Stephen Moore st690445@ucf.edu University of Central Florida Orlando, Florida, USA



Figure 1: Italian Army Maj. Stefano Catania (right) and U.S. Army Maj. Keith Weaver discuss potential locations of their troops during a game of "Land power" as U.S. Army Maj. Colin Bair (back left) observes at the U.S. Army Command and Staff College, Fort Leavenworth, KS. 2018. [3]

#### Abstract

Military tactical planning requires rapid analysis and clear communication of complex battlefield variables to support commander decision-making. While recent initiatives have introduced automated analysis tools, these systems still produce raw data that requires manual interpretation and conversion into actionable information. This research introduces a novel approach to tactical planning by leveraging Large Language Models (LLMs) to automatically interpret analytical outputs and generate doctrinally sound military plans. This research introduces a customizable planning tool that combines traditional tactical analysis with few-shot prompted LLMs to generate Operations Orders (OPORDs) in natural language. The tool's effectiveness was evaluated by a panel of five military domain experts using standardized Task Evaluation Outlines across three different OPORD styles with varying numbers of few-shot examples. Results demonstrate that LLMs can effectively generate military plans meeting doctrinal standards, with optimal performance achieved using three to five few-shot examples. Unlike previous research utilizing commercial gaming platforms, this approach enables organizations to customize force compositions, terrain, and tactical considerations to match their specific operational requirements. This research suggests that LLMs can successfully bridge the gap between automated tactical analysis and human decision-making, potentially accelerating the military planning process while maintaining plan quality.

#### **CCS Concepts:**

Simulation types and techniques; Neural networks; Applied computing—Military.

#### **Keywords:**

military planning, large language models, few-shot learning, course of action development, operations orders

#### 1. Introduction

Military tactical planning has traditionally relied on analog tools - maps, acetate overlays, printed reference guides, and standardized checklists. While these methods have proven reliable over decades of military operations, they require significant manual effort to compile, analyze, and synthesize information for commander decision-making. More recent initiatives have introduced computer-based tools, primarily centered around spreadsheets with embedded formulas and interactive dashboards, to assist in data organization and basic analysis. Some specialized software applications can even conduct automated terrain analysis or calculate weapons effectiveness. However, a critical limitation persists across both analog and digital approaches: they produce raw data that military staff must manually convert into actionable information and knowledge before commanders can make informed decisions.

This manual interpretation process creates a significant bottleneck in the military decision-making cycle. In modern warfare, where the speed of decision-making can provide a decisive advantage over adversaries, this bottleneck represents a critical vulnerability. The concept of "decision advantage" - the ability to process information and act faster than an opponent - has become increasingly central to military doctrine. Yet current planning tools, while effective at gathering and processing data, still rely heavily on human analysts to translate technical outputs into natural language assessments that commanders can quickly comprehend and act upon.

Recent advances in artificial intelligence, particularly in Large Language Models (LLMs), offer a potential solution to this challenge. These models have demonstrated remarkable capabilities in natural language processing and generation, including the ability to interpret complex data and present it in clear, narrative formats. By integrating LLMs with existing military analysis tools, we could potentially automate not just the data processing, but also the critical step of converting analytical outputs into clear, actionable information for commanders. This automation could significantly reduce the time required for tactical planning while maintaining or even improving the quality of information provided to decision-makers.

This research explores the feasibility of developing a tactical planning tool that leverages LLMs to bridge the gap between automated analysis and human decision-making. Specifically, how few-shot learning techniques can be applied to adapt existing LLMs for military planning applications, without the need for extensive model retraining. Additionally, the research also addresses the crucial requirement for customization, ensuring that such a tool can accommodate the unique operational contexts of different military organizations. Through experimental evaluation with military domain experts, the research assesses both the technical performance and practical utility of this approach in generating tactical plans that meet doctrinal standards.

#### 2. Features of LLMs

Before delving into current research, it is crucial to establish a baseline understanding of LLMs. In essence, an LLM is a machine learning model trained to generate text-based responses from text-based prompts. While there were predecessors capable of similar tasks, LLMs stand out due to three distinguishing features: size, architecture, and versatility [5].

#### Size

The scale of LLMs, both in terms of training data and model parameters, sets them apart from the earlier models. For instance, the BERT model, an early breakthrough in language modeling, was trained on approximately 3.3 billion words (about 16 GB of text data), resulting in 110-340 million parameters. [4] In contrast, GPT-2, one of the first widely recognized LLMs, used a dataset nearly triple this size (about 40 GB of text data), with 117 million to 1.5 billion parameters [10]. Subsequent LLM releases have continued this trend of growth in both dataset size and parameter count. The increased size of LLMs contributes significantly to their performance and capabilities. According to Brown et al. [2], larger models with more parameters can capture and utilize a broader range of knowledge and patterns from the training data. This allows them to generate more contextually appropriate and diverse responses to prompts, as well as demonstrate improved performance across a wide range of tasks without task-specific fine-tuning.

### Architecture

LLMs employ Transformer architectures, which offer several advantages over the previously used Long Short-Term Memory (LSTM) networks [8]. Key benefits include:

1. Parallel processing: Transformers can conduct parallel processing due to their self-attention mechanism, which allows them to process all input tokens simultaneously rather than sequentially [12]. This parallel computation is possible because the self-attention operation can be implemented as matrix multiplications, which are highly efficient on modern hardware like GPUs. As a result, Transformers can process

long sequences much faster than recurrent architectures like LSTMs

- 2. Improved handling of long-range dependencies: Transformers excel at handling long-range dependencies because their self-attention mechanism allows each token to directly attend to every other token in the sequence, regardless of their distance [12]. This direct connection enables the model to capture relationships between distant parts of the input without the information degradation that occurs in sequential processing of RNNs and LSTMs. As a result, Transformers can maintain context over much longer sequences, which is crucial for understanding and generating coherent text.
- 3. Self-attention mechanism: This allows the model to weigh the importance of different parts of the input when producing each part of the output. The self-attention mechanism works by computing attention weights for each token with respect to all other tokens in the input sequence [12]. For each token, the model calculates query, key, and value vectors. The attention weights are then computed by comparing the query of one token with the keys of all tokens, determining how much focus should be placed on other parts of the input when encoding that specific token. These weights are used to create a weighted sum of the value vectors, producing a context-aware representation for each token. This process allows the model to dynamically focus on relevant parts of the input, regardless of their position in the sequence.

#### **Versatility**

A consequence of their size and architecture is the remarkable versatility of LLMs. They can perform a wide range of tasks with minimal fine-tuning or retraining. Recent developments have even expanded LLMs' capabilities to process and produce images by combining the Transformer architectures with various machine learning image and audio processing techniques [5].

## 3. Related Work

Recent advances in artificial intelligence, particularly in the development of Large Language Models (LLMs), have demonstrated remarkable capabilities in natural language processing and generation. These models, trained on vast datasets of text. show potential for applications ranging from simple text completion to complex reasoning tasks. However, implementing domain-specific applications of LLMs presents significant challenges, particularly in specialized fields that require precise outputs and domain expertise. Researchers have explored various approaches to adapting these models to specific use cases, with particular attention to resource-efficient methods that can leverage existing models rather than training new ones from scratch. This review examines key findings regarding few-shot learning approaches, the importance of prompt engineering, and domain-specific applications, with particular focus on their implications for military planning tools.

#### In-Context and Few-Shot Learning

In-context learning represents a paradigm shift in how AI models can be adapted to new tasks. Unlike traditional approaches that require extensive model fine-tuning with thousands of examples, in-context learning allows models to learn from a few demonstrations provided directly in the input prompt. Few-shot learning, a specific type of in-context learning, involves providing the model with a small number of example pairs showing the desired input and output format. This approach effectively "teaches" the model how to

perform a task through demonstration rather than parameter updates.

Brown et al. [2] first demonstrated the effectiveness of this approach in their seminal work on GPT-3. By testing the model across a wide range of tasks with varying numbers of examples (from zero to 100), they showed that performance generally improves with additional examples, though with diminishing returns. Their research revealed that few-shot learning success depends heavily on the model's pre-existing domain knowledge, suggesting that while this approach offers significant resource efficiency, it requires careful evaluation of the model's baseline capabilities. This finding has important implications for tool development, indicating that preliminary domain knowledge assessment should precede few-shot implementation.

#### Prompt Engineering and Example Selection

Liu et al. [9] advanced our understanding of few-shot learning by examining the relationship between example selection and model performance. Through systematic testing of different prompt compositions across multiple tasks, they demonstrated that prediction accuracy improves significantly when the vocabulary and phrasing in few-shot examples closely align with the desired output. Their work involved creating a retrieval-augmented prompt selection system that dynamically chose relevant examples based on semantic similarity to the target task. This research suggests that tool developers should prioritize careful curation of few-shot examples that closely match their intended output format and domain terminology.

Rubin et al. [11] further refined prompt engineering best practices through their work on efficient prompt retrieval. By comparing performance between randomly selected examples and carefully curated ones, they showed that specific, detailed examples consistently outperform randomized ones. Their methodology involved developing an automated system for selecting and evaluating prompt effectiveness, providing a framework for systematic prompt optimization. These findings emphasize the importance of maintaining a well-curated library of detailed examples when implementing few-shot learning in practical applications.

#### **Domain-Specific Considerations**

While few-shot learning shows promise, Gutierrez et al. [7] provided important cautionary findings regarding its limitations in high-stakes applications. Through comparative analysis of few-shot learning versus fine-tuned models in biomedical information extraction tasks, they demonstrated that in technically demanding domains with low error tolerance, fine-tuning approaches may be more suitable. Their research involved extensive testing across multiple biomedical tasks, showing that while few-shot learning could achieve reasonable performance, it fell short of fine-tuned models in critical accuracy metrics. This work highlights the importance of carefully evaluating the trade-offs between implementation efficiency and output reliability when choosing an approach.

#### Military Planning Applications

In the military domain, Goecks and Waytowich [6] explored the application of LLMs for Course of Action (COA) development using StarCraft II as a simulation environment. Their research demonstrated the potential of LLMs in military planning by successfully generating tactical plans that matched human expert performance in specific scenarios. However, their reliance on a commercial gaming platform revealed significant limitations: the rigid constraints of gaming environments cannot adequately represent the

diverse operational contexts faced by different military organizations. Each organization operates in unique terrain, against different adversaries, and with varying force compositions and capabilities - factors that cannot be accurately modeled within the constraints of commercial gaming platforms. This work highlights both the potential of LLMs in military planning and the critical need for customizable simulation environments that can accurately represent specific operational contexts.

This body of research suggests that while few-shot learning offers a promising approach for leveraging LLMs in specialized applications, its successful implementation requires careful consideration of domain requirements, prompt engineering, and the limitations of available simulation environments. The findings collectively indicate that a successful military planning tool must balance the efficiency of few-shot learning with the need for accuracy and customization in military applications.

#### 4. Method

As stated in the research presented by Brown et al. [2], a LLM must possess some knowledge of the domain for few-shot prompting to have results. Therefore, the first step in evaluating if a tactical planning tool could capitalize on the resources expended by others to train an LLM was to determine the level of knowledge the model possessed. By asking whether the LLM could describe the composition of a US Army Infantry Platoon, what comprised of a platoon level OPORD, and what steps were involved in conducting a platoon level attack, it was determined that Anthropic's Claude 3 LLM could accept few-shot prompt engineering for the purpose of the tactical planning tool.

In exploring the possibility of leveraging the advancements in LLMs for use in developing tactical plans, the research was guided by two principles - the tool must be customizable, and the tool must be easy for the end user. The customization principal deals with the fact that each organization is purpose built for its unique area of operation. The force composition for the friendly and enemy organizations, in both equipment and personnel, and the logic behind the tactics employed for either side vary across the vast military enterprise. If an organization cannot tailor the tool to suit its needs, it is unlikely the organization will adopt the tool as a useful component within the organization's arsenal. The ease-of-use principal deals with the fact that a staff officer or non-commissioned officer is inundated with a multitude of applications, some of which are very niche and require a special training regimen prior to use, and that their cognitive load is near peak given the nature of their job. So, if the tool is cumbersome and amplifies the cognitive load, the adoption of the tool is highly unlikely.

#### Customization

Within military decision-making processes, there are frameworks that guide the planner to understand the variables necessary to the problem. The process employed in this tool is the "Troop Leading Procedures" where a military leader analysis a tactical problem through the "Mission Variables" to ultimately develop a tactically sound plan known as an Operations Order (OPORD). The mission variables, simplified into an acronym – METT-TC, represent how the leader considers the critical components of the Mission given the Enemy's composition and capabilities

within the Terrain for the operation. The analysis of how to react to the threat given the mission help the leader determine how to synchronize the Troops available given the Time and Civilian presence considerations. As stated before, the variables change based upon the organization and its area of operations; therefore, the following aspects of the tool were created to afford the organization the ability to customize the variables in its operation.

#### 1. Modeling of Units.

To serve as a proof of concept and keep the classification level within the realm for further academic research, the information regarding friendly and enemy force composition was derived from publicly releasable sources. Furthermore, the aggregation of formation was reduced to a standard US Army Infantry Platoon and a squad from a Russian Armed Forces Assault Detachment [1]. The result of these sources help defines the "Troops Available" and "Enemy" variables and are captured in two files: US\_Army\_PLT\_Composition.py and Russian\_AF\_ASLT\_DET\_Cap\_SQD.py.

The unit modeling system implements a flexible, objectoriented structure that mirrors the hierarchical nature of military organizations while capturing the key attributes that influence tactical decision-making. Rather than modeling every aspect of military units, the system focuses on the critical factors that affect tactical planning: observation capabilities, weapons ranges, and formation geometries.

The data structure uses a nested object model that reflects military organization:

```
Platoon
— Leader
— Squads[]
— Leader
— Alpha Team
— Leader
— Members[]
— Bravo Team
— Leader
— Members[]
— Gun Teams[]
— Javelin Teams[]
```

Each soldier maintains key tactical attributes that aggregate up through team, squad, and platoon levels:

- Observation range (typically 480m, representing human visual detection capability)
- Engagement range (based on weapon system, e.g., 500m for M4 rifle)
- Position coordinates
- Health status
- · Weapon systems with ammunition counts

The modular design allows organizations to easily modify force structures by adjusting the dataclass definitions. For example, an organization could modify the weapon definitions to match their specific equipment:

```
M4 = Weapon("M4 Rifle", 50, 210, 1, "rifle_fire",
False)  # 500m range, 210 rounds
PKM = Weapon("PKM", 110, 600, 6, "mg_fire", True,
6)  # 1100m range, 600 rounds
```

The system processes this information through several stages:

- Initial unit creation with default positions and capabilities
- 2. Formation application that positions units according to doctrinal templates
- 3. Movement execution that maintains unit cohesion and proper spacing
- Combat capability calculation that considers weapons effects and ranges

#### 2. Modeling of Terrain.

The terrain modeling system was developed to capture the essential elements that influence tactical movement and positioning while remaining computationally efficient. The system uses a grid-based representation where each cell contains multiple layers of tactical information.

The terrain system uses five basic terrain types (BARE, SPARSE\_VEG, DENSE\_VEG, WOODS, STRUCTURE) and three elevation levels (GROUND\_LEVEL, ELEVATED\_LEVEL, LOWER\_LEVEL). Each terrain type has associated characteristics that directly impact tactical planning:

- Movement costs (ranging from 1.0 for bare ground to 3.0 for structures)
- Visibility factors (1.0 for bare ground to 0.0 for structures)
- Cover values (0.0 for bare ground to 0.9 for structures)

Data structure for terrain cells:

```
TerrainInfo:
    terrain_type: Enum(BARE, SPARSE_VEG, DENSE_VEG, WOODS, STRUCTURE)
    elevation_type: Enum(GROUND_LEVEL,
ELEVATED_LEVEL, LOWER_LEVEL)
    movement_cost: float # Base movement cost
    visibility_factor: float # How visible units
are in this terrain
    cover_bonus: float # Protection provided by
terrain
```

The system processes terrain information through several analytical layers:

- 1. Basic terrain characteristics (movement costs, visibility)
- Elevation effects (movement penalties, observation advantages)
- 3. Cover calculations (protection from fire)
- 4. Concealment calculations (protection from observation)

Organizations can easily modify these values through the PathCosts class to match their specific operational environment:

```
TERRAIN_MOVEMENT_COSTS = {
   TerrainType.BARE: 1.0,
   TerrainType.SPARSE_VEG: 1.2,
   # ... etc
}
```

#### 3. Position Identification.

The position identification system implements a militarystyle analysis process that evaluates potential positions based on their tactical utility. The system was designed to replicate how a human commander would evaluate terrain for different tactical purposes.

The tactical\_position\_analyzer.py file implements three main position types:

- FIRE\_SUPPORT: Long-range positions with good observation
- SUPPORT\_BY\_FIRE: Medium-range positions for direct fire support
- ASSAULT: Final covered and concealed positions before assault

The analysis occurs in several phases:

- 1. Initial Filtering
  - Check basic position requirements (size, accessibility)
  - O Eliminate obviously unsuitable locations
- 2. Detailed Analysis
  - O Calculate fields of fire to objective
  - Evaluate cover and concealment values
  - O Assess mutual support capabilities between positions
  - Consider enemy threat exposure
- 3. Position Scoring
  - O Weight various factors based on position type
  - O Calculate final quality score
  - $\,\circ\,$  Rank positions by score

For example, when evaluating a support-by-fire position, the analyzer considers:

```
quality_score = (
   los_quality * 0.4 +
   elevation_score * 0.3 +
   cover_score * 0.2 +
   concealment_score * 0.1
)
```

Organizations can modify these weights or add additional factors to match their tactical doctrine.

## 4. Route Planning.

The route planning system combines traditional pathfinding algorithms with military movement considerations to generate tactically sound routes. The

tactical\_route\_analyzer.py file implements an enhanced A\* pathfinding algorithm that accounts for multiple movement considerations while maintaining unit cohesion and tactical advantage.

The planning process occurs in several stages:

- 1. Tactical Cost Calculation
  - Movement costs through terrain
  - Exposure to enemy observation
  - Exposure to enemy weapons
  - O Available cover and concealment
  - Formation requirements
- 2. Route Generation
  - Modified A\* algorithm with tactical costs
  - Formation-specific movement constraints
  - Coordination point identification
  - Movement technique selection
- 3. Route Refinement
  - Smoothing of sharp turns
  - Addition of coordination measures
  - Movement timing calculations

Route costs are calculated using a weighted combination of factors:

```
segment_cost = (
   movement_cost * 0.3 +
   exposure_cost * 0.3 +
   (1 - cover_value) * 0.2 +
   (1 - concealment_value) * 0.2
)
```

The route planning system also considers different movement techniques (traveling, bounding) and formation types (wedge, column, line), adjusting its calculations accordingly. For bounding movements, the system alternates between moving and overwatch positions, maintaining tactical security throughout the movement.

Organizations can adjust these weights to emphasize different factors based on commander's guidance. For instance, increasing the exposure\_cost weight would result in routes that prioritize avoiding enemy observation over finding the shortest path.

### 5. Few-Shot Prompting.

Although there is a doctrinal foundation for the format of an OPORD, organizations have the latitude to tailor the format to suit their commander's needs. To set the foundation for the experiment, one general format for the OPORD was used; however, three distinct styles were developed that emphasize certain considerations depending upon the style selected by the user. The idea is that this will help determine how much information could be translated from the input source given the style selected.

The OPORD\_Converter implements three distinct styles for order generation:

 Task-Oriented: Emphasizes specific unit tasks and detailed coordination measures. Example: "1st Squad

- conducts support-by-fire from POS ALPHA (100,200) to suppress enemy positions."
- Effects-Based: Focuses on desired battlefield effects rather than specific unit tasks. Example: "Establish fire superiority from POS ALPHA to enable freedom of movement in the objective area."
- 3. Terrain-Centric: Emphasizes terrain exploitation and control of key terrain. Example: "Control elevated terrain at POS ALPHA (100,200) to dominate western and southern approaches."

These styles can be customized by modifying the fewshot examples in the OPORD\_Converter class to match an organization's preferred order format while maintaining the essential tactical information.

#### Ease of Use

There are two facets to the ease-of-use principle for this tool: is it easy for the planner to use, and is it easy for the planner to debug during customization? With regards to debugging, troubleshooting a digital tool used in the military often requires additional money for the developer to send a contractor for support. The proprietary nature of the software in most of these digital tools prohibits US Army personnel from directly modifying the code and creates a dependency on the company, often referred to as "vendor lock." To avoid this limitation, this tool's backend code was developed using the widely popular Python programming language. Additionally, Anthropic's Claude model was chosen as the LLM to integrate within the tool. The vast number of online resources and documentation for both Python and Claude make this an ideal design decision to support potential novices in computer coding languages.

For the user interface facet, the tool draws inspiration from the significant user experience research conducted by both OpenAI and Anthropic for their LLM interfaces. The simple chat log approach not only reduces cognitive load on the user but also brings familiarity by mimicking interfaces they likely already know through ChatGPT or Claude. To implement this design philosophy, the front-end application was developed using Streamlit, another widely documented resource. Streamlit's extensive library of visually appealing packages and its use of Python creates an accessible foundation that organizations can easily customize to match their specific needs while maintaining a professional, intuitive interface for their planners.

The tool's underlying architecture further enhances user experience by seamlessly gathering and processing the complex variables required for tactical planning, significantly reducing the cognitive burden on military planners. This is achieved through two distinct prompt engineering strategies that balance analytical rigor with intuitive interaction. The XML Tagging strategy, implemented in Prompt\_Tagger.py, structures the complex tactical planning process into clearly defined components:

## <ROUTE\_ANALYSIS>...</ROUTE\_ANALYSIS> /TACTICAL ANALYSIS>

This structured approach serves multiple purposes:

- Ensures consistent processing of tactical information across different planning scenarios
- 2. Maintains clear separation between terrain analysis, position identification, and route planning
- Allows for systematic validation of each planning component
- Makes it easier to trace how the LLM processes military decision-making steps

The Few-Shot Prompt strategy, implemented in Response\_Processor.py, helps maintain natural conversation flow while ensuring tactically sound responses. The processor includes pre-defined response templates for common tactical situations:

- · Initial mission analysis and confirmation
- Force composition validation
- Route and position analysis completion
- Error handling and parameter adjustment requests

For example, when a user asks about specific aspects of the plan, the Response\_Processor.py can recognize the query type and format the response appropriately:

```
'analysis_complete': """I've completed the tactical analysis for your mission. Here's a summary of the key points:

{summary_points}

The detailed OPORD and tactical overlay are available in the right panel. Would you like me to explain any specific aspect of the plan?"""
```

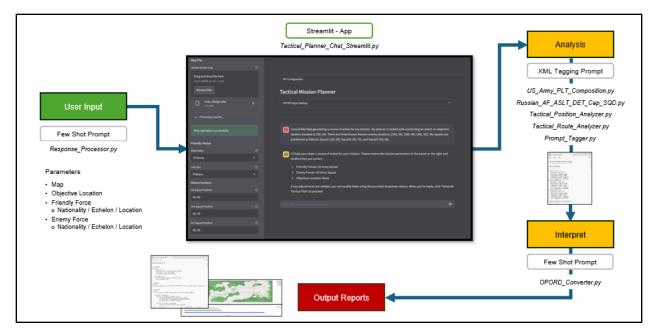
This dual-prompt strategy allows the tool to:

- Process complex tactical calculations in a structured manner behind the scenes
- Present information to users in a natural, conversational format
- Maintain consistency in how tactical information is communicated
- 4. Anticipate and handle follow-up questions about the plan

The result is a tool that maintains rigorous tactical analysis while presenting information in an accessible, intuitive manner that reduces cognitive load on the user. This balance between analytical depth and user-friendly interaction helps ensure that military planners can focus on tactical decision-making rather than wrestling with complex software interfaces.

#### Tactical Planner Tool

Below is a diagram that illustrates the how developed tool operates and pulls together the approach described above.



The process begins with the user providing the essential parameters through a Streamlit interface:

- Map data
- Objective location
- Friendly force details (nationality, echelon, location)
- Enemy force details (nationality, echelon, location)

The input is processed through Response\_Processor.py and Prompt\_Tagger.py, which structures the data for analysis through several specialized modules:

- US\_Army\_PLT\_Composition.py and Russian\_AF\_ASLT\_DET\_Cap\_SQD.py for force composition
- Tactical\_Position\_Analyzer.py for position evaluation
- Pathfinding.py and Tactical\_Route\_Analyzer.py for route planning

The system then interprets the analyzed data through OPORD\_Converter.py, which transforms the tactical analysis into written documentation and tactical map overlays, providing a comprehensive tactical solution.

#### **Experiment Design**

To evaluate the tactical planning tool, an experiment was designed to address two primary research questions:

- 1. How effective is few-shot prompt engineering for LLMs in converting information into formatted military documents?
- 2. What impact does the number of few-shot examples have on processing time, accuracy, and document quality?

The experiment utilized a panel of domain experts from the University of Central Florida's Modeling and Simulation Program. The panel consisted of five active-duty US Army Officers, each with an average of 13 years of service and distinguished leadership evaluations. Each expert evaluated the tool's output while using a standardized Task Evaluation Outline (TE&O) - a Department of Army approved checklist that details required performance measures for specific tasks.

To accommodate research time constraints while maintaining meaningful evaluation criteria, the TE&O was adapted to focus on 16 key performance measures. Rather than the traditional "Go/No Go" evaluation system, a three-point scale was implemented:

- 0.0: Performance measure not demonstrated
- 0.5: Performance measure demonstrated with minimal context
- 1.0: Performance measure demonstrated with ample context

The experimental design included three variables:

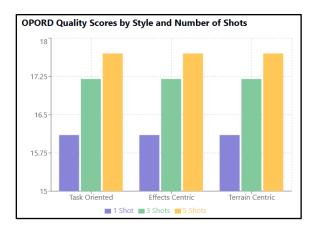
- Document Quality: Measured through expert scoring of the 18 performance measures using the adapted TE&O scale (Task: Prepare and OPORD / Number: 171-123-1095).
- Few-Shot Example Impact: Each expert evaluated OPORDs generated using 1, 3, and 5 few-shot examples. The examples were sequentially constructed with increasing levels of context and description, with the fifth example containing the most detailed descriptions.
- 3. Technical Performance: Two metrics were tracked:
  - Processing Time: Measured through built-in logging functionality during each iteration
  - Accuracy: Assessed by comparing numerical data points (enemy size, friendly force size, objective location) between input and output

Each domain expert evaluated the tool while sitting at an active session of the Tactical Mission Planner, using a standardized prompt to ensure consistency across evaluations. This comprehensive approach allowed for measurement of both the tool's technical performance and its practical effectiveness in military planning scenarios.

#### **Experiment Results**

The experimental results revealed a consistent pattern of improvement across shots, regardless of OPORD style. A three-way ANOVA was conducted to examine the effects of:

- OPORD style (Task Oriented, Effects Centric, Terrain Centric)
- Number of few-shot examples (1, 3, 5)
- Evaluator expertise (5 experts)



#### Statistical Calculations:

- 1. Mean Scores by Number of Shots:
  - $\circ$  1 Shot:  $\mu_1$  = 16.1 (SD = 1.21)
  - $\circ$  3 Shots:  $\mu_3$  = 17.2 (SD = 0.73)
  - $\circ$  5 Shots:  $\mu_5$  = 17.7 (SD = 0.89)
- 2. ANOVA Calculations:
  - o Significant main effect for number of shots: F(2,36) = 8.94, p < .001,  $\eta^2 = 0.33$
  - No significant main effect for OPORD style: F(2,36) = 0.00, p > .99
  - Significant evaluator effect: F(4,36) = 3.21, p = .024, n² = 0.26
  - Inter-rater reliability: ICC = 0.86, 95% CI [0.81, 0.91]

The results indicate that increasing the number of fewshot examples significantly improves OPORD quality, with the most substantial improvement occurring between 1 and 3 shots. Post-hoc Tukey tests showed significant differences between 1 and 3 shots (p < .01) and between 1 and 5 shots (p < .001), but not between 3 and 5 shots (p = .06).

The consistency across OPORD styles suggests that the tool is equally effective regardless of the chosen format. The significant evaluator effect primarily stems from variations in scoring three specific areas:

- Enemy composition and strength assessment
- · Higher headquarters mission context
- · Logistics detail requirements

## **Conclusion and Future Work**

The experiment demonstrated that a few-shot prompted LLM can effectively generate military OPORDs that meet doctrinal standards. The consistently high scores across all three OPORD styles (Task Oriented, Effects Centric, and Terrain Centric) suggest that the system successfully captures the essential elements required for tactical planning. The significant improvement in quality between one and three examples, followed by marginal gains with five examples, indicates that a moderate number of few-shot examples is sufficient for optimal performance. This finding has important implications for the efficient use of computational resources and prompt engineering design.

Future research on this tactical planning system should focus on several key areas to validate its robustness and expand its capabilities. First, comprehensive testing across diverse environmental conditions is essential. The system should be evaluated using various terrain types including urban, mountainous, and desert environments, along with different enemy force compositions and dispositions. Such testing would validate the system's ability to correctly identify and apply tactical patterns from few-shot examples across a broader range of scenarios.

The evaluation methodology could be refined to provide more nuanced insights. While the current three-point scale (0.0, 0.5, 1.0) provided clear differentiation between performance levels, expanding to a continuous scale from 0.0 to 1.0 would allow for finer discrimination between OPORD quality levels. This enhanced granularity might reveal subtle differences between OPORD styles and shot counts that weren't apparent in the current study.

The scope of evaluation should also be expanded. Increasing the sample size to approximately 30 domain experts would provide more robust statistical analysis and better represent the broader military planning community. This expanded evaluator pool should include personnel from different organizations, as well as officers with varying levels of command experience. Such diversity would offer valuable insights into the system's effectiveness across different user populations and use cases.

#### References

- Bartles, C. (2023, March 1). TRADOC: Russian assault groups' evolution in Ukraine – OE TRADOC. Foreign Military Studies Office. https://archive.li/2024.01.06-102733/https://oe.tradoc.army.mil/2023/12/15/tradocrussian-assault-groups-evolution-in-ukraine/
- Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., ... Amodei, D. (2020). Language models are few-shot learners. arXiv. https://arxiv.org/abs/2005.14165
- 3. Deitz, C. (2018). CGSC tests board-based strategy game. Army . US Army. Retrieved December 1, 2024, from https://www.army.mil/article/202457/cgsc\_tests\_board\_based strategy game.

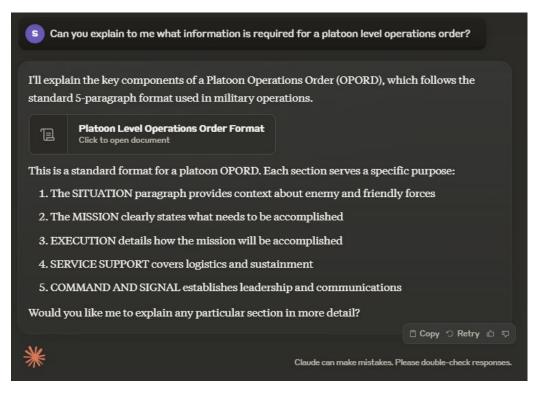
- Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding. arXiv. https://arxiv.org/abs/1810.04805
- Gallotta, R., Todd, G., Zammit, M., Earle, S., Liapis, A., Togelius, J., & Yannakakis, G. N. (2024). Large language models and games: A survey and roadmap. arXiv. https://arxiv.org/abs/2402.18659
- Goecks, V. G., & Waytowich, N. (2024). COA-GPT: Generative pre-trained transformers for accelerated course of action development in military operations. arXiv. https://arxiv.org/abs/2402.01786
- Gutiérrez, B. J., McNeal, N., Washington, C., Chen, Y., Li, L., Sun, H., & Su, Y. (2024). Thinking about GPT-3 incontext learning for biomedical IE? Think again. arXiv. <a href="https://arxiv.org/abs/2203.08410">https://arxiv.org/abs/2203.08410</a>
- 8. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.
- Liu, J., Shen, D., Zhang, Y., Dolan, B., Carin, L., & Chen, W. (2022). What makes good in-context examples for GPT-3? arXiv. https://arxiv.org/abs/2101.06804

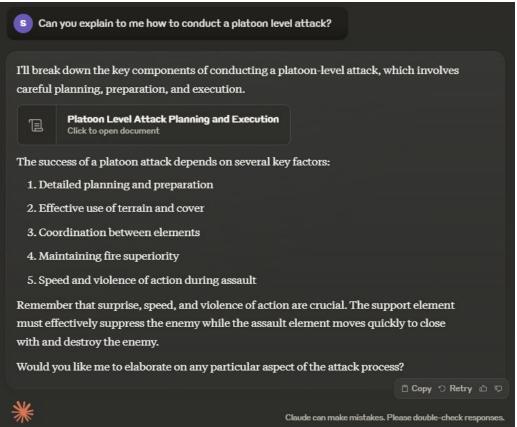
- Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI Blog, 1(8), 9.
- Rubin, O., Herzig, J., & Berant, J. (2022). Learning to retrieve prompts for in-context learning. arXiv. https://arxiv.org/abs/2112.08633
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998-6008.
- 13. Wang, X., Zhang, H., Liu, S., Liu, Y., Li, M., & Wang, Y. (2022). Path planning of scenic spots based on improved A\* algorithm. Scientific Reports, 12, Article 1320. https://doi.org/10.1038/s41598-022-05386-6

### **Appendices**

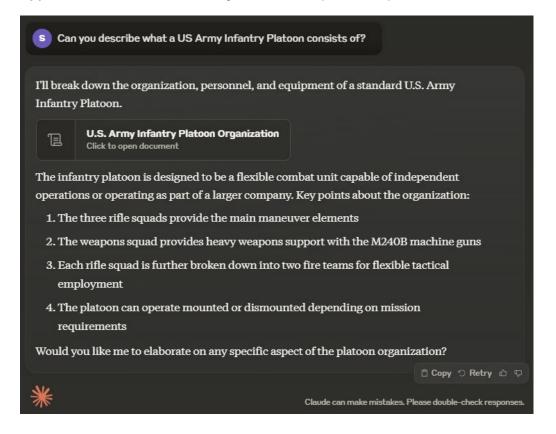
- A. Few-Shot Feasibility Assessment
- B. Few-Shot Examples (Task Oriented)
- C. Modified TE&O Survey Results

## Appendix A - Few-Shot Feasibility Assessment





## Appendix A - Few-Shot Feasibility Assessment (continued)



## Appendix B - Few-Shot Examples (Task Oriented)

Changes between examples are highlighted.

```
(1) Intelligence reports a squad-sized element operating around OBJ ALPHA (350,50). atellite imagery confirms three enemy Soldiers at the following locations:
               Suspected leader located at (346, 50)
                             security elements located at (340, 48) and (342, 52)
```

```
able to observe out to 480m (Area:
```

```
(1) Intelligence reports a Russian Armed Forces Assault Detachment operating around OBJ ALPHA (350,50). It is believed that only a squad-sized element remains. Satellite imagery confirms three enemy Soldiers at the following locations:
              Based upon the known equipment set capabilities, the enemy is able to observe out to
                 3823m²) from their current locations.
              Given the recent reports, they are believed to be equipped with AK12 rifles with
       (3) They are positioned in a way that could allow them to provide mutual support and
verlapping fields of fire, potentially forcing friendly forces to maneuver carefully to avoid
 eing pinned down or flanked
```

```
"example4": {
                                 analysis_report": [Same as example1],
"opord": """OPERATION ORDER 01-24
(3) They are positioned in a way that could allow them to provide mutual support and overlapping fields of fire, potentially forcing friendly forces to maneuver carefully to avoid peing pinned down or flanked.
- Defending the current positions and engaging friendly forces with small arms.
- Withdrawing to a more defensible position if the friendly forces gain momentum threaten to outflank the current positions.
    (5) MDCOA: Defending the current positions, fixing friendly forces with small arms, and
```

```
"example5": {
    "analysis report": [Same as example1],
```

```
- The phase ends with 1st Squad initiating movement to assault p
otification that 2nd and 3rd Squads have reached their support positions.
        Phase 2: Establish Support (H+40 to H+90)
         - This phase begins with 2nd and 3rd Squads establishing their support by fire
          The phase continues with 1st Squad moving towards its assault position.
          This phase ends with 1st Squad reaching its assault position and 2nd Squ
he support by fire position is ready.
          This phase begins with the signal to initiate the assault and 2nd Squad beginning
       ve fire on OBJ ALPHA.
          On command, 3rd Squad moves to OBJ ALPHA to assist with consolidation activities.
          This phase ends with the delivery of the SITREP to Company HO.
```

# Appendix C – Modified TE&O Survey Results

	Expert 1								Expert 2									
	Ta	ask Orier	ited	Ef	fects Cer	ntric	Te	rrain Cer	ntric	Ta	sk Orien	ited	Ef	fects Cer	ntric	Te	rrain Cer	ıtric
Performance Measure	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots
Ensure the OPORD is prepared in accordance with approved doctrine and procedures.		-			-	-				-	-			-	-			-
a. Follow unit SOP on OPORD development and publication.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
c. Use only approved acronyms and abbreviations.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
e. Use standard naming conventions for routes, battle positions (BPs), and so on.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2. Develop the situation paragraph		-	-	٠	-	-	٠		-	-	-	-	٠	-	-	-		-
f. Enemy forces.		-	-	٠	-	-	٠		-	-	-		٠	-	-	-		-
(1) Composition.	1	1	1	1	1	1	1	1	1	0.5	1	1	0.5	1	1	0.5	1	1
(2) Disposition.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(3) Strength.	1	1	1	1	1	1	1	1	1	0.5	1	1	0.5	1	1	0.5	1	1
g. Friendly forces.		-	-		-	-				-	-			-	-			
(1) Higher headquarters mission and intent.	1	1	1	1	1	1	1	1	1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
(2) Missions of adjacent units.	1	1	1	1	1	1	1	1	1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
3. Develop the mission paragraph.			-		-	-				-	-			-	-	-		-
Note: This is the WHO, WHAT, WHEN, WHERE, and WHY which states essential task(s) to be																		
accomplished by the entire unit, to include on-order missions, and clearly defines the	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
platoon's objective																		l
4. Develop the execution paragraph.	-	-	-		-	-		-	-	-	-	-		-	-		-	-
b. Commander's intent.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
c. Concept of operations	0.5	1	1	0.5	1	1	0.5	1	1	1	1	1	1	1	1	1	1	1
k. Task to subordinate units.	0.5	0.5	1	0.5	0.5	1	0.5	0.5	1	1	1	1	1	1	1	1	1	1
L. Coordinating instructions.	0.5	1	1	0.5	1	1	0.5	1	1	1	1	1	1	1	1	1	1	1
5. Develop the sustainment paragraph.			-		-	-				-	-			-	-	-		
a. Logistics.	1	1	1	1	1	1	1	1	1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
c. Health service support	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6. Develop the command and signal paragraph	-	-	-		-	-		-	-	-		-		-	-	-	-	-
(1) Location of commander and key leaders.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(2) Succession of command.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(3) Signal.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Total	16.5	17.5	18	16.5	17.5	18	16.5	17.5	18	15.5	16.5	16.5	15.5	16.5	16.5	15.5	16.5	16.5

	Expert 3										Expert 4							
	T	ask Orier	nted	Ef	fects Cer	itric	Te	rrain Cer	ntric	Ta	sk Orien	nted	Ef	fects Cer	ntric	Tei	rrain Cer	ntric
Performance Measure	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Sho
Ensure the OPORD is prepared in accordance with approved doctrine and procedures.		-	-		-			-	-	-			-	-	-	-	-	-
a. Follow unit SOP on OPORD development and publication.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
c. Use only approved acronyms and abbreviations.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
e. Use standard naming conventions for routes, battle positions (BPs), and so on.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2. Develop the situation paragraph		-			-			-	-	-			-	-	-	-	-	-
f. Enemy forces.	-	-	-	-	-	-		-	-		-	-	-	-	-		-	-
(1) Composition.	0.5	1	1	0.5	1	1	0.5	1	1	0.5	1	1	0.5	1	1	0.5	1	1
(2) Disposition.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(3) Strength.	0.5	1	1	0.5	1	1	0.5	1	1	0.5	1	1	0.5	1	1	0.5	1	1
g. Friendly forces.		-	-		-			-				-		-	-		-	-
(1) Higher headquarters mission and intent.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	1	1	1	1	1	1	1	1	1
(2) Missions of adjacent units.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	1	1	1	1	1	1	1	1	1
3. Develop the mission paragraph.		-			-			-	-	-			-	-	-	-	-	-
Note: This is the WHO, WHAT, WHEN, WHERE, and WHY which states essential task(s) to be																		
accomplished by the entire unit, to include on-order missions, and clearly defines the	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
platoon's objective																		i
4. Develop the execution paragraph.		-			-			-	-	-			-	-	-	-	-	-
b. Commander's intent.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
c. Concept of operations	1	1	1	1	1	1	1	1	1	0.5	1	1	0.5	1	1	0.5	1	1
k. Task to subordinate units.	1	1	1	1	1	1	1	1	1	0.5	0.5	1	0.5	0.5	1	0.5	0.5	1
I. Coordinating instructions.	1	1	1	1	1	1	1	1	1	0.5	1	1	0.5	1	1	0.5	1	1
5. Develop the sustainment paragraph.		-			-			-	-	-			-	-	-	-	-	-
a. Logistics.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	1	1	1	1	1	1	1	1	1
c. Health service support	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6. Develop the command and signal paragraph		-	-		-	-		-	-		-	-		-	-			-
(1) Location of commander and key leaders.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(2) Succession of command.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(3) Signal.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	1	1	1	1	1	1	1	1	1
Tota	15	16	16	15	16	16	15	16	16	15.5	17.5	18	15.5	17.5	18	15.5	17.5	18

	Expert 5								
	Task Oriented			Eff	fects Cer	ıtric	Te	ntric	
Performance Measure	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots	1 Shot	3 Shots	5 Shots
Ensure the OPORD is prepared in accordance with approved doctrine and procedures.	-	-						-	-
a. Follow unit SOP on OPORD development and publication.	1	1	1	1	1	1	1	1	1
c. Use only approved acronyms and abbreviations.	1	1	1	1	1	1	1	1	1
e. Use standard naming conventions for routes, battle positions (BPs), and so on.	1	1	1	1	1	1	1	1	1
Develop the situation paragraph	-	-	1	i	-	-	٠		-
f. Enemy forces.	-	-	1	i	-	-	٠		-
(1) Composition.	1	1	1	1	1	1	1	1	1
(2) Disposition.	1	1	1	1	1	1	1	1	1
(3) Strength.	1	1	1	1	1	1	1	1	1
g. Friendly forces.	-	-	1	1	-	-	٠		-
(1) Higher headquarters mission and intent.	1	1	1	1	1	1	1	1	1
(2) Missions of adjacent units.	1	1	1	1	1	1	1	1	1
3. Develop the mission paragraph.	-	-	1	1	-	-	٠		-
Note: This is the WHO, WHAT, WHEN, WHERE, and WHY which states essential task(s) to be									
accomplished by the entire unit, to include on-order missions, and clearly defines the	1	1	1	1	1	1	1	1	1
platoon's objective									
Develop the execution paragraph.	-	-		1	-	-	٠		-
b. Commander's intent.	1	1	1	1	1	1	1	1	1
c. Concept of operations	1	1	1	1	1	1	1	1	1
k. Task to subordinate units.	1	1	1	1	1	1	1	1	1
l. Coordinating instructions.	1	1	1	1	1	1	1	1	1
5. Develop the sustainment paragraph.	-	-	-	-	-	-		-	-
a. Logistics.	1	1	1	1	1	1	1	1	1
c. Health service support	1	1	1	1	1	1	1	1	1
6. Develop the command and signal paragraph	-	-		·			٠		
(1) Location of commander and key leaders.	1	1	1	1	1	1	1	1	1
(2) Succession of command.	1	1	1	1	1	1	1	1	1
(3) Signal.	1	1	1	1	1	1	1	1	1
Tota	18	18	18	18	18	18	18	18	18