**Technical Report 1382**

# Can Artificial Intelligence Systems Improve Information-Gathering Efficiency in Army Mission Command Processes?


**Cary R. Stothart**
U.S. Army Research Institute

**Brett R. Burland**
**Henry C. Strickland**
**Francis D. Messina**
Mission Command Battle Lab

**Jeffrey D. From**
**Deborah S. Couch**
Apex Analytics Group, Inc.



**January 2020**

**United States Army Research Institute**
**for the Behavioral and Social Sciences**

**U.S. Army Research Institute**
**for the Behavioral and Social Sciences**

**Department of the Army**
**Deputy Chief of Staff, G1**

**Authorized and approved:**

**MICHELLE ZBYLUT, Ph.D.**
**Director**

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Technical review by

Elizabeth Uhl, Ph.D., U.S. Army Research Institute
William Anthony Scroggins, Ph.D., U.S. Army Research Institute

**NOTICES**

# REPORT DOCUMENTATION PAGE

*Form Approved*
*OMB No. 0704-0188*

| | | |
|---|---|---|
| **1. REPORT DATE** *(DD-MM-YYYY)*<br>January 2020 | **2. REPORT TYPE**<br>Final | **3. DATES COVERED** *(From - To)*<br>November 2018 – January 2020 |

**4. TITLE AND SUBTITLE**
Can Artificial Intelligence Systems Improve Information-Gathering Efficiency in Army Mission Command Processes?

**5a. CONTRACT NUMBER**

**5b. GRANT NUMBER**

**5c. PROGRAM ELEMENT NUMBER**
622785

**6. AUTHOR(S)**
Stothart, Cary R; Burland, Brett R; Strickland, Henry C; Messina, Francis D; Couch, Deborah S; From, Jeffrey D.

**5d. PROJECT NUMBER**
A790

**5e. TASK NUMBER**

**5f. WORK UNIT NUMBER**

**7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)**
U. S. Army Research Institute
for the Behavioral & Social Sciences
6000 6TH Street (Bldg. 1464 / Mail Stop 5610)
Fort Belvoir, VA 22060-5610

**8. PERFORMING ORGANIZATION REPORT NUMBER**
Technical Report XXXX

**9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)**
U. S. Army Research Institute
for the Behavioral & Social Sciences
6000 6TH Street (Bldg. 1464 / Mail Stop 5610)
Fort Belvoir, VA 22060-5610

**10. SPONSOR/MONITOR'S ACRONYM(S)**
ARI

**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**
Technical Report 1382

**12. DISTRIBUTION/AVAILABILITY STATEMENT:** Approved for public release; distribution is unlimited.
Destroy this Technical Report when it is no longer needed. Do not return it to the U.S. Army Research Institute for the Behavioral and Social Sciences.

**13. SUPPLEMENTARY NOTES**
ARI Research POC: Dr. Cary Stothart, Fort Leavenworth Research Unit. Prepared in cooperation with the U.S. Army's Mission Command Battle Lab.

**14. ABSTRACT**
Due to the growing number of sensors and increasing use of artificial intelligence (AI) in our world, future military operations will be characterized by abundant information and decision-making at machine speeds. Thus, Army leaders will need the ability to make decisions and sift through large amounts of information more quickly. AI systems have the potential to provide this ability. We examined the utility of AI for information gathering in operational contexts. Participants searched Army doctrine for specific information using one of two versions of a commercial AI software system or a more traditional search method. One version of the AI system used prototype algorithms, data sets, and AI application development to deliver Army-relevant knowledge to aid information gathering, and the other did not. Participants were neither faster nor more accurate at searching when using an AI system than when using the traditional search method. Participants were also no more confident in their search results when using an AI system rather than the traditional method. Participants were, however, faster, but less accurate, when using the Army AI system rather than the non-Army one. The results of the research inform future use of AI systems in military contexts, and speak to the importance of empirically validating assumptions about AI and its impact on human performance.

**15. SUBJECT TERMS**
Psychology, Leadership, Machine Learning, Military Doctrine, Human Performance, Command and Control

| **16. SECURITY CLASSIFICATION OF:** | | | **17. LIMITATION OF ABSTRACT** | **18.** | **19a. NAME OF RESPONSIBLE PERSON** |
|---|---|---|---|---|---|
| **a. REPORT** | **b. ABSTRACT** | **c. THIS PAGE** | | 39 | Dr. Angela Karrasch |
| Unclassified | Unclassified | Unclassified | Unlimited Unclassified | | **19b. TELEPHONE NUMBER**<br>913-684-9758 |

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Apex Analytics Group, Inc.

**Ft. Leavenworth Research Unit**
**Angela I. Karrasch, Chief**

**United States Army Research Institute**
**for the Behavioral and Social Sciences**

**January 2020**

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CAN ARTIFICIAL INTELLIGENCE SYSTEMS IMPROVE INFORMATION-GATHERING EFFICIENCY IN ARMY MISSION COMMAND PROCESSES?

## EXECUTIVE SUMMARY


Research Requirement:

Due to the growing number of sensors and increasing use of artificial intelligence (AI) in our world, future operational environments will be characterized by abundant information and decision-making at machine speeds. Thus, Army commanders and their staffs will need the ability to make decisions and sift through large amounts of information more quickly. Commercial AI systems have the potential to provide this ability, but the Army cannot assume full capability from "out-of-the-box" commercial AI systems as such systems need to be sufficiently trained for U.S. Army contexts. Additionally, research is required to understand what is and what is not currently possible with AI in the Army. Overall, AI tends to excel at tasks that can be solved primarily with pattern recognition, and tasks from which predictions can be made from task data, such as image recognition, medical diagnosis, and transcription. However, it is currently unknown if AI can be used to increase information gathering efficiency in U.S. Army contexts. Thus, in the current research, we addressed the following question: Can AI be used to increase information gathering efficiency in U.S. Army mission command processes?

Approach:

To answer our research question, we used a commercial AI application system, which reflected the first development effort for an Army mission command AI application prototype. In this research effort, we compared participant performance on an information-gathering task between this Army-tailored AI system and two other information gathering methods: a traditional information gathering method (searching PDFs in a computer folder), and a non-Army-tailored version of the AI system. The Army-tailored system used Army-relevant knowledge to aid search (e.g., it knew that "MDMP" was equivalent to "Military Decision Making Process"), and the non-Army-tailored system did not. We compared the three search methods on: 1) the amount of time it took participants to find accurate search results, 2) the accuracy of participants' search results, 3) the amount of confidence participants had in their search results, 4) participants' perceived workload from using the system, and 5) participants' perceived usability of the system.

Findings:

Participants were neither faster nor more accurate at searching when using an AI system than when using the traditional search method. Participants were also no more confident in their search results when using an AI system rather than the traditional method. Participants were, however, faster, but also less accurate, when using the Army-customized AI system rather than the non-Army customized system. Finally, participants' perceived workload and usability did not significantly differ between search methods.

Utilization and Dissemination of Findings:

This research is a first step in determining the impact that AI systems have on information gathering efficiency. Overall, our findings suggest that the AI systems may not substantially increase information gathering efficiency in U.S. Army mission command processes, at least not immediately. While this research focused on an innocuous task (i.e., finding doctrinal solutions to tactical situations) in a controlled laboratory, future planned uses will not be as innocuous, indicating the need for future research to test assumptions. Investments in AI should be accompanied by investments in training and research to gain the full benefit of AI and to mitigate risks. It would not be prudent to assume AI systems are a silver bullet, in fact, this research indicates AI systems need to be fully vetted.

CAN ARTIFICIAL INTELLIGENCE SYSTEMS IMPROVE INFORMATION-GATHERING EFFICIENCY IN ARMY MISSION COMMAND PROCESSES?

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# CAN ARTIFICIAL INTELLIGENCE SYSTEMS IMPROVE INFORMATION-GATHERING EFFICIENCY IN ARMY MISSION COMMAND PROCESSES?

## Introduction

War is becoming increasingly complex. Army commanders need to think about the fight on the ground, in the air, and on/in the sea, and also the fight in the information and cyber environments (Department of the Army, 2017). With the advent of social media and the increasing power of computers, actions in these environments can result in geopolitical losses that, in the past, could only be achieved with more traditional actions, such as ground assaults, air strikes, and naval bombardments. Additionally, Army commanders should not only expect sophisticated and consequential strikes to come from the forces of other nation states, but seemingly unsophisticated adversaries as well, as online retailors make it easy to purchase products that in the past were difficult to obtain (both legitimately and illegitimately), such as drones, night vision goggles, and firearms. On top of all of this, Army commanders need to make accurate and timely decisions on an unprecedented level as artificial intelligence (AI) is being implemented in many military functions and areas, such as cyber warfare, aviation, and information gathering. Together, these factors create a complex operational environment for Army commanders.

To operate effectively in complex environments, Army commanders and their staffs need the ability to collect a vast amount of data from diverse sources, and quickly process the information collected in order to act on the information in a timely manner. For example, if an adversary is preparing a large-scale combat operation, new but subtle multivariate patterns in the information environment, the cyber environment, and the physical environment might betray the adversary's intentions. To detect these patterns in time, however, Army commanders and their staffs will need the ability to quickly aggregate and analyze data coming in from every environment. Moreover, to quickly act on such data, Army commanders and their staffs will need the ability to quickly find relevant Army and joint doctrine in order to implement tactics and strategy, and lessons-learned in order to leverage the experiences of commanders who had faced similar situations. For both of these tasks—detecting patterns and acting upon the patterns—artificial intelligence might prove to be an extremely useful tool.

As suggested by its name, AI is intelligence demonstrated by machines rather than non-artificial entities such as humans or animals. Intelligence, in this case, comprises the cognitive functions normally associated with humans, such as reasoning, planning, learning, and perception. As such, the primary purpose of AI is to either replace or augment humans for certain tasks, such as driving, flying, and image recognition (e.g., automatically detecting and identifying faces in a crowd). For example, companies such as Google and Uber are currently using AI in automated vehicles, where AI is acting as the driver of the vehicle and, therefore, is the entity that makes the automated vehicle automated. Additionally, the U.S. Army is currently exploring the use of AI for automated vehicle identification.

AI is made "intelligent" in primarily two ways. One way is by programming the AI's software to accept certain inputs and make certain outputs based on the inputs. For example, an AI competitor in a video game might be programmed to move left (the output) if the player moves right (the input), or block if the player attacks. This method uses simple algorithms—rules for the AI to follow (e.g., if this, then that)—and is inefficient for all but the most basic of tasks, because the AI's software programmer has to think of and manually program each rule. Doing this can quickly become unwieldy as many tasks require numerous rules and nested rules—rules within other rules (e.g., if approaching a yield sign, yield if another car is present, but only if the other car is near). Additionally, thinking of every possible rule for a task quickly becomes difficult, even for tasks that humans find easy (e.g., driving).

A better method for making AI intelligent is by using machine learning, which is the process of creating statistical models from data in order to increase the accuracy of predictions and decision-making. Instead of explicitly telling an AI system how to respond to certain events in its environment, machine learning allows the AI system to learn from the actions it makes in its environment. More simply, machine learning allows AI systems to learn from experience. For example, Google trained an AI system to successfully play the video game Atari Breakout by feeding the AI system the pixels that composed the game display and allowing the AI system to make actions on those pixels via the game controller (Leo Benedictus, 2016). The AI system was simply programmed to maximize its game score by taking actions with the game controller and using the game score to determine whether or not an action was beneficial. Initially, the AI system made seemingly random actions in the game, but after a while, it started gaining score points, and ultimately learned a useful technique that no human player had ever used.

Machine learning has allowed AI to become very pervasive in everyday life, so much so that AI is considered by some to be the "new electricity" (Lynch, 2017). AI tends to excel at tasks that can be solved primarily with pattern recognition. Thus, AI excels at tasks such as image recognition, medical diagnoses, and transcription. Tasks such as driving pose a greater difficulty for AI to conduct as the sensors on current automated vehicles are unable to detect patterns on roads that have obscured markings (e.g., snow-covered roads). AI is exceptionally useful for making predictions from data. For example, doctors can use AI for help with medical diagnoses as AI is able to process all of a patient's data, compare those data with known medical conditions, and generate a medical diagnosis from the comparison. AI is also useful at visual search: One company used an AI system to search aerial images to find evidence of water waste in residential neighborhoods (Griggs, 2016). The AI system was able to accurately determine if a household was wasting water by using factors such as the presence of a pool, the number and size of shrubs, and the greenness of the grass around the house. The AI system was able to do this task at a rate of 208 aerial images per second.

Information gathering is another task for which AI has potential. Information gathering is the process of extracting desired information from a source, such as a library of documents or the internet. With the use of natural language processing—a branch of AI used to process natural language data—AI can pull information from unstructured data, which comprises 80% of the world's data (High, 2012). Unlike structured data, which is organized in a pre-defined way and includes spreadsheets and logs, unstructured data is not organized in a pre-defined way. Unstructured data includes text documents, photos, videos, and audio recordings. AI can be used to pull relevant information and meaning from unstructured data and leverage that information and meaning in a variety of ways. For instance, the U.S. Army and U.S. Air Force are exploring the use of AI to predict vehicle failures from vehicle maintenance and on-board system logs

(Osborn, 2017; Vincent, 2018). Additionally, future AI mission command systems might continuously mine data streaming in from numerous sources, including social media, news channels, and satellite data, and use those data to predict the actions of strategic competitors. This approach would work by taking past unstructured data (maintenance logs, social media posts, etc.) and determining what characteristics of those data are predictive of vehicle failures and competitor actions. For example, an AI system might find a relationship between vehicle running temperature and vehicle failure and use this relationship to predict future failures. Relationships like this would form a mathematical model that the AI system would continuously update when new data become available.

With the use of natural language processing, AI might also be useful for extracting desired information from Army doctrine and lessons learned. The Army has numerous doctrinal publications, and commanders and their staff oftentimes need to find information in more than one publication. For example, if planning a movement toward contact, a commander might not only need to consult operations doctrine, but also doctrine relevant to the commander's echelon, civil affairs doctrine if the commander's unit is moving through a population center, and cyber warfare doctrine if the commander is using cyber capabilities. Additionally, a commander might also need to find relevant doctrine quickly, especially if faced with unexpected actions by an adversary. When planning an operation, a commander might also consult the Army's collection of lessons learned to leverage the experience of commanders who have conducted similar operations in the past.

It might be possible to use AI to aid commanders and their staffs in finding desired information in doctrine and lessons-learned. To do this, a number of steps must be taken. First, a corpus must be built for the AI system by loading doctrine and lessons-learned publications into the AI system. From this corpus, the AI system can learn the relevant language, including jargon, and build a lexicon using natural language processing. The AI system can then pre-process the data by building indices and metadata, making it more efficient to work with the data. Finally, human subject matter experts must train the AI system in order to make the AI system provide more precise answers and identify patterns. Training can be done by uploading into the AI system training data in form of question and answer pairs. This training data would not provide the AI system with the answer to every possible question, but the data would help the AI system learn the linguistic patterns in the relevant domain. Once the AI system is deployed, the system could learn further through ongoing interactions with users.

By creating an AI system using the aforementioned method, commanders and their staffs might be able to gather desired information from doctrine and lessons-learned faster and more accurately than if no AI system was available for use. Without the AI system, a commander would have to find the desired information by manually searching every doctrine or lessons-learned publication possibly related to the desired information. This manual search is a time-consuming process that might not result in an optimal information product, especially if the person conducting the search is under time pressure. Indeed, humans oftentimes search for information until an acceptable threshold is met (e.g., the minimum amount of information needed to make a decision) in order to avoid expending too many cognitive resources and effort to find a perfect result (Simon, 1955; 1956; 1957). By using this method, however, humans might produce results that are less than adequate. Moreover, Simon observed that this method is unlikely to produce an optimal result as humans oftentimes do not search long enough to find such a result. Attempting to find the optimal result, however, may not be ideal as doing this takes time, and by the time the optimal result is found, the result might no longer be useful. Thus, if a commander attempts to find an optimal result, the commander may fail to get inside the adversary's decision cycle; the commander needs to balance time to find a result with result quality. On the other hand, an AI information-gathering system may be more likely to find the optimal result, and the AI system may be more likely to do so in much less time than it would take a human.

Although an AI system may be more efficient than a human at finding desired information in doctrine and lessons learned given limited human information-processing capabilities (Baddeley, 1992), this outcome is with the assumption that the AI system is sufficiently trained to identify the linguistic patterns in doctrine and lessons-learned publications. If the AI system is not sufficiently trained, then users of the AI system would likely find sub-optimal results and, as a result, grow frustrated with the AI system, ultimately putting the AI system to disuse. Additionally, the AI system would only be useful insofar that the human users of the AI system appropriately calibrate their trust in the system (Hancock et al., 2011; de Visser, Pak, & Shaw, 2018). Many AI systems are inconsistent in their performance due to a variety of reasons including environmental context, user error, and inconsistency in training across contexts (Rovira, McGarry, Parasuraman, 2007). For example, an AI system that produces accurate results related to the fires warfighting function may produce less accurate results compared to the maneuver warfighting function. If the human users of the AI system place full trust in the system's results, a decrement of performance may occur (Hancock et al., 2011). Training the human users on understanding when the AI system is likely to be accurate and when it is not likely to be accurate is critically important (de Visser, Pak, & Shaw, 2018). Conversely, if the human users of the AI system place little trust in the AI system, the system would likely go to disuse. Thus, the AI system would not improve a commander's efficiency in finding information even if the system itself was exceptional at doing so (Hancock et al., 2011).

**Current Research**

Although AI tends to excel at tasks that can be solved primarily with pattern recognition, and tasks from which predictions can be made from task data, such as image recognition, medical diagnosis, and transcription, it is currently unknown if AI can be used to increase information gathering efficiency in U.S. Army contexts, especially in contexts where Army commanders and their staffs are required to find information in Army doctrine. Thus, in the current research, we addressed the following question: Can AI be used to increase information gathering efficiency in U.S. Army mission command processes? To answer this question, we used a commercial AI application system, which reflected the first development effort for an Army mission command AI application prototype. In this research effort, we compared participant performance on an information-gathering task between this Army-tailored AI system and two other information gathering methods: a traditional information gathering method (searching PDFs in a computer folder), and a non-Army-tailored version of the AI system.

## Method

### Participants

Participants were a convenience sample of 8 retired Army officers (major – lieutenant colonel) and 1 Army Civilian recruited by the U.S. Army's Mission Command Battle Lab. Participants had a mean time in service of 25.36 years (*SD* = 4.97). Figure 1 shows the Army positions held by the retired Army officers across their entire Army career. With a sample of 9 participants, our power analysis revealed a Cohen's *d* of 1.38 as the smallest population effect size that we would have a 95% chance of detecting at an alpha level of .05

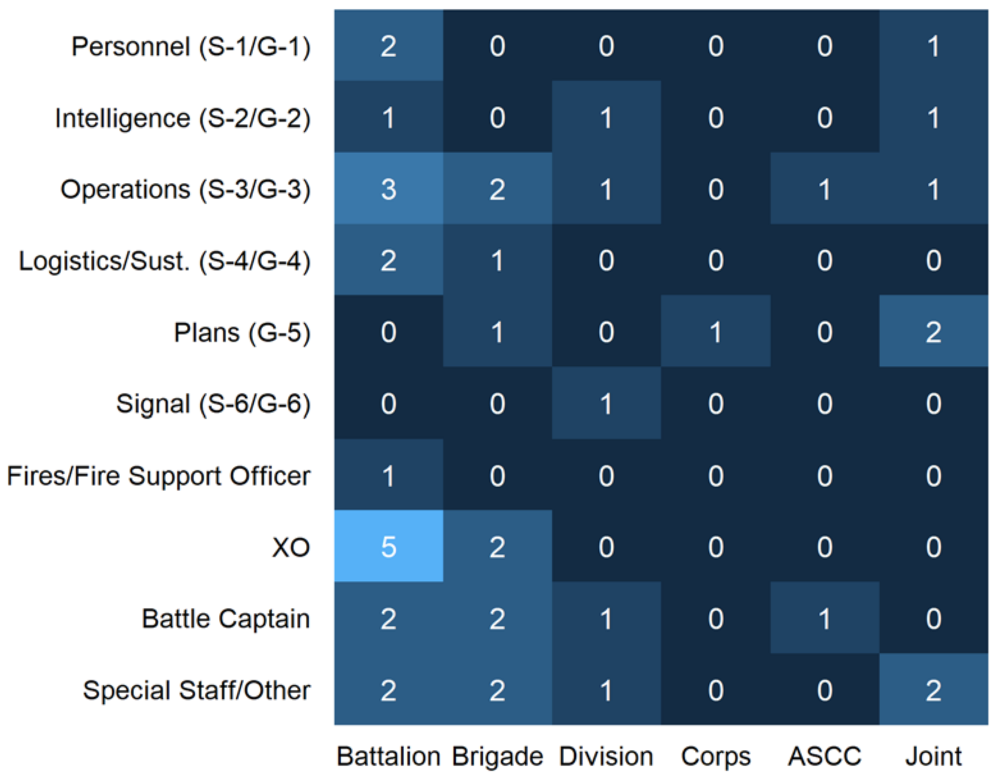


*Figure 1*. Heat map of Army positions held by the retired Army officers while in the Army. Lighter colors represent greater numbers. Note that all of the retired officers held multiple positions across their Army career. ASCC = Army Service Component Command.

### Search Methods

Participants searched for answers in Army doctrine from all of the Army warfighting functions (protection, sustainment, mission command, intelligence, fires, and movement and maneuver). Participants searched for answers using three methods: 1) using the search functionality of an Army-tailored AI system (Army System), 2) using the search functionality of a non-Army-tailored system (Non-Army System), and 3) using a more traditional search method (PDF Search).

The Army and non-Army AI systems were procured for the U.S. Army from a major information technology corporation. The non-Army AI system was an out-of-the-box system, ready for commercial use. The non-Army AI system was previously trained on general knowledge. The Army AI system was trained on both general knowledge and U.S. Army-relevant knowledge. The Army AI system was created using the following method: First, a corpus was created using Army-relevant information, including acronyms, and terms. From this corpus, the Army AI system learned general language and built a lexicon. The Army AI system then increased its efficiency by building indices and metadata. Finally, human subject matter experts trained the Army AI system by providing question and answer pairs on questions related to general knowledge.

To give both AI systems the capability to search Army doctrine, both systems "ingested" doctrine from all of the Army warfighting functions. To do this, both AI systems used identical machine learning and natural language processing algorithms to analyze the doctrine, and both systems created a searchable index using the results of the analysis. These searchable indexes were made accessible by a front-end search display. Figure 2 shows a screenshot of the Army system's search display.

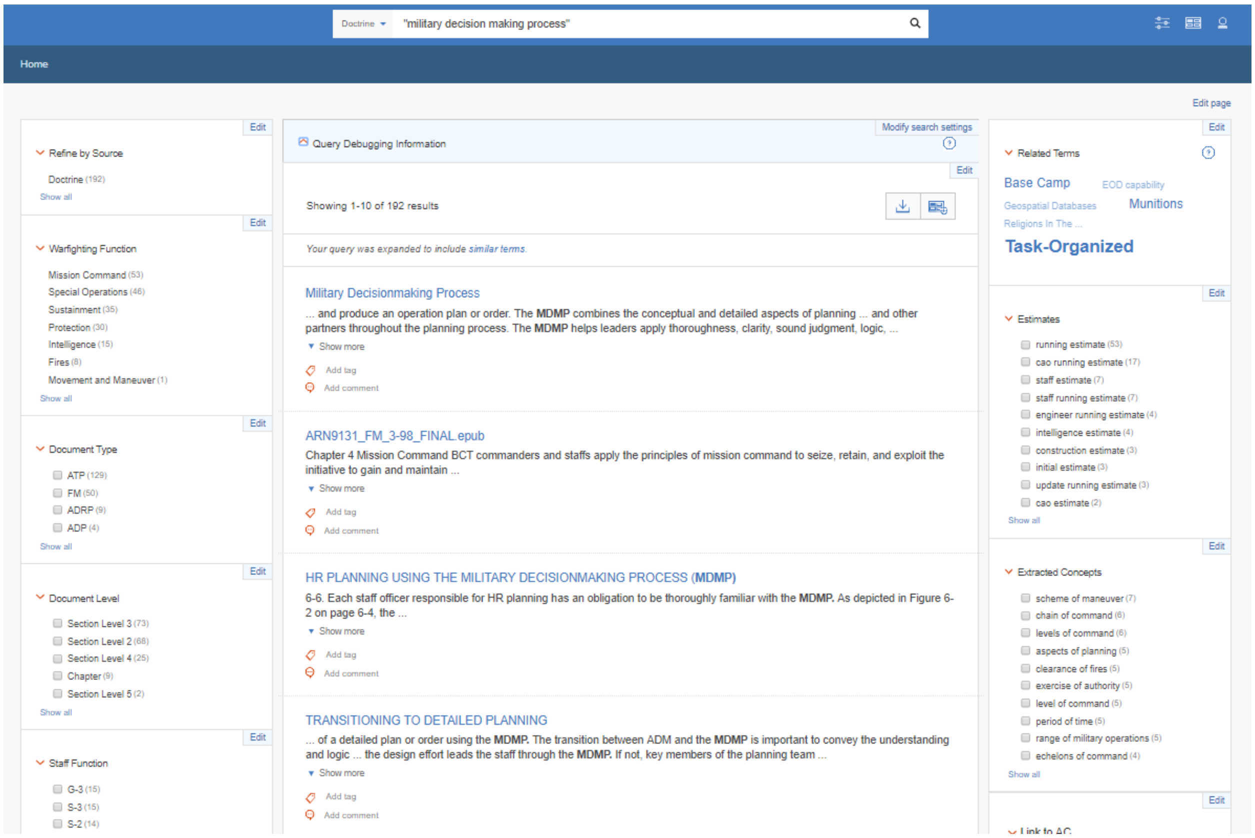

*Figure 2.* A screenshot of the Army system's search display.

Although both AI systems could be used to search Army doctrine, the purpose of the Army-tailored AI system was to make it easier for commanders and their staff to find information in Army doctrine. For instance, searching for "military decision making process" would also bring up results for "MDMP." The Army AI system also allowed participants to narrow their search by filtering for warfighting function, staff function, echelon, combatant command, running estimate type, country, and document type (e.g., ADP, ADRP, FM, etc.).

When participants used the PDF search method, they simply searched for answers in U.S. Army doctrine PDF files located in a computer folder. These files were identical to the files mined by using the Army and non-Army AI systems.

## Task and Procedure

The research was completed at the U.S. Army's Mission Command Battle Lab at Fort Leavenworth, KS. Before starting the research, participants attended a 3 hour training session in which they were familiarized with the functionality of the two AI systems. Specifically, participants were instructed on how to use the AI system functions, including how to search for information.

In the research, participants attempted to answer 90 doctrine-related questions (e.g., "What are the staff inputs to the Battle Update Brief?"). The questions were developed by 2 active duty U.S. Army officers (2 majors) and 2 retired U.S. Army officers (1 lieutenant colonel and 1 major). The questions were designed to reflect common questions asked about Army mission command processes. Appendix A lists the full set of questions. Participants answered these questions across three 180 minute sessions (30 questions/session) that were completed in a span of 2 days (Day 1 = Sessions 1 and 2; Day 2 = Session 3). Each session was divided into three runs lasting 50 minutes each, and participants received a 15-minute break between runs. Participants used a single search method during each session, and the search method that participants used during each session was counterbalanced using a Latin square design (see Table 1). For example, three participants used PDF search during Session 1, the Army AI system during Session 2, and the non-Army AI system during Session 3. By counterbalancing the order of presentation of search method in this way, we minimized any effects that time in the experiment might have on search performance.

Table 1
*Experimental Design*

| **Session** | ***n* = 3** | ***n* = 3** | ***n* = 3** |
|---|---|---|---|
| 1 | PDF Search | Non-Army System | Army System |
| 2 | Army System | PDF Search | Non-Army System |
| 3 | Non-Army System | Army System | PDF Search |

Participants received questions via customized software programmed in JavaScript. The software sequentially presented participants with each question and measured the amount of time participants took to answer the question (answer time). Answer time was automatically measured by asking participants to click a button when they answered the question and measuring the difference in time between when the question was presented and when participants clicked the button. After clicking the button, the software asked participants to rate their confidence in their answer by using a 7-item rating scale (1 = Not at All Confident, 7 = Extremely Confident). We collected confidence data as higher confidence in a piece of information may result in quicker decision-making based on the piece of information (Desender, Boldt, Verguts, & Donner, 2019). Participants entered their answers into a Microsoft Word document. After the experiment was completed, 2 to 3 coders rated the accuracy of the participants' answers (the coders were the same group that developed the questions). Whenever the coders had a rating disagreement, they conducted consensus discussions in order to agree on a rating.

After each session, participants completed two surveys: The National Aeronautics and Space Administration (NASA) Task Load Index (NASA TLX) and the System Usability Scale (SUS). The NASA TLX (Hart & Staveland, 1988) is a 6-item scale that assesses respondents' perceived workload from doing a task. The 6 items on the scale assess mental demand, physical demand, temporal demand, perceived task performance, effort required, and frustration with the task. Participants responded to each item using a 20 item scale ranging from "very low" to "very high." The SUS (Brooke, 1986) is a 10 item scale that assesses respondents' perceived usability of a system, and respondents rated each item on a 5 item Likert-type scale (1 = Strongly Disagree, 2 = Disagree, 3 = Not Sure, 4 = Agree, 5 = Strongly Agree).

## Results

We analyzed the data using R Version 3.5.1 (R Core Team, 2018). We calculated mixed-effects models using the lme4 package (Bates, Maechler, Bolker, & Walker, 2015). We calculated mixed-effects model effects using the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2017), and we generated plots using the ggplot2 package (Wickham, 2016). We set alpha at .05 for each analysis.

As we were interested in determining if using a commercial out-of-the-box AI system or an early prototype of an Army-tailored AI system results in superior search performance compared to the traditional PDF search method and, if so, if one type of AI system is better than another, we created two orthogonal contrasts for the search method variable: 1) PDF search vs. AI system, and 2) Army system vs. non-Army system.

### Question-Level Analysis

Considering that each of our 9 participants answered 90 questions, we had a maximum of 810 data points to analyze at the question-level. However, because of computer issues, 295 of these data points were missing an answer time, an answer confidence, and an answer accuracy. Additionally, another 31 data points were missing an answer accuracy. Thus, for all analyses below, we were left with 515 data points with an answer time and an answer confidence (PDF Search $n$ = 165, Non-Army System $n$ = 164, Army System $n$ = 186), and 484 data points with an answer time, an answer confidence, and an answer accuracy (PDF Search $n$ = 158, Non-Army System $n$ = 152, Army System $n$ = 174).

Figure 3 shows the distributions of the three performance variables as a function of search method. In the sections below, we further assess how search method impacted these variables.

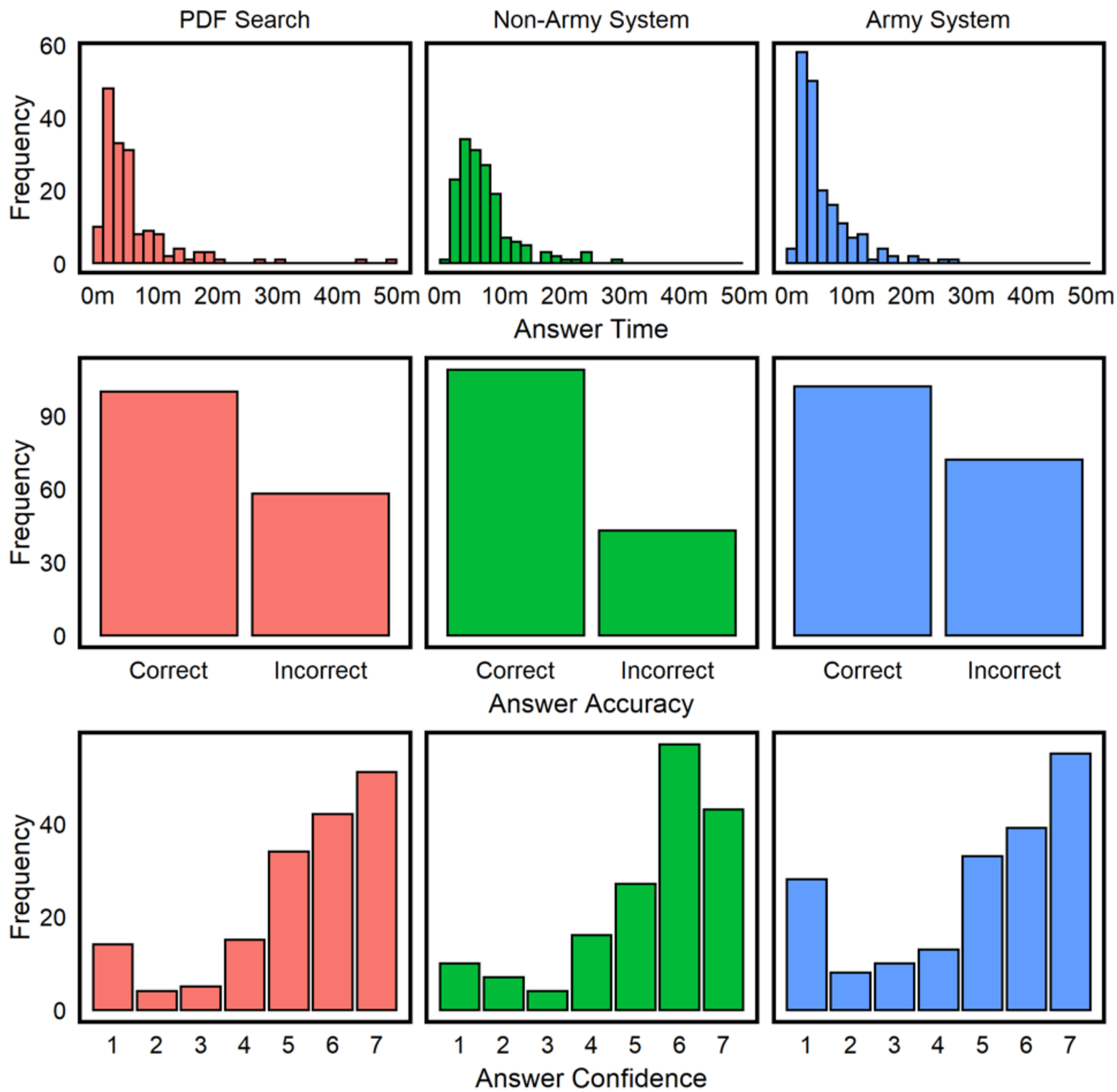


*Figure 3*. The distribution of each performance variable as a function of search method.

**Answer times.** We restricted our analysis to answer times that generated a correct answer because faster answer times are only beneficial if the answers they generate are correct. This restriction left us with 311 answer times to analyze (PDF Search $n$ = 100, Non-Army System $n$ = 109, Army System $n$ = 102). Figure 4 displays a boxplot of these answer times as a function of search method and participant identification (ID). Figure 5 displays the answer times as a function of search method only.

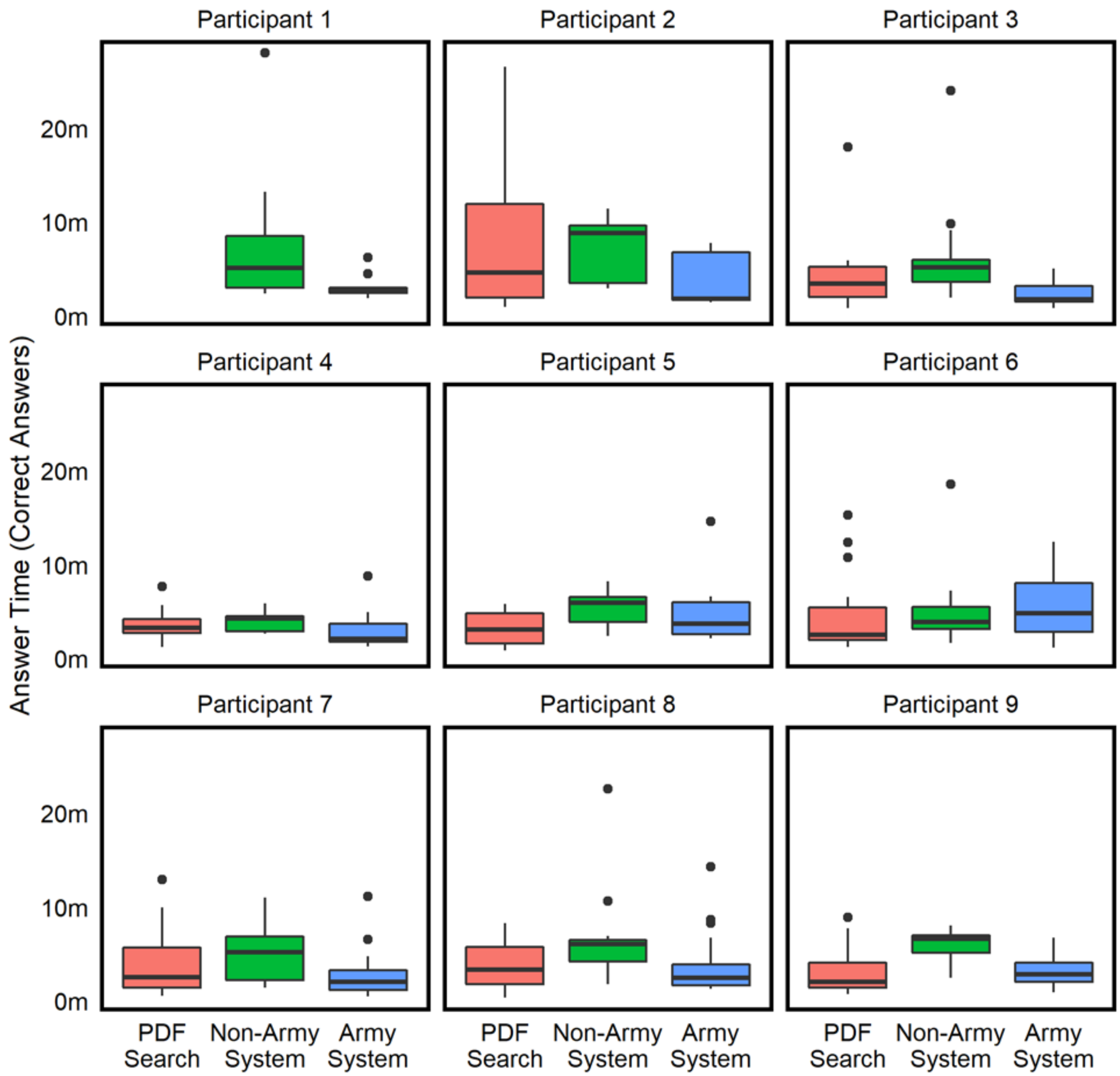


*Figure 4.* Boxplot of answer times for correct answers by search method and participant ID.

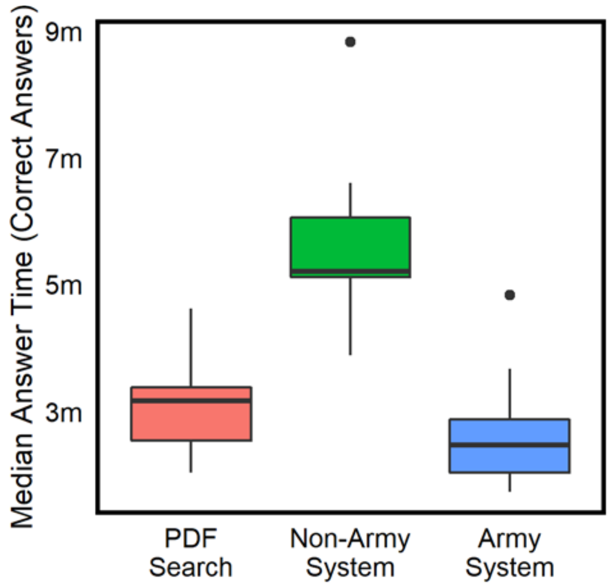


*Figure 5*. Boxplot of median raw, uncorrected answer times for correct answers by search method.

To analyze the answer times, we used maximum-likelihood, linear mixed-effects modeling with random intercepts for participant ID and question ID. We added question ID as a random intercept since the questions we included in our experiment did not comprise the full set of questions that a commander would be expected to answer using a search method like PDF search or any of the AI systems. Adding question ID as a random effect also reduced our likelihood of making a Type I error (Judd, Westfall, & Kenny, 2012). Moreover, we implemented these intercepts as crossed rather than nested intercepts considering that participant ID was crossed with question ID in our dataset (i.e., each participant answered each question). Additionally, given that this type of analysis assumes normally distributed residual errors, we used a logarithmic transformation on the non-normal answer times to normalize them.

We used a model comparison approach to determine if search method can explain a significant amount of the variance in answer times. The base model included only the random effects for participant ID and question ID and the final model included search method in addition to the two random effects. The predicted answer times from the final model are shown in Figure 6. By comparing the two models using a likelihood ratio test, we found that the final model had better goodness of fit than the base model, $X^2(2) = 43.72$, $p < .001$. Thus, search method explained a significant amount of the variance in the answer times. Additionally, participants were faster at providing correct answers when using PDF search rather than an AI system, $b$ = 0.08 [95% Confidence Interval (CI): 0.02, 0.13], $t(270) = 2.77$, $p = .006$. As shown in Figure 6, however, this effect was carried by the non-Army system, which also had slower answer times than the Army system, $b$ = 0.28 [95% CI: 0.19, 0.37], $t(282) = 6.19$, $p < .001$.

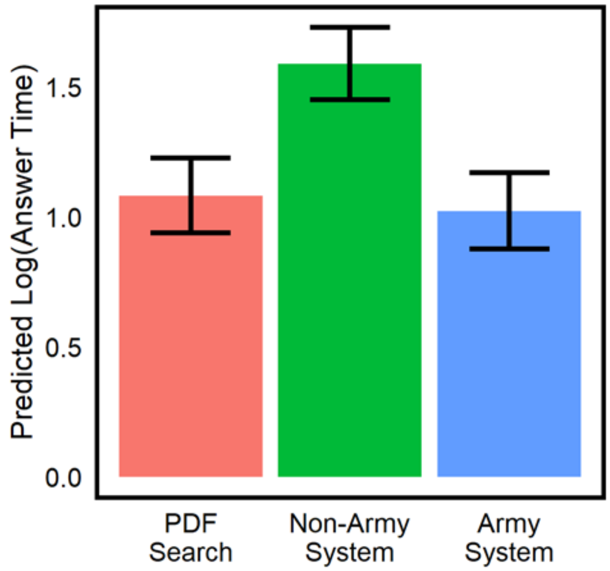


*Figure 6*. Predicted logarithmic-transformed answer times by search method. Error bars represent 95% confidence intervals. [Note: Using predicted answer times made it possible to calculate 95% confidence intervals.]

**Answer accuracies.** Figure 7 displays the probability of an accurate answer by search method and participant ID. Figure 8 displays mean accurate answer probability by search method.

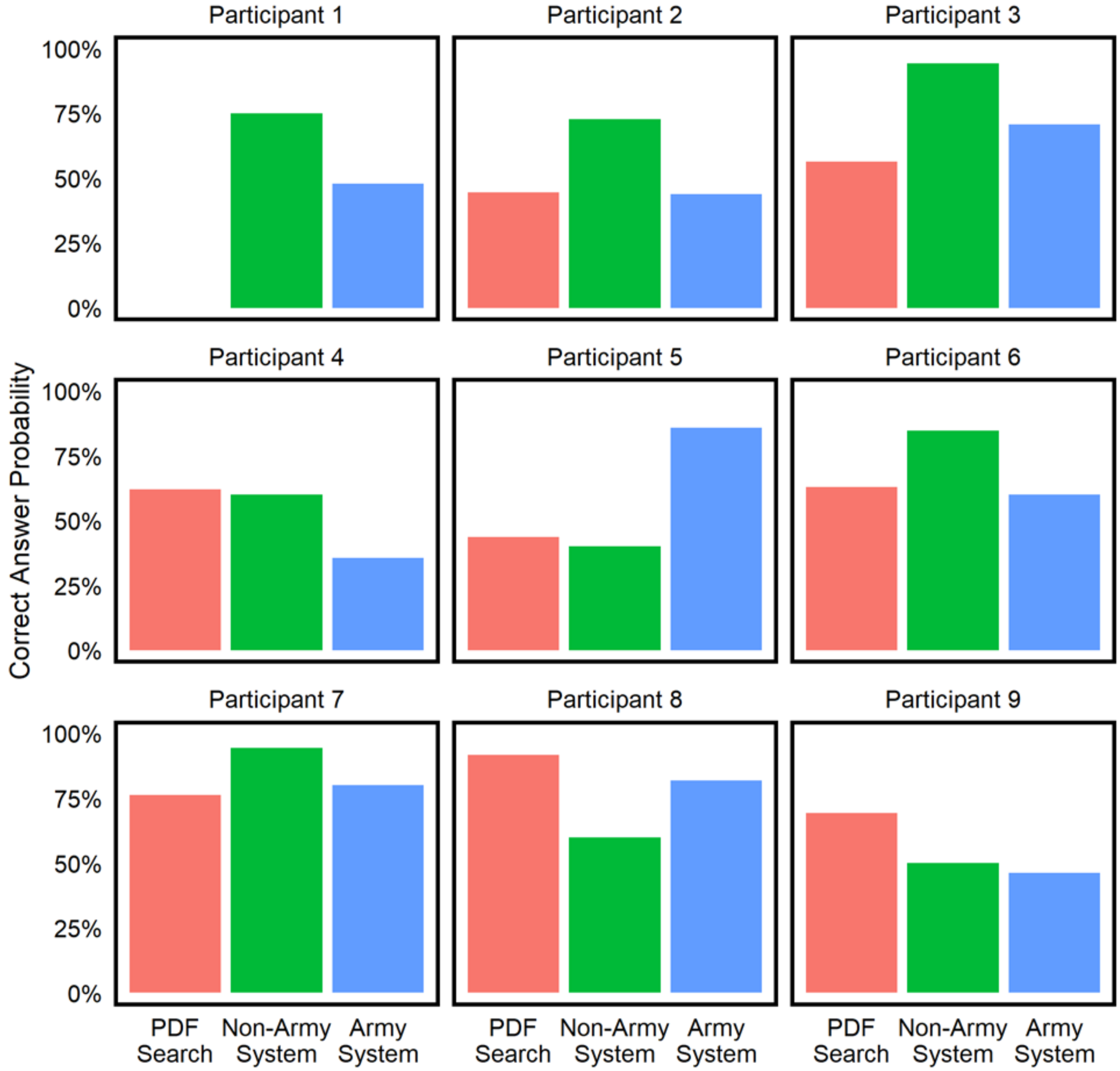


*Figure 7*. Accurate answer probabilities by participant ID and search method.

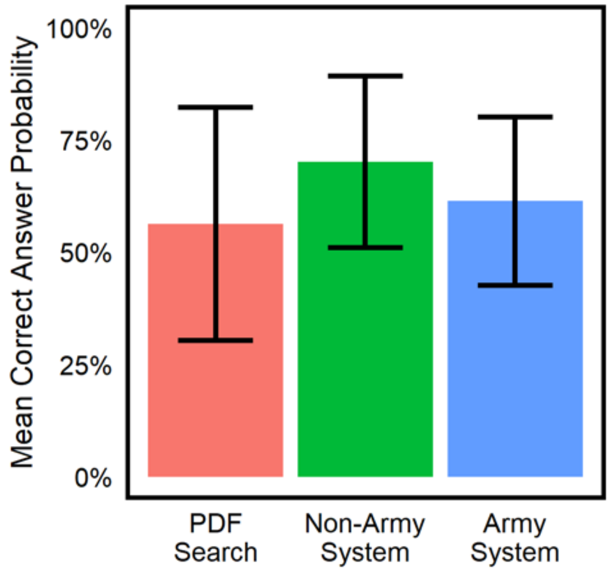


*Figure 8*. Mean correct answer probability by search method. Error bars represent one standard deviation.

To analyze the answer accuracies, we used binomial generalized linear mixed-effects modeling with a logit link function and random intercepts for participant ID and question ID. As with the answer times, we used a model comparison approach to assess the impact search method has on answer accuracy. The base model included the random intercepts for participant ID and question ID. A second model expanded the base model by including answer time (logarithmic-transformed and scaled) as a fixed effect. We wanted to statistically control for answer time because the accuracies of participants' answers likely varied with the time it took participants to answer the questions. The final model expanded the second model by including a fixed effect for search method.

Using a likelihood ratio test, we found the second model had a better goodness of fit than the base model, $X^2(1) = 35.02$, $p < .001$. Indeed, as shown in Figure 9, the longer it took participants to answer a question, the more likely they were to provide an incorrect answer to that question, *OR* = 0.43 [95% CI: 0.32, 0.57], $p < .001$. Additionally, we found that the final model had a better goodness of fit than the second model, $X^2(2) = 13.79$, $p < .001$, indicating that search method explained a significant amount of the variance in answer accuracy. As shown in Figure 10, there was no significant difference in the answer accuracies when using an AI system than when using PDF search, *OR* = 1.08 [95% CI: 0.93, 1.26], $p = .311$, but there was a significant difference between the two AI systems: Participants were more likely to provide a correct answer when using the non-Army system rather than the Army system, *OR* = 1.62 [95% CI: 1.25, 2.13], $p < .001$.

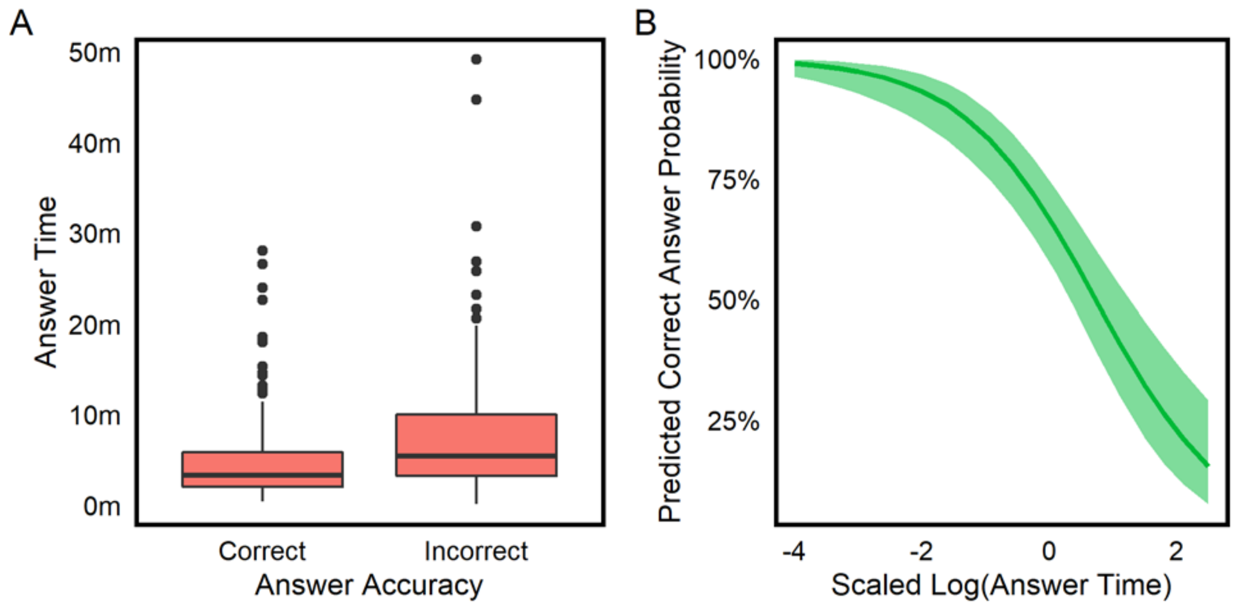


*Figure 9*. A) Boxplot of answer accuracy by answer time. B) The predicted probability of a correct answer by answer time (logarithmic-transformed and scaled). The shaded region represents a 95% confidence band.

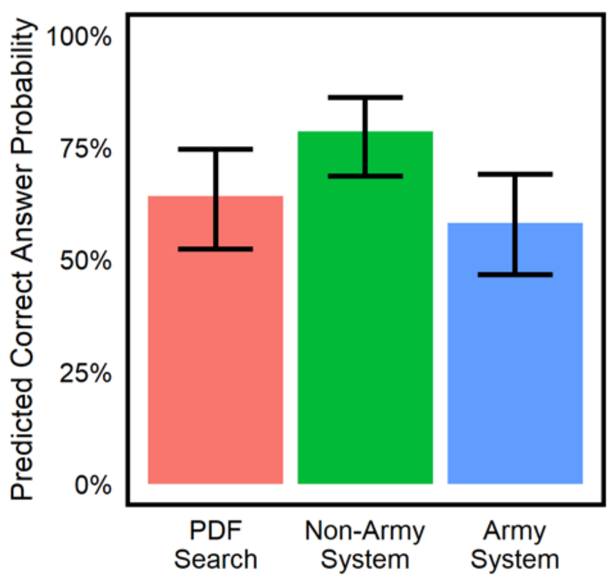


*Figure 10*. Predicted correct answer probability by search method. Error bars represent 95% confidence intervals. [Note: Using predicted answer times made it possible to calculate 95% confidence intervals.]

**Answer confidence ratings.** Figure 11 displays the median confidence rating as a function of search method and participant ID. Figure 12 displays the median confidence rating as a function of search method only.

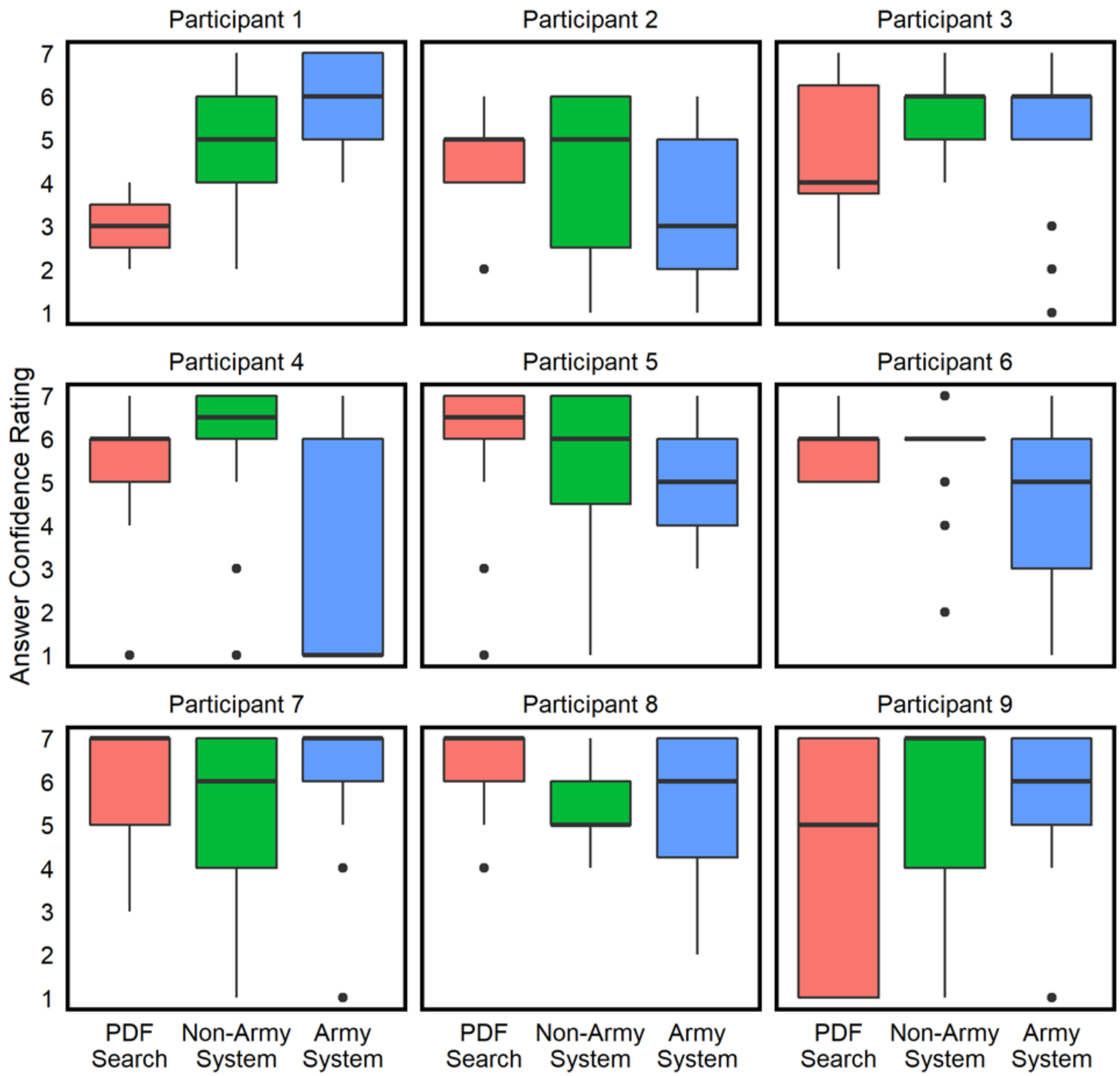


*Figure 11*. Boxplots of answer confidence rating by search method and participant ID.

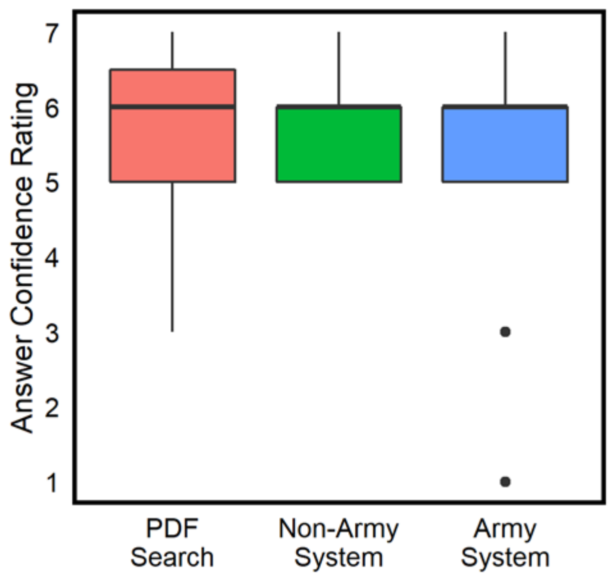


*Figure 12*. Boxplot of answer confidence rating by search method.

To analyze the answer confidence ratings, we first divided the confidence ratings into two new ratings: low confidence (rating <= 4) and high confidence (rating > 4). We did this division into two new ratings because current mixed-effects methods for analyzing ordinal data only allow for one random effect (e.g., cumulative link mixed-effects modeling). Given that we needed the ability to include two crossed random effects (participant ID and question ID), these current techniques were not ideal for our analysis. Additionally, if we simply used one of these techniques by removing one of our random effects, we would have increased our chances of making a Type I error (Judd, Westfall, & Kenny, 2012). Moreover, submitting ordinal data to a regular linear mixed-effects model is also inappropriate because this type of model assumes a continuous dependent variable.

To analyze the new confidence ratings, we again used binomial generalized linear mixed-effects modeling with a logit link function and random intercepts for participant ID and question ID. The base model in this analysis only included the two random effects of participant ID and question ID, and the final model included the two random effects and the fixed effect of search method. We found that the final model did not have a better goodness of fit than the base model, $X^2(2) = 4.74$, $p = .094$, indicating that search method did not explain a significant amount of the variance in the confidence ratings.

## Participant-Level Analyses

**NASA Task Load Index (TLX).** We calculated an overall NASA TLX score by adding all of the sub-element scores. Figure 13 displays the mean overall score by search method. Figure 14 displays each mean sub-element score by search method. Using a within-subjects ANOVA, we found that search method did not explain a significant amount of the variance in the overall NASA TLX scores, $F(2, 215) = 0.30$, $p = .744$, or any of the NASA TLX sub-element scores (all $p$'s $\geq .339$).

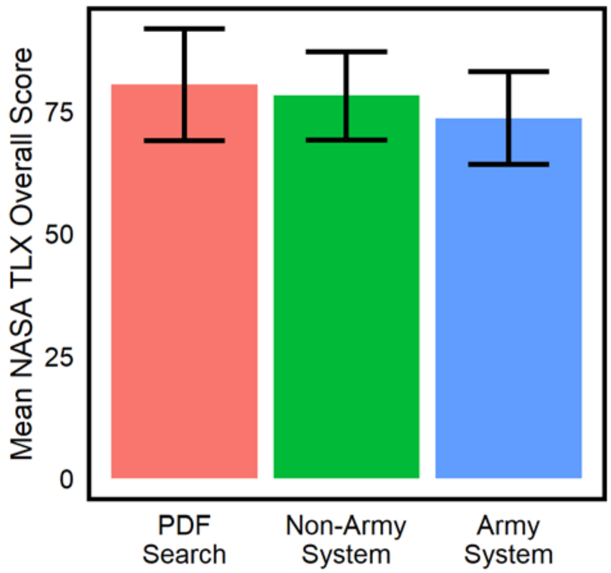


*Figure 13*. Mean NASA TLX overall score by search method. Error bars represent 95% confidence intervals.

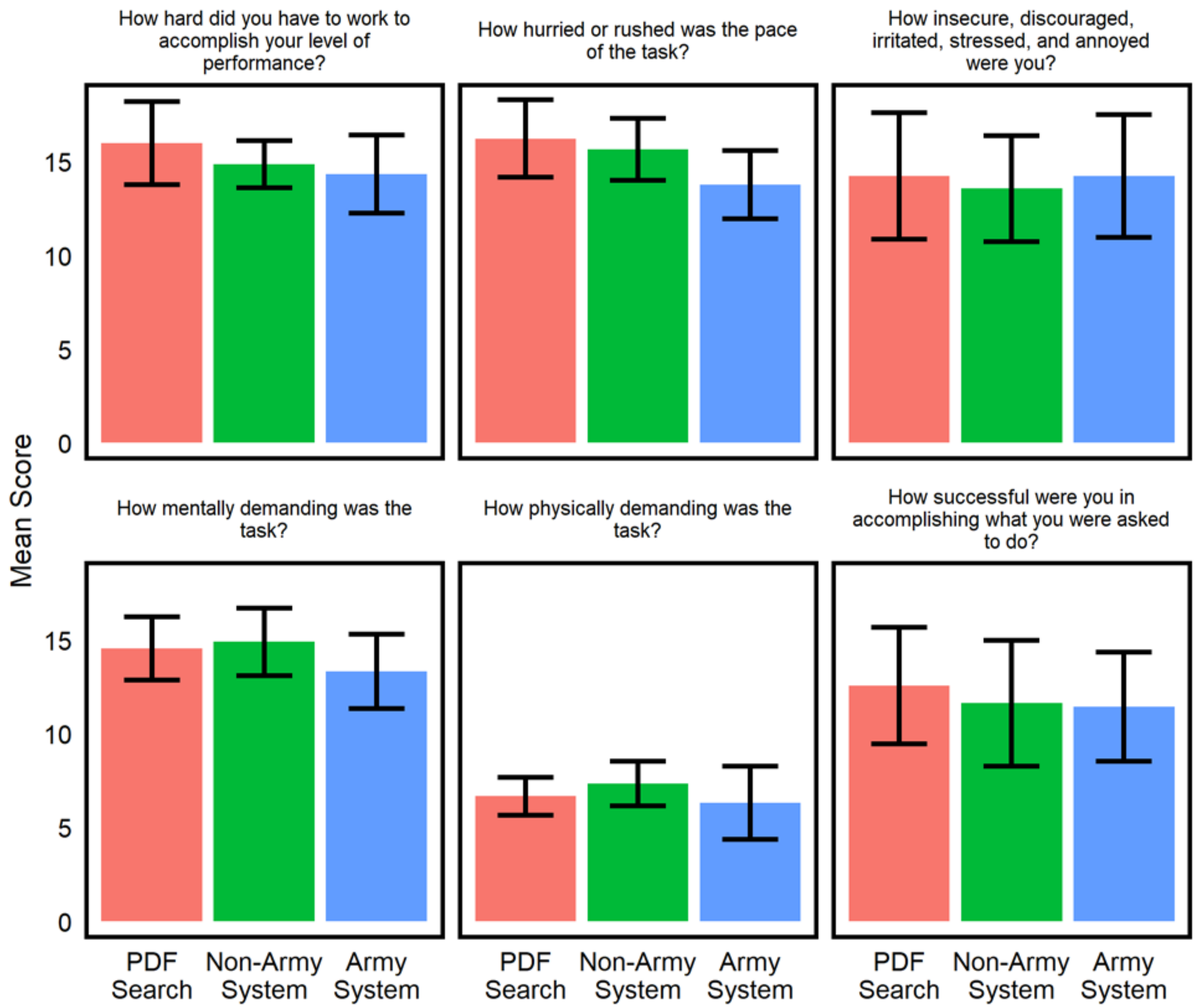


*Figure 14*. Mean NASA TLX sub-element score by search method. Error bars represent 95% confidence intervals.

**System Usability Scale (SUS).** Before analyzing the SUS scores, we first reversed the scores for the items that had reverse-coded response options—items in which a higher score reflected a more negatively valenced response. By reversing the scores for these items, we made it so that higher scores reflected more positively valenced responses for all items. Additionally, we subtracted 1 from all items that did not have reverse-coded response options. We calculated the overall SUS score by adding the scores for each item and multiplying the sum by 2.5. Doing the subtraction and reversal restricted each participant's overall SUS score to a number between 1 and 100

Figure 15 shows the overall SUS scores by search method. Figures 16 and 17 show the SUS scores for each item as a function of search method. Using a within-subjects ANOVA, we found that search method did not explain a significant amount of the variance in the overall SUS scores, $F(2, 179) = 0.21$, $p = .816$, or any of the SUS item scores (all $p$'s $\geq .080$).

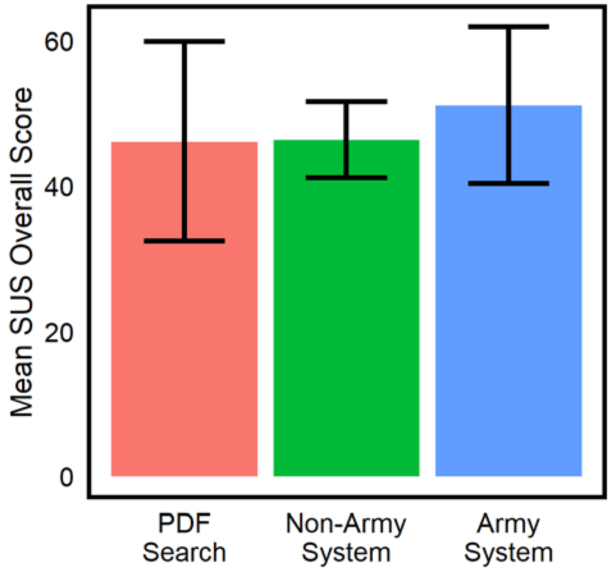


*Figure 15*. Mean SUS overall score by search method. Error bars represent 95% confidence intervals.

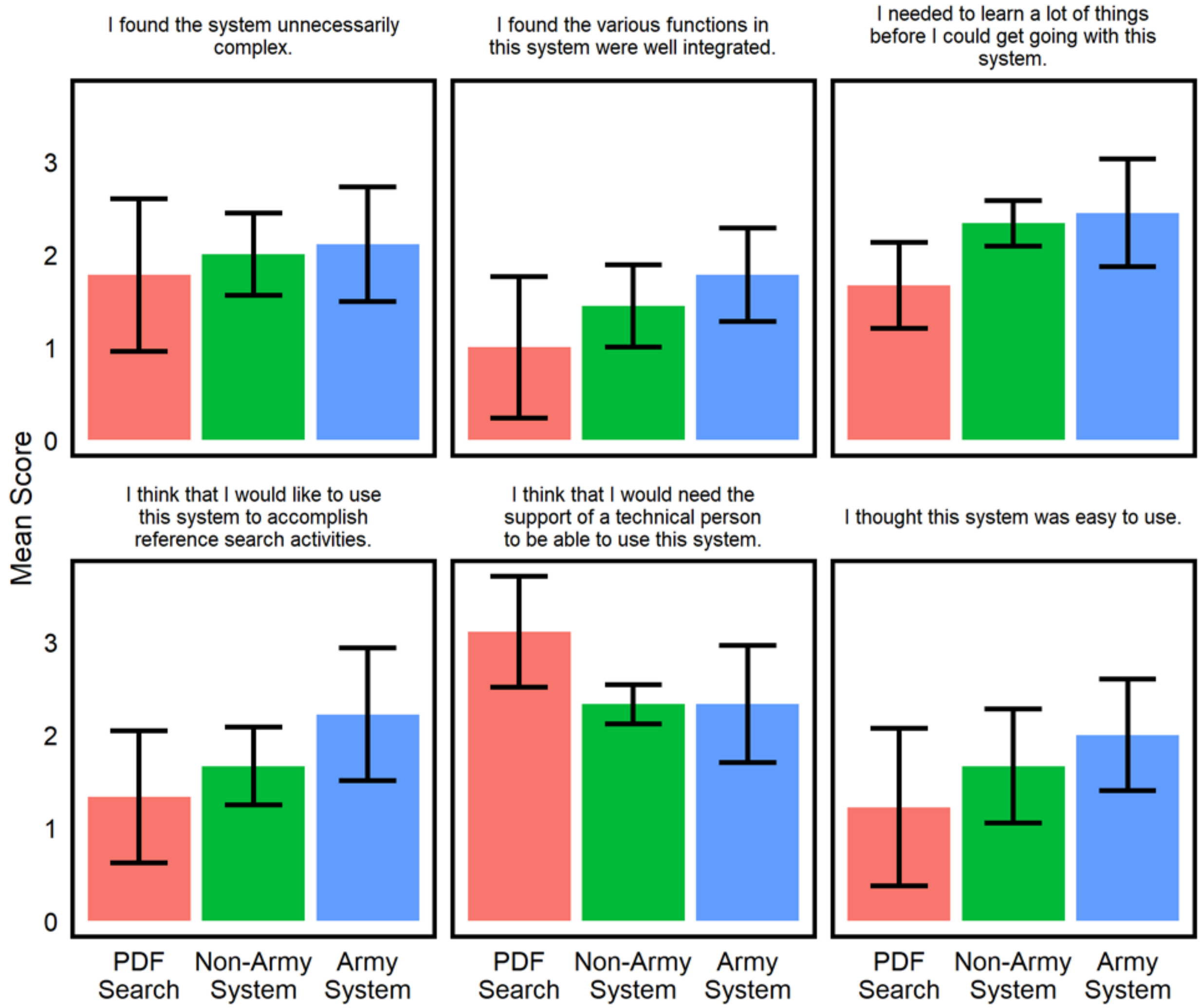


*Figure 16*. Mean SUS item score by search method. Error bars represent 95% confidence intervals.

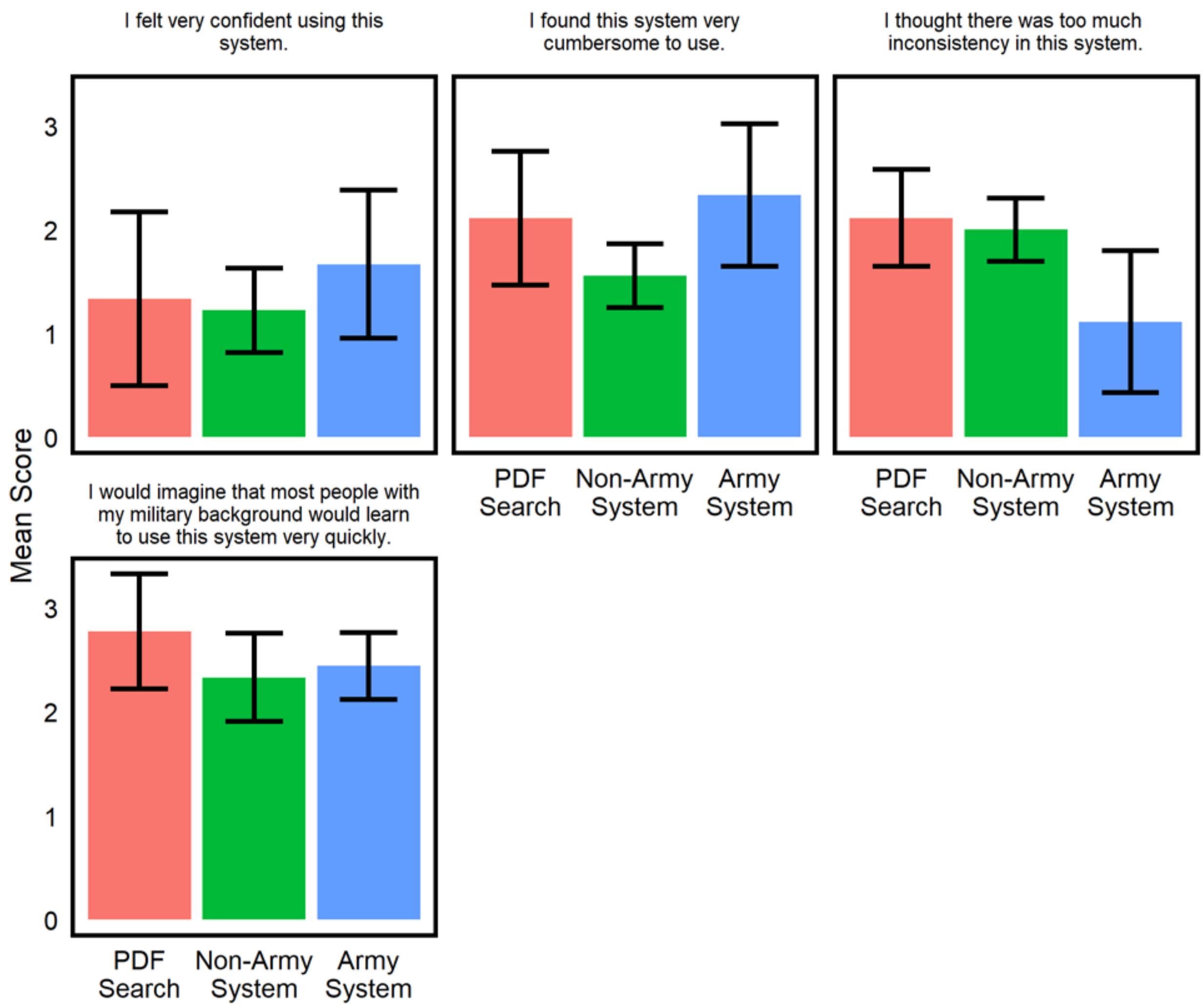


*Figure 17*. Mean SUS item score by search method (continued). Error bars represent 95% confidence intervals.

## Discussion

In the current research effort, we sought to determine if AI can be used to increase information gathering efficiency in U.S. Army mission command processes. We attempted to answer this question using a commercial AI application system from a major information technology corporation. We found that participants were neither quicker nor more accurate at answering questions about U.S. Army doctrine when using an AI system than when using a traditional PDF search. We did find, however, that participants were faster when using the Army AI system than when using the non-Army AI system. We also found that participants were less accurate when using the Army system than when using non-Army system. Finally, we found no differences in both perceived usability and perceived task workload between any of the search methods. Overall, these findings suggest that AI systems, such as the one used in our research, do not substantially increase information gathering efficiency in U.S. Army mission command processes.

There are, however, several aspects of our research that likely impacted our findings. First, because our sample consisted primarily of retired U.S. Army officers, the age range in our sample was likely restricted to older ages. Although we do not have the ages of our participants, the mean time-in-service in our sample of retirees was 25.36 years. Assuming that each retiree commissioned at the age of 22 (after 4 years of college starting at the age of 18), we can assume that the mean age in our sample of retirees is at least 25.36 + 22 = 47.36 years old. The average age in our sample is likely older, however, because the age above does not include post-Army service years. Increased age is associated with less experience with computer software (Nagle & Schmidt, 2012), such as the AI system. Thus, our participants might have required more experience with the AI system before any benefits of using the AI system could appear. Therefore, our findings might have been different with a younger sample.

On the other hand, because our sample consisted primarily of retired U.S. Army officers, we can assume that our sample had substantial experience with U.S. Army doctrine, considering that Army officers are required to familiarize themselves with Army doctrine throughout their career. It is possible that our findings were due to this increased expertise with Army doctrine. Given their substantial expertise with doctrine and their past experiences of having to search for information in doctrine, many of our participants might not have needed an AI system to aid them in searching doctrine publications. Thus, while the AI system might not be useful for those who have a lot of knowledge of Army doctrine, the AI system might be useful for those who do not have a lot of knowledge of Army doctrine.

Another factor that likely impacted our findings is the amount of time participants were given to learn the AI system before the research started. Although we gave participants a 3-hour training session on how to search for information using the AI system, 3 hours may not have been sufficient for improving information-gathering performance over the more traditional PDF search. Moreover, as detailed above, additional training may have been required given the age range of our sample. Similarly, our sample may have simply required more experience with the AI system for benefits to appear: Our participants used each search method for 2.5 hours, and this length of time might not have been enough for the participants to become proficient. Our findings indicate, however, that in circumstances in which training and experience are limited, large benefits from using the AI system are not likely to appear.

Finally, the sample size in our research was small and only gave us enough statistical power to detect a large population effect size. Thus, if the population effect size were smaller than what we could detect, then the population effect would go unnoticed by our analyses. Our findings suggest, at the very least, that AI systems, such as the one used in our research, do not immediately result in large improvements in information gathering efficiency.

Because our sample consisted of eight retired U.S. Army officers and one Army civilian, our sample did not belong to the target population for the AI system, which is enlisted or commissioned U.S. Army Soldiers. This situation is because of logistical limitations the research team faced when recruiting participants. If we had been able to recruit the participants from the AI system's target population, our sample would likely have consisted of younger participants with more computer experience, and our findings might have been different.

Future research should focus on the factors that likely impacted our findings. First, a sample more representative of the AI system's target population should be used. This sample should consist of commanders and staff, including enlisted Soldiers, officers, and NCOs, who would possibly use the AI system in a future operation. Second, participants should be given more time with the AI system before and during research. At the very least, participants should be trained to a basic proficiency with the AI system before research begins. Finally, future research should use larger sample sizes in order to be capable of detecting small to medium population effect sizes. Although larger effects might provide more immediate benefits, small to medium effects can provide benefits that are realized in the long term.

Although we did not find any evidence for improved information-gathering efficiency from using an AI system, this result does not necessarily mean that AI is of little use for information-gathering tasks in mission command processes, even with individuals who have substantial expertise with U.S. Army doctrine. The information-gathering task in the current research was relatively straightforward: participants simply looked for answers to simple, doctrine-related questions. It is possible that our task was too simplistic for AI-related benefits to appear, and that AI might only be useful for more complex information-gathering tasks: tasks that have multiple solutions of varying quality, and that have solutions that are not obvious or straightforward. Additionally, AI might be more useful for tasks that involve finding signals in streams of information that have a large-bandwidth. This supposition is an idea that future research should also address.

Overall, our findings should not be taken as strong evidence that AI is unhelpful for information-gathering tasks in mission command processes. In addition to the study limitations mentioned above, another factor that may have impacted our results is simply the usability of the AI system. The AI system used in our research not only consisted of the AI, but the user interface as well. Even an incredibly powerful AI system might go to disuse if its user interface was poorly designed. Thus, when comparing an AI system to a control condition such as the traditional search method used in our study, it cannot be concluded that the results of the comparison are solely due to the AI. In future research, conducting usability testing on an AI system before comparing it with other systems or methods might be a way to disentangle the usability of the system from the system's AI component.

Beyond information-gathering, AI offers the Army countless benefits. As mentioned earlier, AI is considered by some to be the new electricity (Lynch, 2017): AI currently plays a large role in everyday life, from improving the pictures we take on our smartphone (Vincent, 2019) to helping doctors detect cancer (Abbott, 2020). In military contexts, AI has the potential to impact many functions, including satellite imagery search (Erwin, 2019), vehicle maintenance (Vincent, 2018), and training (Pawlyk, 2019). A very salient function for which AI has promise is combat (Scharre, 2018). Although there are ethical considerations for incorporating lethal AI into the battlefield, doing so may reduce both friendly-force and civilian casualties (Scharre, 2018). As with information gathering, however, AI needs to be vetted in each of these tasks before it is deployed.

In terms of priority, the Army should first focus on AI that will save Soldier lives. A possibly obvious candidate is lethal AI: replacing the infantry Soldier and tank crew with a machine, thereby reducing the risk to the Solider. Possibly less obvious candidates, however, are training, counseling, and medicine, considering that improvements to these functions may reduce accidents, suicides, and injury, which had been reported as the leading causes of death in the U.S. military between 2006 and 2018 (Mehta, 2018). Within the above-mentioned priority, the Army should focus on the lowest-hanging fruit first: tasks that AI is already known to excel at, such as tasks that primarily require pattern recognition. For example, Soldier lives might be saved by incorporating AI into medical screening, something that has already been shown to be beneficial (Abbott, 2020). By investing in such AI, the Army will likely improve the wellbeing of its Soldiers.

In conclusion, our research was a first step in determining the impact that AI systems can have on information gathering efficiency in Army mission command processes. Additionally, in line with Department of Defense and Army initiatives on AI, our research expands the knowledge base of AI in the military. The Army will face many challenges in future complex operational environments, and our research was one of many steps that will help the Army better understand how to deal with these challenges.

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# Appendix A. Questions

## Session 1 Questions

- What are the Army planning Methods?
- Intel tasks in the MDMP include?
- What are the staff inputs to the Battle Update Brief?
- What are the responsibilities of the XO in the CP?
- What is the commander's role in planning information collection requirements?
- What are the elements of combat power?
- What are the characteristics of information that answers an information requirement?
- What are the continuing activities of the staff?
- What are the staff functional cells?
- How does knowledge management enable the mission command warfighting function?
- The Mission Analysis step of the MDMP includes what inputs?
- The Army Design Methodology is used primarily at what echelon?
- The current operations cell includes representatives from which staff sections?
- What staff officer within current operations cell is responsible for maintaining the COP?
- What is the difference between direct and general support relationships between units?
- What staff section performs orders production?
- In what paragraph of the operations order does the S/G6 contribute?
- What data is common between running estimates and staff estimates?
- What role does the battle captain play in KM?
- How does KM inform the BUB/CUB?
- Where is the commander's intent included in the order?
- What components are included in the commander's intent?
- How is the running estimate linked to Situational Understanding (SU)?
- What is included in battlefield geometry?
- How are unit boundaries determined?
- When is the MCOO developed in the MDMP Process?
- What are control measures and how are they used in a plan?
- What is the primary difference between commander and staff tasks in the mission command WfF?
- How is the Mission Command Information System (MCIS) defined?
- How does the commander interact with the MCIS while in the Command Post?

## Session 2 Questions

- What are the guides to effective planning?
- What is the XO's role in MDMP?
- What are the staff inputs to the commander's update brief?
- What are the responsibilities of the Battle Captain in the CP?
- What should the staff consider in information collection planning?
- What are the operational sub-variables?

- What are the considerations for determining the appropriate degree of control in an operation?
- What are the characteristics of an effective battle rhythm?
- What are the staff integrating cells?
- How does knowledge management assist in organizing the mission command system?
- COA Analysis involves what staff sections/WfFs?
- How is the Synchronization Matrix related to decision points?
- What are the steps included in wargaming a COA?
- What are the elements of the COP?
- What staff section leads development of the Battle Update Brief (BUB)?
- How is the Decision Support Matrix (DSM) used in the BUB?
- What staff sections participate in mission analysis and the Intelligence Preparation of the Battlefield (IPB) process?
- What data are different between running estimates and staff estimates?
- What is Battle Damage Assessment (BDA)?
- What is a support relationship between units?
- How is BDA linked to the intelligence collection and/or unit reporting?
- What defines a unit's battle rhythm?
- How are Information Operations (IO) defined?
- Who identifies the main supply route (MSR) and alternate supply route (ASR)?
- Where are specified tasks found in the order?
- Where are implied tasks found in or derived from the higher order?
- What are the activities of preparation for an operation?
- What are the types of plans?
- What component of the MCIS displays the operational COP at the BDE?
- How does a staff manage the transition from FUOPS (Plans) to CUOPS (execution)?

**Session 3 Questions**

- What are the key concepts in design methodology?
- How do sustainment planners participate in the MDMP?
- What are the staff inputs to the operations synchronization meeting?
- What activities should be addressed in the CP SOP?
- At division and higher level what staff members participate in the ops & intel working group?
- In what process are the mission variables typically employed?
- The science of control is comprised of what elements?
- Running estimates consider the effects of new information on what factors?
- What are the roles and responsibilities of the staff integrating cells?
- What are the responsibilities of the knowledge management officer?
- What are the differences between Troop Leading Procedures (TLP) and the MDMP WRT the commander's role and echelon?
- What information elements are included in CCIR?
- What is the S/G3's Role in documenting the Wargaming activity of the MDMP?
- What does the Intelligence Officer (S/G2) contribute to the COP?

- What intelligence factors are important when planning shaping operations
- How are orders presented and disseminated to subordinate units?
- What components of the operational COP in the Current Ops cell are also components of the sustainment or Logistics COP?
- What is the relationship between CCIR and Decision Points (DP)?
- What components of the operational COP in the Current Ops cell are also components of the Intelligence COP?
- What is a command relationship between units?
- Intelligence, Surveillance and Reconnaissance (ISR) planning is documented in what annex of the OPORD?
- What is the relationship between the ISR Plan, High Value Targets (HVT) and High Payoff Targets (HPT)?
- What is the Information Operations Working Group's (IOWG) purpose?
- How is the IOWG linked to the broader operation?
- What are the potential roles of field artillery units?
- What is Mission Command on the Move?
- How are the roles and responsibilities of counterfire HQs stipulated?
- Where in the order is the location of the commander indicated during an operation?
- How does the MCIS integrate or include Joint partners?
- How does the commander interact with the MCIS while on the move?