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THESIS

**INTEGRATING DIGITAL TWIN CONCEPTS
TO ENHANCE AGILITY OF THE UNITED STATES
MARINE CORPS' DECISION SUPPORT FRAMEWORK**

by

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TO ENHANCE AGILITY OF THE UNITED STATES MARINE CORPS'
DECISION SUPPORT FRAMEWORK**

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ABSTRACT

Digital twin (DT) application and related technology has the potential to enhance the accuracy of wargame simulations in order to provide risk-informed decision support recommendations. A DT of the operating environment could theoretically be developed to continuously gather data from the operating forces and create computational models or simulations to test battlespace conditions. Effective implementation of DT can provide commanders with timely updates and adjustments to recommendations, aiding the decision-making process. Real-time updates would then inform commanders if the previously recommended course of action is no longer considered optimal based on the continuously running simulations. This thesis performs a qualitative assessment on the integration of a DT-enabled decision support system into the Marine Corps planning process and as an effective tool for leadership at various levels of command. The researchers determined that the wargaming process can be enhanced by incorporating real-time data into simulated future conflict to facilitate the inclusion of data analysis into time-sensitive decisions and potentially improve the management of uncertainty in the decision-making process. Leaders would benefit from increased awareness and quantitative assistance with resource allocation decisions. Expected challenges will be the digitization process of the operating force as well as acculturating leaders to the new technology.

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TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	PROBLEM STATEMENT	2
B.	PURPOSE STATEMENT	2
C.	RESEARCH QUESTIONS.....	2
D.	ORGANIZATION OF THESIS	3
II.	LITERATURE REVIEW	5
A.	PRELIMINARY DEFINITIONS.....	5
B.	INTRODUCTION TO DECISION SCIENCE	6
	1. OODA Loop.....	7
	2. The Information Hierarchy	7
	3. Measuring Uncertainty.....	8
	4. Dual Process Theory	10
C.	CLASSICAL DECISION ANALYSIS.....	10
	1. Heuristics and Biases	11
	2. Bias Mitigation	13
D.	WARGAMES	14
	1. Evolution of Wargaming	14
	2. Wargaming as a Methodology	18
E.	DIGITAL TWINS.....	19
F.	DIGITAL TWIN APPLICATIONS.....	22
III.	METHODOLOGY	25
IV.	ANALYSIS	29
A.	DIGITAL TWIN INTEGRATION FOR ENHANCED WARGAMING	29
	1. Digital Twin, an Extension of Modeling and Simulation	29
	2. Wargaming Applications of Digital Twins	30
B.	DIGITAL TWIN INTEGRATED DECISION SUPPORT	40
	1. Improving Decision Speed.....	41
	2. Reducing Uncertainty	43
	3. Data Inputs for a Comprehensive Digital Twin	47
	4. Automated Decision-Making	50
C.	COMMAND IMPLEMENTATION OF DECISION SUPPORT SYSTEM.....	52

1.	Implications for Decision Support at the Tactical Level.....	54
2.	Implications for Decision Support at the Operational Level	56
3.	Implications for Decision Support at the Strategic Level	60
V.	CONCLUSION	63
A.	RESULTS AND INSIGHTS	63
1.	Improving Wargaming with Digital Twins	64
2.	Improving the Commander’s Decision-Making Cycle.....	65
3.	Appropriate Level of Command for a Digital Twin- Enabled Decision Support System.....	66
4.	Challenges.....	68
B.	RECOMMENDATIONS.....	69
C.	AREAS FOR FUTURE RESEARCH.....	71
	APPENDIX. VIGNETTE.....	75
	LIST OF REFERENCES.....	77
	INITIAL DISTRIBUTION LIST	85

LIST OF FIGURES

Figure 1.	Communication/Interaction between Digital and Real Twins. Source: El Saddik (2018).....	20
Figure 2.	Proposed Methodology for Rationalist Inductive Approach. Source: Sousa-Poza et al. (2008).	26
Figure 3.	The Operational Mode of Digital Twin-Enabled Online Battlefield Learning in Unmanned Combat. Source: Wang et al. (2021).....	37
Figure 4.	Operational Concept and Architectural Overview of DARPA’s Deep Green. Source: Surdu and Kittka (2008).....	39
Figure 5.	The Extended OODA Loop. Source: Silvander and Angelin (2019).	43
Figure 6.	Levels of War. Source: USMC (2018b).	53

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LIST OF TABLES

Table 1.	Digital Twin Levels. Source: Madni et al. (2019).	22
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LIST OF ACRONYMS AND ABBREVIATIONS

4IR	Fourth Industrial Revolution
ABCS	Army Battle Command System
ACE	aviation combat element
AI	artificial intelligence
AM	additive manufacturing
AR	augmented reality
ARG	Amphibious Ready Group
BFT	blue force tracker
C2	command and control
C4I	command, control, communications, computers, and intelligence
CAS	close air support
CASEVAC	casualty evacuation
CE	command element
COA	course of action
COP	common operating picture
C-RAM	Counter Rocket, Artillery, and Mortar
DARPA	Defense Advanced Research Projects Agency
DCGS	Distributed Common Ground System
DOD	Department of Defense
DSS	decision support system
DT	digital twin
DTA	digital twin aggregate
DTI	digital twin instance
ESDT	earth system digital twin
FRAGO	fragmentary order
GCE	ground combat element
GPS	global positioning system

GUI	graphical user interface
IDEAS	Integrated Digital Earth Analysis System
IOT	internet of things
IPB	intelligence preparation of the battlespace
LCE	logistics combat element
MAGTF	Marine Air-Ground Task Force
MBSE	model-based systems engineering
MCP	Marine Corps planning process
MEF	Marine Expeditionary Force
MEU	Marine Expeditionary Unit
ML	machine learning
NASA	The National Aeronautics and Space Administration
NGW	next-generation wargaming
OE	operating environment
OODA	observation-orientation-decision-action
OR	operations research
PD	predictable desirable
PU	predictable undesirable
QRF	quick reaction force
R2P2	rapid response planning process
RAID	Real-time Adversarial Intelligence and Decision-making
RFID	radio frequency identification
S&T	science and technology
UAV	unmanned aerial vehicle
UD	unpredictable desirable
USMC	United States Marine Corps
UU	unpredictable undesirable
WWI	World War I
WWII	World War II

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I. INTRODUCTION

The Marine Corps has traditionally used wargaming as a training tool to develop Marines' decision-making skills and evaluate the planning process of leaders in a controlled environment which can provide useful feedback. Wargaming has also been used to test different warfighting concepts and develop doctrine (Bae & Brown, 2021). In 2017, the Commandant of the Marine Corps, General Robert Neller established the Marine Corps Wargaming and Analysis Center. Scheduled to open in 2024, the primary mission of the Wargaming and Analysis Center will be capability development. The lab will be located in Quantico, VA where it can be employed by the Marine Corps Warfighting Laboratory, Marine Corps University and Marine Corps Systems Command to generate analytically supported recommendations to shape future force design and development activities (Gonzales, 2021).

The Marine Corps is also looking to leverage emerging technologies such as big data analytics, artificial intelligence (AI) and machine learning (ML) to run simulations in excess of 1,000 repetitions to determine the probabilities of various outcomes in combat scenarios (South, 2018). This will enable the development of analytical decision support tools to provide data driven recommendations to tactical commanders. In order for the system to produce actionable recommendations, the simulations must be driven by data that is both accurate and up to date. The creation of a digital twin (DT) of Marine Corps forces along with data collected from the internet of things (IOT) could provide the necessary tools to build the decision support apparatus the Marine Corps would like to employ (Madni et al., 2019). Present Marine Corps DT initiatives are largely confined to network management and supply chain coordination. However, the state-of-the-art AI/ML enhancement to DT along with faster data transferring and the proliferation of the IOT, can ameliorate DT integration into all facets of command, control, communications, computers, and intelligence (C4I) as a driver for battle space awareness, continuous decision support analysis, and the maintenance of decision superiority in the complex connected battlefield.

A. PROBLEM STATEMENT

Harnessing artificial intelligence and big data analytics for decision support will only be beneficial if the data itself is reliable. For example, by the time a commander reviews the data and decides on a course of action, the recommendation feeding his decision may be obsolete. Bad recommendations based on faulty or outdated data inputs can potentially be more damaging than having no data at all. Even if the simulations are using accurate and up-to-date data, the recommendations provided by the system will only be valid for as long as the variables remain static. Since tactical recommendations need to be agile and adapt to the dynamic nature of battlespace conditions, there is a need to adopt systems that can incorporate real-time data feeds to decision support simulation tools.

B. PURPOSE STATEMENT

The purpose of this research is to explore the potential of DT application and related technology to enhance the accuracy of wargame simulations in order to provide commanders risk informed decision support recommendations. A DT of the operating environment could theoretically be developed to continuously gather data from the operating forces and create computational models or simulations to test battlespace conditions. Effective implementation of DT can provide commanders with timely updates and adjustments to recommendations aiding the decision-making process. Real-time updates would then inform commanders if the previously recommended course of action is no longer considered optimal based on the continuously running simulations. We will look to DT initiatives in the private sector and government to determine the potential for such a system.

C. RESEARCH QUESTIONS

1. Would wargaming benefit from the integration of DT?
 - 1.1 What application of wargaming would benefit from a DT?
 - 1.2 How can DT enhance the Marine Corps Planning Process and Rapid Response Planning Process?

- 1.3 Can DT enhance the knowledge processes of the participants?
- 2. How would a DT integrated decision support system enhance a commander's decision-making cycle?
 - 2.1 Can the decision support system reduce uncertainty on the battlefield?
 - 2.2 What data inputs are needed to develop a comprehensive DT of Marine Corps forces or the operating environment?
 - 2.3 Can the decision support system decrease the time needed to reach a decision?
 - 2.4 When should decisions be automated and when is a human decision necessary?
- 3. At what level of command should the decision support system be incorporated?
 - 3.1 What are the implications of integrating the decision support system at the tactical level of warfare?
 - 3.2 What are the implications of integrating the decision support system at the operational level of warfare?
 - 3.3 What are the implications of integrating the decision support system at the strategic level of warfare?

D. ORGANIZATION OF THESIS

The remainder of this thesis is comprised of four additional chapters. Chapter II is a review of available literature on the subjects of decision science, wargaming and digital twin applications and related technologies. Chapter III is an overview of the chosen research methodology. Chapter IV is an analysis of potential digital twin integration into wargaming and decision support to assist commanders at the different levels of war. Chapter V presents the resulting conclusions including recommendations as well as suggested areas for future research.

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II. LITERATURE REVIEW

A. PRELIMINARY DEFINITIONS

Many of the terms and concepts discussed in this paper are still evolving and the definitions may change with time. In the conduct of this research, the following definitions will be used. This is not an exhaustive list but should serve to provide clarification for some of the terms found in available literature on the subject.

- Decision support system – “An interactive computer-based system to aid decision-makers in utilizing data and models toward the solution of unstructured problems” (Sprague & Carlson, 1982, p. 4)
- Digital twin – “A digital informational construct about a physical system, created as an entity on its own and linked with the physical system in question” (Kritzinger et al., 2018, p. 1016)
- Digital twin instance – “A specific corresponding physical product that an individual Digital Twin remains linked to throughout the life of that physical product” (Grieves & Vickers, 2017, p.94)
- Digital twin environment – “An integrated, multi-domain physics application space for operating on Digital Twins for a variety of purposes” (Grieves, & Vickers, 2017, p.94)
- Digital model – “A digital representation of an existing or planned physical object that does not use any form of automated data exchange between the physical object and the digital object” (Kritzinger et al., 2018, p. 1017)
- Digital shadow – “An automated one-way data flow between the state of an existing physical object and a digital object” (Kritzinger et al., 2018, p. 1017)

- Wargame – “Application of game theory, typically by an operations-research professional, to gain insight into an armed conflict” (Caffrey, 2019, p. 26)
- COA wargame – “Relatively ‘quick and dirty’ wargame conducted to explore, typically, three COAs to clarify the likely outcomes of each before a final strategy is selected” (Caffrey, 2019, p. 14)
- Uncertainty – “Situations in which the probabilities of the possible outcomes are unknown (as opposed to risk, in which they are known)” (Hertwig et al., 2019, p. 370)
- Epistemic uncertainty – “Uncertainty associated with the state of ignorance or incomplete individual knowledge” (Hertwig et al., 2019, p. 367)
- Aleatory uncertainty – “Uncertainty that stems from the statistical properties of the environment that exist independent of a person’s knowledge” (Hertwig et al., 2019, p. 349)
- Strategic uncertainty – “Uncertainty about the actions of others in interactive situations. Sources of strategic uncertainty include the preferences, beliefs, and knowledge of the interacting others” (Hertwig et al., 2019, p. 369)

B. INTRODUCTION TO DECISION SCIENCE

In order to develop a decision support system with maximal utility, it is necessary to understand human decision-making processes. A great deal of research is presently available on decision science and relating theories. While new theories are still emerging and existing ones evolving, there exist disagreements over whether solutions can be optimized and how optimization can be measured in a complex and dynamic environment. However, reducing uncertainty or the time required to reach a decision can be among the merits to demonstrate utility for a decision support system.

1. OODA Loop

The framework for decision-making in the military that forms the basis of the command-and-control (C2) process is John Boyd's observation-orientation-decision-action (OODA) loop (USMC, 2018a). The OODA loop is a continuous process that exists at every level of command; for instance, a leader receives information about a conflict, makes an analysis and forms a judgment about the situation, formulates a choice about what to do, then puts the plan into action (USMC, 2018a). Actions in conflict will have effects which then necessitates beginning the process anew. The effects must be observed and then incorporated into an updated orientation. The importance of this doctrinal concept is that how all decision-makers operate can be captured with a single framework; as a result, the speed with which the cycle can be executed can often provide a decisive advantage in warfare.

One of the primary goals of a decision support system should then be to reduce the time associated with the OODA loop process by increasing the speed of observations and orientation. The purpose is to enhance the commander's ability to arrive at a decision quickly, but not to diminish the commander's role in the process. The commander is accountable for the consequences of the decision and must bear the responsibility of making decisions and putting them into action. The process of observation and orientation can theoretically be expedited with an effective decision support system, but leaders will still be needed to make decisions and oversee the requisite actions.

2. The Information Hierarchy

One of the challenges associated with the decision-making process is uncertainty. War is uncertain by nature and the information gathered during the observation phase of the OODA loop may lack clarity and require additional interpretation before it can be incorporated into the orientation process. This is due in part to the hierarchical nature of the information itself. Doctrinally, information can be categorized sequentially as raw data, processed data, knowledge and understanding (USMC, 2018a). Raw data has to be processed in order to have any meaning associated with it, but even processed data has to be analyzed to provide context and inform the decision process for a commander (USMC,

2018a). Understanding is the highest class of information and not always achievable in uncertain conditions. It requires judgment and intuition to really know what is happening in a given situation (USMC, 2018a).

Military commanders are often required to make decisions without full understanding of the situation developing around them. Time constraints often require decisions to be made despite various levels of uncertainty. Sometimes gaining more information can result in a reduction of uncertainty but comes at the expense of time (USMC, 2018a). In other cases, more information, particularly with less context can serve to increase uncertainty (Menon & Kyung, 2020). While improving the speed associated with the decision process is a valuable goal for a decision support system, so too is reducing uncertainty. It is not possible to completely negate uncertainty on the battlefield, but if the information received can be quickly processed and analyzed, decision-makers could benefit from the ability to make decisions with higher degrees of certainty.

3. Measuring Uncertainty

The idea of whether complete certainty can ever be attained and the possible methods for achieving certainty has been at the center of various philosophical and epistemological movements dating back at least to the skeptical philosophers of Ancient Greece in the third century BC (Hertwig et al., 2019). Total skepticism which denies the possibility of grounding truth makes scientific discovery impossible. If truth cannot be established, then it is impossible to proceed forward with any greater claims. René Descartes (2013) proposed a solution by grounding his metaphysical system on the first principle of a thinking being which gives a justification for reason, but still fails to fully account for uncertainty of empirical knowledge. Blaise Pascal offered an alternative approach by accepting uncertainty as inevitable and applying the calculus of probability to reconcile the unknown (Arnauld & Nicole, 1850).

Looking at uncertainty as probabilistic is necessary to enable quantifiable measurements. The need to measure uncertainty had practical implications in gambling, legal disputes, annuities and the insurance industry (Hertwig et al., 2019). There are

however continued disagreements on how to quantify uncertainty and both objective and subjective interpretations have developed in response. Economist Frank Knight was an early proponent of objective interpretation, and he made a distinction between risk and uncertainty. To Knight (1957), risk is the appropriate term for measurable probability whereas uncertainty refers to instances when measurement is not possible. Knight (1957) identified three probability situations which have different implications for the measurement of uncertain events as a priori probability, statistical probability, and estimates.

A priori probability refers to events which are random in nature, yet easily conform to mathematical principles such as games of chance; statistical probability refers to events which can be statistically quantified based on historical data such as insurance companies measuring risk to assets (Hertwig et al., 2019). Estimates however deal with unprecedented events and emergent phenomena and therefore cannot be appropriately quantified (Knight, 1957). A potential decision support apparatus could compute a priori and statistical probability of various outcomes. Knightian “estimates” however would be excluded from calculations because they defy quantification, but decision-makers should be made aware of potential ramifications from immeasurable uncertain conditions.

Subjective interpretations of uncertainty include all facets of uncertainty as measurable probabilities. In Savage’s subjective expected utility framework, he assigned a subjective value to possible outcomes as a quantifiable personal utility function and he proposed a personal probability distribution which would incorporate personal beliefs about the likelihood of future outcomes (Hertwig et al., 2019). While this framework was highly regarded because it incorporated a wide array of variables in a quantifiable solution, it has more recently come under scrutiny for failing to account for additional factors impacting human decision-making such as heuristics and biases (Stanovich & West, 2008). In other words, people do not always base decisions on whichever outcome will produce a greater quantifiable unit of utility. This also begs the question of which metric of utility will be selected. Additionally, there is no concrete way to quantify the personal probability distribution proposed by Savage because personal beliefs of external decision-makers are often unknown. For these reasons, the objective method of

interpretation is a better fit for decision support within the Department of Defense (DOD).

4. Dual Process Theory

Once data is processed and refined into knowledge or understanding, people still employ various processes which determine how they will arrive at a decision. Keith Stanovich and Richard West (2000) suggested that humans typically use two separate and distinct, but complementary systems of thought prior to making decisions. System I is intuitive and relies on tacit knowledge, emotion and experiences; System II is analytical, computational and deliberate (Stanovich & West, 2000). System I thinking is much faster and less cognitively taxing than System II; however, it can be prone to errors in judgment as opposed to the more methodical and logical orientation of System II (Milkman et al., 2009). That is not to say that System II thinking is inherently superior to System I. In many situations experience and tacit knowledge provide necessary context for the analysis provided by System II thinking. The challenge is knowing when to employ each process and how they can be used in a complementary fashion (Milkman et al., 2009).

Dual process theory can provide a useful framework for the development of a decision support system for the military. Data analytics can rapidly process large quantities of data and reduce the time requirements associated with computational analysis (Huggins, 2018). Theoretically then, if time is the biggest constraint to employing System II processes, a technology driven decision support system could perform the System II analytical processes while the commander uses his own tacit knowledge to apply System I dynamics in conjunction with the knowledge provided by the system.

C. CLASSICAL DECISION ANALYSIS

Many of the early analytic approaches to decision-making involved the use of economic models for the purpose of maximizing the expected utility of outcomes. On the modeling end of the research spectrum, this typically involved decision trees and the determination of probabilities of outcomes for various events (Davis et al., 2005). Utility theory can be traced back to Daniel Bernoulli in the 18th century as a normative theory to

determine optimal decisions and policies (Tversky, 1975). This is done by measuring the probability and expected utility of all resulting consequences from a proposed course of action and making a decision based on whichever resulted in the highest cumulative utility (Davis et al., 2005). Utility theory and subsequent related theories such as multi-attribute utility theory have been widely used in business where utility is easily measurable and various outcomes can be translated into dollar implications (Davis et al., 2005). These theories have come under criticism for inadequately describing decision-making under risk by failing to account for risk aversion and risk-seeking behaviors (Tversky, 1975).

Utility theory nests easily, given enough time, within the System II dynamic for objectively analyzing a problem set and seeking a singular solution. It may not perfectly account for all of the dynamics for how people actually make decisions, but it provides a basis for analytic recommendations. The challenge when applying this approach to warfighting is translating various tradeoffs into a common/generalizable metric of utility. The value of various capabilities would need to be translated into a common unit of measure and leaders would have to begin thinking in terms of equivalencies as a means of quickly comparing opposing forces (Davis et al., 2005). The time requirement for this process can be greatly reduced with the application of big data analytics and artificial intelligence. Military leaders also have to balance a myriad of external factors such as political implications, troop morale and public perception which will inform their decision-making process. Most of those external factors are difficult to measure and may not be included in an analysis of maximizing utility, but will need to be accounted for in decisions nonetheless. For this reason, a decision support system could be constructed to provide System II analysis with the intention of complementing the tacit knowledge and System I processes that the commander will employ.

1. Heuristics and Biases

Classical decision analysis models have received a great deal of criticism for being too steeped in theory and failing to adequately describe the way people actually arrive at decisions (Stanovich & West, 2000). This is largely a result of the human

tendency to use heuristics as a means of arriving at a decision quickly (Tversky & Kahneman, 1982). Heuristics are basic rules which can be quickly applied to a range of scenarios and are often beneficial when uncertainty is high or available time is low and determining an optimal solution may not even be possible (Gigerenzer, 2008). Heuristics are often valuable tools for making quick decisions, but human judgment is always susceptible to errors. Errors are sometimes random in nature and are referred to as noise, but errors can also result from cognitive bias (Kahneman et al., 2019). With cognitive bias, the misapplication of heuristics can result in “systematic errors in estimates of known quantities” or “discrepancies between the regularities of intuitive judgments and the principles of probability theory” (Kahneman, 2003, p.707).

There are over 175 identifiable biases that can result in a misapplication of System I processes (Benson, 2016). A few examples of commonly identified biases are confirmation bias, the sunk cost fallacy and recency bias. Confirmation bias is the tendency to seek and assimilate information to lend spurious support to a hypothesis under consideration (Arkes, 1991). In a military context, a commander might have already formulated a theory based on tacit knowledge and System I thinking, and seek out data which confirms this suspicion while disregarding any information that is contradictory. This selective misapplication of the analytical processes would result in greater confidence in a false conclusion rather than cause the commander to reconsider the original assumptions.

The sunk cost fallacy is a type of bias where a decision is made because resources have already been expended in pursuit of an objective even when an alternative exists with greater utility (Kahneman, 2011). In a military context, the resource expended might be human lives and abandoning an objective although prudent, might have detrimental effects on troop morale. This is a good example of where the commander might need to balance the analytical processes with the very real human dynamics of the organization.

Recency bias is an example of familiarity skewing the perceived likelihood of an event. If a rarely occurring traumatic event takes place, it could cause observers to overestimate the likelihood that it will happen again. Conversely, an event which has not

occurred in recent memory might be underestimated as a potential issue (Sunstein, 2019). With this example, the personal experiences of the commander can cloud their judgment.

Each of the aforementioned examples of bias results when System I thinking fails to adapt to new information received from processed analytics. Decision support systems can provide strong analytical recommendations to balance out intuitive thinking, but will not necessarily overcome all of the psychological factors leading to biased decisions by commanders. The best way to address biased decision-making is for the commander to be aware of these various issues and mitigate them internally.

2. Bias Mitigation

Heuristics can be useful to arrive at a decision quickly. Military commanders have spent their careers accumulating tacit knowledge to help effectively employ heuristics and make sound decisions. However, if biases are not properly mitigated, it can lead to a misapplication of heuristics and cause leaders to make faulty conclusions. In certain cases then, heuristic assumptions need to be overridden with analytically derived information. When this override function of available mental processes is unable to be accessed for any reason such as lack of training, Stanovich and West (2008) referred to it as a mindware gap. Mindware gaps can nullify any advantage presented by comprehensive data analysis because the bias will still impact the final decision. The best response seemingly is to train commanders to reduce the impact of mindware gaps in decision-making. Unfortunately, this is not always an achievable goal.

Ariella Kristal and Laurie Santos (2021) described something called the “G. I. Joe fallacy” where “knowing about a bias is enough to overcome it” (p. 3). Attentional biases can be overridden through awareness, but often prevail due to distractions during decision-making. Encapsulated biases are not cognitively penetrable if the emotional baseline is strong enough to prevent the bias from being overridden (Kristal & Santos, 2021).

As long as the final decision is being made by a human, there is always the potential that it could be affected by biases. Leaders are selected in part due to their ability to make good decisions and have to learn to mitigate the impact of biases. Any

proposed decision support tool can only strengthen the analytical capacity of the decision-maker but will not completely prevent biased decision-making.

D. WARGAMES

Wargames have been executed over the course of history to answer key questions or concerns regarding historical context, wars, and technological changes (Schechter et al., 2021). The term wargame has been used and defined in many ways. Early on it became a decision support tool developed as a way for leaders to communicate ideas through the use of training aides and simulations (Caffrey, 2019). The Merriam-Webster Dictionary (n.d.) defined it as “a simulated battle or campaign to test military concepts and uses.” Games are typically performed in various settings by officers and subject matter experts (SMEs) acting as adversary forces. Dr. Peter Perla (1990) of the Naval War College viewed wargames as “a warfare model or simulation whose operation does not involve the activities of actual military forces, and whose sequence of events is affected by the decisions made by the players representing opposing sides.” Without human decision-making and experience in conflict, wargames may be viewed more as models or simulations than a game (Wong et al, 2019). Wong et al. (2019) went on to propose wargaming design as an art and a science. The aggregation of modeling and simulation (M&S) with human judgement in a structured way enables participants to address assumptions about a task or adversary. Testing those assumptions through wargaming provides both quantitative and qualitative data on likely outcomes and facilitates informed analysis (Cancian et al., 2022). Wargames induce degrees of learning, but in the end, wargames test a human’s ability to navigate the ever-changing flow of combat, confront assumptions, and improve overall decision-making abilities (Perla, 1990).

1. Evolution of Wargaming

Matthew Caffrey (2019), a wargaming expert from the Naval War College, distinguished the transformation of wargaming into four major phases. He characterized the first phase as abstract games where outcomes are the result of decision-making efforts solely by the games participants. Abstract games, like chess and Go, began in early civilizations. The shift to Caffrey’s second-generation wargames, or phase two games,

occurred around 1800 and focused on simulation games depicting combat. These kinds of games are still executed today at all levels of command. Third-generation wargames consist of simulation games. This phase initiated around the time of World War I (WWI) and continues today, placing an emphasis on the strategic level of games focused on political-military gaming and some insurgency/counterinsurgency games. The next shift in wargaming, which can be argued has already begun, is one in which peace is a likely route to victory. Caffrey (2019) called this fourth generation “peace games” in which results see adversaries become allies, trading partners, or popular travel destination where conflict does not occur. Wargaming origins are rooted in ancient civilizations when human beings first used small toy-like objects to emulate maneuvers over a piece of terrain (Perla, 1990). The first game board was no more than the flat ground littered with stones to represent warriors. These were not refined games with established rules and standards, but merely a way for leaders of the time to communicate ideas through simulations and training aids (Caffrey, 2019). Years later, archaeologists uncovered sets of miniature soldiers representing ancient Sumerian and Egyptian armies in what were believed to be pawns used for strategizing military concepts (Hausrath, 1971). In India around the year 550 AD, a four-sided board game known as Chaturanga was developed. An elaborate game consisting of intricately designed game pieces representing foot soldiers, chariots, elephants, and cavalry, Chaturanga maneuvered pieces over a playing board to a fixed set of rules. This was the first structured game of its kind (McHugh, 1966). Also, a game left to chance and luck as outcomes of moves were originally determined by the roll of dice. Chaturanga’s popularity spread across Persia and into Europe during the 800s. As the gameplay changed, Chaturanga evolved into what we know today as the game of chess (Caffrey, 2019).

The centuries to follow expounded upon the game of chess as increasing emphasis on quantitative and scientific exploration grew more important (Crosby, 1997). Establishing causes and effects and reducing chance became the focus leading to simulations that tested the quantification and rationalization of weaponry, terrain, infrastructure, and analyzing the disposition of friendly and enemy forces (Caffrey, 2019). Caffrey (2019) eluded that the problems faced by the simulations were that the

results did not adequately represent “a thinking, reacting enemy.” Early wargames executed by ancient civilizations and the birth of games like chess and Go were developed as tools to build up strategic thinking and decision-making abilities (Wong et al, 2019). These early games were wargames in a very abstract way and were never intended to be anything more than an introduction to basic principles of military thinking. To move beyond this way of gaming and create a tool which teaches the finer points of the art of war, a new wave of gaming was developed adding more military detail and flavor (Perla, 1990).

Second generation wargames moved beyond the abstract strategy games reserved for the ruling class and turned the focus towards simulation of movement, attrition, and occasionally logistics. The first game of this new generation to receive any attention was the “Kings Game” invented by German Christopher Weikhsann in 1664. Kings Game was based on chess with an expanded game board and a game pieces symbolizing the political and military world of its time (Perla, 1990). Kings Game and several others similar games developed during this time became known as “war chess.” As wargaming began to evolve taking on more militaristic traits, the basis of these early games still sided with those of first-generation games (Caffrey, 2019). It was not until the early nineteenth century that the foundations of modern gaming were born under the guise of the Prussian Army staff, specifically Baron Leopold von Reisswitz. Wong et al. (2019) discussed Reisswitz’s game known as Kriegsspiel that divided officers into two teams, typically friendly and enemy, who would execute moves in a specific battle. Once both sides finished their turn, the moves would be adjudicated based on a set of rules to determine the outcome of actions. The game umpire used historical data to calculate attrition and damage based on range, terrain, and other factors. This was the first time results could be mapped to real world situations; far more than any previous game had demonstrated (Wong et al, 2019). Another key innovation Wong et al. (2019) alluded to during this period was the development of 3-D terrain models. Reisswitz ditched his sand table and built a table with a 3-D model of actual terrain and units associated with the game being played.

No longer were wargames purely a teaching tool, but now used to synthesize plans in battle. Kriegsspiel's expanded use saw a shift in focus to the execution of campaign plans and operational plans at the strategic and operational level as well as combat at the tactical level (Vego, 2012). The number of games taking place increased significantly making the demand for adjudicators high. This spawned the creation of "free" Kriegsspiel as an alternative where games relied on experienced veterans to adjudicate outcomes. This change made game play more expedient and simpler than the rules-based approach and allowed the adjudicators to account for intangible factors like unit behavior and the will to fight (Wong et al, 2019). The idea of "free" Kriegsspiel is still in place today as adjudicators are senior officers and enlisted personnel considered to be subject matter experts in the areas being gamed.

Wargaming efforts increased heavily as Prussian success spawned a global wargaming frenzy during the 1800s into the early 1900s. British, German, and Russian forces remained focus on likely battles and campaigns, but refocused their thinking toward a more strategic level area in force posture (Wong et al., 2019). The next-generation wargaming (NGW) report identified a demonstrated weakness by operational gaming and skeptical commanders was not capturing the political context which drove much of the conflict. For operational commanders, political motivation as well as social and economic considerations were not the priority, as they sought to win physical battles. These concerns were reserved for those at the strategic level. The 1920s saw a rise in the use of strategic games to deliberate these high-level motives by senior leaders. Early science and technology (S&T) games also took rise, leading to experimentation of new equipment and capabilities (Hofmann, 1952). The British used live naval and army wargames during exercises to determine the effectiveness of airborne intelligence, surveillance, and reconnaissance (ISR) capabilities (Caffrey, 2019).

While not yet a part of WWI, the U.S. executed wargames across both services at the Naval War College and the Army War College, focusing efforts on operational approaches, technology, and fighting a fleet of the likes of the Japanese or British. Though the British were an ally, the size and strength of their navy would offer U.S. Naval wargamers the most challenging adversary (Nofi, 2010). During execution of the

“Great War,” wargaming efforts declined as unit-level tactics took precedence, however, the U.S. Army continued to train and educate officers at its command and staff college stateside as well as at forward staff schools (Kretchik, 2012). Although wargaming went global at the turn of the twentieth century, it is likely further development of wargames did not occur as a result of multiple world wars.

A key result of WWI was the inception of what is known today as operations research (OR). Originally, OR employed the power of applied math and engineering towards industrial-style problems (Wong et al., 2019). Thomas Edison pioneered OR, as he donated his time and resources to the war effort (Whitmore, 1953). British wargaming during the second world war (WWII) saw the true emergence of OR becoming an institutional practice (Caffrey, 2019). The growth of OR brought about two new approaches to gaming: the use of computer models for decision-making support and the use of games to elicit information from players (Wong et al., 2019). Results of OR efforts included requests for technical innovation which led to the development of radar, a pivotal instrument to the war. Seeing success early on, scientists began to branch out and identified concepts to enhance decision-making efforts.

2. Wargaming as a Methodology

Wargames can be categorized into three sub-groups: experimental wargames, educational wargames, and analytical wargames (Cancian et al., 2023). The need to determine the correct methodology to apply emanates from the intended objective and purpose of the wargame. According to Cancian (2023), experimental wargames aimed to better understand the human decision-making process while educational wargames were designed to create decision-making simulations for military and political leaders. This left analytical games to evaluate a military problem to inform policy.

Experimental wargames aid in the study of the decision-making process (Cancian et al., 2023). Scientists, policy makers, and wargame designers can leverage experimental wargames to better understand the effects risk has on a commander’s ability to make decisions. Cancian (2023) distinguished that manipulation of key variables within the

wargame allowed researchers to better understand thought processes and to what extent a commander was willing to accept greater amounts of risk.

Educational wargames focus on the development of participants to become better thinkers and therefore decision-makers. These types of wargames put a leader in scenario where the uncertainty of war or conflict forces one to draw upon their own experience and knowledge and make decisions under pressure induced situations (Perla and McGrady, 2011). Educational games allow students to be evaluated on their performance while teaching new lessons and reinforcing old lessons (Perla, 1990).

Analytical wargames attempt to create as much data as possible about a problem so that it can be tested and analyzed. This method is synonymous with Perla's research wargames. Research games are built around scenarios for developing or testing strategy and plans, identifying issues, and building a consensus or understanding about the issues (Perla, 1990). These analytical approaches call upon OR and modeling and simulation departments to develop quantitative models, which analyze data outputs from the wargame and can be applied to future wargame iterations (Compton, 2019). It's a human-in-the-loop model where data feeds the wargame, but the human or subject matter expertise validates the input data and makes a decision based on knowledge and experience (Mittal & Davidson, 2021).

E. DIGITAL TWINS

A digital twin is simply a virtual representation of a physical entity and has a wide variety of current and potential applications (Vermesan & Bacquet, 2020). Digital twins typically use the Internet of Things (IOT), and a digital thread to connect the physical and virtual entities (Madni et al., 2019). The purpose of DT technology is to transmit data between the physical and virtual worlds to enable the monitoring, understanding and optimization of the physical entity's functions (El Saddik, 2018). DT is one of many related disruptive technologies along with IOT, big data, artificial intelligence (AI), augmented reality (AR), and additive manufacturing (AM) emerging in what is collectively known as the Fourth Industrial Revolution (4IR) (Aheleroff et al., 2020).

Increased data transfer capacity from 5G and tactile internet applications allows for constant communication and real-time updates between the DT and physical entities (Vermesan & Bacquet, 2020). This forms the basis for DT applications with common characteristics to include unique identifiers; sensors and actuators; AI integration; communication; representation; trust; and security (El Saddik, 2018). DT applications incorporate unique identifiers to allow direct communication with their twin and establish trust between entities (Wright & Davidson, 2020). Sensors and actuators on the physical entity can transmit sensor data back to the DT in near real-time (within 1 ms) following 5G and tactile internet standards (El Saddik, 2018). Digital twins may include a virtual depiction such as an avatar or hologram, but could also be strictly software applications (El Saddik, 2018). Finally, AI and deep learning can be applied within the virtual space of the digital twin making decisions which directly impact actions taken by the physical twin (Wang et al., 2018). Figure 1 shows a general data flow structure between a physical system and its digital twin.

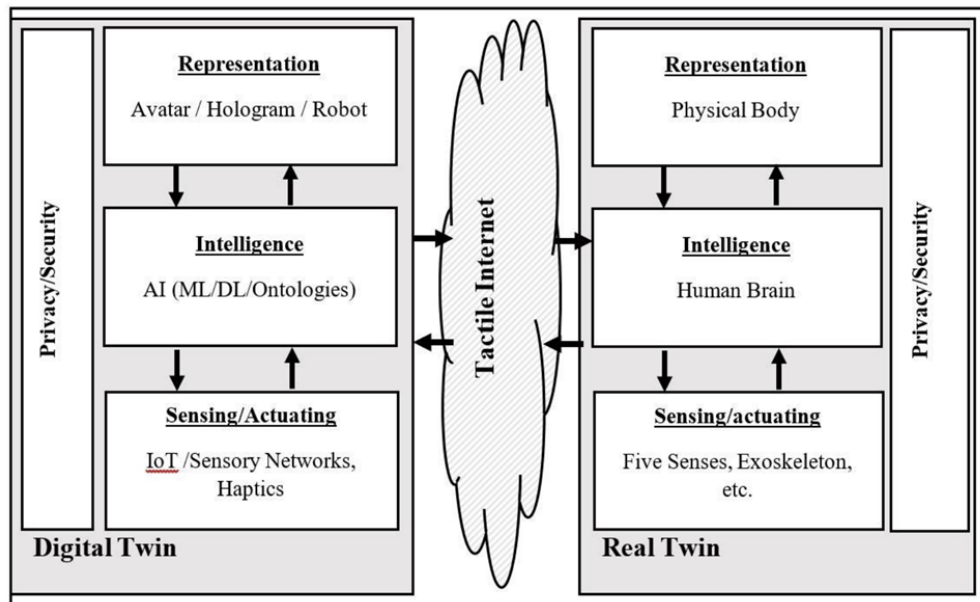


Figure 1. Communication/Interaction between Digital and Real Twins.
Source: El Saddik (2018).

The DT concept is still emerging, and current use cases are highly varied. Early definitions of DT simply referred to any digital counterpart to a physical entity, however depending on the level of data integration between the counterparts, distinctions can be made between DT, digital models and digital shadows (Kritzinger et al., 2018). Digital models are simply digital representations of physical assets which involve no data exchange, whereas digital shadows involve one-way data flows from the physical item to its digital shadow (Kritzinger et al., 2018). The digital shadows will adapt to changes in the physical counterpart, without impacting the physical asset. Unlike a digital shadow, a DT must have bi-directional data flows between both the digital and physical objects. Once the bi-directional flow is established, changes can occur in both the digital and physical environments (Kritzinger et al., 2018).

DT applications can be differentiated based on four distinct levels of sophistication (Madni et al., 2019). Level one is a virtual prototype referred to as pre-DT (Madni et al., 2019). Virtual prototypes are usually developed prior to building the physical prototype to facilitate decision-making throughout the preliminary design process (Madni et al., 2019). Because there is no physical counterpart, the virtual prototype cannot be classified as DT, but it will demonstrate some similar characteristics.

Level two is simply referred to as DT and is characterized by a virtual model capable of analyzing data relating to the physical counterpart's maintenance and operational status received from embedded sensors. (Madni et al., 2019). Communication between the systems is bi-directional, which enables the physical twin to receive feedback from the DT and make corrections in real time. This concept also enables the virtual counterpart to analyze the expected performance of the physical counterpart under various what-if scenarios and use the results to support future decisions to enhance performance (Madni et al., 2019). The next two DT levels deal with the integration of AI/ML. Level three is adaptive DT which incorporates user preferences and priorities and features an adaptive user interface for the physical and digital counterparts (Madni et al., 2019). Level four is intelligent DT and incorporates unsupervised machine learning capabilities in addition to the level three framework which enables enhanced pattern recognition and reinforcement learning to adapt to various environments (Madni et al.,

2019). Intelligent DT is described by Madni et al. (2019) as maintaining a high level of autonomy, but this characterization ultimately creates more questions as to how the authors define autonomy and where the system will be allowed autonomous decision-making. Table 1 illustrates the differing characteristics associated with the digital twin levels.

Table 1. Digital Twin Levels. Source: Madni et al. (2019).

Level	Model Sophistication	Physical Twin	Data Acquisition from Physical Twin	Machine Learning (Operator Preferences)	Machine Learning (System/ Environment)
1 Pre-Digital Twin	virtual system model with emphasis on technology/ technical-risk mitigation	does not exist	Not applicable	No	No
2 Digital Twin	virtual system model of the physical twin	exists	performance, health status, maintenance; batch updates	No	No
3 Adaptive Digital Twin	virtual system model of the physical twin with adaptive UI	exists	performance, health status, maintenance; real-time updates	Yes	No
4 Intelligent Digital Twin	virtual system model of the physical twin with adaptive UI and reinforcement learning	exists	performance, health status, maintenance, environment; both batch/real-time updates	Yes	Yes

F. DIGITAL TWIN APPLICATIONS

The DT concept has a wide range of current applications and new ideas are still emerging which will shape future implementation. The National Aeronautics and Space Administration's (NASA) Integrated Digital Earth Analysis System (IDEAS) project created an Earth System Digital Twin (ESDT) which feeds data into various models to analyze the current state of Earth systems, make predictions and test hypotheses about systemic behavior under different conditions. It is being applied to water cycle science to further understanding of things like freshwater availability in different environments,

extreme conditions like floods and droughts and their impact on other environmental ecosystems (Huang et al., 2022). This could be highly beneficial to enhance the accuracy of wargames by enabling environmental randomization and determining potential operational impacts.

DT applications have the potential to greatly enhance problem-solving and innovation through conceptualization, comparison, and collaboration (Grieves, 2014). Most humans process information they receive with mental images, but this conceptualization process can result in lost information. Instead of processing numbers and letters from data reports and mentally reconstructing visualizations, DT capabilities can display the physical and virtual product information simultaneously (Grieves, 2014). This is a more efficient way to process information and results in a shared model for the observers.

DTs also allow for quick comparisons between intended or ideal functions and the actual recorded operations. Grieves' (2014) example for DT enabled comparison was to measure ideal characteristics against actual performance to assess a "tolerance corridor" that is the acceptable range or deviations from standard. To differentiate between outputs, Grieves (2014) produced a color-coded visualization tool where zero deviations are displayed in green, measurements within the tolerance corridor are coded yellow and anything outside the tolerance corridor would be red.

Collaboration is enhanced through DT applications because the virtual displays can be observed anywhere and include data processed from distributed physical twins in various locations around the world (Grieves, 2014). The military applications are immediately apparent, as the common operating picture could be generated from forces in a wide range of physical locations and transmitted to decision-makers who would then have access to a shared visual model in use by commanders in different geographic regions.

DT capabilities also have the potential to mitigate some of the challenges associated with complex systems. According to Sargut and McGrath (2011), systems could be classified as simple, complicated or complex. Both simple and complicated

systems are predictable but differ only in the number of component parts. Complex systems however are much more difficult to predict due to the number of interacting elements (multiplicity), the interdependence of the connected elements and the diversity of those elements; this means the interactions are constantly changing (Sargut, & McGrath, 2011). These complex systems are difficult to predict due in part to the concept of emergence. Emergence is defined as a dynamic interaction between multiple system components; this results in a feature or element that was not previously present and qualitatively changes the whole of the system (Moore et al., 2018).

Grieves and Vickers (2017) categorized emergent behavior within a complex system as predicted desirable (PD), predicted undesirable (PU), unpredicted desirable (UD), and unpredicted undesirable (UU). Catastrophic failure is typically associated with the UU category and is often the result of human inconsistency and a lack of sensemaking (especially in stressful conditions) by human operators (Grieves & Vickers, 2017).

DT applications present two potential methods for handling complexity: running simulations prior to system production to identify potential system states and UU conditions which might not have been considered; and “front-running” simulations in real-time for systems in use to show possible system states in the immediate future and mitigate the rise UUs that arise during operation (Grieves & Vickers, 2017). The potential for real-time simulations to front-run operations is dependent on computing capability to outpace the physical activity being analyzed (Grieves & Vickers, 2017). Both of these solutions have potential military applications for mission analysis. Various courses of action (COAs) could be simulated prior to an operation, or continuously running simulations could offer real-time insight into potential decision outcomes.

III. METHODOLOGY

This thesis conducted a qualitative technology assessment on the use of DTs as a decision support tool for leaders within the United States Marine Corps (USMC) to leverage and enhance decision-making skills and planning processes. In order to analyze three key research questions, the researchers developed a greater understanding of USMC wargaming efforts, planning processes, and decision-making processes by conducting a thorough review of current literature. This included a review of academic papers, practitioner documents, practitioner presentations, and USMC doctrine to develop baseline knowledge. The research approach centered on a rationalist inductive method (Figure 2) using an exploratory framework to analyze the key research questions. This entailed the further exploration of the potential implementation of DTs in wargaming and decision support through engagement in academic discussions with NPS professors in the fields of systems engineering, systems thinking and modeling, wargaming, artificial intelligence, and big data. The researchers also attended wargaming simulations and presentations to gain foundational and experiential knowledge of how current wargaming efforts are being executed and better understand the technologies leveraged within those wargames to generate future results. The engagements with the practitioners in these meetings were in the form of social discussion, and data collection did not take place in any of these meetings.

The nature of this research requires a system-of-systems engineering approach. Meaning, due to the conceptual nature of the work and lack of empirical foundations, a rationalist inductive approach allows for exploratory examination of a multitude of theories and concepts (Sousa-Poza et al., 2008). Therefore, Sousa et al. (2008) posits employing a rationalist approach in which knowledge is obtained deductively by appealing to different concepts, laws, or theories and then justifying the knowledge through coherence of a system of premises establishes truths about the system. The researchers can draw upon requisite knowledge of some truths related to the research questions and use logic and reason to associate these truths to communicate the findings of the research. For example, in the context of this research, framing the premise of the

thesis on a rationalist approach enables the researchers to analyze the complex forms and capabilities of a DT and its emerging uses across the different decision-making processes of the Marine Corps.

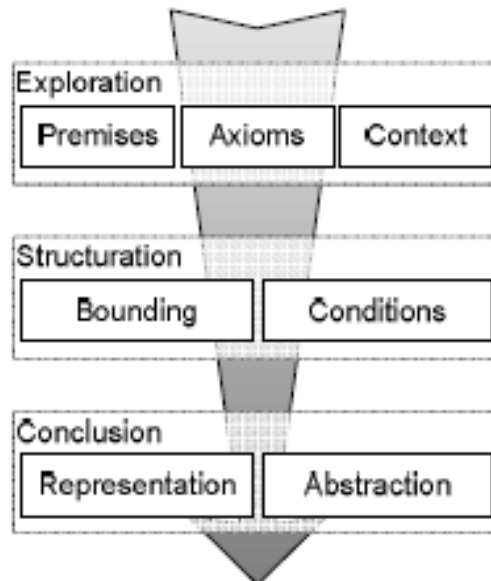


Figure 2. Proposed Methodology for Rationalist Inductive Approach.
Source: Sousa-Poza et al. (2008).

Using the rationalist inductive approach methodology provides a practical method to analyzing the three research questions of this study:

1. Would wargaming benefit from the integration of a DT?
2. How would a DT integrated decision support system enhance a commander's decision-making cycle?
3. At what level of command should the decision support system be incorporated?

The exploration step allows the researchers to explore all possible domains related to the research questions, thus laying the premise for the direction and focus of the thesis. Structuration formulates the coherence of conceptual research and the ideas which are presented and supported through the analysis of literature review, case studies, and

logical discussions conducted regarding each research question. By using this approach, the researchers can draw upon inductive knowledge and existing models and theories to strengthen and fine tune the newly developed model. From this analysis, the researchers can demonstrate in conclusion how the new or improved systems or models can be employed to current knowledge processes and concepts of a particular subject area.

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IV. ANALYSIS

A. DIGITAL TWIN INTEGRATION FOR ENHANCED WARGAMING

1. Digital Twin, an Extension of Modeling and Simulation

Mittal and Davidson (2021) identified military wargaming as a process used when a capability gap is identified, and a new solution is required to counter that gap. Wargames also allow design teams, analysts, decision-makers, or military officers to evaluate many different scenarios and inject new COAs into those scenarios assessing how each side adapts toward actions taken. As wargames take on a qualitative manner, Mittal and Davidson (2021) suggested implementing modeling and simulation (M&S) techniques as an addition to the game. In doing so, the resulting quantitative output provides wargame practitioners additional data for COA evaluation. Before incorporating a DT into wargaming applications the advantages of DTs as an extension of M&S must be understood. In doing so, the differences between DT and M&S in augmenting wargaming applications can be accentuated.

M&S significantly aids wargaming by creating conceptual and computerized data driven models in a controlled environment to explore the behaviors of the models under various conditions and to develop strategies and solutions based on the outcomes of the simulations (Menner, 1995). M&S provides several advantages. For example, the quantitative data acquired from a simulation allows for real-time comparison of alternative COAs; can present cases for future analysis in areas such as logistics and military readiness; or may allow for the identification of secondary or tertiary effects not realized during the wargame (Mittal and Davidson, 2021). On the contrary, some critics caution against the use of M&S in support of wargaming because the effects of morale and fatigue cannot be captured accurately with simulation; therefore, rendering many military models inaccurate. Beyond human factors, areas such as weapons performance are often evaluated under constraint free environments rather than under operational conditions therefore skewing results (Krishnan, 2016).

Incorporating a digital twin is different because it creates a virtual representation of a physical system or process that twins with the physical system; in part, using DT results in a dynamic model which can then capture the behavior of an actual real-world system, not just a conceptual one, in real-time by incorporating/analyzing data collected from the IOT, sensors, and other data gathering sources (Kritzinger et al., 2018). It is important to note that the DT is designed to monitor and optimize performance of physical systems and simulate their behavior under a multitude of conditions. By leveraging real-time data, a DT can abstract more detailed and specific information through its communication with the physical object instead of solely relying on mathematical models, empirical data, or historical information to create a simulation. The DT can use all the aforementioned data sources combined with AI/ML and simulation capabilities and can provide a more comprehensive and ecologically relevant approach to modeling or wargaming (Segovia and Garcia-Alfaro, 2022).

As a result, decision-makers, design teams, military organizations, and other wargaming participants can use DTs to improve the effectiveness of scenarios, enhance situational awareness models, ameliorate understanding of risk, optimize resource allocation, improve training, increase mission effectiveness, and reduce costs. But overall, DTs can help wargame participants make more informed decisions and respond quicker to changing environments. These outcomes will be discussed further in later sections of this chapter as we look at how a DT can support different wargaming applications and Marine Corps planning processes at the tactical and operational levels.

2. Wargaming Applications of Digital Twins

Military wargaming is done as part of a decision-making process to educate and train leaders or test a plan and ensure that plan will be able to resist unforeseen actions which may delay the desired outcome. The intent of the game is to generate, analyze, and compare different options or COAs and assess which one optimizes the greatest bid for success (Mittal and Davidson, 2021). Wargaming is not only used for the development of operational and tactical plans but also is centered on many different events and activities across the DOD. For example, some games are categorized based on the goal of the game

versus the type of problems it addresses, by adjudication style, level of analysis, or by organizational purpose. In a study conducted for the USMC, the RAND Corporation identified six types of wargames:

1. wargaming for concept development;
2. wargaming to support capability development;
3. science and technology (S&T);
4. senior leader engagement and strategic discussion;
5. wargaming for operational decisions and plans;
6. wargaming for training and education. (Wong et al., 2019)

Besides these six categories, there are three aim categories, which are:

1. Experimental,
2. Educational,
3. Analytical. (Cancian et al., 2023)

To better assist the decision-making process, understanding the aim of the wargame helps determine the medium through which the wargame is executed and ultimately how a DT can be employed to better assist the decision-making process.

a. Wargaming Methodologies

When executing a wargame, one must first consider the methodology in which the game approach is intended to satisfy. This requires a more precise understanding of the objective or hypothesis of a system, operational plan, or capability the wargame is testing or executing intends to fulfill. The three wargame approaches: experimental, educational, and analytical, focus on understanding how and why decisions are made, testing decision-making abilities through various exercise scenarios, and lastly, evaluating military problem sets to generate data and metrics to support policy decisions. The purpose of most wargames falls between decision support and capabilities development (i.e., educational wargaming with some experimental mixed in and then analytical wargaming) (Caffrey, 2019).

For officers, much of the wargaming execution is undertaken during periods of formal military schooling, training and education, or during operational planning in preparation for combat. The wargaming purposes here tend to always fall under the educational or experimental categories. During educational wargaming, the officer is

being tested on their ability to make decisions in a timely manner while facing emerging internal and external threats to the environment. The outcome is an improved decision-making experience with greater awareness and understanding of varying unforeseen factors which may influence an operation and how to make improved decisions in complex situations.

Experimental wargaming aims to understand various factors and conditions that can influence the decision-making processes. For example, a series of wargames were executed using both manned and unmanned aircrafts against a high value target. As the scenario unfolded, there were times in which the manned aircraft was shot down and alternatively the unmanned aircraft. Results of the wargame demonstrated various outcomes regarding what happened to the human in the systems verses the machine (Cancian et al., 2023). This type of scenario provides insight into potential risk involving situations in which a commander might be facing (i.e., the loss of human life verse loss of machine or potential to escalate the use of force).

In both educational and experimental wargames, decision-making is being executed based on human experience in similar situations and time in which information is collected and analyzed as the scenario unfolds (Gallego-Garcia et al., 2019). A result of this is a potential delay in one's decision-making process until all the fact-finding analysis has been performed. For the military, this is more aligned with the operational level of planning or wargaming where time is more abundant, and commanders and planning staff can conduct deliberate planning. At the tactical level, educational and experimental wargaming puts stress on the decision-maker to produce a COA under time-constrained, high-risk situations. This enables commanders to sharpen their OODA loop and make decisions at a more cyclical rate. Developments in technology like M&S and the use of AI/ML have helped bridge the decision-making gaps presented in wargaming through the ability to build and solve complex mathematical problems providing quantitative outputs to decision execution. A DT approach could offer highly detailed models enabling foresight of the outcomes of decisions that are made (Frank and Bartels, 2022).

Not only can DT increase mission effectiveness through improved training and simulation, it can provide all participants with the opportunity to practice different scenarios with real-time application by twinning physical objects and the environments in which they interact. This creates improved decision-making capabilities against unforeseen and rapidly emerging situations. In executing various scenarios, wargaming participants can identify risks and hazards, as mentioned earlier with the manned versus unmanned aerial systems example and decide upon alternate COAs or branch plans to execute based on the assessed outcome of those risks. Michael Birnbaum (2008) discussed several paradoxes related to risk and how they tend to affect people's decision-making loops. The Allais paradox demonstrated the effects of risk-aversion on decision-making by showing that people will often choose the option with a higher probability of success and a lower expected value than a higher risk option even if it has a higher expected value due to a larger payoff (Birnbaum, 2008). By running realistic scenarios that represents the physical environment and operational factors with twinned data, DTs can be used to further model risk decisions by accounting for paradoxes driven by a range of individual cognitive biases and heuristics therefore assessing the future effects of executing the COA with a lower payoff instead of taking on a more high-risk, high-payoff, low probability of success target or mission.

Lastly, analytical wargaming consumes a preponderance of the Marine Corps Warfighting Lab's (MCWL) attention, as at least four of the six wargaming categories fall under this methodology. Analytical wargaming has become the primary focus as the USMC looks to revamp its force with the release of the Commandant's Planning Guidance (CPG) in 2019 and Force Design 2030 (FD2030). "Divest to invest" has become the mantra to support a plan which transitions the Marine Corps from the way it has fought over the last twenty years in Iraq and Afghanistan back to its amphibious roots conducting sea control and sea denial operations.

The Marine Corps is building a force around the expeditionary advanced base operations (EABO) concept and this effort requires detailed information. To do this the Corps must test out new capabilities, build partnerships, and gain access to denied or austere areas across the globe. Importantly, these efforts require wargaming of different

concepts and ideas to be implemented across the force. Analytical wargames provide the means and ways to have ends (in the form of data on the USMC end) for these efforts (Cancian et al., 2023). Current efforts in support of analytical wargaming have seen a rise in computer simulated capabilities bringing to the forefront the technological advancements of AI/ML. The U.S. Air Force leverages Rhombus Guardian, a data-driven technology that uses AI/ML enabled tools to wargame and test possible solutions and find ways to employ those solutions in the battlespace.

“The Marine Corps envisions its next-generation wargaming (NGW) as a combination of time-tested best practices and emerging technology to expand gaming possibilities” (Wong et al., 2019, p. 27). This concept presented by Wong et al. (2019) bolstered a vision of wargaming with continuous play without turns, real-time adjudication, evolving scenarios, and an emphasis on immersion. To achieve the level of rapid-pace decision-making and adjudication desired by the Marine Corps Wargaming Division, this concept of NGW will be heavily reliant upon computer simulations and artificial intelligence (Wong et al., 2019). The signal demand for the inclusion of AI into wargaming is at an all-time high, however gaming efforts are still only able to simulate a model based off a snapshot in time. Developing and incorporating a DT aided by AI/ML would allow wargaming practitioners to transition from notional operating environments to scenarios driven by actual, real-time data pulled from the physical environment.

Inclusion of DTs into the Marine Corps NGW concept requires further development of DTs beyond manufacturing, supply chain management, or life cycle management and into organizational DTs presents several advantages to analytical wargaming. “A DT of a complex organization is a dynamic model that integrates operational and contextual data to understand how an organization employs its business model, connects with its as-is state, responds to change, deploys resources and delivers customer value” (Frank and Bartels, 2022, p. 404). This type of model would allow for the creation of real-time simulation of the battlefield environment, enhanced collaboration between organizations, improved data analysis, future generation of COAs or capability testing, and reduced costs by running models and simulations vice having to conduct live exercises. All of these key advantages would interact with the physical

environment to provide synthesis and key performance indicators driving more informed decision-making to achieve desired outcomes.

b. DT-enhanced Planning Processes

The Marine Corps planning process (MCP) and rapid response planning process (R2P2) are two approaches to planning used at the operational and tactical levels to enable the execution of assigned tasks. Both methods provide a framework in the form of a six-step process which enables the conceptual planning of military actions across the range of military operations (United States Marine Corps [USMC], 2020). The six steps of MCP/R2P2 are:

1. Problem framing,
2. Course of action (COA) development,
3. COA war game,
4. COA comparison and decision,
5. Orders development,
6. Transition. (USMC, 2020)

MCP offers a more deliberate planning approach than R2P2 where commanders, planners, and staff have less time constraints to analyze and assess a given problem. R2P2 is a dynamic process expected to be completed in a matter of six hours. This process is used heavily by the Marine Expeditionary Units (MEUs) which are postured to respond to crisis in a 24-to-48-hour time frame.

Incorporating a DT aggregate (DTA), a combination of DT instances (DTIs), into the planning process may provide commanders and staff with a more detailed and readily available picture of the operating environment (OE). The purpose of problem framing is to gain an enhanced understanding of the area of operation and what is in it. This involves looking at the intelligence preparation of the battlespace (IPB) and many outside silos of information provided from higher headquarters or joint partners to analyze and assess both friendly and enemy centers of gravity, identify risk factors, and determine estimates of supportability. The staff compiles all acquired information and defines the problem set and its operational approach. In doing so, a commander can issue mission

statements, commander's intent, and COA development guidance (USMC, 2020). This step lays the foundation for the rest of the planning process.

Implementing a DT of the operating environment could potentially speed up the familiarization process, as the DT is built to twin with the physical environment by leveraging information technologies to acquire real-time geospatial data, weather forecasts, current sea states, possible enemy locations and unit types, as well as synthesize future enemy COAs. The use of DT early in the planning process as a supplement to IPB can provide commanders at all levels with greater situational awareness of the battlespace, leading to a more nested understanding of the OE up and down the chain of command. By leveraging information created between the physical and virtual space, Wang et al. (2021) suggested “battlefield learning will occur faster through the sensing of entities on the battlefield rapidly, understanding the current situation comprehensively, and predicting future actions accurately before decision-making occurs” (pp. 2–3).

Improved understanding of the long-term behavior of the battlefield is dependent upon the DT's ability to bridge the physical objects with its sensors to the virtual environment, providing timely and accurate information during evolving situations. In doing so, the DT can test possible COAs by running simulation models (based on twinned data) of real combat entities employed in the OE. The results of the virtual representations become a decision support tool for the commander to determine the best COA (Wang et al., 2021). DTs continually update the battlespace representation as information flows come in and out. A depiction of these information flows between the physical environment and virtual representation can be seen in Figure 3, Wang's depiction of the operational mode of DT-enabled online battlefield learning.

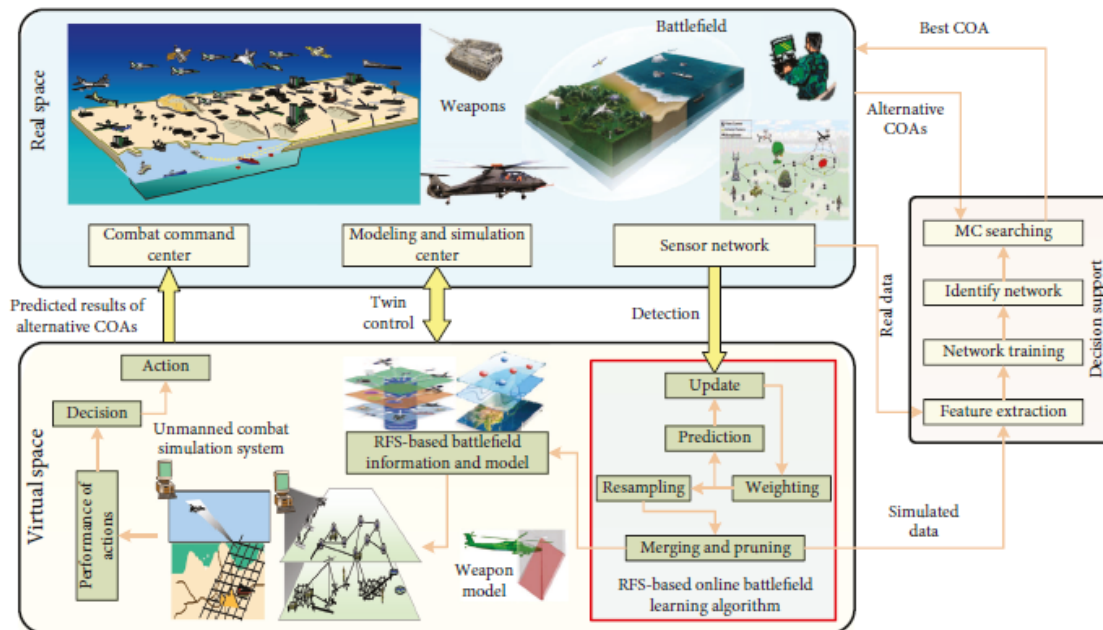


Figure 3. The Operational Mode of Digital Twin-Enabled Online Battlefield Learning in Unmanned Combat. Source: Wang et al. (2021).

Figure 3 demonstrates the DT's bidirectional flow of real-time data between the sensors in the battlespace and their corresponding DT in the virtual space. The benefit of this is the DT conducts battlefield learning in the virtual space and in turn provides real-time battlefield information and helps to evaluate the likely outcomes of available COAs (Wang et al., 2021).

Possessing an automated system which can generate future maneuvers and options while continuously analyzing and evaluating a rapidly changing battlespace can aid in reducing the time in which staffs and commanders take to develop COAs and wargame them against possible adversary actions. Potential outputs of a DT system can affect planning and execution both at the operational and tactical levels. Especially, at the tactical level where commanders directly in the fight would be able to leverage the DT at any time to generate alternative COAs in the form of branch plans to achieve mission success. The intent of the system is to shorten the decision-making process through a systems analysis approach with human intervention and experience in order to limit the influence of decision-makers' internal ambiguity in the battlespace. Current systems

relied upon for battlefield awareness are the common operational picture (COP) for both friendly and enemy locations, blue force tracker (BFT), and a network of intelligence sensors and reporting mechanisms used for collection and dissemination of intelligence information. All of these systems have inherent feedback loops, however none of them execute two-way data synthesis between a real and virtual environment. Most feedback loops involved in these systems require the analysis of a human to interpret the data being collected.

Around 2007, Defense Advanced Research Projects Agency (DARPA) in support of the U.S. Army developed the Deep Green program as an automated decision support system (DSS) to be used by U.S. Army and Marine Corps commanders and staff, shown in Figure 4. The goal of developing this tool was to deliver capabilities that could out-cycle adversary decision loops by prompting officers to make decisions at key points during combat (Kenyon, 2007). The program would provide commanders with the technology to generate and analyze options quickly using information from current operations to assess probable COAs and develop branches and sequels to counter enemy actions. Humans generate the options and make the decisions, but the system is meant to help explore how the options will play out, thus giving commanders insight to potential second and third order effects of actions taken (Surdu & Kittka, 2008).

As a DSS, Deep Green looked to offer commanders the ability to make decisions more rapidly by creating a new OODA loop paradigm (Surdu & Kittka, 2008). According to Surdu and Kittka (2008), observe and orient steps would run continuously in the background, building out options and making predictions based on the current operation. This fusion of the planning and execution phases to run simultaneously within the Deep Green system allows commanders to focus efforts toward the decide and act steps at a more cyclical rate, thus promoting a more proactive approach to battlefield decision-making. As an early model of a DT, Deep Green (shown in Figure 4) used the Commander's Associate component to turn a commander's thoughts and ideas into a COA. Deep Green's Blitzkrieg component would then run simulations and produce a broad set of possible future actions, both friendly and enemy. The last major component of Deep Green called Crystal Ball served several functions. It controls how Blitzkrieg

generates rules, but more importantly Crystal Ball is the component which interacts with the physical environment, monitoring data from an ongoing operation and updating information associated with potential future battlespace maneuvers. The major goal behind both Blitzkrieg and Crystal Ball is that over time they learn to be better predictors of possible futures (Kenyon, 2007).

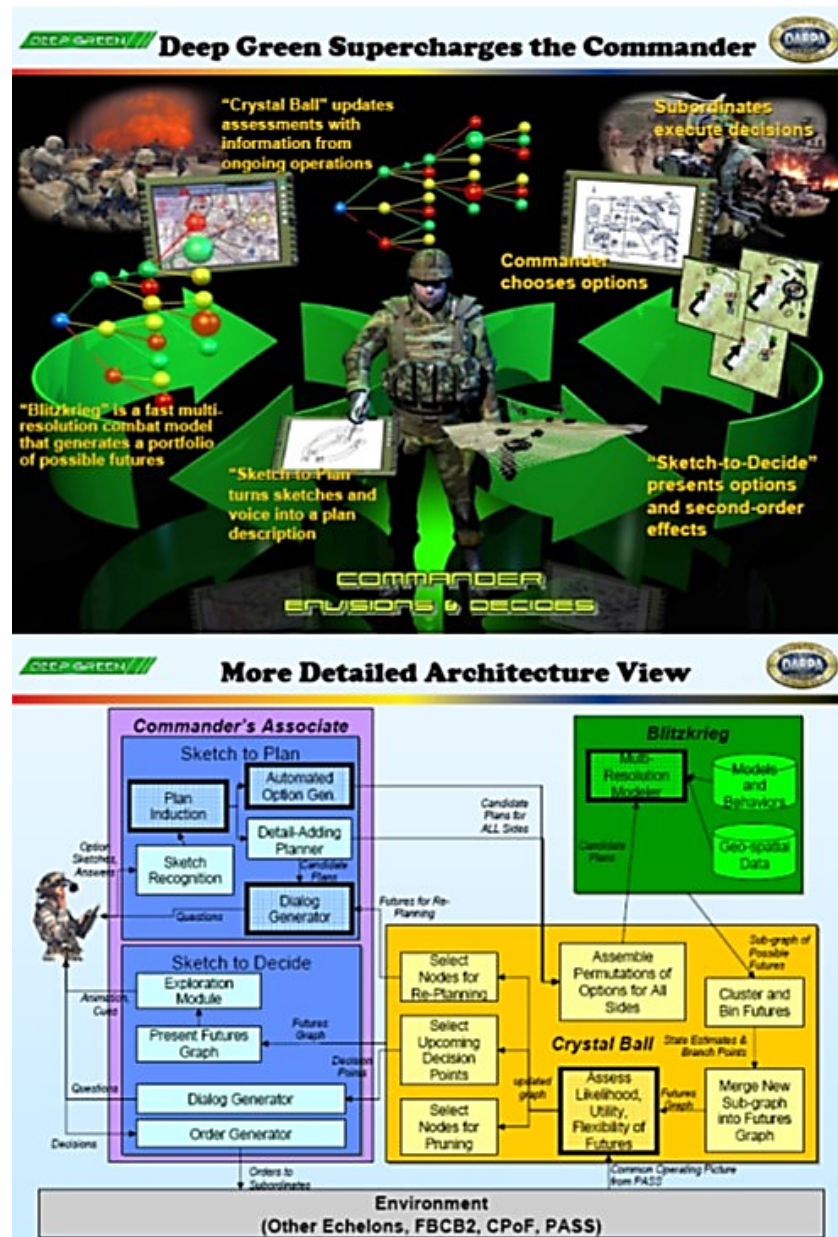


Figure 4. Operational Concept and Architectural Overview of DARPA's Deep Green. Source: Surdu and Kittka (2008).

Deep Green along with another DARPA project called Real-time Adversarial Intelligence and Decision-making (RAID) which proposed COAs for tactical leaders demonstrated initial success running controlled trials; however, both systems would ultimately fail in an operational environment due to the lack of information readily available (Banks, 2013). Banks (2013) found that both systems demonstrated high levels of performance under controlled environmental settings. When relying upon information and data flow in a tactical environment, Deep Green and RAID lacked the ability to obtain the required information from the Army Battle Command System (ABCS).

Bridging the information gap is still a significant concern within today's military force. Although the birth of DTs and increased access to data through the IOT and big data analytics has helped bridge this gap, issues with systems integration and data flow still exist within the US Army and Marine Corps. Interoperability within the Marine Corps is difficult to begin with due to silos created by current programs of record. Adding other services' systems to the mix would make data flow processes more extreme. Once these issues are worked through, integration of a DT in the planning processes will significantly aid commanders at all levels on the battlefield.

B. DIGITAL TWIN INTEGRATED DECISION SUPPORT

Building a reliable decision support tool for military leaders is a complex undertaking. It must be built on accurate data and make analytical recommendations based on the recorded variables. There is a danger of expanding the scope of the recommendations to the point that reliability suffers. The intent is to deliver a tool that commanders will use to aid in decision-making which requires a certain level of trust which can only be developed by sustained performance improvements. Ideally, reducing the time required to reach a decision and reducing overall uncertainty are two measurable goals that would demonstrate the value of such a tool. The decision support tool is intended to augment the commander's own cognitive processes and not to supersede the necessary human faculties. To evaluate the feasibility of the undertaking, it is worth examining how the decision support tool might go about improving speed and reducing uncertainty associated with the decision-making process.

1. Improving Decision Speed

According to the dual-process theory for reasoning, System I thinking is intuitive, relatively fast and cognitively undemanding, whereas System II thinking is analytical, relatively slower and much more cognitively demanding (Stanovich & West, 2000). Because of the higher burdens associated with System II thinking, there may not be enough time or information available to fully execute the analytical process prior to rendering a decision. Or, as Kahneman (2011) observed, it is extremely common for people to switch from System II thinking to System I thinking out of sheer laziness to avoid the difficult cognitive process associated with analytical thinking. Former Secretary of State Colin Powell proposed a 70/40 rule for decision-making where at least 40 percent of the information must be available to avoid making a mistake, but no more than 70 percent of the information should be acquired because of the assumed time associated with the information gathering process (Garcia, 2018). Time and effort are then prohibitive factors preventing decision-makers from exhausting their System II faculties prior to reaching a decision. By integrating DT with AI/ML capabilities, adaptive or intelligent DT will be able to rapidly analyze a large volume of data in a relatively short time (Madni et al., 2019). The machine learning algorithm can be programmed to perform the System II processes at a speed that matches or even outpaces the decision-makers intuitive System I thinking. There will of course be the interplay between receiving the output from the decision support tool and the decision-maker processing the recommendation in the context of their wider experiences. The key advantage is that the analytical process is no longer constrained by time or effort and can be more fully incorporated into military decisions.

To improve the speed of decision-making, the adaptive DT will have to reduce the time associated with the OODA loop. The first two processes of the OODA loop are “observe” and “orient.” Observation is simply an accumulation of data while orientation involves estimating and analyzing data while making judgments and assumptions (USMC, 2018a). This is an often time-consuming process, but can be reduced through effective integration of DT. The observation process can be done in real-time through the collection of sensor data, intelligence reports and anything else deemed relevant to

inform the decision-maker. The value of the DT application is the continuous updates between the physical and digital entities (El Saddik, 2018). The digital representation of the operating force will provide comprehensive and up to date depiction of the physical counterparts enhancing the observation process. One of the current challenges to intelligence analysis is that a report will only be comprehensive as of the time it was generated; however, with DT, the continual updating will allow the observer access to a dynamic model that reflects current conditions on the battlefield.

The orientation process can be very time consuming as well and increasing the amount of data collected typically increases the time associated with analysis. However, by utilizing DT with integrated AI/ML capabilities, the data can be collected, processed and analyzed quickly, such as at the edge, to provide greater clarity (Madni et al., 2019). Part of the orientation process will still involve human cognition but can be aided by the quantitative analysis performed by machines. The decision-maker can still rely on their experience and intuition to perform System I thinking which is faster and less cognitively taxing than System II. The adaptive DT (with its embedded AI/ML capabilities) is needed to perform the system II analytical thinking fast enough to be incorporated into the orientation process to help arrive at a decision which utilizes both thinking systems in a complementary fashion.

Silvander and Angelin (2019) proposed an extended OODA loop (shown in Figure 5) which included intent as well as explicitly delineated the continued interaction of each process with a box labeled “evaluation and learning and knowledge and beliefs” which created a logical framework that could be incorporated by AI processes.

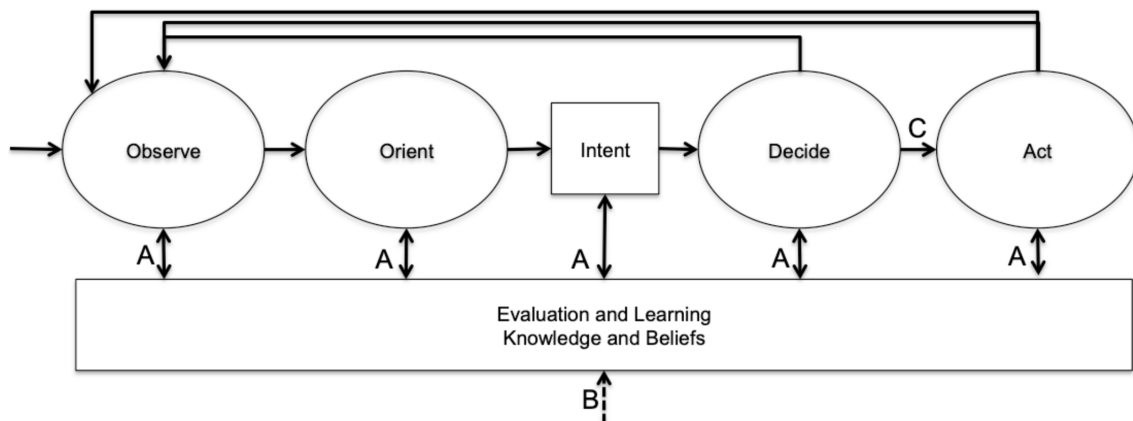


Figure 5. The Extended OODA Loop. Source: Silvander and Angelin (2019).

This extended model recognizes that any attempt to automate the OODA loop will require the inclusion of the programmers' overall intent and underlying assumptions. A DT-integrated decision support system does not need to be fully automated (although potentially could in specific applications), but rather created to complement the commander's intuition. Different decision-makers will have different beliefs and experiences that impact their final decision. This does not need to be automated. An effective decision support system can simply provide rapid data collection (observe) and quantitative analysis (orient) to aid the decision-maker and reduce the burdens of System II processes.

2. Reducing Uncertainty

Developing a decision support tool capable of reducing uncertainty is a difficult undertaking. A good example to start with would be the game of chess. In chess, there is a clearly defined objective and all the possibilities for each movement are known; everything about the game objective and possible moves are on the chess board. Optimal decisions can be quantified based on the probability of winning the game. From an epistemic uncertainty point of view, therefore, given enough time this can be resolved. This is not conducive for analyzing decisions in warfare which have to reconcile with the challenges presented by epistemic uncertainty. Since the players in the game have clear

objectives, and boundaries are well established, the unknowns from one of the player's perspectives about the other player is constrained by the objective and probable moves. In warfare, the situation is different; there are two types of uncertainty, epistemic and aleatory uncertainty (Kvam & Pleskac, 2017).

Epistemic uncertainty comes from a lack of knowledge of the situation and relegates probabilities to quantification of known variables (Atmanspacher, 2002). This condition is much more common in warfare in which decisions are informed by intelligence estimates and uncertainty is understood as inherent to the process.

In addition to epistemic uncertainty, military decision-makers will also encounter aleatory uncertainty and strategic uncertainty. Aleatory uncertainty differs from epistemic uncertainty in that it relates to the inherent statistical unpredictability in the environment without regard to anyone's knowledge (Hertwig et al., 2019). An example might be flipping a coin which is generally understood to have an even chance of landing on either side. However, the actual chances of landing on either side might vary slightly due to factors such as the force of the flip, the distance to the ground, wind resistance, dirt on the coin etc. One other source of aleatory uncertainty is ontic uncertainty, which represents the internal ambiguity of the decision-makers (Kvam et al., 2021). For example, even in a highly quantifiable game such as chess, ontic uncertainty could arise if a player exhibits a higher preference for certain pieces or even an unskilled player who makes counterintuitive decisions to impress the audience or to increase a possible social media post. This type of uncertainty can only be known if the decision-maker elicits the decision. The ontic type of uncertainty is the foundation of strategic uncertainty and arises from the inability to predict the behavior of others in an interactive situation (Hertwig et al., 2019). Warfare involves a conflict between opposing forces, so strategic uncertainty will be a constant factor. Also, as larger conflicts involve more interactions of forces, there is a great potential for increased strategic uncertainty.

A DT-augmented decision support system for the DOD will encounter epistemic, aleatory, and strategic uncertainty. It is impossible to truly know all battlefield variables in an ontological sense, the decision support tool will have to make estimates based on the variables feeding the system. Whether or not this constitutes a reduction in

uncertainty is difficult to assess. Especially the ontic type of uncertainty, is challenging to reduce. The expansion of information operations, embedded sensor networks, and big data means that there is a large volume of data being received from the battlespace. There is an advantage in being able to rapidly analyze that data so that it can be incorporated into time-sensitive decisions that would otherwise be made with less total information. However, more information does not necessarily mean less uncertainty. In some cases, such as military deception (MILDEC) operations by the enemy, some information could be intentionally misleading and its inclusion without the missing wider context will distort the overall model. In the context of ontic uncertainty, one can know everything about the system of interest, and yet cannot assess the true system state, unless elicited by the system (Kvam et al., 2021).

Decision-makers have to rely on available information to inform their decisions. A DT of the operating forces will provide up to date information that was previously inaccessible. Available information about the enemy disposition of forces can also be included in the model to drive probabilistic decisions. Because the amount of potentially unknown variables is itself unknown, it is impossible to assess how much additional information constitutes a reduction in epistemic uncertainty. That said, military decisions must be made with commanders' assumptions as a way to deal with uncertainty. These can and should be included in the decision support tools recommendation. Moreover, as additional information becomes available during operations, the DT can rapidly integrate the new information into the model so that the previously unknown variables become known. The near real-time communication between the digital and physical assets means that due to the nature of the DT, decision support recommendations can be amended if incoming variables change the recommended course of action. In this sense, the decision support tool might not be able to truly reduce epistemic uncertainty but does provide options to manage it.

Aleatory uncertainty is somewhat different because it deals with the multitude of immeasurable variables that will impact the outcome of events. While the individual variables might not be measurable, that is not to say that their cumulative effects cannot be. The decision support tool should integrate AI/ML algorithms which incorporate data

to build models that assign probabilities to potential systemic outcomes. An example of this would be weather prediction that cannot be predicted with complete certainty, but can be modeled with some accuracy, although that accuracy declines the further out the prediction is made. Aleatory uncertainty may account for unprecedented events and emergent behavior which is difficult to predict. However, simulations can show different system states which will give rise to unpredicted emergent behavior (Grieves & Vickers, 2017). The aleatory uncertainty is still present, but emergent behavior is sometimes predictable with the aid of DT simulations. This is another case of the uncertainty being managed if not effectively reduced.

Strategic uncertainty is another factor that is endemic to warfare but might be properly managed with limited applications of modeling. Strategic uncertainty is often derived from the preferences, beliefs and knowledge of the other members involved (Hertwig et al., 2019). It might not be possible to ascertain the individual preferences or beliefs of all opposing decision-makers, but DT applications present a valuable opportunity to model the behavior of nations in conflict. If modern conflicts are digitally modeled, various patterns of behavior can be detected; in part, the captured patterns enable eliciting long-term behavior of adversaries and develop what-if analysis for future scenarios. This will work more effectively when modeling tactics and doctrinal procedures for opposing forces because those behaviors are more likely to be repeatable. Higher level decisions made by individual leaders will be more difficult to predict because they will be more reliant on the personal disposition of the leader. For example, it is much easier to predict the behavior of troops in contact who will rely on learned tactics, techniques, and procedures than to predict the threshold that will cause a foreign leader to commit forces to a conflict. For this reason, the decision support tool will have to be limited in scope to mitigate the increasing complexity and situational uncertainty moving from the tactical to the operational and strategic levels of warfare.

In each of these cases, it is debatable as to whether uncertainty was effectively reduced or just properly managed. Ultimately, uncertainty is inherent to the nature of the battlefield, but a decisive advantage can be had by whichever side is more effective at managing it. A DT integrated decision support tool has the potential to effectively

manage uncertainty to the point where it can make useful recommendations in analyzing known variables. However, epistemic, aleatory, and strategic uncertainty will continue to be significant factors impacting the outcome of decisions in future conflicts.

3. Data Inputs for a Comprehensive Digital Twin

The DOD is presently faced with the task of modernizing the force and incorporating the various disruptive technologies that will shape the battlefield of the future. What has been termed the Fourth Industrial Revolution comprises a variety of new advances to include: big data, AI, automated decision-making, unmanned systems and robotics, human-machine teaming, quantum computing, hypersonics, additive manufacturing technology and a host of other innovations with the potential to change the nature of warfare (Zysk, 2021). Each of these technologies is data driven and will create additional data that must be effectively curated. The net result is a massive growth in the information warfare domain. Whichever nation most effectively adapts to this new environment will have a decisive advantage in future conflicts.

Although not directly providing decision support, big data management will influence the decision processes. The characteristics of big data which are volume, velocity, variety, and veracity can also include value. Value is big data's ability to produce insights for the owner (Song et al., 2015). However, to realize the value in the data sets, it has to be extracted from the right sources, effectively farmed to produce insights, and then translated into visualizations that convey meaning to decision-makers.

Information from the battlefield has been collected in a myriad of ways throughout history, whether it was verbal reports from scouts, written communications, radio transmissions or photographs from aircraft. This data helped drive decisions but could only be generated by a limited number of sources. A recent phenomenon has been the expansive integration of physical objects to the internet through sensor data in what has been termed the internet of things (Rose et al., 2015). The growing IOT provides an incredible opportunity to harvest massive amounts of data from the battlefield but will require the adoption of new technologies by the DOD to ensure the right data is being captured. The IOT is comprised of three different layers which perform different roles

and require unique technologies: the perception layer, the network layer and the application layer (Donghao et al., 2021).

The perception layer exists to perform object recognition and information gathering by employing radio frequency identification (RFID), global positioning system (GPS) and wireless sensor networks (Donghao et al., 2021). The military sensor network distributed through the IOT must be able to register activity and then categorize the activity into measurable data. Wireless sensor networks can employ acoustic, infrared, and magnetic sensors to detect physical information of the local area and through RFID can create visualizations assigned to unique objects (Donghao et al., 2021).

One of the primary challenges at the perception layer is using the IOT to gather data about enemy forces. Embedded sensors in military equipment can be used to keep leaders apprised of the status of friendly forces, but there is a need to gather information about opposing forces as well. One proposed implementation of the military IOT is to create a network of detector nodes and classifier nodes where the detector nodes register when and where an event has occurred while the classifier nodes will differentiate the source of the event and whether it was conducted by friendly or enemy forces (Zhu et al., 2018).

Once data is captured in the perception layer, it has to be transmitted and processed. This is the role of the network layer which can be accomplished on mobile, wireless, radio, television, machine to machine or wide area network access technology (Donghao et al., 2021). The network layer presents a host of problems for the DOD. This is primarily because expeditionary operations in austere environments have limited infrastructure capable of handling the volume of data being gathered from the distributed military IOT. Even when operating in urban environments with native 5G capabilities, the military will face spectrum management challenges and may not have the authority to commandeer local networks for military use. The DOD is working on dynamic spectrum sharing capabilities to facilitate operations in contested spectrum environments (Office of the Under Secretary of Defense for Research and Engineering, 2020). Various communication hubs such as satellites, unmanned aerial vehicles (UAVs) and early

warning aircraft will be needed to create a mobile digital network capable of supporting massive data from expeditionary units (Donghao et al., 2021).

Another challenge presented at the network layer of the IOT is scalability. As the IOT expands to include additional items carried by individuals, the number of entities accessing the network will grow exponentially. Also, the dynamic nature of warfare means that different entities will be entering and leaving the area of operations frequently and the network architecture must be capable of handling the joining and detaching of billions of individual nodes on a constant basis (Said & Tolba, 2021). The expansion of the IOT at the perception layer is a great opportunity to gather more data than ever before, but the network layer must be poised to handle the increased volume, or the value of the data will be lost.

Once data is extracted at the perception layer and transmitted via the network layer, it is fused to form useful information at the application layer (Donghao et al., 2021). The data is collected from a wide variety of sources but through ingestion and analysis, the application layer can provide usable information to decision-makers. Some of the technologies used at the application layer include, spatio-temporal unification technology, target location recognition technology, special computing technology and increasingly the use of artificial intelligence and machine learning (Donghao et al., 2021). One example of a widely used application layer platform is the Distributed Common Ground System (DCGS), which performs data ingestion and analysis to provide a display of the locations and disposition of both friendly and enemy forces to better enable effective command and control of operational units (Zheng et al., 2015).

As the IOT furthers the growth of big data, effective analysis becomes increasingly important for the DOD. Data analytics is a means of harnessing the value of massive data sets, but predictive analytics involves analyzing historical data to make predictions (Zakir et al., 2015). One of the recent innovations enabling predictive analytics is the use of data farming methods. Data mining involves filtering large volumes of data to find specific relevant data points, whereas data farming is the use of large data sets to run experimental simulations and identify relationships between variables (Sanchez, 2018). Traditional simulations would run one time and produce only

a singular data point. Data farming is a way to provide holistic analysis by injecting data into the model and running repetitive simulations to observe possible outcomes in response to “what if” prompts (Song et al., 2015). Data farming is a way to analyze large datasets, but the result is the generation of even more data that will have to be managed.

An important application of big data analytics for the DOD is course of action analysis. When evaluating potential options, military planners can inject real-time data from the active intelligence gathering network into the model and simulate different options at multiple decision points to gain probabilistic insight into likely outcomes (Song et al., 2015). This provides tremendous value to decision-makers allowing them to validate their assumptions quantitatively.

4. Automated Decision-Making

The primary intended purpose for developing a DT-integrated decision support tool is to assist with human decision-making. There may, however, be specific instances where human-in-the-loop decisions are unnecessary or even suboptimal and automated decision-making is more appropriate. Extreme time constraints are an example of a situation where automated decision-making is appropriate. The Counter Rocket, Artillery, and Mortar (C-RAM) automated gun system was used in Iraq to defend against incoming projectiles because the time available for an effective reaction requires a compressed OODA loop that does not allow enough time for human decision-making (Singer, 2009). This was relatively uncontroversial because the system operated within a narrow scope of objectives. The decision to shoot down an incoming rocket requires very little contemplation because the consequences of failing to act greatly outweigh the cost of acting.

The use of automated decision-making is appropriate when applied to a limited scope of objectives. A human decision is still required when creating the algorithm and authorizing autonomy, but that decision is made in advance of any use case. For simple applications of limited scope, advanced authorization is practical. DT technology has been used to improve condition-based maintenance capabilities by running simulations of different systems to predict component part failures before they occur from usage

(Harrison, 2021). These enhanced predictive maintenance capabilities will enable more efficient scheduling of repairs as well as a reduced logistical burden and increased operational readiness (DOD, 2020). Ordering replacement parts or scheduling maintenance on a vehicle can be automated efficiently. This application of automation works well because the routine task of ordering replacement parts is standard procedure and can be authorized in advance. It is also easy to quantify because operational usage is measured, and repair parts and labor hours are already managed with dollars and hours respectively.

The process of automating decisions rapidly becomes more complicated as soon as ethical dilemmas come into play. Philosopher David Hume famously posited the is-ought problem also known as Hume's Law, demonstrating that ethical statements cannot be logically inferred from descriptive statements (Boyles, 2021). Boyles (2021) argued descriptive statements could be assessed as true or false, but evaluative assertions such as ethical judgments were not statements of fact and were human-dependent expressions of values. Even if a highly functioning DT enabled decision support tool can provide greater understanding of the operating environment, it does not follow that it can then make moral judgments through logical analysis. Ethical interpretations are human-dependent, but typically follow one of three normative frameworks: consequentialist ethics involve making decisions based on which choice will produce the best aggregate consequences; deontological ethics ground morality in an overarching sense of duty which must be upheld by an agent regardless of outcome; and virtue ethics evaluate morality by gaining favorable perceptions by others and demonstrating moral characteristics such as kindness, bravery or justice (Yu et al., 2018). An ethical dilemma occurs when a decision is required that will inevitably violate the principles of at least one of the aforementioned frameworks (Yu et al., 2018).

Humans have to make moral decisions by evaluating different frameworks. Different people might come to different conclusions based on which framework they favor more heavily, but their decision will result from a confluence of all three. This manner of thinking is not conducive with pure logical AI/ML capabilities. This is the reason why ethical decisions will require human authorizations and not simple

automation. Even operating exclusively within one of the frameworks will still result in dilemmas. For instance, if a target with strategic value could be destroyed by an airstrike but will result in non-combatant deaths, each framework will still have internal dilemmas. Someone using a consequentialist framework might still have to evaluate whether the value of the potential lives saved by advancing the strategic goal of destroying the target will outweigh the value of the non-combatant lives taken in the attack. The deontological framework will have to contrast whether the duty of the military to defend national interests supersedes the obligation to protect the rights of the non-combatants. The application of virtue ethics also results in an internal conflict over the value of different virtues and which action best exemplifies the chosen virtue.

Another challenge with programming ethical decisions is the application of utility theory. As utility theory developed over the years, a persistent problem was the inability to arrive at a transitive unit of measure (Moscati, 2021). For an algorithm to recommend an ethical decision, it would have to evaluate the subjective value of a multitude of variables. A programmer would have to assign a measure of utility that compared the value of the lives of service members stratified by rank and skill; the value of operational and strategic objectives; the monetary value of equipment; the value of time gained or lost; the value of political implications and perceptions and innumerable other variables which have no objective transitivity. Ultimately, a human who has been entrusted with the responsibility to make such difficult decisions and will have to bear the weight of the consequences will be required to make the evaluation, consider the ethical implications, and arrive at a decision.

C. COMMAND IMPLEMENTATION OF DECISION SUPPORT SYSTEM

In order to better elucidate how a DT enabled decision support system might be implemented to assist commanders with decision-making during combat operations, it is helpful to analyze a realistic vignette of a potential future scenario. ChatGPT, the open-source AI platform, was used to create a vignette scenario in response to the following prompt: *develop a vignette detailing an amphibious operation* (Appendix 1). By enlisting ChatGPT in the construction of the scenario, the researchers gain insight into how AI can

be employed to develop a baseline for operational analysis. This is useful from a modeling perspective and can be further enhanced by modifying the prompt or injecting new data collected from the battlefield. For the purpose of this analysis however, it provides a simple depiction of an amphibious operation that could be undertaken by a Marine Air-Ground Task Force (MAGTF) against an adversary in an engagement in various locations around the globe.

Decision support tools will have different requirements depending upon the types of decisions being analyzed. The hierarchical nature of the military means that higher level decisions will constrain the decisions made at subordinate levels. Depending on which level of command is using the decision support tool may result in different effects on the battlefield. For this reason, it is useful to analyze how decision support tools can be used to assist leaders at the different levels of war (shown in Figure 6) from tactical through operational and up to the strategic level.

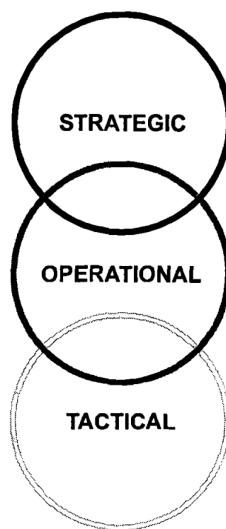


Figure 6. Levels of War. Source: USMC (2018b).

The Marine Corps (2018b) defined the focus of each level of war as: accomplishing policy objectives at the strategic level; applying combat power to defeat the enemy at the tactical level; and using tactical results to accomplish strategic

objectives by determining when and where to engage or refuse to engage the enemy in battle at the operational level. With the aid of the vignette, each level of war can be analyzed to determine the appropriate application of decision support tools in support of the commanders' objectives.

1. Implications for Decision Support at the Tactical Level

The tactical level is the lowest level of war. According to Marine Corps (2018b) doctrine, MCDP 1, the tactical level's focus is "the application of combat power to defeat an enemy force" (p. 29). The art and science of achieving victory in battle revolves around the use of a combined arms approach by directing fire and maneuver elements to achieve an advantage and immediately exploit moments of success to defeat the enemy (USMC, 2018b). This is done through initial planning efforts in which a MAGTF or MEU commander and their staff conduct mission orders planning to assess, analyze, and implement a plan to achieve success in combat. For the amphibious landing vignette, the tactical leadership analysis will be centered around implementing a DT-enhanced decision support tool for a MEU commander and each respective combat element under the MEU's control.

A DT of the operating environment would be beneficial to all components of the MEU/Amphibious Ready Group (ARG) by providing an integration of real-time situational awareness, pre-mission planning, COA wargame simulation, resource optimization, actions on the objective, and follow-on COA generation and simulation. As mission orders and tasking are received from higher headquarters, the commander could leverage the DT to familiarize themselves with the current operating environment and conduct pre-mission planning. Using organic sensors and the IOT to update the DT model, commanders could start setting parameters within the DT and establish likely COAs to determine probabilities of success. The aviation combat element (ACE) could look at weather and wind patterns to determine flight operations. The ARG staff could use sea state data and acoustic signaling to determine ability for amphibious insertion as well as potential enemy threats. The ground combat element (GCE) would leverage the DT to gain better awareness of terrain and possible avenues of approach. This will help

determine what combat capabilities to take ashore. Lastly, the logistics combat element (LCE) could do an analysis of main supply routes (MSRs) in order to facilitate the flow of logistics and sustainment once a beachhead has been established.

During execution of the operation, each company commander and platoon commander would carry a graphical user interface (GUI) which enables them to interact with the DT to provide updates to the system while homing in on their specific tasks to be completed. An infantry company commander could employ a RAVEN or PUMA unmanned aerial system which relays directly to the DT updating terrain and enemy location and disposition as detected. This would then allow the platoon commander to reorient their troops and place them in more advantageous positions to execute fire and maneuver operations. In the rear, the MEU commander could watch the battle unfold via the DT while simultaneously running future simulations to project follow-on operations, branch plans, or contingency operations.

The beachhead is taken, ground forces consolidate into a security position and begin to treat casualties and assess the ability to continue the fight. At this point, commanders on the ground can begin to update the DT with simple beans, bullets, band-aids, and bad guy metrics. Beans refers to water and food supply. Bullets denotes the amount of ammunition retained for follow-on operations. Band-aids updates casualties and injuries. This could also be done by outfitting the troops with biometric data sensors or biopsychosocial DT sensors, monitoring the human persona through sensed data from physical, social, and cognitive behavior models (Frank and Bartels, 2022). Twinning these models digitally would provide the necessary pieces to create a basic, functioning model of human decision-making and behavior; providing the landing force commander with a better understanding of the abilities of their forces to physically continue fighting. Lastly, adversaries provide the DT with quantifiable data of size of the forces and capabilities involved in the fight, how many have been captured, killed, or potentially still fighting. The commanders can now make more informed decisions as to what COA to execute next. This could also trigger the LCE to begin preparations to conduct resupply missions or prisoner detaining operations. Securing the beachhead may allow the ARG to

maneuver ships into more advantageous positions where they can leverage both water-borne and aerial capabilities.

Once consolidated, regrouped and follow-on tasking has been received, the forces on the ground can leverage the DT to analyze optimal routes, coordinate scheme of maneuvers based off terrain analysis and enemy disposition as they decide to defend, reinforce, attack, withdraw, or delay (DRAW-D). The DT can then generate future COA simulations and analysis providing ground commanders options to execute to achieve overall mission success. Incorporation of the DT could help the MEU execute an amphibious landing more effectively across all domains by providing realistic simulation of the landing area and optimizing resource allocation based off mission analysis, enemy analysis, troops and fire support simulations, terrain analysis, time analysis, and civil considerations (METT-TC).

2. Implications for Decision Support at the Operational Level

The operational level of war is the connective tissue between the tactical and strategic levels (USMC, 2018b). Once the strategic objectives are determined, planning takes place at the operational level to determine how to best utilize available assets to accomplish the specified mission. For the amphibious landing vignette, the operational leadership analysis will be centered around implementing a DT-enhanced decision support tool for the Marine Expeditionary Force (MEF) commander as well as the commanders of each MAGTF element within the MEF.

A DT of the operating environment would be beneficial to the command element (CE) for integration into the planning process. The digital model could be shared by staff elements both up and down the chain of command as well as with adjacent units and partner forces to create a common operating picture that rapidly responds to changes in the physical environment. This would allow for improved collaboration between units and enable the rapid ingestion of new information through the visual representation of designated key performance parameters (Grieves, 2014). Different staff sections could also filter the display to highlight areas of interest. The intelligence, operations and logistics sections might be focused on different information, but it could all be

consolidated within the digital model. This method would also decrease the requirement for staff sections to pull information from subordinate units directly engaged in combat operations. The model would be incorporating updates from the network of sensors and staff sections would not have to wait for updated reports to confirm their assumptions.

The decision support tool would be highly advantageous to the CE during COA analysis. After developing several COAs, the CE would be able to run simulations to determine the likelihood of success for each of the alternatives. For the amphibious landings, different locations could be selected. The current known disposition of enemy forces would be captured by the digital model and likely enemy reactions could be simulated based on historical data. The model would also capture environmental data such as weather and tidal patterns to determine the optimal timelines to begin the operation. One of the most significant advantages to the DT-enhanced COA analysis is the agility of the model and its ability to incorporate changes. After running simulations, the decision support tool might recommend a particular landing area as having the highest probability of success. However, prior to execution, the operating environment could change due to a variety of factors such as the movement of enemy forces, environmental changes, delays in the arrival of supporting units or increased awareness of enemy defenses. These changes could impact the COA analysis simulation and change the probabilities associated with the alternatives, ultimately amending the recommended COA. The speed of the data analytics will allow for the incorporation of changes and give the commander a quantitative assessment that would not otherwise have been possible with such a short notice. The commander may decide whether to continue on with the original plan or whether the changes are significant enough to warrant a fragmentary order (FRAGO) with the new recommended COA for the subordinate units. The language processing tools would also allow for a quick generation of a FRAGO without having the CE go through the full order writing process.

After receiving the operations order from the CE, the GCE would begin preparation for their role in the amphibious assault. Having access to the digital model would allow the GCE commander and his staff to plan with the same information as the CE. The operations order would include objectives that were determined to be critical

vulnerabilities to the enemy's defense during the course of the simulations. These objectives would drive the planning process for the GCE, but the agile nature of the decision support tools would allow the GCE to shift the main effort based on feedback from the battlefield. Tasks such as fire support coordination could be simplified to a much greater extent as the plan is fed into the model and viewable by supporting elements. This would allow for the algorithm to incorporate fire support into the scheme of maneuver based on predetermined doctrinal concepts. This would further reduce the burden of planning considerations by the GCE staff.

Once the operation is in progress, the decision support tools would monitor the advancing units and provide continued operational support by twinning with the data from battlefield environment. For example, once the digital twin reported that a unit was in contact with the enemy and pinned down, this information would be incorporated and used to make further recommendations such as when to launch a quick reaction force (QRF). The decision of when to launch the QRF would be based on the bid for success of the scheme of maneuver, but the decision support tool could make a probabilistic recommendation for when it is necessary to commit the QRF and influence the outcome of an engagement to meet mission requirements. Similarly, the decision support tools would recommend when it is appropriate to execute a casualty evacuation (CASEVAC) based on data received from the battlefield. Depending on the detail of biometric data from wearable technology, the decision support tool could potentially support triage decisions as well. Medical personnel have to make difficult decisions about how to commit limited resources to prevent loss of life, but this analytical process could be enhanced by machine learning provided the data inputs can register the extent of the sustained injuries.

The ACE will use the decision support tool for the planning process in a similar manner to the GCE, but with a few notable differences. Aviation platforms benefit from digitization because the existing internal sensor network can provide diagnostic data for the aircraft and make recommendations to the pilots for optimal performance and to minimize degradation of component parts. The monitoring of component parts would also enable predictive maintenance procedures to replace parts before they reach failure.

This would minimize overall maintenance time and increase the availability of aircraft in an operational status.

In similar fashion to the QRF and CASEVAC prioritization decisions, the decision support tools could recommend how to maximize the availability of aircraft providing close air support (CAS) to ground units. Any time resources are limited, decision support tools can be employed to maximize the use of available resources. Flight plans could be devised by an algorithm to support maximum time on station. Prioritization based on the scheme of maneuver could also play a factor in determining the distribution of aircraft in a support role. The DT would also be valuable for airspace deconfliction. By tracking the location and flight paths of all aircraft in the battlespace, the decision support tool could recommend redirections and notify adjacent units when friendly aircraft will approach their location automatically. This would serve to reduce the likelihood of friendly fire incidents.

Wargaming simulations could also determine the probability of various occurrences for mission parameters depending on the resources assigned. For example, during the amphibious landing, high value targets would be assigned, and the analytical tools could determine the likelihood of destroying the target depending on the number of sorties assigned. Additionally, known enemy anti-aircraft defenses would be incorporated in the model and survivability predictions could be incorporated during the planning process to help commanders measure risk to mission.

The LCE would also be augmented by employing effective analytical decision support tools. Marine Corps employment of the push method of logistics requires detailed planning and accurate forecasting to enable timely and dependable support (USMC, 2023). The push method requires enhanced coordination but fosters greater efficiency by reducing the logistical footprint and the required inventory. Fortunately, much of the planning process can be automated with accurate historical consumption data as well as simulated forecasting based on feedback from the digital model. This could enhance the effectiveness of the LCE and free the staff to focus on coordinating efforts for the sourcing and movement of materiel support rather than extending the planning process with analytical tasks. Additionally, the shared digital model would foster improved

communication with the rest of the MAGTF by keeping the supply nodes as well as the various lines of communication highlighted for improved situational awareness.

3. Implications for Decision Support at the Strategic Level

Decision support becomes exceedingly more complex at the strategic level due to several reasons. First, tactical and operational decisions are made in support of overarching strategic objectives that have already been established. The decision to conduct an amphibious landing in a contested environment would only take place after the National Security Council established what are America's interests in the region. Analytical approaches to decision-making require a defined objective in order to determine the likelihood of success with differing COAs. Decisions at the strategic level have a much broader range of possibilities and competing interests to satisfy. Determining the prioritization of interests is often a matter of preference and not necessarily quantifiable.

Another challenge presented with strategic decision-making is strategic uncertainty. It is difficult to predict the behavior of other decision-makers with the ability to influence the outcome. This includes allies, adversaries and neutral parties with the potential to intervene. Game theory assumes all participants to be self-interested, rational actors, but even if this assumption holds true, it is extremely difficult to account for all potential motivating factors which might influence rational decisions (Hertwig et al., 2019). If historical data exists that demonstrates how key decision-makers reacted in very similar circumstances, it could give some insight into their expected future behavior. However, if the interaction has no precedent, then game theory refers to it as a one-shot game in which it is thought to be impossible to reduce uncertainty through inductive learning as players most often resort to decisions based on heuristics (Hertwig et al., 2019).

That is not to say that digital modeling has no utility at the strategic level. It is possible to simulate variables that will have strategic effects in the future. For example, if America has strategic interests in a region and is competing with an adversary to gain influence over the local population and leadership, different simulations could be

employed to determine how to maximize influence to the greatest extent possible. Building schools, improving the infrastructure, forging economic partnerships or introducing American media could each have the ability to reach different population centers. Through simulated wargaming, it could be determined how to employ resources to maximize influence and undermine the strategic interests of an adversary in the region. This application can be done because it has a limited scope and a defined objective of extending influence, and it would absolutely have strategic implications for future operations. Analytical tools can be employed to provide similar limited insights to strategic decision-makers, but the application of the decision support tool would be much more impactful at the tactical and operational levels.

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V. CONCLUSION

Modernization efforts are increasingly important as the disruptive technologies of the 4IR shape the nature of warfare in the future. Modern battlefields currently produce large volumes of data, and this trend is likely to increase exponentially as sensor networks are embedded into more combat systems and incorporated into the IOT. The value of this data will be in its application, and it is imperative that American forces effectively harness its potential in order to maintain a competitive advantage against potential adversaries.

This data-centric warfare will have multiple ramifications across each military community, but improved decision support tools offer the potential to radically enhance the capabilities of military leaders. COA wargames provide a solid foundation for quantitative analysis of military problems but can be limited by time constraints. The analysis is also limited to a fixed point in time because changes in the variables can alter the proposed solution to the wargame. The dynamic nature of warfare must contend with constantly shifting factors which greatly diminishes the long-term utility of any analysis.

DTs offer a solution to these issues because the two-way information flow between the physical assets and the digital model will enable near real-time updates to be continuously incorporated into an ongoing analysis. This will allow for agile solutions that can adjust as new information becomes available. The speed of the analysis is only limited to the processing power of the embedded AI/ML capabilities which will allow it to be incorporated into time-sensitive decisions. It will be crucial to adopt this emerging capability before it is employed by hostile forces.

A. RESULTS AND INSIGHTS

The following sections contain the most significant insights derived from the analysis in an attempt to answer the three research questions. Additionally, some of the expected challenges of implementation are addressed.

1. Improving Wargaming with Digital Twins

Current Marine Corps wargaming efforts focus primarily in the areas of force design, education, and training which fall in line with the three wargaming approaches: educational, experimental, and analytical (USMC, 2019). Under General Berger's leadership, the Marine Corps has placed a heavy emphasis on revamping its wargaming resources in these areas to advance its warfighting force but has fallen short (USMC, 2019). General Berger has stated that given the heavy commitment to developing new concepts over the last two decades, the rigorous proofing of new concepts through wargaming, modeling and simulation, experimentation, and analysis has been inadequate and will change (USMC, 2019).

Throughout the course of this research, it was determined that a DT-enhanced decision support tool has the capacity to effectively integrate into Marine Corps wargaming harnessing real-time data inputs of the physical environment coupled with its simulation capabilities. Furthermore, this provides decision-makers the ability to rapidly test and analyze current operations and future capabilities against the variability of the operating environment and fluidity of a pacing threat. Leveraging organic operational sensors and the IOT, a DT-enhanced decision support tool would allow wargaming participants to explore and execute conceptual testing against dynamic, real-time, real-world scenarios. In doing so, this method generates more contemporary quantitative data to assess emergent activities and force development.

Not overly emphasized in the Commandant's Planning Guidance nor the Marine Corps' next-generation wargaming (NGW) analysis conducted by the RAND Corporation, operational planning and tactical wargaming take a back seat to the Marine Corps' series of force design and capabilities development wargaming efforts. Throughout this research, it was determined that a DT-enhanced decision support tool would provide a significant advantage to commanders and their leaders at the tactical and operational level. The DT would serve as a tool to aid commanders in training, planning, and executing operations orders. In a training environment, the DT would help commanders wargame different COAs against a true depiction of the current battlespace without having to deploy a platoon, company, or battalion of troops into the training area

or actual operating space. The same is true for executing COA wargaming and analysis during MCPP or R2P2. Whether in training or pre-combat mission planning, different elements of the MAGTF or MEU could filter the DT to identify for example the current status of forces, meteorological and oceanographic (METOC) data, or supply levels and run multiple COAs against the current situation to determine highest probability of mission success. More so, once the mission is underway and executed, the DT can use its AI/ML capabilities to generate future COAs for follow-on missions or the execution of branch plans as unforeseen events may occur in the battlespace and require a commander to alter their plans.

Implementing a DT-enhanced decision support tool gives the Marine Corps and Commandant a command-and-control system that can integrate advanced wargaming functions for not only force design, education, and training, but can be allocated across the scope of all wargaming efforts. The DT can place Marine Corps leaders in the virtual operating space and yield real-time, real-world results from the outputs of the decisions being made and directly impact the physical space. These capabilities are not enabled by current wargaming, M&S, and experimentation efforts. However, they are capabilities which must be realized sooner rather than later before the adversary gains the upper hand by developing their own DT-enhanced decision support tool.

2. Improving the Commander's Decision-Making Cycle

Modifying the way that military commanders make decisions is a significant undertaking and should only be pursued if there can be a tangible improvement to the current process. Through the course of this research, it was determined that a DT-enhanced decision support tool has the capacity to both improve the speed of the decision process and improve the management of uncertainty. The deadline for a decision may be dictated by outside events, but the time required for analysis can be reduced with the proposed tools. Within the context of the dual process theory, commanders are able to access their tacit knowledge quickly to arrive at decisions but require more time for thorough analytical thinking (Stanovich & West, 2000). The DT-enhanced decision support tool will be able to conduct the data analysis function at a speed that allows it to

be incorporated into time-sensitive decisions. It does so by rapidly gathering data from the battlefield through the embedded sensor networks and other intelligence gathering apparatus and analyzing the data into actionable information that can improve the knowledge process of the commander prior to reaching a decision. Additionally, and perhaps most importantly, the DT offers the commander a dynamic model which adapts to changes in the physical environment. This gives commanders greater agility to modify decisions when appropriate due to changes in the operating environment that will affect their preferred COA.

When it comes to reducing uncertainty for commanders, this might not be a feasible goal due to the inability to properly quantify the cumulative level of uncertainty in any given situation. However, the proposed decision support tools show excellent potential in the effective management of uncertainty. Any recommendations made by the decision support system will be probabilistic and based on the known variables. Unknown variables which are not incorporated into the model have the potential to alter the outcome of any course of action and thus the fog of war can never be fully eliminated, but digital models have demonstrated the capacity to predict emergent behavior within specific system states (Grieves & Vickers, 2017). Again, while the decision support system is not an exact window into the future, it can provide clarity as to what conditions are likely to give rise to desirable and undesirable outcomes.

3. Appropriate Level of Command for a Digital Twin-Enabled Decision Support System

Determining the appropriate level of command to employ the decision support system is an important consideration because it helps to clarify the system's requirements. Through the course of the research, it was determined that the decision support tool would be most effective at the tactical and operational levels. The DT can absolutely help convey important information to strategic leaders which will help to inform decisions. The challenge is that the tactical and operational levels will be able to develop COAs with the intent of accomplishing objectives passed down from the strategic level. Strategic leaders do not have this luxury and will have to determine the desired end state on their own. Also, strategic uncertainty adds a level of complexity that

undermines the ability to make probabilistic estimates due to the inability to measure the adversary's motivations in a one-shot game (Hertwig et al., 2019).

Once strategic objectives are passed down to the operational level, the decision support system can assist leaders via COA wargaming methods to give probabilistic recommendations for mission success. At the operational level, many of the decisions have to do with allocating resources for maximum effectiveness. Whether the decision is when to commit a QRF, CAS, CASEVAC or where to position logistical nodes, the DT can give recommendations as to how they can be employed to support the most troops on the ground or prioritized in support of the mission's main effort. Having a shared digital model also enhances collaboration between units and reduces the time required to disseminate information both to higher headquarters and to subordinate elements. This should have the effect of decreasing the burden of requests for information and allowing staff sections to remain focused on mission accomplishment.

At the tactical level, the decision support tool would be shared with higher headquarters which ensures that the tactical COAs are within the scope objectives established by operational leadership. This facilitates rapid planning and communication between echelons. When conditions change, FRAGOs can be rapidly generated from higher headquarters allowing units to react quickly and exploit emerging opportunities. It would have to be at the commander's discretion when to issue the FRAGO to avoid too many rapid changes from unnecessarily adding confusion, but the capability to issue new orders as conditions change would be available.

The real advantage of the DT at the tactical level would be increased awareness. Using the DT during pre-mission planning for familiarization and then building a scheme of maneuver with a digital model showing real-time information about terrain and the disposition of enemy forces would be an invaluable tool. Finally, during the conduct of the operation itself, the maneuver element would have access to a GUI which would inform the unit of any changes in the operating environment while simultaneously collecting data to feed back to the DT and inform all parties involved.

4. Challenges

Effectively implementing a decision support tool is a disruptive process likely to face many initial challenges. There will be practical concerns about implementation and how to ensure functionality as well as process concerns regarding how to incorporate the tool into the decision cycle. Finally, there will likely be challenges stemming from human factors and resistance to change.

When it comes to practical challenges, a major challenge in the design of the system will be collecting relevant data. The IOT enables the extraction of a large quantity of embedded sensor data, but it needs to be relevant data that will ultimately drive decisions, otherwise it is just noise. To do this effectively, the information requirements need to drive data collection rather than just capturing all possible available data. Once the data is captured, the challenge will be filtering it for relevance to a specific application or query. The volume of the data can be overwhelming, and an important challenge will be using data mining practices suited for proper mission analysis. This will likely require partnership with industry to find the proper data mining techniques suited for the task.

Another practical challenge will be managing the data transmissions in the operating environment. This will entail detailed planning of spectrum management and allocation of bandwidth to ensure the system can function as intended. There should also be a capability to access the digital model when communications are degraded. This would mean the model would be static from the last instance of connectivity, but would still be capable of running simulations and would reintegrate with the updated shared model when communication is restored. This would allow units to operate in austere environments and maintain access to information in a denied environment.

When it comes to disrupting processes, the biggest challenge for implementing the decision support tool will be mitigating against underutilization and over reliance. Underutilization is likely to occur before leaders have established trust with the new application. Trust can be gained through sustained performance but will be a barrier initially causing leaders to disregard recommendations from the decision support tool.

Conversely, after being embraced by the force, there is a challenge that leaders could become overly reliant on the system's recommendations. The intent of the system is to complement the tacit knowledge of the commander and not to provide a definitive solution to complex situations. This will require a collective understanding of what the tool can and cannot do so that leaders will incorporate it into the planning process but will still be empowered to make decisions independent of the recommended COAs.

Finally, like any groundbreaking change there will likely be an instinctive initial resistance from leaders invested in current practices. It will be crucial to gain the buy-in of influential leaders within the DOD to achieve eventual acceptance for this new process. It cannot simply be a mandate from Congress to acquire the technology without leaders interested in the potential new capability. Organizational resistance can jeopardize the success of any innovation and it should be addressed during the development of the new capability.

B. RECOMMENDATIONS

(1) Begin Modeling/Digitization Efforts

The USMC is waves away from utilizing a digital twin for command and control, decision support, and wargaming for the following reasons. First, the Marine Corps must understand best practices to leverage the data produced by all of its sensors and the IOT and then be able to facilitate the flow of data and information to and from the tactical environment. Bridging this gap requires immediate action mandating digital twinning of all new systems and platforms going through the procurement process. Second, every new system which comes online becomes a digital twin instance that feeds into the overall digital twin aggregate, the DT-enhanced decision support tool. Simultaneously, efforts must be undertaken to update all legacy systems by emplacing sensors to build a robust DT network of current programs of record, commercial off-the-shelf (COTS), and government off-the-shelf (GOTS) equipment and systems. Updating these legacy systems and building out a digital footprint of the force will be labor and time intensive which is why these efforts must be underway immediately. Therefore, considering proliferation of

the DT capabilities, it is recommended to advance system engineering efforts of DT to the legacy systems' environment.

(2) Implementation of Digital Twin into Wargaming to Change Mental Models

Wargaming continues to be executed using constructive, live, or virtual means to test decision-making abilities. These mediums come in the form of sand table or tabletop exercises, matrix games on a board, Kriegsspiel games, live exercises, or computer-aided games. M&S was a significant addition aiding wargame results with quantitative data, but there have not been many in game technological advancements to assist the decision-making process. While a DT-enhanced decision support tool is being developed, the Marine Corps must incorporate advanced AI/ML tools like Rhombus Guardian which is used by the Air Force for wargaming to support live decision-making during the wargame. Leaders at all levels of war, not just the strategic or the higher headquarters operational level, need to be accustomed to these kinds of tools and learn how to incorporate them into their own decision cycles as well as institutional planning processes. Decision support tools need to be incorporated across the wargaming approaches to improve professional military education, operational planning, campaign execution, and so on. The only way to make people comfortable with technological advancement is by inducing its use in all facets of military operations.

(3) Maintain Information Sharing between Agencies

This thesis focused specifically on the incorporation of a DT into Marine Corps decision support process, however development of a digital twin for command and control and decision support must facilitate interoperability across all branches of the DOD and intelligence community (IC). The 9/11 Commission Report suggests information sharing must expand beyond the individual organization and across all networks in order to reach as many customers as possible (National Commission on Terrorist Attacks upon the United States, 2004). That said, the long term goal will not be a separate DT for each respective service nor the IC, but rather all branches of service being incorporated as a part of an all-inclusive DT. Individual services can develop DT in

the aggregate, but should follow some degree of standardization that would enable integration and interoperability in the future. Because of the DTs' universality, it may be best suited for ownership of this type of DT to reside within USCYBERCOM or National Security Agency/Central Security Service. The system is cyber in nature and will require defense of its networks as well as censoring of an aggregation of sensitive systems.

C. AREAS FOR FUTURE RESEARCH

(1) Battlefield Data Extraction Supporting Digital Twins

In order to build a comprehensive DT of operating forces, data will have to be extracted from a wide range of sources. The information requirements of commanders will dictate what data needs to be incorporated into the DT. Future research could be conducted on what those data inputs are and how to best capture the useful data from the operating environment. Additionally, the research could analyze best practices for data management and data mining or data farming techniques necessary for the proposed decision support algorithms.

(2) Autonomous Decision-Making

The decision support tool proposed in this research is intended to provide quantitative analysis that will assist leaders in reaching a decision. There may however be specific applications when maintaining a human-in-the-loop is unnecessary and potentially even disadvantageous. Some decisions are routine enough that efficiency would be gained through automation. Also, if a decision cycle becomes compressed to the point where there is no time to incorporate human decision-making, automation may become a necessity. Future research could be conducted on which type of decisions should be automated and when a commander's decision is still required.

(3) Acquisition Strategy for Developing Technology

Some of the necessary supporting technology may be presently available in the private sector, while some of it may require partnership with industry to reach the necessary technology readiness level to begin the acquisition process. Future research could be conducted to determine the COTS and GOTS availability of component

technology as well as the recommended acquisition strategy for developing the technology to meet projected requirements. This would entail looking at initiatives internal to the DOD as well as in the private sector relating to DT applications.

(4) Policy Recommendations

Building a DT of the operating forces is a major undertaking that will require the support of many government agencies. In order for this initiative to be successful, it will have to receive both a high level of prioritization and funding. This will entail policy changes within the Executive Branch and may even require modification to existing legislation. Future research could be conducted as to what new policies would need to be implemented and what existing policies would impede progress and need to be amended in support of this initiative.

(5) Modeling Techniques for Digital Twins

This research identified the ability to support conceptualization, comparison, and collaboration among users as a major benefit of DT (Grieves, 2014). To fully take advantage of the enhancement to knowledge processes of the DT application, a proper modeling technique will need to be selected to give users the ability to effectively interface with the application and filter out the requisite knowledge for a given task. Future research could be conducted that would contrast different digital modeling techniques and make a recommendation about which is best suited for this application.

(6) Cyber-Security Concerns

The growth of the information environment made cyber-security an area of increasing concern throughout the DOD. Creating a DT of the operating forces is a consolidation of information that presents an extremely attractive target for an adversary to gain an unprecedented look at American capabilities. The importance of maintaining the security of this information is extremely high, but part of the value of the DT is the ability to share information. This undertaking will raise difficult questions about how much access to the DT should be compartmentalized and whether that might impede upon its value for interoperability. The expansive data gathering environment also

presents an opportunity to engage in military deception or potentially fall prey to enemy MILDEC operations. Future research could be conducted to determine how to best implement cyber-security in this environment and when to allow information sharing among partner forces.

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APPENDIX. VIGNETTE

To discuss the command implementation of the proposed decision support system, it was helpful to analyze a vignette of a potential scenario. To create the vignette, the artificial intelligence chatbot ChatGPT was given the prompt “Develop a vignette detailing an amphibious operation.” In response, it produced the following vignette:

“The amphibious assault operation was planned with military precision. The naval vessels had been assembled off the coast, their decks laden with the necessary equipment, weapons and personnel for the landing. The troops had been briefed and trained for weeks on the upcoming operation, ready to execute their duties with maximum efficiency.

The target was a beachhead on the enemy-held territory, a strategic location that had to be taken to secure the allied advance. The operation had to be carried out with utmost care to avoid detection by enemy patrols and to prevent any potential counter-attack.

As the naval convoy approached the coast, the amphibious assault vehicles were lowered into the water. The sea was choppy, and the waves crashed against the hulls of the boats as they made their way towards the beach. The troops were packed tightly in the vehicles, their faces grim and determined.

The enemy coastal defenses had been pounded by allied naval artillery for several hours, creating a smoke-filled screen that shrouded the beach. The landing craft made their way towards the shore, their engines roaring as they pushed through the surf. The first wave of troops emerged from the vehicles and rushed towards the beach, their weapons at the ready.

As they approached the shore, the enemy’s coastal defenses opened fire. Bullets whizzed past the soldiers, sending plumes of sand into the air. The troops returned fire with deadly accuracy, their shots ringing out across the beach.

The beachhead was quickly secured, and the troops moved inland to secure the area. The amphibious vehicles continued to ferry troops and equipment from the ships to the shore, as the allied forces established their foothold on the enemy-held territory.

Despite the initial success of the landing, the troops knew that the operation was far from over. The enemy was sure to mount a counterattack, and the soldiers remained vigilant and alert, ready for whatever may come their way.

As the sun began to set over the beach, the amphibious landing operation continued, with the troops working tirelessly to secure the area and push further into enemy territory. The success of the operation would hinge on the bravery and dedication of the soldiers, as they fought to secure victory for their country and their cause” (OpenAI, 2023).

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