Scaling Expertise: Automating Knowledge Elicitation for Designing Simulations

LIA A. DIBELLO, DEE ANDREWS
Applied Cognitive Sciences Labs Inc.

ABSTRACT
Simulation has become indispensable in modern military training due to technological advances, safety needs, cost efficiency, and the complexity of contemporary conflict. It now plays a critical role in competency development, mission rehearsal, operator safety, multinational interoperability, and adapting to emerging threats. Incorporating cognitive learning models has further enhanced simulation, accelerating expertise development. However, simulation design has been limited by access to subject matter experts (SMEs), whose tacit knowledge ensures realism and training value. Naturalistic Decision Making (NDM) research, pioneered by Gary Klein and colleagues, has long provided systematic methods for eliciting and modeling expert perception, decision-making, and action in complex environments. Building on these foundations, this paper introduces an Artificial Intelligence (AI)-driven, automated knowledge elicitation framework that extends NDM by scaling SME insight and directly embedding it into simulation design. The approach enables SMEs to design realistic, learning-optimized simulations without requiring expertise in cognitive science or computer code.

KEYWORDS
Simulations, expertise, accelerated learning, complexity, learning under uncertainty

INTRODUCTION

Simulation-based training has assumed an increasingly prominent role in military education, accelerated by rising operational complexity, multi-domain readiness requirements, budgetary constraints, and logistical limitations. Incorporation of accelerated learning principles into simulation environments expedites expertise development and promotes long-term retention (e.g., Hussen et. al 2025; DiBello et al., 2024; Syandus, 2024; Abich & Skkorsky 2022; DiBello, 2019).

Despite their scalability and ability to standardize instruction, simulation platforms face two principal limitations. First, the development of realistic training scenarios requires either direct input from subject matter experts (SMEs) or extensive analysis of SME knowledge. Naturalistic Decision Making (NDM) methodologies have facilitated the elicitation of tacit expert knowledge, though these approaches are inherently resource-intensive and SMEs are sometimes unavailable (Spiro et. al 2019; Schraagen, 2015; Klein 2015). Second, simulation content must continually evolve to keep pace with changing operational requirements, necessitating lengthy redevelopment, complex software adaptation, and considerable financial investment—often resulting in obsolescence upon delivery (Hoffman et al., 2016; Ericsson et al., 2018).

This paper examines ACSILabs' approach to overcoming these constraints via its FutureView Platform. Rather than endorsing a specific solution, the intent is to analyze the cognitive and methodological foundations underpinning its architecture. Developed by NDM specialists and cognitive scientists, FutureView is grounded in Cognitive Transformation Theory and recent research in expertise formation (DiBello et al., 2024; Hughes-Jones, 2025). Its design enables direct SME participation and future adaptability, allowing SMEs to author scenarios while platform automation supports expert-level instructional processes—thus preserving the accelerated learning benefits established in the literature (DiBello & Missildine, 2013; DiBello et al., 2009; Ross et al., 2019; Ross et al., 2018; Spiro et al., 1987; Syandus, 2024; Ward et al., 2019).

The Nature of Implicit Expertise and its Critical Role in Simulations: Foundations of NDM and Intuitive Expertise

Implicit or intuitive expertise, as conceptualized within the NDM framework, refers to the capacity of experienced individuals for rapid, effective choices under complexity and uncertainty by recognizing patterns from accumulated experience, instead of relying strictly on rule-based analysis (Klein, 1998; 2015; Schraagen, 2018; Ward et al., 2019; Hoffman et al., 2016.). NDM diverges from classical decision models by focusing on expert performance in naturalistic, high-stakes contexts such as military, clinical, and emergency scenarios. Intuitive expertise emerges from one's ability to quickly interpret and assess situations, recognize meaningful patterns, utilize mental models, and make fine-grained, perceptual judgments not accessible to novices (Kahneman & Klein, 2009). This expertise depends on tacit, often unconscious knowledge and cannot be fully captured in explicit, declarative form (e.g., Gore et al., 2023; Seifert, 2024).

Key Empirical Insights

Empirical NDM studies affirm that expert intuition depends on reliable calibration with environmental cues and extensive exposure to diverse situations, confirming pioneering work in this field (e.g., Kahneman & Klein, 2009; Ericsson et al., 2018). The validity of intuitive judgments is strongly tied to the regularity and predictability of the context, as well as the frequency and clarity of feedback. Experts excel in domains with dependable feedback but may underperform in volatile or low-feedback environments.

Methods and Applications

NDM researchers leverage cognitive task analysis and qualitative methods to systematically examine the structure of expert intuition and sensemaking during authentic, complex tasks (Schraagen, 2015). This research informs training and development by simulating real-world situations that foster perceptual discrimination and pattern recognition (Klein & Calderwood, 2008; Moon et al., n.d.).

Current State and Limitations

The study of implicit expertise within the NDM field remains vibrant and has deepened insight into professional judgment under uncertainty. Theoretical critiques continue to emphasize the challenges in clearly distinguishing robust intuition from unwarranted confidence, and in transmitting tacit knowledge through conventional knowledge management channels (Ward et al., 2019). Efforts are ongoing to improve measurement techniques and to systematically accelerate intuitive expertise.

Cognitive Transformation Theory and Cognitive Flexibility Theory: Foundational Perspectives

Emerging research in learning theory provides important guidance for new simulation architectures. ACSILabs' FutureView platform operationalizes Cognitive Transformation Theory (CTT) by leveraging simulation-based instructional design to speed the acquisition of expert cognition in ill-structured domains. Unlike theories positing learning as mere accumulation of facts, CTT highlights learning as the continuous adaptation, revision, and replacement of learners' mental models (DiBello et al., 2024; Hughes-Jones, 2025). A core tenet of CTT is the existence of "knowledge shields"—persistent, reductive mental models that hinder accurate interpretation or response to novel problems (DiBello et al., 2024). The FutureView system actively destabilizes these shields by placing learners in goal-driven simulations that force iterative model testing and replacement under compressed, feedback-rich conditions.

Cognitive Flexibility Theory (CFT) complements CTT within FutureView. Where CTT prioritizes transformation and elaboration of mental models, CFT focuses on the learner's adaptive capacity to reorganize and flexibly apply knowledge across varying contexts (Spiro et al., 1987; Hughes-Jones, 2025). CFT is particularly vital in preventing the oversimplification or ossification of knowledge. It achieves this by engaging learners with multiple representations, structured cross-case comparisons, and problem variations that encourage the revision of invalid mental models (Spiro et al., 1987; Syandus, 2024). Together, these theories help establish a dynamic learning ecology—one designed to promote sensemaking, adaptive reflection, and robust model-building aligned with complex real-world demands.

The Issue of Time, Modifications and Agility

The design of powerful simulation-based training environments, underpinned by Cognitive Transformation Theory (CTT), has proven to be a powerful approach to accelerating learning (DiBello et al., 2024; DiBello & Missildine, 2013; DiBello et al., 2009) However, this approach continues to face two notable constraints: (1) the difficulty and time intensive process of encoding implicit expert knowledge, and (2) the requirement for rapid, frequent scenario updates responsive to changing operational realities. The ACSILabs FutureView platform, equipped with a No-code Simulation Editor (No-Code Editor) designed specifically for Subject Matter Experts (SMEs) is meant to directly addresses these barriers.

Encoding Implicit Expert Knowledge

As indicated, expert cognition in naturalistic settings is characterized by tacit know-how and the ability to deploy context-sensitive strategies derived from hard-earned experience. In practice, most simulation platforms depend on instructional designers or technical teams to elicit, translate, and encode expert insights into scenarios, often resulting in significant loss of subtlety and fidelity (DiBello et al., 2024; Hoffman et al., 2016). The translation gap risks reinforcing superficial or fragmented mental models and fails to expose learners to the complex, iterative reasoning patterns that define true expertise. This has been overcome mainly through iterative design over many months or years, with SME feedback and testing. The No-Code Editor resulted from roughly 15 years of seeking ways to overcome this limitation. We realized early on that enabling Experts to directly author simulations was a potential solution.

Specifically, the FutureView platform circumvents this bottleneck by allowing SMEs to author scenarios directly. It's generally observed that experts are effective at passing on their insights and expertise through sharing meaningful events or experiences in the form of stories about significant experiences that shaped their thinking. The No-Code Editor allows SME's to directly author a "story" in a virtual environment and then represent all the critical decision points and options. The No-Code Editor has a number of tools that permit complex scenario development. Using a visual graph system the Editor provides a way for experts to construct decision points, embed feedback mechanisms, and dynamically link actions to outcomes based on their own cognitive processes and mental rehearsal. It also permits the creation of intelligent agents, (things that have self-knowledge that can respond to a simulation user's decisions about them). These can be objects, people or even situations that can dynamically respond to user decisions. Through direct SME authorship, the platform preserves nuanced judgments and cognitive agility.

Working with the USMC Marine Corp Basic School at Quantico under Office of Naval Research SBIR Contract N6833522C0650, we had the opportunity to test this method and then test the effectiveness of the expert-designed missions. During this process, experienced warfighters designed two Missions. We assigned a non-programmer assistant to help with the Editor, but this was mostly for convenience and as a way of training the SMEs. No design choices were made with our help.

A particularly distinctive feature of the resulting FutureView Missions designed by the USMC officers is the fidelity to the actual problem-solving strategies of experts. By capturing and translating the tacit strategies of SME practitioners into immersive, interactive scenarios, novice learners benefit from accelerated exposure to realistic challenges and immediate feedback on the quality of their decisions, empowering them to adapt their own mental frameworks and unlearn outdated approaches (DiBello et al., 2024).

Perhaps more important the Editor enabled the SMEs to easily refine the scenario through iterative design. An unfolding situation can be created and played through or tested for realism. While playing through a scene, for example, SME's saw ways that the scenario can be better or represent more subtlety. Using the Node editor, changes were made nearly instantly, saved, replayed, refined and so on. Because the platform is cloud-based, all users with access get these updates instantly. In general, experienced warfighters made hundreds of small changes before the scenario "felt right". Being able to do this nearly instantly without re-coding greatly speeds up the design process while also making the scenarios more powerful.

Does this Approach Work?

We tested the SME-designed mission with three groups of Marines at The Basic School (TBS) in Quantico. Each group consisted of 12–20 Marine second lieutenants at different stages of the TBS Program of Instruction—some had graduated and were awaiting Military Occupational Specialty school, others were partway through the Basic Officer Course, and some were preparing for graduation.

The first group tested an early version of the first mission, while the second group worked with a much more complex version of the same scenario. The third group completed two highly complex missions, each requiring up to 200 micro-decisions per hour.

Because the No-Code editor makes it easy to apply complex scoring schemes, the SMEs also created an innovative scoring system reflecting each decision's placement on a novice to expert scale, and which cognitive capability would be brought to bear for that decision. For example, every decision was rated on a novice-to-expert scale, and each decision point was tagged with the specific capability required, such as "judgment," "operational efficiency," or "cultural sensitivity." The SMEs collaborated with academic leadership to ensure this scoring framework aligned with The Basic School's Program of Instruction. They were then able to produce instant complex feedback on the overall performance and the areas of strength and weakness in the capability matrix. This was represented in various ways: an overall "mission success" score, specific capabilities represented in a radar plot, and color-coded bar charts showing the quality of each decision within each situation or event. FutureView records all decisions of all users and generates automated reports while the user is going through the scenarios. The No-Code editor is used to score each decision and create a record of progress for each user.

Figure 1. Screenshots of the No-Code Editor manipulating phases of the Mission – Preparing the well deck of the ship and organizing a convoy once ashore

Looking for evidence of accelerated learning, we evaluated how students progressed along the expertise scale from time one to time two, focusing on patterns of movement toward more expert-like choices rather than just counting the frequency of specific decisions. This analysis of navigation patterns provided greater insight because each simulation unfolds differently based on students' early decisions, i.e., the trajectory of the mission is unique for every learner.

Cognitive transformation theory holds that improvement arises through iterative feedback—where trial-and-error cycles not only reinforce productive strategies but also help students *unlearn* ineffective assumptions. This model is built into the platform, so that SME's do not have to be experts in the methods of cognitive transformation. They have only to identify what is the best choice, a good choice, bad choice, or something in between through simple tagging when creating decision points using the Editor. Then, using the Editor, they could design consequences and link them to decisions.

In practice, the simulation's opportunities and sequence of events are driven entirely by student choices. The intelligent agent system adapts dynamically, creating a tailored experience for each individual. For instance, two students starting with the same mission profile reached the same conclusion, but one completed it in 20 minutes with about 60 micro-decisions, while the other took over an hour and made more than 100 micro-decisions. Many of the latter's decisions were corrective, reflecting a less direct path. This same student also got more "novice" or "intermediate" scores and a lower overall mission success score. However, the feedback, regardless of the starting point, pulled each learner forward. All students moved up the expertise scale with repeated exposure, regardless of the mission or its complexity.

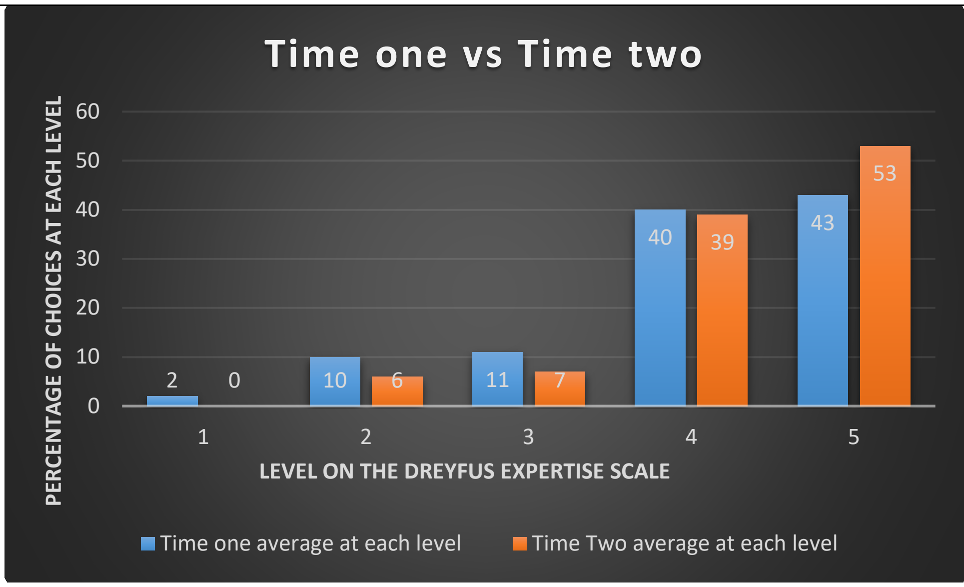

Figure 2. Average % of choices at each level across all participants, Time One and Time Two. A five-level scale was used with Level 5 representing intuitive expertise.

Using a t-test to look at the impact of the simulation and feedback we found statistically significant elevation of "expert" or "near expert" choices on the second try ($t(25) = -4.91$, $p<0.001$) ($SD =<.0459$) for all groups. For the third group, this result was found on both missions ($t(24) = -4.06$, $p<0.001$) ($SD = .09$). The pattern of movement up the scale was similar regardless of the complexity of the mission experienced by each group. This indicated to us that the users were learning on a "first principles" level. In other words, they did better with repeated missions even though the missions were different, and in many cases, more complex.

The USMC saw this as a success at using simulations to rehearse missions too risky to rehearse in other ways. The speed of development and ability to author their own missions was a plus. They are transitioning some of their courseware into the platform at this point, with a plan to engage thousands of students for 40 hours of time in the FutureView simulations beginning in 2026.

This is clearly a good result; however, we see this project as presenting a breakthrough in simulation design, with the use of subject matter experts at the helm. Our team did not have to become experts in warfighting, the SMEs were not held back waiting for refinements, and the academic leadership could determine the content and scoring scheme and implement it easily with the No-Code Editor. As simulations become more important and offer the advantage of rehearsing risky and complex situations, speed of delivery, realistic scenarios, and speed of refinement are critical to offering valuable learning opportunities. We also think this may offer a way to scale accelerated learning approaches.

CONCLUSION

Rapid Scenario Iteration and Operational Responsiveness

In dynamic domains such as military operations, the pace of change presents a second major constraint for simulation-based learning: the challenge of keeping scenarios relevant and representative of current threats, technologies, or standards. Traditional scenario development cycles are slow and resource-intensive, often leading to version lag and diminishing the real-world utility of training interventions. The same iterative design capability used to design and refine scenarios can be used to instantly upgrade and modify scenarios or repurpose scenarios with new challenges.

By integrating direct SME authorship via no-code scenario development tools, FutureView addresses the central design constraints of simulation-based training for expertise: the encoding of tacit knowledge and the need for ongoing scenario adaptation. This architecture enables high-fidelity transfer of expert reasoning, continuous learning, and the robust updating of organizational mental models—positions crucial for advancing research and practice in the NDM community.

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