Designing for Humans in Complex Maritime Systems: Lessons for Advanced Technologies, Artificial Intelligence, and Autonomy

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The introduction of autonomous technology to a wide range of naval applications brings great opportunities for improving operator safety and mission effectiveness. Advanced technologies such as artificial intelligence can reduce operator workload, decrease crew size, and increase capabilities. However, systems still require human input for asset allocation, mission planning, task prioritization, decision-making, ethical judgements, and other processes; even potentially "fully autonomous" systems require human inputs for mission command. Truly realizing the benefits of these advanced capabilities requires mature human engineering design approaches. We discuss a proven methodology for optimizing human-automation tasking allocation as well as strategies for integrating human and autonomous teammates to enhance mission success as part of a holistic systems engineering approach.

INTRODUCTION

Technology has developed to a point at which we can build more capability and functionality into systems than users can extract; the human is now the limiting factor in overall system performance. Advanced technologies, namely artificial intelligence (AI) and autonomy, are promising solutions to break this bottleneck and maximize mission effectiveness in complex, fast-moving situations. Complete automation is notnot always possible, practical, or desirable, especially in complex maritime systems, and so we adapt the implementation of this technology to the unique needs of each solution and mission. This requires two complementary approaches: (1) design effective AI/automation to reduce human-in-the-loop decision-making requirements and (2) apply proven human engineering principles to enhance human performance when interacting with these technologies.

COLLABORATIVE AUTONOMY FRAMEWORK

It is critical to recognize that no system is truly autonomous: even the most capable technologies require human interaction for command, control, critical decision-making, and overall mission integration. Figure 1 illustrates the spectrum of human/AI collaboration and the ways we can think about humans interacting with and leveraging advanced technology to achieve their mission. Increasing levels of automation offers more capabilities but with greater technology needs, risks, and design challenges. Human engineering is a critical part of addressing these risks and challenges to maximize the capability.

Figure 1. Spectrum of Autonomy Capabilities

There are many opportunities for deploying autonomous technology across the naval domain, with large potential pay-off for greater mission effectiveness with fewer crew members, increased personnel safety, and decreased operator workload. However, an advanced technology not designed around the needs of the mission and user may not add value and may even negatively impact performance. Successful implementation of advanced technology requires deliberate design and integration to the needs of the user and mission, achieved through proven human engineering practice and a holistic systems engineering approach.

Human Performance × Technology Performance = System Performance

Figure 2. Contributors to System Performance

System performance is the product of human performance and technology performance (See Figure 2). The most advanced technology is useless if the human cannot use it effectively to achieve their mission. Monterey Technologies, Inc. applies human engineering as a scientific discipline to incorporate human needs and performance throughout system, software, process, and tool development. Fields within human engineering include human factors engineering, cognitive science, user-centered design, user experience (UX) research and design, and human systems integration. We primarily aim to understand requirements and inform design choices in the context of the human operators. Using our expertise in human psychology, cognition, behavior, and human-machine interaction, we design systems that augment and enhance human performance in an operational mission context. Technological advancements in AI and autonomous technology raise unique and interesting questions related to human-autonomy teaming, human trust in automation, and overall technological capabilities in the naval domain. Human engineering approaches identify limitations and concerns upfront, study mission and user needs, and design effective solutions to optimize the introduction of autonomous agents to a team while avoiding common risks and pitfalls.

Many examples of bad design exist across domains, from distracting car infotainment systems to confusing signage to unintuitive control systems and alarm overload. Recent examples where failures can be traced directly to insufficient human engineering include the USS *John McCain* collision with *Alnic MC* (confusing helm interfaces), the crash of Air France Flight 447 (overreliance on autopilot causing loss of situational awareness), and the survivability concerns of the US Navy's Littoral Combat Ship (lacking analysis of manpower and personnel concept, optimistic reliance on key technology maturation). These examples highlight how application of advanced technologies can make systems brittle when the automation fails or a situation arises which the automation cannot handle. Human-centered design approaches ensure that the user retains ultimate situational awareness and control while maximizing the capabilities of the technology to achieve their mission.

HUMAN ENGINEERING METHODOLOGICAL APPROACH

Human-autonomy teaming is a great use case for the naval setting because it can significantly enhance overall effectiveness while improving human safety and survivability. It is critical to understand optimal teaming prior to introducing an autonomous agent to a functional human team to ensure that the capability is improving mission effectiveness without causing undue burden on the human teammates. Here, we outline our proven human engineering methodological approach to analyze the mission goals, team tasking, and opportunities for autonomous agents that will have the biggest payoff. Characterizing the mission goals, understanding the specific tasks and cognitive functions involved, evaluating the human's capabilities to perform those tasks, and understanding the expertise and complexity of the required decision making will reveal optimal opportunities for autonomous agents to insert seamlessly into the human team. We are intentionally agnostic to the exact application of this technology within the naval domain, as the approach can work across any mission-oriented domain, including command and control, mission planning, and autonomous vehicle technology.

Step 1. Understand the Mission

The first step to designing optimal systems for the warfighter is to fully understand the mission, context, and use cases. Needs vary both within and among missions and can be very wide-ranging. Working with subject matter experts to define the desired outcome of a mission is critical for having an accurate idea of what success looks like, prior to designing any assistive technology to support it.

The primary human factors engineering approach to understanding mission requirements is to conduct Hierarchical Task Analyses (HTAs) to determine the goal-task hierarchy of a particular mission. HTAs have been used in many applications, including interface design, error prediction, workload analysis, team performance assessment, and training requirement identification (1). These approaches involve diving deep into the subject matter and fully understanding the goal and scope of the mission with a high level of detail. Data for these analyses may be gathered from subject matter expert (SME) discussions, decomposing available sources of information such as doctrine documents, and observation of mission activities. An HTA should include the overall goal, meaningful sub-goals, and then decomposition of those sub-goals further into operations, or actions made by an agent to achieve an associated goal. The output of an HTA may be a visual or textual model depicting the mission goals, sub-goals, operations, and contingencies.

A skilled engineer maximizes the utility of the HTA process by effectively decomposing, generalizing, and capturing mission objectives. A common pitfall in this process is overreliance on *how* the mission is accomplished today, which unnecessarily constrains the problem and solution space; Henry Ford did not actually say "If I'd asked my customers what they wanted, they would've said a faster horse", but the sentiment applies here. HTA focuses on deep understanding of the mission needs rather than the specific approach used currently. It is important to get this step right because the results will drive the rest of the effort; misunderstanding the mission will result in developing the right solution for the wrong mission.

Step 2. Understand the System, Workflow, and User's Tasks

After identifying the mission goals and tasks, the next step is to understand the existing process for how the user performs the task. Workflow analyses provide a model of the phases, tasks, and sub-tasks of the actions being taken by each user using verb-noun format. Through detailed discussions with SMEs, user engagement, and observational process studies, workflow models provide an overview of a user's tasking in a given domain along with pain points and shortcomings. For example, in the anti-submarine warfare domain, our detailed workflow analysis identified 9 phases of work for ASW mission planners: 0) Review Maintained Data Sources, 1) Review High-Level Directives, 2) Analyze Mission Tasking, 3) Determine Mission Requirements, 4) Establish Communications Flow, 5) Set Target List, 6) Create Tactical Plan, 7) Consolidate Water Space and Air Assignments, and 8) Complete Mission Planning Brief. Within each phase, tasks, such as (4.1) Set Flight Communications Flow, and sub-tasks, such as (4.1.1) Review Emissions Control Directives, are specified. Workflow models can also specify inputs and outputs, contingencies and alternate paths, and more, providing a flexible means for understanding and modeling a given process. They are especially helpful as a point of departure, indicating how the workflow will change with the implementation of the solution. Referring to these models throughout analyses and design activities ensures that the solution design is consistent with the requirements of the mission workflow and provides all members of the design team a shared reference point.

Cognitive Task Analyses (CTAs) are another human engineering tool that more specifically describe the cognitive activities being performed by the human operator(s). Rather than focusing on the goals or physical tasks, CTA probes the cognitive processes underlying goal generation, decision-making, and judgments (2). Many specific CTA techniques exist, including Critical Decision Method, Critical Incident Techniques, Cognitive Work Analysis, Cognitive Walkthrough, and Applied Cognitive Task Analysis, but the common thread among techniques is the focus on determining the cognitive demands of performing the task (3). Though time intensive to perform, these methods can provide rich data about an operator's cognitive processes during their mission tasking: is an operator "deciding", "calculating", or merely "inputting" information; how does their mental model match the system and support their activities; what are the likely sources of error and the impacts of mistakes. Certain cognitive tasks may be faster and more accurate for an autonomous agent to perform, and CTA can help to identify those opportunities.

Critical to the often-collaborative naval domain, workflow analyses and CTAs should be applied to understanding team tasking and how each individual's work and cognition contributes to the team's goal. The scope of these analyses often depend on the scope of the project; an effort to make incremental improvements will have very different task analysis needs than a project to revolutionize the mission. Expert human engineering practitioners select the appropriate type(s) of workflow analyses and methods depending on the specific mission under study, while considering time and budget constraints.

Step 3. Quantify Human Requirements and Performance

Once the mission goal and operator tasking have been well defined and understood, the next step is to quantify the human requirements, including human performance challenges and bottlenecks in the process. Cognitive task analyses can help to characterize the type of cognitive activity occurring, but it must be quantified with metrics that can be measured and objectives that translate into mission performance. This is a critical step for establishing baseline understanding of how the current system works for the human operators in order to identify opportunities for introducing an autonomous teammate.

At each stage of the workflow, human engineering practitioners use a selection of metrics to quantify the human factors during those tasks, which may include human workload, performance, situation awareness, or cognitive, physical, and emotional states. Most commonly, human performance is indexed by metrics related to task time, completion rates, and/or error rates, which are strongly affected by the user's cognitive load, or the mental resources and effort required to perform a task(s) (4). As such, both performance metrics relevant to the task and measures of cognitive load should be acquired.

Cognitive Load Metrics. Task characteristics (e.g., time pressure, novelty, feedback), environmental characteristics (e.g., noise, temperature), user "trait" characteristics (e.g., working memory capacity, visuo-spatial abilities), and user "state" characteristics (e.g., motivation, fatigue) can all impact the user's cognitive load during task performance, implicating a wide range of factors. To accurately represent and consider these varying effects on cognitive load, it is advantageous to assess cognitive load in representative and ecologically valid experimental contexts. The following sections outline three common metric types for assessing cognitive load—behavioral, subjective, and physiological—and discuss their pros and cons.

Behavioral metrics. Behavioral indices of cognitive load can include measurements of mental load, mental effort, or performance. Behavioral data can be gathered on a primary task, where longer task time or poorer performance can indicate higher cognitive load (but may also reflect other factors such as boredom). Behavioral data can also be gathered with dual-task-paradigms, where users perform a secondary (unrelated) task while concurrently performing the primary task of interest. To perform both tasks, the pool of cognitive resources must be divided (5). As such, the addition of the secondary task can be used to increase the cognitive load of the overall tasking. Comparing performance (on the primary task) in the single-task condition to the dual-task condition allows human engineering practitioners to examine effects of additional tasking on cognitive load.

Alternatively, performance on the secondary task can itself be interpreted as an index of the mental effort in the primary task. Reaction time to a simple secondary stimulus-response task is a well-studied and reliable metric of cognitive load (6,7). Stimuli can be auditory, visual, or tactile and are meant to be unrelated to the primary task. A slower response or lower hit rate in the secondary task indicates a higher cognitive load of the primary task (i.e., the primary task required more cognitive resources at the time of response). This method has been used in many studies of driving in passenger vehicles (for a review, see (8)) and can be deployed in dynamic real-world environments. Data can be collected concurrently on multiple users and timestamped to allow for later evaluation against tasking at the time of the response. For naval operations, using dual-tasking paradigms to assess cognitive load for each operator during typical tasking would reveal the average cognitive load of the operation, the cognitive load of individual sub-tasks, and potentially, how the cognitive load changes based on teaming variations.

Limitations of this method include the technology requirements for acquiring data and the concern that the measure is not continuous (stimuli occur at discrete instances). The task itself, while meant to measure cognitive load (mental effort) of the primary task, may also induce some cognitive load itself because it requires continual monitoring and response.

Subjective metrics. Subjective measures include rating scales where users provide assessments of their cognitive load after they complete the task or sub-task. In general, rating scale methods have the benefit of being inexpensive and relatively easy to administer. There are many self-report scales of cognitive load and mental effort that range in complexity, time requirements, validity, and reliability (9). One of the most commonly used subjective measures of cognitive load is the NASA-Task Load Index (TLX; (10)) which includes six subscales: Mental Demands, Physical Demands, Temporal Demands, Performance, Effort, and Frustration. Measures such as the NASA-TLX are useful because they provide multi-dimensional information about what type of load the user perceived to be the greatest. The NASA-TLX has been cited over 100,000 times across a wide range of domains and continues to be a well-respected and useful metric (11) that can now be administered on a tablet. This increases ease of use in dynamic real-world testing environments in the naval domain.

Limitations of subjective methods largely arise from the fact that ratings are typically made after the task is complete. As such, scores may be subject to either forgetting and/or recency effects. Rating scales are also considered less reliable, with some data showing only weak correlations with other metrics (12,13). Self-report metrics also do not take into account time on task, or general individual differences in perceived mental effort. Given these limitations, rating scales should be included as additional, but not necessarily the only, measures in a study.

Physiological metrics. Physiological measures of cognitive load are taken simultaneously during task performance and offer continuous assessment of cognitive load. A wide range of physiological and neuroimaging techniques have been employed in the measurement of cognitive load, including heartrate, heartrate variability, pupillometry, electrodermal measures (skin conductance), electroencephalography (EEG), functional Magnetic Resonance Imaging (fMRI), Position Emission Topography (PET), and functional Near-Infrared Spectroscopy (fNIRS), among others (5,13,14). Each technique offers a unique window into the human physiological and neurological activity underlying cognitive load, but also has its pros and cons in terms of administration and sensitivity.

EEG is one metric that allows for continuous monitoring of brain electrical activity during a task, which allows researchers to measure fluctuations in cognitive load over time (see (15) for a review). While EEG has excellent sensitivity to timing, it has poor spatial resolution, making it difficult for researchers to map out exact locations of neural activity. However, the timing sensitivity of EEG allows researchers to identify points of maximum load during a task (16). It should be noted that EEG is sensitive to movement artifacts and has significant materials and setup requirements, making it impractical for many types of systems. Pupillometry is another commonly used physiological metric of cognitive load. Eye trackers can measure both eye movements and pupil size continually during a task. Many studies have shown that, in general, pupil size increases with higher cognitive load (e.g., (17)). Pupil size is also affected by light, age, and other psychological and physiological factors (such as emotional arousal). As such, using pupillometry as a metric of cognitive load requires controlled experimental design. The availability of affordable and portable eye trackers makes pupillometry a viable option for quantifying cognitive load in naval domains, though researchers must consider movement artifacts and light levels when designing a study with an eye tracker.

Together, physiological measures can provide continuous, objective measures of cognitive load over time, but are often resource- and time-intensive. Incorporating physiological measures in a study also reduces the ecological validity, as tasks may need to be performed in simulators to allow for enough experimental control, and physiological measures sometimes require bulky or restrictive equipment that users may not typically wear during task performance.

Human engineering practitioners are adept at selecting appropriate metrics given time, budget, and other project constraints. Data collection with these metrics should occur during normal operations, to the extent possible, to capture the range of contributors to cognitive load (environmental factors, stress, fatigue, etc., in addition to the load imposed by the task itself). Combined with results from cognitive task analyses, the cognitive load data could reveal those areas that have the largest negative effects for humans. High cognitive load and poor human performance can stem from multiple sources, including tasks that are too complicated, or conversely, those that are boring or require sustained attention and monitoring (18). Gathering extensive cognitive load data across example missions would highlight the human performance bottlenecks that could potentially be alleviated by an autonomous teammate.

The most common error in this step is choosing the wrong metrics and measurement techniques, resulting in excellent data that are not useful in the design and evaluation process. Another common error is insisting on the most sophisticated data collection techniques when an easier and less expensive approach would be good enough, unnecessarily increasing cost and risk.

Step 4. Identify Opportunities for Autonomous Teammates

Those activities that have been quantified as being particularly difficult, boring, risky, or dangerous for the human operators may be good candidates for autonomous technology involvement. However, to determine who should perform a given task (a human operator or an autonomous agent) and at what level of autonomy, it is necessary to fully understand the complexity of the decision or task under question. Methods from the Naturalistic Decision Making subset of human engineering are appropriate for understanding decision making in complex environments (19). While many methods exist and overlap with cognitive task analysis approaches, the process generally involves identifying the decisions being made and analyzing the human expert's process for making the decision. When analyzing the expert decision-making process, the human engineering practitioner should consider the ambiguity of the situation and the moralistic judgments required as well as the relative capabilities of the human and technology.

Given this information, the design team should consider how to best position an autonomous agent within the team to maximize mission effectiveness. Possibilities for the role of an autonomous agent in a given task or stage of work are illustrated in Figure 1, with options ranging from simple decision aids to multiple types of human-automation teams to replacing the human completely. Taking a human engineering approach to understanding optimal human-autonomy teaming results in mission-oriented teams where tasking is mutually understood and trust is shared.

A common mistake is not integrating human engineering into the system engineering effort or fully understanding technology capabilities and constraints when conducting human engineering analyses. This can result in designing a great solution which is not practical or possible to implement. Another mistake is automatically categorizing certain tasks as autonomous or human based on set criteria and heuristics. While it is true that, for example, technology is generally better at complex calculations and repetitive tasks, such oversimplification leads to solutions that reduce the operator's situational awareness and understanding of automation performance. It's important to purposefully design the workflow, integration, and interfaces to maximize overall system (human + technology) performance using the understanding developed through the human engineering effort.

Step 5. Develop Concepts and Prototypes for Initial Test

Naval domains that pursue autonomous technology should conduct prototype development and testing to ensure that mission effectiveness is improved and the human operators are supported. Iterative testing early and throughout the effort verifies and validates that the designed solution meets user and mission needs. A common failure is waiting until the solution is more mature to begin these efforts, at which point it becomes too expensive to correct any deficiencies identified. Human engineering approaches to gathering quantitative and qualitative usability data and user feedback should be incorporated early and often. Developing prototypes and conducting early-stage user testing of systems that include autonomous technology will minimize the risk of a flawed system that human operators do not understand or trust. Often this involves mockups of solutions that inexpensively demonstrate the concept prior to significant development effort.

Step 6. Evaluate Impact on Mission and Team Performance

Relying on the already-validated success metrics described in Step 3, we must measure the impact of the solution on the mission and the team performance. Comparing performance data and cognitive load with and without an autonomous teammate or other advanced technology capability provides a quantifiable metric of the impact of the technology. It is important to measure effects on both mission effectiveness and human operator metrics such as cognitive load, workload, performance, situation awareness, and possibly cognitive, physical, and emotional states. With any system involving autonomous technology, the design team should also measure human operator trust and acceptance of the autonomous technology (20). This is a critical step for ensuring that the system is useful and usable, and that mission effectiveness is improved. A common shortcoming is overlooking the impact of user trust in the solution; calibrated trust is important as under-trust means the user may not use the solution when it would be helpful and over-trust may cause users to over-rely on it to the detriment of mission success.

Step 7. Develop Solutions with Ongoing, Iterative Verification and Validation

Extensive research, evaluation, and validation of the mission requirements, goal hierarchy, workflow, cognitive tasking, and prototype concepts supports effective solution design. The impact continues into development with the human engineering team continuing to engage in the systems engineering effort and support implementation. The human engineering team can adapt solutions and interface design as necessary as the solution matures to ensure the actual implementation continues to support user and mission needs. User-centered, iterative design should be included throughout the development cycle to provide low-risk solutions for complex, critical naval applications.

CONCLUSION

The introduction of autonomous technology to a wide range of naval applications brings great opportunities for improving operator safety and mission effectiveness. Truly realizing the benefits of these advanced capabilities requires mature human engineering design approaches. Measuring and accounting for the human factors upon introduction of an automated system will ensure that automation is an additional asset, rather than a hindrance, to mission performance.

System performance is the product of technology performance and human performance. Scientific approaches such as those applied by Monterey Technologies, Inc. are proven to improve system performance by meeting human needs and performance as part of a holistic systems engineering process.

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