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Extending Cognitive Assistance with AI Courses of Action

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Extending Cognitive Assistance with AI Courses of Action for Wargaming

by

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14. ABSTRACT
The objectives of this study is to research and assess the evolving stages of Human-Machine Teaming (HMT) mission workflows which is focused on transitioning of automation tasks from humans to machines. Also, to study the advanced stage(s) of the evolution of HMT to include various machine learning (ML) techniques for Courses-of-Action (COA) in wargaming decision-making (DM) AI functions and what role natural language processing (NLP) plays. In addition, this study will explore the viability of how NLP in HMT with human peer-to-machine peer COAs generation as opposed to other approaches. The theoretical framework will be grounded in Naturalistic Decision Making (NDM). Finally, this study will leverage complex Joint Naval Force EABO scenario (UNCLASS) designed by MCWL to explore NLP and AI/ML COA's distributed agents managing the decision making of operators using various modes of HMT interface of AI run-time execution agents thereby reducing human decision making errors.

15. SUBJECT TERMS
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TABLE OF CONTENTS

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LIST OF TABLES

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I. INTRODUCTION

Historically, decision support systems (DSSs) have focused on the "systems" aspect. This is evidenced by the definition of a decision support systems having the components of "1) the data management system, 2) the model management systems, 3) the knowledge engine, 4) the user interface, and 5) the user(s)" (Marakas, 1999, pp. 9-10). The user interface is simply the ability for the end user to communicate information and present language in a human readable format (Marakas, 1999). The user must be considered in the design and development of the DSS to ensure the system is usable within the appropriate context, or problem space to assist the user in making decisions (Runde, 2019).

The focus of this research is on the end user and a class of decision support systems called nonprocedural. In a nonprocedural DSS, artificial intelligence can transform a standard, static, and defined DSS into a cognitive agent (also called a cognitive assistant) (CA) that can learn and assist a human decision maker to make more accurate decisions while adapting to a changing environment. The goal of this research is to conceptualize the framework of a CA that can improve decision quality and situational awareness.

Cognitive agents date back to the early 20th century when V. Bush envisioned an information retrieval system in 1945 where a device could store "all his books, records, and communications, and which is mechanized so that it may be consulted with exceeding speed and flexibility" (Bush, 1999). During this early stage of decision support systems, Turing is also credited with creating the Turing Machine which enabled the decoding of German encryption. Intelligent systems have exploded since post-WWII not only for government and industry applications but in personal, home use such as when Apple released Siri in 2011 and then Samsung Bixby, Amazon Alexa, Windows Cortana, and the Google Assistant providing "features that aid in daily life" (Maier, Menold, McComb, 2019). There is no doubt that Bush's vision of progressing intelligent systems has exceeded his "incentive for scientists when the fighting [of WWII] has ceased…to turn to the massive task of making more accessible our bewildering store of knowledge" (Bush, 1945).

We are currently in the Information Age and finding our way through new advances in AI/ML (Vorobiova, 2022). The Digital Age is the new era emerging, however, this new Digital Age has not been a sudden change from the Information Age to the Digital Age. Rather, the transition has been incremental (Birkinshaw, 2015). If Bush's ideas seemed too far reached in 1945, only to come to fruition less than a century later, presumably our abilities today will exceed our imaginations in the next century. If this is to be presumed, we must carefully turn our attention to the human decision maker and the digital assets used in complex military environments as a matter of national security. The Executive Order on Ensuring Responsible Development of Digital Assets (2022) states, "growing development and adoption of digital assets and related innovations, as well as inconsistent controls to defend against certain key risks, necessitate an evolution and alignment of the United States Government approach to digital assets." In addition, the Department of Defense (DOD) published the "Responsible AI Strategy and Implementation Pathway" that identifies six tenets:

- Modernize governance structures and processes that allow for continuous oversight of DOD use of AI, taking into account the context in which the technology will be used;
- Achieve a standard level of technological familiarity and proficiency for system operators to achieve justified confidence in AI and AI-enabled systems;
- Exercise appropriate care in the AI product and acquisition lifecycle to ensure potential AI risks are considered from the outset of an AI project, and efforts are taken to mitigate or ameliorate such risks and reduce unintended consequences, while enabling AI development at the pace the Department needs to meet the National Defense Strategy;
- Use the requirements validation process to ensure that capabilities that leverage AI are aligned with operational needs while addressing relevant AI risks;
- Promote a shared understanding of RAI [(Responsible Artificial Intelligence)] design, development, deployment, and use through domestic and international engagements; and

- Ensure that all DOD AI workforce member possess an appropriate understanding of the technology, its developmental process, and the operational methods applicable to implementing RAI commensurate with their duties within the archetype roles outlined in the 2020 DOD AI Education Strategy.

To this end, this research is motivated to conceptualize a framework for a cognitive assistant that puts the human decision maker at the forefront of the decision-making process rather than creating systems from a technological point of view where the human adapts to the system. The goal in conceptualizing a framework for a CA that is human-centered and human-focused will provide "familiarity and proficiency for system operators, promote a shared understanding of the technology, and ensure that the AI workforce member possesses an appropriate understanding of the technology" as stated in the above six tenets. This will be accomplished through the theoretical lenses of Knowledge Flow Theory and the Recognition Primed Decision-Making model.

A. THEORETICAL PERSPECTIVE

The two main perspectives of this research will be grounded in Knowledge Flow Theory (KFT) and Recognition Primed Decision-Making (RPD) model. Knowledge Flow Theory will be the theory for which this research aims to contribute through the study of knowledge friction. In turn, RPD provides a framework of how decision makers actually make decisions in time-stressed, dynamic, and complex environments that do not follow the standard decision-making steps such as an analysis of alternatives. RPD provides peer reviewed research findings to support the application of this research in a military environment. Knowledge friction may be better understood by understanding the role of knowledge flows in a naturalistic environment.

1. Knowledge Flow Theory

Knowledge Flow Theory (KFT) has distinguished between explicit and tacit knowledge flows (Nissen, 2014). The novelty of KFT may allow one to: 1) observe the flows of explicit and/or tacit knowledge, and 2) identify potential knowledge friction factors, and the effect(s) on situational awareness. This is important to this study because as information flows bi-directionally, the researcher will gather data through observations, questionnaires/surveys, and sensor data collection. The presumption is that the analysis of the data collection to support SA will identify the system characteristics that require testing to determine which knowledge friction characteristics have the most impact, either positively or negatively, on knowledge flows and hence, SA.

Shigley (2021) studied knowledge friction variables of clarity, relevance, certification, and experience on knowledge transfer. This study used a factor analysis to analyze DAU post-course survey data (Shigley, 2021). While this study identified important characteristics of knowledge friction, it did not address knowledge friction in a military tactical environment.

2. Recognition Primed Decision-Making Model

Recognition Primed Decision-Making (RPD) model developed by "Gary Klein, Roberta Calderwood, and Anne Clinton-Cirocco…describes how decisionmakers can recognize a plausible course of action (COA) as the first one to consider," in other words, the first intuitive response is usually the best (Ross, et al., 2004). A key feature of cognitive agents is the ability to identify goals, generate courses of action based on known information and making predictions about possible outcomes (Fan, McNeese, and Yen, 2010).

Naturalistic Decision-Making (NDM) is a conceptual model born out of RPD. "Naturalistic Decision Making (NDM) is a framework used to study, inform, and improve how people make decisions in demanding, real-world situations" (Naturalistic Decision Making Association, 2022; Gary Klien). The military is an ideal population to apply the NDM framework since many decisions are made under time-stressed constraints combined with information ambiguity and can have potentially catastrophic consequences.

Hutchins (2008), in her work based on NDM published the study, "Tactical Decision Making Under Stress (TADMUS) [which] studied the relationships between independent variables such as dynamic versus static situations, time pressure, and task complexity with dependent variables including cognitive load, situational awareness, and decision-making errors" (Hutchins, 2003).

Fan, McNeese, & Yen (2010) used the R-CAST (Recognition Primed Decision-Cognitive-Agent-Simulation-Team) agent framework which is a "team oriented cognitive agent architecture built on top of the concept of shared mental models, the theory of proactive information delivery, and Klein's Recognition Primed Decision framework (RPD)" (Fan, McNeese, and Yen, 2010). The independent variables were human-human teams, agent teams, and human-agent teams. The dependent variables were the "number of key insurgents captured with high, medium, and low threats, respectively; the numbers of IEDs removed with high, medium, and no threats, respectively; and the numbers of crowds dispersed with high, slightly high, medium, and low threats, respectively" (Fan, McNeese, and Yen, 2010). Results by team types showed that agent and human agent teaming had statistically significant better outcomes than simply human agents.

3. Summary of Theoretical Perspective

Knowledge Flow Theory is an emerging theory that may explain how knowledge is transferred from individuals to teams and organizations. Knowledge flow is critical in dynamic and complex environments such as tactical military operations. Understanding the friction factors of knowledge flow may improve decision quality, situational awareness, and reduce cognitive load.

Naturalistic decision-making (NDM) is a framework that sets decision-making in "realistic settings that typically involve ill-structured problems" where individuals or team members do not have the time or relevant information to make decisions according to traditional decision-making theory (Fan, McNeese, Yen, 2010). Studies using an R-CAST cognitive agent (CA) have demonstrated that CAs "empowered with NDM models…could help achieve reduced cognitive load and effective human-agent collaboration" (Fan, McNeese, Yen, 2010).

B. PURPOSE OF THE STUDY

The purpose of this research is to test kinds of knowledge friction (Shigley, 2021) that slow, hinder, or obstruct knowledge transfer from disparate information sources which impedes optimal, acceptable situational awareness. It is hypothesized that by identifying and reducing knowledge friction, decision quality and situational awareness will improve. This research will be applied specifically to the USMC Fire Support Coordination Unit (FSCU) Officer, however, it is generalizable to any organization that faces dynamic and complex problem sets revolving around knowledge management, knowledge transfer, or learning.

This research is important because in the USMC FSCU, lives are at stake if situational awareness and decision quality are impaired by lack of knowledge, accurate knowledge, or timely knowledge. The importance of this research also extends to other organizations where there may be financial or market impacts that could be devastating if knowledge does not flow from one person to another, one unit to another, or one organization to another. The application of this research has the potential to reach far and wide beyond the application to the USMC FSCU.

C. PROBLEM STATEMENT

The problem is that in the United States Marine Corps (USMC) Fire Support Coordination Unit (FSCU) the FSCU Officer often does not have the correct, optimal information for SA and, as a result, can make poor decisions in the battlefield. This is a problem because it leads to fratricide and unintended civilian casualties.

Decision making in the tactical military environment depends on training, experience, and high situational awareness once in the battlefield. Improving situational awareness is important because:

- Operators are often unable to process data at fast rates due to limits on cognitive capacity,
- Operators must be trained on disparate systems that often provide conflicting information, and,
- Information from different systems is often ambiguous or conflict with other forms of information leading to poor SA (Hutchins, 2003).

D. RESEARCH QUESTION

The working research question is, to what degree will situational awareness and decision quality improve by using a cognitive agent that reduces friction factors in knowledge flows? This research question hints at the hypothesis that will be discussed in Section II Research Design.

These high-level concepts may be illustrated in the following table where situational awareness and decision quality are dependent on friction factors and knowledge flows.

	FRICTION FACTORS (FF) KNOWLEDGE FLOWS (KF) *HIGH*	FRICTION FACTORS (FF) KNOWLEDGE FLOWS (KF) *LOW*
SITUATIONAL AWARENESS (SA) DECISION QUALITY (DQ) *HIGH*	FF & KF HIGH SA & DQ HIGH A	FF & KF LOW SA & DQ HIGH B
SITUATIONAL AWARENESS (SA) DECISION QUALITY (DQ) *LOW*	FF & KF HIGH SA & DQ LOW C	FF & KF LOW SA & DQ LOW D

Table 1. Illustration of situational awareness/decision quality and friction factors/knowledge flow

Each combination of high and low friction factors within knowledge flows with decision quality and situational awareness may be a result of any number of scenarios. In box A, high situational awareness and decision quality may be coincidental, which is not a desirable state because SA and DQ should be predictive and reliable. In box C, friction factors within knowledge flows are high resulting a low situational awareness and decision quality, which is basically the null hypothesis. Box D, could be much like box A resulting from coincidence, or could be a result of a lack of training, education, or experience. Regardless of the cause, box D is not desirable since SA and DQ remain low. The purpose of this study is to focus on box B, reducing friction factors within the knowledge flows to result in high situational awareness and decision quality.

E. CONTRIBUTION TO KNOWLEDGE

The gap being addressed is testing previously identified knowledge friction factors (Shigley, 2021) to determine their effects on knowledge flows in a dynamic military environment. The research will address these friction factors in knowledge transfer flows since they are not well defined in KFT (Shigley, 2021). Second, the study will apply the lens of naturalistic decision making to better understand and explain the phenomena of knowledge friction factors.

It is hypothesized that understanding and reducing these friction factors should improve DQ and SA. The practical application of this study is to decrease fratricide and unintended casualties, although a natural side effect may also improve enemy casualty rate.

Beyond testing previously identified knowledge friction factors, this research aims to develop a framework for a cognitive agent that provides better situational awareness and decision quality as compared to not having a cognitive agent. There are several advanced decision support systems in the subclass of cognitive agents that attempt to address ways to improve decision-making, however, many of them are characterized by a rule-based system. This assumption is unrealistic for the dynamic and complex nature of tactical military operations. This study will lay the foundation for developing an advanced decision support system such as a cognitive agent grounded in theory, observations, data collection and analysis.

II. RESEARCH DESIGN

This research aims to identify which factors affect knowledge flows in extreme decision-making contexts to extend our understanding of knowledge friction. The working research question is, to what degree will situational awareness and decision quality improve by using a cognitive agent that reduces friction factors in knowledge flows?

A factorial, discovery, quasi-experimental design will be implemented as described by Kerlinger and Lee. As discussed by Runde (2020) Discovery experiments can be very economical because they do not employ large amounts of infrastructure and resources… Discovery experiments are an important element in the experimentation process as some ideas may fail early on. These failures provide a rich learning source prior to investing resources. Discovery experiments may be successful yet, further discovery testing may continue to be explored to validate findings, refine concepts, and determine the best fit for implementation (Alberts & Hayes, 2009).

Quantitative methods will be used to analyze data collected on the variables to show a relationship between the use of a cognitive agent and improved situational awareness and decision quality versus without the use of a cognitive agent. The design will be 'quasi-experimental' because it may not be possible to have more than one group that receives the experimental treatment and the other group would not receive the experimental treatment (Kerlinger & Lee, p. 536, 2000). This may lead to a nonequivalent control group design as described by Cook and Campbell as follows:

- No-treatment control group designs,
- Nonequivalent dependent variables designs,
- Removed treatment group designs,
- Repeated treatment designs,
- Reversed treatment nonequivalent control group designs,
- Cohort designs,
- Posttest only designs,
- Regression continuity designs (Kerlinger & Lee, p. 537, 2000).

The training scenario will be provided by the Army through an existing program called Scarlet Dragon. The Army Times describes Scarlet Dragon as a series "designed to increase our joint warfighting capability and how AI-augmented decision making significantly increases the scale, speed and accuracy of our targeting process" (Army Times, 2022). The availability of this training series is an ideal match for this research study due to its focus on AI within the Navy and joint forces.

The trainees in the training exercises are assigned their roles based on their military designators. The trainees are also selected based on their experience level; sometimes a trainee will never have been through a particular training exercise. In these cases, a more experienced trainee will be present as an observer. While the trainees are pre-selected by the training base, the experimental treatment of this research will be assigned to trainees randomly. To address equivalence of trainees, information such as age, rank, and years of experience will be collected so that during the statistical analysis (e.g. ANOVA with blocking variables), these factors can be separated to reveal any correlations.

The experimental and control treatment will be in two groups: Group A using standard operating procedures (SOPs) and information systems (ISs), and Group B using standard operating procedures (SOPs), information systems (ISs), *and a cognitive agent (CA)*.

This research will observe the relationships between operators using SOPs and ISs compared to operators using the same tools but with the assistance of a CA. The observations include collecting data on types of errors made both with and without the use of a CA. Error types include unintended casualties (civilian or friendly) and decision errors (errors of omission and commission). In addition, cognitive load will be controlled by the complexity of each scenario. Scenario complexity at the beginning of the experiment has a low cognitive load with less than five (5) assets to manage, gradually increasing in complexity over the course of two scenarios each day for six (6) days. The most complex scenario is the last scenario on the last day of the experiment.

A factorial design contains the following independent variables (IV) and dependent variables (DVs):

IV_1: Scenario without a cognitive agent

IV_2: Scenario with a cognitive agent

DV_1: Decision Quality

DV_2: Situational Awareness

	Scenario Without CA	Scenario With CA
Decision Quality (DQ)		
Situational Awareness (SA)		

Table 2. Illustration of Independent and Dependent Variables

The main effect, directional hypothesis is that the FSCU Officer makes higher quality decisions with improved situational awareness by reducing friction of knowledge flows from bidirectional sources: a) *from* various fires and munitions units *to* the FSCU Officer and, b) *from* the Generals and Admirals down *to* the FSCU Officer. In the operational environment for the FSCU Officer, knowledge flows generally from the top down and from the subordinate units up to the Officer. Thus, the hypothesis is that by reducing knowledge flow friction, the effect will be improved decision-making and situational awareness for the FSCU Officer resulting in a reduction of unintended casualties. As demonstrated in the R-CAST studies, a cognitive agent can improve significantly improve decision making (Fan, McNeese, Yen, 2010).

The independent and attribute variables may include:

- Scenario complexity (ordinal: high, medium, low)
    - Cognitive load (ordinal: high, medium, low)

The dependent and attribute variables may include:

- Decision Quality & Situational Awareness
    - Number of unintended casualties (interval or ratio),
    - Decision errors (nominal, interval, or ratio),
        - Errors of omission (yes/no, within acceptable ranges, percentage),
        - Errors of commission (yes/no, within acceptable ranges, percentage).

The studies cited in Section 1 demonstrate the breadth of decision making where Knowledge Flow Theory may be explored and expanded by looking at decision quality and situational awareness, for example. The following tables represent the multiple angles in which this study may be conducted where in the overall design, decision quality and situational awareness are the dependent variables and scenario complexity is the independent variable manipulated by high, medium, and low complexity and cognitive load, correspondingly.

The experiment design intends to leverage the "Scarlet Dragon-related work into its Project Convergence initiative that will link all sensors, shooters and joint systems for an integrated battlefield management platform" (https://executivegov.com/2021/10/army-conducts-ai-enabled-target-identification-exercise-under-scarlet-dragon/).

The researcher will coordinate with the Army to obtain the details of each training scenario design. The researcher will have access to the scenarios prior to execution of the training scenarios.

The researcher will attend a week-long training exercise in 29 Palms as an observer to collect data to document how FSCU Officers currently conduct operations without the use of a cognitive agent. This data will provide a foundation of existing decision-making tools and models for FSCU Officers. The data collection is considered to be the pre-test data collection.

Since a cognitive agent has yet to be designed and developed, the researcher will simulate a cognitive agent in a wargaming design. The FSCU Officer will be interacting and making decisions within the scenario provided through Scarlet Dragon. The scenarios provided through Scarlet Dragon run twice daily in an A.M. and P.M. schedule. The A.M. and P.M. scenarios on each day provide the same or similar level of complexity each day. However, as each day of the week advances, the scenarios become more complex. The researcher will provide 'injects' from a white cell to simulate what a cognitive agent might do during one of the scenarios each day. For example, the A.M. scenario on Day 1 will allow the FSCU Officer to complete the mission objectives without the assistance of a cognitive agent. Then, in the P.M. scenario on Day 2, the researcher will inject additional information such as status updates from the artillery unit, information about the movement of enemy forces, logistics, network connectivity status, etc. The additional information provided as an inject by the 'cognitive assistant' would mimic the type of information that a cognitive assistant would provide through AI/ML. This pattern of treatment each day would continue throughout the duration of the experiment, 6 days. Table 3 shows the anticipated experiment schedule:

MON	**CA**	**TUES**	**CA**	**WEDNES**	**CA**	**THURS**	**CA**	**FRI**	**CA**	**SATUR**	**CA**
0800 – 1200	NO	0800 – 1200	NO	0800 – 1200	YES	0800 – 1200	YES	0800 – 1200	NO	0800 – 1200	YES
1300 - 1700	YES	1300 - 1700	YES	1300 - 1700	NO	1300 - 1700	NO	1300 - 1700	YES	1300 - 1700	NO

Table 3. Experiment Schedule

The researcher will coordinate with the points of contact with Scarlet Dragon to observe each scenario and participate with the team as a white cell. Data collection will be obtained through system logs and observations compared to mission objectives. For example, the white cell knows in advance which missions and submissions must be completed as part of the scenario design. It is the objective of the FSCU Officer to meet the mission objectives by the end of the scenario.

III. RECOMMENDATIONS AND FUTURE RESEARCH

This research explored the availability of potentially existing cognitive agents that could provide situational awareness and context to an operator in an operational military environment. While there is active research ongoing in this area, a cognitive agent has yet to be designed and developed to meet this need. Since such a tool does not yet exist, it is recommended that this line of research continue so that the described discovery experiment plan can be executed. By continuing this research, a baseline of experimentation can provide insights into how a technology may be designed and developed with various AI/ML algorithms. Future research beyond the exploratory and discovery phases could look at how a cognitive agent could provide courses of action based on all data sources available. Further, a CA with the ability to provide courses of action would shift from 'human-in-the-loop' to 'human-on-the-loop' thereby, reducing cognitive load.

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LIST OF REFERENCES

Alberts, D. S. (2009). Overview of experimentation. In *Code of best practice: Experimentation* (pp. 19–39). Office of the Assistant Secretary of Defense Washington, DC Command and Control Research Program (CCRP).

Army Times (2021, October 7) https://www.armytimes.com/news/your-army/2021/10/07/armys-scarlet-dragon-uses-ai-with-navy-air-force-and-marine-assets-to-rapidly-find-id-and-destroy-targets/#:~:text=%E2%80%9CThe%20Scarlet%20Dragon%20series%20is,our%20targeting%20process%2C%E2%80%9D%20Lt. Retrieved October 18, 2022.

Beierl, & Tschirley, D. R. (2017). *Unmanned Tactical Autonomous Control and Collaboration situation awareness*. Monterey, California: Naval Postgraduate School.

Birkinshaw, Julian, L. B. S. (2015, August 7). *Beyond the information age*. Wired. Retrieved October 19, 2022, from https://www.wired.com/insights/2014/06/beyond-information-age/#:~:text=We%20live%20in%20the%20information,based%20on%20information%20and%20computerization.

Bush, V. (1999). As we may think. *Library Computing*, *18*(3), 180–188.

Clarke, & Knudson, D. (2018). *Toward a Framework for Autonomous Systems Employment in Human Machine Teams.* Monterey, California: Naval Postgraduate School.

Defense Science Board. (2012). *The Role of Autonomy in DoD Systems.* https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjnkNqOlZD7AhWeGDQIHXn5CtAQFnoECBQQAQ&url=https%3A%2F%2Firp.fas.org%2Fagency%2Fdod%2Fdsb%2Fautonomy.pdf&usg=AOvVaw0QgNS6Ogirp1lZ5QVhn3qB

Deliberate Universal Needs Statement. (2018). Fire Support Coordination Cognitive Assistant (FSC CA) Capability.

DOD Responsible Working AI Council , U.S. Department of Defense Responsible Artificial Intelligence Strategy and Implementation Pathway (2022).

U.S. Department of Commerce. Executive Order 14067 (2022) Responsible Advancement of US Competitiveness in Digital Assets.

Fan, X., McNeese, M., & John Yen. (2010). NDM-Bases Cognitive Agents for Supporting Decision-Making Teams. *Human-Computer Interaction*, *25*(3), 195–234. https://doi.org/https://doi.org/10.1080/07370020903586720

Herbold, Ben. (2020). *Toward a Fire Support Coordination Cognitive Assistant.* Monterey, California: Naval Postgraduate School.

Hutchins, S. G. (2003, July 16). Application of Naturalistic Decision Making Models to Support Command and Control Decision Making. Monterey.

Kerlinger, F.N. & Lee, H. B. (2000). *Quasi-experimental and N = 1 designs of research.* Foundations of behavioral research (4th ed., pp 535-554). Harcourt College Publishers.

Marakas, G. M. (1999). *Decision Support Systems in the 21st Century.* Upper Saddle River: Prentice Hall.

Naturalistic decision making association. Naturalistic Decision Making Association. (n.d.). Retrieved August 11, 2022, from https://naturalisticdecisionmaking.org/

Nissen, M. (2014) *Harnessing dynamic knowledge principles for competitive advantage in the technology-driven world.* Hershey, PA : IGI Global.

Ross, Klein, G. A., Thunholm, P., Schmitt, J. F., & Baxter, H. C. (2004). The recognition-primed decision model. Military Review, 84(4), 6–.

Runde, S. (2019). *Decision Support System PhD Exam Questions.* The Naval Postgraduate School. Unpublished.

Shigley, P. (2021). *Conceptualizing Knowledge Friction* (dissertation). Defense Technical Information Center, Ft. Belvoir, VA.

Smith. (1980). "Memex" as an image of potentiality in information retrieval research and development. Annual ACM Conference on Research and Development in Information Retrieval: Proceedings of the 3rd Annual ACM Conference on Research and Development in Information Retrieval; 23-27 June 1980, 345–369. https://doi.org/10.1145/227181.227186

Stilman, B. (2000). *Linguistic geometry: From search to construction*. Springer Science+Business Media, LLC.

The United States Government. (2022, March 9). *Executive order on ensuring responsible development of Digital assets*. The White House. Retrieved October 19, 2022, from https://www.whitehouse.gov/briefing-room/presidential-actions/2022/03/09/executive-order-on-ensuring-responsible-development-of-digital-assets/

Vorobiova, A. (2022, June 21). *The digital age: The era we all are living in*. dzone.com. Retrieved October 19, 2022, from https://dzone.com/articles/the-digital-age-the-era-we-all-are-living-in-and-d

Wikimedia Foundation. (2022, October 19). *Information age*. Wikipedia. Retrieved October 19, 2022, from https://en.wikipedia.org/wiki/Information_Age

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