JDAL
10,1

Received 3 December 2024
Revised 8 January 2026
31 March 2026
Accepted 14 April 2026

A conceptual model of combat marksmanship

Joseph A. Hamilton, Nathan C. Carnes, Ken Javes, Greg Huffman and Joel Suss
Naval Health Research Center, San Diego, California, USA
Anthony Viggiani
USMC Training and Education Command, Quantico, Virginia, USA
John Costa
USMC Weapons Training Bn, Quantico, Virginia, USA
Rachel R. Markwald
Naval Health Research Center, San Diego, California, USA, and
Adam T. Biggs
Uniformed Services University of the Health Sciences, Bethesda, Maryland, USA

Abstract

Purpose – Marksmanship tests are often determined by inherited standards or individual subject-matter experts rather than via a consistent and repeatable framework based on firearms engagements. Better process development in evaluations and better outcome modeling will optimize performance among military and law enforcement, thereby producing greater safety and effectiveness in field performance.

Design/methodology/approach – Simulation experiments depicted the operational advantage provided by different night vision goggles using either a cognitive experimental approach, a simple Monte Carlo simulation or multiple Monte Carlo simulations integrated into a computation modeling approach.

Findings – Whereas the cognitive experimental approach could only quantify a combat advantage in terms of reaction times, computational modeling provided a more practical interpretation while fully accounting for data granularity. The combat advantage could be described as a 40% increased likelihood to win in combat rather than a one second advantage.

Originality/value – We provide a process-oriented conceptual approach to identify the sequence involved during firearms use. Eight common behavioral and decision nodes are situated with feedback loops that return, where applicable, to prior steps when addressing any errors in the marksmanship process. With this information, military or law enforcement personnel can structure their dialogue around the most important tasks to incorporate when creating a marksmanship evaluation or training program.

Keywords Marksmanship, Simulation, Lethality, Systems analysis, Shoot/Don't shoot

Paper type Conceptual paper

1. Introduction

Although training and assessment of armed professionals should be addressed systematically to simulate components of the intended end use, there are no process-oriented models of combat marksmanship that would identify the steps involved in using a firearm during a lethal force encounter. In turn, marksmanship tests cannot be optimized by modeling the requisite steps during a marksmanship assessment. Approaching marksmanship assessment in a systematic manner would provide instructors and administrators with the tools necessary to design assessments that (1) provide valid metrics, (2) serve as a feedback mechanism that instructors can use to improve training and (3) allow individuals to track their own performance. The underlying problem remains the critical need for more process-oriented

Journal of Defense Analytics and Logistics
Vol. 10 No. 1, 2026
pp. 58-74
© Emerald Publishing Limited
e-ISSN: 2399-6447
p-ISSN: 2399-6439
DOI 10.1108/JDAL-12-2024-0026

development in creating marksmanship proficiency evaluations for both military and law enforcement personnel. Process-oriented models support better practical test development and readiness evaluations by ensuring the purpose of the test aligns with the actions involved during the intended end use.

The current discussion proposes a conceptual framework for modeling the combat marksmanship process, intended to guide future simulation and analytical models. Foremost, the discussion will begin by explaining why use-of-force should be approached as a cognitive model rather than emulated through cognitive experiments. This advantage will then be illustrated through a use case – identifying how field-of-view can impact combat effectiveness while using night-vision goggles (NVGs) – and estimating the practical value through controlled experiments versus combat modeling. Finally, a conceptual model of combat marksmanship will be proposed to create a scaffolding for future cognitive modeling in combat simulations. Although every individual use-of-force scenario is unique, the goal is to identify a basic sequence so that these steps can be properly represented and implemented into future data modeling efforts. Taken together, the purpose of this study is to demonstrate the practical differences for interpretations when using a cognitive experimental approach versus a computational modeling approach and to provide a conceptual model as a guide for future use scenarios.

2. Why use-of-force should be approached as a computational cognitive model

Military and law-enforcement organizations regularly measure individuals' firearm proficiency through standardized weapon qualifications. These assessments vary greatly from one organization to the next, which cannot be attributed solely to differing mission requirements or professional responsibilities (e.g. Special Weapons And Tactics personnel versus patrol officers). Variability in testing creates a challenge in comparing and contrasting performance across organizations. Still, marksmanship drills are a component of the larger issue. The core problem is not the realism in marksmanship exercises conducted under controlled circumstances on standard live fire shooting ranges, but rather the thinking of marksmanship skills in use-of-force as isolated elements or individual drills. The use of force, whether in combat or an individual lethal-force encounter, should be understood as a complex system-of-systems process (cf. Shi and Zhang, 2020).

Despite these issues, the common approach is to evaluate use-of-force issues through cognitive experiments. This method has experimental value in isolating variables to evaluate elements within the larger system. That said, especially when developing test designs or evaluating field readiness, use-of-force decisions should be considered a complex series of interrelated cognitive and motor functions rather than compartmentalized processes. One failure or decision can feed forward to affect subsequent perceptions, decisions and actions. This reality creates two major challenges: first, identifying the many cognitive and human factors involved in the use-of-force process; and second, communicating these influences succinctly to support clear decision-making among military and law enforcement leadership (for a thorough discussion, see NATO Research and Technology Organisation, Studies, Analysis and Simulation Panel, 2004; Tolk, 2019).

2.1 Human factors in the marksmanship process and the inherent limitations of a cognitive experimental approach

Marksmanship performance can be influenced by any number of cognitive, physiological and environmental factors (Rao *et al.*, 2020). These include grip strength (Copay and Charles, 2001), helmet use (Lim *et al.*, 2017), clothing (Brown *et al.*, 2017), physical load (Swain *et al.*, 2011), sleep (Smith *et al.*, 2019), fatigue (Head *et al.*, 2017) and stress (Nieuwenhuys and Oudejans, 2010). Furthermore, each marksmanship manipulation represents an important component to evaluate on its own, which is why the relevant studies conducted controlled experiments in the particular context of that question." Mounting evidence also supports the practical contributions of a cognitive framework. Systematic evaluation of simple tasks in a laboratory environment has effectively supported predicting performance on simulated, but combat-relevant tasks using both military-grade shooting simulators and military personnel (Anglin *et al.*, 2017; Biggs and Pettijohn, 2022; Brunyé *et al.*, 2024; Rao *et al.*, 2020; Zanesco *et al.*, 2025). This evidence suggests that the study of combat marksmanship can be meaningfully linked to techniques from cognitive task performance because both draw on the same underlying cognitive abilities.

However, each method also imposes the same assumption by using the typical experimental approach, wherein circumstances are controlled and performance becomes trial-based. One performance iteration leads immediately into the next while isolating variables to record speed and accuracy, amongst other potential dependent variables. The problem involves the assumptions made within this format when interpreting use-of-force behaviors. Specifically, if the marksmanship task used for the performance assessment does not adequately represent the intended end use, or if the variables are not collected with sufficient granularity to allow their use in simulation, then the assumptions – accurate or not – carry forward into modeling and the decision-making processes. A suboptimal marksmanship task thus becomes the critical weak link of a "garbage in, garbage out" model.

2.2 Existing combat modeling efforts

Combat modeling complements the experimental approach by extending empirical observations into simulated operational outcomes. Whereas the experimental method intentionally isolates variables to measure relative influence, combat modeling relies on behaviors in sequence to better resemble cognitive computational models that integrate a series of functions and behaviors. Both methods have their advantages. More importantly, the combination of controlled experimental research, theory, naturalistic observation and real-world corroboration depicts a full-cycle approach to theory and application with the potential to yield more effective applied research than laboratory results alone could provide (Mortensen and Cialdini, 2010).

Combat modeling tools also continue to become more sophisticated. Modeling techniques range from tactical decision games designed to support military training through sample exercises (Klein, 2015; Schmitt, 1994) to multifaceted mathematical modeling as a means of simulating combat performance (Strickland, 2011; Washburn and Kress, 2009). Formal modeling tools likewise continue to evolve. Simple Lanchester models once simulated combat largely based upon mathematical attrition in differential equations (Artelli and Deckro, 2008; Lanchester, 1916), but modeling platforms now can incorporate a variety of combat-related factors using systems such as One Semi-Automated Forces (Logsdon *et al.*, 2008) and the Infantry Warrior Simulation (Kalnins *et al.*, 2014; Samaloty *et al.*, 2007). Among these tools, the advantage of combat modeling involves converting the raw metrics of experimental observations into tangible combat advantages, such as a force winning some percentage of the time and suffering some number of casualties to achieve victory.

The challenge of any modeling effort is to provide simulated systems that are manageable, meaningful and useful (Kress, 2012). Sophisticated modeling platforms typically approach this idea by exploring the relative influence of different variables among a variety of factors, where terrain, maneuver warfare and equipment become variables in simulation. In this context, the military emphasis becomes clear as these applications typically are designed for military use rather than law enforcement applications. These simulations also involve large-scale platforms such as tanks or missiles and emulate troop movements with limited adaptation for the decision-making process involved in combat marksmanship to individual personnel. One proposed solution is to involve more stochastic modeling methods that could emulate human performance variance from real-world observations. Monte Carlo simulations have been one such technique suggested to fill the gap in combat modeling (Biggs and Hirsch, 2022). Shot speed and accuracy can be sampled from human performance observations to provide a more meaningful representation of speed and accuracy differences.

A core disadvantage of this approach is that Monte Carlo simulations focus on sampling of uncertainty and may not model the sequencing and timing of behaviors as well as other methods (Birta and Arbez, 2013). For modeling efforts, especially when intended to focus on smaller engagements involving close combat or law enforcement, the proposed solution is to integrate a Markov Chain into the Monte Carlo simulations (cf. Brooks *et al.*, 2011; Geyer, 1992). Multiple behaviors can then be simulated in the appropriate sequence as informed by the order of cognitive functions progressing from sustained attention to decision-making and motor responses involved in firing a weapon. By utilizing stochastic model-building techniques for a sequence of behaviors, combat modeling better depicts the interconnected cognitive processes involved in combat than the compartmentalized approach required of cognitive experiments to isolate variables. Moreover, there has been growing adaptation of combat modeling into military marksmanship efforts in recent years. Several combat marksmanship projects have integrated combat modeling to advance training and doctrine in the armed forces with tangible benefits to combat marksmanship programs (Biggs *et al.*, 2023a, b; Weapons Training Battalion Quantico, 2024).

3. A practical example for the combined value of cognitive experiments and cognitive modeling

An existing equipment evaluation can help demonstrate the comparative value of a cognitive experiment approach versus a combat modeling approach when evaluating marksmanship and use-of-force performance – and how the combination of the two yields better results than either method alone. This specific use case involves a study designed to explore the relative impact of different NVGs on close-combat performance (Hamilton *et al.*, 2020). Its goal involved determining whether advanced "panoramic" NVGs created a substantial combat advantage since they provided personnel with a field-of-view more than double that of binocular NVGs. As a study, its experiments followed expected cognitive science procedures by isolating factors such as centrally or peripherally located targets and target eccentricity in the field-of-view. Individual experiment outcomes were aggregated to conclude that an individual with panoramic NVGs engaged an identified enemy target more than a full second faster than with binocular NVGs.

This interpretation indicated a clear combat advantage, but inevitably required a follow-up question: How long is 1 s during close combat? A time difference can seem meaningful, and an effect size can supplement the difference with inferential statistics aimed at interpreting the practical application. That said, relative differences can be lost in translation unless the audience already has advanced statistical training. As such, the illustration here is to apply a combat modeling approach to the existing observation and demonstrate how modeling approaches can better represent multiple cognitive factors in sequence while providing a concise outcome that can be summarized for subsequent decision-making. The first section will be a discussion of the existing data since it represents a cognitive experimental approach and provides the basic information for human behaviors. Next, a simple Monte Carlo approach will demonstrate how stochastic modeling can improve the interpretability of the empirical findings, which is important in conveying the applications to end users who do not have advanced statistical training. Third, the cognitive modeling approach will incorporate a Markov Chain to simulate multiple behaviors in sequence. The goal of this example is to show how a cognitive modeling approach can take real-world human performance observations from cognitive experimental methods and enhance the information available for subsequent decision-making.

3.1 Cognitive experimental approach

3.1.1 Method. Hamilton *et al*. (2020) conducted three within-subjects experiments to assess the human performance advantage associated with NVG use in close-quarters combat (CQC) scenarios. The participants ($N = 10$) were highly trained military operators conducting a live-fire room-clearing exercise with experimentally manipulated NVG equipment (i.e. panoramic NVGs, binocular NVGs or no NVGs under fully lighted conditions to serve as a baseline). Performance was operationalized using reaction time (RT), as measured using shot timers. Accuracy was not used as a measure of performance because none of the participants missed the targets. This accuracy may seem high, but well-trained individuals would be unlikely to miss a torso-sized target when the maximum distance does not exceed 7 m. Experiment 1 emphasized foveal vision by asking participants to sweep the room for a single target located at one of three possible positions (i.e. 0°, 45° or 90°) along a 90° arc from the point of entry. Experiment 2 emphasized peripheral vision by asking participants to first engage a target located directly ahead (0°) and then a second target located in a corner of the room either to the left (90°) or right (270°) from the point of entry. Experiment 3 emphasized decision-making by asking participants to engage two of three centrally located photorealistic targets that were holding either a weapon or a cellphone (i.e. a shoot/do not shoot task).

3.1.2 Results. Experiment 1 revealed that single-target acquisition was significantly faster with panoramic NVGs, yielding an estimated 0.65-s RT advantage relative to binocular NVGs. Experiment 2 demonstrated that peripheral-target acquisition was significantly faster with panoramic NVGs, yielding an estimated 0.28–0.57 s RT advantage relative to binocular NVGs. Experiment 3 revealed only a marginally significant effect of panoramic NVGs on shoot/don’t shoot decision-making, with an estimated 0.37-s RT advantage on the first shot relative to binocular NVGs. Aggregating these different components yields a human performance advantage between 1.30 and 1.59 s.

3.1.3 Discussion. This study utilized cognitive engineering to isolate and precisely measure different human factor components in a CQC scenario, including single-target acquisition, visual sweep and decision-making. The use of random assignment for target positions, typical of the cognitive experimental approach, permitted causal inference concerning the effects of different types of NVGs with the added benefit of high ecological validity. Despite these notable strengths, this study is limited in its ability to answer the translational question – the presumed tactical advantage associated with panoramic NVGs – thereby reflecting a broader weakness of the cognitive experimental approach in bridging the gap between statistical significance and practical application. We suggest that the Monte Carlo simulation approach can help bridge this gap.

3.2 Monte Carlo simulation approach

3.2.1 Method. We simulated a CQC scenario under low light conditions with two individual combatants using the findings available from the Hamilton *et al*. (2020) study. Combatants were assumed to engage simultaneously (i.e. no ambush advantage) but were labeled attacker (i.e. combatant who is entering/clearing the room) and defender (i.e. combatant inside the room who is waiting for the attacker to enter). Each of the combatants fired one or two shots – an initial shot (which included behaviors such as entry, visual sweeping and shoot/don’t-shoot decision-making) and a faster subsequent shot on the same target; targets were assumed to be peripherally located to emphasize the effect of field of view. Each of these shots had a shot time and, as in the cognitive experiment described previously, was assumed to hit the shooter’s intended target. Hits were tracked over time and a combatant was neutralized – immediately ending the trial – once a combatant had been hit twice. The winner was the combatant who neutralized their opponent.

These shot times were stochastically simulated using the Monte Carlo simulation technique. More specifically, the shot times were first drawn from a normal distribution parameterized using reasonable means and standard deviations based on the cognitive experiment described previously. Then, each shot time was constrained to be greater than 0.075 s, representing the physical limitations of time; a weapon can only be fired so quickly and obviously cannot be fired back in time. After a draw of the Monte Carlo simulation, the shot outcomes for both combatants were interleaved on time with appropriate logic applied to calculate a simulated CQC outcome (i.e. who won the gunfight). Many draws of the Monte Carlo simulation were then performed under different experimental conditions to generate the data for the present research (i.e. the probability of winning the gunfight).

We experimentally manipulated the NVG equipment of the combatants, which affected the average speed of their first shot (but not the average speed of the subsequent shot). Consistent with the findings of Hamilton *et al*. (2020), combatants in the Panoramic NVG condition did not have any penalties to their first shot time ($M_{First} = 2.5$, $SD_{First} = 0.7$; $M_{Second} = 0.5$, $SD_{Second} = 0.1$) and combatants in the Binocular NVG condition had a 1.3-s penalty applied to their first shot time. To demonstrate the effects of different kinds of NVG technology, the attacker was randomly assigned to either the Panoramic NVG or Binocular NVG condition and the defender was always assigned to the Binocular NVG condition.

3.2.2 Procedure. The Monte Carlo simulation was run 10 times in every experimental condition, with each iteration performing 5,000 draws of the simulation to generate the data ($N = 20$ simulations). The outcome of interest was the probability of the attacker winning the gunfight, calculated by averaging simulation outcomes across draws of each simulation iteration.

3.2.3 Apparatus. The Monte Carlo simulation was implemented in Python 3.10.8 using the Monaco 0.9.1 library (Shambaugh, 2022). This library instantiates a simulation object that first takes in the random variables (as well as any constants) defining behavior in the simulation and then implements Sobol random sampling on these probability distributions to generate random draws of the simulation variables. The simulation object has three processing functions that together perform the simulation, which are performed in parallel. The *preprocessing* function extracts randomly generated simulation variables as input values and structures the data. The *run* function executes the simulation and its associated helper functions. Finally, the *postprocessing* function processes and logs outcomes.

3.2.4 Results. To evaluate the effect of NVG equipment, we conducted a one-way ANOVA on the mean likelihood of winning. The single factor – with two levels – was Attacker Equipment (Panoramic NVG, Binocular NVG). Unsurprisingly, our analysis revealed a large, significant main effect of Attacker Equipment ($F(1, 18) = 9.51 \times 10^{31}$, $p < 0.001$, $\eta_p{}^2 = 1.00$). More importantly, it demonstrated that the attacker won 49.88% of the trials when equipped with binocular NVGs and 90.24% of the trials when equipped with panoramic NVGs – a 40.36% tactical advantage in the likelihood of victory associated with using panoramic NVGs.

3.2.5 Discussion. The validity of any simulation depends on the data used to parameterize its underlying sampling distributions. Therefore, the cognitive experimental approach is a necessary precursor to this approach. That said, this Monte Carlo simulation, albeit quite simple, does something that the cognitive experimental approach cannot; it can answer the translational question by describing the human-performance advantage in a metric that is meaningful to an operational decision-maker. This information can shape a cascade of decision-making processes such as cost–benefit analyses associated with acquisition, casualty estimation for use in medical capability modeling and infantry marksmanship training doctrine. Rather than simply describing a 1.30–1.59-s time advantage for panoramic NVGs, this same outcome can be described as a more than 40% increase in the chance of tactical victory. However, the validity of this simulation can be strengthened by layering greater complexity into the underlying model. One way of doing so is by incorporating a Markov chain capturing the sequence of behaviors and decisions involved in firearms use.

3.3 Markov chain approach

3.3.1 Method. We improved our simulation of the CQC scenario described previously by representing the combatants' behaviors with a Markov chain comprising shot times (i.e. speed) and shot outcomes (i.e. accuracy). The outcome of each shot could include a miss, a glancing hit or a direct hit on the shooter's intended target. Each of the combatants fired an initial shot, as before, as well as up to four subsequent shots on the same target. These outcomes were tracked over time and a combatant was neutralized, immediately ending the trial, once a combatant had been struck by three glancing hits, two direct hits or any combination of the two types of hits (e.g. one glancing hit and one direct hit). Again, the winner was the combatant who neutralized their opponent.

Both the shot times and shot outcomes were stochastically estimated using the Monte Carlo simulation technique, with the shot times calculated as before. The outcome of each combatant's shot, for each stage of the Markov chain, was calculated in four steps. First, by drawing the probability of a miss, a glancing hit and a direct hit for a given shot from a series of normal distributions; second, by constraining each of these probabilities to be between 0.005 and 0.995, representing the mathematical limitations of probability ($0 \leq P \leq 1$); third, by normalizing these three probabilities to generate a multinomial probability distribution for each shot ($\sum P = 1$); and fourth, by randomly drawing an outcome from this probability distribution. Many draws of the Monte Carlo simulation were then performed under different experimental conditions to generate the data for the present research.

We again experimentally manipulated the equipment of the combatants, which affected the average speed of their first shot, except this time we included a third condition: tactical light. A tactical light is a flashlight that is attached to a weapon. We implemented this condition to capture situations in which a combatant is not equipped with NVG but has something that may offer a performance advantage over unaided (i.e. no NVG and no tactical light) performance. Combatants in the Panoramic NVG condition did not have any penalties applied to their first shot time, combatants in the Binocular NVG condition had a 1.3-s penalty applied to their first shot time and combatants in the Tactical Light condition had a 2.3-s penalty applied to their first shot time (i.e. an additional 1.0 s penalty). To demonstrate the effects of different kinds of NVG technology against different adversaries, the attacker was assigned to either the Panoramic NVG or Binocular NVG condition, and the defender was assigned to either the Binocular NVG or Tactical Light condition.

We also experimentally manipulated combatant accuracy and skill. To manipulate accuracy, we adjusted the average probability of the different shot outcomes together, given their non-independence. The probability of a direct hit, glancing hit or miss in the High Accuracy condition was set using sensible means and standard deviations drawn from human performance marksmanship data ($M_D = 0.85$, $SD_D = 0.05$; $M_G = 0.1$, $SD_G = 0.025$; $M_M = 0.05$, $SD_M = 0.025$). In the Medium Accuracy condition, the probability of a direct hit was decreased by 1 standard deviation, and the probability of a miss was increased by 2 standard deviations. In the Low Accuracy condition, the probability of a direct hit was decreased by 2 standard deviations and the probability of a miss was increased by 4 standard deviations. Both the attacker and defender were assigned to all three accuracy conditions.

3.3.2 Procedure. This study had a 2 (Attacker Equipment: Panoramic NVG, Binocular NVG) × 2 (Defender Equipment: Binocular NVG, Tactical Light) × 3 (Attacker Accuracy: Low, Medium, High) × 3 (Defender Accuracy: Low, Medium, High) factorial design. The Monte Carlo simulation was run 10 times in every experimental condition, with each of these iterations performing 5,000 draws of the simulation, to generate the data for the present research ($N = 360$ simulations). The outcome of interest was the probability of the attacker winning the gunfight, calculated by averaging simulation outcomes across draws of each simulation iteration.

3.3.3 Apparatus. See Section 3.2.3.

3.3.4 Results. To evaluate the effect of equipment on the mean likelihood of winning, we tested a factorial ANOVA. This model included the main effects of Attacker Equipment

(Panoramic NVG, Binocular NVG), Defender Equipment (Binocular NVG, Tactical Light) and, as covariates, the main effects of Attacker Accuracy (low, medium, high) and Defender Accuracy (low, medium, high). Importantly, the model included the Attacker Equipment × Defender Equipment and Attacker Accuracy × Defender Accuracy two-way interactions to investigate whether an adversary's characteristics moderate the effect of equipment or skill, respectively. Finally, the model also included the Attacker Equipment × Attacker Accuracy and Defender Equipment × Defender Accuracy two-way interactions to investigate whether one's own skill moderates the effect of equipment.

Our analysis revealed a large, significant main effect of both Attacker Equipment ($F(1, 344) = 1.17 \times 10^5$, $p < 0.001$, $\eta_p^2 = 0.99$) and Defender Equipment ($F(1, 344) = 1.17 \times 10^5$, $p < 0.001$, $\eta_p^2 = 0.99$), but these effects were qualified by a large, significant Attacker Equipment × Defender Equipment two-way interaction ($F(1, 348) = 3.90 \times 10^4$, $p < 0.001$, $\eta_p^2 = 0.98$). These main effects suggest that better equipped combatants were, on average, more likely to win the gunfight. However, a simple slopes analysis revealed that when the defender was relatively poorly equipped (i.e. using a tactical light), attackers using panoramic NVGs ($M = 0.991$, $SD = 0.003$) won approximately 10% more often than attackers using binocular NVGs ($M = 0.887$, $SD = 0.015$). When the defender was relatively better equipped (i.e. using binocular NVGs), attackers using the panoramic NVGs ($M = 0.888$, $SD = 0.014$) won approximately 38% more often than attackers using binocular NVGs ($M = 0.502$, $SD = 0.026$). This interaction pattern is visualized in Figure 1.

The effect of equipment was also moderated by one's own skill, as there was a small but significant two-way interaction between both Attacker Equipment × Attacker Skill ($F(2, 344) = 56.87$, $p < 0.001$, $\eta_p^2 = 0.02$) and Defender Equipment × Defender Skill ($F(2, 344) = 69.90$, $p < 0.001$, $\eta_p^2 = 0.02$). These interactions indicate that the difference in the probability of winning between the panoramic NVG condition and the binocular NVG condition was greatest for low skill attackers and high skill defenders; this is likely because high skill attackers and low skill defenders led to more of a ceiling effect. As to the covariates, there was a significant main effect of both Attacker Accuracy ($F(2, 344) = 521.26$, $p < 0.001$, $\eta_p^2 = 0.75$) and Defender Accuracy ($F(2, 344) = 241.80$, $p < 0.001$, $\eta_p^2 = 0.58$), indicating that higher skill combatants were, on average, more likely to win the gunfight. The effect of these covariates was not moderated by adversary characteristics because the two-way

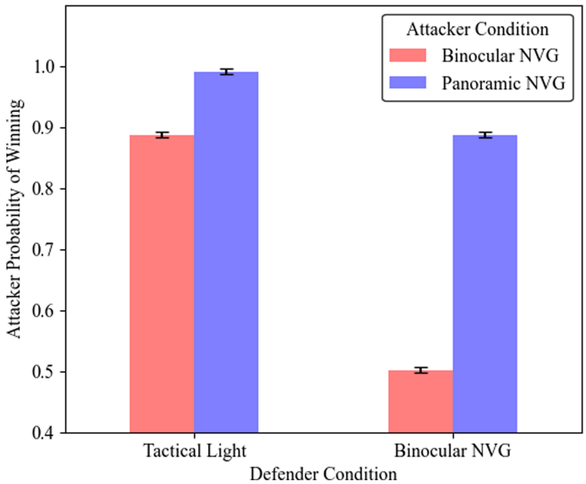

Figure 1. Effect of equipment on the probability of winning the combat engagement. Note: Error bars represent 99% CI

interaction between Attacker Accuracy and Defender Accuracy was non-significant (F(4, 344) = 0.31, p = 0.869).

3.3.5 Discussion. Using a Markov chain to add greater complexity to our Monte Carlo simulation revealed that the effect of NVG equipment was context dependent. For example, panoramic NVGs conferred a substantial advantage against a well-equipped adversary, but when engaging a poorly equipped adversary, this advantage was attenuated because of a ceiling effect in the probability of winning. Interestingly, skill had only a small effect on the advantage associated with equipment. These three interpretations used the same basic input data, but to substantially different effects. Still, introducing a Markov Chain represents the more important step for combat modeling. By introducing some basic complexity into the modeling process, we demonstrated how a cognitive modeling approach can extend the interpretation further than a simple Monte Carlo interpretation of raw human-performance observations.

4. Operationalizing marksmanship in the use-of-force

Although the previous data demonstrated the importance of a modeling-based approach to performance, existing data largely build upon experimental or controlled paradigms. This technique limits modeling to the methods demonstrated here without fully embracing the range of behaviors involved. As such, the next purpose of this discussion is to create a more conceptual scaffolding for marksmanship in a use-of-force sequence so that future data collection need not be limited to a trial-based, experimental approach.

The operationalized marksmanship process here proposes several key steps: understanding the situation (scenario monitoring), identifying a target (positive identification), presenting the weapon (weapon manipulation), aligning the weapon with the target (aiming behaviors) and firing upon the target (trigger press). Therefore, it is important to identify how each test reflects these essential steps in using a firearm so that multiple operational tests with different purposes may be built around these fundamental marksmanship processes. Different assessments may begin or end at different stages depending on logistical constraints and training objectives. The proposed process framework comprises a feedback loop with eight behavioral nodes (Figure 2) representing key decisions and actions in a lethal-force engagement. The nodes include readiness and priming, five stages in the primary shot sequence and feedback loops that allow the process to return to earlier stages. Each node represents a behavioral stage in the engagement process in which prior outcomes influence subsequent behavior. This framework illustrates one possible model structure for constructing marksmanship simulations and assessments rather than a single comprehensive model of marksmanship.

The proposed model should be interpreted as a conceptual behavioral process model of the use-of-force engagement sequence. Each node represents a stage in the cognitive and motor processes involved in detecting, evaluating and engaging a threat, while the connecting links represent the progression of actions and feedback loops that occur during an engagement. The model is not intended as a formal stochastic model but rather as a conceptual structure that can inform the design of experiments, training assessments and future simulation models.

4.1 Readiness and priming

Foremost, no shooting scenario begins at a truly blank state. Every person enters a scenario or situation with different training levels and prior experience, so assuming a truly equivalent start would be inaccurate. However, despite individual differences in training, any priming can play a critical role in how an individual responds to a threat (Hommel, 2000; Taylor, 2020; but see also Mitchell and Flin, 2007). As such, there should be some acknowledgement of the state in which an individual finds themselves prior to the assessment. For an actual use-of-force event, the practical interpretation might be dispatch priming, use-of-force policy or rules of engagement. Shooting behaviors could be directly impacted if someone enters a scenario

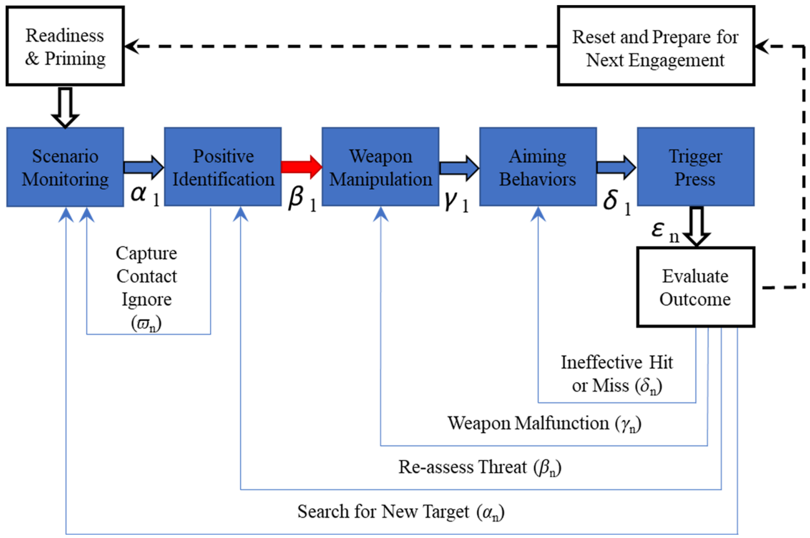

Figure 2. The operationalized sequence for the use of force (OSUF). Solid blue nodes represent key steps involved in the primary shot sequence. Additional nodes, especially the Evaluate Outcome node, enable feedback loops to address errors and continue firing to reach the intended outcome. Furthermore, the feedback loops are illustrative of possibilities as to how decisions and behaviors could return to a previous stage following the trigger press. Feedback loops here are illustrative, not exhaustive

expecting to see non-hostile persons such as civilians or hostages versus an entirely hostile environment. This expectation could affect threat perception and decision-making, as well as how quickly and appropriately with which an individual reacts to potential targets.

For an operational readiness assessment, a primary consideration involves the established starting point for a marksmanship assessment given the more comprehensive span of behaviors. This information will include aspects of the drill such as shots to be fired, target types, target locations and likely the starting position or condition of the weapon (e.g. loaded vs. unloaded, safety on vs. safety off). More experienced personnel may employ strategies to maximize performance given the constraints of a drill, whereas inexperienced or indifferent personnel will not respond in the most efficient manner. The role of the readiness and priming stage is ultimately to enable the types of behaviors that can be explored within the shooting assessment.

4.2 Primary pathway in the marksmanship sequence

4.2.1 Scenario monitoring. The next component represents the first key step during the application of force as it drives the decision to apply that force. Scenario monitoring broadly incorporates search and scanning behaviors where an individual tries to find a legitimate target. These visual search behaviors better resemble surveillance and dynamic scanning with constant updating of the visual area, which differs significantly from the scenario of scanning a static image. The key distinction of scenario monitoring thus involves factors such as vigilance and the nature of scanning a dynamic versus a static environment. Vigilance can wax and wane across different scenarios such as a protracted military checkpoint simulation, especially compared to scenarios that simulate intense but brief firefights. Priming can further augment vigilance by manipulating these expectations. For visual search, there is a substantial amount of nuance involved in the search and scanning behaviors undertaken during a lethal force scenario. Experts have different search behaviors than non-experts (Drew *et al*., 2013; Savelsbergh *et al*., 2005), and in a lethal force scenario, scanning differences could range from where an individual looks during a simulation or how long they linger with every fixation. Unfortunately, this component is also largely missing from marksmanship assessments where the individual is often in a specified shooting lane firing at an easily visible (and often readily identifiable) target.

Consider the example of a turning target, where the target is not faced directly toward a shooter until some given cue. Although there is a visual cue when the target turns to initiate a shot sequence, the manipulation involves identifying the target rather than visual search. Shooters may not know what each turning target might be, but they do know where the target is located. Visual search behaviors could be planned in advance as all items of interest are already visible. The dynamics of turning targets introduce elements of decision-making while limiting or negating the role of visual search to find a possible target. By comparison, a sniper searching for another sniper must conduct a careful and labored visual search process to locate the adversary. This process is not well represented with a turning target, demonstrating a limitation of the technique. For the scenario monitoring stage, the key takeaway is that the burden remains primarily cognitive as the shooter engages in visual search in an attempt to locate a hostile target or anything else requiring further evaluation.

4.2.2 Positive identification. Although scenario monitoring represents scanning behaviors, there is a subsequent step once the scanning process identifies a possible hostile target. Detecting a possible target initiates the positive identification step. Hostile determination will likely require immediate intervention and initiate further steps in the marksmanship sequence. If the possible threat is identified as non-hostile, then the process returns to scenario monitoring. Actions taken in response to a non-hostile determination, such as contacting the individual, will be discussed alongside other feedback loops. Regardless of the determination, this component represents the perception and judgment involved in identifying someone as a possible threat.

From an attention-related perspective, the rules of engagement or other priming factors will have created a target template for the individual shooter (Wolfe and Gray, 2007). The target template is a cognitive representation of perceptual factors associated with the presumed target set. For example, a military engagement would likely have the shooter develop a target template for hostile threats incorporating the clothing, insignia and weapons used by the enemy as well as hostile intent indicators (e.g. posture, emotion, weapon employment). Perceptual influences must be addressed in this step as many different factors could influence the perception of a hostile target, cf. (Junior *et al*., 2013; Witt and Brockmole, 2012; Witt *et al*., 2020). Because threat perception is subject to biases in perceptual judgment, such as racial biases (Correll *et al*., 2014; James *et al*., 2014), the judgments associated with threat perception must be represented in the marksmanship sequence. Depending on whether the potential target is identified as hostile or non-hostile, the positive identification step will either initiate subsequent steps in the marksmanship sequence or return the cognitive process to a previous stage.

An important note should be made about the difference between *detection* and *identification*, because these labels may have different interpretations across military and law enforcement organizations. For example, one community may use identification to mean a possible target has been detected and thus a threat assessment must be made, thereby implicating different steps, whereas another community may use detection and identification almost interchangeably, thereby implicating them as the same step. Here, the intent is to have a progression where detection of a possible threat in scenario monitoring moves the shooter to the positive identification stage, which will include decision-making elements related to a threat assessment. A critical issue thus becomes whether detection should receive its own node in the model. In the proposed conceptualization, detection is conceived as the step initiating progression from scenario monitoring to positive identification. So, detection is not part of the identification process in this model but instead represents the final step that shifts cognitive functions in marksmanship behaviors from sustained attention and visual search into perceptual judgements and decisions involved in a threat assessment. Specific applications could choose to include a detection node as appropriate for the given context, such as monitoring a crowd where there might be many possible targets, and detection of a possible threat becomes a more nuanced component.

4.2.3 Weapon manipulation. Upon a positive identification of a hostile threat, the next stage involves preparing the weapon to fire. This stage represents weapon handling abilities commonly used in shooting assessments, such as drawing a pistol from a holster, presenting a rifle or pistol from a prescribed starting position, manipulating a light or laser during a given drill and more. As such, weapon manipulation could include moving the position of the shooter as well as the position of the weapon during the assessment. The key element to consider is whether the behavior represents primary or ancillary weapons handling. Primary weapon manipulations are required to get the gun into the fight, and ancillary weapon manipulations are required to sustain the gun throughout the fight. Therefore, primary weapon handling dictates the movements necessary to move the gun into the fight from the given position at time of positive hostile identification. Alternatively, ancillary weapon handling behaviors often refer to subsequent behaviors such as clearing a weapon stoppage/malfunction or reloading under pressure. For the marksmanship process, the difference is whether the behavior is necessary to initiate a shot or if the behavior is in reaction to some error or change in the situation (transitioning to another target, delivering follow-on shots to defeat cover or armor, etc.).

4.2.4 Aiming behaviors. This step encompasses all behaviors used to aim the weapon, including obtaining sufficient sight alignment, sight picture and calculating distance when applicable. Aiming behaviors could be quite simple, depending on proximity. At shorter distances, this may only require superimposing the sight or reticle on the desired location of impact. As such, these factors affect performance most at extremely close or extremely far distances. Issues such as height over bore – the distance between the center of the optic and center of the barrel – might need to be taken into account when aiming at close range. Conversely, longer distances are more likely to induce complex aiming behaviors given that ballistic and environmental factors, such as bullet drop and wind, must be incorporated into the aim calculations. Cognitive factors thus include numerous perceptual judgments of distance and motion needed to ensure that the correct assumptions are made to ensure an accurate shot. More than the other components, this factor will be impacted by weapon type and distance as aiming behaviors are substantially impacted by proximity and available time.

4.2.5 Trigger press. The final component directly affecting a shot is the trigger press. This physical action is primarily a motor response and can be measured in milliseconds during a shooting scenario. However, for novice shooters, the trigger press may be a more protracted step that involves greater concentration on proper execution. There are also other aspects associated with the trigger press, such as positioning of the finger on the trigger, direction of force applied, tension in the remaining fingers of the hand and methods used to prevent the action of manipulating the trigger from affecting the alignment of the weapon with the target (anticipation, changes in grip tension, "forcing" a shot, etc.). Although the trigger press is largely an issue of grip and smooth motor initiation of the trigger press, and given the totality of the situation, it is a refined psycho-motor skill and not simply a physical manipulation. Due to the complexity of this specific portion of the engagement process, there is ample opportunity to impact the outcome even if the marksmanship process has advanced to the final trigger manipulation.

4.3 Evaluating the outcome and feedback loops

Terminal ballistic realities, along with low accuracy rates in real-world shootings (Morrison and Vila, 1998), mean that marksmanship performance during use of force often does not end with a single shot. Moreover, feedback can play a large role in modeling marksmanship

(Glazebrook and Washburn, 2004). Following the trigger press, another behavioral node describes an opportunity to evaluate the outcome and impact subsequent behaviors. This opportunity is the second potential initiation of feedback loops. The first feedback loop is initiated following a non-hostile determination during the positive identification step. This determination is more complex than simply classifying an individual as non-hostile, as different responses might be required. Someone who is not hostile and is not a combatant could potentially be ignored. But a non-hostile combatant might need to be captured or contacted, depending on the situation. The step may also impact cognitive processes as visual search may be biased towards previously acted upon objects (Buttaccio and Hahn, 2011; Huffman and Pratt, 2017; Weidler and Abrams, 2014). Still, the first feedback loop follows the positive identification stage, where each non-hostile identified and processed could potentially slow the time to fire upon a hostile target.

Following evaluation of the outcome, the process may return to earlier stages in the sequence depending on the result of the shot or changes in the engagement. For example, a miss may require returning to the aiming stage, a malfunction may require weapon manipulation and a change in threat status may require reassessing the target. These feedback loops allow the model to represent the repeated adjustments and actions that commonly occur during real-world engagements. The feedback paths shown in Figure 2 are illustrative rather than exhaustive and are intended to highlight how the process can return to earlier stages as new information becomes available. Each feedback loop provides a categorical description of the associated behaviors much as the behavioral nodes represented a range of behaviors. For example, a weapon stoppage/malfunction may represent both clearing a stoppage (failure to feed from a magazine or failure to extract a cartridge from the chamber) and/or performing a subsequent reload of the weapon (inserting a magazine and chambering a round) – the latter representing a technical “stoppage” because the weapon fails to fire due to no ammunition, albeit it is really a categorical description that the weapon must be manipulated to enable further firing. The graphical representation (Figure 2) denotes the initial shot sequence with notation sub-1 because each behavior represents the first corresponding action when considering an additive effect on the final shot time. Subsequent behaviors during feedback loops are denoted with sub-*n* because there is no set number of behaviors that might need to be conducted. In essence, the notation merely differentiates a feedback step from the preliminary sequence as additional manipulation of the weapon will be required to make the weapon operable following a stoppage/malfunction. The intent is to provide a sequence to enable multiple appropriate behaviors based upon where the evaluated outcome determines that the failure occurred. The requisite behavior might be new aiming behaviors due to missing the target or re-assessing the threat if the individual drops a weapon following being fired upon. The iterative step thus incorporates both the behavior to address the error and new behaviors in a subsequent shot process.

Another important consideration involves feedback loops within the primary sequence. For example, the shooter may positively identify a target and move into the weapon manipulation stage, but in the process of getting the weapon ready to fire, the target may disappear behind a building. This specific instance could result in continued aiming at the spot where the individual disappeared or the individual could move back to scenario monitoring with a very precise target template definition for the possible threat. Subsequent target identification procedures would then be expedited in that particular case. The key point is that the model enables feedback loops, where actions at subsequent stages revert to a prior stage in the model while updating the process with new information. Feedback loops provided here are illustrative, not exhaustive – that is, there are likely additional feedback loops that could occur and revert the process to a prior stage based on the simulated sequence. The proposed model only provides a base scaffold for structured conversation between modelers and practitioners rather than every possible iteration that could unfold in the combat marksmanship sequence. Still, the takeaway from the feedback loops should be the potential to revert to prior stages.

5. Concluding remarks

The proposed model aims to fill the gap in structured marksmanship models to provide guidance during debate and test development. When developing marksmanship tests, a common practice is to focus too explicitly on individual drills. For example, a military marksmanship debate can immediately dive into whether a given shooting range is long enough to accommodate a 300-m marksmanship drill and whether multiple ranges could accommodate this drill throughout the organization to support a standardized assessment. These drills may prove valuable for field readiness assessments, but the debate should always begin with the purpose of the assessment – not the specific drills. If practitioners have no existing model upon which to build, then they could be more likely to debate specific iterations of different exercises that could be conducted without the high-level discussion of the marksmanship process. This model is intended to provide a starting point for those discussions as a means to inform marksmanship test development with conceptual guidance before debating the merits of including particular behaviors.

Ultimately, marksmanship training and assessment benefits from a more process-oriented approach that allows instructors and evaluators to contrast different behaviors in testing to their intended end use. Practicality will impose some limitations on any marksmanship evaluation, but practical limitations do not mean the marksmanship design cannot be optimized within those constraints. If the marksmanship assessment collects data on speed, accuracy and variability, these data can be expressed as an operational advantage using Monte Carlo simulations (Biggs and Hirsch, 2022). Data can then improve overall simulation models conducted for force-on-force simulations on a much larger scale (Liao, 2005; Poggie *et al.*, 2022). Any simulation is limited by the data entered into it, and any marksmanship data collected for simulation are limited by the granularity of the marksmanship tasks. Begin by identifying the purpose of the assessment and then use a process-oriented marksmanship analysis to determine the behaviors most important for the intended operational task.

Disclaimer

I am a military service member or employee of the US Government. This work was prepared as part of my official duties. Title 17, U.S.C. x105 provides that copyright protection under this title is not available for any work of the US Government. Title 17, U.S.C. x101 defines a US Government work as work prepared by a military service member or employee of the US Government as part of that person's official duties. This work was supported by the Office of Naval Research under work unit no. N2027. The views expressed in this study are those of the authors and do not necessarily reflect the official policy or position of the Department of War, Department of the Navy, Uniformed Services University, nor the US Government.

References

Anglin, K.M., Novell, C.A., Murphy, J.S. and Goodwin, G.A. (2017), "Identifying predictors of Army marksmanship: a cognitive, affective, and psychomotor perspective", *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Sage Publications, Los Angeles, CA, Vol. 61 No. 1, pp. 838-842, doi: 10.1177/1541931213601683.

Artelli, M.J. and Deckro, R.F. (2008), "Modeling the Lanchester laws with system dynamics", *The Journal of Defense Modeling and Simulation*, Vol. 5 No. 1, pp. 1-20, doi: 10.1177/154851290800500101.

Biggs, A.T. and Hirsch, D.A. (2022), "Using Monte Carlo simulations to translate military and law enforcement training results to operational metrics", *The Journal of Defense Modeling and Simulation*, Vol. 19 No. 3, pp. 403-415, doi: 10.1177/15485129211021159.

Biggs, A.T. and Pettijohn, K.A. (2022), "The role of inhibitory control in shoot/don't-shoot decisions", *Quarterly Journal of Experimental Psychology*, Vol. 75 No. 3, pp. 536-549, doi: 10.1177/17470218211041923.

Biggs, A.T., Hamilton, J.A., Huffman, G., Javes, K., Viggiani, A. and Markwald, R.R. (2023a), "Simulating lethality through human performance data", *Military Operations Research*, Vol. 28 No. 4, pp. 39-56.

Biggs, A., Huffman, G., Hamilton, J., Javes, K., Brookfield, J., Viggiani, A., Costa, J. and Markwald, R.R. (2023b), "Small arms combat modeling: a superior way to evaluate marksmanship data", *Journal of Defense Analytics and Logistics*, Vol. 7 No. 1, pp. 69-87, doi: 10.1108/jdal-11-2022-0012.

Birta, L.G. and Arbez, G. (2013), *Modeling and Simulation*, Springer, London.

Brooks, S., Gelman, A., Jones, G. and Meng, X.L. (2011), *Handbook of Markov Chain Monte Carlo*, CRC Press, Boca Raton, FL.

Brown, S.A., McNamara, J.A. and Blake Mitchell, K. (2017), "Dynamic marksmanship: a novel methodology to evaluate the effects of clothing and individual equipment on mission performance", *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 61 No. 1, September, SAGE Publications, Los Angeles, CA, pp. 2020-2024.

Brunyé, T.T., Goring, S.A., Cantelon, J.A., Eddy, M.D., Elkin-Frankston, S., Elmore, W.R., Giles, G.E., Hancock, C.L., Masud, S.B., McIntyre, J., McKenzie, K.L., Mitchell, K.B., O'Donovan, M.P., Racicot, K. and Ramsay, J.W. (2024), "Trait-level predictors of human performance outcomes in personnel engaged in stressful laboratory and field tasks", *Frontiers in Psychology*, Vol. 15, 1449200, doi: 10.3389/fpsyg.2024.1449200.

Buttaccio, D.R. and Hahn, S. (2011), "The influence of action on visual search: behavioral response toward stimuli modifies the selection process", *Attention, Perception, and Psychophysics*, Vol. 73 No. 5, pp. 1453-1466.

Copay, A.G. and Charles, M.T. (2001), "The influence of grip strength on handgun marksmanship in basic law enforcement training", *Policing: An International Journal of Police Strategies and Management*, Vol. 24 No. 1, pp. 32-39, doi: 10.1108/13639510110382241.

Correll, J., Hudson, S.M., Guillermo, S. and Ma, D.S. (2014), "The police officer's dilemma: a decade of research on racial bias in the decision to shoot", *Social and Personality Psychology Compass*, Vol. 8 No. 5, pp. 201-213, doi: 10.1111/spc3.12099.

Drew, T., Vo, M.L.H., Olwal, A., Jacobson, F., Seltzer, S.E. and Wolfe, J.M. (2013), "Scanners and drillers: characterizing expert visual search through volumetric images", *Journal of Vision*, Vol. 13 No. 10, p. 3, doi: 10.1167/13.10.3.

Geyer, C.J. (1992), "Practical Markov chain Monte Carlo", *Statistical Science*, Vol. 7 No. 4, pp. 473-483, doi: 10.1214/ss/1177011137.

Glazebrook, K. and Washburn, A. (2004), "Shoot-look-shoot: a review and extension", *Operations Research*, Vol. 52 No. 3, pp. 454-463, doi: 10.1287/opre.1030.0086.

Hamilton, J.A., Roush, G., Kinney, L.M.J., Suss, J. and Biggs, L.A.T. (2020), "Comparison of night vision technology for close-quarters combat operations: how field of view impacts live-fire scenarios", *Human Factors and Mechanical Engineering for Defense and Safety*, Vol. 4, pp. 1-15, doi: 10.1007/s41314-020-00036-z.

Head, J., Tenan, M.S., Tweedell, A.J., LaFiandra, M.E., Morelli, F., Wilson, K.M., Ortega, S.V. and Helton, W.S. (2017), "Prior mental fatigue impairs marksmanship decision performance", *Frontiers in Physiology*, Vol. 8, p. 680, doi: 10.3389/fphys.2017.00680.

Hommel, B. (2000), "Control in stimulus-response translation", *Control of cognitive processes: Attention and performance XVIII*, Vol. 18, p. 247.

Huffman, G. and Pratt, J. (2017), "The action effect: support for the biased competition hypothesis", *Attention, Perception, and Psychophysics*, Vol. 79 No. 6, pp. 1804-1815.

James, L., Klinger, D. and Vila, B. (2014), "Racial and ethnic bias in decisions to shoot seen through a stronger lens: experimental results from high-fidelity laboratory simulations", *Journal of Experimental Criminology*, Vol. 10 No. 3, pp. 323-340, doi: 10.1007/s11292-014-9204-9.

Junior, O.F., Portugal, L.C.L., Alves, R.D.C.S., Campagnoli, R.R., Erthal, F.C.S., Mocaiber, I.F. and Pereira, M.G. (2013), "How you perceive threat determines your behavior", *Frontiers in Human Neuroscience*, Vol. 7, p. 632.

Kalnins, R., McKearn, M., Wilson, P., Zecha, A. and Eaton, J. (2014), “An analysis of the Infantry Warrior Simulation (IWARS) through engagement effectiveness modeling and statistical data collection”, *IIE Annual Conference. Proceedings*, Institute of Industrial and Systems Engineers (IISE), p. 404.

Klein, G. (2015), “A naturalistic decision making perspective on studying intuitive decision making”, *Journal of Applied Research in Memory and Cognition*, Vol. 4 No. 3, pp. 164-168, doi: 10.1016/j.jarmac.2015.07.001.

Kress, M. (2012), “Modeling armed conflicts”, *Science*, Vol. 336 No. 6083, pp. 865-869, doi: 10.1126/science.1217724.

Lanchester, F.W. (1916), *Aircraft in Warfare: The Dawn of the Fourth Arm*, Constable, London.

Liao, S.H. (2005), “An Intranet-based architecture for building military scenario training systems”, *Journal of the Operational Research Society*, Vol. 56 No. 5, pp. 504-513, doi: 10.1057/palgrave.jors.2601843.

Lim, J., Palmer, C.J., Busa, M.A., Amado, A., Rosado, L.D., Ducharme, S.W., Simon, D. and Van Emmerik, R.E. (2017), “Additional helmet and pack loading reduce situational awareness during the establishment of marksmanship posture”, *Ergonomics*, Vol. 60 No. 6, pp. 824-836, doi: 10.1080/00140139.2016.1222001.

Logsdon, J., Nash, D. and Barnes, M. (2008), “One semi-automated forces (OneSAF): capabilities, architecture, and processes”, *Proceedings of the DoD Modeling and Simulation Conference*, March, Orlando, FL.

Mitchell, L. and Flin, R. (2007), “Shooting decisions by police firearms officers”, *Journal of Cognitive Engineering and Decision Making*, Vol. 1 No. 4, pp. 375-390, doi: 10.1518/155534307x264861.

Morrison, G.B. and Vila, B.J. (1998), “Police handgun qualification: practical measure or aimless activity?”, *Policing: An International Journal of Police Strategies and Management*, Vol. 21 No. 3, pp. 510-533, doi: 10.1108/13639519810228804.

Mortensen, C.R. and Cialdini, R.B. (2010), “Full-cycle social psychology for theory and application”, *Social and Personality Psychology Compass*, Vol. 4 No. 1, pp. 53-63, doi: 10.1111/j.1751-9004.2009.00239.x.

NATO Research and Technology Organisation, Studies, Analysis and Simulation Panel (2004), “NATO code of best practice for command and control assessment”, RTO Technical Report TR-081 / SAS-026; Accession No. ADA422189, North Atlantic Treaty Organisation.

Nieuwenhuys, A. and Oudejans, R.R. (2010), “Effects of anxiety on handgun shooting behavior of police officers: a pilot study”, *Anxiety, Stress and Coping*, Vol. 23 No. 2, pp. 225-233, doi: 10.1080/10615800902977494.

Poggie, J., Matei, S.A. and Kirchubel, R. (2022), “Simulating military conflict with a continuous flow model”, *Journal of the Operational Research Society*, Vol. 73 No. 2, pp. 273-284.

Rao, H.M., Smalt, C.J., Rodriguez, A., Wright, H.M., Mehta, D.D., Brattain, L.J., Edwards, H.M. III, Lammert, A., Heaton, K.J. and Quatieri, T.F. (2020), “Predicting cognitive load and operational performance in a simulated marksmanship task”, *Frontiers in Human Neuroscience*, Vol. 14, p. 222, doi: 10.3389/fnhum.2020.00222.

Samaloty, N.N.E., Schleper, R., Fawkes, M.A. and Muscietta, D. (2007), “Infantry warrior simulation (IWARS): a soldier-centric constructive simulation”, *Phalanx*, Vol. 40 No. 2, pp. 29-31.

Savelsbergh, G.J., Van der Kamp, J., Williams, A.M. and Ward, P. (2005), “Anticipation and visual search behaviour in expert soccer goalkeepers”, *Ergonomics*, Vol. 48 Nos 11-14, pp. 1686-1697, doi: 10.1080/00140130500101346.

Schmitt, J.F. (1994), *Mastering Tactics*, Quantico, VA.

Shambaugh, W.S. (2022), “Monaco: a Monte Carlo library for performing uncertainty and sensitivity analyses”, *SciPy 2022*.

Shi, X. and Zhang, S. (2020), “Research on complex system-of-systems combat experiment”, *Journal of Physics: Conference Series*, Vol. 1624 No. 2, 022073, doi: 10.1088/1742-6596/1624/2/022073.

Smith, C.D., Cooper, A.D., Merullo, D.J., Cohen, B.S., Heaton, K.J., Claro, P.J. and Smith, T. (2019), “Sleep restriction and cognitive load affect performance on a simulated marksmanship task”, *Journal of Sleep Research*, Vol. 28 No. 3, e12637, doi: 10.1111/jsr.12637.

Strickland, J. (2011), *Mathematical Modeling of Warfare and Combat Phenomenon*, Lulu.com, Raleigh, NC.

Swain, D.P., Ringleb, S.I., Naik, D.N. and Butowicz, C.M. (2011), “Effect of training with and without a load on military fitness tests and marksmanship”, *The Journal of Strength and Conditioning Research*, Vol. 25 No. 7, pp. 1857-1865, doi: 10.1519/jsc.0b013e318220dbcf.

Taylor, P.L. (2020), “Dispatch priming and the police decision to use deadly force”, *Police Quarterly*, Vol. 23 No. 3, pp. 311-332.

Tolk, A. (2019), “Tutorial on the engineering principles of combat modeling and distributed simulation”, *2019 Winter Simulation Conference (WSC)*, IEEE, pp. 18-32.

Washburn, A.R. and Kress, M. (2009), *Combat Modeling*, Vol. 139, Springer, New York.

Weapons Training Battalion Quantico (2024), “Continuously revolutionizing small-arms lethality”, *Marine Corps Gazette*, available at: https://www.mca-marines.org/wp-content/uploads/NCO-SNCO-Sep24.pdf

Weidler, B.J. and Abrams, R.A. (2014), “Enhanced cognitive control near the hands”, *Psychonomic Bulletin and Review*, Vol. 21 No. 2, pp. 462-469.

Witt, J.K. and Brockmole, J.R. (2012), “Action alters object identification: wielding a gun increases the bias to see guns”, *Journal of Experimental Psychology: Human Perception and Performance*, Vol. 38 No. 5, pp. 1159-1167, doi: 10.1037/a0027881.

Witt, J.K., Parnes, J.E. and Tenhundfeld, N.L. (2020), “Wielding a gun increases judgments of others as holding guns: a randomized controlled trial”, *Cognitive Research: Principles and Implications*, Vol. 5 No. 1, pp. 1-17, doi: 10.1186/s41235-020-00260-3.

Wolfe, J.M. and Gray, W. (2007), “Guided Search 4.0”, in *Integrated Models of Cognitive Systems*, pp. 99-119.

Zanesco, A.P., Denkova, E., Barry, J., Alessio, C. and Jha, A.P. (2025), “Examining cognition in action: laboratory-based attentional control tasks predict performance on combat-relevant tasks in an augmented reality training environment”, *Frontiers in Psychology*, Vol. 16, 1543161, doi: 10.3389/fpsyg.2025.1543161.

Further reading

Gibson, J.E., Scherer, W.T. and Gibson, W.F. (2007), *How to Do Systems Analysis*, John Wiley & Sons, Hoboken, NJ, Vol. 47.

Hamilton, J.A., Lambert, G., Suss, J. and Biggs, A.T. (2019), “Can cognitive training improve shoot/don’t-shoot performance? Evidence from live fire exercises”, *The American Journal of Psychology*, Vol. 132 No. 2, pp. 179-194, doi: 10.5406/amerjpsyc.132.2.0179.

Ku, X., Hyun, S. and Lee, B. (2022), “The role of death anxiety on marksmanship performance: a virtual reality simulator study”, *Ergonomics*, Vol. 65 No. 2, pp. 219-232, doi: 10.1080/00140139.2021.1965222.

Corresponding author
Adam T. Biggs can be contacted at: adam.biggs@usuhs.edu