits_{i=1}^{5} \lambda_{ui} u'_i}{1 + \sum\limits_{i=1}^{4} \lambda_{ci} c'_i} \tag{2.35}$$

Wang et al. [238] defined the value of information as "the difference in information user's benefit between without information and with information." The researchers modeled the value V of information in supply chains using a conditional payoff function H to decide on a wholesaler's optimum ordering amount. This function is used to calculate the expected reward for the best tactic t' without information and the best tactic with the information t_i^* for a state of the environment s_i [238].

$$V = H(t_i^* | s_i) - H(t' | s_i) \tag{2.36}$$

2.6. Key Findings from the Literature Review

This research aims to investigate the impact of information quality on the value provided by the information. The following conclusions are drawn from the review of the existing body of research:

Artificial intelligence AI solutions are not yet easily adaptable for sensor management applications. Advances in computer and information sciences have ushered in a new era of AI [216], but further innovations are required to unlock the full potential of AI [270]. Researchers mainly focused on using AI for "tame" problems for which the goal is straightforward and can easily be assessed as achieved. These traits do not apply to "wicked" problems [271] as those found in the context of military operations where decision-makers face complex, uncertain, and novel issues in everyday situations [272]. Human involvement makes these situations essentially unknowable [272]. Further, current AI systems are poorly suited for mission-critical applications [27].

Humans will remain part of the sensor management system for the foreseeable future. Tracking operator goals and context-dependent requirements is a critical capability of adaptive systems [273], but the difficulty of inferring users' needs and assessing the context limits these systems' capabilities [232]. Humans can assess the context using mechanisms of perception and cognition [274]. Since they will remain part of any system for the foreseeable future [219, 220], this strength could be leveraged for methods aiming to validate systems at run-time. Additionally, keeping the operators "in the loop" is a key success factor for automated systems [275, 26], and cooperation between humans and AI-based systems has the potential to surpass the performance of either one. These findings highlight the need to adopt a new view in which humans are not seen as a problem to control but rather as a solution waiting to be harnessed [276].

The pilots' informational demands are context-dependent and linked to the operators' tasks. Internal and external influences, e.g., political processes, can change human roles, goals, and tasks [277]. Humans working in complex and dynamic environments need to adapt to changing task demands [194], e.g., pilots are required to adapt their flight path to a multitude of dynamic elements such as meteorological conditions or other aircraft [5]. The information required by pilots depends on the tasks they have to perform in a given situation (c.f. section 2.1.5).

The value of information depends on its subjective utility for the operators. Sensor management systems process and provide information of the type *information-as-thing* since this is the only type that can be processed by automated systems [244]. The literature provides three categories of information valuation approaches: commodity-based, information-theoretic, and utility-based (c.f. section 2.5). Behavior-based utility functions, e.g., Markowitz curves [259], are promising for modeling the subjective value of information that incorporates the valuation context.

Human factors have to be considered when developing sensor management reward functions. Automation issues are often caused by a failure to consider human factors in the early phases of the system development process. A first step for considering human factors in the development process is to follow the guidelines reviewed in section 2.4.2.2. Further human factors research needs to be performed to keep up with the fast-paced advances of computing and sensing technology [191, 278], e.g., explainable AI [26, 279]. Additionally, it is crucial to clearly define what constitutes "good decisions" from the human operators' perspective [224].

Correctly defining the reward function is critical for developing sensor management systems. Developing sensor management systems is challenging and best described as designing decision processes, called policies, to maximize the reward associated with performing a sensing task [14]. The review of sensor management applications in section 2.2.3 shows that these policies are either implemented through a rule-based system, a Bayesian method, or a system aiming to maximize a specified reward function. Selecting the goal pursued by the system through this reward function is a critical part of the sensor manager design process [73]. This aspect becomes ever-more important due to the rapid rise in the capabilities of AI systems [26].

Similarities are observed between human information processing and sensor management applications. Many parallels are found between the human information processing described in section 2.3 and sensor management applications described in section 2.2. Both loops contain elements that collect data about the environment: senses and sensors. Likewise, both concepts feature detection and data fusion mechanisms, which are part of the perception and working memory elements for humans. These mechanisms are based on the same theories, e.g., signal detection theory (c.f. section 2.3.4.6) is adopted in perception studies and sensing applications. The humans' long-term memory and the systems information databases contain knowledge and information used to augment the available sensory data and feed perception and decision-making processes. The prevalent human decision-making theories are also part of sensor management implementations. Finally, human information processing and sensor management systems are both resource-constrained. Table 2.13 lists the parallels observed between elements of both processing loops.

Table 2.13.: *Parallels between elements of the sensor management loop and human information processing.*

Human Information Processing	Sensor management
Senses	Sensor systems, incl. onboard data processing
Perception	Data fusion and detection algorithms
Working Memory	
Long-term memory	Information databases
Response selection	High-level decision making
Attention resources	Power, cooling, computing resources

Current reward functions do not explicitly assess the relative value of information for the operator. Several reward functions have been put forward in previous research and are based on low-level data qualities, information-theoretic metrics, or higher-level concepts (c.f. section 2.2.3). Approaches based on data qualities are not adequate as an overall reward function since data without context nor use has no value of its own [240]. The information provided by the data is the element that is meaningful for operators [243] and which provides the value [241] (c.f. section 2.5). While some research has been conducted on reward functions that consider the operators' mission and goals, these do not explicitly address the benefit of capturing information for the operators and have the following shortcomings:

1. Using mission-independent objectives, e.g., maximizing the expected information gain for the management of sensor systems, cannot ensure gathering the most valuable information for the operators since the value of sensed data usually depends on the goal to be achieved [14].

2. Bolderheij [16] and Katsilieris [17] approaches use a risk assessment to select the sensor tasks to be performed. This criterion is useful in naval radar operations but challenging to transfer to airborne radar systems due to the diversity of missions conducted by swing-role aircraft. De Groot's use of "the optimality for the mission" as decision criteria is more general. It eliminates the need for heuristically defined task qualities, priorities, and expert opinions [18], but this criterion requires designers to define a metric to measure the "optimality for the mission."

3. Designing a sensor management system based on operator-defined priorities is complex and requires a thorough understanding of the sensor systems, operator needs, and operational context [19, 20]. For example, the goal lattice approach requires system designers to enumerate all the system's goals and quantify the interrelationship among them [33]. The same issue arises in the approach by Molina et al. [22, 23, 24]. Using expert opinion is relatively complex [16], and reward functions are not always explicitly given [25].

4. The sensor resource allocation directly affects the quality of the information distilled from sensed data, e.g., the estimated state vector of a track. This relationship could be exploited to allocate resources more efficiently [17]. For example, the energy assigned to a search task can be reduced by up to 48%[11] if the reduction of the single pulse detection probability from 99% to 98% is acceptable. Leveraging this potential requires designers to model the relationship between sensor resource allocation and expected information quality. The resulting interdependency between sensor tasks makes the design of rules challenging.

The development of sensor management applications must consider the expert bottleneck issue. The reliance on domain experts for the design of expert systems makes knowledge acquisition the main bottleneck in developing this type of sensor management system [280]. Accordingly, the development of reward functions should aim to optimize the domain experts' participation.

[11] Based on the single pulse SNR table found in [58]. Assuming a probability of false alarm equal to 10^{-9} and an initial SNR equal to 15.75 dB

3. Research Concept and Methodology

The literature review highlights the need for a novel approach to designing reward functions for sensor management systems, which mirrors the human operators' subjective information valuation (see Chapter 2).

Research Objective

The main objective of this study is to develop an information valuation modeling approach that delivers the reward function of a sensor management system based on the operators' tasks.

Research Motivation

The research performed for this study will advance the knowledge on how to specify the right kind of reward function for complex automated systems, which is a challenge for all types of systems using AI [26]. A model of the information's value to pilots can help alleviate the expert bottleneck issue by enabling the automatic preliminary assessment of results, which can help focus the knowledge elicitation process, e.g., by reducing the number of alternatives to discuss with experts.

The approach could be used to provide AI systems with a construct of human values and improve their ability to learn and make timely, robust, and secure decisions in dynamic environments [27]. Further, involving human domain experts in the development process of complex automated systems has shown that these experts can learn from their interaction with artificial intelligence, as shown by the progress made by Go players that played against Google's AlphaGo [28].

Chapter Outline

This chapter describes the information valuation model designed for this study, the theory on which it is based, and the methodology conducted to assess the model. The first section explores the theoretical framework that underpins the valuation of information and discuss the characteristics of information and its main valuation factors for sensor management applications. The second section lists the research hypotheses. Finally, the methods used to test the research hypotheses are discussed in the last section.

3.1. Theoretic Framework

This section explores the theoretical framework that underpins the valuation of information and answers the following explorative research questions:

- What are the characteristics of information in sensor management applications?
- What are the main factors in the value of information for sensor management applications?

First, the research's metamodel is detailed to define the elements and relationships that link the pilot's goals to the value of the information delivered by the sensor systems. Then, the impact of measurement accuracies on the information content is analyzed and exemplified. Finally, the concept of information value is defined for this research.

3.1.1. Meta Model

This subsection describes elements used in the information valuation approach and the relationships between these elements. The modeling is based on a simplified and adapted Unified Architecture Framework (UAF) domain metamodel [281]. UAF enables the modeling of several perspectives, ranging from strategic capabilities to low-level measures [281]. The following five UAF model domains are involved in the modeling of the operational value of information:

Strategic Domain This domain describes the goals to be achieved and the capabilities required to achieve these goals.

Operational Domain This domain describes the logical system architecture and activities performed solution-independently.

Resource Domain This domain describes the functional architecture in a solution-dependent manner.

Parameter Domain This domain describes the measurable properties of real-world objects.

Information Domain This domain addresses the information perspective on all levels of the domain stack, from strategic to actual resources.

Figure 3.1 illustrates the connections between the various UAF model domains and the color code used to represent elements from these domains in the figures of this subsection. Elements colored in orange are introduced to extend the UAF metamodel.

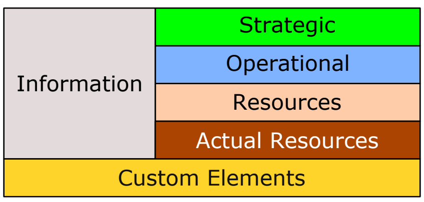


Figure 3.1.: *UAF model domains involved in the modeling of the value of information.*

3.1.1.1. Strategic Domain

The strategic view is used to describe the connection between the mission, its goal, its phases and the tasks performed to accomplish the mission. Figure 3.2 illustrates the strategic elements and their relationships. As shown, mission tasks are prioritized based on their relation to the overall mission goals.

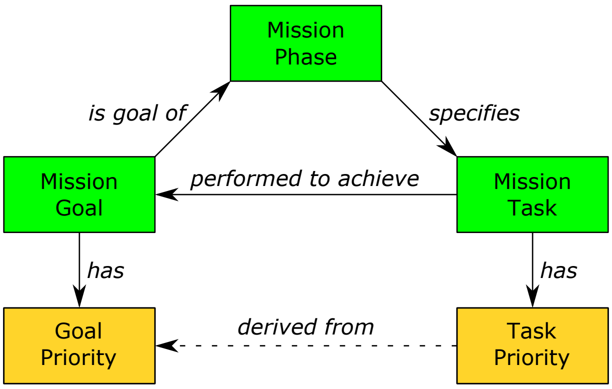


Figure 3.2.: *Strategic domain elements of the research's model.*

3.1.1.2. Operational Domain

Activities in the operational domain implement mission tasks. These activities are performed under a given set of actual conditions by an operational performer, a logical entity. Operational activities (OAs) can require information elements that are provided by other operational activities. The priority of operational activities is derived from the mission tasks these activities implement. Figure 3.3 illustrates the relationships between elements from the operational perspective.

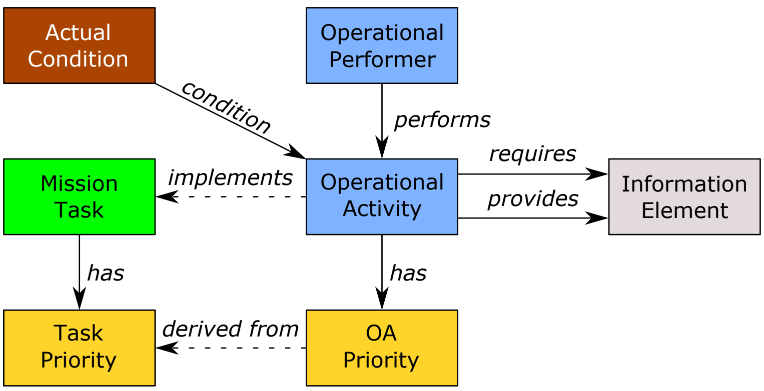


Figure 3.3.: *Operational domain elements of the research's model.*

3.1.1.3. Resource Domain

The functional architecture of a solution is illustrated by the resource domain perspective shown in figure 3.4. Functions implement operational activities and are performed by resource performers that are either technical systems or human operators. These functions can consume and produce data elements that implement information elements in a physical form, e.g., messages consisting of a set of bytes.

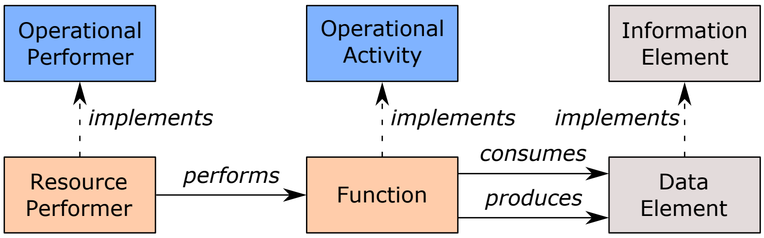


Figure 3.4.: *Resource domain elements of the research's model.*

3.1.1.4. Information Domain

Additional elements are introduced for the information perspective to model the value of the information provided in a given scenario. First, the information elements required by operational activities performed in a given context are aggregated into an overall information need. This information need has a fulfillment priority, which is derived from the priorities of the operational activities. Information that fulfills the operational need is obtained from data produced by functions on the functional level. This actual information has thus some value, which is driven by the information fulfillment priority, as shown in figure 3.5.

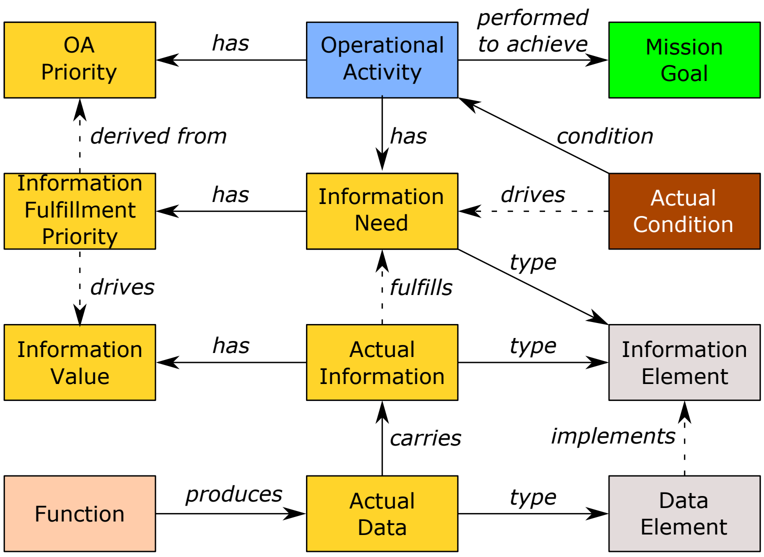


Figure 3.5.: *Information domain elements of the research's model.*

3.1.2. Information Value

Information has the ability to improve decisions [1] and gain an advantage in high-stakes situations [2]. In the research context, the term information follows Buckland's [244] *information-as-knowledge* definition. This information is carried by elements that can be transmitted from one actor to another, which follow Buckland's [244] *Information-as-thing* definition (see section 2.5.1). Brown and Sukkarieh defined the value of information as "the extent to which knowing the information helps achieve a mission" [70, p. 2].

Subjective Operational Information Utility Applying the neoclassical economic school's definition of utility as "the satisfaction that an individual derives from the consumption of a good" [249, p. 157] to the context of single-seater aircraft operations leads to the definition of information value being the subjective satisfaction experienced by pilots, which is driven by the decision makers' information needs and wants. Providing large quantities of information can hamper the pilot's decision-making [133], and, therefore, providing additional information or marginal information quality improvements can have a negative marginal utility.

Operational Information Value For the purpose of the research, the value of information follows Porter's [247] definition of value-in-use, which reflects the utility of the specific information. The operational value concept can be extended to cover the definitions of value-in-exchange and the value-in-money as defined by Porter [247], e.g., to model the value of information for multiple decision makers or to model the return on investment for the acquisition of sensing equipment. These aspects do not fall within the scope of the research. The actual information, which is derived from the environment, has value through its ability to fulfill the pilots' information needs and wants, as shown in figure 3.6. Appendix B.1 provides an illustrative example of information demand and supply.

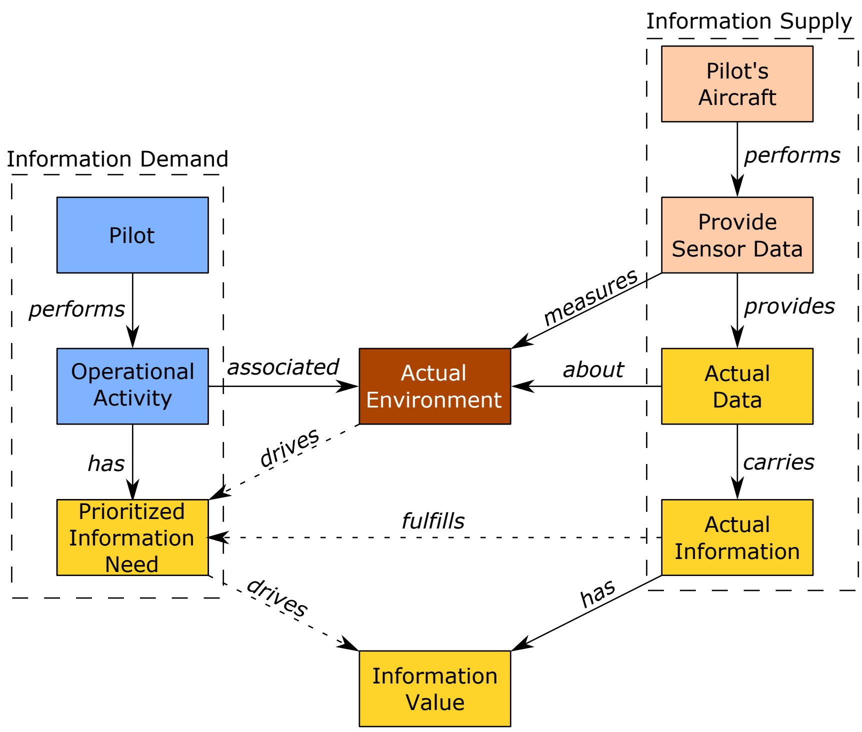


Figure 3.6.: *Information demand and supply driven concept of information value.*

3.2. Research Questions and Hypotheses

This research aims to develop a metric to measure the operational performance of sensor management approaches based on information demands linked to tasks that operators associate with specific targets. This section lists the hypotheses that guide the research methodology and that are associated with the following three topics:

- Information value modeling inputs,
- Domain expert information preferences, and
- Information value metric performance.

3.2.1. Information Value Modeling Inputs

As used in this research, the value of information is based on the information quality demanded by domain experts to fulfill tasks they associate with specific targets in their environment. The research questions and hypotheses linked to this topic are divided into two sub-topics: The operator tasks' information demands and the operator task to target associations.

3.2.1.1. Operator task's information demands

The first set of hypotheses deals with operators' information demands linked to specific operator tasks.

Consistency of the task-related information demand Modeling the value of information with a common model for all domain experts assumes that experts use similar decision-making processes that have comparable information demands. The question is, therefore:

> Do domain experts have the same task-related information demands?

This question is split into two points to facilitate the comparison. The first addresses the assumption that if domain experts have the same information demands, then they will require the same target parameter information for the selected set of operator tasks, which leads to the hypotheses below:

H_0^A: There is no consensus between experts on the target parameter information demanded to perform an operator task.

H_1^A: There is a consensus between experts on the target parameter information demanded to perform an operator task.

Importance of the demanded track parameter accuracy The information about a target is encoded by several parameters, e.g., range and velocity. Some of the operators' target parameter accuracy demands can be more important for the success of a task than the demand for other parameters, which leads to the question:

> Are all the track parameter accuracy demands of equal importance?

This question leads to the following hypotheses:

H_0^B: The operators' target parameter accuracy demands are of equal importance.

H_1^B: The operators' target parameter accuracy demands are not of equal importance.

Range dependency of the task-related information demand The sensor power required to capture information of the desired accuracy increases with increasing target range. This relationship can lead experts to consider the trade-off between resource usage and information accuracy in their demands. This premise leads to the following question:

> Do the experts' information accuracy demands decrease with increasing target ranges?

The following alternative hypotheses capture the expected decrease in the experts' information accuracy demands:

H_0^C: The information accuracy demanded by domain experts to fulfill their task does not decrease monotonically with increasing target range.

H_1^C: The information accuracy demanded by domain experts to fulfill their task decreases monotonically with increasing target range.

3.2.1.2. Operators' task to target association

The second set of hypotheses is linked to the operators' association of tasks to specific targets in their environment.

Consistency of the operators' task to target association Modeling the value of information with a common model for all domain experts assumes that experts use similar decision-making processes that result in the same association of actions. The question is, therefore:

> Do domain experts associate the same tasks with targets in a scenario?

The following hypotheses are, therefore, tested in the scope of the research:

H_0^D: There is no consensus between experts on the tasks they associate with a target.

H_1^D: There is a consensus between experts on the tasks they associate with a target.

Range dependency of the task to target association The actions taken by fighter aircraft operators follow structured processes, e.g., the F2T2EA cycle for air-to-ground operations. In these structured processes, actions are taken once a target fulfills specific conditions, e.g., within a pre-defined range. It can thus be assumed that operator task associations are range dependent, which leads to the following question:

> Is the association of tasks with targets range-dependent?

The experts' task associations are analyzed to probe the following hypotheses:

H_0^E: The association of operator tasks with target does not allow for the segregation of these tasks into distinct range classes.

H_1^E: The association of operator tasks with target does allow for the segregation of these tasks into distinct range classes.

The constancy of task-related information demands within association ranges Modeling the range-dependency of information demands increases the complexity of the valuation model, which raises the following question:

> Are the information demands linked to an operator task constant within the span of the associated target's ranges?

The following hypotheses are put to the test to answer this inquiry:

H_0^F: The operators' task's information demand is not constant within the span of the associated target's ranges.

H_1^F: The operators' task's information demand is constant within the span of the associated target's ranges.

Target priority and task priority correlation The priority of a target is assumed to be dependent on the priority of tasks operators associate with it, which leads to the following question:

> Does the priority of a target provide an additional benefit for the information value modeling?

Suppose the priority of a target is driven by the priority of tasks associated with it. In that case, the target's priority is of no benefit for modeling an information's value. This presumption is addressed by testing the following hypotheses:

H_0^G: The priority of tasks associated with a target has no effect on the target's priority.

H_1^G: The priority of tasks associated with a target has a positive effect on the target's priority.

3.2.2. The operators' information set preference

The goal of sensor management systems addressed by this research is to collect the most valuable information for the operators' mission performance. Operators are expected to prefer sets of information about the environment that contain more valuable information for their tasks. The operators' information set preference is, therefore, used as a validation metric. The following hypotheses are tested to assess the validity of the validation metric.

Preference consistency Validating the information value model based on the operators' preferences assumes that experts use similar decision-making processes and thus have similar information set preferences. The question is, therefore:

> Do domain experts have the same information set preferences?

The following hypotheses are tested to investigate the previous question:

H_0^H: There is no consensus between the experts' information set preferences.

H_1^H: There is a consensus between the experts' information set preferences.

Selection confidence and aggregated preferential choice Experts can be questioned on the level of confidence they have in their preferences between two information sets, and an interval scale can be applied to the experts' aggregated preferences to reflect the preferential choice agreement [282], which leads to the following question:

> What is the relationship between the selection confidence and the preferential choice agreement?

The following hypotheses are probed:

H_0^I: The confidence expressed by domain experts choosing between information sets has no relationship with the preferential choice agreement.

H_1^I: The confidence expressed by domain experts choosing between information sets has a positive relationship with the preferential choice agreement.

3.2.3. The information value metric performance

The present thesis's main objective is to design and assess an information valuation approach based on operator needs, which could be used as the objective function of a sensor management system. Its overall performance is measured by its ability to mirror the experts' information set preferences.

Information value performance and sensitivity Suppose it is assumed that the information value metric does reflect the experts' information preferences. In that case, these experts should prefer information sets that receive a higher information value score, which leads to the following question:

> Are information sets with higher information value scores preferred by domain experts?

This question is tackled by testing the following hypotheses:

H_0^J: Domain experts do not prefer information sets with higher information value scores in pair-wise comparisons.

H_1^J: Domain experts prefer information sets with higher information value scores in pair-wise comparisons.

The information value metric quantifies the difference between the information's value in information sets. Smaller differences are assumed to choose between information sets more difficult for domain experts and reduce their selection confidence, which leads to the following question:

> Do information set pairs with a lower difference in information value have a higher uncertainty in domain experts' preferential choice uncertainty?

The effect of information value score differences is probed through the following hypotheses:

H_0^K: The difference in information value between two information sets collected from the same environment has no effect on the aggregated preferential choice uncertainty.

H_1^K: The difference in information value between two information sets collected from the same environment has a negative effect on the aggregated preferential choice uncertainty.

3.3. Research Methodology

Developing objective functions for sensor management systems is challenging because it requires a thorough understanding of the systems, the operators' needs, and the operational context. The reward obtained from the capture of specific data is highly dependent on the operational context and the goals to be achieved by the pilots. Further, explicitly describing these functions is difficult for domain experts, and the reliance on domain experts makes knowledge acquisition the main development bottleneck.

This thesis presents the engineering viewpoint on the result of a joint research approach with psychologist Benedikt Petermeier. We collectively selected the research topic, aligned our research objectives, and defined the scope of the research's use case, described in section 3.3.1. Data collection studies are performed jointly, but the collected data is processed independently to answer the hypotheses discussed in the two theses. The present thesis covers the design of objective functions for sensor management applications. In his thesis [283], Petermeier covers the methods for eliciting expert knowledge and judgments needed for the functions modeling and evaluation. Figure 3.7 provides an overview of the joint research approach. Individually and jointly performed activities are described in this section.

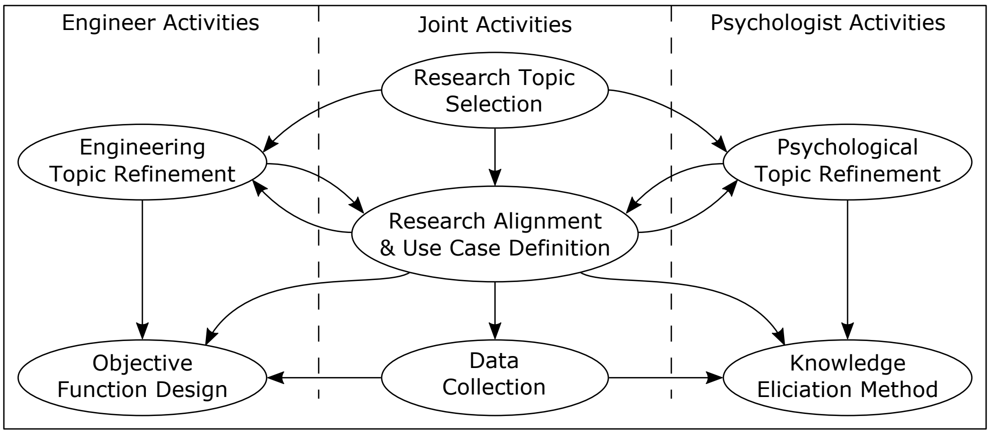


Figure 3.7.: *Joint research approach overview.*

3.3.1. Operational Use Case

The fighter sweep mission, see section 2.1.1, was selected as a use case mission to evaluate the validity of the information value approach to sensor management because fighter sweep is the preferred fighter mission [38], and targets can appear from anywhere [46]. *Fighter sweep* is defined as an "offensive mission by fighter aircraft to seek out and destroy enemy aircraft or targets of opportunity in a designated area" [30]. It is generally conducted over hostile territory to establish air superiority to protect friendly forces by suppressing enemy fighters and other airborne targets [38].

Avoiding midair collisions is the primary reason for using sensor systems in the mission phases leading up to the ingress. Since the demanded information remains constant over time for these tasks and applies to objects at close range, the demand will likely remain within the sensor systems' collection capabilities. The same is valid for the phases from egress to landing. During the ingress and sweeping phases of the mission, targets can appear from anywhere [46]. Thus, from a sensor employment perspective, the most interesting phases of the mission described in section 2.1.2 are the ingress (Phase 6) and the sweeping of the area (Phase 7).

Research Scenario The scenario selected for the research into modeling information value for fighter pilots is the ingress into the mission area during a sweep mission. This setting is selected for the following reasons:

1. During ingress, pilots will adapt their flight path based on the tactical situation [47], making it the phase where pilots are making the most tactical decisions.

2. Due to the preparation that occurs before the *fighter sweep* mission, the threat level from surface-based air defense, e.g. surface-to-air missiles (SAMs), is low [46] and can thus be ignored for the research.

3. For the first wave of sweeping aircraft, the airspace can be "sanitized" of all friendly forces [38]. Thus the identification of detected objects can be simplified for the research.

Figure 3.8 illustrates the scenario retained for the research, in which a fighter sweep is performed by four aircraft to ensure the safe travel of a package and hostile SAMs are disabled.

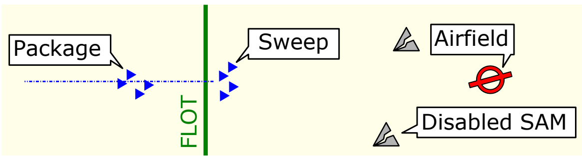


Figure 3.8.: *Use case mission scenario.*

Research Snippet For the research, the scenario contains a sweeping package composed of the following objects: (1) The aircraft piloted by the pilot referred to as *ownship*, (2) a wingman, (3) a friendly two-ship group cooperating in the sweep. The sweep flies ahead of (4) a package of friendly aircraft outside the sensor's field of regard. Finally, (5) several threats composed of two hostile airplanes are flying in the contested airspace. Figure 3.9 illustrates the simple scenario setup.

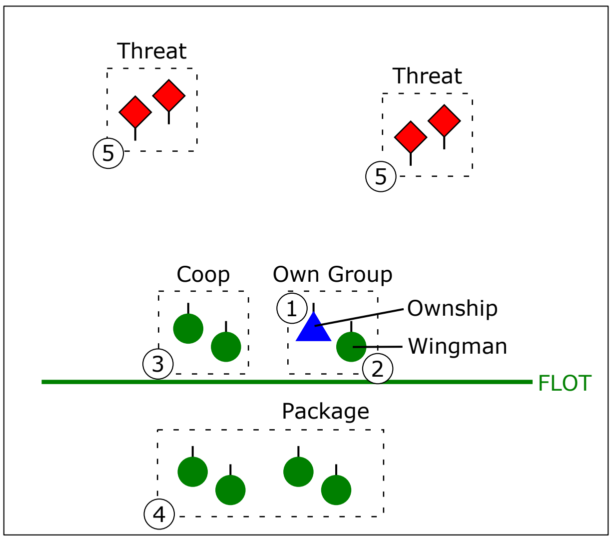


Figure 3.9.: *Simple scenario setup.*

3.3.2. Research Overview

The main aim of the research is to develop an approach to modeling the operational value of the information carried by a set of sensed data. Inputs for the value calculation are the information set and the operators' information demands, as illustrated in figure 3.10. A prototypical function is designed for the limited scope of the research's use case and used to assess the approach's viability.

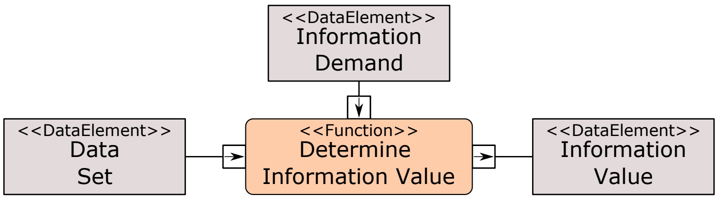


Figure 3.10.: *Information value inputs and outputs.*

The research is split into the design of the information valuation model and its assessment based on a collection of information sets. Information sets are generated using a radar simulation with a pseudo-random resource allocation. Insights into modeling the operational value of information are gained through the analysis of collected task demands. These insights are used to design the prototypical information valuation model. Further, the analysis delivers the scenario-specific model inputs used to adapt the model to the research scenario, as shown in figure 3.11. The valuation model's output is assessed against the experts' preferences to determine the model's ability to predict the experts' information set preferences, as shown in figure 3.12.

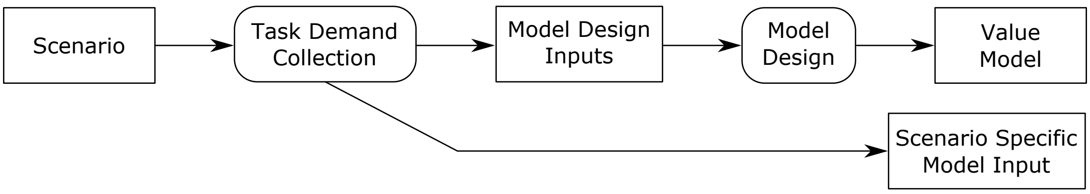


Figure 3.11.: *Model design activity overview.*

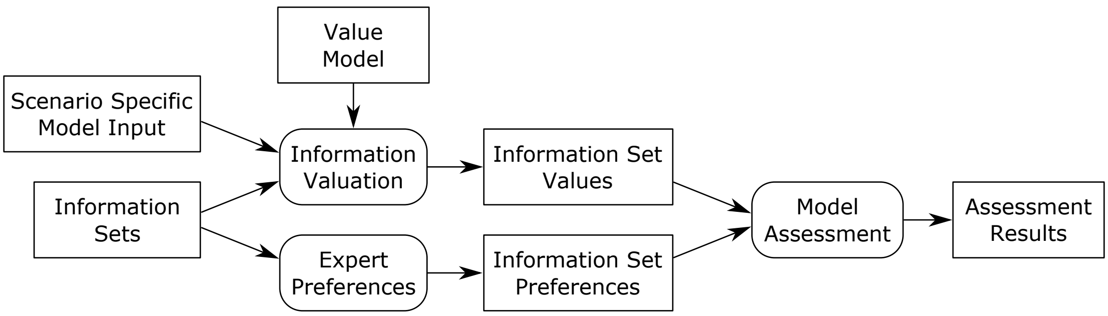


Figure 3.12.: *Model assessment activity overview.*

3.3.3. Data Collection

Three studies are conducted to collect the following data:

- The relevant operator tasks, their link to data provided by the aircraft's sensors, and the data accuracy demands wanted and needed by operators to fulfill their tasks.

- The association of operator tasks with targets in the research scenario.

- The domain experts' selection preferences in pair-wise information set comparisons.

3.3.3.1. Task-Specific Information Demand Study

Figure 3.13 illustrates the activities performed to capture the task-specific information demands. The task-specific demand study is conducted to determine the set of relevant operator tasks and collect the information that operators need to perform these tasks. A task analysis is performed for the specified use case to obtain the list of relevant operator tasks, see [283]. An operational analysis is conducted to identify the information flowing in the use case scenario and link the information flows to the operators' goals and activities. Functional analysis is performed to identify the data elements exchanged between the aircraft and the pilot on the resource level and link the data provided by the aircraft's sensors to the information required by pilots to achieve their mission goals. Task-specific data quality demands are elicited from domain experts through a questionnaire, see [283]. Questionnaire responses are analyzed to assess the set of operators' task-specific information demands hypotheses H_0^A, H_0^B, and H_0^C. Further, questionnaire responses are mapped to the data exchanges identified in the functional analysis step and transformed into a data input for the information valuation model.

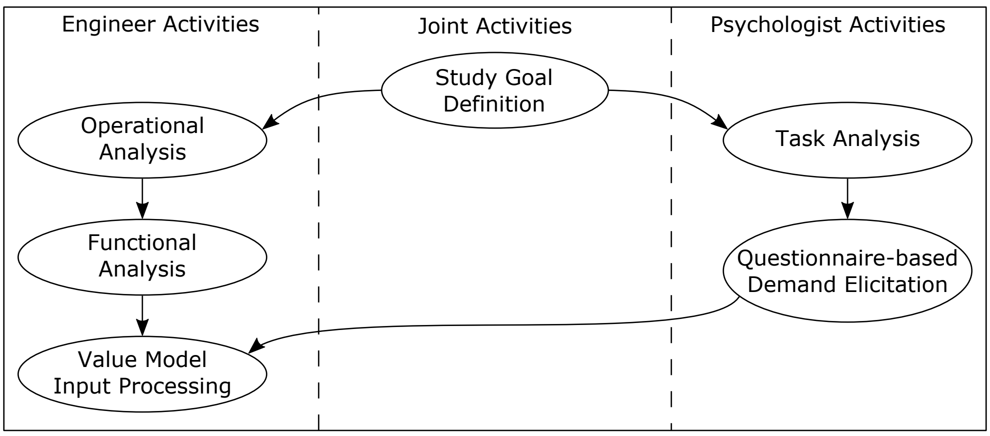


Figure 3.13.: *Activities conducted collaboratively to collect the operators' task demands.*

3.3.3.2. Task Assignment and Prioritization Assessment

The task assignment and prioritization assessment study is conducted to map operator tasks to targets in the research scenario. Figure 3.14 illustrates the activities performed to elicit the task assignment data. Participants prioritize the groups and the tasks they assign based on their operational experience. A dedicated human-machine interface (HMI) is developed to simplify the data collection and animate the situation snippets. The collected data is used to provide input data for the information valuation model and to assess the null hypotheses H_0^D, H_0^E, H_0^F, and H_0^G.

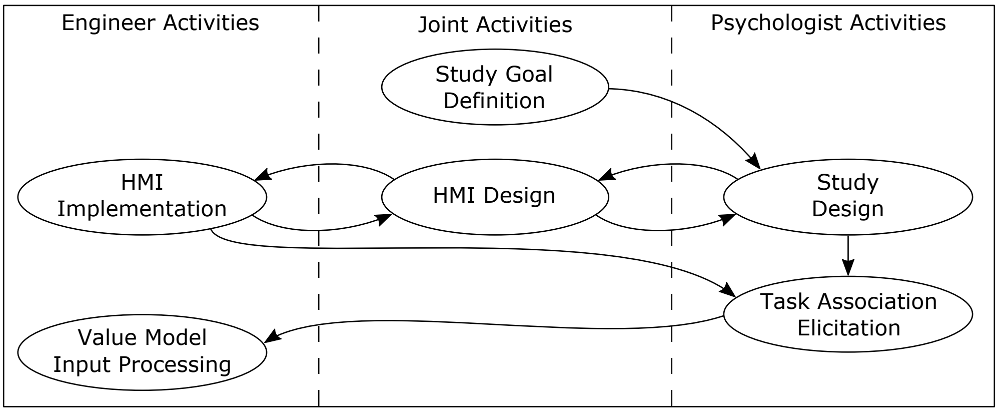


Figure 3.14.: *Activities conducted collaboratively to collect the operators' tasks to target associations and prioritization.*

3.3.3.3. Information Set Preference Elicitation

The third study is conducted to elicit expert preferences for a set of information sets, which are generated using a simple radar simulation. Preferences are collected in pair-wise comparisons. The collected data is processed to provide a validation metric for the information value model and to assess hypotheses H_0^H and H_0^I. Figure 3.15 illustrates the activities performed to acquire the experts' information set preferences.

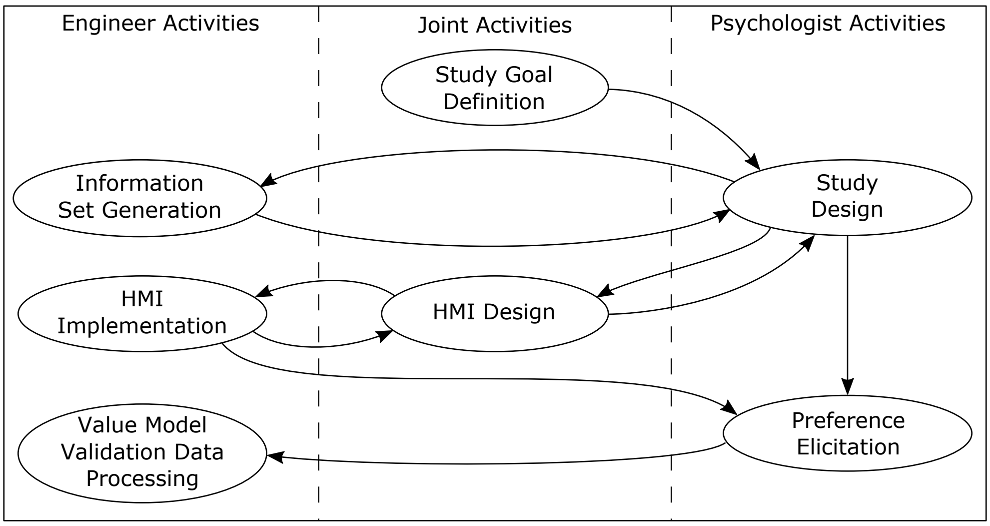


Figure 3.15.: *Activities conducted collaboratively to collect the operators' information set preferences.*

3.3.4. Information Value Model Design and Assessment

The present thesis's main objective is to design and assess an information valuation approach based on operators' needs. It could be used as the objective function of a sensor management system. Three steps are performed to achieve this objective and investigate the main research hypotheses H_0^J and H_0^K: model design, information valuation, and model output assessment. Figure 3.16 illustrates the interaction between these steps and their information consumption and production.

Model Design Insights and data gained from previous studies and through the review of available literature are used to model the prototypical value mode. Results from testing information valuation hypotheses H_0^A to H_0^G provide the rationale for the model input variable selection. The model structure is inspired by the human information processing described in section 2.3. Guidelines for the design of human-centered automation, discussed in section 2.4.2.2, are considered in the design of the information valuation model to facilitate the metrics integration into sensor management applications.

Information Valuation The designed model is used to value the information contained in the information sets used in the information set preference elicitation (see section 3.3.3.3). The list of relevant operator tasks and associated operator demands are processed to initialize the information valuation model. Information on the tasks associated with objects is used to tune the model for the specific snippets.

Model Assessment The model's information set values are compared against the preferences of domain experts to assess whether the model is able to reflect these preferences and the selection uncertainty. The assessment results are used to test hypotheses H_0^J and H_0^K.

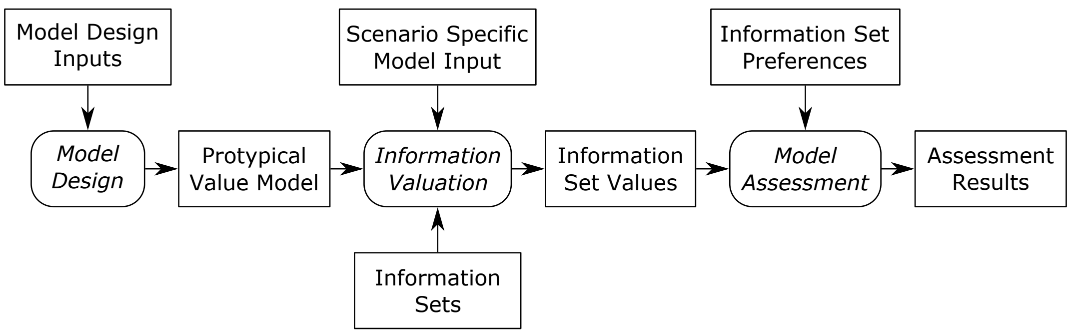


Figure 3.16.: *Model design activity overview.*

4. Task-Specific Information Demand Study

This chapter describes the activities performed to study the pilot's task-specific information demand and reports the study's findings.

4.1. Study Overview

The study's objective is twofold, (1) analyzing task-specific information demands and (2) testing the set of hypotheses linked with this demand to provide input and insights, which can be used to model the operational value of information for pilots.

4.1.1. Approach

The study is split into the following three parts detailed below:

Operational analysis Designing a task-based system requires a deep understanding of operational objectives and restrictions as well as the operators' tasks, goals, and capabilities. An operational analysis is conducted to identify the information flowing in the use case scenario described in section 3.3.1 and link these information flows to the operator's goals and activities.

Functional analysis The functional analysis is performed to identify the data elements exchanged between the aircraft and the pilot on the resource level and link the data provided by the aircraft's sensors to the information required by pilots to achieve their mission goals.

Expert questionnaire data analysis Finally, questionnaire responses collected by Petermeier [283] are analyzed to validate the set of hypotheses dealing with the operators' task-specific information demands described in section 3.2.1.1. The null hypotheses are listed below:

H_0^A: There is no consensus between experts on the target parameter information demanded to perform an operator task.

H_0^B: The operators' target parameter accuracy demands are of equal importance.

H_0^C: The information accuracy demanded by domain experts to fulfill their task does not decrease monotonically with increasing target range.

Further, questionnaire responses are mapped to the data exchanges identified in the functional analysis step and transformed into a data input for the information valuation model.

4.2. Operational Analysis

The fighter sweep mission was selected as a use case for the research (see section 3.3.1). This mission is defined as an "offensive mission by fighter aircraft to seek out and destroy enemy aircraft or targets of opportunity in a designated area" [30, p. 86]. Figure 4.1 illustrates the interaction between the conceptional elements. The following assumptions are made to simplify the use case:

- The acquisition of information by active sensors is limited to non-cooperative objects.
- Information about the position, heading, and velocity of friendly air assets is assumed to be provided through communication.

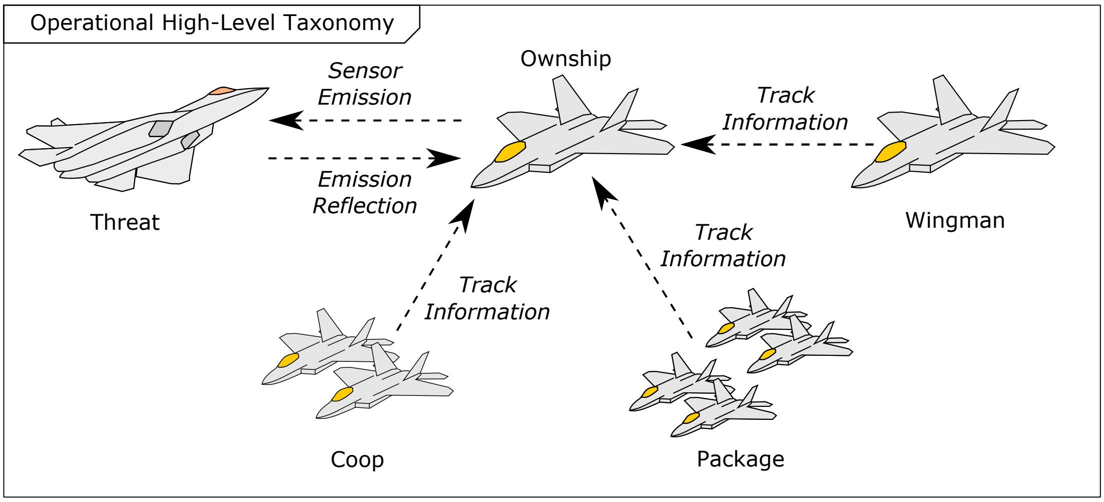


Figure 4.1.: *Operational high-level taxonomy diagram.*

The operational focus is on the aircraft and its pilot, which compose the ownship operational performer, as shown in figure 4.2.

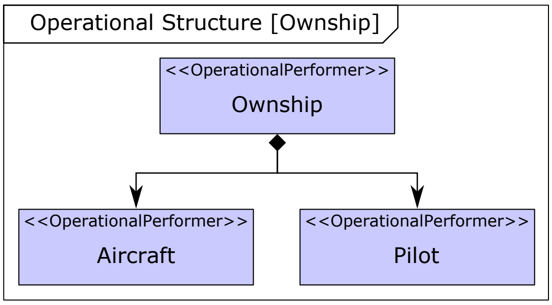


Figure 4.2.: *Operational structure of the ownship.*

The operational analysis is performed for the ingress phase of a fighter sweep mission to answer the following exploratory questions:

- What goals govern the pilot's decisions in the selected use case?
- Which operational activities are performed by the pilot and their aircraft within the context of the selected use case?
- What are the information elements needed by the pilot to perform the mission?

4.2.1. Use Case Goals

Only a subset of the Air Force goals from McIntyre's [21] Air Force goal lattice, listed in section A.1, applies to the fighter sweep scenario. Table 4.1 lists the ten identified Air Force goals, and figure 4.3 shows the goal lattice resulting from the pruning of the goal set based on the following constraints:

- Only goals linked to the fighter sweep mission are retained.
- Goals are limited to the ingress phase of the mission.
- Ground threats are not considered within the scope of the research.
- Neutral targets are not present in the scenario.
- The identification goals 78, 84, 85, and 86 are merged into goal 89.
- Situation awareness goals 48, 49, and 74 are merged into goal 21.
- The detection goal 79 is merged into goal 90.
- The loss-related goals 10 and 11 are merged into goal 9.
- The sweep goals 12, 22, 23, and 24 are incorporated into goal 50.
- The detection avoidance goal 19 is incorporated into the loss minimization goal 9.

Table 4.1.: *Pruned air force goal lattice, based on McIntyre [21].*

Goal Number	Goal
3	Obtain and maintain air superiority
9	Minimize losses
21	Minimize uncertainty about the environment
35	Navigate
36	Avoid threats
50	Neutralize enemy aerospace forces
75	Engage enemy targets
88	Track all detected targets
89	Identify targets
90	Search for targets

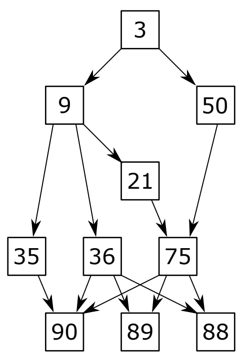


Figure 4.3.: *Pruned Air Force goal lattice.*

4.2.2. Ownship Operational Activities

Pilots carry out activities to achieve the goals listed in the previous section. As described in section 2.1.4, these activities can be clustered into three categories [50]: flight safety tasks, combat survival tasks, and mission accomplishment tasks. Figure 4.4 illustrates the operational activities performed during the use case scenario that is selected for the research. The analysis performed to identify these operational activities is documented in section C.1.2 of the appendix. The following assumptions have been made in addition to those made during the mission goal analysis (see section 4.2.1):

- The ownship is operated at an altitude in which a collision with the terrain can be excluded.
- The engagement and assessment phases of the F2T2EA cycle are not performed during the ingress.
- Aircraft are the only type of objects of interest in the environment.

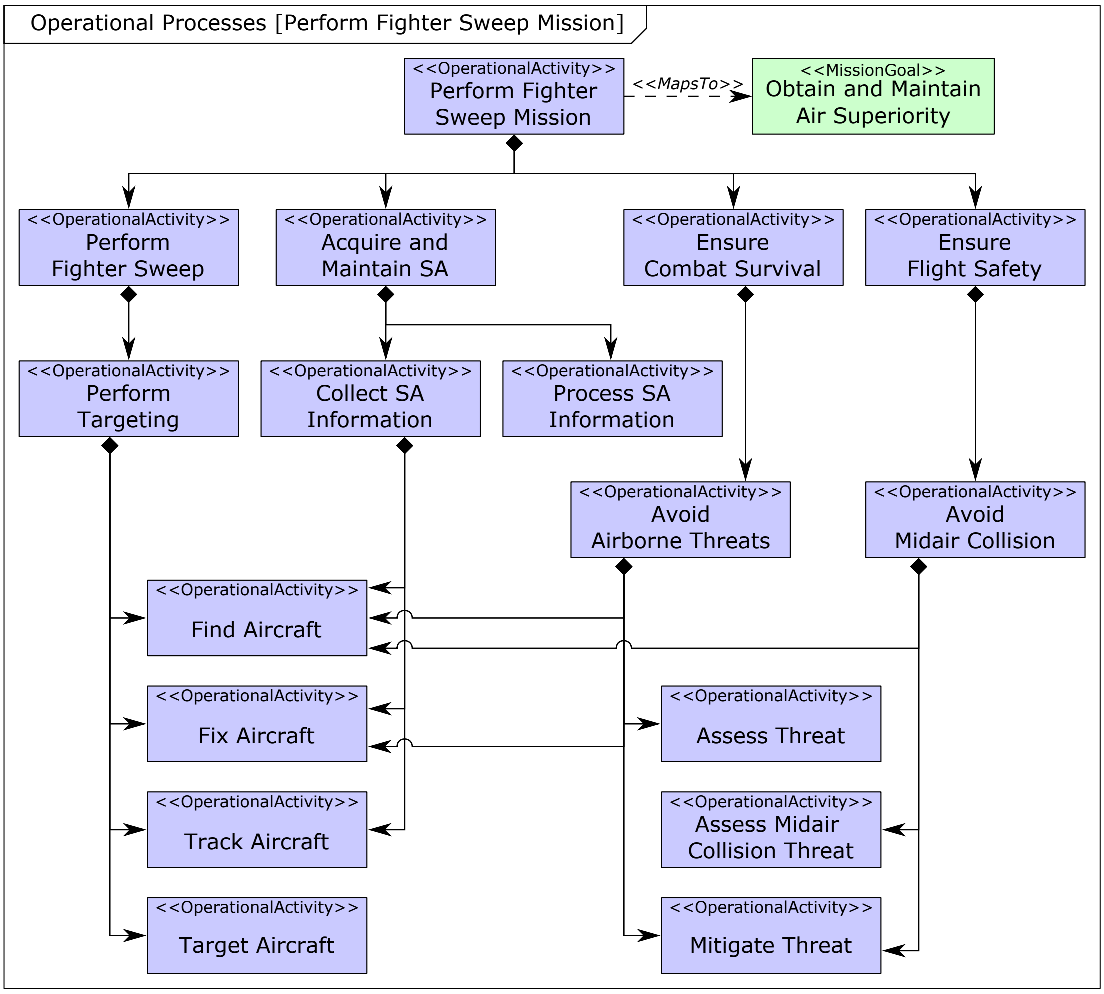


Figure 4.4.: *Perform fighter sweep mission operational process diagram.*

Operational activities are listed and described in table C.2 in the appendix.

4.2.2.1. Produced and Consumed Information Elements

Performing operational activities can require informational inputs to be carried out successfully. Further, information can be made available through the execution of an operational activity. Table 4.2 lists the information sources and sinks in the scenario obtained from a review of the pilot's information needs (see section 2.1.5). Information elements linked to threat assessment and situation awareness are derived from Brett et al. [284]. Targeting-related information elements are identified from a review of [53]. Table 4.3 lists the definitions of the information elements that are produced by operational activities performed in the ingress phase of the fighter sweep mission.

Table 4.2.: *Information elements consumed and produced by operational activities.*

Operational Activity	Consumes	Produces
Find Aircraft	-	Detection
Fix Aircraft	Detection	Aircraft Characteristics
Provide Track Updates	Aircraft Characteristics	Track Information
Process SA Information	Detection	Tactical Picture
	Aircraft Characteristics	
	Track Information	
Sort Aircraft	Aircraft Characteristics	Aircraft Responsibility
Prioritize Target	Track Information	Prioritized Track List
Monitor Target	Track Information	Engagement Decision
Assess Midair Collision Threat	Detection	Threat Information
Assess Threat	Aircraft Characteristics	Threat Information
Mitigate Threat	Detection	Threat Mitigation Action
	Threat Information	

Table 4.3.: *Information element descriptions.*

Information Element	Description
Detection	This element contains the information linked with the detection of an aircraft by a sensor system, e.g., relative position to the ownship.
Aircraft Characteristics	This element encompasses the information captured about an aircraft, incl. location, type, and identity.
Track Information	This element conveys information about changes in the aircraft's position and characteristics over time.
Threat Information	This element carries information about the type of threat, the danger posed, and its urgency.
Tactical Picture	This element carries information about all detected aircraft.
Aircraft Responsibility	This element conveys the responsibility to monitor and handle an identified aircraft.
Prioritized Track List	This element delivers a prioritized list of tracks.
Engagement Decision	This element transports the decision made about engaging a tracked and identified aircraft.
Threat Mitigation Action	This element conveys the selected action to be performed to mitigate the threat posed by a detected threat.

4.2.3. Information Exchanges between Aircraft and Pilot

The information flowing between the aircraft and the pilot can be determined by modeling the interaction between the operational activities assigned to both operational performers. Figure 4.5 shows the targeting cycle operational process flow. The aircraft detects other aircraft in the environment and subsequently fixes the aircraft. The pilot utilizes obtained aircraft characteristics to sort the detected aircraft. Further, the information is provided to the aircraft's tracking mechanism, which ensures regular track updates for the pilot's prioritization and engagement planning tasks.

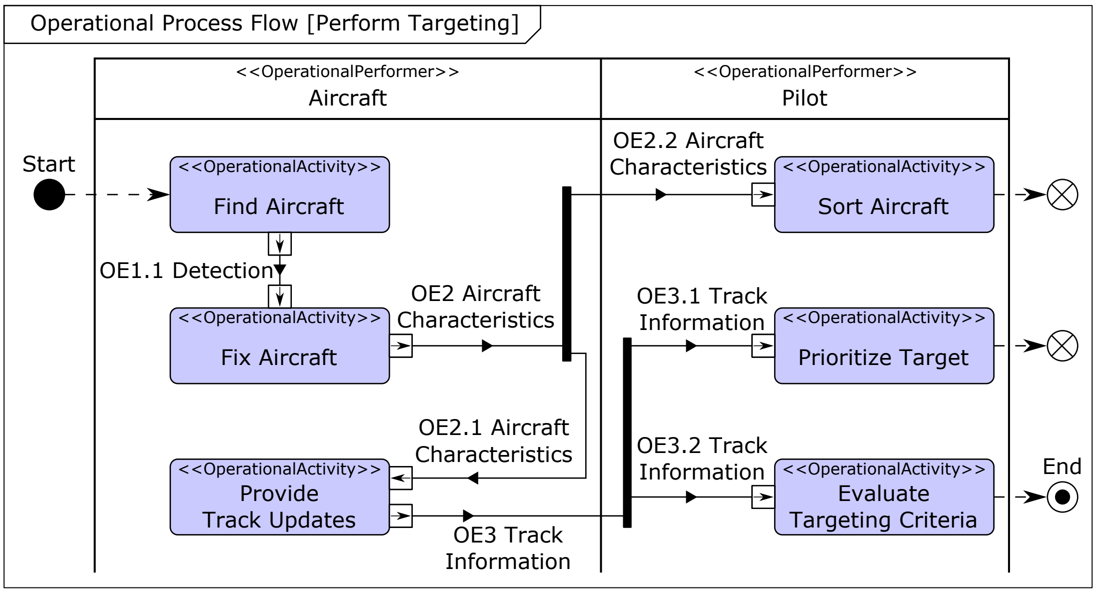


Figure 4.5.: *Operational process flow for the operational activity perform targeting.*

Figure 4.6 illustrates the information flow between the aircraft's F2T2EA activities and the pilot's activity to acquire and maintain situational awareness.

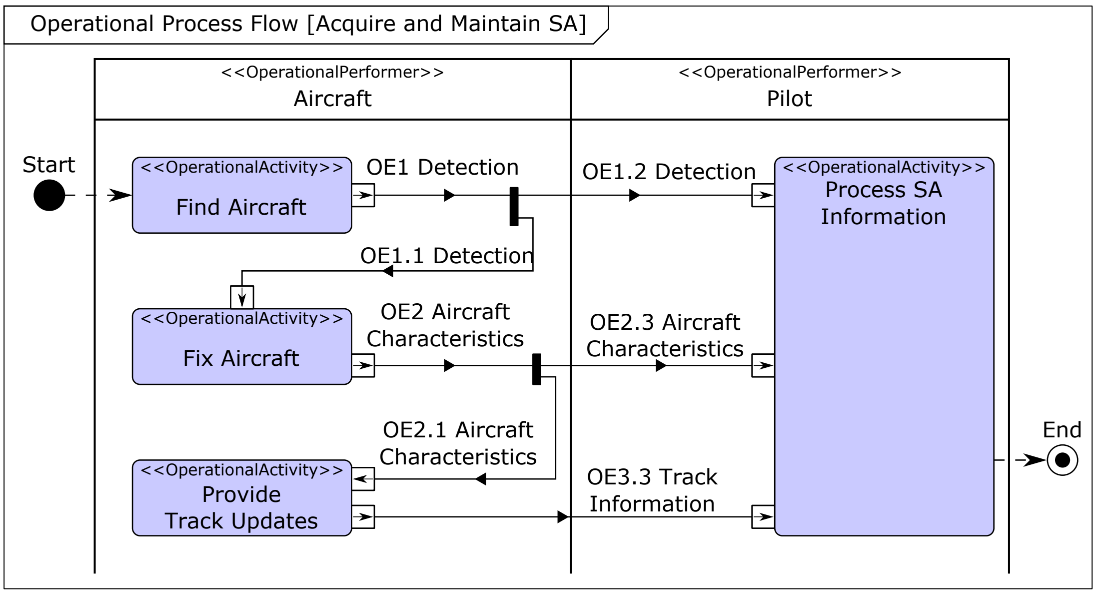


Figure 4.6.: *Operational process flow to acquire and maintain SA.*

Figure 4.7 shows the operational process flows for the combined collision and threat avoidance activities. Like the previous activities, the activity is based on the data aircraft detection and characterization performed as part of the F2T2EA cycle. The assessment of the risk of collision is assigned to the pilot and performed for all detected aircraft.

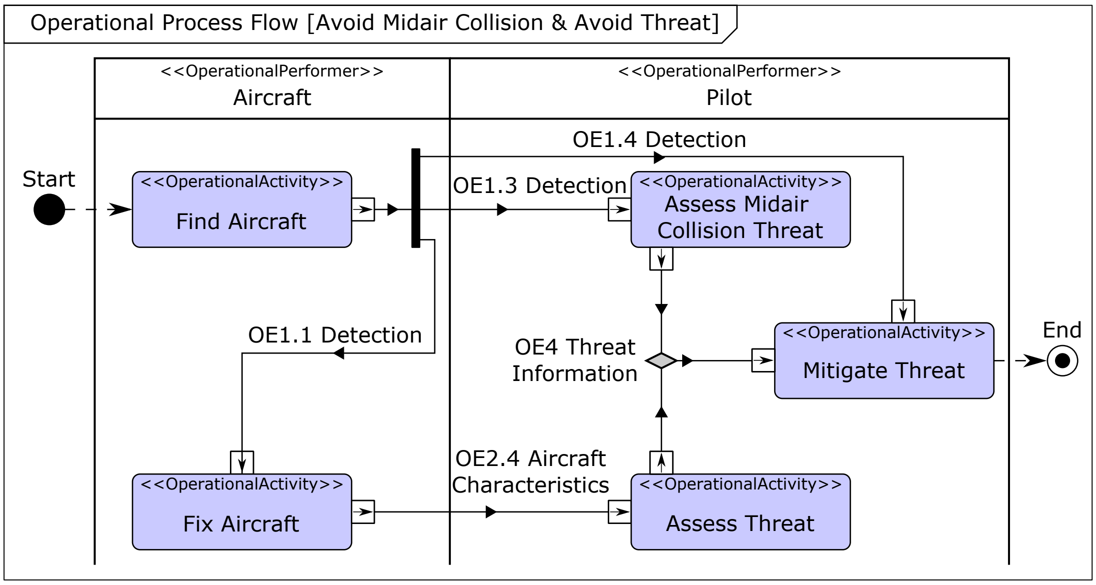


Figure 4.7.: *Operational midair and threat avoidance process flow.*

4.2.3.1. Information Flows between Aircraft and Pilot

Table 4.4 lists the information flows between the aircraft and the pilot, which have been identified in this section for the ingress phase of a fighter sweep mission.

Table 4.4.: *Information flows between the aircraft and the pilot.*

OE	Information	Aircraft Activity	Pilot Activity
OE1.2	Detection	Find Aircraft	Process SA Information
OE1.3			Assess Midair Collision Threat
OE1.4			Mitigate Threat
OE2.2	AC Characteristics	Fix Aircraft	Sort Aircraft
OE2.3			Process SA Information
OE2.4			Assess Threat
OE3.1	Track Information	Provide Track Update	Prioritize Target
OE3.2			Monitor Target
OE3.3			Process SA Information

4.3. Functional Analysis

A functional analysis is performed to identify the data elements exchanged between the aircraft and the pilot on the resource level. This section first describes the structure of the aircraft and sensor management system and then describes the functions performed by the aircraft. Finally, an overview of the subsystem functions is provided.

4.3.1. System Structure

Based on the sensor management loop described in section 2.2, the aircraft's simplified structure is composed of four elements: a single radar sensor, a sensor manager, a data processor, and a display, as shown in figure 4.8.

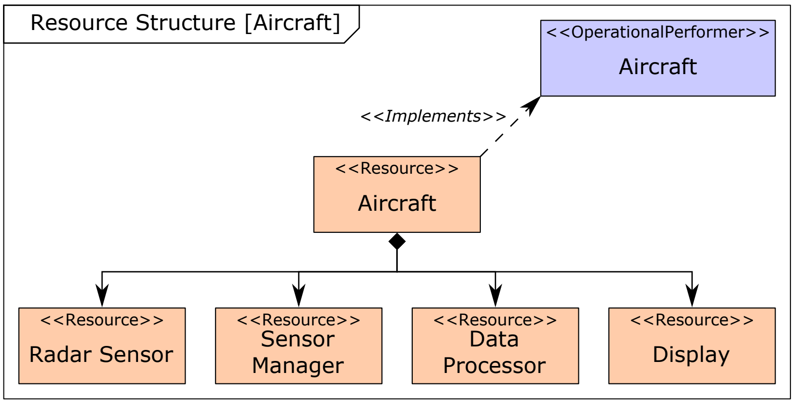


Figure 4.8.: *Simplified aircraft resource structure.*

4.3.2. System Functions

This study focuses on the provision of sensor data to the pilot; thus, this functional analysis only covers the aircraft's function "provide sensor data." The aircraft has to perform functions that implement the three operational activities listed in section 4.2.2. As shown in figure 4.9, these functions provide detections, aircraft characteristics, and track data. A detailed analysis of the three functions is provided in section C.1.3.2 of the appendix.

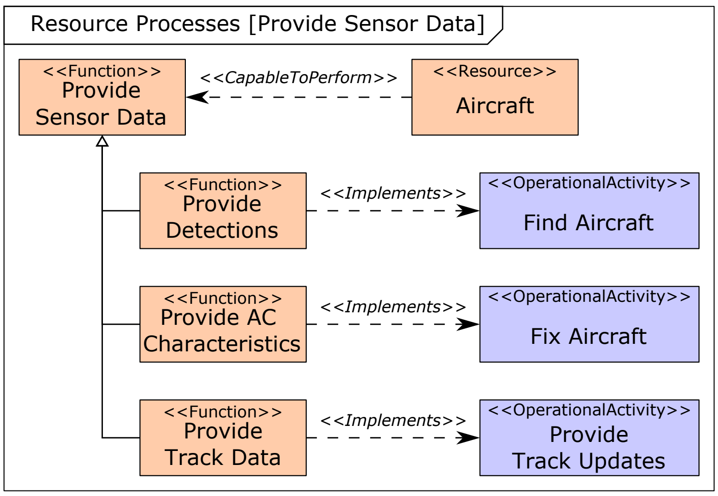


Figure 4.9.: *Resource processes diagram describing the functions performed by the aircraft.*

4.3.3. Subsystem Function Overview

Figure 4.10 summarizes the functions performed by subsystems to provide detections, aircraft characteristics, and track data to the pilot.

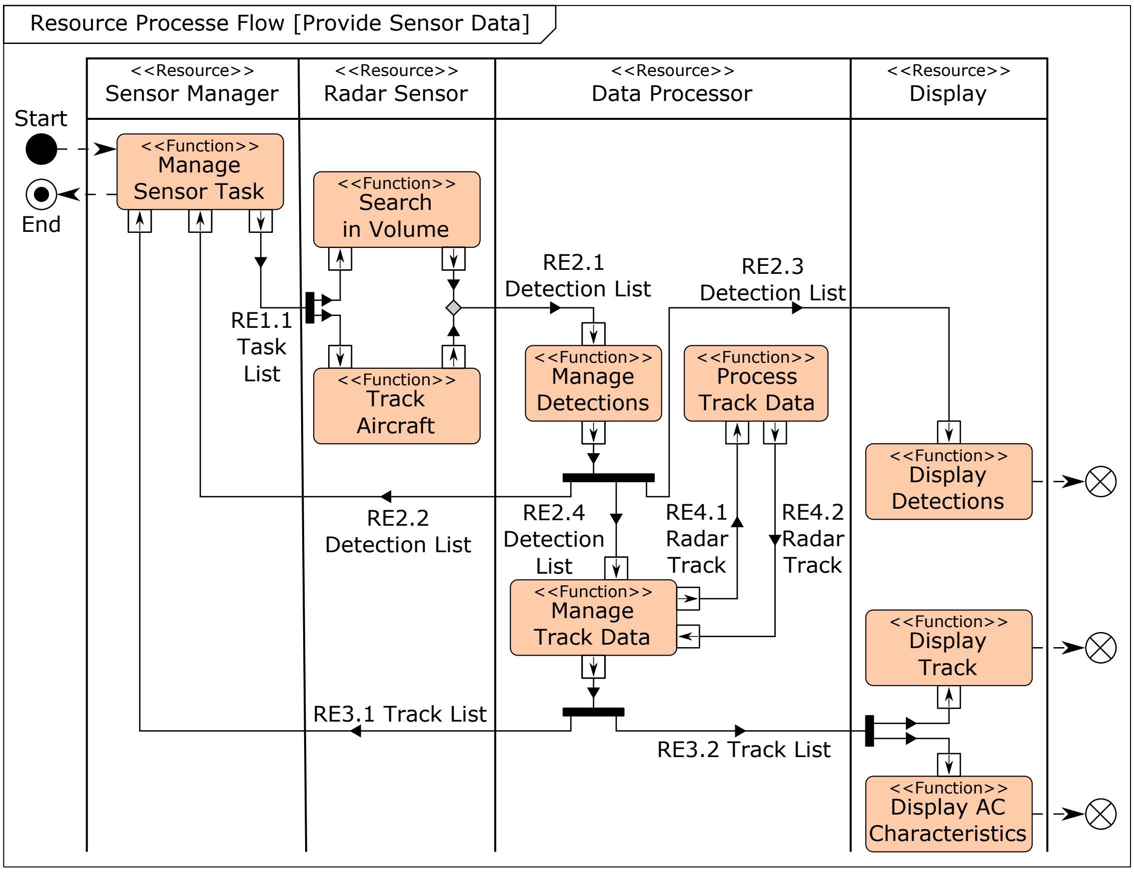


Figure 4.10.: *Resource process flow diagram describing the provision of sensor data.*

4.3.3.1. Data Exchanged to Implement Information Flows between Aircraft and Pilot

Table 4.5 lists the functions performed by the aircraft to implement the information flows to the pilot.

Table 4.5.: *Data exchanged to implement information flows between the aircraft and the pilot.*

OE	Pilot Activity	Aircraft Function	Data
OE1.2	Process SA Information	Display Detection	Radar Detection
OE1.3	Assess Midair Collision Threat		
OE1.4	Mitigate Threat		
OE2.2	Sort Aircraft	Display AC Characteristics	Radar Track
OE2.3	Process SA Information		
OE2.4	Assess Threat		
OE3.1	Prioritize Target	Display Track	
OE3.2	Monitor Target		
OE3.3	Process SA Information		

4.4. Task Data Quality Demand Elicitation

The information required to perform a specific activity is determined by the aircraft system's or human operators' needs. Information requirements driven by the operators' preferences are elicited using a questionnaire. Building on the information requirements for air-to-air fighter missions identified by Endsley [7], information quality requirements are elicited at the data level, e.g., slant range accuracy, as well as higher information levels, e.g., projected minimum separation accuracy.

4.4.1. Operator Task Analysis and Questionnaire

Designing a task-based system requires a deep understanding of operational objectives and restrictions as well as the operators' tasks, goals, and capabilities. To this end, a task analysis is performed for a specific use case. The task analysis delivers a list of relevant tasks with regard to modeling the value of sensor information. This step was performed jointly with Petermeier, and the methodology and rationale can be found in his Ph.D. thesis [283]. The retained tasks are mapped to the operational exchanges (OEs) from section 4.3.3.1 in table 4.6. The activities' names used by Petermeier have been mapped to task names used in the system analysis as described in the appendix C.1.1.

Table 4.6.: *Retained pilot tasks and their mapping to identified information flows.*

Task	Pilot Activity	OE	AC Function	Data
O_1	Process Position	OE1.2		
D_2	Assess Midair Collision Threat	OE1.3	Display Detection	Radar Detection
D_3	Mitigate Threat	OE1.4		
O_3	Sort Aircraft	OE2.2	Display AC Characteristics	
O_2	Process Characteristics	OE2.3		Radar Track
D_1	Assess Threat	OE2.4		
O_4	Prioritize Target	OE3.1		
O_5	Monitor Target	OE3.2	Display Track	Radar Track
O_6	Process Commit Criteria	OE3.3		

Petermeier [283] designed a questionnaire and elicited demanded data accuracies from 13 pilots and weapon systems officers. The detailed demographics of the study participants are listed in section C.1.4 of the appendix. The questionnaire answers collected by Petermeier provide the raw data used to infer the task-dependent data quality demand and are available in the format shown in table 4.7, which contains 1371 entries. These demands are linked to a generic, hypothetical payload and do not reflect real-world demands. To shorten the notation, the "minimum" and "fully satisfactory" requested qualities are referred to as "needed" and "wanted" respectively.

Table 4.7.: *Exemplified task demand input data.*

Task	Parameter	Range Interval	Subject	Importance	Needed	Wanted	Unit
O_4	Velocity	15-35 NM	1	3	x	x	m/s
O_4	Velocity	35-100 NM	1	3	x	x	m/s
O_4	Velocity	40-60 NM	2	3	x	x	m/s
...	...	...	...	...	...	...	...

4.4.2. Data Processing

The data collected by Petermeier [283] is processed before the analysis step to address the following aspects:

- The data contains apparent errors.
- The units of the parameter quality demands are not standardized.
- Participants were asked to select the range interval boundaries for their data demands, and these intervals were not consistent between participants.
- The sample size is small due to the limited number of experts and their limited availability.

The preprocessing is composed of three steps: data clean-up, data point harmonization, and bootstrapping.

4.4.2.1. Data Clean Up

The first preprocessing step removes input errors and converts demands to standardized units.

Error Correction The following errors can be found in the task demand dataset:

- Subject 7 provided inconsistent demands for the update rate for task O_6 in a single range interval. The error is corrected by switching the wanted and needed values.
- Subject 12 did not select a unit for the update rate demands of task O_5.

Parameter Conversion The demands are converted to the scientific system of units, except for the degree unit, which kept its more intuitive interpretability. Further, the position accuracy demands are transformed into range, and azimuth angle demands to simplify the data analysis step. Figure 4.11 shows the relationship between the position accuracy and the resulting transformed accuracy. Radar systems have an excellent angle resolution, e.g., solving the angle uncertainty for an object in a range of 100 NM returns an estimated angle uncertainty of less than 0.2° for a single pulse from the research's radar model. The system's accuracy surpasses the demanded accuracy for all data points, and this demand parameter is therefore disregarded for the remaining assessments.

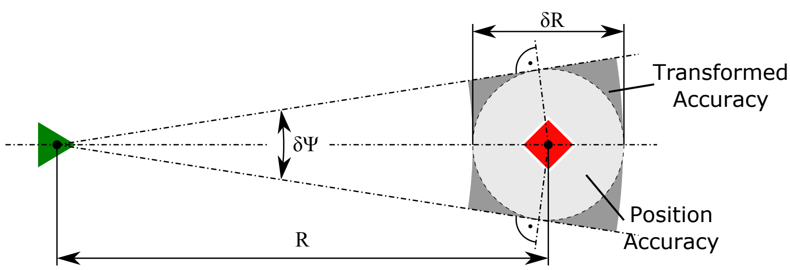


Figure 4.11.: *Position uncertainty δR conversion into an angle uncertainty $\delta\Psi$.*

4.4.2.2. Data Harmonization

Petermeier's questionnaire allowed participants to provide their parameter accuracy demands for up to three range intervals of their liking. These intervals are, therefore, not the same from one participant to the next, and the collected data needs to be split along a unified range interval list, pruned, and extended.

Interval Splitting Splitting the data into the least amount of intervals leads to 18 range intervals, starting between 0 and 1 NM and ending with the interval between 90 and 100 NM, as shown in figure 4.12. These intervals have a width of between 1 and 10 NM.

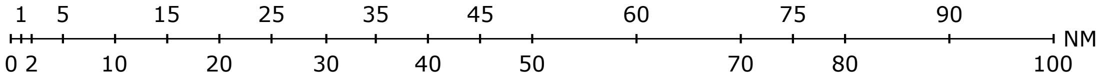


Figure 4.12.: *Range intervals.*

Data Pruning The differences in the participants' range selection results in small samples for range intervals at the edges of the range demands. Data corresponding to a task and a range interval for which demands are available for less than half of the respondents are dropped from the dataset.

Extension The respondents' range selection leads to data gaps at the range extremities of the demand dataset. These gaps appear when not all but more than half of the respondents provided their task-dependent demands for a specific range interval. Leaving these gaps can negatively impact the computation of average demand, e.g., it can lead to the demand for more accuracy with an increase in range, which is not in line with the observed dependency. This issue is mitigated by extending the participants' demands to cover the whole range associated with a task, as shown in figure 4.13. Extending the data to cover the far end of the range interval is a conservative assumption since the actual demand of the participant will not be lower than this level. The near-side extension is an optimistic assumption since the actual demand will be at least as high.

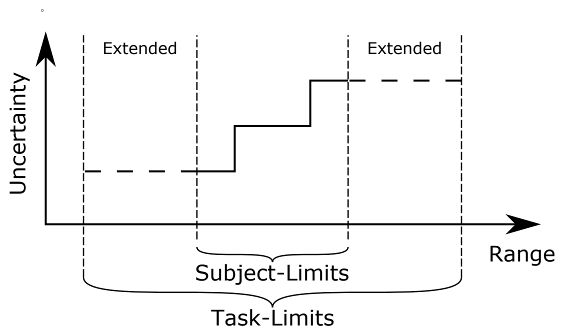


Figure 4.13.: *Range covered by participant responses.*

Normalization The data is rescaled to a scale where 0 represents perfect information, and 1 represents the highest mean demand of any task-parameter combination.

4.4.2.3. Bootstrapping

The amount of data contained in the results of Petermeier's study is relatively small, given the small number of study participants. The questionnaire data is bootstrapped to estimate the confidence interval of the mean data accuracy demands. Subjects used one to three different value sets to describe their parameter demands. The bootstrapping method assumes that the samples are independent of each other and represent the population. The scope of the study is limited to the set of available experts, which are rated for the same aircraft type, operated in the same national air force, and received the same education. The study participants represent this limited population. A sample is defined as all responses given by a single participant. These samples are independent of each other since there was no interaction between participants during the study. Individual data points within a sample are interrelated and cannot be considered independent. The bootstrapping procedure is therefore not applied to individual data points but to subject data, as shown in figure 4.14. Each circle in the sample represents the demand a test subject provides for the complete range interval.

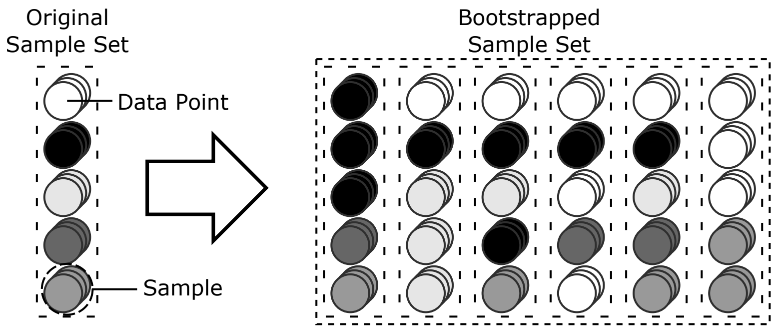


Figure 4.14.: *Bootstrapping process illustration.*

Selecting the number of bootstrapped samples is, therefore, a tradeoff between the computational effort and the accuracy of the computed confidence interval. Figure 4.15 illustrates the effect of bootstrapping on the sample distribution and visualizes the sample's mean and 95%-confidence interval. For all bootstrapping steps, the resampling number is set to 10.000.

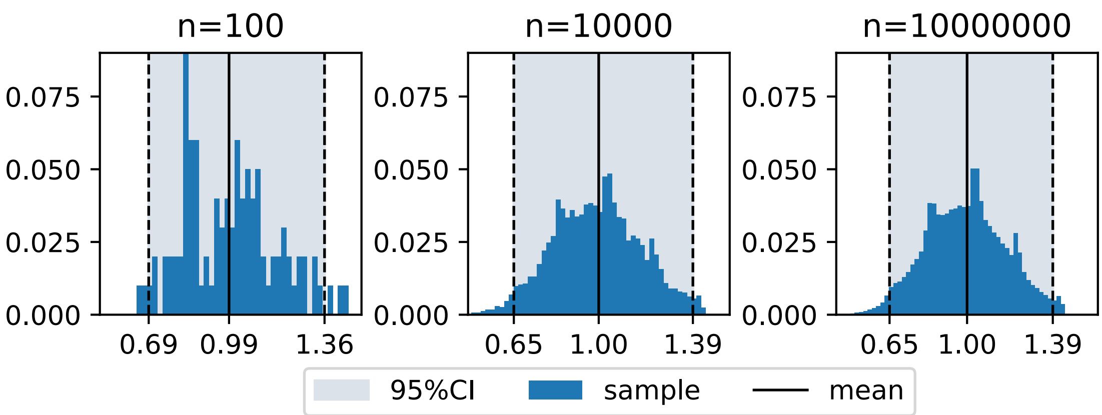


Figure 4.15.: *Bootstrapped sample distribution for two resamples.*

4.4.3. Results

The data collected by Petermeier's questionnaire is analyzed to investigate the following four aspects of the participants' demand:

- Task-Specific Demand Range (Interval Dataset)
- Parameter Selection (Initial Dataset)
- Parameter Importance (Initial Dataset)
- Demand Range Dependency (Initial Dataset)

4.4.3.1. Task-Specific Demand Range

Participants defined range intervals between 0 NM and 120 NM with a median of 2 range intervals per task. Participants 6, 10, 11, and 13 always defined three range intervals per task, while participants 2, 4, 9, and 12 usually defined only one range area for every task. Table 4.8 illustrates the number of samples per range interval and task.

Table 4.8.: *Number of participants task demands by range interval.*

Range	D1	D2	D3	O1	O2	O3	O4	O5	O6
0-1 NM	7	9	8	0	0	0	0	8	0
1-2 NM	7	10	8	0	0	0	0	8	0
2-5 NM	7	11	8	0	0	0	0	8	0
5-10 NM	7	11	8	0	0	0	0	8	0
10-15 NM	8	11	10	7	7	7	7	8	8
15-20 NM	8	10	10	8	8	8	8	8	9
20-25 NM	10	0	12	10	10	9	9	9	11
25-30 NM	12	0	11	10	10	9	9	11	12
30-35 NM	13	0	9	10	10	9	11	11	13
35-40 NM	13	0	8	10	10	9	11	11	13
40-45 NM	8	0	7	10	10	13	12	11	10
45-50 NM	8	0	7	10	10	13	12	11	10
50-60 NM	8	0	7	12	12	11	11	10	10
60-70 NM	8	0	0	13	12	8	7	7	7
70-75 NM	8	0	0	12	12	8	7	7	7
75-80 NM	8	0	0	12	12	8	7	7	7
80-90 NM	7	0	0	8	8	0	0	0	0
90-100 NM	7	0	0	7	8	0	0	0	0

Ranges for which at least 50% of the participants have provided their information accuracy demands are listed in table 4.9.

Table 4.9.: *Task-demand range interval limits.*

Range	D1	D2	D3	O1	O2	O3	O4	O5	O6
min	0	0	0	10	10	10	10	0	10
max	100	20	60	100	100	80	80	80	80

4.4.3.2. Parameter Selection

With the exception of the geographic position, all parameters were used by participants to formulate their task information demands. Table 4.10 lists the number of participants requesting a specific parameter by task. The position is only requested for task O_5 by 8 participants. All participants require the update rate T_{update} and group resolution Δ_{Group} since the questionnaire has explicitly requested these parameters. The following object parameters were requested in addition by participants: altitude h, aspect angle Δ_{Aspect}, closing velocity v_c, heading Ψ, range R, and velocity v.

Table 4.10.: *Number of participants using a given parameter.*

Task ID	h	Δ_{Aspect}	v_c	Δ_{Group}	Ψ	R	T_{update}	v
D1	12		13	13	12	12	13	12
D2	13			13	13	13	13	
D3	12	10	13	13	12	12	13	12
O1	13			13		13	13	
O2	12	10		12	13	8	13	13
O3	13			13	12	13	13	8
O4	13	11		12	12	13	13	13
O5	13			13		8	13	13
O6				13	8	13	13	8

4.4.3.3. Parameter Importance

The questionnaire contains 424 unique task-related parameter importance ratings. Table 4.11 lists the number of ratings by importance category, with higher categories representing a higher importance rating. Over 80% of all parameter demands are rated with high importance. The importance of parameters is listed in section C.1.5 of the appendix.

Table 4.11.: *Number n and ratio r of importance ratings by category.*

Type	1	2	3	4
$n_{Ratings}$	4	79	196	145
$r_{Ratings}$	0.9%	18.6%	46.2%	34.2%

These ratings are clustered by task, and the t-test procedure is used to test whether the importance ratings of one parameter differ significantly from the remaining importance ratings. The resulting p-values are corrected for multiple hypothesis testing using the Bonferroni correction method, which is a conservative correction approach [285]. Table 4.12 highlights the two results of task-parameter combinations with a p-value lower than 0.05.

Table 4.12.: *Parameter importance T-test statistics.*

Task ID	Parameter	Symbol	P-Value	Effect Size
D1	Range	R	0.008	3.3
D2	Heading	Ψ	0.047	-2.5

4.4.3.4. Demand Range Dependency

None of the pilots' demanded accuracies increase with increasing object range. The demanded accuracy decreases from one range interval to the next for most task-parameter demands, as shown in table 4.13.

Table 4.13.: *Proportion of task-parameter demands D increasing or staying constant from one interval (i) to the next interval $(i+1)$.*

Type	$D_i > D_{i+1}$	$D_i = D_{i+1}$	$D_i < D_{i+1}$	Total
Wanted	478 (66.9%)	237 (33.1%)	0	715
Needed	611 (85.5%)	104 (14.5%)	0	715

The group resolution parameter is categorical and is more likely to remain constant from one interval to the next. Removing this parameter and comparing the demands in successive intervals shows that the demand remains constant in only 3.1% of all 131 interval changes, as shown in table 4.14.

Table 4.14.: *Proportion of task demands increasing with smaller ranges.*

Type	All	Partial	Constant
Needed	65.6%	34.4%	0.0%
Wanted	51.1%	45.8%	3.1%

4.4.3.5. Aggregated Task Data Quality Demands

Figure 4.16 illustrates the aggregated parameter accuracies demanded by pilots to perform task O_1 . Detailed demands for all tasks are listed in table 4.6, found in Appendix C.1.6.

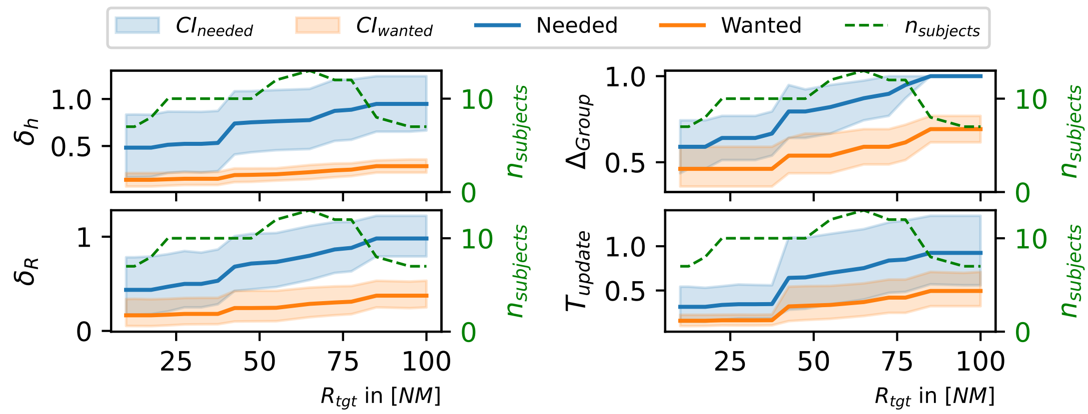


Figure 4.16.: *Accuracy demand for task $O_1$for the range accuracy σ_R, the altitude accuracy σ_h, the group resolution ΔR, and the update time T_{update} of an object.*

4.5. Discussion

This section discusses the study results of task-specific information demands and concludes the tested hypotheses for the information value modeling.

4.5.1. System Analysis Correction

Merging the identified data exchanges, information exchanges, and the demanded parameter highlights that pilots request more information than identified in the system analysis step for the collision threat assessment and threat mitigation activities, as highlighted in table 4.15. The following object parameters were requested by participants: altitude h, aspect angle Δ_{Aspect}, closing velocity v_c, heading Ψ, range R, and velocity v.

Table 4.15.: *Parameter demand for each pilot activity.*

ID	Pilot Activity	Data	h	Δ_{Aspect}	v_c	Ψ	R	v
O_1	Process Position	Radar Detection	·				·	
D_2	Assess Midair Collision Threat	Radar Track	·			·	·	
D_3	Mitigate Threat		·	·	·	·	·	·
O_3	Sort Aircraft		·			·	·	·
O_2	Process Characteristics		·	·		·	·	·
D_1	Assess Threat		·		·	·	·	·
O_4	Prioritize Target		·	·		·	·	·
O_5	Monitor Target		·				·	·
O_6	Process Commit Criteria					·	·	·

The operational activity *Avoid Midair Collision & Avoid Threat Activity* is modified to correct the model by removing OE1.3 and OE1.4 and introducing new operational exchanges, as shown in figure 4.17.

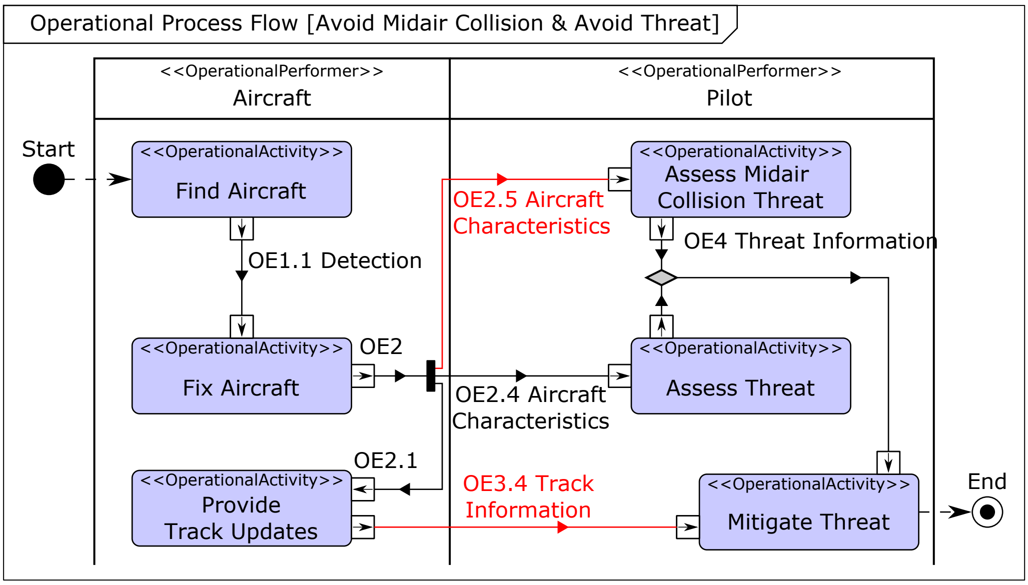


Figure 4.17.: *Corrected operational process flow for the Avoid Midair Collision & Avoid Threat activity.*

Table 4.16 lists the corrected information and data exchanges between the aircraft and the pilot in the research use case.

Table 4.16.: *Pilot activities and associated information and data exchanges.*

ID	Pilot Activity	Information	Data
O_1	Process Position	Detection	Radar Detection
D_2	Assess Midair Collision Threat	AC Characteristics	Radar Track
O_3	Sort Aircraft		
O_2	Process Characteristics		
D_1	Assess Threat		
O_4	Prioritize Target	Track Information	
D_3	Mitigate Threat		
O_5	Monitor Target		
O_6	Process Commit Criteria		

4.5.2. Demand Consistency

Experts used the same parameter to state their data accuracy demands, with all parameter-task combinations demanded by over half of the participants and over 86% of the combinations requested by over 90% of the study participants. Hypothesis H_0^A is rejected, and hypothesis H_1^A is adopted, which states that there is a consensus between experts on the target parameter information demanded to perform an operator task.

4.5.3. Parameter Importance

The expert's importance ratings show a difference in importance between demanded parameter accuracies, which is both statistically significant and of a large t-test score. This difference was only observable in two cases in which the differentiation was made between very important and important parameters. All requested parameters are important, and further differentiation between them is not needed to model the value of the carried information. The null hypothesis H_0^B is rejected, and the hypothesis H_1^B is adopted, which states that the operators' target parameter demands are not of equal importance.

4.5.4. Range-dependency

The data analyzed in section 4.4.3.4 doesn't contain a single data point in which the accuracy demanded by experts increases with range. Therefore, the null hypothesis H_0^C is rejected and hypothesis H_1^C is adopted, which states that the accuracy demanded by experts decreases monotonically with increasing target range.

Further, a range-dependency is observed for requesting tasks-specific demands, e.g., the demands linked to the activity *Assess Midair Collision Threat* (D2) are limited to an interval between 0 and 20 NM. This observation leads to the conclusion that activities could be linked to range intervals.

4.5.5. Additional Observations

Missing Azimuth Angle Accuracy Demands The azimuth angle is not demanded explicitly by pilots, which can be explained by the high azimuth accuracy of radar systems due to their physical design, e.g., with a beamwidth equal to 1°, the positional error perpendicular to the beam direction equals less than 2kms for an object at a range of 100kms.

Large Uncertainty The synthetical use case and the highly contextual nature of data quality assessments can explain the discrepancies between experts. Every data quality assessment in aircraft operations is unique.

4.5.6. Study Limitations

Narrow Use Case The results of the study are limited to the narrow scope of the research's use case, which covers a single air-to-air mission type and mission phase. This scope covers only a small fraction of modern fighter jets' mission roles. Additionally, the operational and functional analyses are focused on operations performed by a single aircraft. The concept of operations should be extended to multi-ship operations for real-world applications. Finally, the applicability of the research is linked to generic sensors and air force assets that do not exhibit real-world performance.

Sensor Type Specific Demand The operational and functional analysis considers only the presence of a single radar sensor on the platform and excludes data collected by other types of sensors and externally provided data. The fusion of data and its impact on the value of imperfect data has not been considered.

Small Sample Size The survey data was collected from only 13 experts that are members of the small population of german fighter pilots.

Interval-based Data Pilots provided their accuracy demands for a limited number of range intervals, with their responses showing a clear range dependency. A constant demand within a specified interval can thus not be assumed. Requesting pilots to provide their demands for every foreseeable object range is not feasible, and the shape of the demand over the range can only be guessed based on the available data.

Range-limited Accuracy Demands The survey data does not contain accuracy demands for objects at a range of over 100 NM from the decision maker. The results can, therefore, only be considered valid within a narrow range interval. This interval is different across the various tasks.

4.6. Conclusion

The study aimed to collect task-dependent data demands required to model the operational value of information and analyze the collected data for modeling to test the stipulated hypotheses linked to the task-dependent data demand and derive implications for the design of an information value model. The null hypotheses H_0^A , H_0^B, and H_0^C have been rejected, as discussed in the previous section, and lead to the following three conclusions:

- There is a consensus between experts on the target parameter information demanded to perform an operator task.
- Target parameter demands are not of equal importance.
- The accuracy demanded by experts decreases monotonically with increasing target range.

The conclusions drawn from the tested hypothesis can be assumed to be valid for use cases other than the research's use case, unlike the collected demands, which cannot be assumed to be valid for other use cases.

Collected Modeling Data The study provides the following data as input for the information valuation model:

1. A list of tasks performed by operators that rely on information provided by the aircraft.
2. Eight parameters compose the data elements which carry the required information.
3. The aggregated accuracy demands are illustrated in section 4.4.3.5, and the range limits for the validity of the collected data, as listed in table 4.17.

Table 4.17.: *List of pilot activities and the demand data's validity range limits R_{min} and R_{max}.*

ID	Pilot Activity	R_{min}	R_{max}
D_1	Assess Threat	0	100
D_2	Assess Midair Collision Threat	0	20
D_3	Mitigate Threat	0	60
O_1	Process SA Information - Position	10	100
O_2	Process SA Information - Characteristics	10	100
O_3	Sort Aircraft	10	80
O_4	Prioritize Target	10	80
O_5	Monitor Target	0	80
O_6	Process SA Information - Commit Criteria	10	80

Implications for the Information Value Model The study results imply the following for the valuation of information:

1. The information value model should be able to accommodate the uncertainty of the aggregated demand.
2. The importance of demanded parameter can be disregarded for the scope of the research.

5. Task Assignment and Prioritization Assessment

The task-driven modeling of information value requires knowledge on the tasks pilots perform at specified times of their mission. This chapter describes the activities performed to study the pilots' task assignments.

5.1. Study Overview

A computer interface is developed to simplify the knowledge elicitation and use the experts' time as efficiently as possible. The study is conducted in cooperation with Petermeier [283], who designed the scenarios, recruited the participants, and supervised the knowledge elicitation. Subjects were fitted with a head-mounted eye-tracker to measure their gazes' location and collect data on the allocation of visual attention. The collected data is analyzed and aggregated with the data collected in the task-demand study described in the previous chapter.

An interface-based study is performed to answer the following research questions:

- How do pilots prioritize groups of aircraft in their environment?
- What tasks do pilots associate with aircraft groups in the environment?
- How do pilots prioritize the tasks they assign to aircraft groups?

The study described in this chapter aims to test the following four null hypotheses:

H_0^D: There is no consensus between experts on the tasks they associate with a target.

H_0^E: The association of operator tasks with target does not allow for the segregation of these tasks into distinct range classes.

H_0^F: The operators' task's information demand is not constant within the span of the associated target's ranges.

H_0^G: The priority of tasks associated with a target has no effect on the target's priority.

5.2. Task Assignment and Prioritization Elicitation

Every experiment conducted as part of the study starts with a briefing phase in which the context and scope of the research are explained to the participant and the mission scenario. Participants are then given time to familiarize themselves with the interface. After ample training, the eye-tracking system is calibrated, and the task assignment and prioritization elicitation is started. The data collection is split into two blocks due to the study duration and the discomfort caused by the eye-tracker. Eye-tracking-related data is only collected for the first block (A). After completing the second block (B), a debriefing is conducted with participants, and the usability questionnaire is filled out. Both study blocks are composed of several snippet task assignments. For block A, the assignment and prioritization of tasks for a specified snippet are preceded by the data collection used for a post-study calibration of the eye-tracking system. For every snippet, the process starts with the snippet's animation, followed by the subjective situation awareness rating by participants. This step is followed by the prioritization of groups present in the snippet, which is followed by the task assignment and prioritization. The process is completed by rating the snippet's subjective tactical complexity. The overview of the study is shown in figure 5.1.

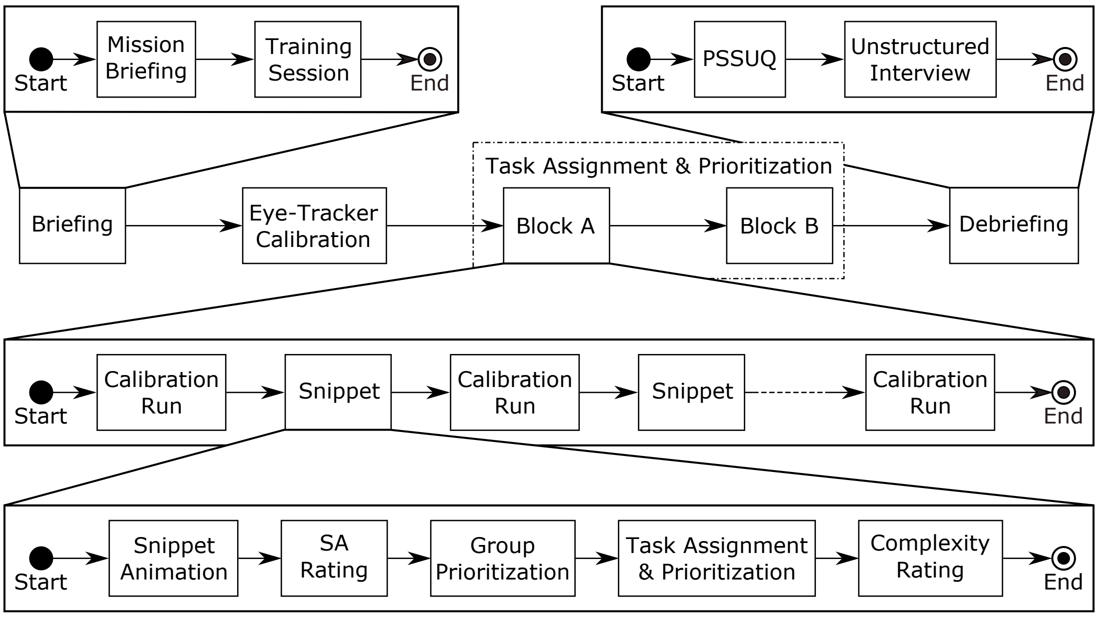


Figure 5.1.: *Overview of the task assignment and prioritization study.*

5.2.1. Scenario Snapshots

The allocation of tasks and prioritization is performed for snapshots of scenarios of the mission and mission phase described in section 3.3.1 to manage the time-dependent nature of the tasks allocated to objects in the environment. Pilots are shown aircraft movements for the 35s preceding the snapshot of the scenario to ensure proper situational awareness. These shortened scenarios are further called snippets. Snippets feature either 4, 6, or 7 hostile two-ship formations as denoted by the first number of their identification number. The remaining two identifying numbers refer to the number of groups in the range categories near, mid, far, and the direction of their travel. An in-depth description of all 24 snippets and their design rationale can be found in Petermeier's dissertation [283].

5.2.2. Participants

The study involved 17 participants with air combat experience as either pilots or weapon system officers (WSOs). The group involved current and former members of the German air force and test pilots. The table containing the participating experts' age, flight experience, and subjective air combat experience is found in section C.2.2 of the appendix.

5.2.3. Collected Data

The objective of the study is to collect scenario-specific data from domain experts. This data is distinguished into the following four types: (1) information value data, (2) visual attention allocation data, (3) usability data, and (4) additional data. The information value data contains the task allocation and prioritization collected to model the value of information. The second category of collected data contains everything related to the study of the allocation of visual attention by participants. The usability of the interface is assessed using a PSSUQ questionnaire, and the last category contains additional data that can be collected in the background. The following list provides an overview of the data collected in this study:

1. Information Value Data
   a) The priority of aircraft groups
   b) Tasks assigned to aircraft groups
   c) The priority of assigned tasks
2. Visual Attention Allocation Data
   a) Gaze points over time
   b) The position of all objects on the interface, incl. moving track symbols
   c) The position of tracking markers on the interface
   d) The position of tracking markers, as seen by a camera mounted to the head of the test subject
   e) Configuration of the interface
3. Usability Data
   a) PSSUQ rating
4. Additional Data
   a) Order of aircraft group and task selection
   b) History of the assigned tasks and priorities
   c) The timestamp of every interaction
   d) Position of the mouse over time
   e) Subjective snippet complexity rating
   f) Subjective situation awareness rating
   g) Study duration
   h) Participant experience

5.2.4. Study Interface Design

The human-machine interface (HMI) shown in figure 5.2 is used to facilitate task allocation and prioritization. The interface is implemented in the general-purpose programming language Python 3 using the graphical user interface library TkInter. A detailed interface description is provided in section C.2.1 of the appendix.

Tracking markers (C) are incorporated to detect the interface's position in the eye-tracking systems reference frame.

The *scenario view* (D) visualizes the movement of objects, which domain experts can select to display further information about the object in the *group information view* (F) on the upper right of the display. The animation is triggered at the start of the allocation process. It can be restarted via a button in the *scenario interaction section* (A). The *group formation view* (G) illustrates the formation of selected groups.

When a scenario is animated, two *tracking markers* (E) appear and switch positions at regular intervals to synchronize the interface data and the eye-tracking data. Another *tracking marker* (B) appears in the *scenario interaction section* (A) to further improve the interface position's tracking.

The activities that can be allocated to tracks are listed in the *task allocation section* (H). Buttons in the *task interaction section* (I) enable the participants to change the assigned group priorities, obtain an overview of the allocated tasks and task priorities, and finalize the task allocation when all objects have been assigned at least one task.

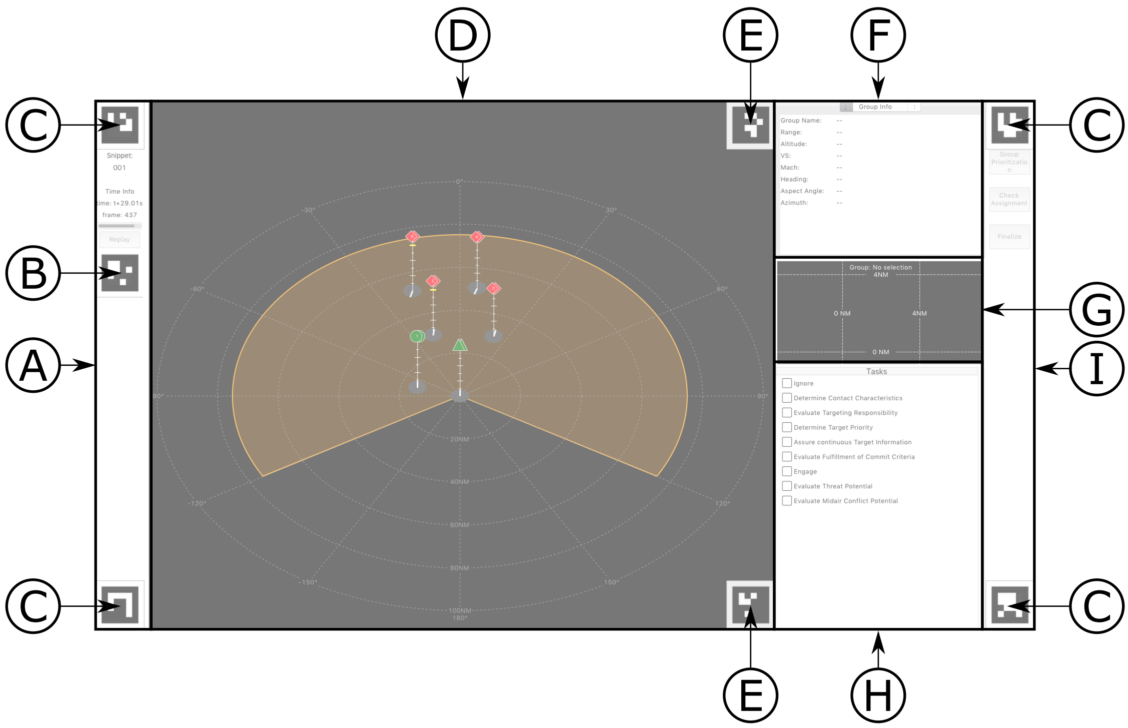


Figure 5.2.: *Overview of the task allocation interface.*

5.3. Data Analysis

A subset of the collected data is processed and analyzed to enable the modeling of the operational information value. The three relevant data items are: (1) the priority of aircraft groups, (2) the tasks assigned to these groups, and (3) the priority of these tasks. Further, the usability ratings are analyzed to validate the developed research interface. The collected eye-tracking data is disregarded for the scope of this research.

5.3.1. Dataset Aggregation

The data collected in the task allocation and prioritization study results from assessments conducted with 17 participants. Due to time constraints, some experts' data collection is split into a set of up to 3 separate assessments. The results from all assessments are aggregated into a single file to simplify later analysis steps.

Every line of the file represents a task priority rating that is uniquely identifiable through four variables: (1) Participant ID, (2) Snippet ID, (3) Group ID, and (4) Task ID. Additionally, the line contains the assigned task priority, group priority, snippet SA rating, and complexity rating. Further, track characteristics, e.g., range, are listed in the line. Additionally, the line contains information about the participant, e.g., flight experience. The duration of all assessments conducted by the same participants is extracted from the log files, added up, and written to an additional log file.

The task allocation and prioritization study is the first study conducted to collect data needed for the validation of the information model. Since the set of snippets is reduced to five in later studies, the data analysis is reported for the complete and the reduced sets. The reduced set contains the ratings for snippets 423, 612, 621, 634, and 721. The selection of these snippets is addressed by Petermeier [283].

5.3.2. Task Allocation

5.3.2.1. Group Priority

The priority of groups in the environment is aggregated after removing outliers with a Z-score greater than 3. The groups are ranked based on their mean rank in the rating of individual participants. The confidence interval for the mean group priority of hostile groups is determined through 10,000 bootstrapped resamples.

5.3.2.2. Ignored Groups

Participants have the option to assign none of the available tasks and select to ignore a group instead. If more than half of the participants ignore a group in a snippet, it will be ignored in further processing steps.

5.3.2.3. Search Priority

In every snippet, participants are requested to rate the priority of a search task in a predefined search volume. The mean search priority is aggregated from individual ratings after removing outliers with a Z-score greater than 3.

5.3.2.4. Conditional Task Assignment

Task priority ratings equal to 0 are dropped since these can only occur by mistake and are thus invalid. The effect of ignoring groups on the overall task rating count is determined by counting the number of dropped tasks. The number of task ratings given by participants is determined by snippet, by group, and by type of task. Tasks very rarely selected with hostile groups are dropped. The conditional probability of a task occurring given the occurrence of another task is determined using Bayesian inference.

$$P\left(T_B|T_A\right) = \frac{n(T_A T_B)}{n(T_A T_B) + n(T_A \bar{T_B})} \tag{5.1}$$

5.3.2.5. Task Prioritization

The mean priority of a type of task is determined by aggregating all task ratings. The relative priority of two tasks is extracted from the dataset, where more than two tasks are assigned to a group.

5.3.2.6. Task Retainment

The tasks assigned to a group can vary by participant. A threshold is thus set to filter out tasks that are not selected by a majority of participants. The effects of the threshold level on the number of groups, the number of task ratings, and the mean task priority are visualized.

5.3.2.7. Usability

The usability of the interface used in the study is rated by the participants using the PSSUQ questionnaire. These ratings are aggregated to infer the average usability. The mean PSSUQ ratings are compared to the norm PSSUQ by Lewis [286].

5.3.3. Task Accuracy Demand Coverage

The collected data is combined with the data collected in the task-specific information demand study (see chapter 4) and analyzed to validate the coverage of the collected demand data and investigate whether the experts' demanded data accuracies remain constant within the range in which the tasks are associated to objects.

5.4. Results

This section reports the results of the process previously described in section 5.3.2.

5.4.1. Group Priority

Participants gave 3162 ratings for 186 groups in 24 snippets. From the 37 outliers ($Z > 3$), 36 were given by subject number 5. Participants rated the priority of 138 hostile groups in 24 snippets. Table 5.1 lists the mean group priority and 95% confidence interval for every hostile group of the reduced snippet set.

Table 5.1.: *Mean priority rating for aircraft groups A to G with its 95% confidence interval.*

$ID_{Snippet}$	A	B	C	D	E	F	G
423	60 ± 7	93 ± 3	30 ± 10	9 ± 3			
612	78 ± 6	56 ± 7	60 ± 7	15 ± 6	92 ± 3	21 ± 8	
621	53 ± 8	93 ± 3	4 ± 2	39 ± 9	68 ± 5	34 ± 9	
634	83 ± 6	56 ± 9	23 ± 8	46 ± 10	50 ± 11	5 ± 2	
721	50 ± 11	52 ± 9	33 ± 9	58 ± 10	66 ± 12	9 ± 4	66 ± 10

5.4.2. Ignored Groups

Fifty-eight (58) of the 138 hostile groups featured in the 24 snippets have been ignored by at least one participant. Three groups were ignored by 14 of the 17 participants, with the remaining three participants submitting 63 task entries for these groups. On the other extreme, 58 groups were ignored by a single participant. The majority of participants ignore nineteen groups. The number of participants ignoring a group correlates strongly with the group's mean priority ($r = -.7687$, $p < .0001$, $n = 138$). This effect is even stronger for groups ignored by at least one participant ($r = -.8451$, $p < .0001$, $n = 58$). Groups are dropped from the dataset if the ratio of participants ignoring the group exceeds the threshold ratio $r_{threshold}$. The removal of groups from the dataset drops all task entries associated with these groups. Figure 5.3 illustrates the relationship between the threshold ratio and the number of groups and task entries retained in the dataset.

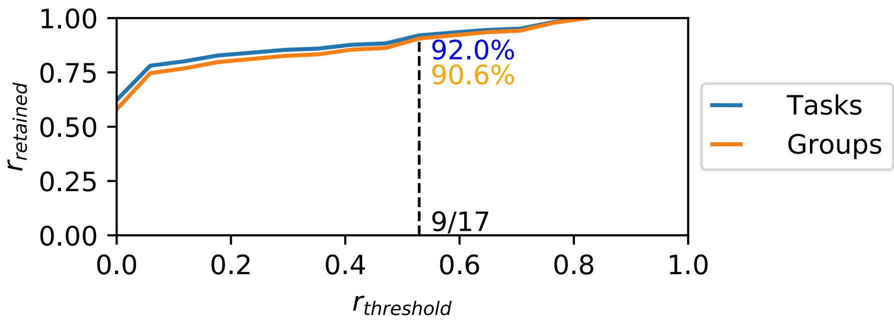


Figure 5.3.: *Effects of the ignored ratio threshold $r_{threshold}$ on group and task retention $r_{retained}$.*

5.4.3. Search Task Priority

The dataset contains 423 entries for the priority of search tasks, 15 more than the expected 408 for 17 participants. The additional entries are errors with a search priority equal to 0, and removing these entries from the dataset leaves exactly 24 valid entries per participant. The search task received a priority rating of 41.5 on average for all snippets, with the mean varying between 30.7 and 57.0. The search priorities grouped by snippets did not pass the Shapiro-Wilk-Test for normality, with $p < .0001$ for all snippets. The mean priority of the search tasks shows a negative relationship with the mean priorities of the groups present in the snippet ($r = -.6745$, $p = .0003$, $n = 24$). This relationship is not present at the level of individual participants. Table 5.2 lists the mean search priorities for the reduced snippet set and their 95%-confidence interval.

Table 5.2.: *Mean search task priorities M with bootstrapped confidence intervals CI for the reduced set of snippets.*

$ID_{Snippet}$	M	95% CI
423	35.12	[26.08, 44.00]
612	31.31	[20.65, 43.57]
621	40.76	[31.33, 50.31]
634	52.80	[40.57, 65.08]
721	41.39	[28.20, 54.69]

5.4.4. Task Assignment

The study collected a total of valid 7498 priority ratings for tasks associated with non-ignored groups. The number of tasks assigned by all participants in a snippet is strongly related to the number of hostile aircraft ($r = -.8474$, $p < .0001$, $n = 24$). The least selected task is the evaluation for the need to react to a threat (D_3), with 271 assignments, and the most selected task is task O_5, with 1,229 selections. As expected, the only task assigned to friendly groups is the avoidance of midair collision (D_2). This task was only assigned to hostile groups by one participant and is thus dropped from the dataset for further analysis. Table 5.3 lists the number of assignments by task type.

Table 5.3.: *Number of assignments by task*

Task ID	Task	n
D1	Eval. Threat	155
D2	Eval. Midair	1
D3	Eval. Reaction	52
O1	Det. Position	144
O2	Det. Charact.	142
O3	Eval. Responsibility	199
O4	Det. Priority	209
O5	Track	252
O6	Eval. Engagement	177

5.4.4.1. Conditional Task Assignment

Participants assigned between 2 and 3 tasks per group for both the complete set ($M = 2.5$, $SD = 1.3$) and reduced set of snippets ($M = 2.4$, $SD = 1.2$). Figure 5.4 illustrates the conditional probabilities between task assignments of over 66% and under 15%. The tasks of the defensive timeline, D_1 to D_3, are rarely assigned together with the tasks O_1 and O_2. If task D_1 is assigned, then D_3 is almost always assigned, but this effect does not occur inversely ($P(D_1|D_3) = 99\%$, $P(D_3|D_1) = 32\%$).

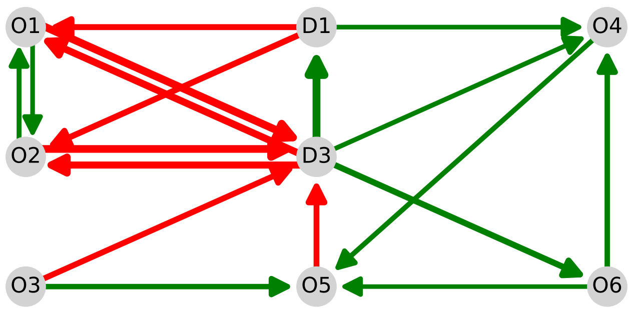


Figure 5.4.: *Illustration of the conditional task assignment likelihoods. Green arrows illustrate a strong conditional assignment likelihood ($P > 75\%$), while red arrows represent the reverse relationship ($P < 15\%$). The thickness of the arrows represents the strength of the conditional likelihoods.*

5.4.4.2. Task Assignment Range-dependency

Figure 5.5 illustrates the distribution of the object's range for each task. The tasks O_1 and O_2 are mostly assigned to groups further away from the ownship. Tasks D_3 and O_6 are mostly assigned to groups in close proximity.

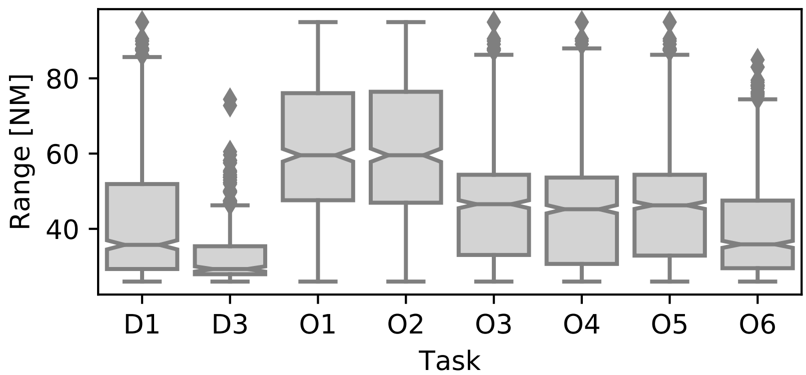


Figure 5.5.: *Boxplot of the object ranges by assigned task type.*

5.4.5. Task Priority

Tasks assigned by participants received a median task priority $\tilde{P}_{Task}$ equal to 64.3, with 25% of tasks surpassing 85.0. The priority of tasks assigned to a group shows a positive relationship with the group's priority (r = .6625, $p < 0.0001$, $n = 6679$). The same relationship is observed for the mean task priority ($r = .7786$, $p < 0.0001$, $n = 2038$) and the highest prioritized task ($r = .7924$, $p < 0.0001$, $n = 2038$) assigned to a group and the group's priority. Figure 5.6 illustrates the relationship between mean task priority and the group's priority.

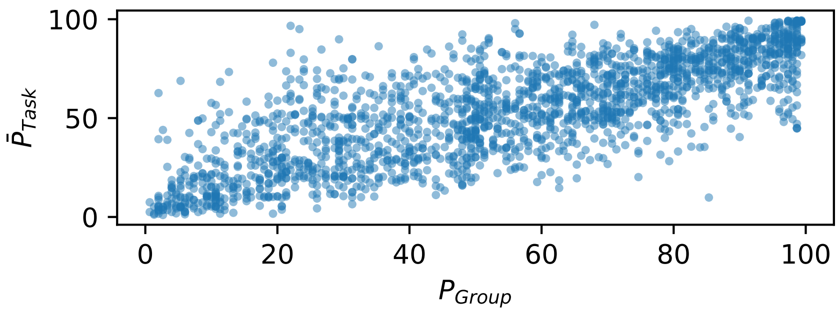


Figure 5.6.: *Scatterplot of the mean task priority $\bar{P}_{Task}$ by group priority P_{Group}.*

Figure 5.7 illustrates the task priority distribution by task type. None of the sets of assigned task priorities by task passed the Shapiro-Wilk test for normality ($p < .0001$). The task D_3 received the highest average priority ($\bar{P}_{D_3} = 72.7$, $\tilde{P}_{D_3} = 83.3$) over the complete dataset, while task O_1 received the lowest average priority ($\bar{P}_{D_3} = 33.2$, $\tilde{P}_{D_3} = 25.3$). Ranking tasks by their mean priority gives the following order: O_1, O_2, D_1, O_3, O_4, O_5, O_6, and D_3. Ranking by median returns the same order as the ranking by their median, except that O_4 and O_5 are switched.

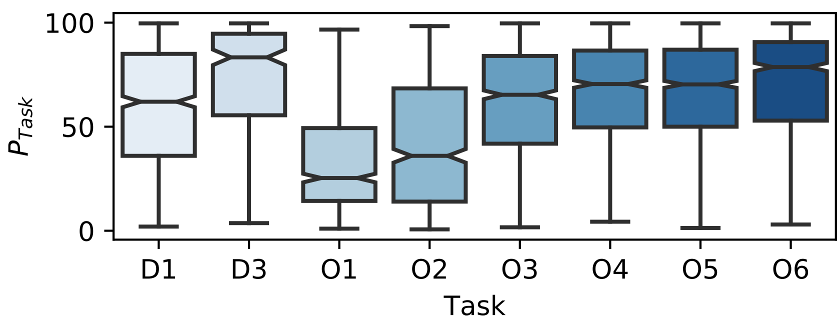


Figure 5.7.: *Boxplot of the task priority distribution by task type.*

5.4.6. Task Retainment

Participants assigned 8 Tasks to 138 hostile groups in 24 snippets for 1004 snippet-group-task combinations. Dropping groups explicitly ignored by more than half of the participants reduces the dataset to 119 hostile groups and 887 unique snippet-group-task combinations. For the reduced set of snippets, participants assigned 193 snippet-group-task combinations to 26 groups. Participants are not constrained in their task assignment, and snippet-group-task combinations are not rated by all participants. As illustrated in figure 5.8, dropping all snippet-group-task combinations with a threshold lower than 6 out of 17 participants retains all groups contained in the dataset. A threshold of 6 participants retains 58.4% of the unique snippet-group-task combinations in all snippets. For the reduced set of snippets, 55.4% of combinations are retained.

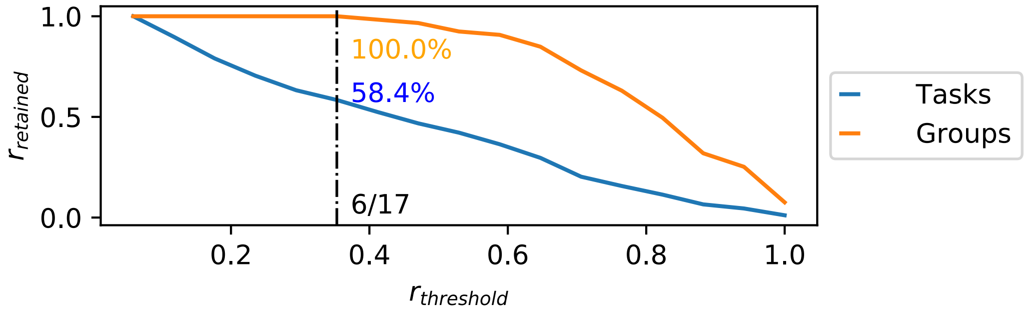


Figure 5.8.: *Effects of the threshold $r_{threshold}$ on the unique number of groups and tasks.*

With an increasing threshold ratio, the mean priority of all tasks increases with the exception of tasks O_1 and O_2, as illustrated in figure 5.9. At a threshold of 6 participants, the mean priority is reduced by 18% for the O_1 tasks and 32% for the O_2 tasks. Other mean task priorities increase between 8 and 19%.

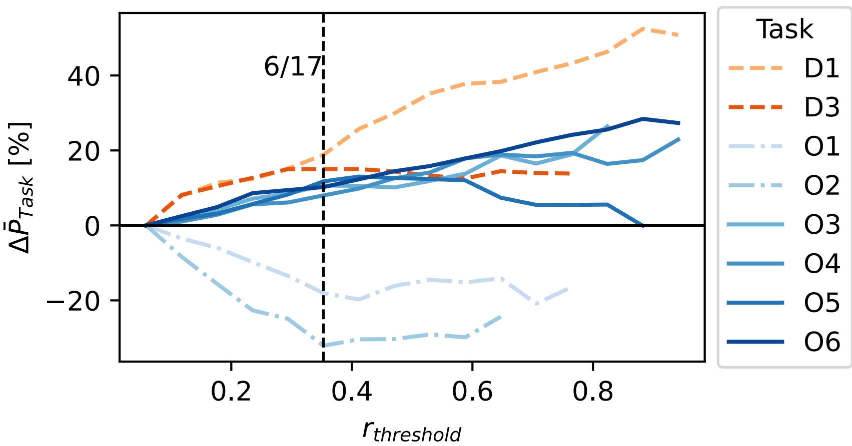


Figure 5.9.: *Effect of the threshold $r_{threshold}$ on the task priority by task type.*

The mean task priority shows a positive relationship with the number of participants assigning the task ($r = .5180$, $p < .001$, $n = 1004$). This effect is observed for all tasks with the following exceptions: $O_1(r = .0206$, $p = .81$, $n = 137)$ and O_2 ($r = -.4080$, $p =< .001$, $n = 138$).

5.4.7. Study Interface Usability

All participants filled out the Post-Study System Usability Questionnaire (PSSUQ) and rated 16 items on a scale from 1 (Strongly Agree) and 7 (Strongly Disagree). Participants had the option to select "not applicable," resulting in incomplete datasets. The average PSSUQ ratings and confidence intervals are calculated based on the available data points. The missing values have been filled using the mean rating given by other participants for the category ratings to avoid an improvement of the information quality score due to the missing data. The dataset has the following gaps:

- Item 6: Participant 19.
- Item 7: Participants 4, 7, 9, 13, 15, 16, and 17.
- Item 8: Participants 4, 7, 9, 13, 16, and 17.
- Item 15: Participants 4, 6, and 8.
- Item 16: Participant 4.

Participants rated the overall usability of the study interface with a mean score of 2.16 (SD = 0.94) on the PSSUQ. The score varied from 1.19 (best) to 3.13 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test: $p = .238$). The overall usability score is better than the norm score (see Lewis [286]), without overlap between the 95%-confidence intervals. The system's usefulness received a mean score of 1.91 (SD = 0.8). The score varied from 1.00 (best) to 3.00 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test: $p = .068$). The system's usefulness received a better rating than the system norm score without overlapping confidence intervals. Participants rated the information quality, with a mean score of 2.32 (SD = 1.11). The score varied from 1.16 (best) to 3.50 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test: $p = .246$). The information quality score is better than the information norm score, without overlap between the 95%-confidence intervals of the participants' rating and the norm score. The interface quality received the worst score of the PSSUQ categories with a mean score of 2.44 (SD = 0.84). The score varied from 1.33 (best) to 4.50 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test: $p = .073$). The 95%-confidence intervals of the participants' ratings and the norm score overlap. The PSSUQ ratings by category are illustrated in figure 5.10 and their respective norm scores.

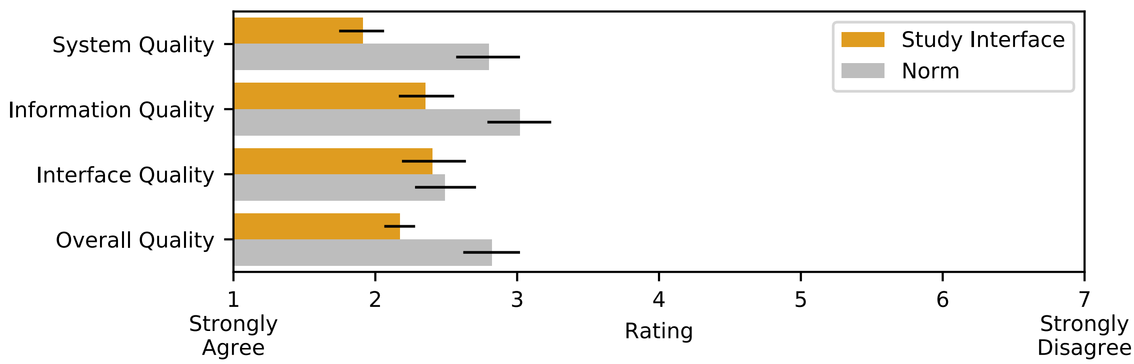


Figure 5.10.: *Mean ratings and 95%-confidence intervals for the PSSUQ categories and norm scores.*

5.4.8. Task Accuracy Demands Coverage

Task O_5 is assigned to one target with a range (83 NM) that falls outside of the range interval covered (0-80 NM). All other tasks are assigned to objects whose range falls within the range interval covered by the demand data collected in the questionnaire-based study. The 95% assignment range quantiles fall within the range intervals covered by the questionnaire-based study, as shown in table 5.4.

Table 5.4.: *List of pilot activities and the demand data's validity range limits R_{min} and R_{max}.*

Task ID	Questionnaire		Task-Assignment	
	R_{min}	R_{max}	$R_{2.5\%}$	$R_{97.5\%}$
D_1	0	100	26.9	57.5
D_3	0	60	26.9	30.6
O_1	10	100	35.9	83
O_2	10	100	35.9	82.8
O_3	10	80	26.9	74.1
O_4	10	80	26.9	72.6
O_5	0	80	26.9	76.1
O_6	10	80	26.9	57.5

Comparing the accuracies demanded by experts in range intervals covering the limits of the 95% assignment range quantile using a two-sided t-test returns statistically significant results for the tasks O_1, O_2, and O_4. Performing a two-sample Kolmogorov-Smirnov test on the same demand samples returns p-values between the limits shown in table 5.5.

Table 5.5.: *Results of the Kolmogorov-Smirnov test for the range overlap.*

Task	$p_{wanted,min}$	$p_{wanted,max}$	$p_{needed,min}$	$p_{needed,min}$
D_1	0.878	1	0.869	0.999
D_3	1	1	1	1
O_1	0.013	0.300	0.003	0.126
O_2	0.008	0.898	0.001	0.300
O_3	0.588	1	0.300	0.898
O_4	0.300	0.998	0.480	0.898
O_5	0.588	0.999	0.283	0.999
O_6	0.588	0.999	0.588	0.999

5.5. Discussion

This section discusses the results from the task-assignment study and the aggregation of the collected data with the data collected in the accuracy demand elicitation.

5.5.1. Ignored Groups

The ratio of participants explicitly ignoring a group increases with lower group priorities. Setting the threshold to 9 of 17 participants drops 19.4% of the groups and 18% of the task allocations from the dataset. Table 5.6 lists the groups dropped from the reduced snippet dataset. The remaining columns list the ratio $r_{Ignored}$ of participants choosing to ignore the group explicitly, the group's mean priority, and the number of task assignments n_{tasks} linked to the group.

Table 5.6.: *List of the groups removed from the data set due to being ignored by more than 50% of the participants*

Snippet ID	Group	$r_{Ignored}$	P_{Group}	n_{tasks}
423	D	52.94%	8.6	26
621	C	76.47%	4.4	22
634	F	58.82%	4.8	23

5.5.2. Task Assignment

The task assignment correlations reflect the range-driven timeline of the targeting cycle. When D3 is assigned to a group, there is a very high assignment likelihood for tasks D1, O4, and O6. This correlation highlights the need for threat evaluation (Task D1), prioritization (Task O4), and engagement assessment (Task O6) to be performed before reacting to a threat (Task D3). Detecting the position (Task O1) and determining the contact characteristics (Task O2) are usually assigned to groups at far ranges. Participants likely assumed these tasks had already been performed for groups at closer ranges. These tasks have rarely been assigned together with tasks D1 and D3, which supports the range-driven hypothesis. The tasks to evaluate the targeting responsibility (O3) and to track the group for SA purposes (O5) cover tasks that have been detected are at medium range and not yet a threat or high priority target. The null-hypotheses H_0^E is therefore rejected. The task to evaluate the midair collision risk (D2) is mostly assigned to friendly aircraft groups and assigned only eight times to hostile groups. This task can thus be dropped from the dataset when modeling the value of information about hostile aircraft. The task assigned to a target could be limited to one main task and the preceding and succeeding tasks on the timeline to reduce the future study's complexity and accelerate the data collection process.

5.5.3. Search Task Priority

Higher average group priorities lead to a lower search task priority rating. Sorting the reduced snippet set from lowest to highest search task priority returns the following: 612, 423, 621, 721, 634.

5.5.4. Task Retainment

Tasks assigned by fewer participants have a lower task priority. Therefore, tasks dropped based on this metric should not be of importance when determining the value of the information provided by onboard sensor systems. The process of dropping all tasks with less than four entries retains all groups that have not been explicitly ignored and more than half of all unique snippet-group-task combinations. The null hypothesis H_0^D is rejected on a qualitative basis, as subjects generally agreed on the tasks assigned to specific groups.

5.5.5. Task Priority

The high prioritization of the assigned tasks indicates that participants focussed mostly on high-priority tasks and assumed lower-priority tasks to have occurred based on range considerations. The task priorities reflect the range-driven timeline of the targeting cycle, as tasks linked to closer objects have a higher priority. Further, the closer tasks are situated to the need for reaction, the higher the priority of these tasks. The group priority strongly correlates with the priority of the assigned tasks, which indicates that the priority of the tasks that are associated with the group drives its priority. The null hypothesis H_0^G is rejected based on these results.

5.5.6. Interface Usability

Given the good overall usability scores, the data collected in this study should not be negatively impacted by the usability of the interface. Nevertheless, the interface and data quality of the interface should be improved for future studies. Integrating more functionalities, e.g., assigning tasks to multiple groups simultaneously and making the interface more user friendly, could help increase the interface's enjoyability. Additionally, integrating clear error messages, simplifying the process of recovering from mistakes, and increasing the clarity of the information displayed on the interface would increase the interface's overall information quality.

5.5.7. Task Demand Range Interval

The data collected in the task-assignment study is consistent with the data collected in the questionnaire-based data accuracy demand study, and both data sets can be aggregated to model the value of information. The accuracy demand for the threat mitigation task (D_3) can be considered constant over the task assignment range. The null hypothesis H_0^F is rejected for this specific task. The accuracy demand associated with the remaining tasks does not show similar behavior. The difference between demands for the tasks O_1, O_2, and O_4 at the task association range limits differ from each other with statistical significance. Neither the null hypothesis H_0^F nor the corresponding hypothesis H_1^F can be rejected outright on the basis of the collected data. Modeling the operational value of information shall therefore assume a range-dependency for the desired data accuracy demands.

5.6. Conclusion

The study aimed to collect task-allocation data demands required to model the operational value of information and analyze the collected data for modeling to test the stipulated hypotheses linked to the task-allocation and prioritization and derive implications for the design of an information value model. The null hypotheses H_0^D, H_0^E, and H_0^G have been rejected, as discussed in the previous section. The null hypothesis H_0^F is neither rejected nor adopted. The results lead to the following three conclusions:

- Study participants generally agree on the most important tasks associated with an object in the environment.
- Tasks have a range-dependent timeline and are not fully independent from each other.
- The information demand required to perform a specific type of task is not constant for all task assignment ranges.
- The priority of a group of objects results from the priority of tasks associated with the group.

Collected modeling data Seventeen (17) experienced operators spent a combined 51 hours assigning prioritized tasks to 186 groups in 24 scenario snippets. The majority of participants ignored nineteen (19) aircraft groups and produced a combined 7498 valid prioritized task assignments. As expected, the only task associated with friendly groups is to avoid midair collisions. Aggregating the results returns 887 unique snippet-group-task combinations. The task assignments collected in the study are retained for further study steps based on the following conditions:

- The group is not ignored by more than 50% of the participants
- The task is associated with a hostile group
- The Tasks assigned by more than 5 participants

Implications for the Information Value Model The study results imply the following for the valuation of information:

1. The information valuation model should feature a range-dependent data accuracy demand function.
2. The information valuation model should consider the interactions between tasks and their timeline.
3. The group priority can be disregarded by the information valuation model if task priorities are provided.

6. Information Set Preference Elicitation

Assessing the performance of a task-driven information value model requires a dataset against which the generated output can be assessed. This chapter describes the activities performed to collect the validation data, which is based on the domain expert's pair-wise information set preferences. Additionally, the results are used to test the following hypotheses:

H_0^H: There is no consensus between the experts' information set preferences.

H_0^I: The confidence expressed by domain experts choosing between information sets has no relationship with the preferential choice agreement.

6.1. Study Overview

The preferences are elicited for the five snippets selected from the task-assignment study based on a range of criteria, e.g., the number of hostile aircraft groups and the snippet's complexity. The reasoning behind the selection can be found in Petermeier's dissertation [283]. The expert's preferences are assessed for ten to twelve information sets per snippet, as listed in table 6.1.

Table 6.1.: *Number of information sets per snippet.*

Snippet	423	612	621	634	721
n_{sets}	10	10	10	12	12

Information sets used to validate the information value model are drawn from pseudo-randomly generated radar simulation results. The selection process is based on k-means clustering to cover a broad spectrum of possible data collection outcomes.

A pair-wise comparison is used to elicit the domain expert's preference between information sets and their confidence in this selection. The collected preferences are analyzed to derive an aggregated set of domain expert preferences and selection confidence.

6.2. Sensor Information Set Generation

The information sets are generated by randomizing the resource allocation of a simple simulated radar. Each simulation run begins with the initialization of the sensor model and is followed by the simulation of a set of discrete steps. The sensor's information from the final is processed after the simulation to return the simulation results, as shown in figure 6.1.

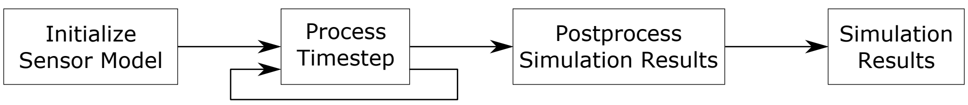


Figure 6.1.: *Information set generation process.*

6.2.1. Simulated AESA Radar

A simple radar model was developed to generate simulated information sets, which reflect the interaction of a radar system with its environment and are slightly more realistic than fully randomly generated information sets. Design parameters and variables are based on assessing a first-generation Russian AESA radar by Kopp [287]. The radar model uses a Kalman filter to track detected objects and is able to perform two types of tasks: search in a volume and track a detected object. These tasks use two distinct scan methods, as illustrated in figure 6.2. The search task simulates the scan of a large volume and calculates the signal-to-noise ratio of all objects present in the volume based on the power allocated to the volume scan and the size of the volume. The tracking task simulates the tracking of an object and returns the signal-to-noise ratio for this target and any object in the beams' path. The probability of detection is inferred using North's approximation [63].

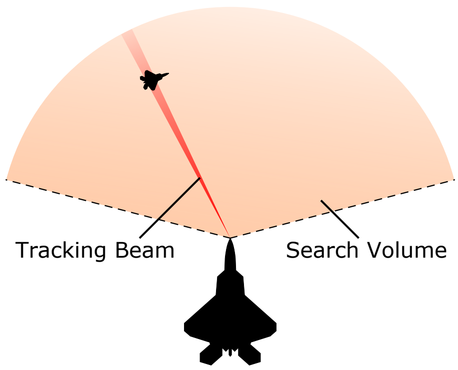


Figure 6.2.: *Simulated sensing tasks.*

6.2.1.1. Data Accuracy Calculation

The accuracy of the simulated measurements is obtained by calculating the deviation from the object's true position for every parameter. Additionally, the 95% confidence interval is calculated as a function of the Root Mean Square Error (RMSE).

6.2.1.2. Information Fusion

Radar detections are generated by multiple tasks and processed to update the Kalman filter's position estimate. Pilots process information about objects in the environment on a group level. The data collected about the aircraft making up a group is therefore fused to provide group-level data. There are three possible cases for the group quality aggregation for two-ship groups:

No track detected: If no aircraft is detected, the group is not detected either, and the qualities are thus set to "None." The group resolution is set to 0.

Single track detection: If only one of the two aircraft is tracked, the group quality is set to be equal to the track quality. The group resolution is set to 1.

Two tracks detections: If both aircraft are tracked, the group quality is set to be equal to the best quality of either track. The group resolution is set to 2.

6.2.1.3. Randomized Sensing Resource Allocation

The sensing resources are divided into two categories, the minimum search power and tracking power. In the first step of the power allocation, the minimum search power $P_{Search,min}$ is defined as a random variable following the discrete uniform distribution $\mathcal{U}$. The set has been limited to 6 entries to reduce the computational burden. The remaining power is allocated to the tracking tasks. The power P_{ac} allocated to an individual object in the environment is a random variable w_{ac} following the discrete uniform distribution over the set $\{0, 1, \ldots, 6\}$. If all objects are assigned a weight equal to 0, one of the objects is randomly given the weight 1 in order to avoid a division by 0. The radar resource allocation is illustrated in figure 6.3. Step 3 is updated each time a new target is detected.

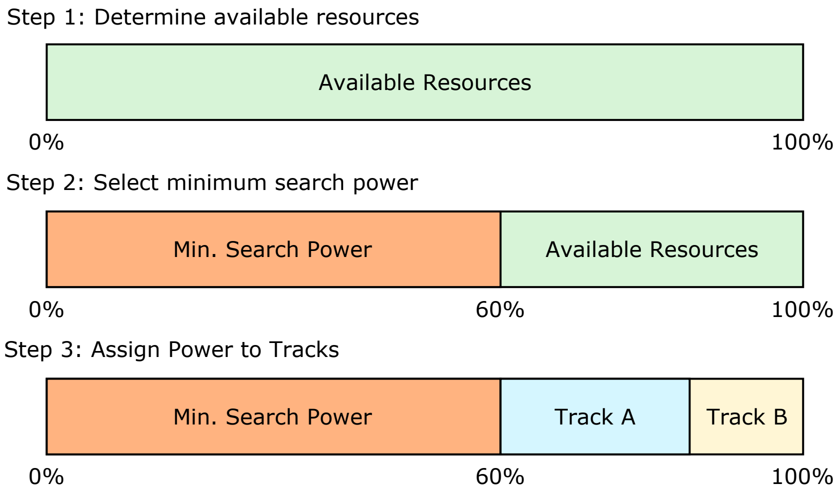


Figure 6.3.: *Simulated resource allocation steps.*

6.2.2. Information Set Selection

The selection of information sets used for the assessment of the information value model is drawn from a list of 5000 pseudo-random sensor simulation results. A clustering-based approach is used to generate a preliminary selection set that is as diverse as possible. The following steps are performed to

1. Standardize the features contained in the dataset.

2. Compute the k-means clustering for a number cluster equal to the number of desired samples.

3. Transform the dataset into a cluster-distance space.

4. Select the two samples with the largest and the smallest distance from the cluster point.

The final selection of the samples was performed by Petermeier [283].

6.3. Expert Information Set Preference Elicitation

To validate the information value concept, we need to determine the correctness of the concept with respect to user needs and requirements [212]. This objective is accomplished by performing a validation in which the assessed information values for sets of information are compared to the preferences of fighter pilots. This section describes the study conducted by Petermeier [283].

6.3.1. Study Design

Every experiment conducted as part of the study starts with a briefing phase in which the context and scope of the research are explained to the participant and the mission scenario. Participants are then given time to familiarize themselves with the interface. The experts' preference is elicited for four different snippets in a systematically variated appearance order. Participants are shown the snippet's animation before being asked to provide their preferences in pair-wise comparisons of information sets. The overview of the study is shown in figure 6.4.

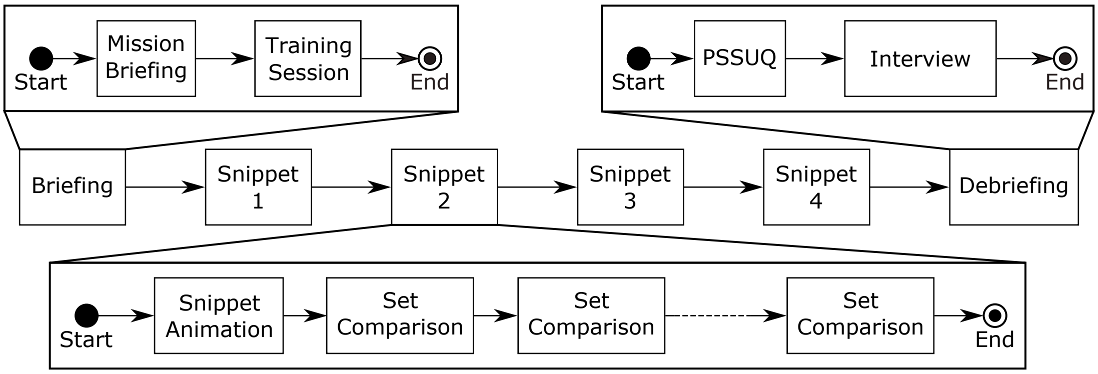


Figure 6.4.: *Overview of the information set preference study.*

6.3.1.1. Participants

The study involved 21 participants with air combat experience, including current and former German air force members and test pilots. The table containing the age, flight experience, and subjective air combat experience of the participating experts is found in section C.3.1 of the appendix.

6.3.1.2. Scenario Snippet

The preferences of fighter pilots are elicited for the following five scenario snippets featured in the task assignment study: 423, 612, 621, 634, and 721. Scenario 621 is used to familiarize participants with the interface. A smaller number of comparisons is performed for this snippet for this reason.

Table 6.2.: *Number of information sets per snippet.*

Snippet	621[1]	423	612	634	721
n_{sets}	10	10	10	12	10
$n_{comparisons}$	22-28	45	45	66	45

[1] training set

6.3.2. Study Interface Layout

The human-machine interface (HMI) shown in figure 6.5 is used to capture the experts information set preferences. Two scenario views are shown in the top half of the HMI that provide an overview of the two options (A, B). Groups can be selected in these views to request a more detailed breakdown of the associated data. Selected groups are highlighted by a selection indicator (C) and their range, heading, aspect angle, altitude, speed, and azimuth angle are listed in the group information box (D). The detailed data accuracy metrics are shown in a comparative list (E, F). The subject participant can rate his preference for one or the other information set using the scale at the bottom of the HMI (G). The selection confidence is derived from the selected position of the slider on the preference scale.

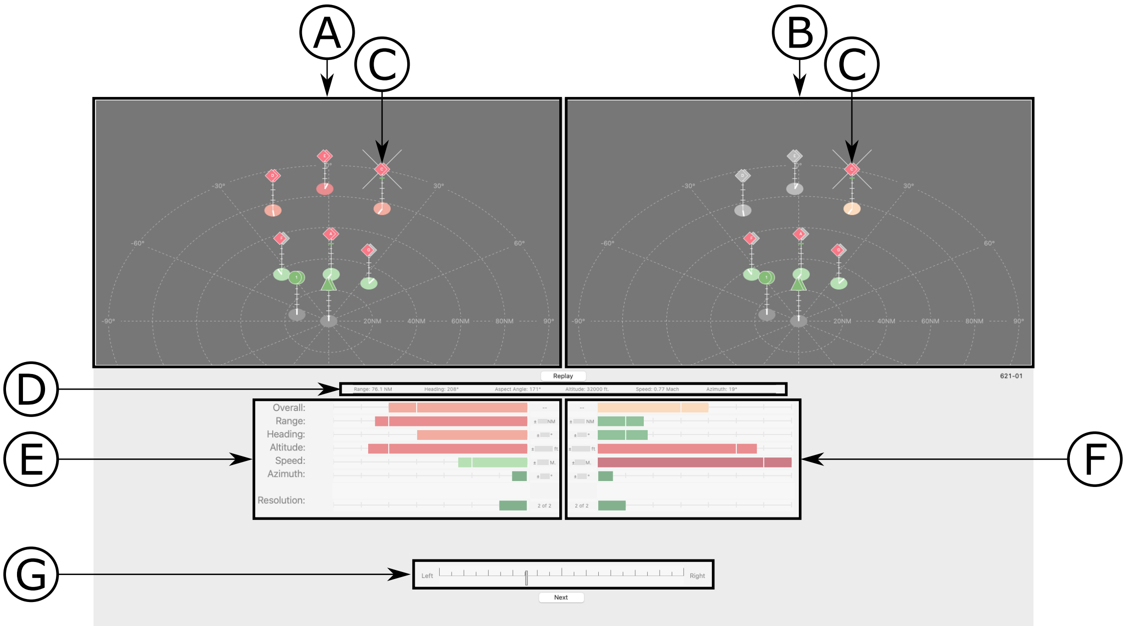


Figure 6.5.: *Overview of the information set preference elicitation interface.*

6.3.2.1. Scenario Views

The scenario views are an adaptation of the task allocation HMI 's scenario view, which is described in section C.2.1.1. The color of the group symbol is modified to reflect the group's resolution, as shown in figure 6.6. The overall data quality is indicated by coloring the group's shadow according to the color map shown in figure 6.7.

(a) *None* **(b)** *One* **(c)** *All*

Figure 6.6.: *Group resolution indication based on the number of detected targets in the group.*

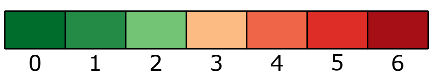


Figure 6.7.: *Data quality color map.*

6.4. Data Processing

The study collected preferences and associated confidences from domain experts. Additionally, the requests for additional information about the data accuracies were logged. This section describes the methods used to analyze the collected data.

6.4.1. Information Set Selection Agreement

Experts rated their preference for one of two information sets on a continuous scale, from 100% for option A to 100% for option B. These ratings are aggregated for all study participants, and a selection agreement metric ΔR is derived for the level of agreement between experts. The metric is equal to 1 if all participants select the same information set and equal to 0 if the participants' selection is equally distributed.

6.4.2. Information Sets Preference Ranking and Confidence

The information sets are ranked using an approach based on the Quicksort method developed by Hoare [288]. The Quicksort approach developed sorts a set of elements iteratively by dividing it into smaller sets. The process starts by randomly selecting a pivot point. Two sets are created based on this point for the elements greater than the pivot and those smaller than the pivot element. These new sets are subsequently divided using the same method until all sets contain no more than one element. The first steps of the quickstep approach are illustrated in figure 6.8. Since the selection ratio will deviate from 0 and 100% and to retain the uncertainty described by the selection ratio, bootstrapping is applied, and the final order of the information sets is determined by sorting these sets by their mean rank. The individual comparisons are aggregated into a table listing the confidence interval for the selection.

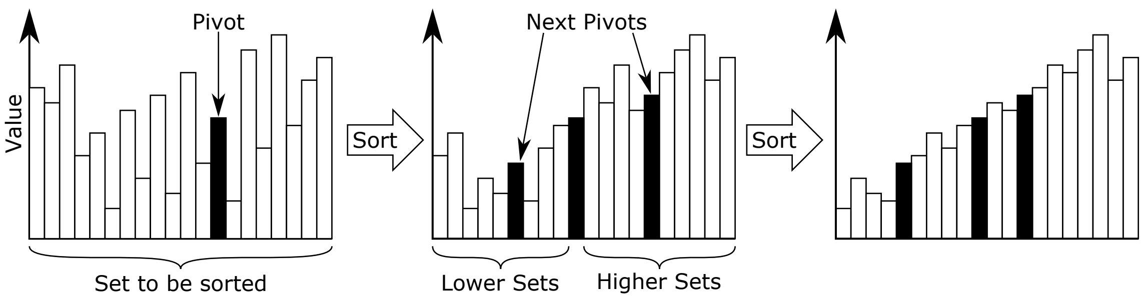


Figure 6.8.: *Quicksort algorithm, based on [288].*

6.4.3. Group Selection

Requests for more information about the data quality are aggregated for each group, and the ratio of participants requesting the details is compared against the groups ignored in the task allocation study.

6.4.4. Study Interface Usability

The usability of the interface used in the study is rated by the participants using the PSSUQ questionnaire. These ratings are aggregated to infer the average usability. The mean PSSUQ ratings are compared to the norm PSSUQ ratings found in the literature.

6.5. Results

Twenty-one pilots compared 4714 pairs of information sets for five scenario snippets, 4221 when the training snippet is excluded.

6.5.1. Information Set Selection Agreement

Full agreement occurred for 31 of the 201 compared pairs of information sets. The number of comparisons n for every selection agreement ΔR are listed in table 6.3. A very strong positive correlation is observed between the selection agreement ΔR and the mean confidence of the selection ($r = .9195$, $p < .0001$).

Table 6.3.: *Number of comparisons by selection agreement* ΔR *.*

ΔR	100%	$> 90\%$	$> 75\%$	$> 50\%$	$< 25\%$	$< 5\%$
n	31	65	92	145	25	7

6.5.2. Information Sets Preference Ranking

Ranking information sets following the process described in section 6.4.2 returns the order listed in table 6.4, with column I_1 containing the most preferred information set.

Table 6.4.: *Information set ranking, with 1 representing the highest preference.*

$ID_{Snippet}$	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	I_{12}
423	1	2	4	5	6	7	3	8	9	10		
612	1	2	4	5	6	7	3	9	8	10		
621	2	5	4	3	1	6	7	10	9	8		
634	1	3	4	5	2	6	7	8	9	11	10	12
721	2	1	3	4	5	8	6	7	10	9		

6.5.3. Group Selection

In 878 of the 4221 comparisons, participants did not look up the individual information qualities for any track. The selection rate varies strongly per group. Group B in snippet 423 is selected for additional information in 82.8% of all comparisons. In comparison, group F in snippet 634 is selected only in 7.4 % of cases, as shown in table 6.5. Groups ignored in the task allocation study have a low selection ratio.

Table 6.5.: *Ratio of group selection by Snippet.*

$ID_{Snippet}$	A	B	C	D	E	F	G
423	55.0%	82.8%	21.3%	21.4%			
612	71.1%	50.3%	52.9%	20.1%	72.2%	17.6%	
634	73.3%	60.5%	20.3%	37.8%	49.8%	7.4%	
721	46.2%	41.2%	18.5%	57.5%	64.7%	9.0%	58.1%

6.5.4. Study Interface Usability

All participants filled out the Post-Study System Usability Questionnaire (PSSUQ) and rated 16 items on a scale from 1 (Strongly Agree) and 7 (Strongly Disagree). Participants could select "not applicable," resulting in incomplete datasets. The average PSSUQ ratings and confidence intervals are calculated based on the available data points. The missing values have been filled using the mean rating given by other participants for the category ratings to avoid an improvement of the information quality score due to the missing data. The dataset has the following gaps:

- Item 6: Participants 6, 7, 17, and 18.
- Item 7: All except participants 1 and 8.
- Item 8: All except participants 4, 6, 8, 11, 12, 15, 18, 20, and 21
- Item 13, 14, and 15: Participant 7.

Participants rated the overall usability of the study interface with a mean score of 2.06 (SD = 0.96) on the PSSUQ . The score varied from 1.00 (best) to 3.50 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test:$p = .692$). The overall usability score is better than the norm score, without overlap between the 95%-confidence intervals. The system's usefulness received a mean score of 1.83 (SD = 0.82). The score varied from 1.00 (best) to 3.50 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test: $p = .208$). The system's usefulness received a better rating than the system norm score, without overlap between the confidence intervals. Participants rated the information quality with a mean score of 2.17 (SD = 1.07). The score varied from 1.00 (best) to 3.75 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test: $p = .510$). The information quality score is better than the information norm score, without overlap between the 95%-confidence interval intervals of the participants' rating and the norm score. The interface quality received the worst score of the PSSUQ categories, with a mean score of 2.33 (SD = 1.04). The score varied from 1.00 (best) to 3.33 (lowest) between participants and is normally distributed (Shapiro-Wilk-Test: $p = .099$). The 95%-confidence intervals of the participants' ratings and the norm score overlap. The PSSUQ ratings by category are illustrated in figure 6.9, together with their respective norm scores by Lewis (2002).

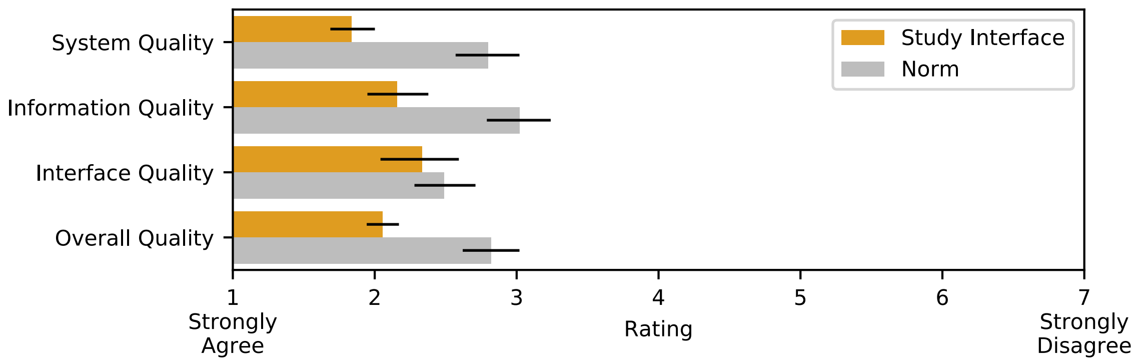


Figure 6.9.: *Mean ratings and 95%-confidence intervals for the PSSUQ categories and norm scores.*

6.6. Discussion

This study collected domain expert preferences for four snippets and 42 information sets. Additional preferences have been elicited during the HMI familiarization session. These additional results were not complete and are therefore not considered for the model validation.

6.6.1. Information Set Selection Agreement

A high degree of agreement was observed, with over 72% of compared pairs having an agreement score of over 50%, which represents 75% of participants selecting the same information set. The confidence rating provided by participants reflects the level of agreement. The agreement level can thus be used as a metric to quantify the relative value of information sets. The null hypotheses H_0^H and H_0^I are rejected.

6.6.2. Group Selection

Participants did not compare all the components that make up the information sets. This comparison is unnecessary for tracks detected only in one of the two information sets. Pairs featuring a large accuracy difference for a high-priority track could make comparing data linked to lower-priority tracks unnecessary. Some experts might have relied on the colored shadow representing the overall data quality metric, which could impact the validity of the comparison data. Future assessments should ensure a more detailed assessment of the expert's preferences to ensure the validity of the collected preferences.

6.6.3. Interface Usability

Given the good overall usability scores, the data collected in this study should not be negatively impacted by the usability of the interface. Nevertheless, the interface and data quality of the interface should be improved for future studies.

6.7. Conclusion

The study aimed to collect pair-wise information set preferences to provide a dataset against which the information valuation model can be assessed.

Collected modeling data The study collected experts' preferences and confidence for 201 information set pairs for four snippets.

Implications for the Information Value Model The study results imply the following for the valuation of information:

1. The information valuation model should be able to compare two information sets and return a selection accompanied by selection confidence.

2. The information valuation should be limited to the tracking quality, as data on the search task is not explicitly part of the preference elicitation.

7. Information Value Modeling

The present thesis's main objective is to design and assess an information valuation approach based on operator needs, which could be used as the objective function of a sensor management system.

7.1. Study Design

Three steps are performed to achieve this objective: the design of the model, information valuation, and assessing the model output, as shown in figure 7.1. The prototypical information valuation model is built using insights gained through the data collection studies and the review of available literature. The model structure is inspired by the human information processing described in section 2.3. Guidelines for the design of human-centered automation, discussed in section 2.4.2.2, are considered in the design of the information valuation model to facilitate the metrics integration into sensor management applications. The model assessment requires information valuation results for the set of information sets for which expert preference ratings have been elicited in the data collection studies. The list of relevant operator tasks and associated operator demands are processed to initialize the information valuation model. Information on the tasks associated with objects in the snippets tunes the model for the specific snippets. Information sets are rated with the tuned information valuation model. The model's information set ratings are compared against the preferences of domain experts to assess whether the model is able to reflect these preferences and the rating uncertainty. The assessment results are used to test the following hypotheses:

H_0^J: Domain experts do not prefer information sets with higher information value scores in pair-wise comparisons.

H_0^K: The difference in information value between two information sets collected from the same environment has no effect on the aggregated preferential choice uncertainty.

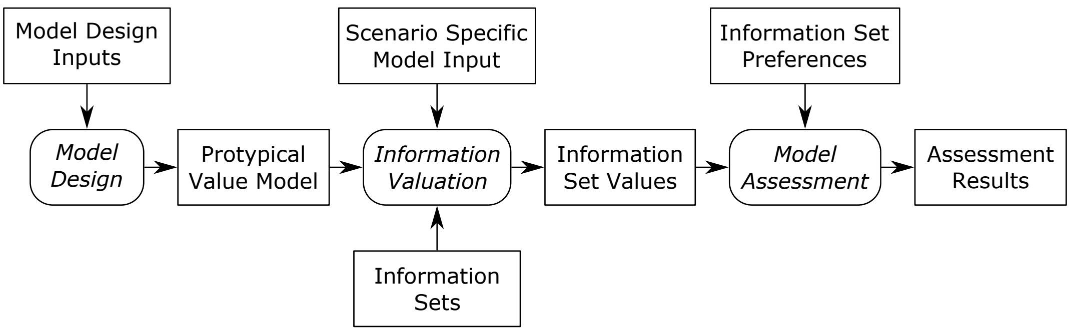


Figure 7.1.: *Overview of model design activities.*

7.2. Information Value Model Design

The value of information is "the extent to which knowing the information helps achieve a mission" [70, p. 2]. It is defined by the subjective satisfaction experienced by the pilot, which is driven by the decision maker's information needs and wants, as detailed in section 3.1.2.

7.2.1. Design Objective

The goal of the development is to implement the function "Determine Information Value," which calculates a numerical information value based on the information demand and a set of tracks, as shown in figure 7.2. This value should reflect the information's ability to fulfill the pilot's information needs and wants.

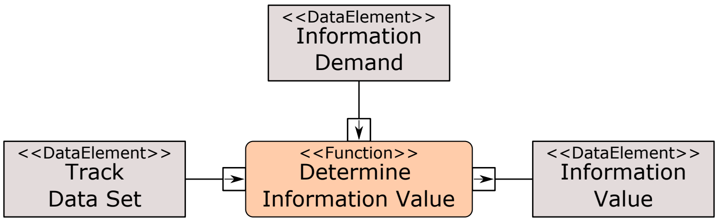


Figure 7.2.: *Information value data inputs and outputs.*

7.2.2. Input Data

Data collected in the studies described in sections 4 and 5 is used as input for the information value calculation. Figure 7.3 illustrates the input data's structure and the associations between the information demand and the track data. The mapping between group-specific information demands and the provided track data is enabled by using the same identifier for a group and its track representation.

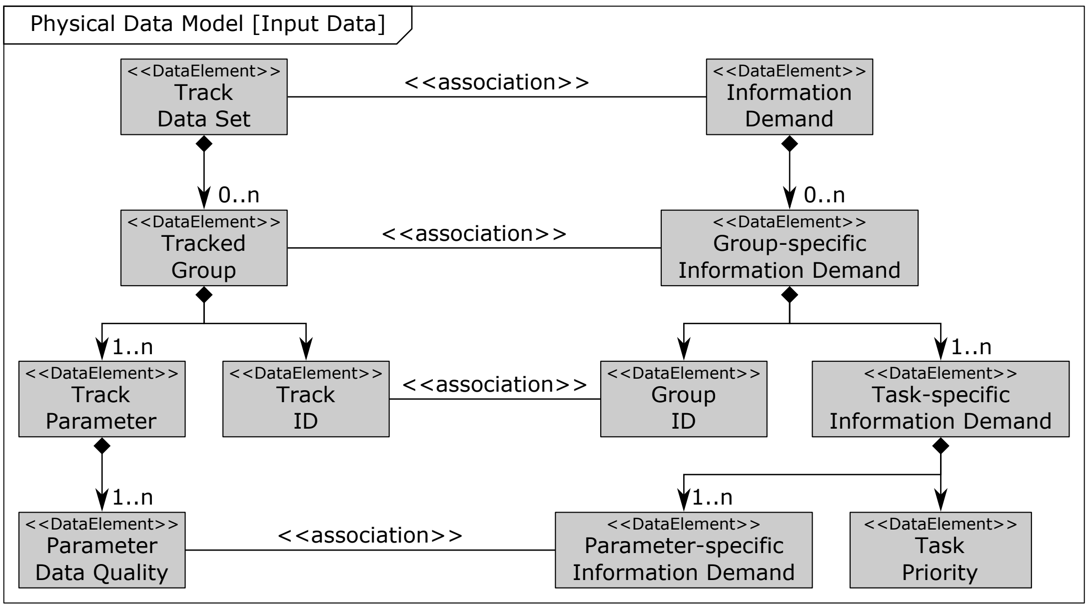


Figure 7.3.: *Structure diagram for the model's input data.*

7.2.3. Model Requirements

The data collection studies in previous chapters provided insights into the information value model in table 7.1.

Table 7.1.: *Conclusions from the data collection studies.*

ID	Conclusion	Impacted Aspect
R1.1	The information value model should be able to accommodate the uncertainty of the aggregated demand.	Data Input & Processing
R1.2	The importance of demanded parameter can be disregarded for scope of the research.	Simplification
R2.1	The information valuation model should feature a range-dependent data accuracy demand function.	Data Input & Processing
R2.2	The information valuation model should consider the interactions between tasks and their timeline.	Processing
R2.3	The group priority can be disregarded by the information valuation model if task priorities are provided.	Simplification
R3.1	The information valuation model should be able to compare two information sets and return a selection accompanied by a selection confidence.	Processing & Data Output
R3.2	The information valuation should be limited to the tracking quality, as data on the search task is not explicitly part of the preference elicitation.	Data Input & Processing

7.2.3.1. Top-Level Requirements

Specifying requirements is a key design process step, as described in section 2.4.2. This section lists the identified information value model requirements and the rationale behind these requirements. The main requirements driving the design are listed in table 7.2.

Table 7.2.: *Top-level requirements.*

ID	Requirement	Rationale
Top-1	The model shall calculate the informational value of a track data set.	The main goal of the model is to rate the value of the information carried by a track data set. Given the study result R3.2, the search quality is not considered.
Top-2	The model shall be adaptable to all types of missions and scenarios through loadable datasets.	Fighter aircraft are designed for multiple roles, and the sensor management system must support these missions.
Top-3	The model shall be operator task-driven.	The operators' information needs are linked to the tasks they aim to perform. The model should reflect this relationship.
Top-4	The model shall be deterministic.	The model should return the same output for a given input to compare the model output to the expert's preferences.

7.2.3.2. Model Input and Output Requirements

Table 7.3 lists the requirements specifying the information valuation model's data input and data output.

Table 7.3.: *Data input requirements.*

ID	Requirement	Rationale
In-1	The model shall accept a track data set as input.	Implementation of the requirement Top-1.
In-2	The model shall load the information demand from an external data set.	Implementation of the requirements Top-2.
In-3	The information demand shall be composed of two data sets: task-specific information demands and contextual task associations.	Implementation of the requirement Top-3.
In-4	The task-specific information demands shall be mission independent.	Implementation of the requirement Top-3.
In-5	The task-specific information demand shall contain the demand's uncertainty.	Application of the study conclusion R1.1.
In-6	The task-specific information demand shall be range-dependent.	Application of the study conclusion R2.1.
Out-1	The value of information shall be provided on an ordinal scale.	Implementation of the requirement Top-1 and application of the study conclusion R3.1.

7.2.3.3. Decision-Making Requirements

Multiple aspects need to be considered by the information valuation model, and therefore, the properties of the valuation model's attribute set should fulfill Keeney and Raiffa's [160] recommendations. Table 7.4 lists the requirements linked to the model's decision-making attribute set.

Table 7.4.: *Decision-making attributes requirements.*

ID	Requirement	Rationale
Sys-1	The set of attributes should be complete.	Consider all the important decision aspects.
Sys-2	The set of attributes should be operational.	Have meaning in the analysis.
Sys-3	The set of attributes should be decomposable.	Make the problem easier to manage.
Sys-4	The set of attributes should be non-redundant.	Avoid multiple counting of attribute impacts.
Sys-5	The set of attributes should be minimalist.	Reduce the problem's dimensionality.

7.2.4. Functional Design

The process that derives the operational value of an information set is guided by insights gained from the review of the following four research domains:

- the information metrics summarized in section 2.5.3,
- the utility theory described in section 2.5.3.1,
- the human decision-making concepts surveyed in section 2.3.4.1, and
- the economic theories of value reviewed in section 2.5.2.2.

For the purpose of the research, the value of information follows Porter's [247] definition of value-in-use, which reflects the utility of the specific information. As stipulated in section 3.1.2, this utility is defined by the information's ability to fulfill the pilot's information needs and wants. The information valuation model is decomposed into the four distinct functions listed in table 7.5. Figure 7.4 illustrates the interaction between the valuation model's four sub-functions. The decomposition simplifies the development of dedicated solutions for demand fulfillment assessment at three levels: parameter, track, and overall.

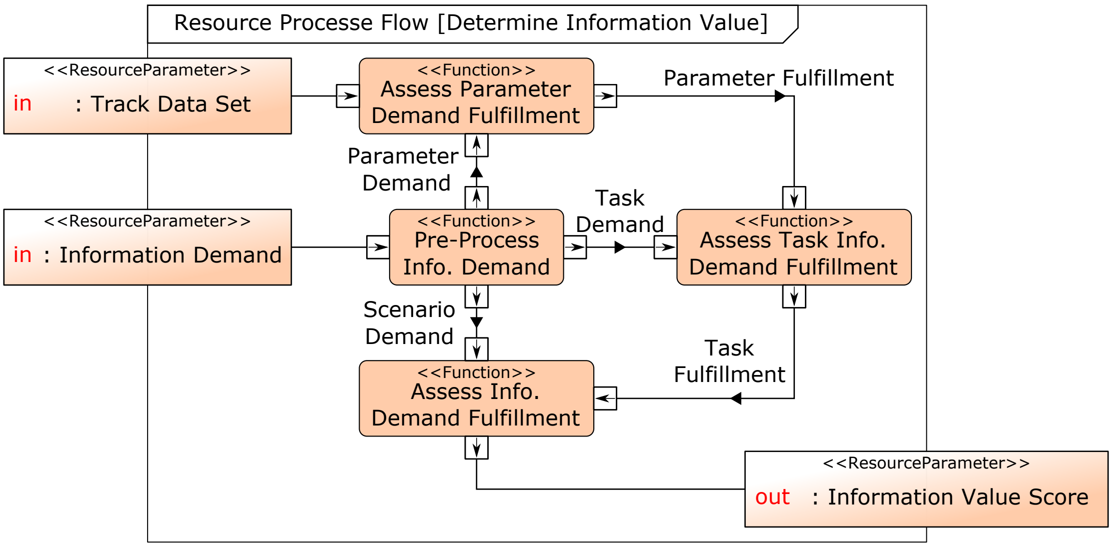


Figure 7.4.: *Information valuation process flow.*

Table 7.5.: *Information value model sub-functions.*

Function	Purpose
Assess parameter demand fulfillment	This function determines the degree to which the accuracy of a track parameter fulfills the accuracy demands imposed by a specific operational task linked to the tracked object.
Assess task information demand fulfillment	This function determines the degree to which the operational task's information demands are met.
Assess information demand fulfillment	This function calculates the value of an information set based on the degrees to which it fulfills the demands of all operational tasks.
Pre-process information demand	This function processes the information demand data and provides the demand-based input required by the other functions.

7.2.5. Task-Specific Parameter Quality Demand Fulfillment

The first assessment step determines if the accuracy of available track data fulfills the pilots' task-specific needs and wants on the track parameter level. This assessment is performed independently for every parameter accuracy demand in the information demand dataset. It aims to reduce the dimensionality of the input data into a value reflecting the probability of fulfilling the wanted and the needed accuracy demands. Figure 7.5 illustrates the parameter fulfillment assessment process.

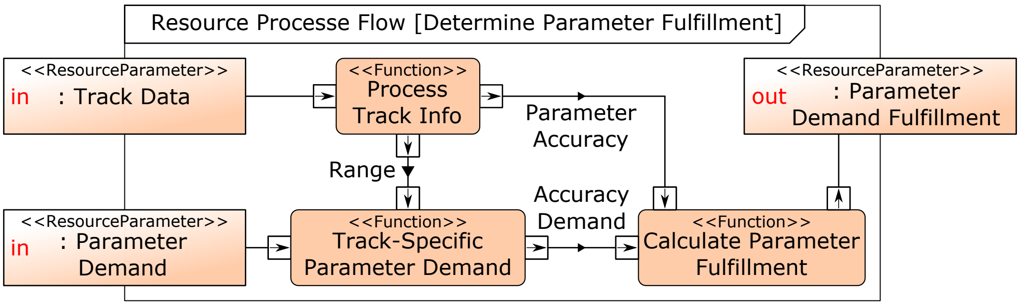


Figure 7.5.: *Process flow diagram for the parameter demand fulfillment assessment.*

7.2.5.1. Function Input and Output

The parameter-specific demand fulfillment comprises two assessment results that express the degree to which the needed and wanted parameter demands are fulfilled. These results are based on the parameter measurement quality and the provided parameter-specific demand based on the range-specific aggregated task demands described in chapter 4. Figure 7.6 illustrates the associations and composition links between the three main data elements handled by the parameter-level function.

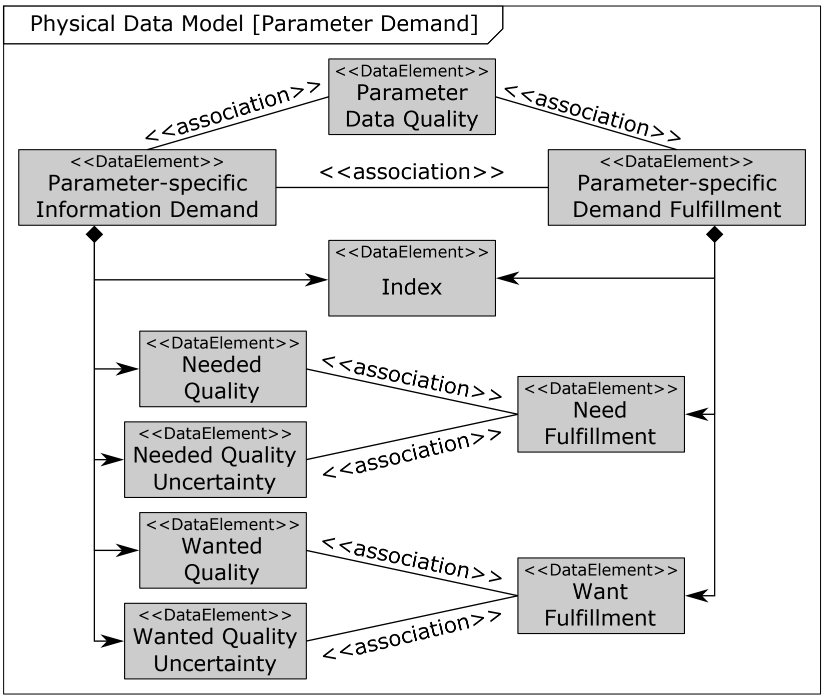


Figure 7.6.: *Parameter-specific demand fulfillment data inputs and outputs.*

7.2.5.2. Function Design Criteria

The inaccuracy value q_p can assume only positive real numbers, $q_p \geq 0, q_p \in \mathbb{R}$, with higher numbers representing a decrease in accuracy. Demand fulfillment F_p is limited to the real numbers between 0 and 1, $F_p \in [0, 1]$, with 1 representing complete fulfillment. An increase in accuracy should always lead to an increase in the fulfillment score, which requires the function to be monotonically decreasing, $\triangle f(x) \geq 0$. Decreasing accuracies beyond a certain point have a negligible impact on the utility of the data, e.g., the difference between a target's range uncertainty of 100km and 1000km does not matter to the pilot as both are way beyond the usable accuracy range. Likewise, increases in accuracy above a specific value have a marginal impact on the data's utility. Finally, the top-level requirement Top-4 requires a deterministic fulfillment function.

7.2.5.3. Parameter Demand Fulfillment Function

The aim of the function is to reflect the likelihood that a provided parameter fulfills the pilots' accuracy demand, which is encoded by two elements: the mean accuracy demand μ and the standard deviation σ. The demand fulfillment function can be viewed as the inverse cumulative likelihood of fulfilling the pilots' demands with increasing accuracy. The cumulative distribution function $F(x)$ is approximated by equation 7.1 for normal distributions, which is based on the error function $\operatorname{erf}(x)$.

$$F(x, \mu, \sigma) = \frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{x - \mu}{\sigma \cdot \sqrt{2}}\right)\right] \tag{7.1}$$

The demand fulfillment function is mirrored on the x-axis since this axis indicates the direction of growing uncertainty and, therefore, a reduction in the likelihood of fulfilling the pilot's demands. Equation 7.2 is used to transform a target's parameter accuracy q_p and the associated pilot demands $(q_{p,\mu}, q_{p,\sigma})$ into a unit-free fulfillment measure. The function is implemented in a Python script that calls the error function from python's SciPy package [289].

$$F_p\left(q_p, q_{p,\mu}, q_{p,\sigma}\right) = \frac{1}{2}\left[1 - \operatorname{erf}\left(\frac{q_p - q_{p,\mu}}{q_{p,\sigma} \cdot \sqrt{2}}\right)\right] \tag{7.2}$$

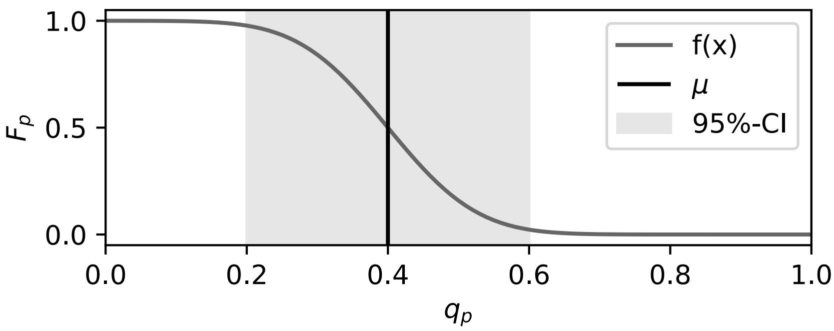


Figure 7.7.: *Fulfillment curve for a demanded accuracy with $q_{p,\mu} = .4$ and $q_{p,\sigma} = .1$.*

7.2.6. Task-Specific Information Demand Fulfillment

The task-specific demand fulfillment function determines the likelihood that a track with a provided track quality fulfills the pilots' information demands based on the fulfillment of the parameter-specific demands.

7.2.6.1. Function Input and Output

The task-specific demand fulfillment is driven by the specified information demand and the degree to which a given track data fulfills these demands on the parameter level. These fulfillment degrees can be aggregated to form an overall fulfillment degree for the pilots' needs and wants. Figure 7.8 illustrates the relationships between the data elements consumed and produced by the task-specific demand fulfillment function.

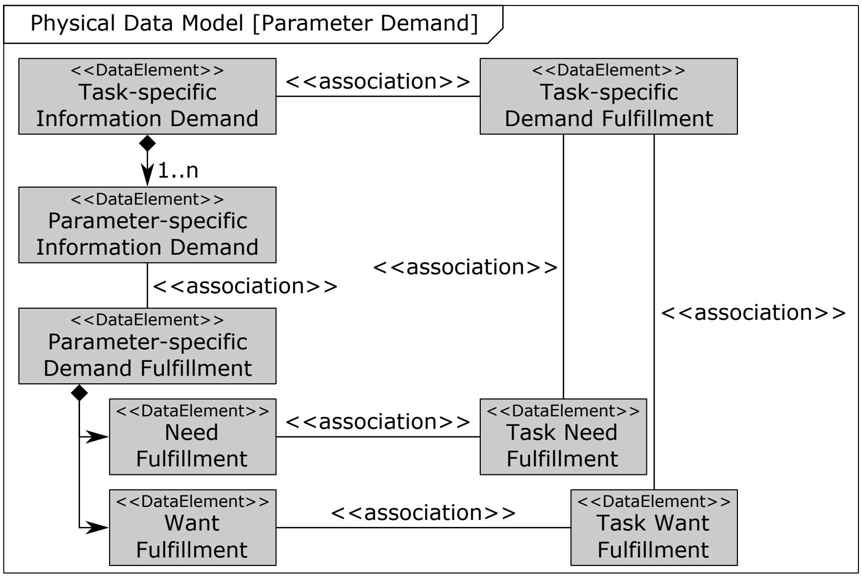


Figure 7.8.: *Parameter-specific demand fulfillment data inputs and outputs.*

7.2.6.2. Function Breakdown

The task-specific demand fulfillment determination is determined for the pilot's needs and wants, which are merged to provide the task demand fulfillment, as illustrated in figure 7.9.

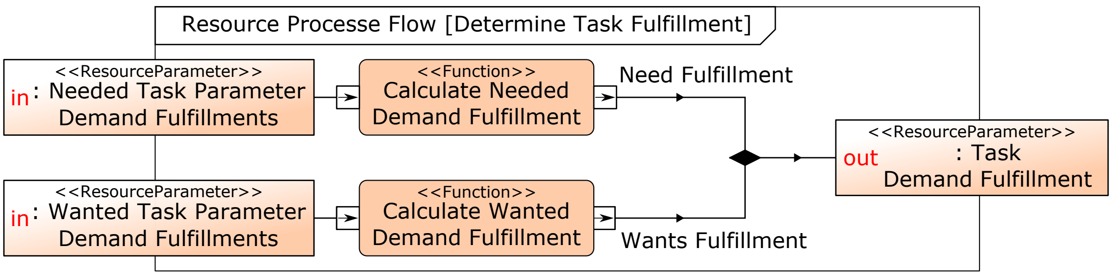


Figure 7.9.: *Process flow diagram for the task demand fulfillment determination.*

7.2.6.3. Function Design Criteria

The specific task demand fulfillment F_t is determined with the same equation for the pilot's needed parameter accuracy fulfillment and for their wanted parameter accuracy fulfillment. This specific demand is based on the parameter accuracy demand fulfillment $F^j_{p,i}$. If all parameter demands are fulfilled, then the specific task demand is fulfilled. Zero is returned if none of the parameter demands are fulfilled. The importance of all parameters can be assumed to be equal based on the study conclusion R1.2. The demand fulfillment function shall be strictly monotonically increasing.

7.2.6.4. Modeling Alternatives

Three simple task fulfillment function alternatives are postulated to fulfill the above-mentioned criteria.

Option A - Multiplicative fulfillment probability The first modeling alternative reflects the view that the fulfillment degree reflects the task demands' fulfillment likelihood and is the result of the product of all parameter fulfillment probabilities (equation 7.3).

$$F_t^A = \prod_{i=1}^{n_p} F_{p,i} \tag{7.3}$$

Option B - Mean The second modeling alternative determines the overall task demand fulfillment score by calculating the mean parameter fulfillment, as captured by equation 7.4.

$$F_t^B = \frac{1}{n_p} \sum_{i=1}^{n_p} F_{p,i} \tag{7.4}$$

Option C - Multiplicative inverse non-fulfillment probability The third alternative models the likelihood of a set of parameters not fulfilling the pilot's task demands and inverses this score to deliver the task fulfillment score, as defined by equation 7.5.

$$F_t^C = 1 - \prod_{i=1}^{n_p} (1 - F_{p,i}) \tag{7.5}$$

Figure 7.10 illustrates the task fulfillment score obtained for the three options for two parameter fulfillment scores.

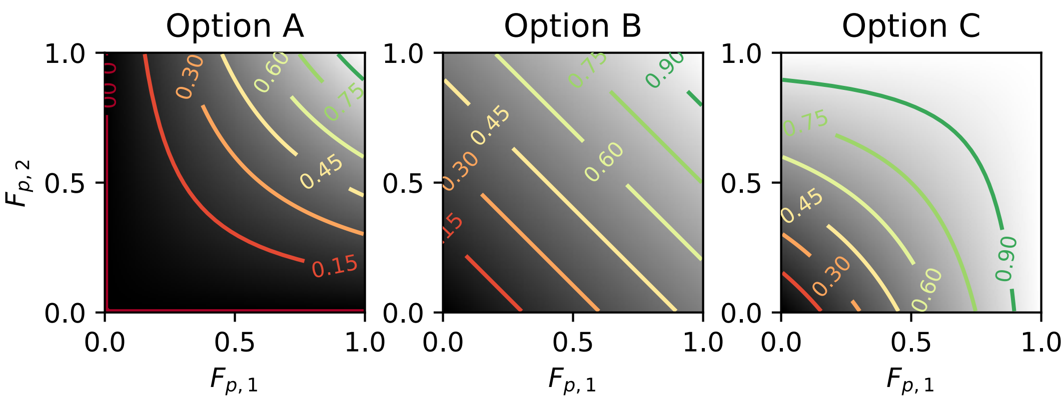


Figure 7.10.: *Task fulfillment map for two parameter fulfillment values $F_{p,1}$ and $F_{p,2}$.*

7.2.6.5. Modeling Alternative Selection

Figure 7.11 illustrates the impact of the parameter fulfillment function on the fulfillment scores calculated by the three alternatives. The large demand uncertainty is selected to highlight the accuracy range with changing fulfillment values.

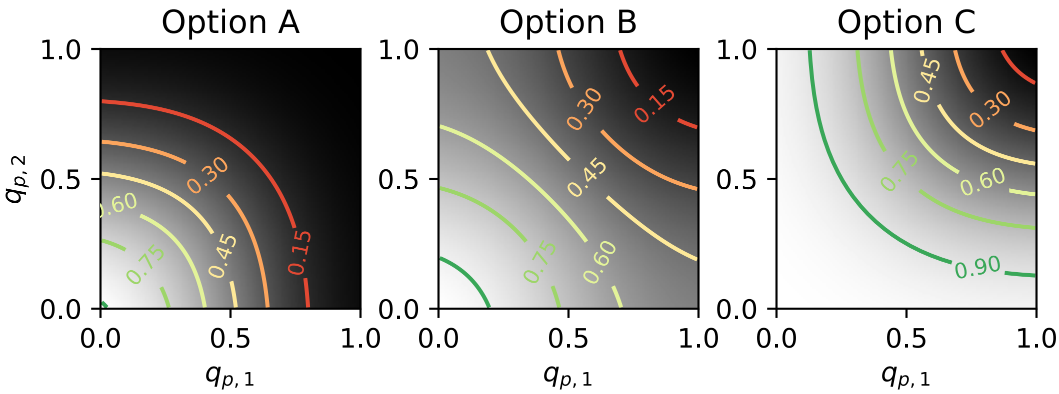


Figure 7.11.: *Task fulfillment map for two parameter quality values $q_{p,1}$ and $q_{p,2}$ with a demand defined by $q_{p,\mu} = .5$ and $q_{p,\sigma} = .3$.*

Table 7.6 illustrates the impact of higher dimensional task demands on the expected fulfillment score $E[\cdot]$ for any number of parameters n_p with a random fulfillment score. Increasing the number of considered parameter fulfillments leads to an exponential decrease in the task demand fulfillment score for Option A. The inverse relationship is observed for Option C, whose expected score tends towards 1 for high numbers of parameters. The expected score for Option B is not affected by the number of considered parameters.

Table 7.6.: *Mean task fulfillment score for the three alternatives for 100.000 randomly distributed parameter fulfillment scores as a function of the number of parameter n_p.*

Option	A	B	C
$E[\cdot]$	0.5^{n_p}	0.5	$1 - 0.5^{n_p}$

Option B is retained for the following reasons:

- Option B doesn't deliver a perfect score if one of the parameter demands is not fulfilled.
- Option B doesn't return zero if only one parameter doesn't fulfill the pilot's demands.
- Option B represents the middle-ground between a function that assesses the likelihood of fulfilling all demands, Option A, and Option C's likelihood of fulfilling any parameter demand.

An additional aspect to consider is the allocation of tasks to aircraft groups of 2 or more aircraft. Therefore, the task fulfillment function F_t^i must consider the ratio between the number of detected aircraft $n_{detected}$ and the group size n_{ac}.

$$F_t^i = \frac{n_{detected}}{n_{ac}} \frac{1}{n_p} \sum_{p=1}^{n_p} F_{t,p}^i \tag{7.6}$$

7.2.7. Scenario Information Demand Fulfillment

The scenario information demand fulfillment determines the overall value of information based on the fulfillment of the task-specific demands. The value of information is driven by its utility in achieving the mission goals, as discussed in section 3.1.2. Additional aspects that potentially impact the value of information are listed in table 7.7 but are disregarded for the scope of the research for the provided rationale.

Table 7.7.: *Effect of non-considered aspects on the value of information, the rationale behind the non-consideration, and required changes to consider the aspect.*

Aspect	Effect	Rational	Required Change
Information can overwhelm the user	-	HMI is not in scope	Add human resource cost function
Post-mission information exploitation	+	Focus on a moment in time	Add tasks and overall valuation trade-off
Additional need by friendlies	+	Focus on a single platform	Add tasks and overall valuation trade-off
Proactive information collection	+	Focus on main operator activities	Add baseline valuation function
Time-dependency	+/-	Focus on a moment in time	Add time-based function
Resource utilization	-	Focus on available information	Add information collection cost function

7.2.7.1. Function Input and Output

The final stage of the information valuation model returns calculated information values encoded into a single float number. The calculation is fed by a set of variables for each operator activity in the scenario: the task priority P_T, the needed demand fulfillment level F_T^N, and the wanted demand fulfillment level F_T^W.

7.2.7.2. Functional Design

The final valuation stage is split into two steps. First, the utility of fulfilling the operator's task demands to the level achieved by the provided information is determined for every operator activity. Secondly, the overall information value score is derived from the fulfillment utilities, as shown in figure 7.12.

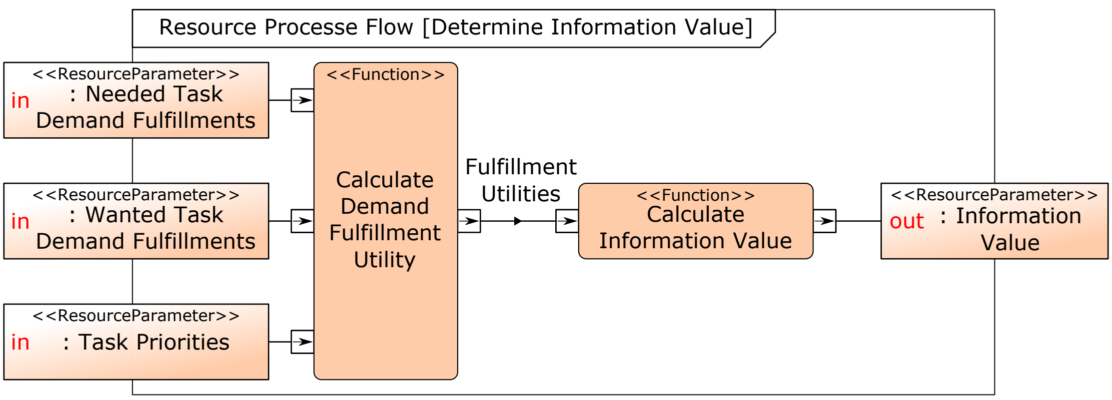


Figure 7.12.: *Process flow diagram for the information value calculation function.*

7.2.7.3. Task Fulfillment Utility

The *utility* provided by a good or a service refers to the satisfaction obtained from its consumption [249]. This satisfaction is subjective by nature for the consumption of information. Savage's subjective expected utility (SEU), described in section 2.3.4.1, models this subjective utility as the sum of all subjective probability-weighted utilities.

$$SEU = \sum_{i} p_i \cdot U_i \tag{7.7}$$

Applying SEU to the utility U_T of fulfilling a single task demand returns a weighted sum of subjective fulfillment probabilities p_i and fulfillment utilities $U_{T,i}$ for the needed and wanted task demands, as captured by equation 7.8.

$$U_T = p_N \cdot U_{T,N} + p_W \cdot U_{T,W} \tag{7.8}$$

Subjective Probabilities The subjective probability p_i is defined to be equal to the task demand fulfillment level F_T^i described in the previous section. A weighted subjective probability function can be used to modify the aggregated utility to over-weigh or under-weigh parts of the fulfillment level curve, e.g., under-weigh low fulfillment levels to account for subjective preferences as stipulated by Kahneman and Tversky's prospect theory [165]. This approach is not applied to the modeling in this research due to a lack of available data.

$$p_i := F_T^i \tag{7.9}$$

Utility Function The utility of fulfilling a specific task demand is determined by a function, which takes a single input parameter: the task's priority P_T. Both utility functions $U_{T,N}$ and $U_{T,W}$ are described by equation 7.10 at the abstract level. The weight w_i and function f_i can be tailored to reflect the specific utility.

$$U_{t,i} = w_i \cdot f_i\left(P_t\right) \tag{7.10}$$

The following assumptions are taken to drive the design of the task demand fulfillment utility functions:

- The relationship between wanted and needed demand fulfillment utilities is independent of the task's priority, leading to $f_W\left(P_t\right) = f_N\left(P_t\right)$.

- The utility of fulfilling a task demand grows exponentially with an increasing task priority, which is encoded by $f\left(P_t\right) = e^{a \cdot P_t}$ with a priority premium factor a.

The utility of fulfilling the task information demand to the levels F_t^N and F_t^W for a task priority P_t is determined by the following equation:

$$U_t = \left(F_t^N \cdot (1-b) + F_t^W \cdot b\right) \cdot e^{a \cdot P_t} \tag{7.11}$$

The selection of the two degrees of freedom, a and b, is discussed in section 7.4.2.

7.2.7.4. Information Value

The value of information is driven by its utility in achieving the mission goals and is based solely on the utility of fulfilling tasks demands for the scope of this research. Assuming no interactions between the calculated task demand fulfillment utilities, the additive multi-attribute utility model as described by Torrance et al. [162] can be applied to determine the overall value of an information set based on its task-based utility, as encoded by equation 7.12. This assumption is based on the assumption that experts focus on the differences when comparing information sets and ignore information elements that have the same accuracy in both sets.

$$V_I = \sum_{t=1}^{n_T} U_t \tag{7.12}$$

7.2.8. Information Model Summary

The value V_I of an information set is the sum of all task demand fulfillment utilities U_t (equation 7.12). This utility is driven by the task's priority P_t, the fulfillment level F_t^W of wanted information demands, and the fulfillment level F_t^N of needed information demands. The utility function has two degrees of freedom, a and b.

$$U_t = \left(F_t^N \cdot (1-b) + F_t^W \cdot b\right) \cdot e^{a \cdot P_t} \tag{7.13}$$

The parameter a reflects the premium associated with the tasks' priority. This parameter can be linked to a factor x with which the maximum utility of a task with the priority P_2 is multiplied to match the utility of a task with a higher priority P_1, as shown in equation 7.14. The premium a can thus be expressed as a function of the multiplication factor and the two priorities (c.f. 7.15).

$$x \cdot e^{a \cdot P_2} = e^{a \cdot P_1} \tag{7.14}$$

$$a = \frac{\ln x}{\Delta P_t} \tag{7.15}$$

The information demand fulfillment level F_t^i for a task t and a demand type i is defined as the mean fulfillment level for parameter-specific information demands $F_{t,p}^i$. A ratio is applied to account for the number of detected aircraft associated with the task.

$$F_t^i = \frac{n_{detected}}{n_{ac}} \frac{1}{n_p} \sum_{p=1}^{n_p} F_{t,p}^i \tag{7.16}$$

The parameter-specific information demand fulfillment level $F_{t,p}^i$ is inferred from the parameter accuracy q_p and the demanded accuracy, defined by a mean accuracy demand $q_{t,p,\mu}^i$ and standard deviation $q_{t,p,\sigma}^i$.

$$F_{t,p}^i = \frac{1}{2}\left[1 - \operatorname{erf}\left(\frac{q_p - q_{t,p,\mu}^i}{q_{t,p,\sigma}^i \cdot \sqrt{2}}\right)\right] \tag{7.17}$$

7.3. Data Analysis

The designed information model is analyzed to assess the impact of the task fulfillment utility's parameters and the validity of the following hypotheses:

H_0^J: Domain experts do not prefer information sets with higher information value scores in pair-wise comparisons.

H_0^K: The difference in information value between two information sets collected from the same environment has no effect on the aggregated preferential choice uncertainty.

The assessment is split into three parts, as illustrated in figure 7.13. First, the performance of the information value model is assessed for a range of model parameter values. Then, the results are analyzed to assess the impact of the model parameters x and b. Finally, a set of parameters is selected to investigate the results further and determine the validity of the study's hypotheses.

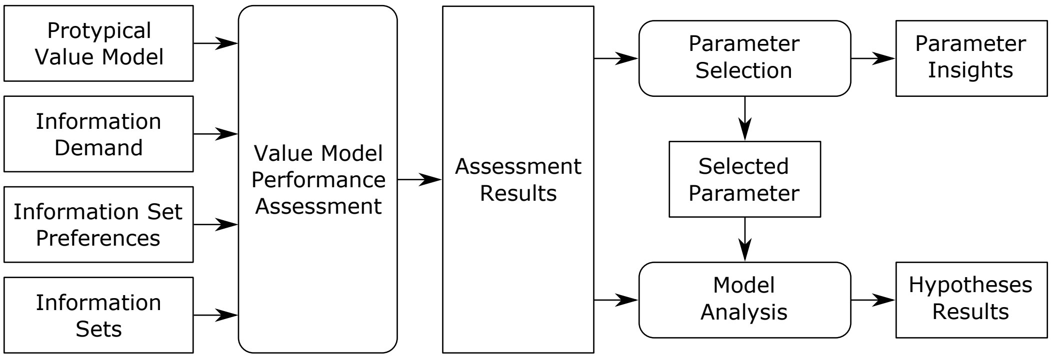


Figure 7.13.: *Overview of model analysis steps.*

7.3.1. Model Performance Assessment

The model performance is assessed for an equally-spaced set of 2000 parameter samples from the following intervals: $x \in [1, 20]$ and $b \in [0, 1]$. A finer grid spacing is used to collect a detailed model performance for the regions defined by $x \in [1, 3]$ and $b \in [0, 1]$, with 1000 samples in each dimension. The validation basis is based on the collected expert preferences described in chapter 6. These preferences are provided for a set of pair-wise comparisons. The option selected by most experts is defined as being selected. A confidence score for this selection is calculated through equation 7.18 based on the ratio of experts selecting the specific option i. Comparisons with a confidence level higher than 50% are retained to assess the overall model score.

$$c_i = 2 \cdot \frac{n_i}{n_p} - 1 \tag{7.18}$$

The model's performance is captured by the score s based on the confidence-weighted sum of correct guesses (c.f. eq. 7.19). The weighing is introduced to favor the correct prediction of expert preferences in comparisons with higher selection confidence.

$$s = \frac{\sum_i^n c_i \cdot \delta_i}{\sum_i^n c_i}, \delta_i \begin{cases} 1 & \text{if correct prediction for comparison } i \\ 0 & \text{else} \end{cases} \tag{7.19}$$

7.3.2. Parameter Selection

The model performance score is based on a set of binary comparisons for a discrete set of parameter values, which results in the lack of a single optimal performance point in the x-b plane. Selecting a single value for the priority premium x and the demand type ratio b is needed for subsequent model performance assessments. The optimum parameter configuration is defined for this step as the optimal region's center of gravity. Figure 7.14 illustrates the process of selecting the optimum parameter configuration for a 6x8 grid.

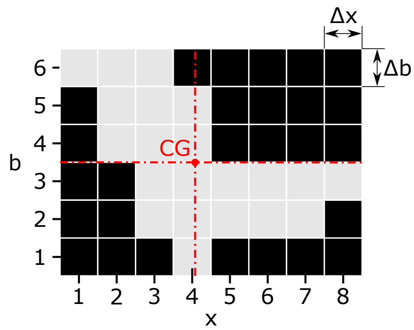


Figure 7.14.: *Illustration of the geometry-based optimum point selection.*

The optimal parameter settings are determined by the weighted average of the region's cell's coordinates in the x-b plane. Equations 7.20 and 7.21 determine the optimum's location based on the number of cells n_i achieving the peak performance at the coordinates x_i and b_i, respectively.

$$x_{avg} = \frac{\sum_i^{n_{columns}} n_i \cdot x_i}{\sum_i^{n_{columns}} n_i} \quad (7.20) \qquad b_{avg} = \frac{\sum_i^{n_{rows}} n_i \cdot b_i}{\sum_i^{n_{rows}} n_i} \quad (7.21)$$

7.3.3. Model Analysis

The following three aspects are analyzed: the model's ability to match the experts' preferences, the relation between the selection uncertainty and the information values, and the impact of the latter on the model's selection performance.

7.3.3.1. Expert's Preferences Match

The ratio of correctly selected information sets reflects the model's ability to match the expert's preferences. This hit rate is determined as a function of the selection confidence lower limit.

7.3.3.2. Correlation between the information value delta and selection confidence

Hypothesis H_0^K is tested through a t-test to assess the correlation between the difference in information value and the confidence in the experts' preferences.

7.3.3.3. Impact of the Information Value Delta on Performance

The information value delta's impact on the model performance is analyzed by plotting the model's hit rate against the difference in information value between the options of a comparison. Further, the information delta required to achieve a perfect hit rate is determined as a function of the selection confidence limit.

7.4. Results

This section reports the results obtained through the previously described model assessment.

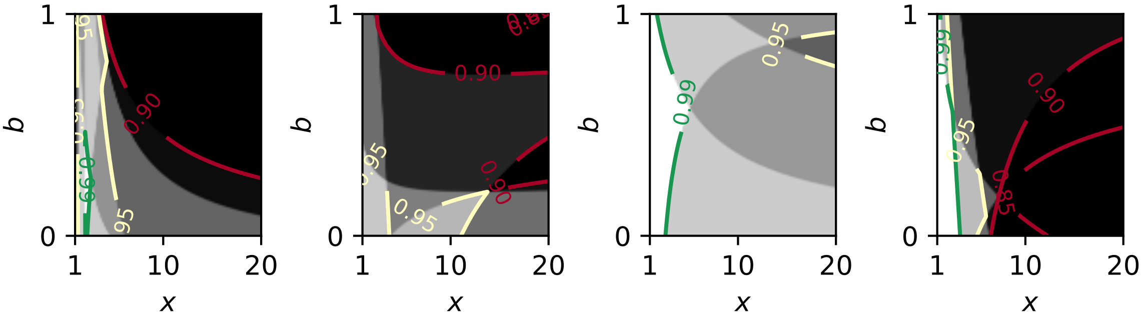
7.4.1. Model Performance Assessment

Table 7.8 lists the highest and lowest achieved scores for the set of points in the x-b plane defined by the intervals $x \in [1, 20]$ and $b \in [0, 1]$ for each snippet. The model achieves a perfect score for all snippets except snippet 612. None of the selected parameter pairs achieved a score lower than 0.78.

Table 7.8.: *Model performance score limits.*

Limit	Overall	423	612	634	721
Min	0.8856	0.8768	0.7795	0.9368	0.8437
Max	0.9947	1	0.9781	1	1

The model performance score as a function of the utility parameter x and b are shown for each snippet in figures 7.15a to 7.15d. A small decrease in the score is observed for increasing values of the priority premium x for all snippets. The same relationship is visible in figure 7.16 for the model's overall performance score.



(a) *423* (b) *612* (c) *634* (d) *721*

Figure 7.15.: *Snippet performance score as a function of the utility variables x and b.*

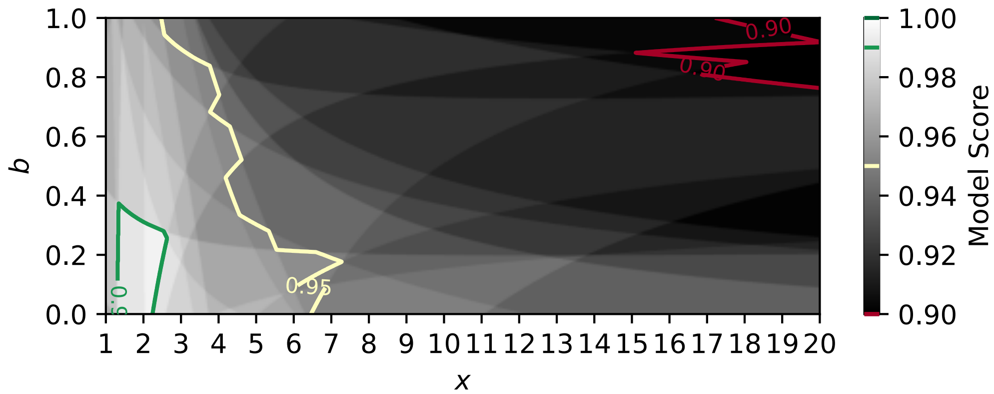


Figure 7.16.: *Model performance score as a function of the utility variables x and b for all information set comparisons.*

7.4.2. Parameter Selection

Table 7.9 lists the calculated center of gravity of the regions of the x-b plane achieving the highest model score. The region's priority premium center is located between 1.8602 and 2.3038, and the demand type weight center is located between 0.1551 and 0.4825. Over all information set pair-wise comparisons, the center of the high-score region is located at $x_c = 2.2478, \quad b_c = 0.1711$.

Table 7.9.: *Center of gravity coordinates of the snippet's optimality regions.*

Parameter	Symbol	Overall	423	612	634	721
Score	s	0.9947	1	0.9781	1	1
Priority Premium	x	2.2478	2.2333	2.1807	2.3038	1.8602
Demand Type ratio	b	0.1711	0.2133	0.1551	0.4825	0.3739

Figure 7.17 shows the center of the high score region for each snippet in relation to the location of the overall center's location. The largest deviation in the center's position from the overall center is observed for snippet 634 in the b-direction and for snippet 721 in the x-direction.

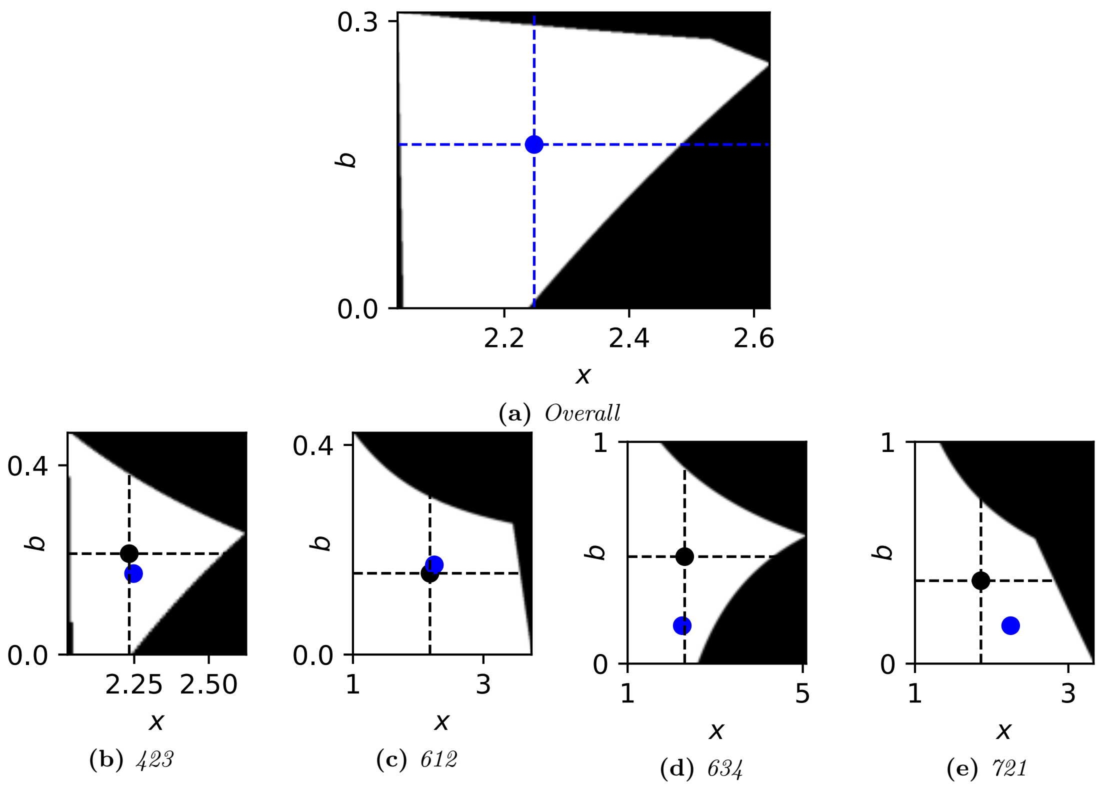


Figure 7.17.: *Region of highest score for all comparisons and per snippet.*

Based on the overall results, the utility function's parameters are set to the following values:

$$x_{Model} := 2.25, \quad b_{Model} := 0.17$$

7.4.3. Model Analysis Results

This subsection lists the results obtained by analyzing the model with the previously selected utility-function parameter values.

7.4.3.1. Expert's Preferences Match

The model has a 100% hit rate for comparisons with a preference confidence score above 0.65 (n=112), meaning that at least 18 out of 21 experts preferred one set over another. Considering all comparisons, the model selects the option preferred by the majority of experts in 93% of all comparisons (n=201).

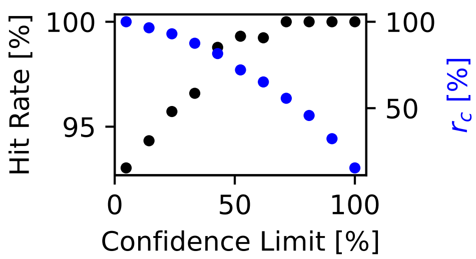


Figure 7.18.: *Model hit rate and comparison retention ratio r_c as a function of the selection confidence limit.*

7.4.3.2. Uncertainty Correlation

The uncertainty in the domain matter expert's preference between two information sets is strongly related to the absolute difference between the information sets' calculated information value ($r = -17.97$, $p < .0001$, $n = 201$).

7.4.3.3. Impact of the Information Value Delta on Performance

The model achieves a perfect hit rate for comparisons between information sets with a large difference in information value scores. Figure 7.19 illustrates this effect for a set of comparisons with an expert selection confidence score over 50%. The information value difference limit for a perfect hit rate decreases with increasing confidence values, as illustrated in figure 7.20.

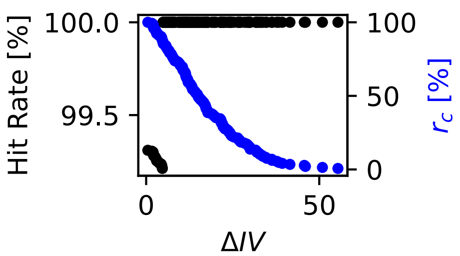


Figure 7.19.: *Hit rate as a function of the information value delta for $c_i \geq 50\%$.*

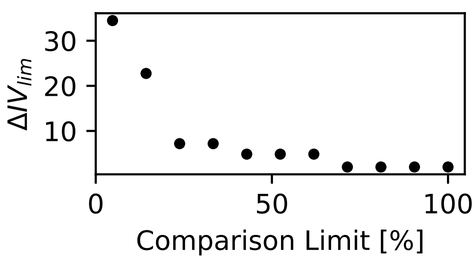


Figure 7.20.: *Information value delta limit for a perfect hit rate as a function of the selection confidence limit.*

7.5. Discussion

The results of the study show a high model score for all combinations of utility parameter settings in the intervals $x \in [1, 20]$ and $b \in [0, 1]$, with a minimum score of 0.89 and a maximum score of 0.99 for all information set comparisons with a confidence rating higher than 50%. The center of the highest score is located at $x_c = 2.25$ and $b_c = 0.17$.

A model with the parameter set to x_c and b_c achieves a 93% match with the expert's information set preferences for all comparisons and 100% for comparisons with a selection confidence level over 65%. The hit rate is higher for comparisons with a larger difference in the calculated information value scores. The expert's confidence score shows an inverse relationship with the delta in information value.

7.5.1. Result Interpretation

Parameter Selection The selected utility parameter represents the scenario in which fulfilling the needs of a task with a priority equal to 100 provides more than twice the value of fulfilling the demands associated with a task receiving a priority equal to 75. With these settings, fulfilling the needed demands provides 83% of the utility.

Expert Preferences The null hypothesis H_0^J is rejected based on the observation that experts preferred the option with the highest information value between 93% and 100% of cases.

Expert Selection Uncertainty The null hypothesis H_0^K is rejected on the basis that the difference in information value of two information sets is lowest for comparisons with a high degree of expert preference uncertainty.

7.5.2. Result Implications

The results indicate a good match between the model's calculated information value contained in sensor data sets and the preferences of domain experts in pair-wise comparisons. Information valuation can thus be considered as an option for the reward function of a sensor management system and can support the targeted capture of expert preferences.

7.5.3. Model Limitations

The small differences in the model score for the tested utility function parameter settings do allow for a confident selection of the utility function's parameter. Additionally, the model does not address the correlation between the fulfillment level of wanted data accuracies and the fulfillment level of needed parameter accuracies. Finally, the model is only assessed for a single mission goal, and the results can thus not be assumed to be applicable to other mission settings.

7.6. Conclusion

The study offers a first iteration of an information value model based on operator needs, which can be refined to serve as a reward function for a sensor management system. Domain experts have shown a preference for information sets that is reflected by the set's information value.

Further research is required to address the gaps observed in the research. The following studies are recommended:

1. Compare additional information sets for the same snippets as in the conducted research, with a focus on sets with a small information value delta. This will support the assessment of the model's sensitivity.
2. Assess the model on additional snippets to determine the model's applicability to the operational context.
3. Assess the model for a different set of missions to determine if the model needs to be adapted for these mission settings.
4. The information's value is expected to decay with time, and the model should be expanded to accommodate this aspect of the value of information, e.g., by following a method similar to the present value calculation.

8. Research Result Discussion

This chapter reviews the concept of information value, the results of the conducted research studies, and the developed information model. It highlights the link between the results and the theoretical and technical background provided in Chapter 2. Further, the chapter discusses the studies' implications and limitations.

8.1. Information Value Definition

The research defined the value of information as its ability to fulfill the pilots' prioritized information needs. Figure 8.1 illustrates the information demand and supply sides of the information value metamodel. The system functions supply information about the current state of the environment through the capture of data elements. The amount of information a data element carries depends on the data's quality. Operational activities drive the demand for information. The priority of fulfilling these information needs derives from the activities priority resulting from the mission goals priority.

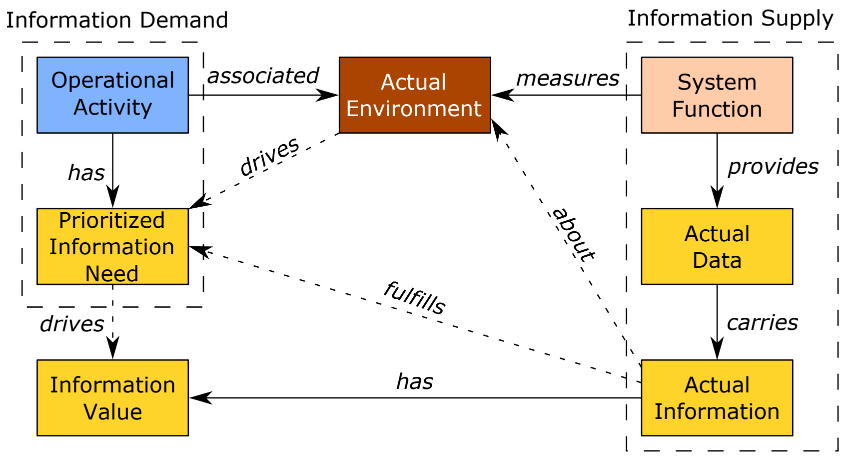


Figure 8.1.: *Metamodel of the information demand and supply-driven concept of information value.*

The values definition refines Brown and Sukkarieh's [70, p. 2] concept of information value as "the extent to which knowing the information helps achieve a mission" by drawing a clear link between the provided data and the operational goals. In the research context, the term information follows the information-as-knowledge definition, and the term data reflects the information-as-thing definition provided by Buckland [244].

The information value definition follows Porter's [247] definition of value-in-use and rejects the labor-driven value theories by Adam Smith [248], Ricardo [250], and Marx [252]. It aligns with Jevon's [254] theory of subjective value and follows Tsoulfidis' [249, p. 157] definition of utility as "the satisfaction that an individual derives from the consumption of a good" attributed to the neoclassical school of economics.

8.2. Expert Knowledge Exploitation

The joint study captured data accuracy demands, prioritized tasks, and expert preferences used to test the nine hypotheses in table 8.1. All hypotheses were rejected except for H_0^F, for which the data collected was insufficient to accept or reject the hypothesis conclusively.

Table 8.1.: *Results of the information demand and expert preference analysis.*

ID	Hypothesis	Result
H_0^A	There is no consensus between experts on the target parameter information demanded to perform an operator task.	Rejected
H_0^B	The operators' target parameter accuracy demands are of equal importance.	Rejected
H_0^C	The information accuracy demanded by domain experts to fulfill their task does not decrease monotonically with increasing target range.	Rejected
H_0^D	There is no consensus between experts on the tasks they associate with a target.	Rejected
H_0^E	The association of operator tasks with target does not allow for the segregation of these tasks into distinct range classes.	Rejected
H_0^F	The operators' task's information demand is not constant within the span of the associated target's ranges.	N/A
H_0^G	The priority of tasks associated with a target has no effect on the target's priority.	Rejected
H_0^H	There is no consensus between the experts' information set preferences.	Rejected
H_0^I	The confidence expressed by domain experts choosing between information sets has no relationship with the preferential choice agreement.	Rejected

While H_0^B is rejected because the parameter importance differences were statistically significant, these differences are insignificant for modeling the information value since all parameters received a high importance rating. The following conclusions were drawn from the knowledge elicitation results about the design of a prototypical information value model:

1. The information value model should be able to accommodate the uncertainty of the aggregated demand.
2. The importance of demanded parameter is insignificant for the research use cases.
3. The information valuation model should feature a range-dependent data accuracy demand function.
4. The model should consider the interactions between tasks and their timeline.
5. The information valuation can disregard the group priority if task priorities are provided.
6. The model should provide a measurable criterion for selecting information sets in pairwise comparisons.
7. The information valuation should be limited to the tracking quality, as data on the search task is not explicitly part of the preference elicitation.

8.3. Operational Information Value Modeling

The review of the literature and the conclusions drawn from the knowledge elicitation studies led to the capture of 16 requirements for an information value model applied in the research use case. The model's architecture comprises three modules that process information sets at the parameter level, the task level, and the overall scenario. An additional module processes the captured information value into the inputs required by the evaluation modules. The decomposition simplifies the development of dedicated solutions for demand fulfillment assessment at three levels: parameter accuracy demand fulfillment, track accuracy fulfillment, and information value. The model design process followed Maguire's [210] human-centered design cycle and considered human factors.

Valuation Functions

The value V_I of an information set is the sum of all task demand fulfillment utilities U_t.

$$V_I = \sum_{t=1}^{n_T} U_t \tag{8.1}$$

The task's priority P_t and the two fulfillment levels, F_t^W and F_t^N, drive the task demand fulfillment utility U_t. The utility function has two degrees of freedom, a and b.

$$U_t = \left(F_t^N \cdot (1-b) + F_t^W \cdot b\right) \cdot e^{a \cdot P_t} \tag{8.2}$$

The information demand fulfillment level F_t^i for a demand type i is defined as the mean fulfillment level for parameter-specific information demands $F_{t,p}^i$. A ratio is applied to account for the number of detected aircraft associated with the task.

$$F_t^i = \frac{n_{detected}}{n_{ac}} \frac{1}{n_p} \sum_{p=1}^{n_p} F_{t,p}^i \tag{8.3}$$

The parameter-specific information demand fulfillment level $F_{t,p}^i$ is inferred from the parameter accuracy q_p, the mean accuracy demand $q_{t,p,\mu}^i$, and the standard deviation $q_{t,p,\sigma}^i$.

$$F_{t,p}^i = \frac{1}{2}\left[1 - \operatorname{erf}\left(\frac{q_p - q_{t,p,\mu}^i}{q_{t,p,\sigma}^i \cdot \sqrt{2}}\right)\right] \tag{8.4}$$

Model Discussion

The priority premium $a \coloneqq \frac{\ln 2.25}{25}$ indicates that fulfilling the information demands of tasks with a priority score equal to 100 could be more as twice as important than fulfilling the informational demands of a task with a priority equal to 75. The calculated demand ratio parameter value $b \coloneqq 0.17$ indicates that over 80% of the information value stems from fulfilling the operator's needs, and the remaining value is obtained from fulfilling his additional wants. These results from the parameter sensitivity analysis do not provide a definitive answer selecting the priority premium a and the demand ratio b due to the minor performance differences.

The value function falls into the normative decision-making theory since it assumes that the pilots prefer information sets that result in the best outcome.

8.4. Prototypical Model Performance Assessment

The results indicate a good match between the model's calculated value of the information in sensor data sets and the preferences of domain experts in pairwise comparisons, with a 93% match for all information set comparisons. This hit rate increases to 100% for comparisons with a low selection uncertainty in the experts' preferences. Therefore, a strong negative correlation between the difference in information value and the experts' selection uncertainty is observed.

The two null hypotheses listed in table 8.2 and linked to the relationship between the information value and the experts' preferences have been rejected. Information valuation can thus be considered as an option for the reward function of a sensor management system and can support the targeted capture of expert preferences.

Table 8.2.: *Results of the model performance assessment.*

ID	Hypothesis	Result
H_0^J	Domain experts do not prefer information sets with higher information value scores in pair-wise comparisons.	Rejected
H_0^K	The difference in information value between two information sets collected from the same environment has no effect on the aggregated preferential choice uncertainty.	Rejected

8.5. Research Implications

The presented research provides a generic model for the value of information carried by a set of data elements and the main implications of the study's results are listed below.

Sensor Management Systems The results indicate a good match between the model's calculated value of the information in sensor data sets and the preferences of domain experts in pairwise comparisons. Information valuation is an option for the reward function of a sensor management system. It can support the targeted capture of expert preferences for developing these reward functions.

Model Adaptability The calculated information value is system-independent and is compatible with different types of sensors and platforms. Additionally, the model is not designed for a specific mission and can accommodate any information-processing scenario. Finally, the modular approach supports an iterative improvement of the valuation model.

Flight Deck Operations A sensor management system based on the information value model put forward in this research could reduce the complexity of the pilots' system management activities while keeping them in the loop and enabling them to retain excellent situational awareness.

8.6. Research Limitations

Several aspects limit the research results' generalizability and require additional research to transform the information value model into a reward function for sensor management applications. The main limitations are listed below:

Narrow Use Case
The results of the study are limited to the narrow scope of the research's use case which covers a single air-to-air mission type and mission phase. This scope covers only a small fraction of a modern fighter jets mission roles. Additionally, the operational and functional analysis are focused on operations performed by a single aircraft.

Small Sample Size
The information demand survey data collected from a few experts that are members of the small population of German fighter pilots. The same limitation applies to the capture of task assignments and information set preferences.

Interval-based Data
Pilots provided their accuracy demands for limited range intervals, with their responses showing an explicit range dependency. A constant demand within a specified interval can thus not be assumed. Requesting pilots to provide their demands for every foreseeable object range is not feasible, and the shape of the demand over the range can only be guessed based on the available data.

Demand type correlation
The model does not address the correlation between the fulfillment level of wanted data accuracies and needed parameter accuracies.

Utility Function Parameter
The minimal differences in the model score for the tested utility function parameter settings do not allow for a confident selection of the utility function's parameter.

Search Task
The informational valuation does not consider the value delivered by the sensors' search task performance due to limitations in the research's setup. Future iterations of the model should consider the impact of the scanning performance.

Time-dependency
The information value is determined for a single point in time and does not reflect the dynamic nature of sensing operations, e.g., the value of information can decay with time.

Despite these limitations, the research nonetheless delivers a valid method for evaluating information for sensor management operations.

9. Conclusion

This thesis describes the engineering perspective of a multi-disciplinary research project and provides a modeling method for the operational value of information based on the operators' tasks.

9.1. Research Achievements

The research answers how to specify the operational value of information for sensor management applications and delivers the following research achievements:

Information Value Definition

The study defines the operational value of information as the information's ability to fulfill the pilots' needs. This definition follows Porter's [247] definition of value-in-use and aligns with Jevon's [254] theory of subjective value.

Expert Knowledge Exploitation

The joint study captured three sets of expert knowledge:

1. Task-specific data accuracy demands for nine pilot activities.
2. Prioritized tasks associated with objects in 24 scenario snippets.
3. Expert preferences in 201 pairwise information set comparisons for four scenario snippets.

Operational Information Value Modeling

The review of the literature and the conclusions drawn from the knowledge elicitation studies led to the capture of 16 requirements for an information value model applied in the research use case. The model's architecture comprises three modules that process information sets at the parameter level, the task level, and the overall scenario level.

Prototypical Model Performance Assessment

The prototypical implementation of the information value model matches expert preferences to 93% for all information set comparisons. This hit rate increases to 100% for comparisons with a low uncertainty in the expert's selection preferences.

9.2. Research Contribution

Modeling the operational value of information addresses the identified short-comings of reviewed approaches by providing an explicit reward function for sensor management applications based on the operators' mission-specific needs. It measures the data quality's impact on the pilots' ability to achieve the mission goal. Further, the model accommodates all current and future mission roles. The performed research advances the knowledge of specifying the right optimization objective for complex systems and integrates the human component in the development process. Additionally, this research showcases the benefit of multi-disciplinary collaboration that harnesses the strengths of multiple scientific disciplines and opens future research avenues.

9.3. Future Work Recommendations

The information value model developed in this research provides researchers and engineers with a tool that can be refined, expanded, and implemented in future studies and systems. Interesting and valuable avenues of future research are listed below.

Model refinement The model described in the thesis is a first iteration and should be refined to improve the model's design. One point worth investigating is the aggregation of multiple demand types into a single demand curve.

Reinforcement learning model The manual selection of test cases examined by pilots is suboptimal, and the integration of study results into the model could be faster. Implementing a reinforcement learning approach promises to speed up the model refinement process.

Additional use cases The conducted research focused on a single air-to-air use case. Assessing the value model design for additional use cases will test the assumption that the modeling approach can accommodate all fighter roles.

Additional types of information The model values only information about the groups present in the operational environment. Sensor data, or the lack thereof, can carry additional information, e.g., that there are no objects in a scanned region that can have a high operational value. Expanding the value model to cover additional information will improve its fit for sensor management applications.

Data acquisition cost model The model does not consider the cost associated with capturing environmental information. This aspect is critical for the optimal management of sensor systems, and a cost function is needed to account for the limited resources. Additionally, the model should incorporate the added value of on-platform data capture.

Information demand prioritization model The current implementation of the information value model relies on externally provided task priorities. An additional model component covering the link between the mission goals and the task priorities can reduce the data required to feed the model.

Operational activity-driven sensor management The information value model provides a reward function for sensor management systems that controls an aircraft's sensors based on the pilot's operational activities and mission objectives. Comparing the performance of such a system against existing sensor management reward functions can measure the value of incorporating expensive expert knowledge into the technical system.

Cross-platform information valuation Fighter pilots do not operate in isolation and share information with other platforms. Research into the value of information for the participants at the tactical, operational, and strategical levels can expand the practical uses of the information value model.

General-purpose assessment The information value model design allows for its implementation in all information processing applications. Research into the value of information in economics is a promising future research avenue.

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C. J. Carey, İ. Polat, Y. Feng, E. W. Moore, J. VanderPlas, D. Laxalde, J. Perktold, R. Cimrman, I. Henriksen, E. A. Quintero, C. R. Harris, A. M. Archibald, A. H. Ribeiro, F. Pedregosa, P. van Mulbregt, and SciPy 1.0 Contributors, "SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python," *Nature Methods*, vol. 17, pp. 261–272, 2020.

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A. Theoretical and Technical Background Annex

A.1. Air Force Goals

This section lists the air force goals that were identified by McIntyre [21].

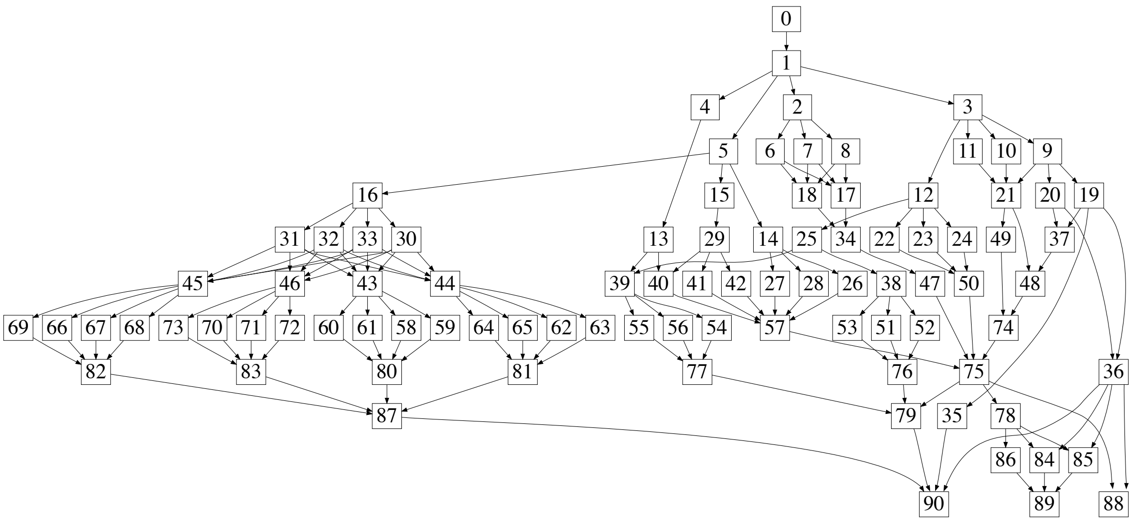


Figure A.1.: *Air Force Goals Lattice, adapted from [21]*

Table A.1.: *U.S. Air Force Goals [21]*

Goal Number	Goal
0	compel adversary to due our will
1	achieve control of the air
2	deny enemy freedom to carry out offensive operations
3	obtain and maintain air superiority
4	allow friendly forces to perform their mission
5	control tempo of battle operations
6	defend lines of communication
7	protect bases
8	protect forces
9	minimize losses
10	minimize personnel losses
11	minimize weapons expenditure
12	seize the initiative
13	protect friendly aircraft

Continued on next page

Table A.1 – continued from previous page

Goal Number	Goal
14	neutralize units not yet engaged
15	support surface forces in the surface battle
16	reduce ability of enemy plan and control units and tempo
17	destroy aircraft trying penetrate airspace
18	destroy enemy aircraft trying attack friendly forces
19	avoid own detection
20	minimize fuel usage
21	minimize uncertainty about environment
22	destroy the enemy's will
23	neutralize enemy's will
24	disrupt enemy's will
25	negate surface based enemy air defenses
26	delay units not yet engaged by land forces
27	disrupt units not yet engaged by land forces
28	destroy units not yet engaged by land forces
29	create opportunities for maneuver or advance of friendly forces
30	divert combat and logistic assets to defend routes
31	delay buildup of enemy combat strength
32	degrade efficiency with which enemy assets can be used
33	deny enemy mobility
34	destroy threatening enemy aircraft
35	navigate
36	avoid threats
37	plan route
38	negate enemy SAM air defense
39	negate enemy AAA air defense
40	protect the flank of friendly forces
41	blunt enemy offensive maneuvers
42	protect the rear of surface forces
43	destroy enemy potential
44	disrupt enemy potential
45	divert enemy potential
46	delay enemy potential
47	intercept threatening enemy aircraft
48	maintain currency of enemy's order of battle
49	assess state of enemy readiness
50	neutralize enemy aerospace forces
51	neutralize SAM air defense
52	degrade SAM air defense
53	destroy SAM air defense
54	neutralize AAA air defense
55	degrade AAA air defense
56	destroy AAA air defense
57	target particular enemy equipment
58	destroy enemy surface forces

Continued on next page

Table A.1 – continued from previous page

Goal Number	Goal
59	destroy enemy movement networks
60	destroy enemy C3 networks
61	destroy enemy combat supplies
62	disrupt enemy surface forces
63	disrupt enemy movement networks
64	disrupt enemy C3 networks
65	disrupt enemy combat supplies
66	delay enemy surface forces
67	delay enemy movement networks
68	delay enemy C3 networks
69	delay enemy combat supplies
70	divert enemy surface forces
71	divert enemy movement networks
72	divert enemy C3 networks
73	divert enemy combat supplies
74	collect intelligence
75	engage enemy targets
76	physically attack SAM air defense
77	electronically attack AAA air defense
78	identify all detected targets
79	detect threats
80	target a particular enemy surface force
81	target a particular enemy movement network
82	target a particular enemy C3 network
83	target particular enemy combat supplies
84	identify enemy targets
85	identify neutral targets
86	identify friendly targets
87	detect a enemy ground target
88	track all detected targets
89	identify targets
90	search for enemy targets

End of table

A.2. Sensor Management

A.2.1. Sensor Management Domains

Hilal (2013) divided the sensor management field into the seven subdomains summarized below. Additionally, the sensor management field covers several activities that are covered in this review. Figure A.2 illustrates the eight sensor management subdomains.

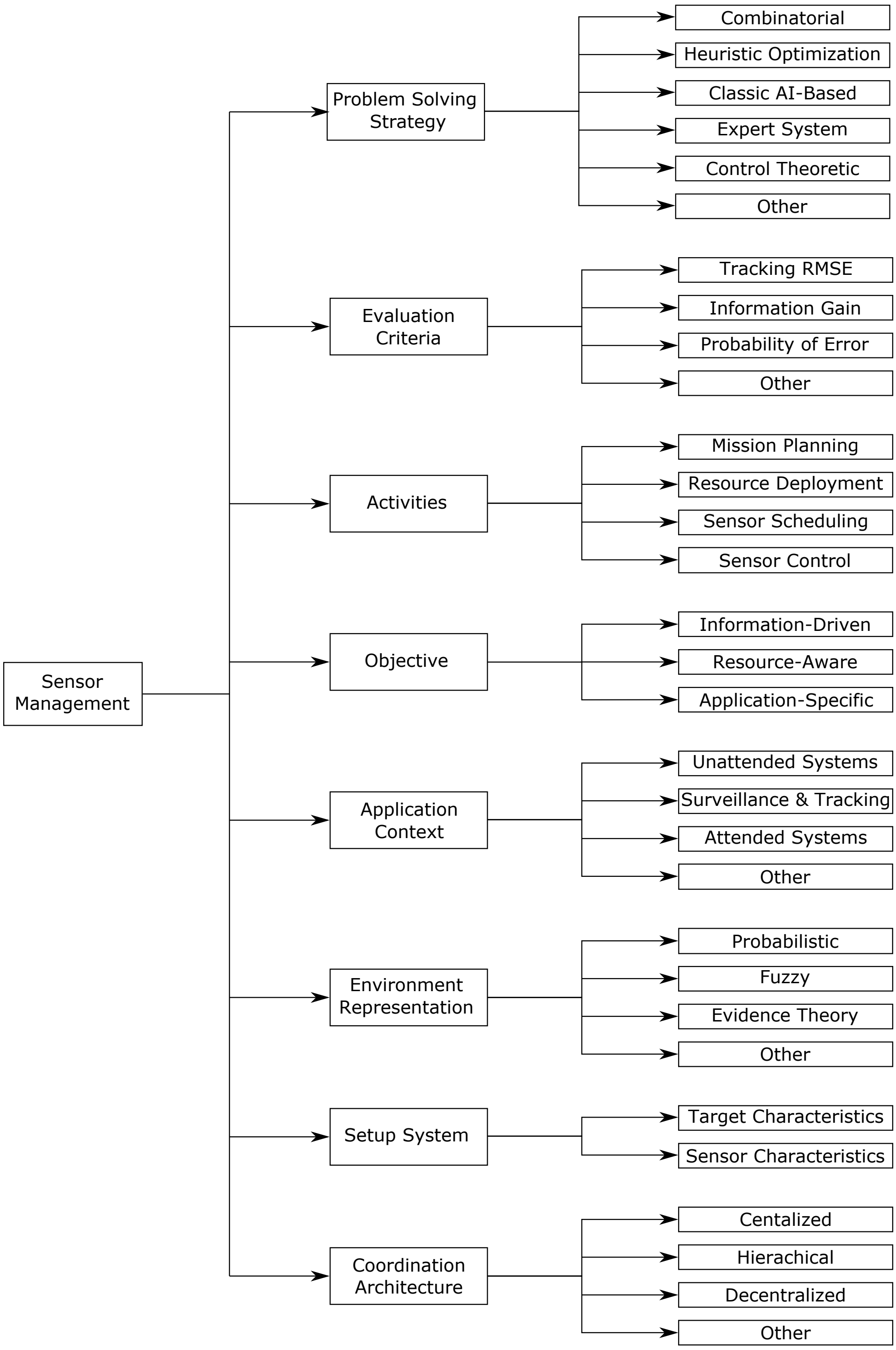


Figure A.2.: *The eight subdomains of sensor management. Adapted from Hilal (2013).*

A.2.2. Problem Solving Strategies for Sensor Management

Multiple approaches have been put forward to determine solutions for this problem that Hilal [71] clustered into six categories: combinatorial strategies, heuristic optimization techniques, artificial intelligence approaches, expert systems, control-based approaches, and other strategies. This subsection reviews expert systems, fuzzy, Bayesian, decision-theoretic, and information-theoretic approaches.

A.2.2.1. Expert Systems

Systems mimicking human reasoning are called expert systems and represent the transfer of task-specific expertise from a human expert to an automated system [81]. Rule-based expert systems use *if-then rules* [82] for their decision-making and have shown to be a viable approach to sensor management [83, 84]. Figure A.3 exemplifies the basic architecture of such a system. The set of rules used by the inference engine in this example links the task priority assigned to tracking an object with the distance between that object and the own aircraft.

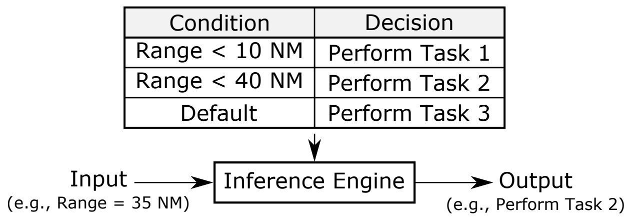


Figure A.3.: *Expert system inference*

Sensor Management Expert Systems Bier et al. [85] used look-up tables to determine the priority of sensing tasks and determine the optimal sensor to identify a target. The priority of sensing tasks is determined by origin, with the following order from highest to lowest: pilot requests, fire control requests, intermitting requests, and multi-source integration requests. A look-up table determines the tasks' priority with three dimensions: track disposition, track imminence, and track loss potential. The optimal sensor for an identification task is determined using if-then rules based on the prior sensor contributions and the probability of success.

McBryan et al. [86] developed an expert system to manage multiple sensors of a fighter aircraft for air-to-air search, air-to-air tracking, and air-to-surface sensor cueing. The sensor manager decides based on information about tracks, threats, the mission context, and the sensor status. These decisions are made by evaluating 60 rules, which McBryan et al. estimate to represent 10 to 20% of the rules needed for a full-scale system [86]. These rules are organized hierarchically into three hierarchy levels rules. High-level rules mimic the pilots' decision-making. Additional sensing task parameters, e.g., the number of beam width scans, are controlled by medium-level rules. Lower level rules are used to translate the selected action into a series of button presses needed to command the sensing task. Rules are prioritized based on the following intended functions from lowest to highest: searching, target sampling, target tracking, identification, navigation updates, weapon delivery, and pilot commands.

Stromberg et al. [87, 88] designed a sensor management system in which task agents buy information from sensor agents. The researchers used the OODA loop by Boyd (1996) to define the concept of tasks. Other expert systems approaches can be found in [180].

A.2.2.2. Fuzzy Logic

The knowledge base of expert systems is based on human expertise and often subjective [89]. This subjectivity makes the simplicity and similarity to human reasoning of fuzzy logic interesting for sensor management applications [90]. Zadeh [91] introduced fuzzy sets as objects assigned a degree of membership between zero and one, representing a generalization of the classical set [92]. Fuzzy decision trees have shown to be particularly good rankers and consistently outperformed non-fuzzy decision trees [93]. These characteristics seem to make fuzzy decision systems well suited for managing the information used in the prioritization and scheduling of sensor tasks [94, 22].

Fuzzy systems can be abstracted into three steps: fuzzification, fuzzy reasoning, and defuzzification. The fuzzification of crisp inputs is exemplified in figure A.4, where the range is associated with the labels near, close, and far to varying degrees of membership. Fuzzy reasoning can then be used to determine a fuzzy output, e.g., the priority of a task. One approach is to use fuzzy if-then-rules like the one below:

```
IF the range IS close, THEN the priority IS high.
```

The fuzzy inference by Mamdani [290] is the most widespread approach to transform fuzzy outputs into crisp values. Figure A.5 exemplifies the defuzzification process performed to obtain the priority value.

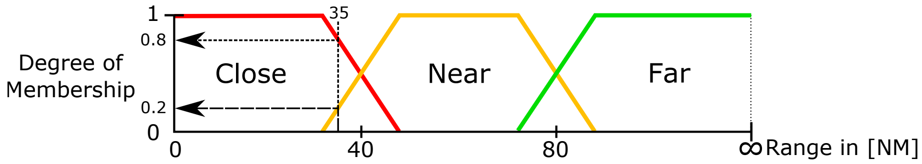


Figure A.4.: *Exemplified fuzzy membership function. The range is associated with the labels near, close, and far to varying degrees of membership, e.g., a range equal to 35 NM is a member of the label close to a degree of 0.8 and to the label near to a degree of 0.2.*

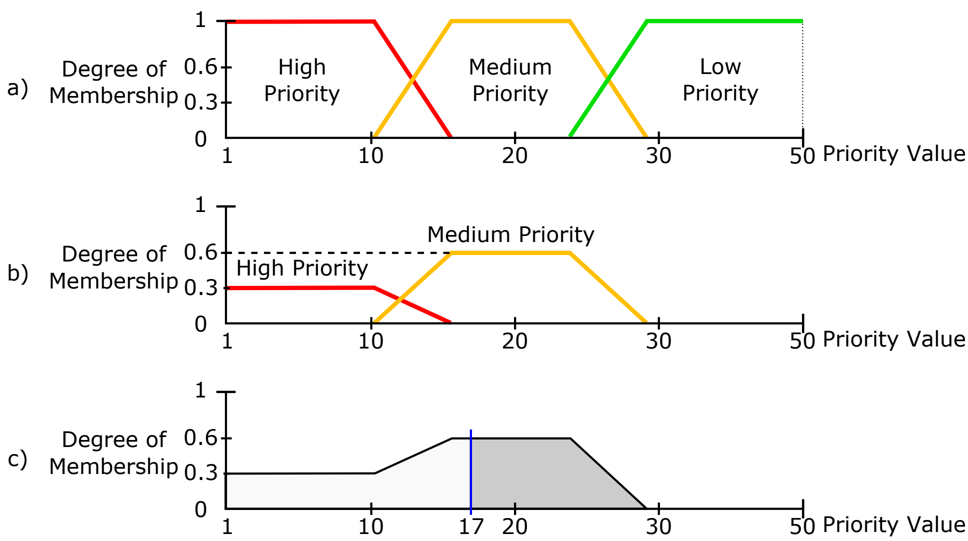


Figure A.5.: *Illustrated example for the fuzzy inference by Mamdani for an object which is part of the* high priority *and* medium priority *fuzzy subsets to a degree of* 0.3 *and* 0.6*, respectively. The membership functions of both subsets are multiplied by the respective degree of membership. The surfaces below these new curves are added together, and the priority value halving the surface into equally sized areas is chosen to be the crisp output.*

Fuzzy Sensor Management Systems Popoli and Blackman [95] constructed a fuzzy expert system to manage the degrees of freedom of an electronically scanned antenna radar. The system's inputs are based on fuzzy concepts, e.g., close, determined from the target's range and range rate. The following fuzzy concepts serve as reasoning base in addition to the target's closeness; lethal, friend, identity uncertainty, identity marginality, bearing-in, loose, exceeds-kill-variance, and large-flux. These concepts are used in fuzzy rules to determine if a track is dangerous or attacking, as exemplified below:

`IF track IS lethal AND close, THEN track IS dangerous.`

Finally, the input and derived fuzzy concepts are used to select sensor tasks to be performed, e.g., if the track is loose, then update it.

Ng et al. [96] developed a fuzzy expert system to determine a sensor's panning rate based on the current bearing error and the previous bearing error, which are assigned to five categories using the triangular membership functions illustrated in figure A.7. One of these rules used by the inference system is:

$$\texttt{If } error_{k-1} \texttt{ IS low AND } error_k \texttt{ IS medium, THEN } r_{panning} \texttt{ IS very high.}$$

The numeric value of the panning rate is calculated using the membership function illustrated in figure A.8.

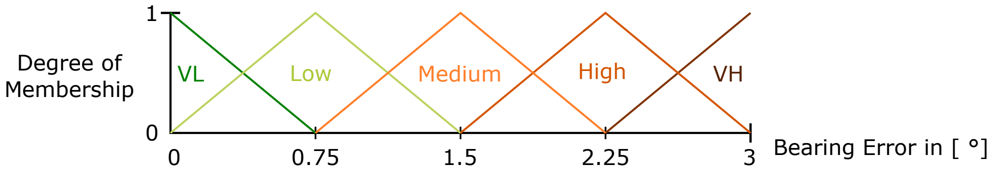


Figure A.6.: *Bearing error membership function used by Ng et al. (2002).*

Panning Rate		Error (k)				
		VL	L	M	H	VH
Error (k-1)	VL	MVL	ML	MVVH	MVVVH	VVVH
	L	MVL	ML	VH	VVH	VVVH
	M	MVL	ML	VH	VVH	MVVH
	H	MVL	ML	MVH	MVVH	MVVVH
	VH	MVL	L	H	VH	VVH

V: Very H: High M: Medium L: Low

Figure A.7.: *Fuzzy rules defined by Ng et al. (2000) to determine the panning rate of a sensor based on the error at a time-step k and the previous error (k-1).*

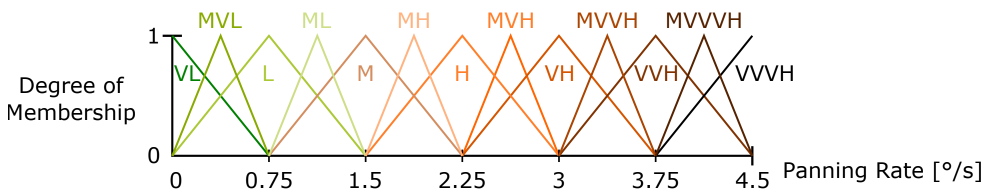


Figure A.8.: *Panning rate membership function used by Ng et al. (2002).*

Molina López et al. [22, 23, 24] applied fuzzy logic to infer the priorities of search, track, and identification tasks performed by a naval sensor system. The tracking priority results from the potential hostility and the level of threat of objects for the ownship and friendly assets.

The object identity and the associated level of confidence affect the estimated hostility of an object. The threat posed by an object is determined based on the object's identity, identity uncertainty, and threatening characteristics of the object's trajectory. The latter is inferred based on the probability of the object being a missile, the potential formation flight of multiple objects, and the estimated object's maneuver capability. Additionally, the object's velocity and altitude are used to detect a diving maneuver threatening friendly assets.

The priority of an identification task results from the object's threat level, its hostility, and the level of confidence in the assigned identity. In their study, the priority of search tasks results from the sector's activity, the sector vulnerability, and the number of targets found in the last search [24, 22]. The tracking task prioritization assesses the hostility, the identity (ID), and the threat level of the tracked object [23].

Figure A.9 illustrates the decision trees used to determine the priority of identification and tracking tasks. This system was shown to be able to cope with challenging multi-target scenarios [24].

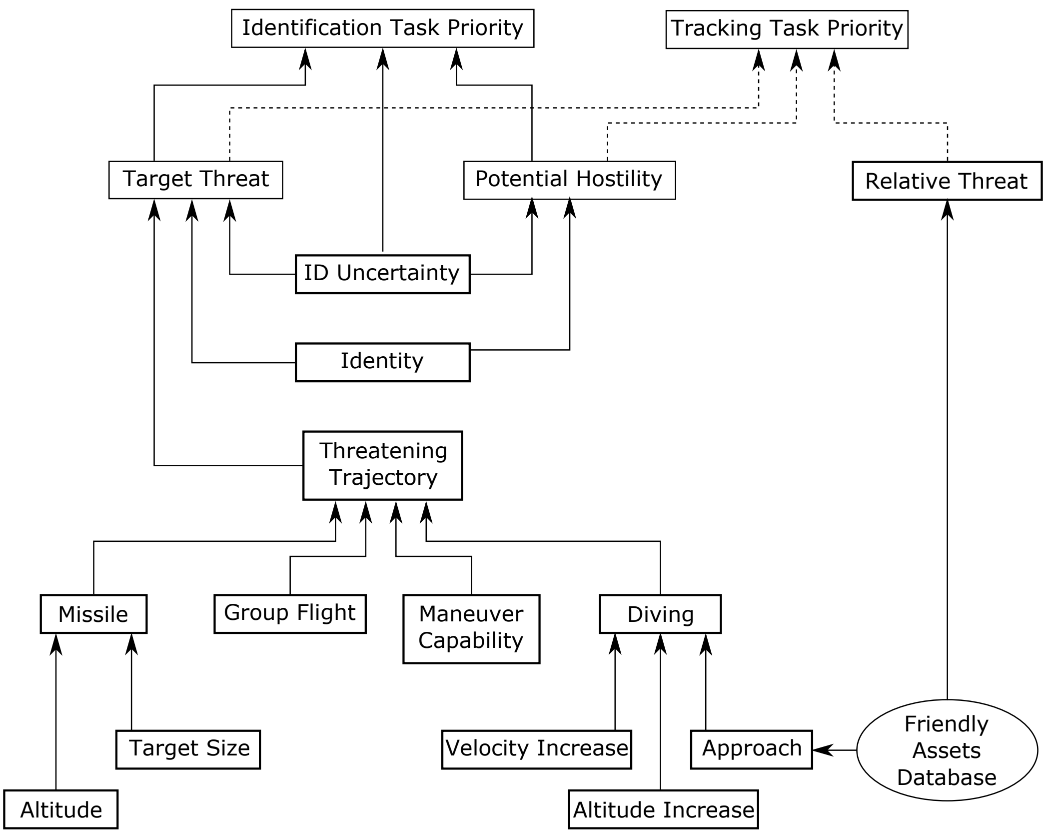


Figure A.9.: *Symbolic decision tree used to determine a naval radar system's tracking and identification task priorities. Adapted from Molina et al. (2002).*

A.2.2.3. Bayesian Methods

Bayesian networks provide a framework for dealing with uncertainty using an underlying graphical structure [97] and are the most popular probabilistic sensor management approaches [71]. Bayesian networks combine prior knowledge and statistical data [98] and are based on prior beliefs that are updated based on collected data using Bayes' Theorem [99].

Bayes' Theorem, published posthumously in 1763 [100], relates the conditional probability $P(H \mid E)$ of a hypothesis H given the evidence E to the likelihood $P(E \mid H)$, the probability of the evidence $P(E)$, and of the hypothesis $P(H)$ [101], as shown in equation A.1.

$$P(H \mid E) = \frac{P(E|H)P(H)}{P(E)} \quad , P(E) \neq 0 \tag{A.1}$$

Bayesian networks are probabilistic directed acyclic graphs (DAG) that are composed of nodes and directed edges [97]. Nodes have mutually exclusive states with a given prior probability or likelihood, e.g., a transaction is either fraudulent or not fraudulent. The edges represent causal relationships between the nodes of the network. Figure A.10 illustrates the bayesian credit card fraud detection network example by Heckerman [98].

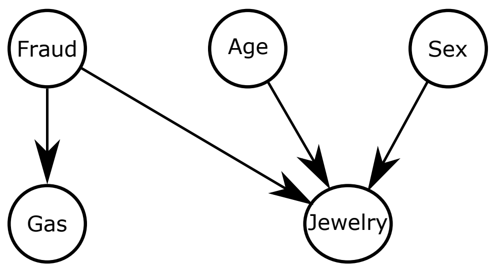


Figure A.10.: *Bayesian network for credit card fraud detection, adapted from [98].*

The propagation of probability in Bayesian networks is updated through inference [291]. The network in figure A.10 can be used to assess the probability of a fraudulent transaction $p(f \mid a, s, g, j)$ made by a male aged under 30 that has previously purchased gas and jewelry. This conditional probability is calculated using the prior probabilities and likelihoods listed in table A.2. Solving the equation A.2 returns a probability of fraud equal to 9.09%.

$$p(f \mid a, s, g, j) = \frac{p(f) \cdot p(g \mid f) \cdot p(j \mid f, a, s)}{p(f) \cdot p(g \mid f) \cdot p(j \mid f, a, s) + p(\bar{f}) \cdot p(g \mid \bar{f}) \cdot p(j \mid \bar{f}, a, s)} \tag{A.2}$$

Table A.2.: *Probabilities and likelihoods from Heckerman (2008).*

Variable	Value	Meaning
$p(f)$	0.00001	Prior probability of the transaction being fraudulent.
$p(\bar{f})$	0.99999	Prior probability of the transaction not being fraudulent.
$p(g \mid f)$	0.2	Likelihood of gas purchases given fraud.
$p(g \mid \bar{f})$	0.01	Likelihood of gas purchases given no fraud.
$p(j \mid f, a, s)$	0.05	Likelihood of jewelry purchase given fraud, age $<$30, male.
$p(j \mid \bar{f}, a, s)$	0.0001	Likelihood of jewelry purchases given no fraud, age $<$30, male.

Bayesian Sensor Management Approaches Kreucher et al. [103] developed a sensor management system based on a JMPD implementation that selects the sensing option that maximizes the information gain. This gain is calculated using the Rényi Information Divergence that is described in section A.2.2.5.

Demircioglu and Osadciw [104] constructed a Bayesian network to control a heterogeneous radar suite's performance parameters. This network estimates the probability of detection, the probability of false alarm, and the accuracy through Bayesian inference. Three nodes with four states each are defined as input into the network:

- the average velocity of the targets in knots (0-50, 50-150, 150-300, 300-500),
- the number of targets (0, 1-5, 6-10, 11-15), and
- the average RCS (-20dB – -10dB, -10db – 0dB, 0dB – 10dB, 10db – 20dB).

Ye et al. [102] developed a Bayesian network that determines the desired detection probabilities (10 States) and update times (1s, 2s, 4s) for an ATC sensor network system. The Bayesian network, shown in figure A.11, is based on expert knowledge and evidence data.

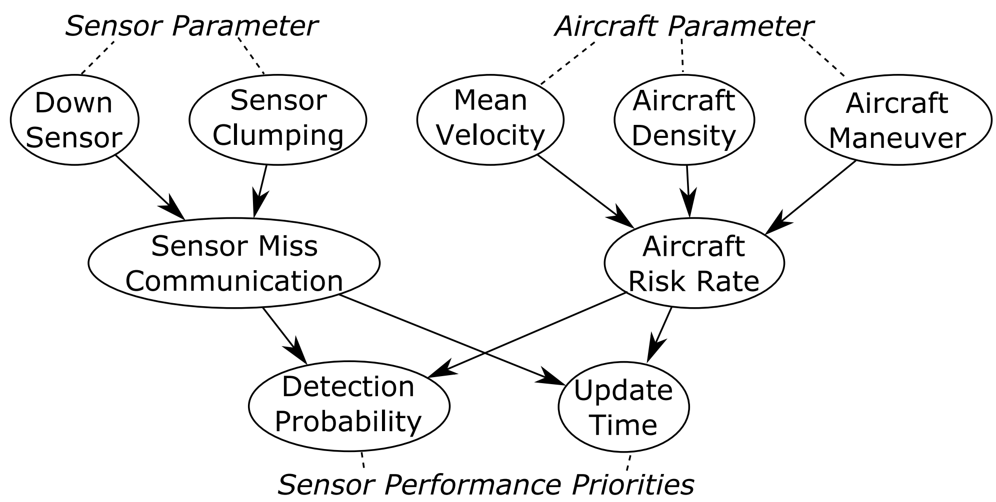


Figure A.11.: *Bayesian network from Ye et al. (2009)*

A.2.2.4. Decision Theoretic Approaches

The management of sensor systems can be modeled as a stochastic decision process, for which the most popular approach is the Markov Decision Process (MDP) [71].

Markov decision process (MDP) MDPs are an extension of Markov Chains that are discrete-time stochastic processes in which the state of a system solely depends on the system's state in the previous time-step [292]. Transition probabilities govern the transition between states in Markov Chains, e.g., there is an 80% probability for the system modeled by the Markov chain illustrated in figure A.12 to change from state A to state B.

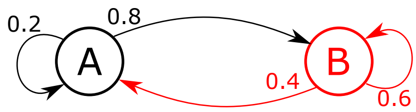


Figure A.12.: *Transition diagram of a Markov Chain with two states showing the transition probabilities.*

MDPs extend Markov Chains by putting the dynamic system under the control of a decision-maker that aims to optimize the system's performance [105]. This decision-maker observes the system, selects an action from the available set of options, and receives a reward for taking action [105]. This reward can depend on the state of the system at the next decision epoch, which is referred to as the expected reward [105]. The goal of decision-makers in MDPs is to find the policy π that specifies the action $a_s = \pi(s)$that maximizes the expected reward [105]. Figure A.13 illustrates an MDP that extends the Markov Chain from figure A.12 with an action space containing three possible actions and the decision maker's rewards. MDPs are described by the following five elements [293]:

- A state-space $\mathbf{S}$,
- An action space $\mathbf{A}$,
- A set of available actions $\mathbf{A}(s)$ at state $s \in \mathbf{S}$,
- Transition probabilities $p(s' \mid s, a)$ to the state $s' \in \mathbf{S}$ after performing the action $a \in \mathbf{A}(s)$ in the state $s \in \mathbf{S}$, and
- Rewards $r(s, a, s')$for the state transition from s to s' as a result of action a.

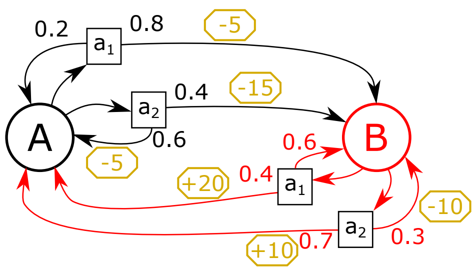


Figure A.13.: *Transition diagram of an MDP with two states (A, B) and two possible actions (a_1, a_2) showing the transition probabilities and rewards (octagons).*

Partially observable Markov decision process (POMDP) The noise present in real-world sensing operations limits the observability of the environment's states and requires decisions to be made under uncertainty [106]. The partially observable Markov decision process (POMDP) extends MDPs to model the limited observability by hiding state features from the decision-making agent [106]. The agent receives an observation of the state of the environment at every decision cycle that is incomplete and/or inaccurate. Various observations can be derived from a single state, e.g., a target can be detected in one observation and remain undetected in the other. An observation can also be observed in more than one state, e.g., no detection can either be obtained from a state with no target or one with undetected ones. Figure A.14 illustrates the transition diagram of a POMDP derived from the MDP described in the previous paragraph.

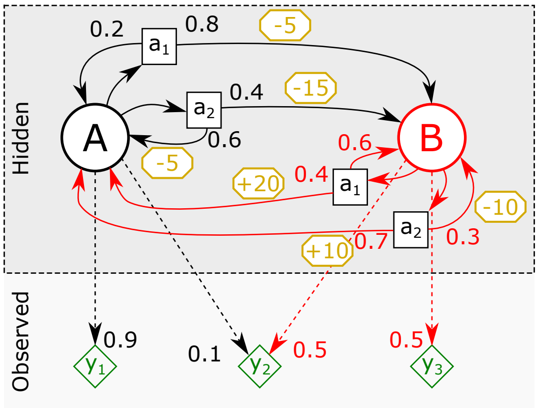


Figure A.14.: *Transition diagram of a POMDP with two states (A, B), two actions (a_1, a_2), and three observations (y_1, y_2, y_3) showing the transition and observation probabilities.*

Agents use their observations to build their belief about the state of the environment and decide on the next actions based on this belief. Figure A.15 illustrates the decision-making process of an agent for the POMDP exemplified in figure A.14. Starting with an initial belief b_{t_0}, the agent makes the observation y_1, updates the belief accordingly, and chooses to perform the action a_1. This action, combined with the hidden state, leads to a change of the environment's state, and the agent receives a negative reward. The process then continues with a new observation y_3.

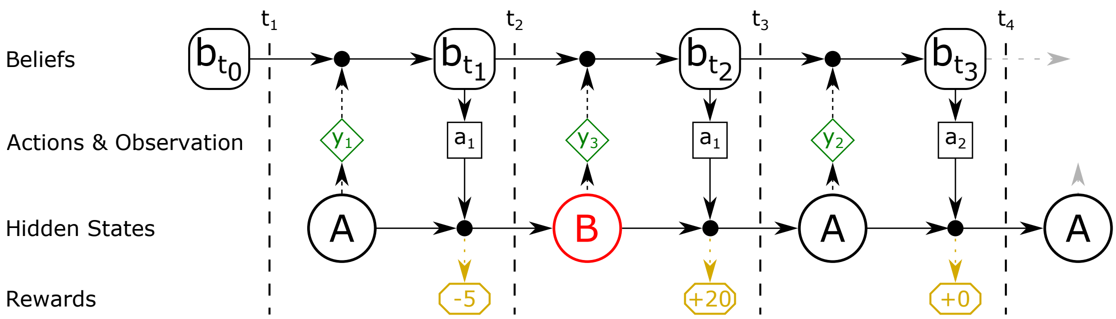


Figure A.15.: *Transition diagram of a POMDP with two states (A, B), two actions (a_1, a_2), and three observations (y_1, y_2, y_3) showing the transition and observation probabilities.*

Partially observable Monte Carlo planning (POMCP) Partially observable Monte Carlo planning (POMCP) accommodates large action, state, and observation spaces by combining the POMDP approach with a Monte Carlo tree search (MCTS). MCTS is a heuristic search algorithm that finds optimal decisions by randomly sampling the decision space [294]. This approach has been applied successfully to games that require decision-making under uncertainty [295], where information is scarce, precious, aging fast, and where the means of acquiring it are limited [296]. Figure A.16 visualizes the MCTS phases. In the first step, a leaf node is selected based on the given criteria. The second step creates a new simulation node, and the third step evaluates the simulation results. The simulation results are then back-propagated to the parent nodes in the last step. The leaf is selected by maximizing every node's upper confidence level U_i, as defined by equation A.3, where v_i represents the value of the node i that was visited n_i times and N counts the number of visits of the parent node. The exploration rate c is used to define the balance between exploitation ($c \to 0$) and exploration ($c \to \infty$) [296].

$$U_i = v_i + c \cdot \sqrt{\frac{\ln N}{n_i}} \tag{A.3}$$

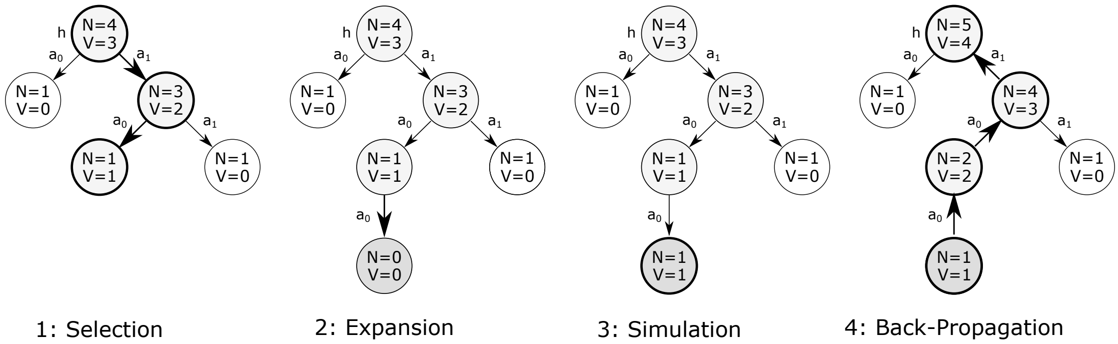


Figure A.16.: *Illustration of the steps occurring in a Monte Carlo tree search with two possible actions (a_0, a_1). The variable N tracks the number of times a decision was visited, and the value V tracks the value associated with the simulation results.*

Partially observable Monte Carlo planning with observation widening (POMCPOW) To enable a deeper tree search, the number of children of each node needs to be artificially limited, e.g., via a POMCP with observation widening (POMCPOW) [297]. A POMCPOW approach provides a near-optimal solution for the scheduling and resource allocation, problems that have been shown to be NP-hard[1]. Real-world applications often require decision-making to be performed under uncertainty due to the scarce, precious, and fast aging information and limited means of acquiring information [296]. Kriegspiel, a variant of chess incorporating the *fog of war* concept by letting players only see their own pieces, provides a good testbed for algorithms aimed to solve real-world problems that require decision-making *under* uncertainty [295].

[1]The computational complexity NP-hard describes a class of problems for which non-deterministic Turing machines cannot provide an optimum solution in polynomial time [78].

Decision-Theoretic Sensor Management Approaches Krishnamurthy and Djonin [107, 108, 109] developed a POMDP-based approach to select the optimal sensor scheduling policy μ based on the Bayesian information state b_k computed at time k, a discount factor β and a cost function $C(b, a)$ when given an initial information state b_0. Three possible cost functions $C(b, a)$ are given by the authors that are based on either the square error, the entropy, or the error probability. The cumulative reward R is given by equation A.4.

$$R(x_k, a_k) = \mathbf{E}\left[\sum_{k=1}^{\infty} \beta^{k-1} C(b_k, a(b_k)) \mid b_0\right] \tag{A.4}$$

Miller [110] implemented a POMDP sensor management approach to improve the tracking of ground targets by UAVs that uses the expected cumulative cost over a finite horizon H to determine the reward of actions given the belief b_0 (eq. A.5). The cost function is based on the mean-squared tracking error.

$$R(x_k, a_k) = \mathbf{E}\left[\sum_{k=0}^{H-1} C(x_k, a_k) \mid b_0\right] \tag{A.5}$$

Chong et al. [111] used a similar POMDP approach as Miller [110] to assess the performance of sensors management policies with regards to object detection, classification, and tracking.

Lauri and Ritaka [112] defined a belief-dependent reward function that takes into account the reduction in uncertainty gained from observation to implement a POMDP-based sensor management approach. Lauri [113] implemented a POMCP approach to find application-specific optimal policies.

Gostar et al. [114, 115, 116] modeled the sensor management challenge as a POMDP with the objective function given by equation A.6 that comprises the following three error terms and their associated user-defined weights $\eta_{|X|}$, η_x, and η_λ: the error number of targets $\sigma^2_{|X|}(s)$, the tracking error $\sigma^2_x(s)$, and the clutter intensity $\sigma^2_\lambda(s)$.

$$R(s) = \eta_{|X|}\sigma^2_{|X|}(s) + \eta_x \sigma^2_x(s) + \eta_\lambda \sigma^2_\lambda(s) \tag{A.6}$$

Other decision-theoretic approaches are found in [298, 299].

A.2.2.5. Information-Theoretic Approaches

Information-theoretic approaches estimate the future increase in information expected to be gained from taking a measurement [71], which is suited to a more considerable amount of objectives [14]. The theory underlying these approaches is a branch of the mathematical theory of probabilities and statistics that is based on the technical definition of information by Fisher [117]. The fisher information $I_X(\theta)$ of a continuous random variable X about the parameter θ is defined by equation A.7 that combines the probability density function $p_0(x)$ and a score function $\frac{\mathrm{d}}{\mathrm{d}\theta} \log f(x \mid \theta)$ based on a statistical model $f(x \mid \theta)$ [300].

$$I_X(\theta) = \int_{\mathcal{X}} \left(\frac{\mathrm{d}}{\mathrm{d}\theta} \log f(x \mid \theta) \right)^2 p_\theta(x)\, \mathrm{d}x \tag{A.7}$$

Shannon Entropy Shannon entropy is the most popular metric used for information-theoretic approaches [118] and was first defined by Shannon [119] to describe the uncertainty of an outcome. Entropy $H(x)$for a variable X is defined by the probability of the outcomes $p(x)$ as shown in equation A.8.

$$H(X) = \begin{cases} -\sum\limits_{x\in X} p(x) \log p(x) & \textit{discrete variable} \\ -\int p(x) \log p(x)\, dx & \textit{continuous variable} \end{cases} \tag{A.8}$$

The entropy of an event with two possible outcomes, p and q, with the linked probabilities $q(x) = 1 - p(x)$ is obtained through equation A.9. The curve of the entropy is shown in figure A.17.

$$H(x) = -p(x) \log_2 p(x) - q(x) \log_2 q(x) \tag{A.9}$$

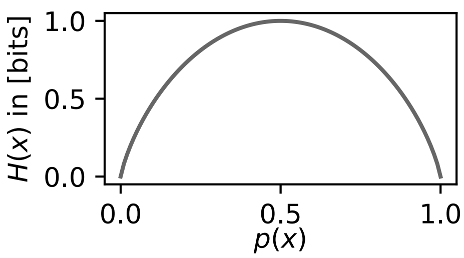


Figure A.17.: *Shannon Entropy $H(x)$for an event with two possible outcomes.*

The entropy linked to the joint occurrence of two events, X and Z, is obtained by solving equation A.10 [119]. The conditional entropy of an event X given then event Z is obtained through equation A.11 [119].

$$H(X, Z) = \begin{cases} -\sum\limits_{x\in X, z\in Z} p(x, z) \log p(x, z) & \textit{discrete variable} \\ -\int\int p(x, z) \log p(x, z)\, dxdz & \textit{continuous variable} \end{cases} \tag{A.10}$$

$$H(X \mid Z) = \begin{cases} -\sum\limits_{x\in X, z\in Z} p(x, z) \log \frac{p(x,z)}{p(z)} & \textit{discrete variable} \\ -\int\int p(x, z) \log \frac{p(x,z)}{p(z)} dxdz & \textit{continuous variable} \end{cases} \tag{A.11}$$

Mutual Information The reduction of uncertainty on the random variable X through the observation of the random variable Z is defined by equation A.12 [120]. This reduction in uncertainty is known as mutual information.

$$I(x; z) = H(x) - H(x \mid z) \tag{A.12}$$

Kullback-Leibler Divergence The Kullback-Leibler Divergence, also referred to as relative entropy, is a measure of the difference between two probability densities p and q [121].

$$D(p(x) \parallel q(x)) = \begin{cases} \sum_{x \in \chi} p(x) \log \frac{p(x)}{q(x)} & \textit{discrete variable} \\ \int p(x) \log \frac{p(x)}{q(x)} dx & \textit{continuous variable} \end{cases} \tag{A.13}$$

Rényi Divergence The information gained from replacing a probability density p with the probability density q is defined as the Rényi divergence, also known as the α-Divergence, which is calculated using the equation A.14 [122]. The Rényi divergence for the edge case of $\alpha \to 1$ returns the Kullback-Leibler Divergence [301].

$$D_\alpha(p(x) \parallel q(x)) = \begin{cases} \frac{1}{\alpha-1} \cdot \sum_{x \in \chi} p^\alpha(x) \cdot q^{1-\alpha}(x) & \textit{discrete variable} \\ \frac{1}{\alpha-1} \cdot \ln \int p^\alpha(x) \cdot q^{1-\alpha}(x)\, dx & \textit{continuous variable} \end{cases} \tag{A.14}$$

Information-Theoretic Sensor Management Approaches Manyika [123] designed a unified sensor management approach for decentralized multi-sensor systems that is based on fisher information. The optimal sensing action $\hat{a}$ is selected based on the likelihood information $I(\cdot)$ for the conditional probability $p(\cdot)$ of the set of observation $\mathbf{Z}_j^k$ by sensor j at time k given the state vector x and the i-th action a_i. Manyika applied his metric to the schedule of four sonar sensors used by a robot for navigational purposes.

$$\hat{a} = \arg\max_{a_i} \sum_j I\left(p\left(\mathbf{Z}_j^k \mid x\right), a_i\right) \tag{A.15}$$

McIntyre and Hintz [124] used information gain, defined as the difference between the Shannon entropy before and after a measurement (eq. A.16), to manage the sensor's trade-off between search and tracking tasks. The assumption of a normal distribution simplifies the information gain I_t from a target update to equation A.17, where $|P|$ represents the normed Kalman filter's covariance matrix. The entropy linked to the search task is determined by updating the probability density function of every cell in the search area.

$$I = H(before) - H(after) \tag{A.16}$$

$$I_t = \log_2\left(\frac{\sqrt{|P_b|}}{\sqrt{|P_a|}}\right) \tag{A.17}$$

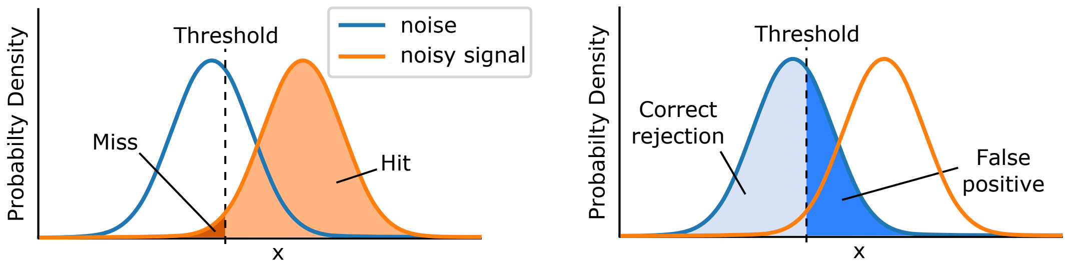
Kreucher et al. [125] compared a task-driven and an information-driven sensor management approach. They came to the conclusion that while the algorithm explicitly designed for the tracking task performed better than the information-theoretic approach, the performance difference was minimal.

Further information theoretic approaches are found in [118, 127, 128, 129, 130, 131].

A.3. Human Information Processing

A.3.1. Signal Detection Theory

Researchers applying SDT usually assume that the noise and signal are normally distributed and that subjects base their decisions on a threshold level [175, 177]. As shown in figure A.18, lowering this threshold increases the hit probability, but the lower cut-off value leads to a higher probability of false positives. Error-free performance can thus not be achieved by the subjects [177].



(a) *Proportion of hits and misses*

(b) *Proportion of correct rejections and false positives*

Figure A.18.: *Depiction of the proportion of SDT events for two equal-variance normal probability distributions for signal and noise, adapted from Proctor and Proctor [302].*

SDT is used to determine the following two measures [302]: sensitivity and response bias.

Sensitivity:

The sensitivity is a measure for the discriminability of a signal from noise [302]. A common sensitivity measure is the sensitivity index d' that measures the distance between the signal's mean μ_s and the mean μ_n of the noise probability densities in standard deviation units σ (eq. A.18).

$$d' = \frac{\mu_s - \mu_n}{\sigma} \tag{A.18}$$

The sensitivity of a test subject can alternatively be calculated based on the hit rate r_H and the rate of false rejections r_{FR} made, which is referred to as the true positive rate r_p (eq. A.19) [303].

$$r_p = \frac{r_H}{r_H + r_{FR}} \tag{A.19}$$

Response bias: The response bias measures the tendency of subjects to have a propensity for one of the possible answers [302]. The bias β is defined as the ratio between the signal's probability density function f_s and the noise density function f_n evaluated at the threshold x_t (eq. A.20) [302]. The subject has no bias if the condition $\beta = 1$ is fulfilled [302]. A score lower than one indicates that the subject tends to answer *yes*, while values above one suggest a subject's bias to answer *no* [302].

$$\beta = \frac{f_s\,(x_t)}{f_n\,(x_t)} \tag{A.20}$$

A.3.2. Perception Theories

Theories of perceptions can be divided into bottom-up and top-down theories based on the direction of the information flow [139]. In bottom-up theories, percepts [2] are suggested to correspond to external objects first perceived at the lowest sensory levels, e.g., points and lines [139]. These low-level sensory percepts are gradually processed into more complex constructs, e.g., trees [139]. Gibson's theory of direct cognition is the most prominent bottom-up theory [139]. The involvement of higher cognitive functions in perception is the main feature that differentiates top-down theories from bottom-up theories [139]. Top-down perception theories can be organized into three classes based on the method used to interpret the stimuli [139]: constructivist, computational, and synthesizing theories. Figure A.19 illustrates the taxonomy of perception theories and the most prominent theories of each category.

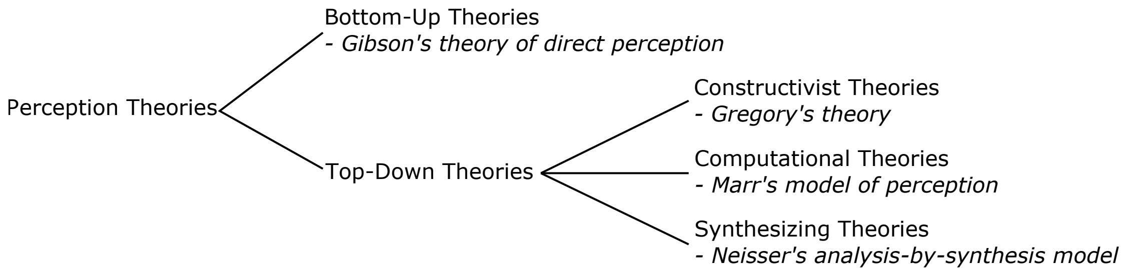


Figure A.19.: *Taxonomy of perception theories and their most prominent examples.*

A.3.2.1. Gibson's theory of direct perception

Gibson's ecological approach to visual perception [304], first published in 1979 [305], rejects the notion that visual perceptions are based on a series of images since this requires perceivers to have ideas about the world. Instead, Gibson [304] argues that perceptions result from the extraction of invariants from a flux, e.g., the light, which does not require knowledge about the world. The following types of invariants are driving perception according to Gibson's theory [304]:

- Invariants of the optical structure under changing illumination,
- Invariants of the optical structure under change of the point of observation,
- Invariants across the sampling of the ambient optic array, and
- Local invariants of the ambient array under local disturbances of its structure, e.g., caused by motion.

Several shortcomings of Gibson's theory have been put forward by Démuth [139]. First, the lack of consideration for prior knowledge in the perception process is contradicted by experiments that have proven that performance in tasks requiring a mental representation of the environment is increased by prior knowledge. Further, the theory does not explain visual illusions and does not discriminate between sensing and understanding stimuli. Finally, the theory assumes that the visual field contains sufficient information about objects to determine their usage and that perceivers must only understand how to find the relevant information.

[2] The Merriam-Webster dictionary [140] defines a *percept* as "an impression of an object obtained by use of the senses."

A.3.2.2. Gregory's theory

According to Gregory [306], humans see objects beyond the meaningless arrangements of marks received by their sense organs. These objects "have pasts and futures; they change and influence each other, and have hidden aspects which emerge under different conditions." In Gregory's theory, the perception of objects is driven by more than the sensory information available to the perceiver. Perception is impacted by experience, the anticipation of the future, emotions, and non-visual characteristics. For Gregory [306], humans perceive their environment by constructing hypotheses based on prior experience and testing these hypotheses using available sensory information.

Démuth [139] points out the shortcoming that the high number of correct hypotheses shared by most humans despite the low probability of correctly guessing is not sufficiently explained. Further, the mechanism behind the acquisition of these hypotheses is lacking.

A.3.2.3. Marr's model of perception

Marr [307] developed a computational approach to vision that builds upon Gregory's theory. Marr's model views representation and information processing as the processes involved in visual perception. Marr [307] defined the following three levels of interest for the understanding of visual perception: (1) computational theory, (2) representation and algorithm, and (3) hardware implementation.

The computational theory layer tackles the understanding of the computation's goals, appropriateness, and logic. Marr considers this layer to be of critical importance, as the computation's nature is driven by the problem to be solved. The representation and algorithm layer investigates the computation's implementation, algorithm, and representation of inputs and outputs. Marr views representation as a system that amplifies specific information chunks while muffling the remaining information. The hardware implementation layer explores the physical realization of the computation.

Marr [307] further put forward three stages of representation. First, primal sketches are used to make the information contained in the image captured by the brain explicit. This stage is followed by rendering a 2.5-dimensional sketch that adds orientation and rough depth from a viewer-centered perspective. Finally, the sketch produces a 3D model representation of the object.

Marr's layered modeling approach is supported by the research into the object recognition of patients with lesions in the brain's parietal lobe made by Warrington and Tylor [308]. They observed that patients with lesions to the right parietal lobe could recognize the object but could not perceive their geometry, while this observation reversed for patients with lesions to the left parietal lobe. This finding indicates that the geometric perception of an object is performed by a separate process than the object's recognition.

A.3.2.4. Neisser's analysis-by-synthesis model

Neisser [309] views perception as one aspect of a complex cognitive process that constantly processes and re-processes sensory information and thus mediates our reality. Neisser defined *cognition* as "all the processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used" [309]. The visual sensory input stems from rays of light that fall onto the retina. These stimuli differ considerably from the real object and the perceiver's constructed object. The stimuli are perceived, stored, and reflected by cognitive processes, e.g., through verbal coding, pattern recognition, focal attention, and figural synthesis.

A.3.3. Atkinson and Shiffrin's model of human memory

Atkinson and Shiffrin [310] developed a model of human memory that assumes the existence of three distinct components: the sensory register, the short-term store, and the long-term store. Information is copied from one component to the next without being removed from the origin.

The sensory register serves as very short-term storage for perceived stimuli, e.g., the photographic trace of a visual stimulus is retained for several milliseconds after its registration. The subject scans the sensory registry and copies chosen information into the short-term store. Additionally, information is retrieved from the long-term store by a search process associated with the registry scan. Figure A.20 illustrates the three components and the main processes of Atkinson and Shiffrin's model of human memory.

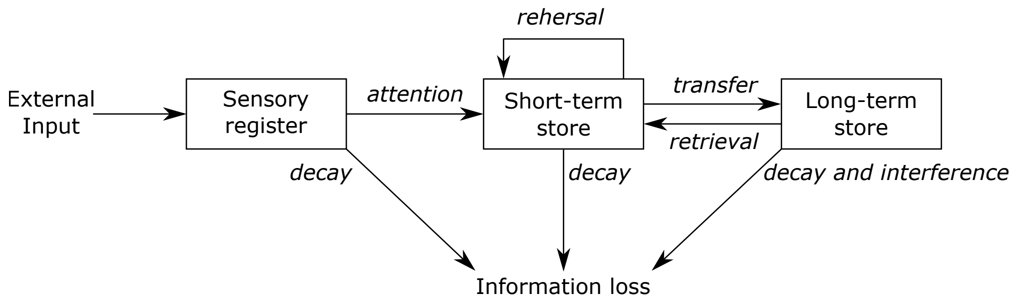


Figure A.20.: *Aktinson and Shiffrin's model of human memory, based on [310].*

The decay of information in the short-term store occurs slower than in the sensory registry, e.g., auditory-verbal-linguistic traces are estimated to disappear within 15 to 30 seconds. Rehearsal is used to actively prolong the stay of the information in the short-term store. Information in the short-term store is copied to the long-term store. This transfer process is more or less pronounced depending on the subject's state. Information stored in the long-term memory is not subjected to the same decay as the other two memory model components and remains relatively stable. According to Atkinson and Schiffrin [310], the endurance of the information is ensured by multiple copies of the information that are more or less complete and that are linked by associations. The subsequent information can displace information in the long-term store and make it irretrievable.

A.3.4. Multi-Attibute Decision Making Approaches

Figure A.21 provides the taxonomy of multi-attribute decision-making models put forward by Hwang and Yoon [161] that classifies decision-making methods based on the information given by the decision-maker and the salient feature of information.

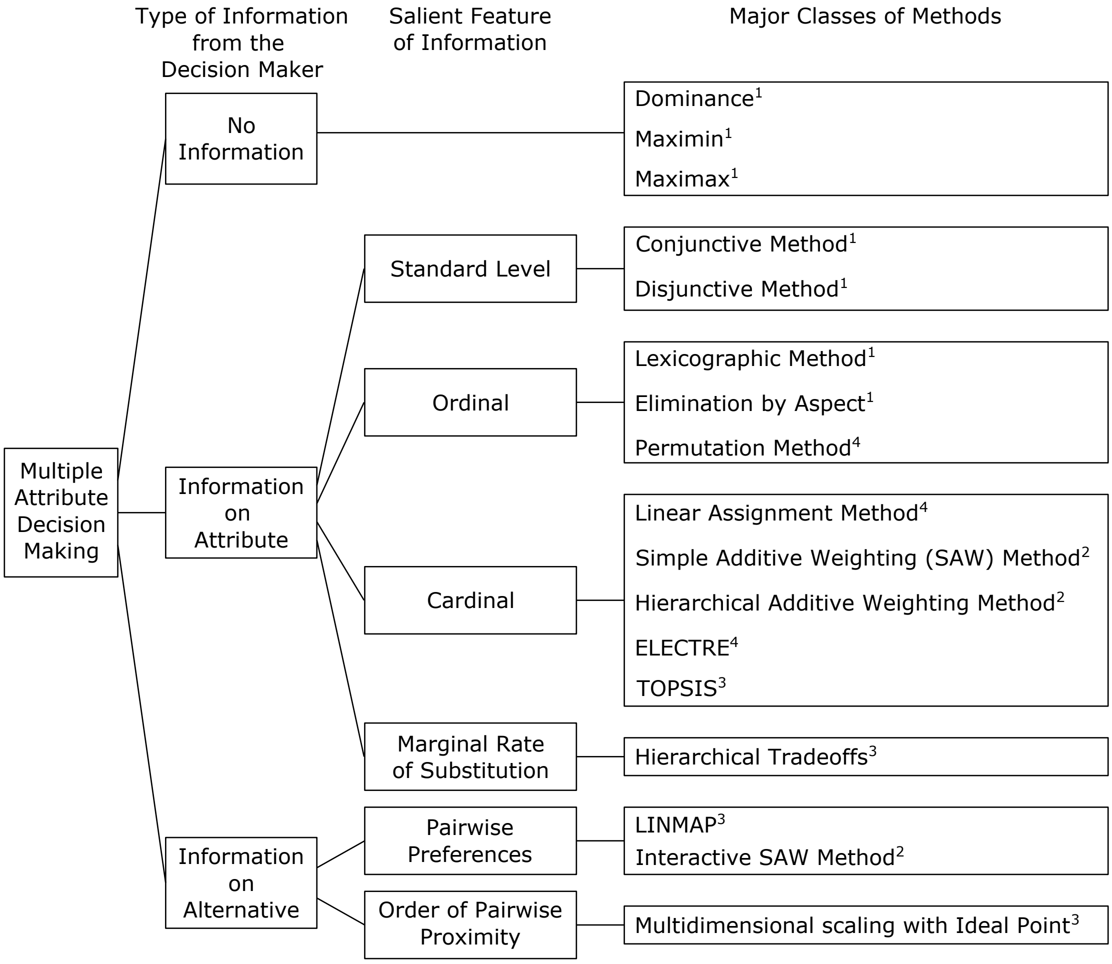


Figure A.21.: *Taxonomy of methods for multiple attribute decision making, adapted from [161]. 1: non-compensatory models, 2: scoring models, 3: compromising models, 4: concordance models.*

A.3.5. Cognitive Biases

Decision-makers do not always behave as defined by normative theories [311]. This departure from normative reasoning is most apparent in cognitive biases that Haselton et al. [166, p. 725] define as cases in which "individuals draw inferences or adopt beliefs where the evidence for doing so in a logically sound manner is either insufficient or absent." Dimara et al. [312] classified biases based on the following underlying phenomena:

- Association: Cognition is biased by associative connections between information items
- Baseline: Cognition is biased by comparison with a baseline
- Inertia: Cognition is biased by the prospect of changing the current state
- Outcome: Cognition is biased by how well something fits an expected or desired outcome
- Self-perspective: Cognition is biased by a self-oriented viewpoint

Table A.3 lists selected biases that affect the processing of information.

Table A.3.: *Cognitive biases, adapted from Dimara et al. [312].*

Cognitive Bias	Phenomenon	Description
Attentional bias	Association	People process information in a weighted manner
Automation bias	Association	Choices are affected by their association with an automated system
Availability bias	Association	Easier to remember events are assessed to be more likely
Framing effect	Association	Choices are affected by whether alternatives are presented as gains or losses
Loss aversion	Association	Tendency of avoiding losses
Anchoring effect	Baseline	Estimation affected by the first piece of information
Focusing effect	Baseline	Beliefs based on the most pronounced part of the given information
Phantom effect	Baseline	Choices are affected by dominant but unavailable alternatives
Risk compensation	Baseline	Risk tolerance is based on constant risk, not minimization
Clustering illusion	Outcome	Seeing patterns in noise
Confirmation bias	Outcome	Favor information that confirms the preferred hypothesis
Experimenter effect	Outcome	Subconsciously influence study participants to confirm a hypothesis
Hostile attribution bias	Outcome	Ambiguous intents read as hostile
Illusion of validity	Outcome	Overconfidence in judgment based on intuition
Information bias	Outcome	Seek additional information irrelevant to a hypothesis or action

A.4. Human-Centered Automation

Underlying Decision Problem Characteristics Automated systems are implemented to solve various decision problems. Ullman and D'Ambrosio [313] put forward the taxonomy of decision problems shown in table A.5. Additionally, decision problems can be wicked, which defines problems that are not understood until the development of a solution and whose solutions are neither right nor wrong and expensive "one-shot operations." They do not have clear alternative solutions [314].

Table A.5.: *Decision problem structure taxonomy, adapted from [313].*

Class	Measure	Description
Decision Space	Problem Completeness	Information describing the alternatives and criteria may be complete (all alternatives are known) or incomplete.
	Abstraction Level	Information describing the alternatives and criteria may be quantitative, qualitative, or mixed.
	Determinism	Information describing the alternatives and criteria may be deterministic or distributed.
Preference Model	Objective Function	Objective functions either call for a formal optimization or a judgment.
	Consistency	Decision problem decisions represent either a single viewpoint (consistent) or multiple conflicting viewpoints (inconsistent).
	Comparison Basis	The measure used to assess decision alternatives is either absolute (criterion-based) or relative to another alternative.
Belief Model	Dimension	The number of information dimensions differentiates three classes of decision problems: none; confidence or knowledge; knowledge and confidence.
	Belief Completeness	The belief model is complete if all decision-makers assess all alternatives relative to all criteria. Otherwise, the model is incomplete.

A.4.1. Automation Level

Parasuraman et al. [188] specified the following four types of automation:

Information acquisition automation supports the human attention in sensing and registering data [188], e.g., through mechanical sensor movements (low level), organizing information (medium level), or filtering information (high level).

Information analysis automation supports the human working memory processes [188], e.g., through data extrapolation (low level), data fusion (medium level), or context-dependent data analysis (high level).

Decision selection automation supports the human decision-making processes [188], e.g., by determining action alternatives (low level), selecting alternatives (medium level), or automatically initiating the implementation of actions (high level).

Action implementation automation supports or performs the required steps to implement a selected course of action [188], e.g., through simple macros (low level), automated action sequences (medium level), or automated agents (high level).

Save et al. [315] specified the “level of automation taxonomy” (LOAT) shown in table A.6. Systems can take different levels of automation, as first described by Parasuraman et al. [188], e.g., the conflict resolution function of a Traffic Alert and Collision Avoidance System (TCAS) is mapped to a C4 and D2 level. The function selects one action that it gives the pilot, but it does not automatically implement a climb or descent.

Table A.6.: *LOAT automation levels, adapted from [315]. “*” requires D5.*

Level	A: Information Acquisition	B: Information Analysis	C: Decision Selection	D: Action Implementation
0	Manual	Working Memory Based	Human	Manual
1	Artefact-Supported	Artefact-Supported	Artefact-Supported	Artefact-Supported
2	Low-Level Automation	Low-Level Automation	Automated	Step-by-step Action Support
3	Medium-Level Automation	Medium-Level Automation	Rigid Automated	Low-Level Support
4	High-Level Automation	High-Level Automation	Low-Level Automatic	High-Level Support
5	Full Automation	Full Automation	High-Level Automatic*	Low-Level Automation
6	-	-	Full Automatic*	Medium-Level Automation
7	-	-	-	High-Level Automation
8	-	-	-	Full Automation

Bonner et al. [316] developed the “Pilot Authorisation and Control of Tasks” (PACT) system to describe the level of automation of military systems. Table A.7 lists the five PACT levels that are associated with commanded (Level 0), assisted (Level 1 to 4), or automatic (Level 5) systems.

Table A.7.: *PACT framework for automation level (adapted from [316]).*

Level	Mode	Autonomy	Pilot	Adaptation
5	Automatic	Full	Interrupt	Computer monitored by pilot
4	Direct Support	Advised action unless revoked	Revoke action	Computer backed up by pilot
3	In Support	Advice and action (if authorized)	Authorizing action	Pilot backed up by the computer
2	Advisory	Advice	Acceptance of advice	Pilot assisted by computer
1	At Call	Advice only if requested	Full	Pilot assisted by computer on request
0	Under Command	None	Full	Pilot

Endsley and Kaber [317] mapped the levels of automation to the performance of four tasks types by the human and the computer: monitoring the system status (M), generating decision alternatives (G), selecting alternatives (S), and implementing the selected alternative (I).

Table A.8.: *Roles performed by the human (H), the computer (C), or both (H/C) depending on the level of automation (adapted from [317]).*

Level	Level Name	M	G	S	I
1	Manual Control	H	H	H	H
2	Action Support	H/C	H	H	H/C
3	Batch Processing	H/C	H	H	C
4	Shared Control	H/C	H/C	H	H/C
5	Decision Support	H/C	H/C	H	C
6	Blended Decision Making	H/C	H/C	H/C	C
7	Rigid System	H/C	C	H	C
8	Automated Decision Making	H/C	H/C	C	C
9	Supervisory Control	H/C	C	C	C
10	Full Automation	C	C	C	C

A.4.2. HFE Design Guidelines

Allocate tasks and functions carefully and consciously The decision of allocating tasks to the operator or the automation should not be based on the ease of automating specific tasks since this arbitrary allocation results in clumsy automation, which doesn't deliver the desired gains [190]. Determining an adequate task allocation is difficult due to human control, automation control, and joint control having benefits and drawbacks, as shown in the collection of associated risks listed in table A.9.

Table A.9.: *Risks of human control, automation control, and joint control, based on [277].*

Human	Joint	Automation
Cognitive bias	Authority ambiguity	Automation bias
Overload	Incorrect knowledge	Out of the loop performance
Fixation	Interaction complexity	Poor SA
Failure to evaluate options	Over-simplified interfaces	Boredom
Forgetting rules	Opaque dynamics	Surprises
Time pressure	Desynchronized SA	Mistrust
Fatigue	Slow decision speed	Unresponsiveness to change
Skill breakdown	Hand-over unreadiness	Skill fade

The task allocation guidelines found in the HFE literature are listed in table A.10.

Table A.10.: *HFE task allocation guidelines*

Guideline	Source
The automated task should have an intermediary complexity.	[318, 319]
Tasks should only be automated if necessary.	[320, 321]
Automate routine tasks rather than complex cognitive functions.	[321]
Automate to aid operators to gain SA rather than providing decisions.	[321]
Automation should collaborate with humans, not replace them.	[322, 323]

Keep the human operator in-the-loop Automation can lead operators to build erroneous mental models of the environment due to the reduced feedback [189]. Human operators should be kept in the loop to avoid adverse performance impacts, e.g., skill loss, clumsy automation, and inadequate trust. Sheridan [318] put forward three criteria to determine if the human can be kept in the loop: a data sampling rate between 0.01Hz and 1 Hz, ample response time, and minimal attentional demands of higher priority. The guidelines to keep the operator in-the-loop found in the HFE literature are listed in table A.11.

Table A.11.: *HFE guidelines to keep operators in-the-loop*

Guideline	Source
Incorporate active information processing by the human operators.	[324]
Avoid the proliferation of automated modes.	[321]
Ensure automation transparency and consistency.	[321, 325, 323, 326]
Keep the automation simple.	[320, 321, 325]
Map system functions to the operator's goals.	[321]
Indicate that data is missing, incomplete, unreliable, or invalid.	[325, 323]
Provide relevant feedback and enable effective monitoring.	[325, 327, 328]
Show the source of automation failure.	[325, 323]
Reduce the need for operators to intervene.	[328]
Provide a good mental model of the situation.	[327]
Give the operator the feeling of being in control.	[320, 327]
Make the machine learning knowledge transfer transparent.	[326]
Use symbolic knowledge representation for AI systems.	[326]

Design for an adequate operator workload While automation often aims to reduce the operator's workload, it can cause an increased workload in high-workload situations [318]. The additional workload can lead to cognitive overload and a steep performance drop-off [329], as shown in figure A.22.

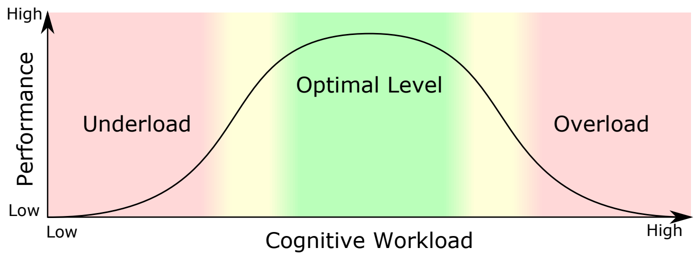


Figure A.22.: *Relationship between cognitive workload and performance, adapted from [329].*

The operator workload guidelines found in the HFE literature are listed in table A.12.

Table A.12.: *HFE workload guidelines*

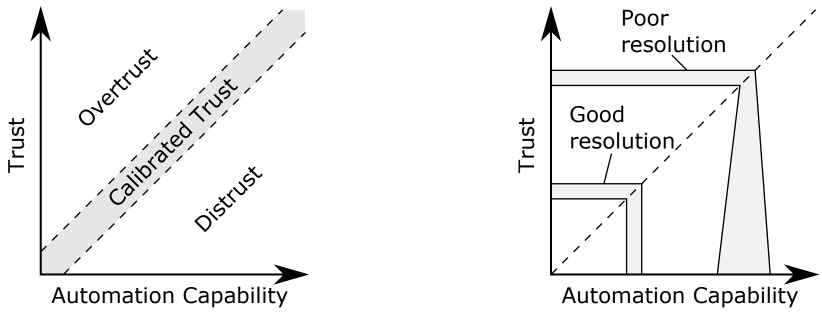
Guideline	Source
The workload should be kept at moderate levels.	[330]
Analyze the automation's impact on workload in critical times.	[318]
Automate exhausting routine actions.	[331]

Avoid information overload Human operators have limited cognitive resources and can only process a finite amount of information. The guidelines for avoiding information overload found in the HFE literature are listed in table A.13.

Table A.13.: *HFE information load guidelines*

Guideline	Source
Avoid information cueing.	[321]
Be careful when using information filtering.	[321]
Integrate available information.	[321]
Provide access to raw data during training and debriefing.	[325, 323]
Automate support to enhance information.	[332]

Calibrate trust in automation An appropriate level of trust in the automated system is necessary for the human-automation system to outperform the performance of either the human or the automation alone [208]. *Trust* is defined as "the willingness of a party to be vulnerable to the action of another party" [333, p. 712]. The level of trust in the system has to be designed to avoid misuse and disuse to maximize the system's effectiveness [334]. This calibration is achieved by matching the trust placed into the automation to the system capabilities. Automated systems usually perform multiple tasks to a varying degree of capability, which should be reflected in the trust placed in the system. The mapping of a range of trust to a capability range has been termed resolution. Figure A.23 shows the areas of trust and exemplifies good and poor resolution.



(a) *Areas of trust* **(b)** *Trust resolution*

Figure A.23.: *Calibrated trust in automation, adapted from [334].*

The guidelines for trust in automation found in the HFE literature are listed in table A.14.

Table A.14.: *HFE trust guidelines*

Guideline	Source
Provide automation transparency	[321]
Support system reliability assessments	[321]
confidence in composite data	[321]
Show the source of automation failure	[325]
Reveal the rules and algorithms used by the automation	[325]
Prefer false alarms to missed positives	[318]
Consider "fail safe" or "fail soft" options	[318]

Align the automation's and operators' goals Aligning system goals to the objectives of the human operator is important to avoid the creation of a gap between what can be achieved efficiently and what can be safely automated [26]. This alignment requires understanding the "good decisions" [224]. Goal-alignment guidelines for automation found in the HFE literature are listed in table A.15.

Table A.15.: *Goal-alignment HFE automation guidelines*

Guideline	Source
Carefully develop the definition of what constitutes a "good decision.".	[224]
Use the right kind of objective function.	[26]
Think about how to avoid unintended consequences and undesirable behavior.	[26]

Automation adaptation Guidelines Architects of human-automation systems with a dynamic task allocation must also consider the adaptation authority, timing, and process [335]. Adapting mission-critical automation dynamically to environments with continuous and unexpected changes is currently not recommended, even for modern machine learning-based artificial intelligence [27]. Adaptation guidelines for automation found in the HFE literature are listed in table A.16.

Table A.16.: *Other HFE automation guidelines*

Guideline	Source
Avoid autonomous adaptation of mission-critical automation.	[27]
The automation must be able to monitor the human operator.	[320]
Each element of the system must have knowledge of the others' intent.	[320]

Fighter Aircraft Specific Guidelines Helldin et al. [323] investigated the applicability of human-centered automation guidelines in the military aviation context. They determined that these guidelines must be tuned for the specific task to be supported. Fighter aircraft-specific automation guidelines found in the HFE literature are listed in table A.17.

Table A.17.: *Fighter aircraft-specific HFE automation guidelines*

Guideline	Source
Adapt general HFE guidelines to the specific task to be supported by the system.	[323]
Adapt automation to the level of expertise of the human operator.	[323]
Design automation to ensure that critical functions are monitored and executed.	[320]
Group and isolate less reliable or vulnerable functionalities if it is possible	[336]
Make the context dependency explicit for the operator	[336]
Give pilots time to train	[336]
Inform the pilot about tasks performed by the automation	[336]
Automatically distribute relevant information within the team	[336]

A.4.3. HFE Design Methods

The context analysis methods applicable to human-centric sensor management systems development are listed in table A.18. Field study and diary-keeping are not applicable when there is no current system available.

Table A.18.: *Context analysis methods for human-centered design [210].*

Method	**When to apply**	**Output**
Stakeholder Identification	For all systems	List of all users and stakeholders for the system
Context of use analysis	For all systems	Background information for design and evaluation
Survey of existing users	When quantitative data is needed	Quantitative data
Task analysis	When it is important to understand task actions in detail as a basis for system development	List and sequence of tasks required to be performed to achieve a goal

A.4.3.1. Tasks Analysis

Task analysis is a human-centered design method that provides a list and sequence of tasks performed to reach a specified goal [210]. This method supports the system developers' understanding of action and provides the basis for system development [210]. The primary applications of the task analysis methods are shown in figure A.24.

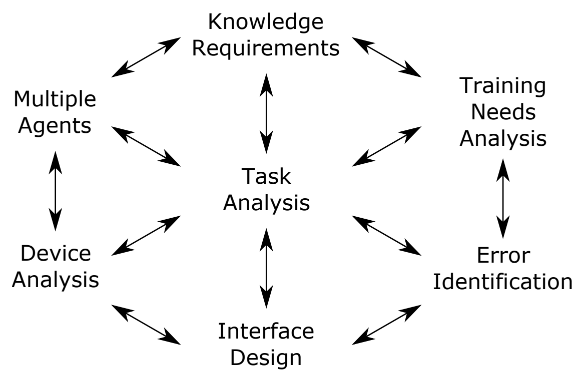


Figure A.24.: *Task analysis applications, adapted from [337].*

Task Definition A task is one or more functions or activities that must be carried out to achieve a specific goal [49]. These tasks can be defined as "consisting of a product and two types of task inputs: required acts and information cues" [338, p. 80]. Products are abstract task qualities, including objects or events created by behaviors, which can be observed independently of the behavior that produced them and constitute sets of attributes [338]. Actions required by a task can be described at several levels of abstraction, ranging from particular activities to complex patterns of behavior with an identifiable purpose [338]. These actions are independent of the individual or system performing the task [338]. Information cues are pieces of information describing certain properties of the stimulus complex of a task upon which the individual can base his or her judgment [338]. Newell [339] defined *tasks* as cognitive processes that have a duration ranging from minutes to several hours, as shown in table A.19.

Table A.19.: *Time scale in human cognition by Newell [339].*

Band	Scale (sec)	Time Units	System
Social	10^7	months	-
	10^6	weeks	
	10^5	days	
Rational	10^4	hours	Task
	10^3	10 min	
	10^2	minutes	
Cognitive	10^1	10 sec	Unit Task
	10^0	1 sec	Operation
	10^{-1}	100ms	Deliberate Act

Task Life Cycle Guerrero Garcia et al. (2008) defined a set of criteria for identifying tasks based on changes in space, resource, time, and nature. The resulting task life cycle is illustrated in figure A.25.

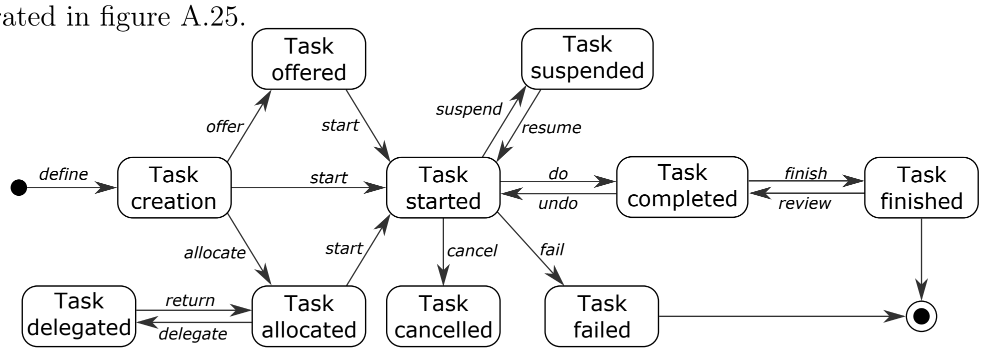


Figure A.25.: *Expanded task life cycle, adapted from [340].*

Hierarchical Task Analysis The hierarchical task analysis (HTA) is a conceptual CTA technique that Ainsworth and Marshall [341, p. 1611] described as "the nearest thing to a universal task analysis technique." It is performed to determine a task breakdown, assess and understand operator activities and system tasks, and assess the human performance [342]. The key concept for HTA is the decomposition of tasks into a hierarchy based on the goals and sub-goals [343].

The requirements analysis methods applicable to the development of human-centric sensor management systems are listed in table A.20. User cost-benefit analysis and persona methods are not considered since the automation is designed for a single group.

Table A.20.: *Requirements analysis methods for human-centered design [210].*

Method	When to apply	Output
Stakeholder analysis	For all systems	Roles and responsibilities of identified stakeholders
User requirements interviews	For all systems	Individual views on user requirements
Focus groups	For all systems	Group-discussed user requirements
Scenarios of use	For all systems	Characterization of users tasks in a specific context
Existing systems analysis	For all systems	Usability baseline
Task / function mapping	To clarify which functions are needed.	Specified system functions required by the user
Allocation of functions	For all systems	Task allocation options
User, usability, and organizational requirements	For all systems	Usability requirements

The design analysis methods applicable to the development of human-centric sensor management systems are listed in table A.21. The wizard-of-oz method is not considered due to the complexity of simulating a sensor management system by a human operator. The operational prototyping is dropped since the operational procedures are considered out of scope. In parallel design, multiple teams develop their version of a system, which can be argued as not being part of the human-centric approach.

Table A.21.: *Design methods for human-centered design [210].*

Method	When to apply	Output
Brainstorming	Early design phase for all systems	Design ideas
Design guidelines and standards	For all systems	Good design practice
Storyboarding	To visualize future interface designs	Sequence of images demonstrating the relationship between users and system
Affinity diagram	To develop the system interface with users	User-agreed HMI structure
Card sorting	To process group data	Hierarchical item structure
Paper prototyping	To perform a quick user test	User feedback
Software prototyping	More realistic user test	User feedback

A.4.4. Post-Study System Usability Questionnaire

The Post-Study System Usability Questionnaire (PSSUQ) by Lewis [286] is a usability questionnaire that encompasses 16 standardized statements that are rated by subjects on a scale from 1 (Strongly Agree) and 7 (Strongly Disagree).

Table A.22.: *PSSUQ Item List*

Item	Description
1	Overall, I am satisfied with how easy it is to use this system.
2	It was simple to use this system.
3	I was able to complete the tasks and scenarios quickly using this system.
4	I felt comfortable using this system.
5	It was easy to learn to use this system.
6	I believe I could become productive quickly using this system.
7	The system gave error messages that clearly told me how to fix the problems.
8	Whenever i made a mistake using the system, I could recover easily and quickly.
9	The information provided with this system was clear.
10	It was easy to find the information I needed.
11	The information was effective in helping me complete the tasks and scenarios.
12	The organization of the information on the screen was clear.
13	The interface of this system was pleasant.
14	I liked using the interface of this system.
15	This system has all the functions and capabilities I expect it to have.
16	Overall, I am satisfied with this system.

Lewis [286] aggregated PSSUQ scores from multiple usability studies to provide benchmarking scores. Table A.23 lists the norm scores aggregated by quality type.

Table A.23.: *Aggregated PSSUQ Norms.*

Category	lim_{low}	Mean	lim_{high}
System Quality	2.57	2.80	3.02
Information Quality	2.79	3.02	3.24
Interface Quality	2.28	2.49	2.71
Overall Quality	2.62	2.82	3.02

A.5. Data and Information Valuation

A.5.1. Information Metrics

The value of an information can be linked to several performance metrics that can be clustered into the following two categories: information quality metrics and utility measurements.

Paggi et al. [344] stated that quality metrics require a clear definition of the metric that is precise, objective, not ambiguous, quantifiably measurable, and can represent multiple aspects of the system. Further, the metric should have a concise, meaningful, comprehensible, and interpretable representation. Finally, the metric should be technology-independent, deterministic, and linked to a specific goal.

A.5.1.1. Scales of Measurements

Values can be measured, as in assigned a numerical value, according to different rules that are linked to the following four different types of scales [345]:

- The *nominal scale* groups objects based on their category [345].
- The *ordinal scale* assigns numbers to objects based on their rank [345].
- The *interval scale* positions objects on a scale with equal units, whose zero point is based on conventions or convenience [345].
- The *ratio scale* is positions objects on a scale with equal units, where absolute zero is always implied [345]. The two sub-types of ratio scales are *fundamental*, e.g. length $[m]$, and *derived*, e.g. density $[{}^{kg}/{}_{m^3}]$.

Table A.24 lists the core concept underlying the measurement scales and the permissible statistics drawn using these scales.

Table A.24.: *Types of measurement scales, adapted from Stevens [345].*

Type of scale	Basic empirical operations	Permissible statistics
Nominal	Determination of equality	Number of cases Mode Contingency correlation
Ordinal	Determination of greater or less	Median Percentiles
Interval	Determination of equality of intervals or differences	Mean Standard Deviation Rank-order correlation Product-moment correlation
Ratio	Determination of equality of ratios	Coefficient of variation

A.5.1.2. Information Quality Metrics

The quality of information items can be described by the timeliness, completeness, consistency, relevance, and quality of the information's data [179, 346]. Table A.25 found in [347] lists the quality of service metrics found in the literature.

Table A.25.: *Information quality metrics for various disciplines, adapted from [347].*

Communication	Information Fusion	Track
Delay	Timeliness	Update Rate
Error Probability	Confidence	Probability of Detection
Delay Variation	Accuracy	Covariance
Throughput	Throughput	Number of Targets
Cost	Cost	Number of Assets

Information-theoretic metrics The following five information theoretic metrics are addressed in section 2.2.3.5: Fisher Information, Shannon Entropy, Mutual Information, Kullback-Leibler Divergence, and Rényi divergence.

Tracking quality metrics Drosos and Malesios [348] measured the accuracy of the Global Positioning System (GPS) receiver based on the planar and spherical position accuracy measures listed below.

The Distance Root Mean Square (DRMS) is calculated from the positional standard deviation σ_i along the x- and y-axis, as shown in equation A.21.

$$\mathrm{DRMS} = \sqrt{\sigma_x^2 + \sigma_y^2} \tag{A.21}$$

The Circular Error Probability (CEP) is defined as the radius of a circle containing 50% of the position. This radius can be approximated using equation A.22 [348].

$$\mathrm{CEP} = 0.62 \cdot \sigma_x + 0.56 \cdot \sigma_y \tag{A.22}$$

The Spherical Error Probable (SEP) is derived from the positional standard deviation σ_i along the x-, y- and z-axis using equation A.23.

$$\mathrm{SEP} = 0.51 \left(\sigma_x^2 + \sigma_y^2 + \sigma_z^2\right) \tag{A.23}$$

The Root Mean Square Error (RMSE) is defined as the root of the sum of the squared positional standard deviation σ_i along the x-, y- and z-axis (eq. A.24).

$$\mathrm{RMSE} = \sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2} \tag{A.24}$$

A.5.1.3. Utility Measurements

The satisfaction obtained from the consumption of a good or service is referred to as *utility* [249]. This subsection first reviews the marginal utility equation and then reviews utility measurement approaches.

Marginal Utility Samuelson [349] inductively derived the equation for the marginal utility $\dot{U}(x)$ of the capital amount x (eq. A.25), which depends on the rate of capital return r, the time t, the rate of discount p, and the Lagrange multiplier λ that depends on the original amount of capital. The total utility is obtained by integrating the marginal utility $\dot{U}(x)$ over a specific period T (eq. A.27).

$$\dot{U}(x) = \lambda \cdot e^{(\pi - r) \cdot t} \tag{A.25}$$

$$\pi = \log_e (1 - p) \tag{A.26}$$

$$U(x) = \lambda \cdot \int_o^T e^{(\pi - r) \cdot t} dt \tag{A.27}$$

Utility functions Hull et al. [257] reviewed utility measurement methods and distinguished the four following categories: (1) unidimensional utility functions, (2) multidimensional utility functions, (3) group utility functions, and(4) behavior-based utility functions.

Unidimensional utility functions Utility functions with a single variable can be divided into: assumption-free methods and methods that assume a specific utility function form [257]. Common assumption-free methods are the direct rating method and the standard gamble method. The direct rating method asks users to rate their preferences on a discrete scale. The standard gamble method lets participants choose between a risk-free amount x_i and a gamble that returns the amount x_A with a probability p_i (eq. A.28) [257]. Several variations of the two methods have been developed, e.g., midpoint methods and ordered metric methods [257].

$$u(x_i) = p_i u(x_A) + (1 - p_i) u(0) \tag{A.28}$$

The most prevalent assumption made for unidimensional utility functions is a quadratic form with the constant values a, b, and c (eq. A.29) [257]. The expected utility $E[u(x)]$of a quadratic utility function is given by the equation A.30 with the mean μ and the standard deviation σ of x [257].

$$u(x) = ax^2 + bx + c \tag{A.29}$$

$$E[u(x)] = a\mu^2 + b\mu + c + a\sigma^2 \tag{A.30}$$

Multidimensional utility functions Decisions are often based on multiple criteria, and therefore, the utility function for these types of decisions has multiple dimensions. The most straightforward approach is the linear utility function (eq. A.31) that adds the attributes x_i multiplied by the constant a_i [257]. Another approach is the additive utility functions that sum up the utility provided by the individual attributes (eq. A.32). Alternatively, the lexicographic approach can be employed if an attribute is more important than the remaining attributes.

$$u\left(x_1, \ldots, x_n\right) = \sum_{i=1}^{N} a_i x_i \tag{A.31}$$

$$u\left(x_1, \ldots, x_n\right) = \sum_{i=1}^{N} u\left(x_i\right) \tag{A.32}$$

Group utility functions Decisions can be made by more than one decision-maker. Hull et al. [257] described the utility function of a group that acts rationally as a whole through equation A.33. This function is based on the subjective probability distribution $f_i\left(\xi\right)$ of the individual i and his utility function u_i for the outcome O that depends on the actions α and the external conditions ξ. The weights $\lambda_i$are selected prior to the maximization.

$$u\left(\alpha\right) = \sum_{i=1}^{N} \lambda_i \int_{\xi} u_i\left(O\left(\alpha, \xi\right)\right) f_i\left(\xi\right) d\xi \tag{A.33}$$

Behavior-based utility functions Friedman and Savage [258] postulated that the utility function of humans could be described by a curve composed of two convex sections that are joined by a concave section. The first inflection point p_1, where the curve transitions from a concave to a concave section, is located at the present worth of the individual making the decision. The two concave sections are theorized by Friedman and Savage [258] to represent two different socioeconomic levels. Markowitz [259] stipulated the existence of a third inflection point $p_3$and an additional concave section in the negative wealth region. Figure A.26 illustrates the theorized utility curve with three inflection points p_1, p_2, and p_3.

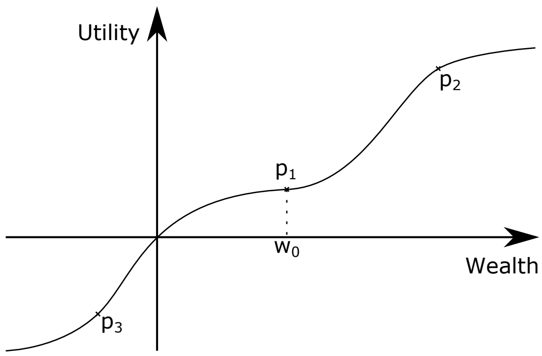


Figure A.26.: *Markowitz's utility curve, adapted from [257].*

Expected utility The following four expected utility metrics are discussed in section 2.3.4.1: subjective expected utility (SEU), multi-attribute utility theory (MAUT), rank-dependent expected utility (RDEU), and risk-weighted expected utility (REU).

B. Methodology Annex

B.1. Information Supply and Demand Example

This section illustrates the relationship between the operations-driven information demand and the resource-driven information supply for the meta model described in section 3.1.2.

B.1.1. Information Supply

This section illustrates the relationship between an actual data element and the contained information in figure B.1. The part of the image showing the aircraft's registration has been magnified and placed at the bottom right corner.

Figure B.1.: *High-resolution picture of an Airbus A350 with registration D-AIXI.*

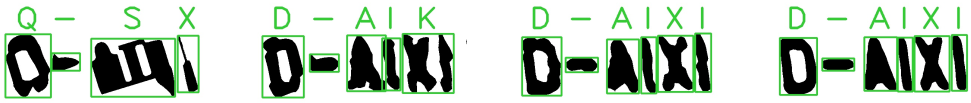
B.1.1.1. Actual Data

The data contained in the image can be either determined by a human looking at the picture, or through automated data analysis methods, e.g., optical character recognition (OCR). The lossy compression algorithm JPEG is used to vary the data retained from the original image. Figure B.2 illustrates the effect of the JPEG quality setting on section of the image that features the aircraft's registration. This setting is varied from 5 (low) to 100 (high).

(a) *cropped,* $q = 5$ **(b)** *cropped,* $q = 10$ **(c)** *cropped,* $q = 20$ **(d)** *cropped,* $q = 100$

Figure B.2.: *Cropped image showing the aircraft registration at four JPEG quality settings.*

The images shown in figure B.2 can be preprocessed to facilitate the recognition of characters with the results shown in figure B.3. Running an optical character recognition (OCR) algorithm on the four images returns the text shown on the top of the boxes shown in figure B.3.



(a) $q = 5$ **(b)** $q = 10$ **(c)** $q = 20$ **(d)** $q = 100$

Figure B.3.: *Recognized text extracted by an OCR algorithm at four JPEG quality settings.*

As illustrated in table B.1, the OCR algorithm isn't able to retrieve the correct set of characters. Some algorithm thus provide a level of confidence wrt. the recognized text.

Table B.1.: *Optical character recognition accuracy at four JPEG quality settings for a set of 200 slightly different cropped images.*

Recognized Text	$q = 5$	$q = 10$	$q = 20$	$q = 100$
D-...	0%	100%	100%	100%
D-A...	0%	99%	100%	100%
D-AIXI	0%	0%	75%	91.5%

B.1.1.2. Actual Information

An international standard (see [350]) dictates that aircraft heavier than air must bear a registration code on their wings and fuselage, which is composed of a nationality mark and registration mark. In Germany, the first letter of the registration mark carries information about the number of engines and the maximum take-off weight of the aircraft [351].

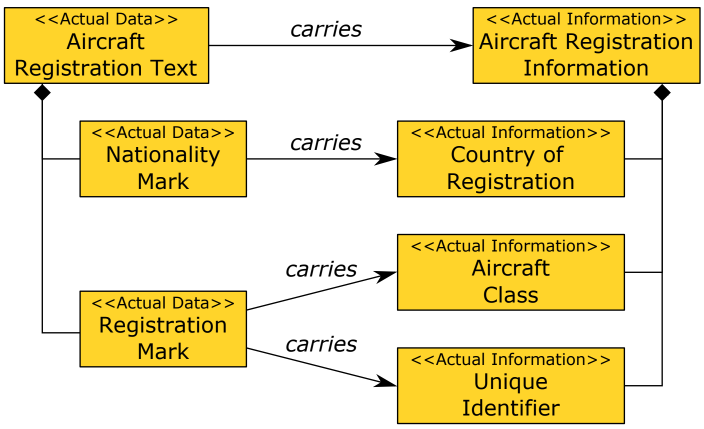


Figure B.4.: *Modeled relationships between actual data and actual information.*

Additional information can be extracted from the image shown in figure B.1, e.g., phase of flight or the weather conditions. This additional information is not required for the simple example and there is thus no added value to extract it from the picture.

B.1.2. Information Demand

The information required by pilots depends on the tasks they have to perform in a given situation (c.f. section 2.1.5). This subsection exemplifies the concept of information need for the task to determine the registration country of an aircraft with the goal to close the airspace to aircraft registered in Russia. For this example, the information is obtained from an image of the aircraft. Figure B.5 shows interactions between the strategic, operational, and information modeling level.

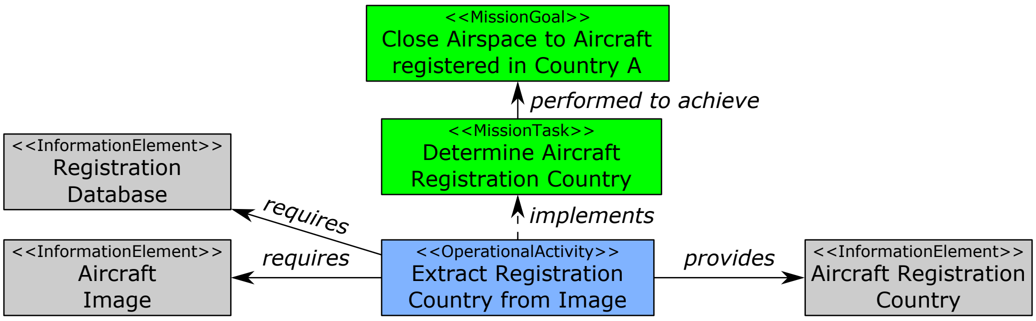


Figure B.5.: *Interactions between the strategic, operational, and information perspectives for a simple image analysis example.*

B.1.2.1. Required Information

Information need, as defined for this study, details the informational elements required by a consumer in order to perform operational activities. Therefore, information need is linked to single operational performer or a set of operational performers. This example focuses on the information need of an operator performing the extraction of information from an image with assistance from an automated system. As shown in figure B.6, the system extracts the nationality mark from an image and delivers the information to the operator, which looks-up the country associated with the registration in a database. The operator thus requires two information elements to perform his activity: the nationality mark and the registration database.

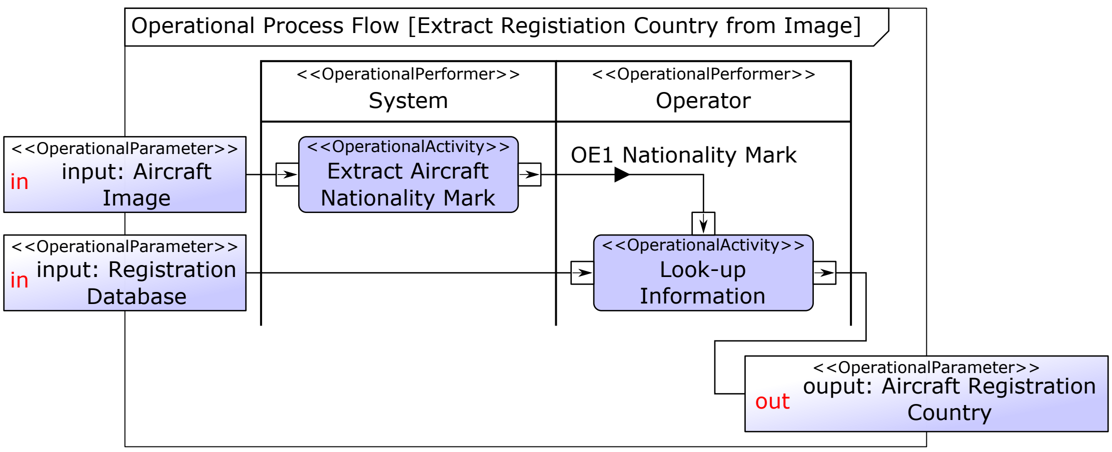


Figure B.6.: *Operational process flow for the extraction of registration information.*

B.1.2.2. Required Information Quality

Modeling the operational process flow and allocating the operational activities helps identifying the information elements consumed by an operational performer. The actual information provided to the operator can vary in quality, e.g. due image compression effects as illustrated in subsection B.1.1.1. The quality of information can be expressed in terms of timelines, completeness, and confidence. The operator can usually perform the operational activity with imperfect information, e.g., the look-up activity can be performed with registration mark character confidence lower than 100%. The acceptable information quality is driven by the context of operations, e.g., a higher confidence is required for the enforcement of legal actions than for the monitoring of aircraft movements. Figure B.7 illustrates the elements driving the information need of an operator which performs an operational activity.

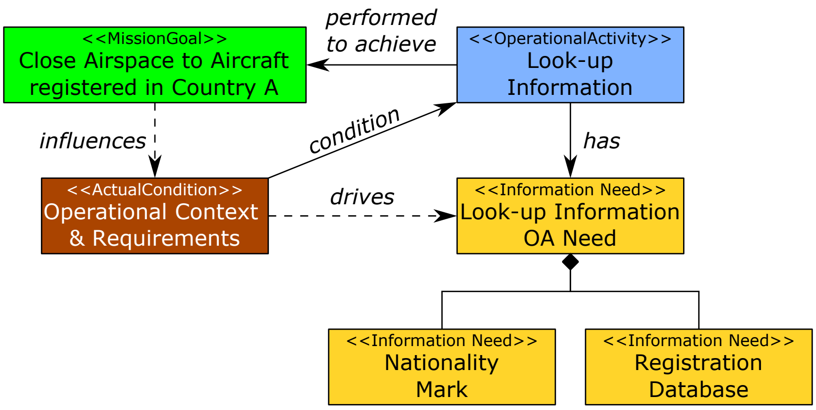


Figure B.7.: *Relationship between elements which influence the quantified information need.*

B.1.2.3. Prioritized Information Need

The importance of acquiring a specific information is dependent on the priority of the associated operational activity and the importance of the information element for this operational activity. Both demanded information elements receive the same priority since the operational activity cannot be performed without the nationality mark nor without knowledge of which nationality mark corresponds to the specified country. Figure B.8 illustrates the elements linked to the information fulfillment priority.

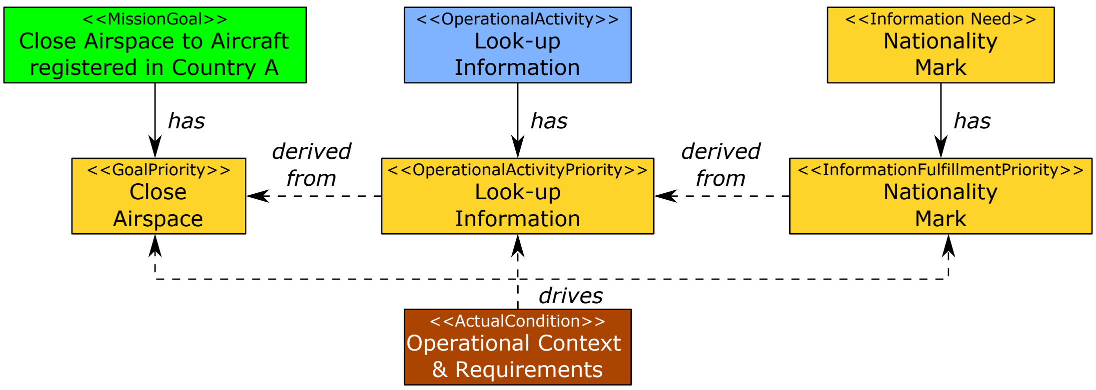


Figure B.8.: *Elements and relationships driving the information fulfillment priority in the simple example.*

C. Study Annex

C.1. Task Data Demand Elicitation Study Annex

This appendix additional the results of the questionnaire-based study from section 4.4.3.

C.1.1. Activity Naming

The activities' names in this theses deviate from Petermeier's notation as shown in the table below.

Table C.1.: *Task naming deviation from Petermeier [283]*

Task	Name	Name in [283]
O_1	Process Position	Determine Group Position
O_2	Process Characteristics	Determine Group Characteristics
O_3	Sort Aircraft	Evaluate Targeting Responsibility
O_4	Prioritize Target	Determine Target Priority
O_5	Monitor Target	Assure Continuous Target Information
O_6	Process Commit Criteria	Evaluate Fulfillment of Commit Criteria
D_1	Assess Threat	Evaluate Threat Potential
D_2	Assess Midair Collision Threat	Evaluate Midair Conflict Potential
D_3	Assess Threat Mitigation Need	Evaluate to Decide on Need for Threat Reaction

C.1.2. Ownship Operational Activities

C.1.2.1. Mission accomplishment activities

The mission accomplishment tasks can be divided into activities performed to acquire and maintain situational awareness and targeting activities that are described by the F2T2EA-cycle. Figure C.1 illustrates the operational activities performed to acquire and maintain SA and their relationship to the identified mission goals. Figure C.2 shows the same content for the activities performed to achieve the mission objectives of the fighter sweep.

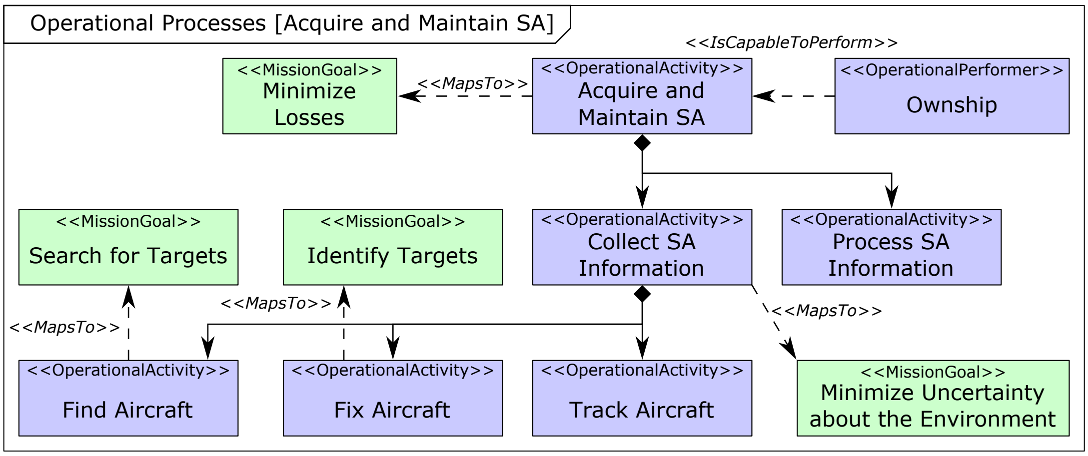


Figure C.1.: *Operational process diagram for the situation awareness (SA) activities.*

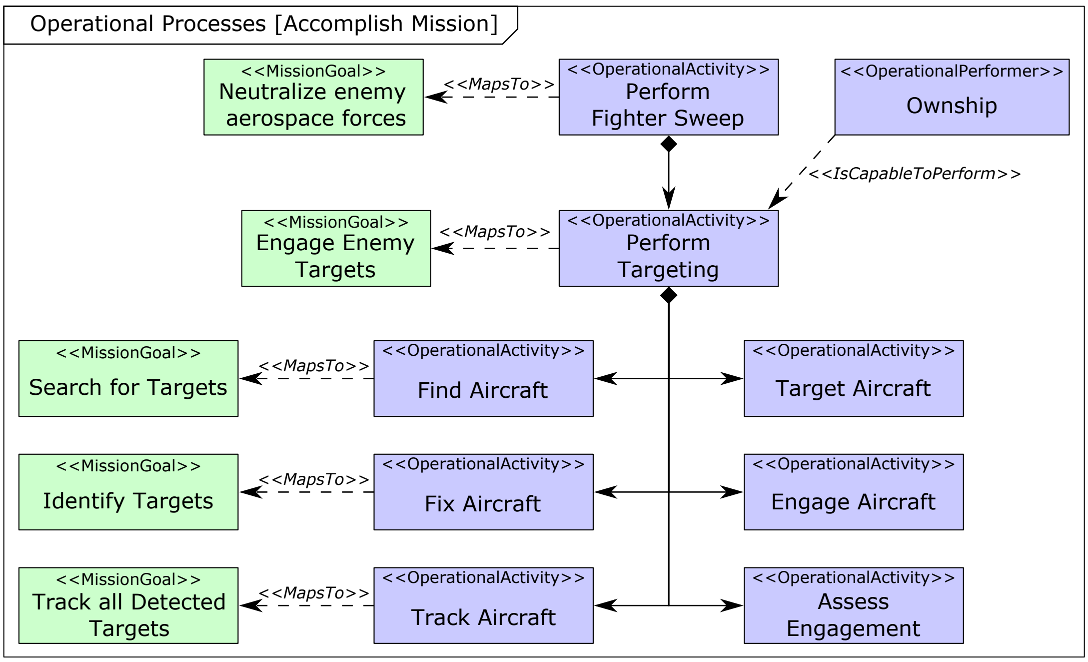


Figure C.2.: *Operational process diagram for the fighter sweep activities.*

Lower-level F2T2EA Activities The F2T2EA activities are composed of several sub-activities [53]. The figure C.3, figure C.4, and figure C.5 illustrate these sub-activities for the fix, track, and target steps respectively. These sub-activities are derived from a simplification of the process described in the literature (c.f. [53]). The engagement and assessment steps of the F2T2EA-cycle are not further detailed due to the research's focus on activities leading to decisions made by pilots.

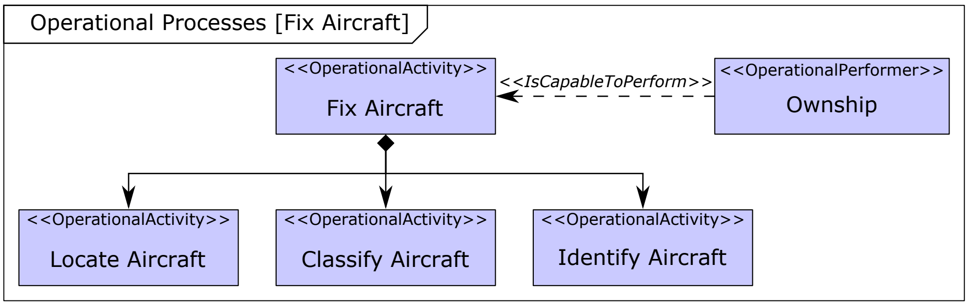


Figure C.3.: *Operational process diagram for the fix activities.*

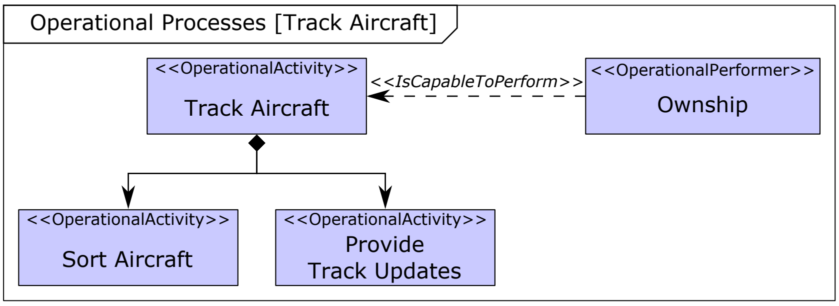


Figure C.4.: *Operational process diagram for the track activities.*

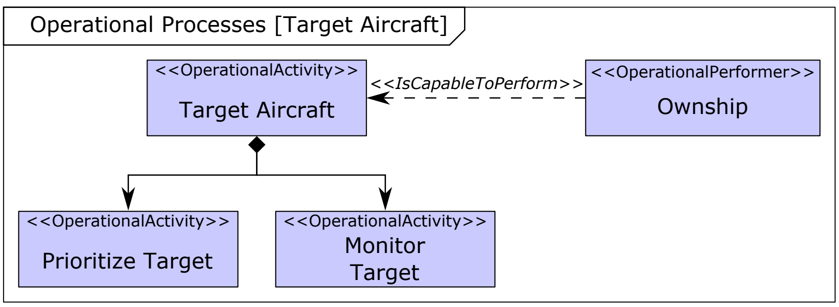


Figure C.5.: *Operational process diagram for the target activities.*

C.1.2.2. Flight safety operational activities

Given the simplification that the fuel management is out of scope and that the terrain avoidance is not an activity that is performed by pilots flying at higher altitudes, avoiding midair collisions is the only remaining flight safety activity considered in this research from the set of tasks listed in section 2.1.4.1. Figure C.6 illustrates the operational activities performed to ensure flight safety and their link to the mission goals.

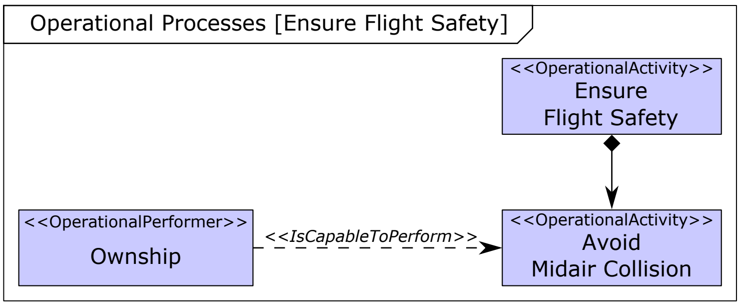


Figure C.6.: *Operational process diagram for the flight safety activities.*

C.1.2.3. Combat survival activities

The combat survival task (see section 2.1.4.2) can be reduced to a single operational activity, *avoid airborne threats*, for the selected scenario. Figure C.7 shows the operational activities performed to ensure the survival of the aircraft.

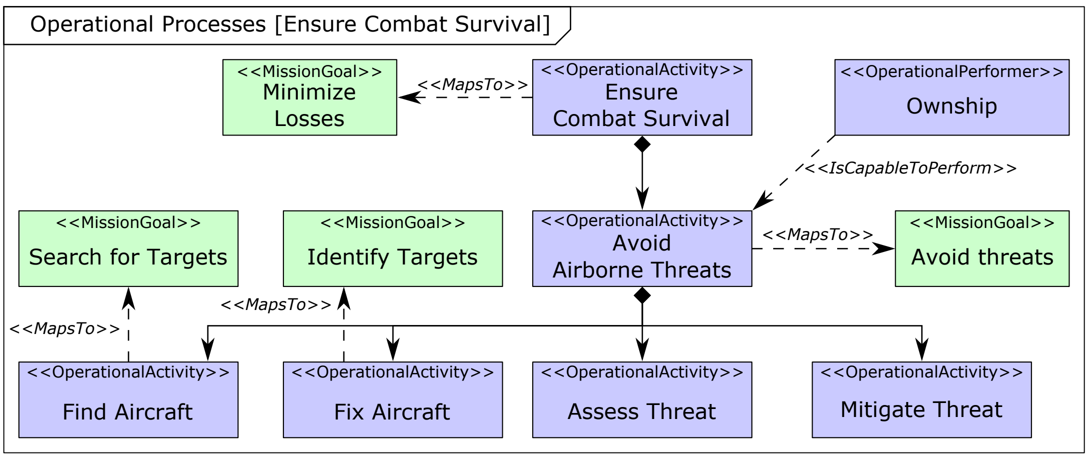


Figure C.7.: *Operational process diagram for the combat survival activities.*

C.1.2.4. Operational Activity Structure

Figure C.8 illustrates the operational activities performed during the use case scenario that is selected for the research. Table C.2 list the descriptions of these activities. The following assumptions have been made in addition to those made during the mission goal analysis (see section **??**):

- The ownship is operated at an altitude in which a collision with the terrain can be excluded.
- The engagement and assessment phases of the F2T2EA-cycle are not performed during the ingress.
- The only objects of interest in the environment are of the type *aircraft*.

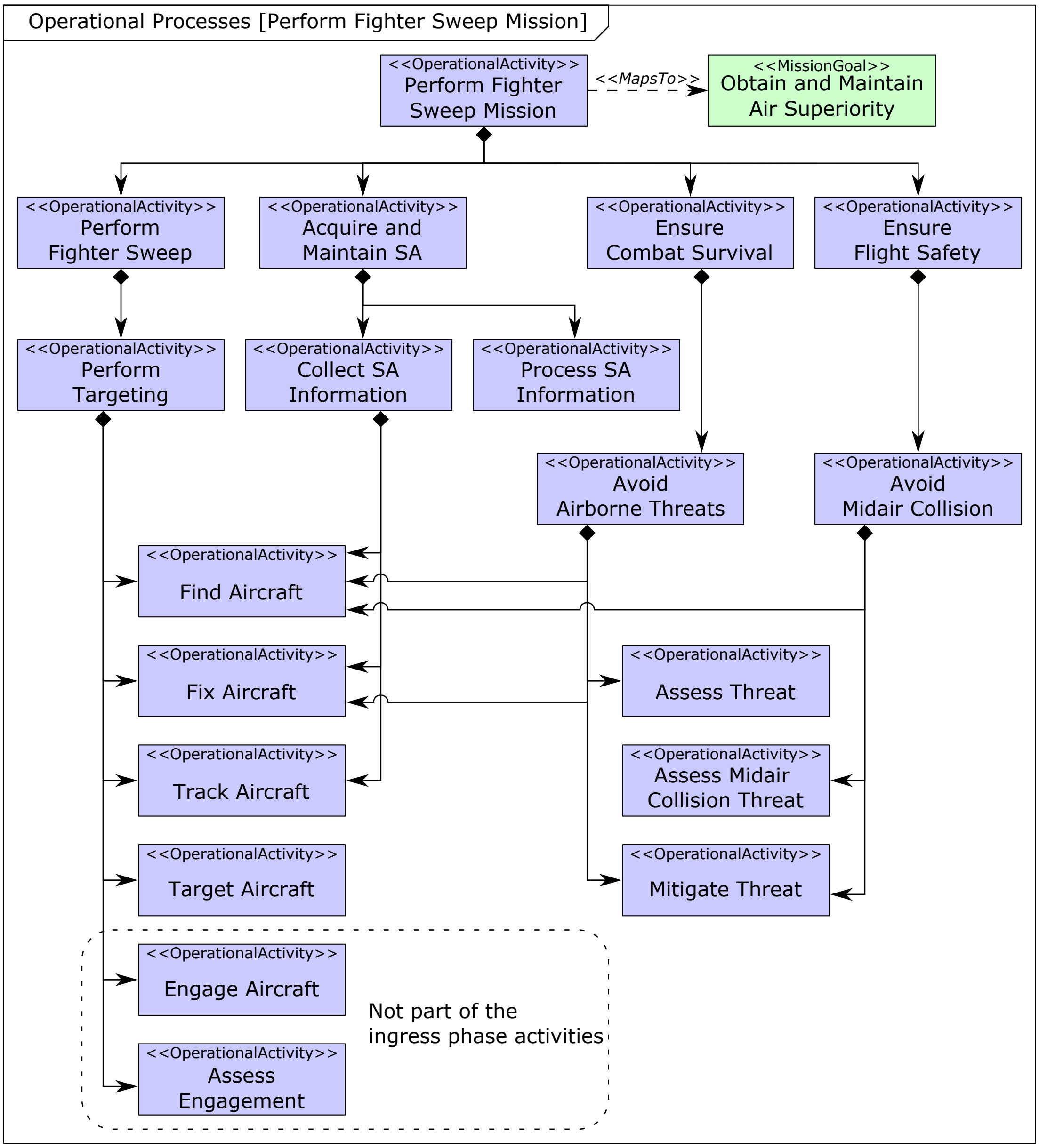


Figure C.8.: *Perform fighter sweep mission operational process diagram.*

Table C.2.: *Operational activities performed in the ingress phase of the fighter sweep mission.*

Operational Activity	**Description**
Perform Fighter Sweep Mission	This activity is performed to obtain and maintain air superiority by neutralizing the opponents air assets.
Perform Fighter Sweep	This activity is performed to seek out and destroy enemy aircraft or targets of opportunity in a designated area.
Perform Targeting	This activity is performed to monitor the environment and process detected objects.
Find Aircraft	This activity is performed to monitor the environment and detect aircraft.
Fix Aircraft	This activity is performed to determine the location, class, and identity of a detected aircraft.
Locate Aircraft	This activity is performed to locate a detected aircraft.
Classify Aircraft	This activity is performed to determine the type of an aircraft.
Identify Aircraft	This activity is performed to identify the allegiance of a detected aircraft.
Track Aircraft	This activity is performed to assign the responsibility for an aircraft and regularly update its known location.
Sort Aircraft	This activity is performed to assign the management responsibility for a fixed aircraft within a flight group.
Provide Track Updates	This activity is performed to keep an up-to-date location of a detected aircraft.
Target Aircraft	This activity is performed to target a tracked aircraft.
Prioritize Target	This activity is performed to determine the priority of a tracked aircraft.
Monitor Target	This activity is performed to assess the fulfillment of targeting criteria by a tracked aircraft.
Acquire and Maintain SA	This activity is performed to acquire and maintain situation awareness.
Collect SA Information	This activity is performed to collect information needed for the acquisition and maintenance of situation awareness.
Process SA Information	This activity is performed to acquire and maintain situation awareness through processing collected information.
Ensure Combat Survival	This activity is performed to ensure the pilot's survival.
Avoid Airborne Threats	This activity is performed to minimize the threat posed by airborne threats
Assess Threat	This activity is performed to assess a potential threat.
Mitigate Threat	This activity is performed to determine steps to be taken in order to mitigate the threat posed by objects in the environment.
Ensure Flight Safety	This activity is performed to ensure a safe navigation.
Avoid Midair Collision	This activity is performed to avoid the collision with an airborne objects.
Assess Midair Collision Threat	This activity is performed to assess the risk of a collision with detected object.

C.1.2.5. Operational Activity Assignment

High-level operational activities, e.g., *Avoid Midair Collision*, identified in the previous have been assigned to the ownship. These activities are performed jointly by the aircraft's systems and the human operator, which both perform dedicated lower level activities. For the context of the research, the assignment of the identified lower-level activities to one of the two operational performers is made based on the following criteria:

- Threat assessments are performed by the human operator.
- Decisions based on the mission goals are made by the pilot.
- Activities linked with the sensor operations, sensor data collection, and sensor data processing are assigned to the aircraft.

Figure C.9 shows the mapping between the operational performers, aircraft and pilot, and the activities they are capable of performing. As illustrated, the aircraft performs all sub-activities that are part of the *Fix Aircraft* operational activity.

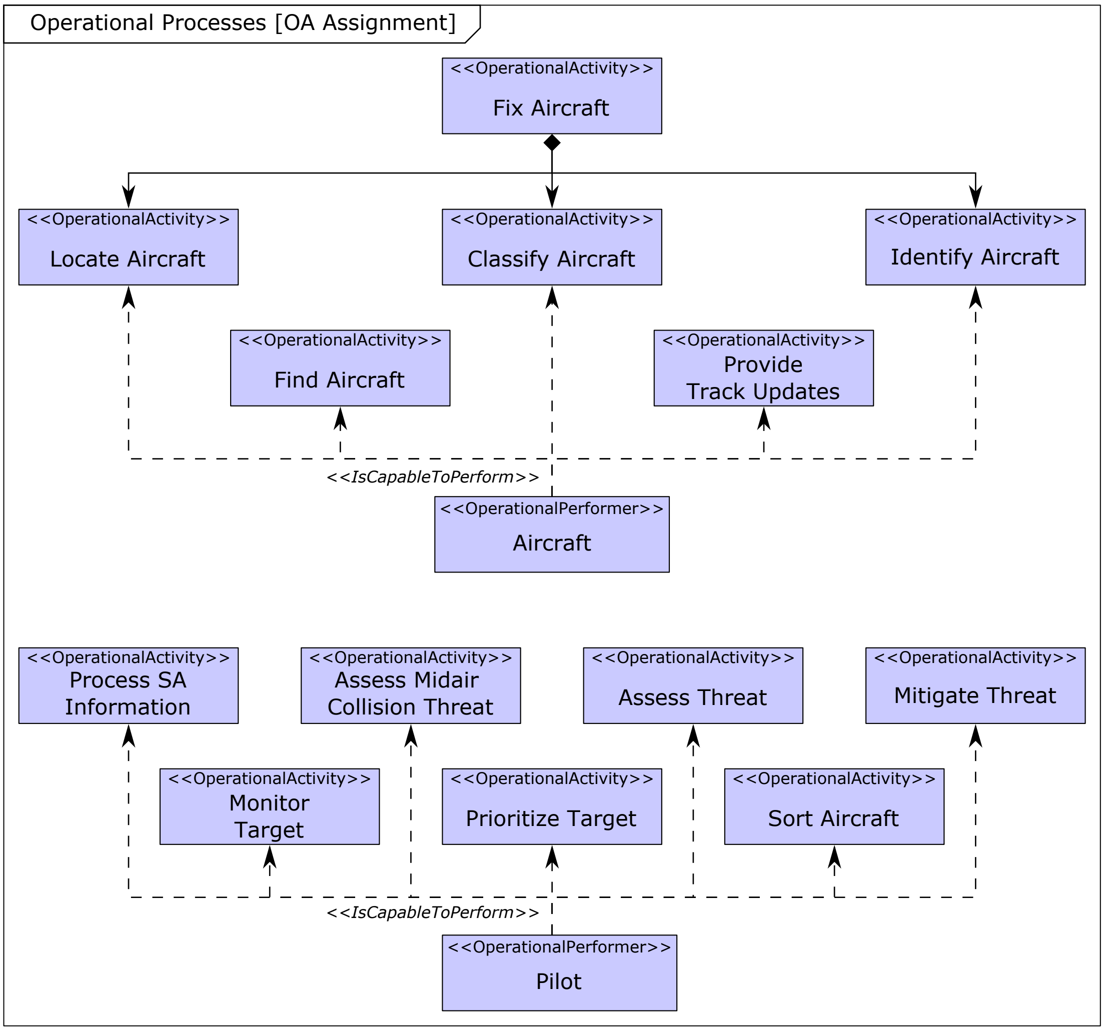


Figure C.9.: *Perform fighter sweep mission operational process diagram.*

C.1.3. Functional Analysis

A functional analysis is performed to identify the data elements exchanged between the aircraft and the pilot on the resource level. This section first describes the structure of the aircraft and sensor management system and then describes the functions performed by the aircraft. Finally, an overview of the subsystem functions is provided.

C.1.3.1. System Structure

Based on the sensor management loop described in section 2.2 (c.f. figure 2.10 on page 17), the aircraft's simplified structure is composed of four elements: a single radar sensor, a sensor manager, a data processor, and a display, as shown in figure C.10.

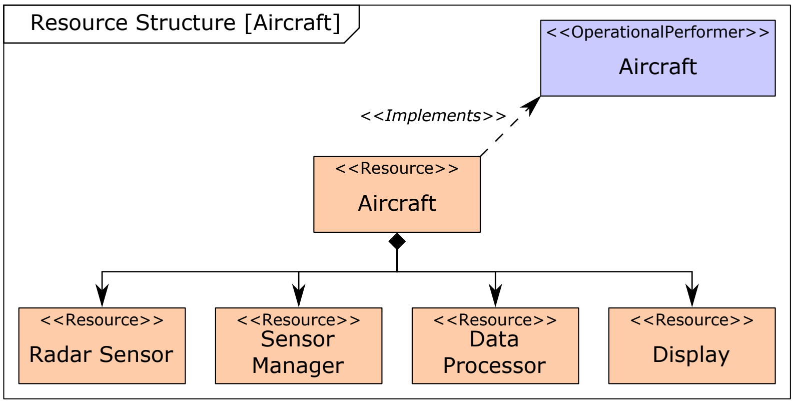


Figure C.10.: *Simplified aircraft resource structure.*

C.1.3.2. System Functions

This study focuses on the provision of sensor data to the pilot and, thus, this functional analysis only covers the aircraft's function *provide sensor data*. The aircraft has to perform functions that implement the three operational activities identified in section C.1.2.5. As shown in figure C.11, these functions are: provide detections, provide aircraft characteristics, and provide track data.

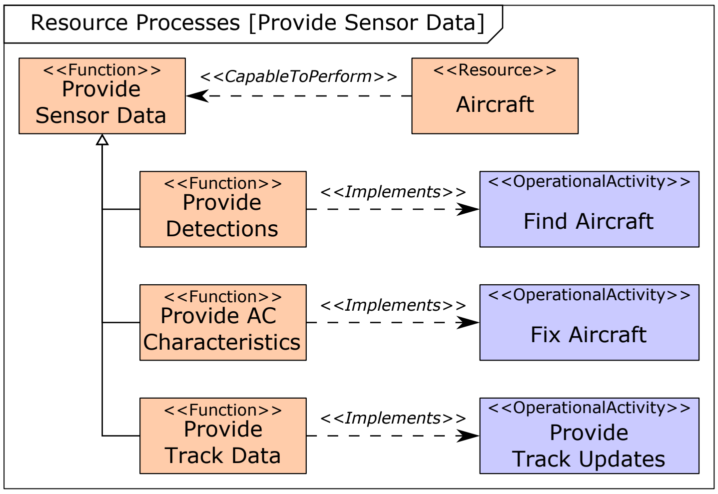


Figure C.11.: *Resource processes diagram describing the functions performed by the aircraft.*

Provide Detections The aircraft collects and provides radar detections the the pilot following the process illustrated in figure C.12. The process starts with the management of the tasks assigned to the sensor system and the allocation of its resources to these tasks. All levels of sensor management activities are covered by the task management function (see section 2.2.2 for the sensor management activity levels). Performing the function yields a lists of tasks to be performed by the radar sensor. The process flow diagram figure C.12 assumes that only a single task is performed for reasons of simplicity. All tasks can be generalized to the active sending and receiving of radar signals in a predefined volume of space in front of the aircraft. Searching in the volume returns a list of detections based on the signal-to-noise ratio of the captured return signals (see section 2.1.7.1). The search task is performed continuously and detections are sent to the data processor at predefined time intervals for storage and handling. Detections are provided to the sensor manager for its management of sensor tasks. Finally, the detections are sent to the display, which provides the information to the pilot. Table C.3 list the descriptions of the functions performed by subsystems to provide detections to the operator.

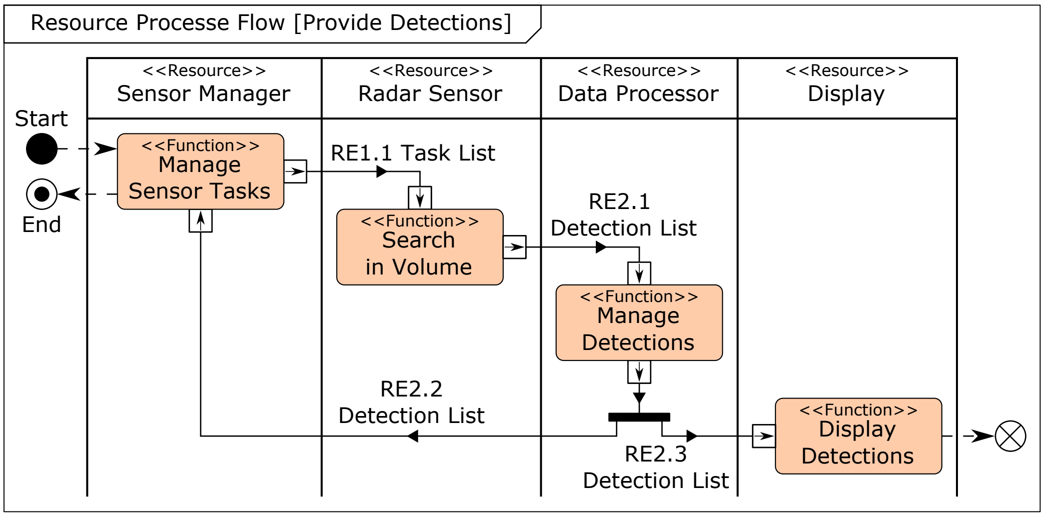


Figure C.12.: *Resource process flow diagram describing the provision of aircraft detection.*

Table C.3.: *Description of the functions performed by the aircraft to provide detections to the operator.*

Function	Description
Manage Sensor Tasks	This function manages the tasks to be performed by the sensor system and allocates sensor resources to these tasks.
Search in Volume	This function utilizes the allocated sensor resources to scan a volume of airspace and returns radar detections.
Manage Detections	This function stores, handles, and provides detections to requesting subsystems.
Display Detections	This function displays radar detection on a screen.

Figure C.13 illustrates the composition of the detection list data element. The main components of a single detection are the radar measurement and measurement accuracies that are described in sections 2.1.7.3 and 2.1.7.4. Table C.4 lists the definitions of the data elements.

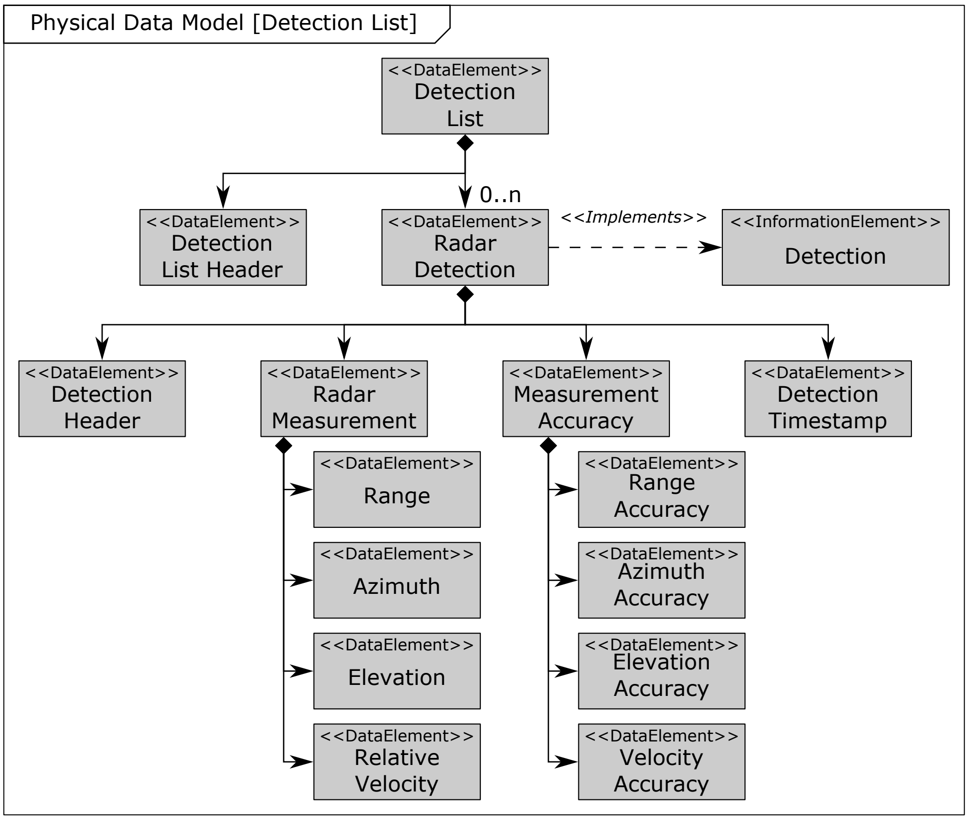


Figure C.13.: *Radar detection data model.*

Table C.4.: *Description of data elements which are processed to provide detections to the operator.*

Data Element	Description
Detection List	This data element contains a set of radar detection and associated meta data.
Detection List Header	This data element holds meta data associated with the detection list, e.g., the detection list id.
Radar Detection	This data element implements the sensor detection information element.
Detection Header	This data element provides meta data associated with the detection, e.g., radar detection id.
Radar Measurement	This data element carries the values of the measurement made by the sensor, in this case range, azimuth, elevation, and relative velocity.
Measurement Accuracy	This data element holds the accuracy estimations of the sensor measurement values.
Detection Timestamp	This data element provides the time at which the sensor detection occurred.

Provide Track Data Tracking is a continuous process to determine a detected object's current position, which requires regular object detections (see section 2.1.7.5). The collection of these detections can be explicitly requested from the radar sensor. To this end, the sensor management function is extended to accept the input of a list of aircraft to be tracked. The collected detections are stored and provided to the track management function, where detections are associated with existing tracks in the data base. If a detection cannot be associated with any of the tracks, a new track is initialized and added to the database. The display provides the information about the tracked aircraft to the pilot. Figure C.14 illustrates the process performed to provide track updates to the pilot. The performed functions are described in table C.5.

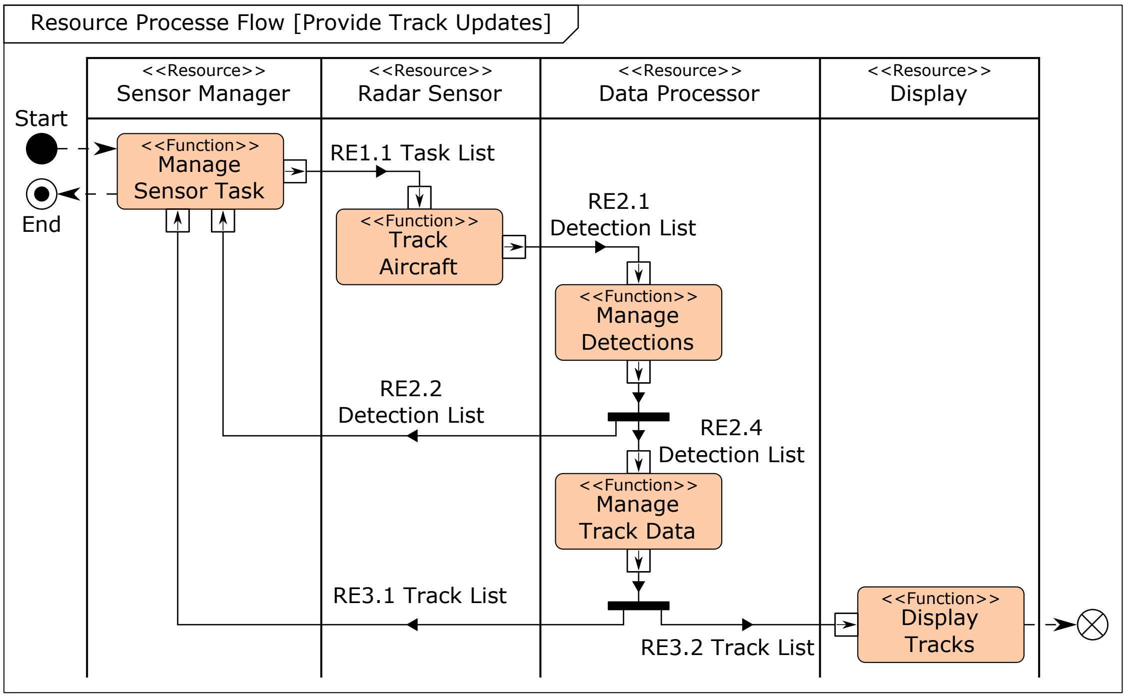


Figure C.14.: *Resource process flow diagram describing the provision of track updates.*

Table C.5.: *Description of the functions performed by the aircraft to provide track updates to the operator.*

Function	Description
Manage Sensor Tasks	This function manages the tasks to be performed by the sensor system and allocates sensor resources to these tasks.
Track Aircraft	This function utilizes the allocated sensor resources to track an aircraft and returns radar detections.
Manage Detections	This function stores, handles, and provides detections to requesting subsystems.
Manage Track Data	This function associates tracks and detections, performs track updates, and initializes tracks for newly detected aircraft.
Display Detections	This function displays radar tracks on a screen.

Figure C.15 illustrates the task list data element structure. Elements shown in the diagram are described in table C.6.

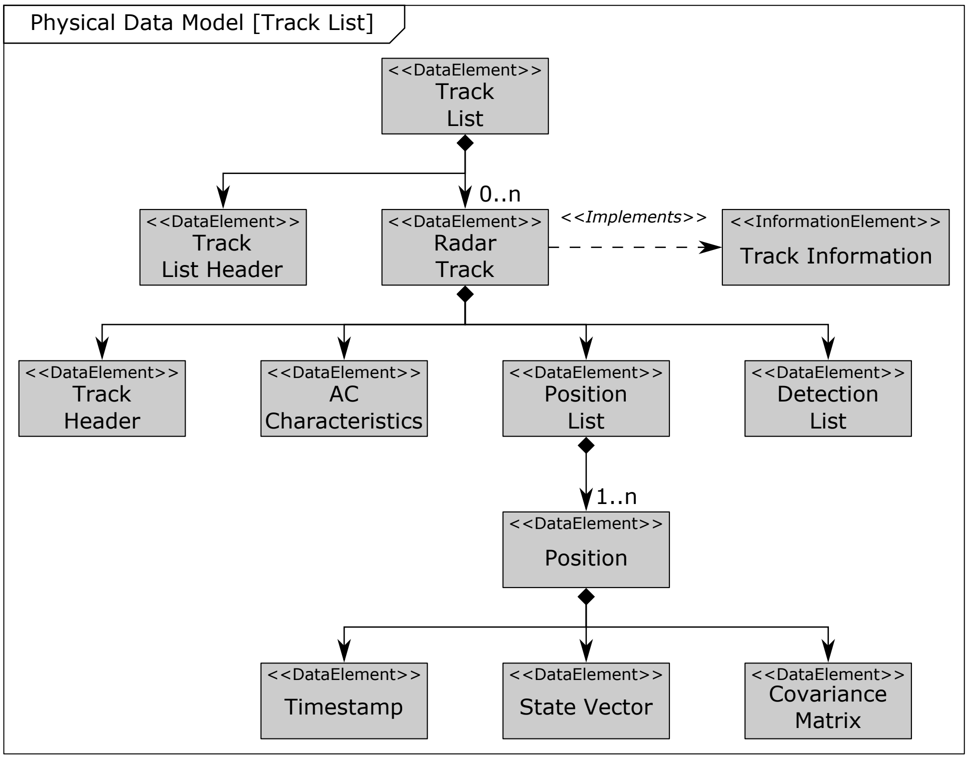


Figure C.15.: *Track list data model.*

Table C.6.: *Description of data elements which are processed to provide track data to the operator.*

Data Element	Description
Track List	This data element contains a set of radar tracks and associated meta data.
Track List Header	This data element holds meta data associated with the track list, e.g., the track list id.
Radar Track	This data element implements the sensor track information. Further, it contains the list of detections that are associated with the track.
Track Header	This data element provides meta data associated with the detection, e.g., radar detection id.
AC Characteristics	This data element describes the aircraft's characteristics.
Position	This element carries the aircraft's state at a specific time.
Position Timestamp	This data element provides the time at which the aircraft was at the calculated position.
State Vector	This data element carries the values describing the position, velocity, and acceleration information.
Covariance Matrix	This data element describes the accuracy of the state vector.
Detection List	This data element contains a set of radar detection and associated meta data.

Provide Aircraft Characteristics The information required to identify targets varies with the operational context and often requires information from third party sources in the real world, e.g., control and command (C_2) assets. To simplify the modeling process, we define the context such that a positive identification can only be achieved by a radar-based identification and the procedural identification is limited to the formation assessment. Radar-based identification approaches analyze the radar returns and compare these to known objects in a database. For example, *Jet Engine Modulation* the radar returns of jet engines to determine the aircraft type [352]. For this study, tracks are identified based on their geographical location.

Formation assessment is an identification method used to apply the identity of one contact to others based on their horizontal range, their altitude separation, their velocity, and their course [46]. The assigned identity is maintained even after the splitting of the group if the group is continuously tracked during the split [46]. This method requires the identification of at least one formation member through other means and an established formation track [46].

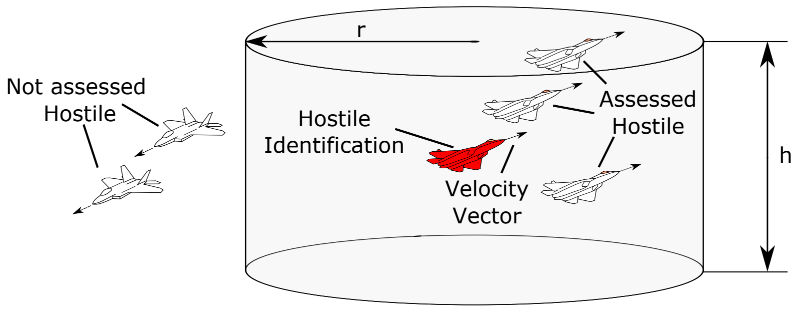


Figure C.16.: *Spacial relationship for formation assessment [46]*

The process performed to provide information about an aircraft's characteristic is illustrated in figure C.17 and starts after the collection of radar detections. The detections and tracks associated with a specific aircraft are processed to derive the type, allegiance, and formation. As described in the previous section, the aircraft characteristics are provided to the display within the track lists.

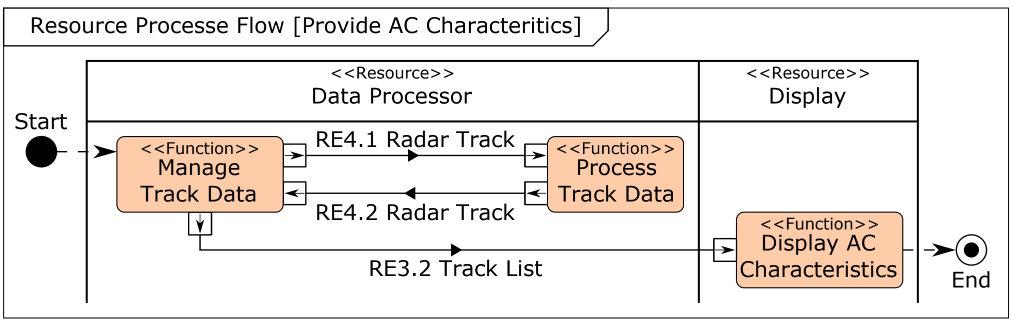


Figure C.17.: *Resource process flow diagram describing the provision of aircraft characteristics.*

Table C.7 lists the descriptions of the functions performed to obtain aircraft characteristics and provide these to the operator.

Table C.7.: *Description of the functions performed by the aircraft to provide aircraft characteristics to the operator.*

Function	Description
Manage track data	This function associates tracks and detections, performs track updates, and initializes tracks for newly detected aircraft.
Process Track Data	This function processes radar tracks to obtain the type and allegiance of a detected or tracked aircraft.
Display AC Characteristics	This function displays the characteristics of a detected or tracked aircraft on a screen.

Figure C.18 describes the structure of the data element used to pass the characteristics of an aircraft to the operator. The elements are described in table C.8.

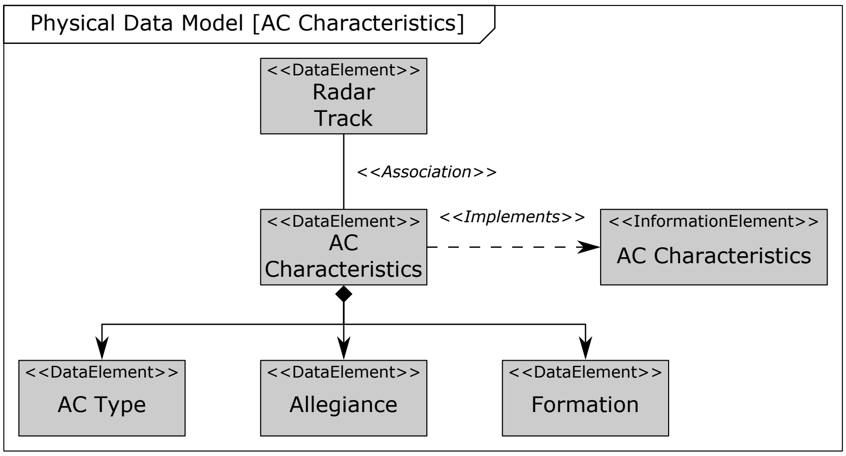


Figure C.18.: *Aircraft characteristics data model.*

Table C.8.: *Description of data elements which are processed to provide aircraft characteristics to the operator.*

Data Element	Description
AC Characteristics	This data element describes the aircraft's characteristics.
Aircraft Type	This data element represents the , e.g., fighter aircraft.
Allegiance	This data element states if the allegiance of an aircraft is friendly, neutral, hostile, or unknown.
Formation	This data element describes if the aircraft is part of a formation.

C.1.4. Participants

Table C.9 describes the study participants' demographic.

Table C.9.: *Demographics of the Knowledge Elicitation Study Participants.*

$ID_{Subject}$	Age	Pilot	Flight Hours	e_{A-G}	e_{A-A}
1	45	0	1,900	2	5
2	50	0	2,400	3	5
3	51	0	2,200	2	5
4	52	0	2,000	2	5
5	60	1	10,000	3	5
6	44	1	3,050	1	5
7	60	1	9,650	3	5
8	41	1	3,000	1	4
9	53	1	2,500	3	5
10	38	1	1,350	3	4
11	55	1	5,930	4	4
12	55	1	3,000	3	4
13	45	1	3,300	4	4

C.1.5. Parameter Selection and Importance

Table C.10 lists the mean importance given to parameter specific data accuracy demands.

Table C.10.: *Mean parameter accuracy demand importance.*

Task ID	h	Δ_{Aspect}	v_c	Ψ	R	v
D1	3.0		2.7	3.1	3.6	2.8
D2	3.5			3.0	3.5	
D3	2.8	3.3	2.7	3.2	3.5	2.9
O1	3.0				3.5	
O2	3.2	2.9		2.7	3.4	3.0
O3	3.3			2.8	3.5	3.0
O4	2.9	3.1		3.2	3.5	3.1
O5	3.2				3.0	2.9
O6				3.4	3.6	3.2

C.1.6. Aggregated Task Tracking Quality Demands

Process SA Information - Position (O1) Figure C.19 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Process SA Information - Position* (O1).

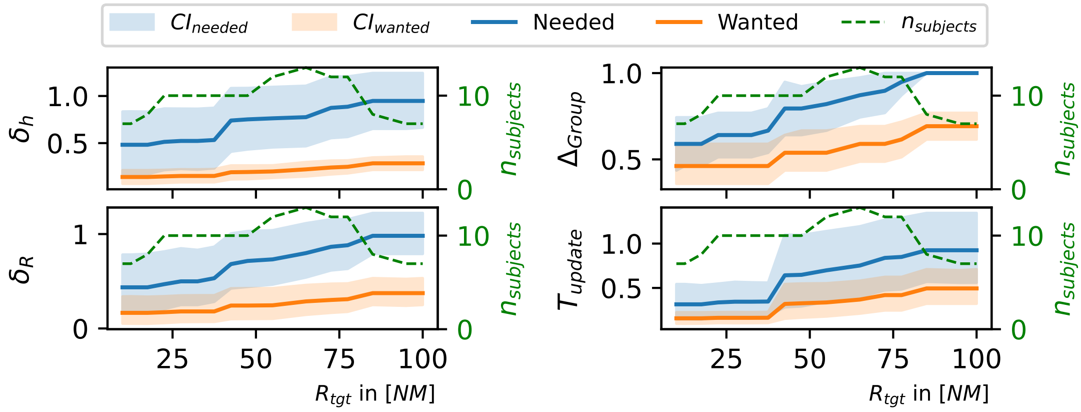


Figure C.19.: *Accuracy demand curve for task O1.*

Process SA Information - Characteristics (O2) Figure C.20 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Process SA Information - Characteristics* (O2).

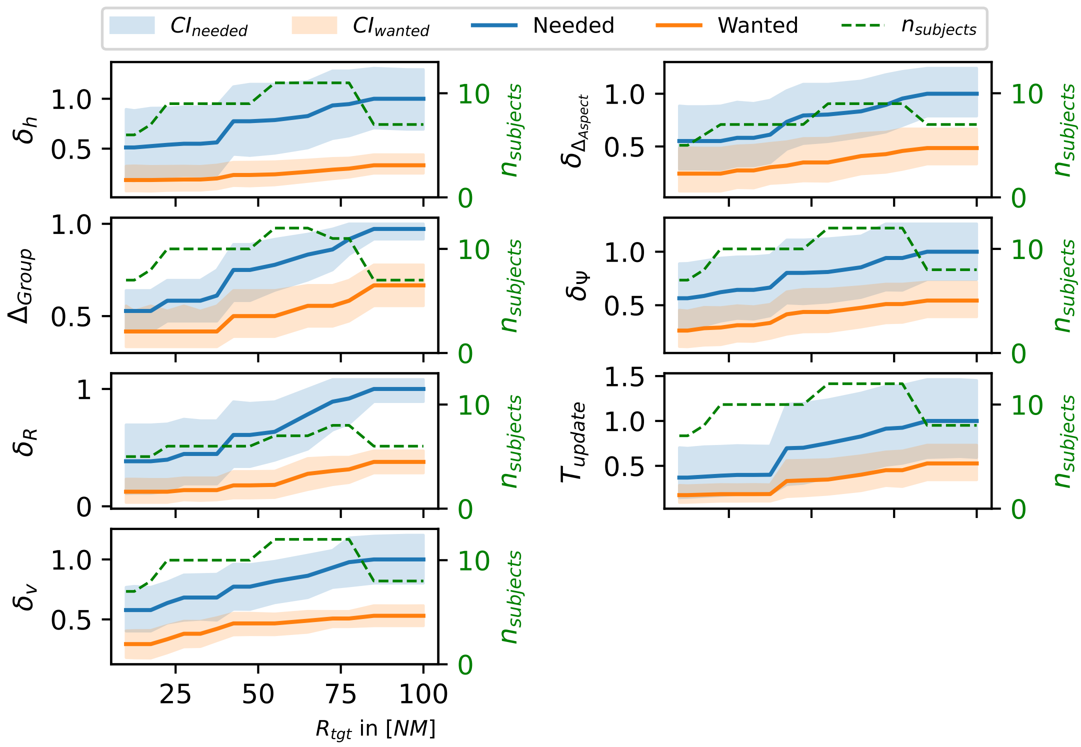


Figure C.20.: *Accuracy demand curve for task O2.*

Sort Aircraft (O3) Figure C.21 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Sort Aircraft* (O3).

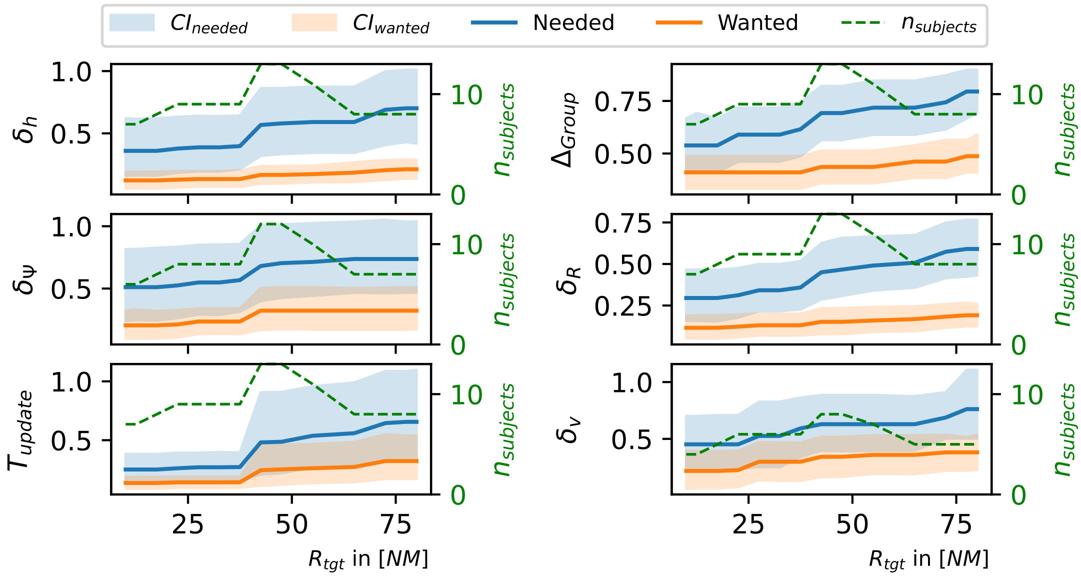


Figure C.21.: *Accuracy demand curve for task O3.*

Prioritize Target (O4) Figure C.22 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Prioritize Target* (O4).

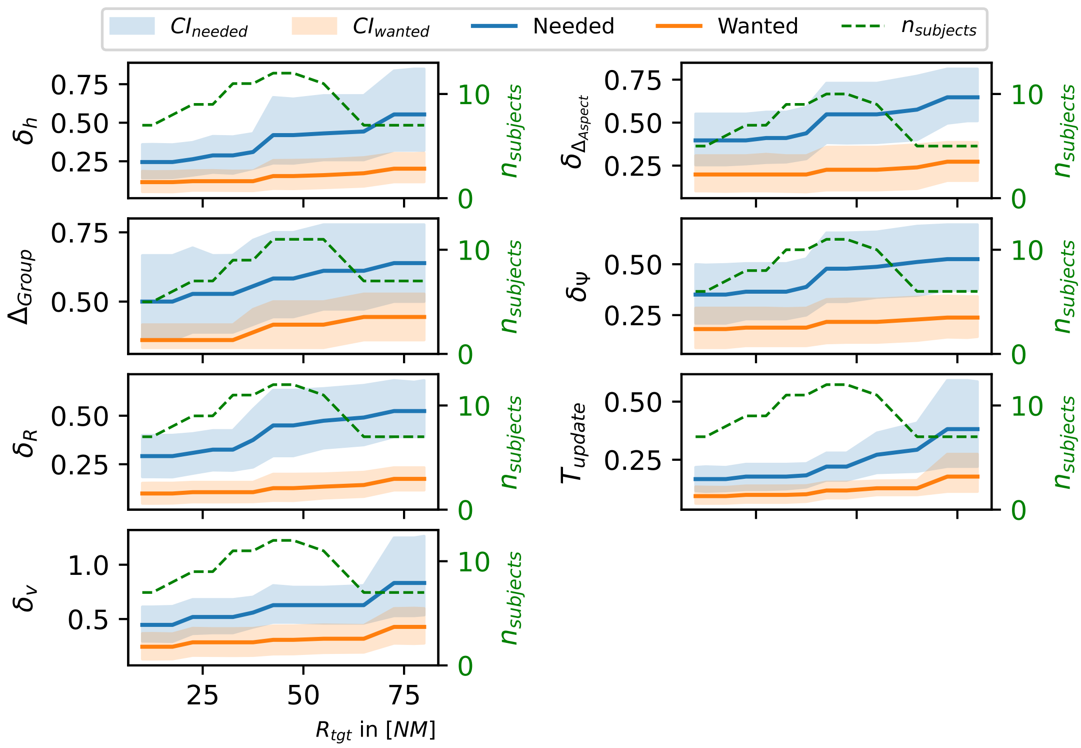


Figure C.22.: *Accuracy demand curve for task O4.*

Monitor Target (O5) Figure C.23 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Monitor Target* (O5).

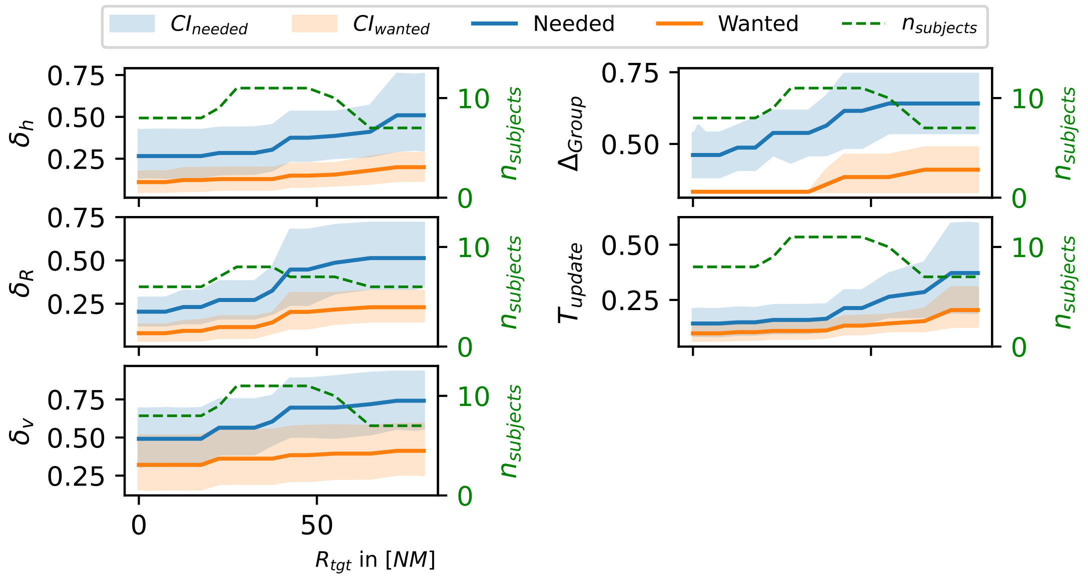


Figure C.23.: *Accuracy demand curve for task O5.*

Process SA Information - Commit Criteria (O6) Figure C.24 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Process SA Information - Commit Criteria* (O6).

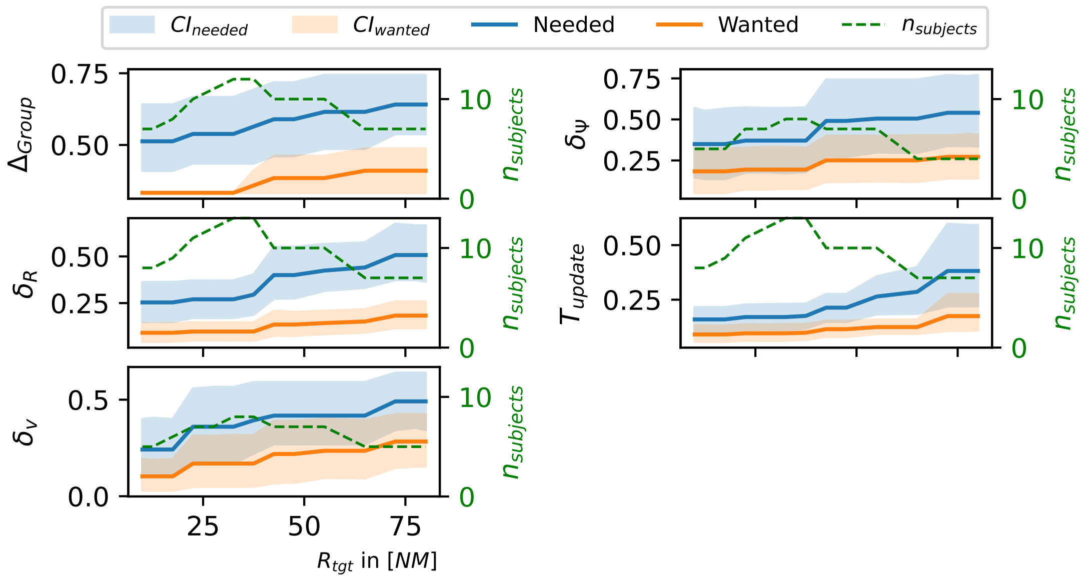


Figure C.24.: *Accuracy demand curve for task O6.*

Evaluate Threat Potential (D1) Figure C.25 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Evaluate Threat Potential* (D1).

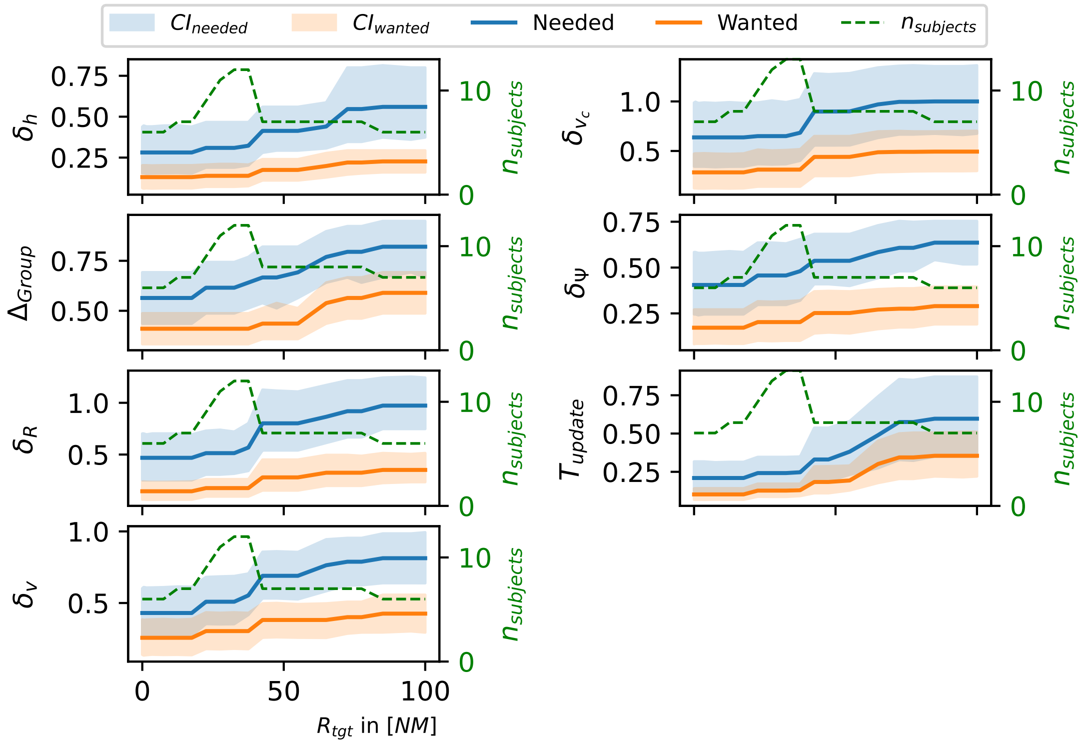


Figure C.25.: *Accuracy demand curve for task D1.*

Assess Midair Collision Threat (D2) Figure C.26 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Assess Midair Collision Threat* (D2).

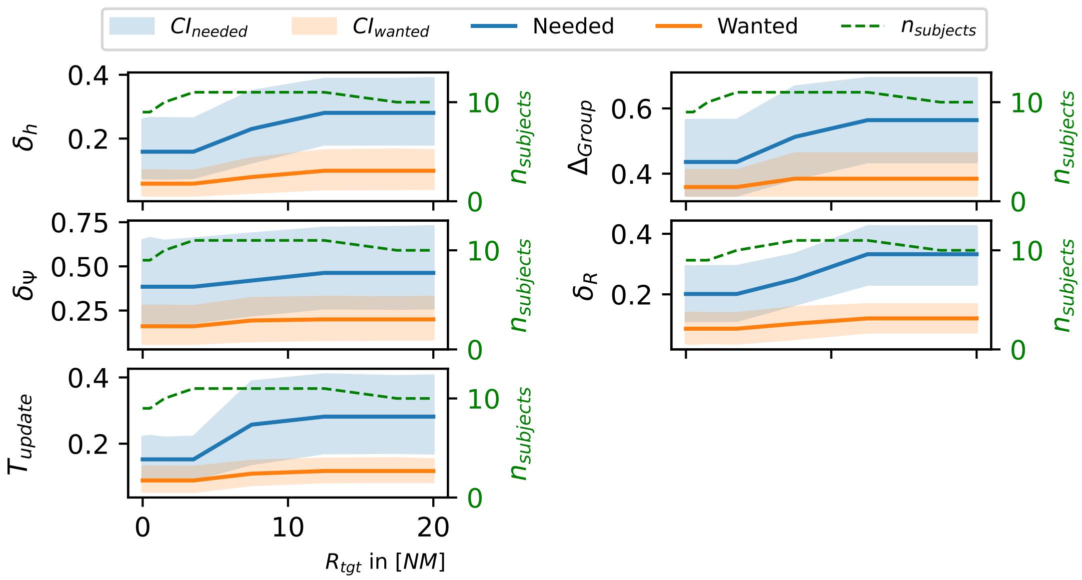


Figure C.26.: *Accuracy demand curve for task D2.*

Mitigate Threat (D3) Figure C.27 illustrates the relationship between the needed and wanted accuracy demands and the range of the corresponding object for the task *Mitigate Threat* (D3).

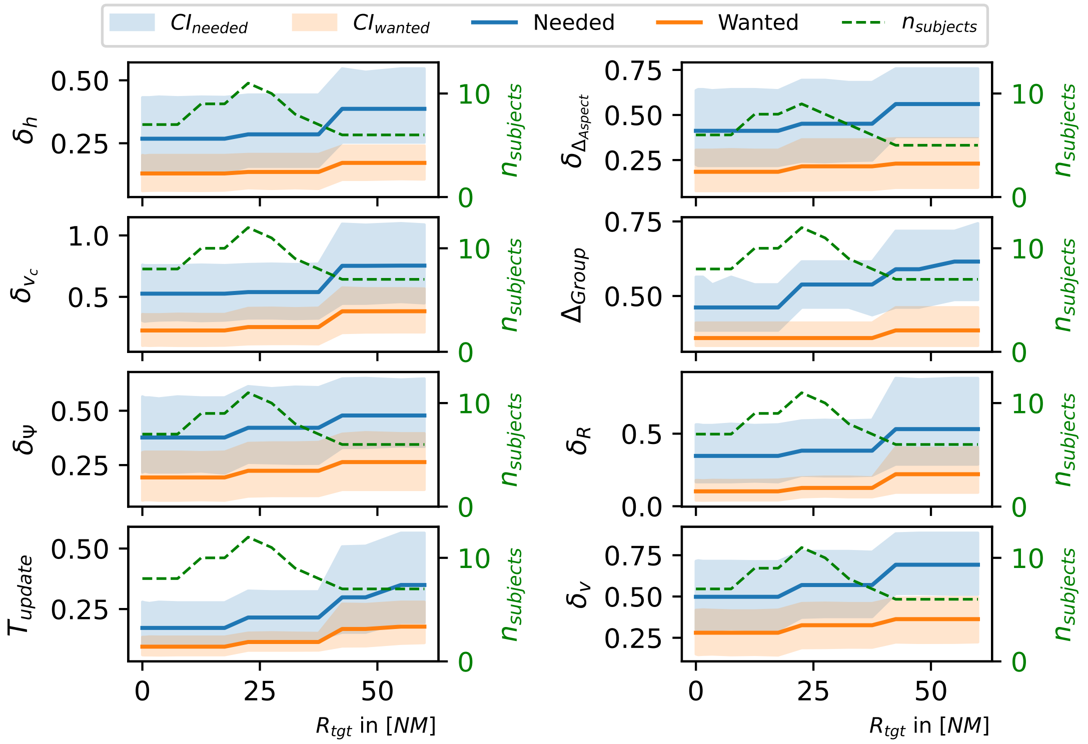


Figure C.27.: *Accuracy demand curve for task D3.*

C.2. Task Assignment and Prioritization Study Annex

C.2.1. Study Interface Design

The human-machine interface (HMI) shown in figure C.28 is used to facilitate task allocation and prioritization. The interface is implemented in the general-purpose programming language Python 3 using the graphical user interface library TkInter. *Tracking markers* (C) are incorporated to detect the interface's position in the eye-tracking systems reference frame. The *scenario view* (D) visualizes the movement of objects, which domain experts can select to display further information about the object in the *group information view* (F) on the upper right of the display. The animation is triggered at the start of the allocation process. It can be restarted via a button in the *scenario interaction section* (A). The *group formation view* (G) illustrates the formation of selected groups. When a scenario is animated, two *tracking markers* (E) appear and switch positions at regular intervals to synchronize the interface data and the eye-tracking data. Another *tracking marker* (B) appears in the *scenario interaction section* (A) to further improve the interface position's tracking. The activities that can be allocated to tracks are listed in the *task allocation section* (H). Buttons in the *task interaction section* (I) enable the participants to change the assigned group priorities, obtain an overview of the allocated tasks and task priorities, and finalize the task allocation when all objects have been assigned at least one task.

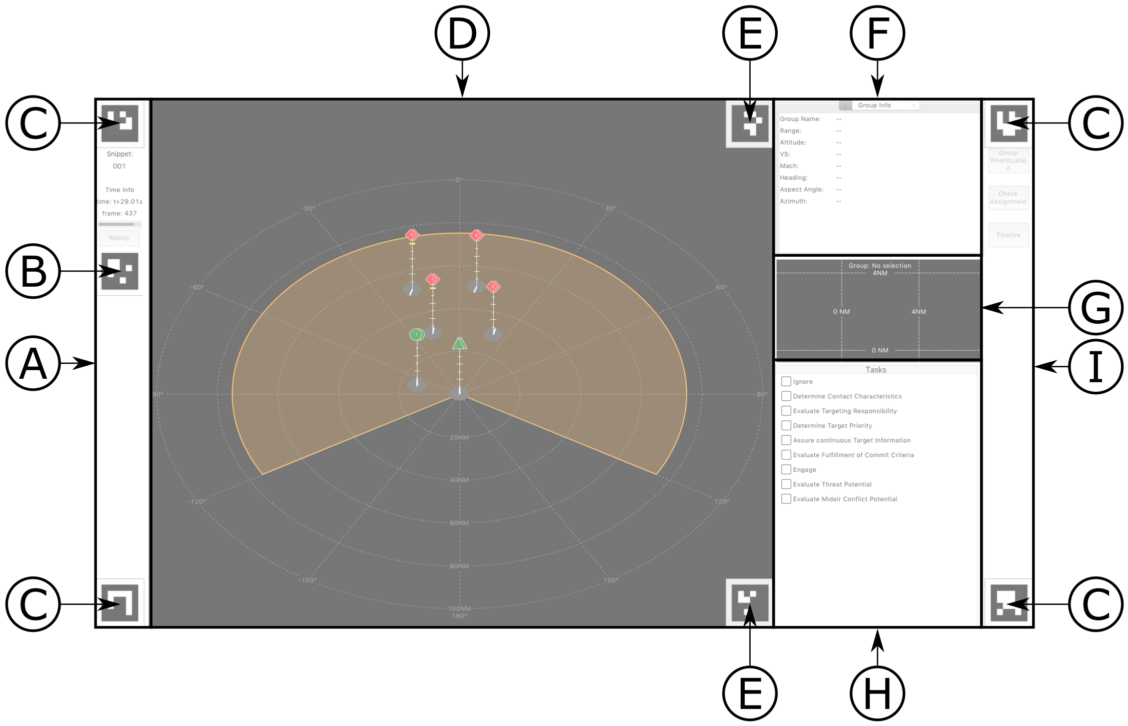
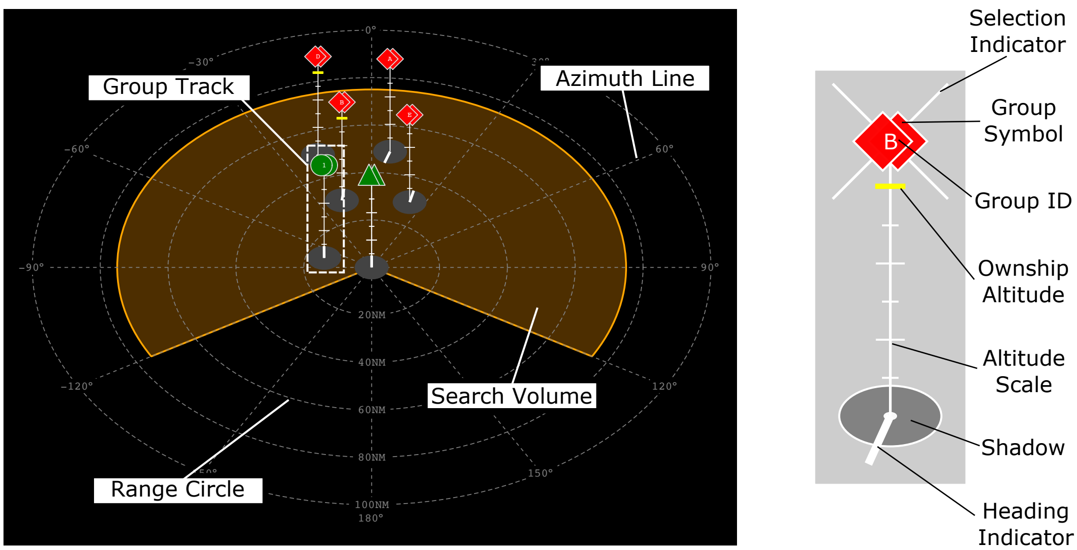


Figure C.28.: *Overview of the task allocation interface.*

C.2.1.1. 2.5D Scenario View

The environment is illustrated in the *scenario view* relative to the participant's aircraft, further referred to as ownship. A two-and-a-half-dimensional perspective conveys the range, position, and altitude of all tracks up to a range of 100 NM. The black background is used to reduce eyestrain and follow the design of tactical displays familiar to the participants. The view is based on a polar coordinate system that lies on the surface and originates at the ownship's projected ground position. Azimuth lines are drawn in 30° increments, and range circles are drawn in 20 NM increments to support the participant's ability to build their situational awareness. The sensor search volume is illustrated as a circular sector in the r, φ-plane of the polar coordinate system. The group tracks are selectable to assign tasks, and the selection of the search volume prompts the request to define the search task priority. The scenario view is illustrated in figure C.29a.

The group tracks are composed of several items, as shown in figure C.29b. The group symbol illustrates the affiliation of the group. A green triangle identifies the ownship, and a green circle indicates the cooperating friendly group. Two red diamonds are used to signify a hostile two-ship formation. All group symbols, except the ownship, contain a letter or number representing the group's ID. This ID is randomized for every participant. The position of the aircraft is projected onto the ground as a shadow. The shadow contains a heading indicator that starts in the center of the shadow and points in the group's direction of movement relative to the ownship. The length of the heading indicator is used to illustrate the group's velocity. If the heading indicator leaves the shadow, the aircraft group is flying supersonic. The group symbol and shadow are connected by an altitude scale, on which small ticks are featured at 5.000ft intervals, and large ticks appear every 10.000ft. The ownship's altitude is shown as a yellow bar on the altitude scale if the group is flying higher than the ownship. When a group is selected, a white selection indicator appears to highlight the group.



(a) *Scenario View* **(b)** *Group Track*

Figure C.29.: *Scenario display*

C.2.1.2. Data Input

SA Rating After the snippet's animation, participants are asked to rate their situational awareness in a pop-up window, as shown in figure C.30. The rating scale ranges from low (0) to high (100) and is separated into seven parts. Participants can freely place a marker onto the scale, and the rating is saved in increments of thirds, e.g., between the values of 50 and 51, the following ratings can be saved: 50.00, 50.33, 50.66, 51.00. The lowest possible value is 0.33 to avoid conflicts with missing data represented by a value of 0.

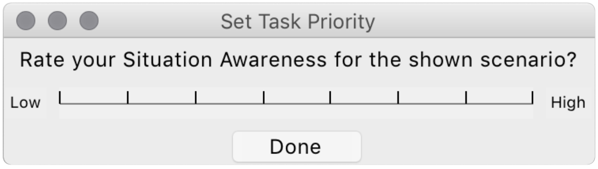


Figure C.30.: *Subjective situation awareness rating pop-up window.*

Group Prioritization The subjective situational awareness assessment is followed by the rating of the group priorities on a scale from low (0) to high (100) with small ticks every five units and large ticks every ten units. Similar to the previously described SA rating scale, the lowest possible value is 0.33 to avoid conflicts with missing data represented by a value of 0. The rating is performed in the pop-up window shown in figure C.31. From left to right, the window contains a group symbol, group ID, rating scale, and select button for every two-ship formation in the snippet. The select button can be used to highlight groups in the *scenario view*.

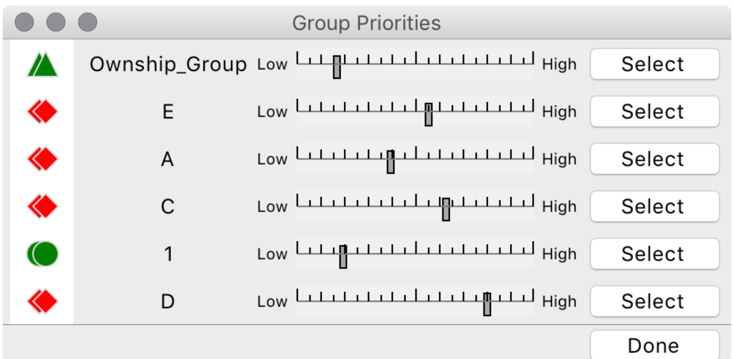


Figure C.31.: *Group priority rating pop-up window.*

Snippet Complexity Rating The snippet task allocation process ends with the rating of the snippet's perceived complexity on the same scale from low (0) to high (100) as described for the situational awareness rating.

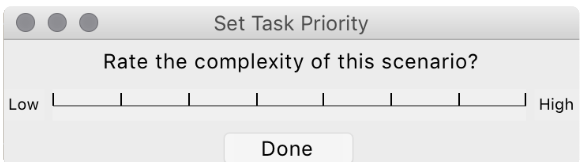
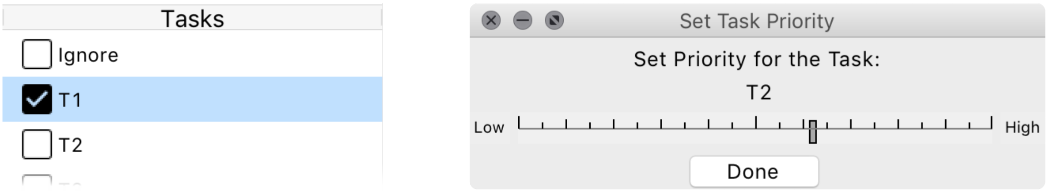


Figure C.32.: *Snippet complexity rating pop-up window.*

Task Allocation Process Participants can assign tasks from the list of nine tasks and listed in the *task allocation section* shown in figure C.33a. Alternatively, participants are given the option to ignore a group if they do not associate any task with this group. The task allocation and prioritization follows the following process:

1. Select the group in the *scenario view*.
2. Either select to ignore the group or assign one of the tasks by ticking the corresponding box in the task allocation section.
3. Rate the task's priority in the pop-up window, as shown in figure C.33b.
4. Repeat steps 1 to 3 until all groups have been assigned a set of tasks or explicitly ignored.



(a) *Task allocation section.* (b) *Task priority rating pop-up window.*

Figure C.33.: *Task allocation*

Participants can also request an overview of the allocated tasks, as illustrated in figure C.34. The order of the groups is determined first by allegiance, and second by the previously assigned group priority. The search task is automatically assigned to the search volume and is listed at the bottom of the overview.

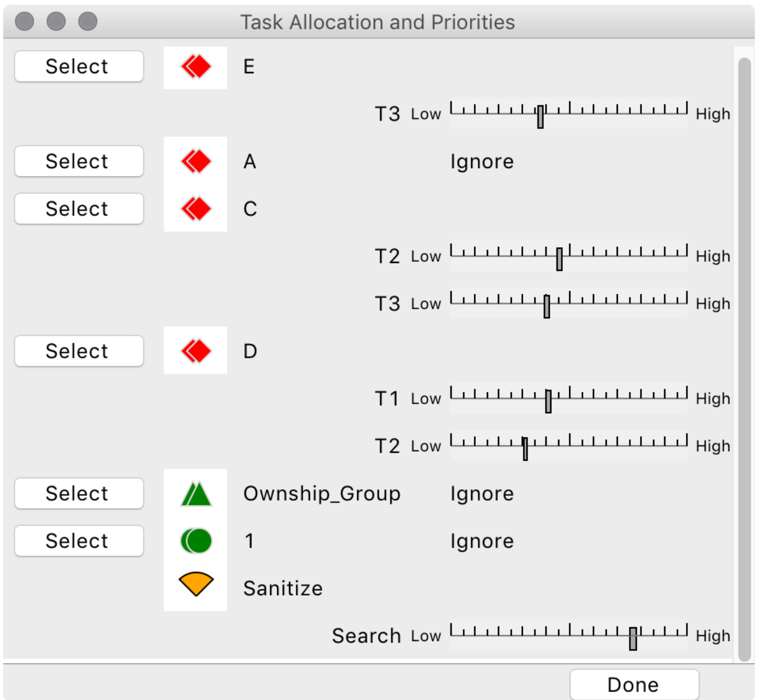


Figure C.34.: *Task allocation overview pop-up window.*

C.2.2. Study Participants

The study involved 19 participants with air combat experience as either pilots or weapon system officers (WSO). The group involved current and former members of the german air force and test pilots. The operational background of the participants with the identifier number 3 and 4 differed from the remaining test subjects and the data collected from their participants is not used to determine the allocated tasks, task priorities and group priorities. Subject 15 had corrective lenses which might interfere with the eye tracking method, the related dataset is not used for the gaze mapping part of the data analysis. Participants were asked to rate their subjective air-to-air experience e_{A-A} and air-to-ground experience e_{A-G} on a scale from 0 (low) to 5 (high).

Table C.11.: *Demographics of the Task Assignment Study Participants.*

$ID_{Subject}$	Pilot	Age	Flight Hours	e_{A-A}	e_{A-G}
1	1	42	3,200	3	1
2	1	50	3,500	4	3
5	0	51	2,300	4	1
6	0	45	1,900	4	1
7	1	45	3,000	4	1
8	0	51	2,400	3	2
9	1	49	3,200	4	2
10	1	38	1,300	3	1
11	1	42	3,100	3	3
12	1	43	1,750	3	1
13	0	43	2,000	4	1
14	1	54	2,500	4	2
15	1	49	2,900	4	1
16	1	48	2,100	3	1
17	1	25	360	2	1
18	1	60	10,000	4	1
19	0	52	2,950	3	1

C.3. Information Set Preference Elicitation Study Annex

C.3.1. Study Participants

Table C.12 lists the study participants' demographics.

Table C.12.: *Demographics of the Task Assignment Study Participants.*

$ID_{Subject}$	Age	Pilot	Flight Hours	e_{A-G}	e_{A-A}
1	50	1	3,500	3	4
2	45	0	1,900	1	4
3	43	1	1,750	2	4
4	42	1	3,200	2	4
5	42	1	2,900	2	4
6	42	1	1,800	4	4
7	54	1	4,800	3	4
8	54	1	2,500	2	4
9	45	1	3,050	2	4
10	49	0	3,200	2	5
11	50	0	3,300	5	4
12	49	1	3,000	3	5
13	34	1	1,700	2	4
14	44	1	2,600	4	3
15	39	1	1,400	2	4
16	30	1	500	2	4
17	36	1	850	2	4
18	46	1	3,600	4	4
19	56	1	5,000	3	5
20	53	0	2,950	2	4
21	47	0		3	4

D. Curriculum Vitae

The CV is not included in the online version for data protection reasons.