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DYNAMIC ANALYSIS AND MONITORING OF AI BEHAVIOR IN A MILITARY SIMULATION ENVIRONMENT USING MACHINE LEARNING TECHNIQUES IN THE ARMA 3 SIMULATOR

Mihai DAN

***Abstract*:** *This study examines the behavior of artificial intelligence in a military simulation environment, focusing on structural stability and temporal dynamics. While AI is widely implemented in simulation platforms, fewer studies investigate how its behavior evolves over time under controlled conditions. The research analyzes AI performance in the Arma 3 simulator using machine learning techniques applied to server-generated telemetry data, including clustering and temporal comparison. The results show distinct differences between skill-based configurations and advanced tactical logic, highlighting the role of tactical mechanisms in shaping behavioral dynamics. This study forms part of a broader doctoral research program, with limitations related to the specificity of the analysed scenarios and simulation environment.*
Keywords: *military simulation, AI behavior, machine learning, clustering, temporal analysis, dynamic monitoring*

1. PROBLEM DESCRIPTION

The use of artificial intelligence in military simulations has, over recent decades, become a central research direction within fields such as security studies, military sciences, and applied artificial intelligence. These environments provide a controlled framework in which the decision-making and tactical processes of artificial agents can be analyzed without the operational constraints of real-world settings. Military simulators enable systematic observation of interactions between AI entities and the operational environment, facilitating the testing of hypotheses related to adaptivity, coordination, and action dynamics in complex contexts.

Existing research has approached the use of artificial intelligence in military and simulation contexts from diverse perspectives, including strategic decision modelling, tactical behavior realism, and the integration of machine learning techniques into decision-making processes [1], [15]. At the same time, recent literature highlights a growing interest in behavioral AI and in the mechanisms through which artificial systems generate plausible actions in complex environments, including simulations and computer games [2], [7]. While these contributions provide a solid conceptual foundation, analyses are often oriented either toward the algorithmic level or toward aggregated outcomes, without capturing the internal dynamics of behavior over time.

Within this context, there is a clear need to extend existing approaches through a systematic analysis of AI behavior as a dynamic process, dependent on controlled configurations and observable over time. The present study adopts an operational perspective on AI behavior, focusing on the distribution, duration, and transitions between behavioral patterns within a military simulation environment. Such an approach enables rigorous comparisons across different skill levels and between the presence or absence of advanced tactical logic, complementing existing literature through an

empirical investigation centered on behavioral dynamics.

The main hypothesis of the research posits that skill level and tactical logic represent distinct factors with different effects on AI behavior. More specifically, skill primarily influences the operational capability of AI entities, whereas tactical logic affects the dynamics and frequency of behavioral transitions. In addition, it is assumed that the introduction of advanced tactical logic generates a distinct behavioral regime that cannot be explained solely by an increase in numerical competence.

The originality of the study lies in treating AI behavior as a dynamic phenomenon analyzed through machine learning techniques applied to behavioral data extracted directly from the simulation environment. To this end, the research proposes a staged methodological framework based on data collection, behavioral clustering, and temporal analysis, implemented within the Arma 3 simulator. This framework enables systematic comparison of AI behaviors under controlled and reproducible conditions.

The primary objective of the research is to identify and characterize behavioral differences generated by variations in skill level and by the activation of advanced tactical logic. Specific objectives include analyzing the distribution of behavioral clusters, evaluating the duration of behavioral patterns, and examining transitions between these patterns over time. The conclusions are derived from comparative analysis of results obtained through replicated simulation runs, ensuring the consistency and validity of the observations.

2. APPLICATION FIELD

The experimental environment used in this study is the military simulation platform *Arma 3*. The simulator was selected due to its high level of operational realism and its widespread use in both military training and defense-related simulation research. Unlike abstract or synthetic environments, *Arma 3* allows artificial intelligence agents to operate under constraints that closely resemble those encountered in real tactical situations, including terrain, line-of-sight limitations, movement restrictions, and engagement rules.

From a research perspective, one of the most relevant features of *Arma 3* is the possibility to directly instrument AI behavior at the server level. During each simulation run, the engine automatically generates detailed log files that record the internal states and actions of AI-controlled units. These logs include temporal information and behavioral indicators that can be extracted without relying on subjective observation or manual coding.



Fig. 1. The scenario in Arma 3
(Source author: Arma 3 simulation screenshot during the missions.)

To examine the impact of advanced tactical reasoning on AI behavior, the study employs the VCOM AI framework as an optional tactical logic layer. VCOM AI is a community-developed artificial intelligence modification for Arma 3 that enhances unit-level and group-level decision-making through dynamic movement, flanking, use of cover, and adaptive repositioning. Unlike standard AI skill parameters, which primarily affect reaction speed and accuracy, VCOM introduces higher-level tactical behaviors that alter how AI units coordinate and respond over time.

In this study, VCOM AI was used exclusively as a behavioral logic modifier. All automatic skill adjustments provided by the framework were disabled, ensuring that observed differences in behavior could be attributed solely to tactical decision-making

mechanisms rather than numerical performance enhancements. Comparative experiments were conducted with VCOM AI enabled and disabled under identical scenario conditions and skill configurations, allowing for a controlled assessment of its effect on behavioral dynamics.

The experiments were conducted within a standardized military scenario designed specifically to generate repeated and comparable tactical interactions between AI entities. A fixed map, a constant number of units, and identical initial conditions were used across all runs, including unit placement and operational objectives. The scenario configuration remained unchanged throughout the entire experimental campaign. As a result, any behavioral differences observed across simulations can be attributed to variations in skill level or tactical logic rather than to environmental changes. In this sense, the scenario functions as a controlled experimental framework rather than as an independent variable of analysis.

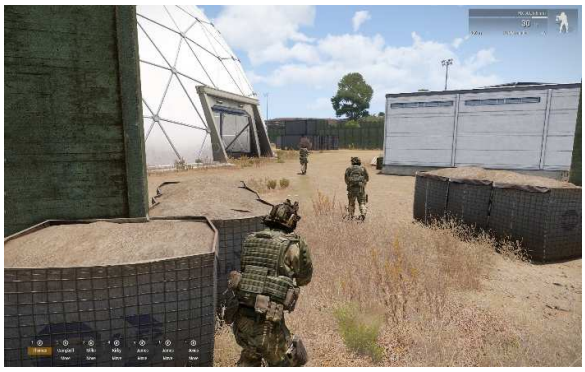


Fig. 2. Advancing towards the enemy
(Source author: Arma 3 simulation screenshot during the missions.)

3. STATE OF THE ART

Research on the use of artificial intelligence in simulation environments and military contexts has developed at the intersection of strategic decision studies, behavioral modelling, and complex systems analysis. A major research direction within this field concerns the application of machine learning techniques to capture the complexity of decision-making processes in dynamic and adversarial settings. Recent studies indicate that machine learning–based approaches can outperform classical theoretical models in describing and predicting strategic behavior, while also providing tools for comparative analysis and more nuanced interpretations of observed decisions [1].

Within the literature focused on military applications, artificial intelligence is most often examined from the perspective of action modelling and operational decision-making, with emphasis placed on realism, efficiency, and decision support. Recent contributions discuss the integration of AI into military action simulation and highlight its potential to generate coherent and adaptive behaviors in relation to the operational environment [15]. However, in many of these approaches, AI behavior is treated primarily as an outcome of system capabilities, rather than being explicitly analyzed as a dynamic process unfolding over time.

An important contribution to the understanding of AI behavior comes from the literature on computer games and interactive simulations. Recent syntheses of decision-making mechanisms for non-player entities identify a wide range of approaches, from rule-based systems and behavior trees to machine learning methods and hybrid architectures [2], [7]. These works are particularly relevant for the present study, as they conceptualize AI behavior as a sequence of states and decisions, providing an analytical language suitable for interpreting behavioral patterns identified through quantitative methods.

In parallel, research focused on the concept of behavior-determining AI emphasizes that the behavior of artificial entities is not determined solely by the underlying algorithms, but also by configuration parameters, simulation environments, and design constraints [3], [6]. This perspective is essential for our approach, as it enables a clear separation between numerical competence (skill) and the mechanisms that shape decision-making dynamics and tactical behavior.

Another relevant direction in recent literature concerns the empirical evaluation of AI behavior in simulated environments using telemetry data and quantitative indicators. Studies in the fields of serious games and virtual environments stress the importance of defining clear and reproducible metrics for analyzing AI-generated behavior [6], [18]. Although these works are not exclusively focused on military simulations, they provide valuable methodological guidance for structuring analyses and interpreting results.

Recent bibliometric syntheses confirm a significant diversification of research on AI in games and simulations, with increasing interest in experimental methods and behavioral analysis alongside algorithmic developments [4], [7]. At the same time, some studies adopt a critical stance toward the use of the term “intelligence” in this context, emphasizing the need for rigorous criteria when evaluating AI behavior beyond subjective impressions or apparent performance gains [5].

A second problematic aspect concerns the strong context dependency observed in many studies, where variations in scenario design, terrain, or objectives significantly influence outcomes. Recent literature highlights the necessity of controlled experimental conditions and replicated runs in order to enable valid comparisons between different AI configurations [1].

Based on these observations, we position our research as a methodological contribution focused on analyzing AI behavior as a dynamic, measurable, and comparable process. The adopted approach responds directly to calls in the literature for the use of observable indicators, temporal analysis, and a clear separation between numerical competence and tactical mechanisms in AI systems.

4. RESEARCH STAGES

The study follows a quantitative experimental design based on controlled and replicated simulations. This design was adopted in order to analyze AI behavior using measurable indicators derived directly from the simulation environment, rather than relying on qualitative impressions or aggregated performance scores.

For each combination of skill level and tactical configuration, three independent simulation runs were executed. Each run covered approximately 30 minutes of simulation time and was performed under identical scenario conditions. Replication was necessary to mitigate the influence of stochastic variation and to ensure that the observed behavioral patterns were consistent rather than incidental.

Behavioral data were collected automatically from server-side log files generated during runtime. A custom software pipeline, implemented in Python, was used to parse these log files and extract variables relevant to the study. These variables included temporal markers of actions, unit posture, movement speed, and distance to enemy units.

The extracted data were stored in CSV format, forming the primary datasets used for analysis. Prior to applying machine learning techniques, the datasets underwent preprocessing steps such as encoding categorical variables and normalizing numerical features. This structured approach supports transparency and allows the analytical process to be reproduced independently.

5. METHODS USED

The analysis of AI behavior was conducted using unsupervised machine learning techniques, primarily behavioral clustering, with the aim of identifying recurring behavioral patterns without imposing predefined categories. The resulting clusters represent emergent behavioral structures characterized by both spatial and temporal properties.

To ensure internal validation of the identified cluster structures, an additional supervised classification stage was employed in order to assess the consistency and stability of the behavioral patterns. This step supported

the robustness of the clustering results and reduced the risk of incidental pattern formation.

The behavioral data analyzed in this study consist exclusively of telemetry information automatically generated by the simulation server during runtime. No manual annotation or post hoc reconstruction of behavior was performed. Consequently, the datasets reflect AI behavior as it occurred during the simulations, providing a direct empirical basis for analysis.

The validity of the results was further supported through replicated simulation runs for each experimental condition and by the systematic comparison of the resulting behavioral and temporal indicators. This approach enabled the testing of the proposed hypothesis within an empirically controlled and reproducible framework.

The adopted methodology is inherently limited by the specificity of the simulation environment and the analyzed scenario, as well as by the fact that the results reflect emergent behaviors observed under controlled conditions. These limitations are explicitly acknowledged and are considered an integral part of a broader doctoral research program aimed at extending the analysis to additional scenarios and experimental configurations.

5.1 Research Hypothesis and Objectives

The research is structured around the following hypothesis: AI behavior in a military simulation environment exhibits significant differences in both dynamics and structure depending on the skill level and the use of advanced tactical logic.

These differences manifest through variations in behavioral distribution, the duration of behavioral patterns, and the frequency of transitions between them.

To test this hypothesis, two main objectives were established. The first objective focuses on analyzing the influence of skill level on the structure of AI behavior in the absence of advanced tactical logic, with the purpose of defining a baseline behavioral reference. The second objective aims to evaluate the impact of introducing advanced tactical logic on behavioral dynamics, through a systematic comparison of results obtained under identical scenario conditions and skill levels.

This structure allows for a clear separation between the effects of numerical competence and those of tactical mechanisms, thereby avoiding the conflation of these two dimensions in the interpretation of results.

Qualitative elements are employed exclusively during the interpretation stage of the results, particularly for the semantic attribution of the identified behavioral patterns.

This combination enables a rigorous analytical approach in which descriptive observations are grounded in measurable and reproducible data.

5.2 Simulation Environment and Variable Control

The skill level of AI entities was explicitly controlled through parameters associated with perception and reaction (spotDistance, spotTime), as well as engagement tendency (courage).

These parameters were defined under three distinct conditions: 0%, 50%, and 100%. Parameters related to operational stability, such as accuracy, reload speed, and the general skill parameter, were kept constant throughout all experiments to ensure the comparability of conditions.

In experiments involving the use of advanced tactical logic, this logic was activated at the server level while automatic skill adjustments were disabled. Consequently, the observed effects can be attributed exclusively to tactical mechanisms rather than to changes in the numerical competence of the AI.

Intermediate and final analysis results were aggregated into CSV files and subsequently synthesized into an Excel file, facilitating the systematic comparison of the analyzed experimental conditions.

6. RESEARCH RESULTS

The research results are presented in relation to the two research objectives and are structured so as to respond directly to the formulated hypothesis regarding differences in the dynamics and structure of AI behavior as a function of skill level and the use of advanced tactical logic.

6.1 Results related to Objective 1

The analysis of results obtained in the absence of advanced tactical logic reveals systematic differences between the analyzed skill levels. These differences are reflected in the distribution of behavioral clusters, the average distance to the enemy, and the duration of behavioral patterns. At low skill levels, AI behavior is characterized by a predominance of clusters associated with maintaining greater distances from the enemy, as well as by longer-lasting behavioral patterns. This configuration suggests a relatively static behavioral profile, with infrequent transitions between patterns, indicating a limited capacity to adapt to the dynamics of the operational environment.

At the intermediate skill level, the results indicate a redistribution of behavioral clusters, accompanied by an increased frequency of patterns associated with medium engagement distances. Compared to the low-skill condition, behavioral durations decrease and transitions between patterns become more frequent, pointing to a more dynamic and balanced behavior between engagement and distance maintenance.

At the highest skill level, the structure of AI behavior is dominated by clusters associated with close enemy distances and shorter behavioral durations. Cluster distributions are more stable across repeated runs, while the sequence of behaviors reflects an increased capacity for reaction and adaptation. These observations confirm that skill level significantly influences the structure of AI behavior and constitutes a key determinant of operational capability.

6.2 Results related to Objective 2

A comparison between results obtained with and without the activation of advanced tactical logic highlights clear differences in the dynamics of AI behavior, observable across all analyzed skill levels. The activation of advanced tactical logic consistently leads to a reduction in the average duration of behavioral patterns and to an increase in the frequency of transitions between clusters. This shift indicates a more pronounced behavioral dynamism, characterized by more frequent changes in posture, movement speed, and positioning relative to the enemy. Under conditions involving advanced tactical logic, the distribution of behavioral clusters becomes more balanced, while differences between skill levels are accompanied by an overall increase in temporal variability. Notably, even at low skill levels, AI entities exhibit less static behavior, suggesting that tactical logic introduces adaptive mechanisms that cannot be reduced to numerical competence alone.

Quantitative analysis shows that enabling tactical logic (VCOM) leads to a consistent reduction in behavioral stability across all skill levels. The average duration of behavioral clusters decreases from approximately 280–540 seconds in the non-tactical condition to 250–280 seconds when tactical logic is enabled, corresponding to a reduction of up to 50% in cluster persistence.

At the same time, the frequency of transitions between behavioral clusters increases noticeably, indicating a higher rate of behavioral reconfiguration. Notably, AI entities operating at 0% skill with tactical logic enabled exhibit behavioral dynamics comparable to those observed at 50–100% skill without tactical logic, demonstrating that tactical mechanisms introduce a distinct behavioral regime that cannot be replicated through skill adjustment alone.

The results indicate that advanced tactical logic does not act as a simple multiplier of skill. Instead, it generates a distinct behavioral regime characterized by temporal and tactical reorganization. This conclusion is supported

by the consistency of results across replicated runs and by the systematic differences observed between experimental conditions.

Table 1

Average behavioral persistence and transition frequency

Condition	Avg. Cluster Duration (s)	Transition Rate
Skill 0%, no VCOM	284–314	Low
Skill 50%, no VCOM	340–388	Medium
Skill 100%, no VCOM	438–541	Medium
Skill 0%, VCOM ON	252–262	High
Skill 50%, VCOM ON	268–280	High
Skill 100%, VCOM ON	271–280	High

The data summarized in Table 1 show that the activation of tactical logic produces a systematic reconfiguration of behavioral persistence across all skill levels. In the absence of tactical logic, average cluster duration increases progressively with skill level, ranging from approximately 284–314 seconds at 0% skill to 438–541 seconds at 100% skill. This pattern suggests that higher skill values are associated with more stable and sustained behavioral states.

When tactical logic (VCOM) is enabled, cluster durations converge toward a narrower temporal range, approximately 252–280 seconds, regardless of skill level. This convergence indicates that tactical mechanisms compress behavioral persistence and reduce the structural differences observed under the non-tactical condition.

At the same time, transition frequency increases from low–medium levels in the non-tactical condition to consistently high levels when tactical logic is activated. Under these conditions, behavioral distinctions based solely on skill become less pronounced, as agents across all skill levels exhibit more frequent transitions between repositioning and engagement-related clusters. This shift reflects a move from skill-dependent structural stability toward a tactically driven, dynamically reconfiguring behavioral regime.

6.3 Synthesis of results and relation to the research hypothesis

Overall, the obtained results confirm the research hypothesis, demonstrating that both skill level and the use of advanced tactical logic influence AI behavior in a military simulation environment, albeit through different mechanisms. Skill level primarily affects the structural aspects of behavior, whereas advanced tactical logic shapes the dynamics and rhythm of behavioral change.

This distinction supports the argument that AI behavioral adaptivity cannot be explained solely through increased numerical competence. Instead, it requires a separate analysis of the tactical mechanisms governing the succession and duration of observed behaviors.

7. FURTHER RESEARCH

The results obtained in this study align with directions highlighted in the existing literature regarding the role of skill level in shaping artificial intelligence behavior within simulated environments. The analysis confirms that skill directly influences the structure and distribution of behavioral patterns, an aspect already noted in prior research on AI in games and simulated systems. However, the empirical data indicate that, in the absence of dedicated tactical mechanisms, increases in numerical competence do not automatically translate into enhanced behavioral adaptivity. This observation supports critical perspectives in recent literature, which caution against equating numerical performance with behavioral intelligence. In the analyzed simulations, high-skill AI entities exhibit faster reactions and more frequent approaches toward the enemy, yet these behaviors remain relatively stable over time when not supported by explicit tactical logic. In such cases, adaptivity appears limited to reaction

capability, without leading to a dynamic reorganization of behavior.

The introduction of advanced tactical logic, however, produces substantial changes in AI behavior across all analyzed skill conditions. The reduction in behavioral pattern duration and the increased frequency of transitions suggest an acceleration of the decision-making process and an improved ability to adjust to the operational context. These findings are consistent with approaches in the literature that conceptualize AI behavior as an outcome of decision architectures and coordination mechanisms, rather than solely as a function of individual performance parameters.

From this perspective, advanced tactical logic can be interpreted as a mechanism that reorganizes the temporal sequence of AI actions, generating a distinct behavioral regime. Unlike the effects of skill, which manifest primarily at a structural level, tactical logic influences the rhythm and variability of behavior, enabling the emergence of more flexible and reactive patterns. The operationalization of adaptivity through structural and temporal indicators represents one of the methodological contributions of this study. By employing behavioral clustering and temporal analysis, AI behavior is evaluated as an evolving process rather than as a set of isolated outcomes. This approach responds directly to calls in the literature for clear, empirical, and reproducible criteria in the evaluation of complex AI systems, particularly within simulated environments.

The limitations of the present research are primarily related to the specificity of the simulation environment and the selected scenario. The results reflect emergent behaviors within a controlled experimental setting, and their generalization to other simulation types or operational contexts should therefore be approached with caution. Nevertheless, the consistency of observations across replicated runs suggests that the identified effects are robust and reflect meaningful behavioral mechanisms rather than scenario-specific artifacts.

An additional layer of interpretation may be achieved by relating the observed behavioral patterns to general tactical principles described in military doctrinal literature. Although the study does not aim to validate AI compliance with specific doctrinal procedures, the observed reduction in behavioral duration and increase in transition frequency can be conceptually associated with notions such as maneuver, operational tempo adaptation, and responsiveness to initiative. This correspondence suggests that tactical mechanisms implemented in AI systems may generate emergent behaviors that abstractly reflect established tactical principles.

In a broader context, the results support recent positions in the literature on the evaluation of complex AI agents, which emphasize that temporal behavior analysis is essential for understanding the actual functioning of such systems. Evaluation based solely on static metrics or isolated performance outcomes risks providing an incomplete picture of AI adaptivity and decision-making mechanisms.

8. CONCLUSIONS AND FUTURE DIRECTIONS

The present study demonstrates that artificial intelligence behavior within a military simulation environment exhibits significant differences in both structure and dynamics depending on skill level and the use of advanced tactical logic. The empirical analysis conducted in the Arma 3 simulator confirms the hypothesis that these two factors influence AI behavior through distinct mechanisms that cannot be reduced to one another. The results indicate that skill level primarily affects the structural dimension of AI behavior, reflected in the distribution of behavioral patterns and in spatial relations to the enemy. In contrast, advanced tactical logic has a substantial impact on behavioral dynamics, leading to consistent changes in pattern duration and transition frequency. This distinction highlights that behavioral adaptivity cannot be explained solely by

numerical competence, but instead requires dedicated tactical mechanisms that govern the sequencing and tempo of actions.

By conceptualizing AI behavior as a dynamic process and applying machine learning techniques to identify emergent behavioral patterns, this research provides a methodological framework applicable to the analysis of AI systems in military simulations. The main contribution lies in the clear separation between operational performance and behavioral adaptivity, as well as in the proposal of temporal indicators that enable empirical evaluation of AI behavior over time. Future research directions include extending the analysis to different simulation scenarios and environments with varying levels of operational complexity. In addition, the integration of further metrics related to coordination and cooperation among AI units, as well as the correlation of behavior with more complex operational objectives, may contribute to refining the proposed analytical framework. The present study represents a stage within a broader doctoral research program aimed at developing a general framework for the dynamic analysis of AI behavior in simulated environments.

All experimental data generated and analyzed during this study, including the complete set of 18 behavioral result files and the aggregated master dataset, are publicly available in an open-access repository hosted on Zenodo [20]. The repository includes raw processed clustering outputs and derived metrics, enabling independent verification and full reproducibility of the reported results.

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Analiza și monitorizarea dinamică a comportamentului AI într-un mediu de simulare militară utilizând tehnici de învățare automată în simulatorul Arma 3

Rezumat: Studiul examinează comportamentul AI într-un mediu de simulare militară, cu accent pe stabilitatea structurală și dinamica temporală. Deși AI este utilizată pe scară largă în platformele de simulare, mai puține cercetări analizează modul în care comportamentul acesteia evoluează în timp, în condiții controlate. Cercetarea evaluează performanța AI în simulatorul Arma 3 prin aplicarea unor tehnici de învățare automată asupra datelor de telemetrie generate la nivelul serverului, incluzând metode de clustering și analiză temporală comparativă. Rezultatele evidențiază diferențe clare între configurațiile bazate pe nivelul de skill și utilizarea unei logici tactice avansate, subliniind rolul mecanismelor tactice în modelarea dinamicii comportamentale. Studiul face parte dintr-un program doctoral mai amplu, iar limitările sunt legate de specificitatea scenariilor și a mediului de simulare analizat.

Mihai DAN, Captain PhD Candidate, Commanding Officer, "Nicolae Bălcescu" Land Forces Academy of Sibiu, Department of Military Sciences, dan.mihai@armyacademy.ro, +40 748 431 299, 3-5 Revolutiei Street, Sibiu, Romania.