Predictors of Human Efficiency in Radar Detection Tasks

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Abstract: Aegis operators simultaneously locate and monitor the activity of several hostile targets, intervening and alerting their team when appropriate. Utilizing the Aegis Combat System, operators find, track, and respond to dynamic targets on a radar screen. The demand that operators undergo is often high, inevitably causing strain on cognitive functions and detriments to performance. We applied model-based measures, Cost and Multitasking Throughput, to quantify the influence of external factors on processing efficiency in radar task(s). We captured the influence of three experimental manipulations, each of three levels, on human efficiency to track the location of hostiles and/or detect brief radar interference. We collected participants' performance to complete a multiple object tracking (MOT) task and an electronic attack detection task (EA) using a radar display. A factorial manipulation of conditions comprised changes to task(s) (EA, MOT, or both), the number of targets to track (2, 4, or 6) and the presence or absence of distractors, deemed 'friendlies' (between 500-1000 total tracks). Our novel individual- and model-based approach provided quantitative estimates of human efficiency. We compared the observed variation in efficiency among predictors including target quantity, visual load, and the presence of one or two interrelated tasks. Through quantifying the relationship of these variables to radar detection tasks, we discuss implications of our findings and provide a framework to examine how system designers may develop tools to alleviate observed cognitive demands and/or counter potential threats of electronic attacks in radar detection and tracking tasks.

Keywords: Radar, Electronic warfare, Human efficiency, Dual-tasking

1. Introduction

Radar operators are responsible for the detection and tracking of entities that pose a threat to military operations or civilian lives. To make accurate and timely decisions, operators rely on the information portrayed through integrated and dynamic visual displays that comprise the input from several powerful electronic radar systems. An Aegis Combat System (ACS) is a platform equipped with protective software to simultaneously track hundreds of entities, continuously updating a visual display for operators to monitor threats and make mission critical decisions in an efficient manner (see Bath, 2020, for a recent overview). An Aegis system on board vessels can provide tactical data such as automatic target labeling and display this information to operators with the aim to facilitate efficient and accurate crisis management. Advanced Aegis technology may fuse input from multiple radars regarding attributes such as entity position, speed, and size to assign and convey meaningful labels to operators by-use-of symbology or text. Effective user interface design can lead to faster identification of potential adversaries, increase the probability of mission success, and reduce casualties of civilian and military personnel.

Importantly, the high-risk and sensitive nature of the information portrayed by an ACS necessarily requires a human operator to posture the appropriate course of action (versus an automated response), following their interpretation and assessment of entities using a graphic user interface (GUI). This heightens the priority for GUI designers of an Aegis system to understand and account for limitations and strengths of human perception and cognition, especially when attempting to make sense of complex and multifaceted dynamic visualizations. For instance, an Aegis system may have no problem reshuffling the use of target tracking numbers as it updates incoming data, but a human operator may commit a unique identifier to a single target in memory. This failure to share a common cognitive representation of entities may lead to false threat identification. Indeed, in 1988 USS Vincennes mistakenly shot down Iran Air Flight 655 killing 290 civilians due to poor human-system integration, lamentably earning recognition as one of the worst outcomes of poorly executed user-interfaces (Pogue, 2016). In addition, the under-evaluated consequences from cuts to training or system maintenance can leave crew members and ACS unequipped for battle readiness (Fisher and Kingma, 2001). As a result, military costs may be reduced but the gap widens between humans and complex radar displays they leverage to detect and act on threats and plan crucial mission operations.

Little research has aimed to investigate how and why human performance changes in realistic threat detection scenarios. Nonetheless, this work is crucial to build effective GUI and intelligent Aegis software and foster efficient human-system integration. The aim of our work described in this paper was to capture and quantify variation in human efficiency to perform tasks similar to that of an Aegis operator while undergoing systematic contextual and cognitive changes relatable to those that may occur in operational environments. We measured human efficiency to follow various numbers of tracks labeled as hostiles (2, 4, or 6) as they dynamically travel across four geographical areas of interest (AoI), occasionally changing in their heading direction. Participants monitored these entities in isolation or in the presence of several hundred friendly tracks. Friendly tracks (i.e., ships, aircraft, drones, etc.) were perceptually distinct from, but closely resembled, hostiles.

In addition to the detection and tracking of hostiles, realistic operations require Aegis operators to be vigilant against electronic attacks (EA). Electronic attacks, in part, make-up electronic warfare (EW). Electronic warfare is divided into three categories, all of which aim to "protect friendly operations and deny adversarial operations within the electromagnetic (EM) spectrum throughout the operational environment" (Joint Chiefs of Staff [JCS], 2013). Electronic attacks involve the use of energy (e.g., EM) to intentionally target an enemy and adversely impact their military capabilities (JCS, 2013). Algorithms to both deploy and counter EA (called electronic protection or EP) are constantly (and necessarily so) developed and revised to account for endless technological advances (e.g., Park et al., 2018; see Spezio, 2002 for a review). An EA may affect one or multiple entities, may be one or multiple modalities (i.e., chaff, cyber, jammer), and may endure for various lengths of time. The attempted EA and its effect on ACS information will depend on the attackers' goals and the (counter-)technology deployed. However, the research field lacks psychological understanding for how the type or timing of EA may differentially influence how operators detect and respond to it, let alone how the mere *possibility* of an attack will influence how an operator performs and makes decisions about entities represented on a GUI – in this work, we focus on the latter. We argue it is pertinent to consider EA in the broader context, that is, embedded as an additional demand among multiple tasks which compete for operators' limited attention and perceptual resources (Kahneman, 1973; Norman and Bobrow, 1974). Monitoring for the presence of EA increases the mental load of an operator and heightens the likelihood of detrimental interruptions and failures to detect and track adversaries.

As mentioned above, how an EA influences the entity (entities) that are represented on the GUI and shown to the operator depends on both the attackers' goals and the EP in place to counter or partially (fully) block the attack. In this work, we instantiated EA through the disappearance of a single, threatening target for one to four seconds without warning – a simplified case of radar *jamming.* It is reported that jamming is one type of EA that may cause an ACS to temporarily lose a target (Blair et al., 1998). Reacquisition and labeling of a lost entity requires sophisticated decision making processing, and current intelligent radar systems still rely on human intervention to appropriately identify and respond to radar jamming (e.g., the lost target was an enemy threat) (Gurbuz et al., 2019). We asked participants to indicate when an EA began (i.e., when a threatening entity disappeared) and when it ended (when the entity reappeared). In addition to manipulations to the number of hostiles (2, 4, or 6) and presence of friendlies described above, we systematically introduced instances of EA on a single to-be-tracked (marked as threatening) entity and compared human efficiency to 1) track hostiles and 2) detect instances of EA in an isolated versus dual-task context.

2. Method

We investigated how the number of targets (2, 4 or 6), the presence (absence) of friendlies, and the nature of the task(s) demands (tracking target location, detecting EA, or both) influences participants' efficiency to make decisions and correctly respond to events – our independent variables, a 3 x 2 x 2 within-subjects design. We computed individuals' Multitasking Throughput (MT; Fox, et al., 2021), a performance-based model of efficiency, to quantify systematic changes among our independent variables of interest – our dependent variable. We hypothesized that efficiency would 1) decrease as the number of targets to track increased, 2) decrease with the presence of friendlies, 3) decrease when performing both tasks, compared to each in isolation.

Our method and unique modeling framework allowed us to equate the intersection between each of our independent variables and efficiency at the individual participant level. For instance, the degree of efficiency deficit observed when tracking 6 targets when no friendlies are present may be equivalent to the deficit observed when tracking 4 targets when friendlies are present and/or the deficit observed when responsible to track the location of 2 targets when friendlies are present and EAs may occur. By identifying such relationships of these variables, our results have theoretical and practical implications: we provide a quantitative mapping between three manipulations of cognitive workload (number of targets, presence of visual distractors, and dual-tasking) that may inform the design of cognitive radar technology to help mitigate or alleviate the workload of operators and help guide the focus to build effective countermeasures of potential threats (e.g., the design of EP software).

2.1 Participants

An a priori power analysis (G*Power 3.1.9.6) indicated we should collect data from 28 participants for an appropriately powered within-subjects, three factor, repeated measure analysis of variance (ANOVA). To obtain this estimate, we assumed a medium effect size (f = .25), power (1-ß = .80), significance level (α = .05), and correlation (r = .50), with a correction for nonsphericity (ϵ = 1.0) (see Kang, 2021 for a full description and guide for using G*Power). We recruited 29 participants from a medium-sized, midwestern university via paper flyers and an online announcement or from a long-term subject panel (Wright-Patterson Air Force Base) and compensated with either visa gift cards ($20/hour + $10 study completion bonus) or through their normal wage, respectively. Participants' (9 = Male, 19= Female, 1 = Other) ages ranged from 19-57 (M = 26.14, SD = 8.44). All participants self-reported normal or corrected to normal hearing and vision, were screened for color blindness (Ishihara Colorblindness Test; Clark, 1924), and had full motor control of both hands and at least one foot. All participants self-reported they learned English prior to the age of one year-old and could read and speak English fluently.

2.2 Hardware and Software

Visual stimuli were presented using an ASUS Intel Core i5 desktop computer. Participants responded to experiment-based events using a Cedrus RB-840 response box and/or an iKKEGOL USB Single Foot Switch Control One Key Customized Computer Keyboard Action Pedal HID. Participants pressed the spacebar on a standard keyboard to proceed after a short break between conditions. We used Python (Van Rossum and Drake, 2009) to build the experiment and R (RStudio Team, 2022) to analyze the data.

2.3 Tasks

We investigated the influence of visual load (number of targets, distractor [i.e., friendlies] present/absent) and overall demands (one or two tasks performed simultaneously) on participants' efficiency to respond to critical events in a multiple object tracking (MOT) task and/or a detection of electronic attacks (EA) task. In both tasks, participants were asked to monitor the targets displayed on a single visual display. Participants could identify targets using shape (circle), color (red), size (larger than friendlies), and/or speed (faster than friendlies). The shapes (octagon, diamond) and colors (pink, magenta) of friendlies were chosen using the psychophysical results of previous research of Glavan and colleagues (2020). The speed and size of tracks were chosen using pilot tests and practical considerations; size: displayed non-overlapping tracks on screen simultaneously (up to 1000 tracks), speed: balanced participants ability to track multiple moving targets (slower is more manageable) while providing an adequate number of instances that demanded a response from the participant (faster leads to more observations). The attributes of this graphical radar interface are not equivalent to the ACS but serve as a laboratory instantiation of the stressors placed on cognitive processing of MOT and detection tasks in Aegis-like contexts. Example stimuli are provided in Figure 1.

The cognitive and response demand were different for the MOT and EA tasks (described in Section 2.3.1 and 2.3.2, respectively). However, the participants' perceptual demands were consistent across tasks – stimuli were embedded within the same visual display, and both required participants to track and make decisions about hostile tracks while ignoring friendlies. For both tasks, perceptual demands systematically varied across conditions, i.e., the number of simultaneously presented targets (2, 4, or 6 hostiles) and the presence or absence of friendlies (see Figure 2 for examples).

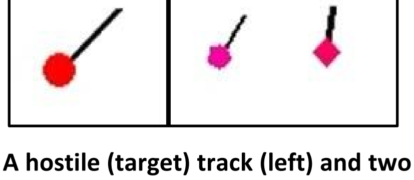


Figure 1. Example stimuli, enlarged. A hostile (target) track (left) and two types of friendly (distractor) tracks (right).

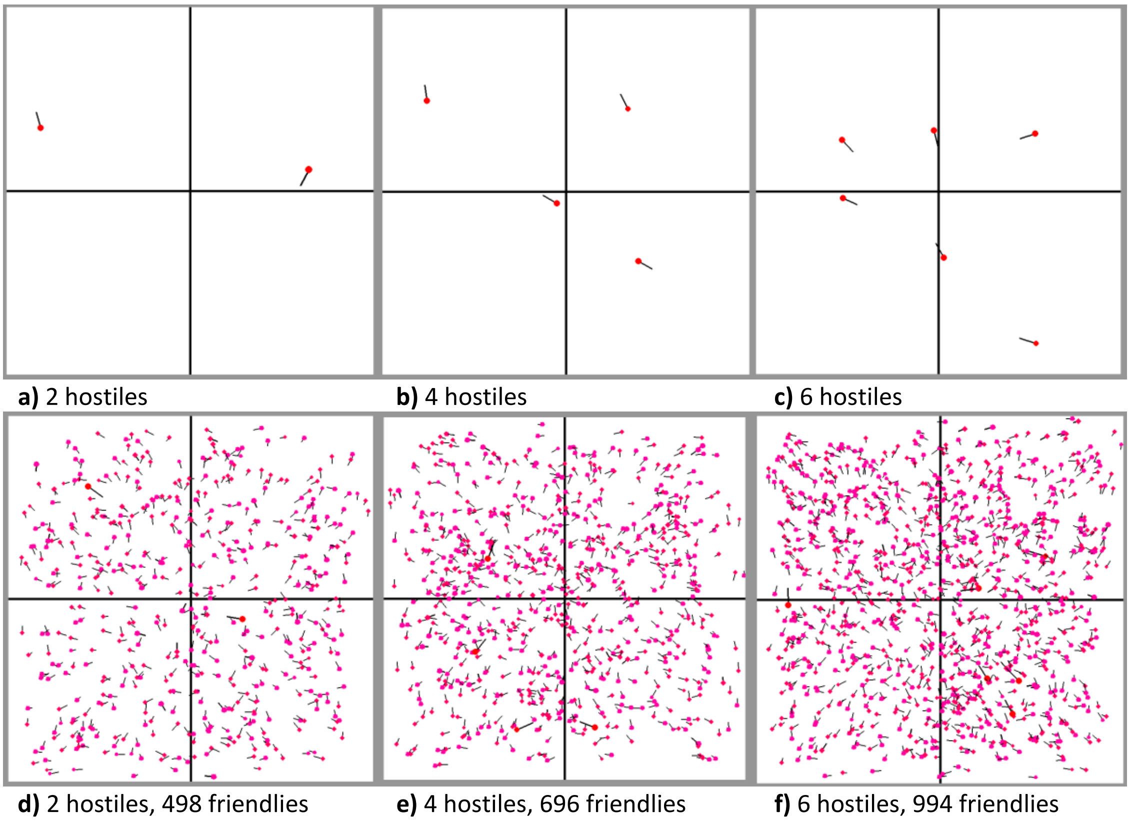


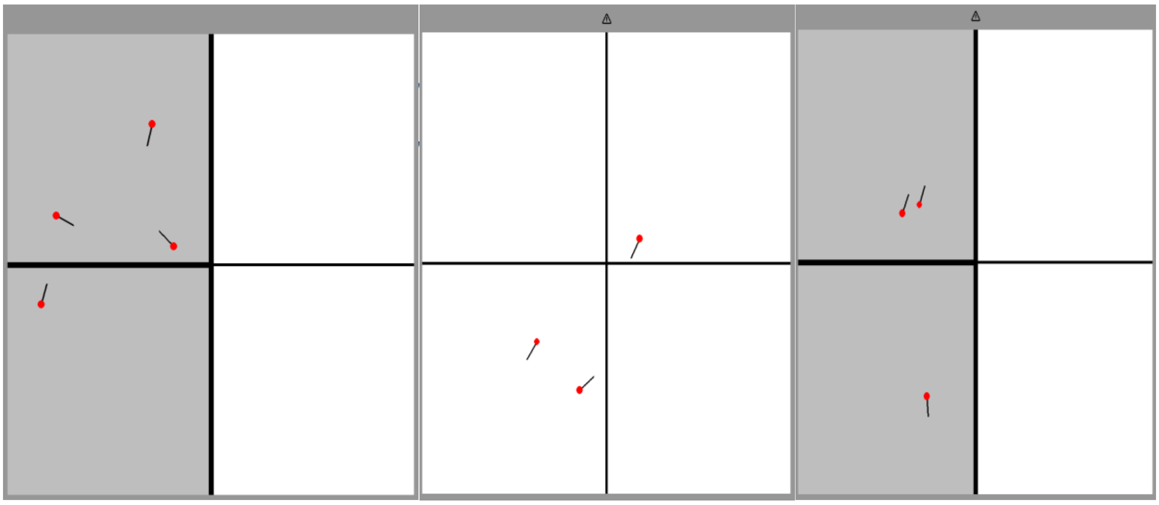
Figure 2. Example displays by factorial combination of number of targets (2, 4, or 6) and absence (subfigure 2a-2c, respectively) or presence (subfigure 2d-2f, respectively) of friendlies.

2.3.1 Multiple object tracking (MOT)

Participants were instructed to closely track hostiles (large red, fast-moving, circles) and ignore friendlies (smaller pink/magenta, slow-moving, octagons/diamonds). Once located, participants used 4 buttons on a response pad to mark quadrants with one or more hostile targets within its bounds, referred to as 'alarm ON'; each button was mapped to either the northeast (right middle finger), southeast (right index finger), northwest (left middle finger), or southwest (left index finger) quadrant. Quadrants with an alarm ON had a gray, as opposed to white, background (Figure 3a). Participants were also responsible to turn OFF the alarm when all hostiles left the quadrant; participants turned OFF an alarm by pressing the corresponding button on the response pad. Participants' accuracy and time to respond to hostiles entering (alarm ON) and leaving (alarm OFF) quadrants was recorded.

2.3.1 Electronic attacks (EA)

Identical to the MOT task, participants were instructed to closely track hostiles (large red, fast-moving, circles) and ignore friendlies (smaller pink/magenta, slow-moving, octagons/diamonds). Once located, participants tracked the hostiles and indicated when one disappeared. An EA occurred for a brief (1-4 seconds) time, once every 30 seconds and at a random time within each non-overlapping interval. The EA caused a single hostile track to disappear from the screen without warning. The participant was instructed to respond by pressing a foot pedal as quickly as accurately as possible when they detected an EA started (i.e., a hostile disappeared) and ended (i.e., a hostile reappeared). The affected hostile track would continue moving and reappear in its new location. The EA task did *not* depend on the quadrant that the hostile was in, rather it was a single alert that was turned ON and OFF by a single foot pedal. As such, an active EA alert was indicated by a visual icon located to the North of the quadrants (Figure 3b-c). Participants' accuracy and time to respond to EA (start, end) was recorded.



a) MOT task, alarms ON **b)** EA task, alarm ON **c)** MOT and EA task, alarms ON

Figure 3. Example display of the appropriate alarms turned ON in the MOT task (3a), EA task (3b), or both (3c).

2.4 Procedure

This within-subjects experiment was 5.5 hours, across three sessions. The first 30 minutes of Session 1 included COVID-19 requirements (i.e., Rapid Response testing, self-reporting vaccination status), the review of and consent to participate, the completion of a demographic survey, and a test for color blindness. The remaining time of Session 1, and all following Sessions, took 1.5 hours to complete. In Session 1, participants were introduced to the MOT task, and told they were to act as a radar operator. They were responsible for alerting their team where hostile targets were located (described in Section 2.3.1.). After adequate training and practice in all conditions – with(out) distractors, and 2, 4, or 6 hostiles – participants performed 6, 13-minute MOT task conditions (Figure 2). All conditions *without* distractors (Figure 2a-2c) were completed first, in a randomized order, followed by conditions with friendlies (Figure 2d-2f), in a randomized order. Participants saw their rough performance score (points based on time and accuracy to respond) at the end of each condition. No incentives were given to participants regarding their score. Participants took a 15+ second mandatory break between conditions (pressing the spacebar to continue). After all conditions, participants were asked to describe their strategy (if any) to complete the task (free response). Identical procedures were repeated in Session 2, however, participants were introduced and trained to complete the EA task (described in Section 2.3.2). In Session 3, procedures were repeated, but participants completed both tasks simultaneously. Participants were compensated for their time after each session and given the completion bonus with their payment for Session 3. The experiment concluded with a debrief of our motivation for research and we thanked them for their participation.

2.5 Analyses

We used a nonparametric measure of performance to quantify how well participants performed each task independently, referred to as the *Cost Coefficient* (c), and both tasks together, *MT*. These measures provided us a quantitative and qualitative interpretation of efficiency, and provided a standardized and individualized, model-based coefficient of the full function of efficiency to appropriately capture variation across multiple independent variables. We provided a summary of the measures here; an interested reader can refer to Fox et al. (2021) for a full derivation and demonstration of the measures. *Cost* was calculated using a transformation of the distribution of response times, called the cumulative reverse hazard function, $K(t)$, which is the cumulative of the reverse hazard function, $k(t)$. The reverse hazard function is defined as the ratio of the probability density function (PDF) and the cumulative distribution function (CDF), $k(t) = f(t)/F(t)$. The *Cost* (Equation 1) of a manipulation on each task was calculated across a full range of performance, rather than just the mean (a common practice in psychological research), i.e., t_{min} - t_{max}.

$$c_i = \int_{t_{min}}^{t_{max}} k_i(t) - k_{i(N)}(t)\, dt = K_i(t_{max}) - K_{i(N)}(t_{max})$$

(Equation 1)

Then, we calculated MT using a weighted sum of the dual-task *Cost* for each task, where the sum of the weights equals 1, $\sum^{N}_{i=1} w_i = 1$:

$$\mathrm{MT} = \sum_{i=1}^{N} w_i c_i. \quad \text{(Equation 2)}$$

In this application, we assumed equal weight to the MOT and EA tasks, following the instruction provided to participants. Both *Cost* and *MT* provide a function of efficiency across all times, *t*, so we calculated their functional *z*-score to serve as a summary coefficient; this allowed for a straightforward way to compare efficiency across our independent measures of interest. For instance, we may find a negative MT coefficient for all dual-task conditions, evidence of a limited function of MT (as expected), but perhaps some conditions are a magnitude more/less efficient (double or triple) than others. The z-score coefficient is interpreted as the number of standard deviations (SD) that observed performance under our independent variable(s), $K_{i(n)}(t)$, falls below or above the baseline performance, $K_i(t)$, and it is representative for the full function of times, *t*. If the *z*-score is above zero, efficiency is labeled as *super capacity*; if it is equal to zero it is labeled as *unlimited capacity*; if it is below zero it is labeled as *limited capacity*. This powerful analytic modeling approach allowed us to make comparisons across the same scale of measurement, and at the functional- and individualized-level.

3. Results

First, we report the summary statistics of task performance by condition, at the group-level (Table 1). Overall, we found expected patterns of variation in performance. Specifically, performance (response time [RT], accuracy) decreased as the number of targets increased and in the presence (versus absence) of friendlies, across both the MOT and EA tasks. Additional performance deficits were observed in both tasks when performed together (dual-tasking) versus each in isolation (single-tasking).

Table 1: Effect of independent variables on mean (SD) of individuals' performance by task.

	MOT		EA	
	RT (SD)	Accuracy (SD)	RT (SD)	Accuracy (SD)
2	796 (1035)	92.3 (26)	851 (739)	96.5 (18)
4	976 (1198)	85.5 (35)	914 (924)	89.5 (31)
6	1021 (1276)	79.3 (41)	917 (1027)	78.3 (41)
w/o Friendlies	723 (828)	88.0 (33)	840 (792)	96.3 (19)
w/ Friendlies	1144 (1420)	83.2 (37)	962 (1004)	79.7 (40)
Single-task	891 (1115)	86.6 (34)	702 (653)	88.0 (33)
Dual-task	971 (1038)	84.6 (36)	1080 (1038)	89.5 (31)

Note. The mean (SD) of participants' response time (RT; milliseconds) and accuracy (percent correct) by task (MOT, EA) and experimental condition: # of hostiles, presence (absence) of friendlies, and single- or dual-task. SD = standard deviation; MOT = multiple object tracking; EA = electronic attack; # = number; w/o = without; w/ = with.

Next, we report the summary statistics of individuals' Cost in efficiency (Table 2) and MT coefficients (Table 3) by condition. Figure 4 illustrates Cost (or lack thereof) of task performance due to tracking more than 2 hostiles, the presence of friendlies, and/or dual-tasking, calculated using Equation 1, for each task. Individuals' *z*-score Cost coefficients are summarized (mean, standard deviation) in Table 2. These Cost coefficients describe the degree of difference between the cumulative reverse hazard functions for each independent variable, standardized by an individuals' reverse hazard function of performance on each respective task in isolation while tracking 2 hostiles without the presence of friendlies, i.e., customized individual-based baselines.

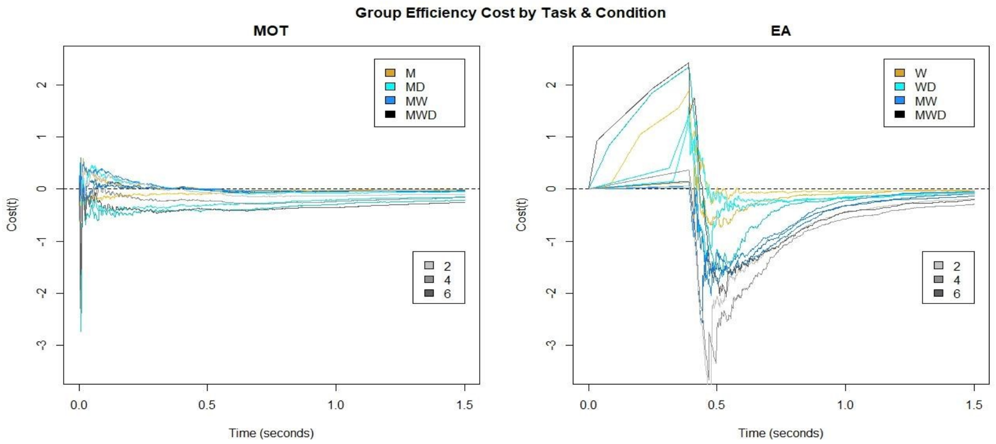


Figure 4: Group Cost as a function of time to respond by task (MOT, EA) and experimental condition: # of hostiles, single- or dual-task, and presence (absence) of friendlies. MOT = multiple object tracking; EA = electronic attack; M = MOT alone, W = EA alone; D = distractors; WD = EA with friendlies; MD = MOT with friendlies, MW = dual-task; MWD = dual-task with friendlies; 2, 4, 6 = number of hostiles to track; # = number.

Table 2: Effect of independent variables on mean (SD) of individuals' Cost coefficients (*z* score) by task.

		Single-task		Dual-task	
Task	# of Hostiles	w/o Friendlies	w/ Friendlies	w/o Friendlies	w/ Friendlies
MOT	2	Baseline	-0.08 (1.36)	0.26 (1.67)	-0.24 (1.95)
	4	-0.92 (1.29)	-2.17 (1.38)	-0.64 (1.91)	-1.66 (1.62)
	6	-0.43 (1.53)	-2.53 (1.28)	-0.45 (1.90)	-2.22 (1.78)
EA	2	Baseline	-0.64 (1.23)	-2.88 (0.76)	-3.25 (0.78)
	4	-0.44 (1.60)	-0.94 (1.32)	-2.98 (0.91)	-2.95 (0.83)
	6	-1.25 (1.34)	-1.47 (0.83)	-2.84 (0.89)	-1.88 (1.45)

Note. The mean (SD) in individuals' Cost by task (MOT, EA) and experimental condition: # of hostiles, single- or dual-task, and presence (absence) of friendlies. SD = standard deviation; MOT = multiple object tracking; EA = electronic attack; # = number; w/o = without; w/ = with.

We combine the Cost for each of the tasks to obtain a MT coefficient of the factorial combination of our dual-task conditions: with and without the presence of friendlies, and 2, 4, and 6 hostiles to track. Individuals' MT coefficients are summarized (mean, standard deviation) in Table 3.

Table 3: Effect of the number of hostiles to track and presence (absence) of friendlies on mean (SD) of individuals' MT coefficients.

# of Hostiles	w/o Friendlies	w/ Friendlies
2	-1.31 (0.89)	-1.74 (1.15)
4	-1.81 (1.13)	-2.30 (1.00)
6	-1.64 (1.10)	-2.05 (1.18)

Note. The mean (SD) in individuals' MT by experimental condition: # of hostiles, and presence (absence) of friendlies. MT = Multitasking Throughput; SD = standard deviation; # = number; w/o = without; w/ = with.

4. Discussion

Our goal was to quantify the variation in human efficiency to perform Aegis relevant tasks under contextual and cognitive stressors which influence attention and performance. We computed coefficients for each individual and condition. We report (illustrate) a summary of our results using functional *z*-score coefficients. In a multisession, controlled laboratory experiment, we asked people to complete a MOT task and/or detect instances of one type of EA on hostile entities, known as jamming. In both tasks, we asked people to monitor the location of hostiles (red circles) in isolation or embedded within several hundred friendlies (i.e., civilians). Friendlies were smaller in size and traveled at slightly slower speeds than hostiles but resembled threats in color (pink, magenta) and shape (octagons, diamonds). The heading direction of an entity could change at any given time, and, in instances of EA, a hostile entity could disappear for a few moments. These factors increased uncertainty in the projected travel path of entities and required participants to continuously track and monitor each hostile (target) entity. We asked participants to track hostiles and ignore friendlies while responding to critical events. Participants pressed buttons with their hands (MOT task) or feet (EA task) to respond when hostiles changed critical locations (i.e., entered/exited a quadrant) or disappeared/reappeared from the radar, respectively.

4.1 Analysis of Variance, Cost, and MT

As expected, we found that overall performance decreased with a larger number of hostiles to track, the presence of friendlies, and when given the responsibility to both track entity location and detect instances of EA – that is, response times increased and accuracy decreased. The model-based and individualized measures we applied, Cost and MT, provided a more rigorous investigation of the effect of our independent variables on individuals' performance, compared to their baseline performance, and across the full function of response times, rather than just the mean. We defined individuals' baselines using the cumulative reverse hazard function of their time to make responses when only two hostiles were to be tracked; an independent baseline was calculated for the MOT and EA task, and each was performed in an isolated condition.

Giving equal weight to the MOT and EA tasks, we computed individuals' MT under each tracking load and with(out) the presence of friendlies. We found individuals' MT was limited in all dual-task conditions, and MT suffered slightly more with the presence of friendlies and when tracking more than two hostiles. More specifically, we found peoples' efficiency, calculated using the Cost metric, to turn ON/OFF alarms (MOT task) decreased between 1.6 and 2.5 SDs in the presence versus absence of friendlies (i.e., limited capacity), but only when the number of hostiles to track increased above two. Participants' efficiency to perform the MOT task was not affected by the presence of the EA task or in any condition where they were responsible to track only two hostiles (i.e., unlimited capacity). In the absence of friendlies, there was only a marginal effect of the number of hostiles on efficiency.

Compared to MOT events, we found opposite effects of our manipulations on peoples' efficiency to detect the (dis)appearance of a hostile, as calculated using the Cost metric to EA task events. Specifically, we found efficiency in the EA task suffered most dramatically in the presence of the MOT task, and this was the primary driver of the decrease observed in participants' efficiency in the EA task, regardless of the presence (absence) of friendlies or the total number of hostiles to track. In other words, the presence of the MOT task evoked very limited capacity for individuals to detect and respond to EA events in *all* conditions. Further, in the absence of the MOT task (i.e., EA alone) the presence of friendlies did not have any practical effect on EA efficiency alone (unlimited capacity), but the number of targets did have some degree of effect on efficiency and did so in an expected way.

4.2 Implications, Limitations, and Future Research

An ACS can be intelligently designed to assist operators to efficiently track, monitor, and make decisions about threats. Our work demonstrates that the degree of deficit (if any) each cognitive manipulation has on efficiency depends on the nature of the task(s). We utilized two tasks that required continuous tracking of hostiles, but they differed in their underlying cognitive demands. We found this difference evoked unique patterns of efficiency. Specifically, the efficiency of participants to report hostiles' locations suffered when simultaneously tracking more than two, and efficiency decreased most drastically when hostiles were embedded within hundreds of closely resembling friendlies. When this type of task is crucial for mission success, designers may prioritize their focus on providing a large visual discrepancy between hostiles and friendlies rather than decreasing the total number of hostiles to track or to offload dual-task responsibilities. This is in line with previous research – peripheral vision and quick eye movements are more susceptible to visual crowding, especially for perceptually similar and moving entities (Kooi et al., 1994). Hence, the largest efficiency deficit was observed in the MOT task when friendlies were present, and we expect this finding to generalize to similar tasks that rely on peripheral and unfocused vision, and, when tracking more than two moving entities.

On the other hand, the presence of the MOT task had the largest influence on EA efficiency. Here, we suspect a strategic shift in how individuals decided to track hostile entities when performing the EA task alone versus with the MOT task. The detection of hostile (dis)appearance required foveal tracking of each hostile, but in dual-task conditions participants reported that they attempted to group hostiles to attain both their location (MOT task) and presence (EA task). This necessarily spread their focal visual attention among several entities, and groups of entities, and led to decreased processing efficiency of each individual entity (i.e., limited capacity processing), a pattern of performance that aligns with limited resource theories of attention (Wickens, 1984; 2002). Further, our participants reported focusing on the general AoI where hostiles were located (MOT) rather than counting hostiles and detecting their (dis)appearance (EA). More generally, we suggest a task requiring foveal vision may suffer when paired with that which demands peripheral vision, as it is unintentionally underprioritized. Future work should investigate whether performance deficits may be partially alleviated when two tasks that require foveal vision (and are embedded within the same framework) are paired; a somewhat counterintuitive prediction based on theories of competition for shared cognitive resources. For example, future research could assess individuals' efficiency when attempting to detect both the disappearance of existing targets and the addition of new targets.

5. Conclusions

In this paper, we modeled the influence of external factors on cognitive load and performance in radar tasks. We captured how, and the degree to which, variation in efficiency changed as participants attempted to track and make decisions about the location and presence of hostiles on a radar display. We found the number of targets to track and the presence of friendlies highly affected efficiency in a MOT task, one that primarily required peripheral vision. Alternatively, we found that the presence of the MOT task substantially influenced efficiency to detect instances of EA, and this was persistent across all conditions. The analytic method we applied accounted for the full function of RTs and allowed us to identify the relationship between meaningful factors that impact performance in operational environments. Our discussion gives fodder to system designers seeking to research and develop tools that may alleviate cognitive demands and/or counter threats of EA in radar tasks. We closed with a few potential directions for future research.

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