When Expertise Fails: Designing for High Uncertainty Decision Making in Virtual Worlds

Whit Missildine
Viion, Inc.
Oakland, California
whit@viionworld.com

ABSTRACT

High risk, high volatility task environments require extensive hands-on training, detailed protocols and the experience of expert decision makers who can anticipate, adapt and respond effectively to complex situations. But what happens when even expert-level decision making reaches its limits? How do people behave when protocols and best practices fail to account for unanticipated sources of risk? How can we develop better learning paradigms to address training needs in environments where the best course of action is unknown? Operators in these environments know that experience is key: exposure to repeated, high risk events helps them develop sophisticated response strategies. But what happens when novel challenges render expert decision models obsolete? Immersive simulations and wargames can create ideal learning environments to address this issue, by rapidly accelerating exposure to a variety of rare, non-routine, or hazardous events. However, two primary issues constrain their ability to deliver effectively: First, many of these programs are focused on replicating events that can assure proficiency among operators. Using the Dreyfus five-stage model of expertise, we argue that immersive simulation is most effective when it pushes decision makers beyond proficiency assurance and is able to destabilize their mental models, challenging them toward innovative approaches to chaotic situations. Second, training needs in industry, military and government organizations are often highly constrained by time, money, capacity, schedule, and staffing requirements. Immersive, multi-player Virtual Worlds allow us to relieve some of this training burden by providing a platform to sandbox novel techniques for expert decision making in extraordinary conditions. However, many limitations and challenges still remain. Drawing from our own implementation efforts, we will discuss some of the successes, failures, constraints and opportunities virtual environments offer as a platform to drive learning outcomes and challenge expert level decision makers.

ABOUT THE AUTHORS

Dr. Whit Missildine has a PhD in Social Psychology and is the Chief Learning Officer at Viion, Inc. For over a decade, Dr. Missildine's work has focused on workplace cognition, immersive learning, accelerated expertise, and learning experience design. He has led research, design and implementation efforts on numerous immersive learning engagements and developed a suite of simulation-based, virtual world products across a variety sectors, including mining, project management, finance, and education. He has co-authored a number of peer-reviewed journal publications on the effectiveness of simulation-based learning methods and Virtual Worlds technologies, and presented findings at international conferences on cognitive science, gamification, and simulation-based learning.

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INTRODUCTION

"The key to good decision making is not knowledge. It is understanding. We are swimming in the former. We are desperately lacking in the latter" – Malcolm Gladwell

"Everybody experiences far more than he understands. Yet it is experience, rather than understanding, that influences behavior." – Marshall McLuhan

In his 19th century essay, "On Strategy," Prussian Field Marshal Helmuth Von Moltke comes to a famous conclusion, often paraphrased in the following quote: "No plan survives first contact with the enemy." Moltke is considered one of the greatest military strategists of his time, and the quote is commonly offered as a caveat to the effectiveness of rigid pre-planning in high uncertainty contexts. The original idea behind the quote was that after the first engagement with the enemy, the situation often changes so drastically that "no human acumen can see beyond the first battle." Moltke continues:

> "Throughout the campaign [the commander] must make a series of decisions on the basis of situations that cannot be foreseen. The successive acts of war are thus not premeditated designs, but on the contrary are spontaneous acts guided by military measures. Everything depends on penetrating the uncertainty of veiled situations…"

Moltke's treatise gets straight to the heart of a fundamental dilemma in training for expertise, both within and beyond the military context: to become an expert means to be prepared for any situation, but raises a paradoxical question: how do we prepare for the experience of being unprepared? In simple operating environments, like chess or sports, an expert operator is one who is able to foresee future inevitabilities based on current actions, react according to rehearsed, pre-determined strategies and then adjust as known risks present themselves. But in high uncertainty environments, an expert operator must be able to make sense of novel scenarios and unknown risks, adapt to shifting conditions, prioritize actions based on incomplete or contradictory information and rapidly course correct. And yet, many learning and training environments devote a disproportionate amount of resources to procedure, compliance, role hierarchy, and proficiency assurance. All of these are worthy and necessary preparations, but what happens when standard operating procedures are insufficient?

There is an implicit assumption that with the right preparation, enough resources, and appropriate technological support, human operators can overcome any obstacle. But Moltke reminds us that sometimes "no human acumen is able to see beyond the first battle," and even with all the advances we have made in the last century, the mysteries of the human mind remains at the center of the problem. This is the central concern of our inquiry: the possibilities and limitations of human acumen and its implications for training and readiness, particularly for high level operators in high uncertainty circumstances. What happens when experts face the limits of their ability in complex operating environments? How do we design learning and training programs to better "penetrate the uncertainty of veiled situations"? And what is the role of technology in helping us achieve these goals?

To shed light on these questions, we will explore some key insights from cognitive science that can help us design appropriate learning environments for expert operators in high uncertainty, high volatility contexts. Specifically, we will discuss Jean Piaget's concept of *disequilibration*, which highlights the importance of failure in the learning process and how it can be used to train for readiness in chaotic circumstances. We will also review Hubert Dreyfus's 5-stage model of expertise, which outlines how cognitive processes evolve in the development of expertise. Together, these learning models provide a framework that help us drive accelerated learning outcomes in synthetic, virtual environments.

THE DREYFUS 5-STAGE MODEL OF EXPERTISE

One of the most powerful approaches to expertise was formalized by Hubert Dreyfus (1997). He proposed a 5-stage model of expertise that can apply to any domain and describes the way in which operators shift from novice to expert along a common developmental continuum.

Dreyfus argued that expertise is an emergent property of experience (as opposed to innate ability) that evolves in stages, from "novice" to "expert," and each stage represents unique, qualitative shifts in one's cognitive abilities. Experience drives a predictable developmental trajectory that is domain specific. As the individual moves up in stages, his or her thinking gets increasingly "intuitive," context-free, holistic and autonomous. Thinking and decision making becomes less rule-driven and increasingly organized around a core set of principles that comprise an adaptive, underlying approach as opposed to a set of recipes for action (See Figure 1).

<table>
<tr><th>Level</th><th>Stage</th><th>Characteristics</th><th>How knowledge is treated</th><th>Recognition of relevance</th><th>How context is assessed</th><th>Decision-making</th></tr>
<tr><td>1</td><td>Novice</td><td>Rigid adherence to rules or plans
Little situational perception
No discretionary judgment</td><td>Without reference to context</td><td rowspan="2">None</td><td rowspan="3">Analytically</td><td rowspan="4">Rational</td></tr>
<tr><td>2</td><td>Advanced Beginner</td><td>Guidelines for action based on global characteristics of situations recognizable only after some prior experience
Situational perception still limited
All aspects are treated separately and given equal importance</td><td rowspan="4">In context</td></tr>
<tr><td>3</td><td>Competent</td><td>Can being coping with complexity and parallel processing
Now sees actions at least partially in terms of longer-term goals
Conscious, deliberate planning
Standardized and routinized procedures</td><td rowspan="3">Present</td></tr>
<tr><td>4</td><td>Proficient</td><td>Sees situations holistically rather than in terms of analytical units
Distinguishes signal and noise, can sort relevance
Perceives deviations from the normal pattern
Decision-making less labored
Uses maxims for guidance, adjusted for situational variables</td><td rowspan="2">Holistically</td></tr>
<tr><td>5</td><td>Expert</td><td>No longer relies on rules, guidelines or maxims
Intuitive grasp of situations based on deep tacit understanding
Analytical approaches used only in novel situations and challenges
Vision of what is possible</td><td>Intuitive</td></tr>
</table>

Adapted from: Dreyfus, S.E. (1981). *Four models of human situation understanding: Inherent limitations on the modeling of business expertise.* USAF Office of Scientific Research, ref F49620-79-C-0063; Dreyfus, H.L. & Dreyfus, S.E. (1984). Putting computers in their proper place: Analysis versus intuition in the classroom. In D. Sloan (ed). *The computer in education: A critical perspective.* Colombia NY, Teachers' College Press.

Figure 1. Dreyfus 5-stage Model of Expertise

An important feature of expertise acquisition is that one can't skip stages – one doesn't go from beginner to proficient, or competent to expert, without passing through interim stages. What differentiates expertise from proficiency is the degree to which "proficient" activity becomes intuitive, opening up the expert operator to act with high efficiency in routine situations, and create innovative solutions to unique or novel challenges.

One of the key goals of expertise research has been to understand how the demands of the operating environment shape the kinds of cognition operators must have to operate efficiently. In particular, expertise researchers are interested not just in how people make decisions in stable, predictable tasks, but how cognitive demands shift in uncertain decision environments. Much of this research has been formalized under the Naturalistic Decision Making approach (e.g., Klein, 1999, 2002, Zsambok & Klein, 1997). These "naturalistic decision" environments are characterized by the following features:

- *High Complexity:* Decisions are highly complex and burden operators with information and decision overload.
- *High Risk.* Decisions have high stakes and high risk and are made under time pressure. Decision environments often include incomplete, changing, or contradictory information.
- *Ill-Defined Goals.* As situations evolve, goals can become ill-defined, and multiple goals often conflict. Decisions must be made even though key variables and complexities may not be fully understood.
- *Lack of Control:* Decision makers must be able to take action, while unable to control a number of intervening factors.

Traditional approaches to decision making, often referred to as "Expected Utility Theory" (EUT), view human decision makers as rational, deductive operators who are able to make internally consistent and context-free decisions about possible courses of action (COA). Studied primarily in the laboratory under stable conditions, these classical approaches assume that decisions are made by a systematic process of mentally reviewing all potentially relevant courses of action, weighing their costs and benefits, and then choosing the most efficient or effective among them.

While these classical models may be relevant for stable, standardized environments, many environments that rely on critical decision-making expertise often present unpredictable scenarios and do not allow room for planning, modelling and optimization (Snowden, 2005). Researchers found that the decision skills needed for stable environments are very different than decision skills employed by operators performing cognitively complex functions in real world situations (Gore, et. al, 2006; March, 1994, Klein, 1999). The "recognition-primed decision" (RPD) model, for example, contends that real-world experts confronting real world problems make decisions in a qualitatively different manner from novice participants in laboratory settings. In other words, expert cognition is not just a matter of the degree of knowledge one has, it represents a fundamental change in how one approaches problem sets. Experts are able to make situation assessments to determine a likely COA based on an intuitive process evolving from years of direct experience and engagement with a particular task environment (Klein, 2002). These intuitive processes allow experts to rapidly "act from the gut" based on principles adapted from encounters with multiple past problem sets. Johnson and Rabb (2003) for example, found that experts were likely to choose a good COA on the first try, and, most strikingly, when experts abandon their initial COA and considered multiple possible scenarios the quality of their decisions declined. The implications of this research are that 'acting from the gut' works if you are a high level expert, but not when you are a novice. Furthermore, acting from the gut is actually the optimal approach at high levels of expertise, and unnecessary deliberation might hamper decision efforts. For the novice, the reverse applies. Rule-based, careful deliberation is the optimal strategy over acting from the gut, because novices have very few intuitive, recognitional patterns to draw from. This is not to say that experts never use deliberation. When encountering novel problem sets, deliberating over alternatives is essential, but the expert knows when and how to apply these different approaches.

These findings point to the need for highly customized training programs that are designed with a deep understanding of the differential needs of novice and expert learners. To illustrate this point further, in a phenomenon called the *expertise reversal effect*, researchers have found that instructional techniques with high levels of effectiveness for novice learners are often not effective and sometimes detrimental to more experienced or expert learners (Kalyuga, Ayres, Chandler & Sweeler, 2003). These findings are based in cognitive load theory, which emphasizes the limited duration and capacity of working memory for processing novel information (Sweller, 2004). Because of the limitations of working memory, designing optimal learning experiences requires a balance between inducing productive cognitive load (which motivates learning) and wasteful or extraneous cognitive load (which can interfere with learning). The key to getting that balance right is understanding the prior knowledge that the learner brings to the problem set. For experts, if they are given worked examples and redundant information that activate a less sophisticated knowledge base, working memory resources are wasted and the learning itself distracts from acquiring new, higher level knowledge. If they are repeatedly exposed to these kinds of learning, it can inhibit or reverse their expertise (Renkl & Atkinson, 2003). In sum, if training programs do not adequately account for prior knowledge and expertise levels, more training can reduce its effectiveness.

Macrocognition

One set of skills that is highly developed in expert operators in high volatility domains falls under the umbrella of *macrocognition* (Klein, Moon & Hoffman, 2006). Generally speaking, macrocognition outlines the common decision tools of problem detection, mental simulation, uncertainty management, coordination and adaptation that are used by expert operators. These macrocognitive decision tools are distinguished from microcognition, which is characterized by elemental cognitive functions, such as information processing, perception, and pattern recognition.

Macrocognition is an umbrella term for an approach to cognition and learning that overturns a number of previous assumptions about how decision makers process and deploy input from their environment, including the following:

- Experts do not deductively weigh a set of options and choose the best one, but rather, draw on previous patterns to make sense of situations and adjust.
- Operators don't always need a clear set of goals. Goals can be emergent.
- Expert decision making is largely unconscious (tacit, intuitive)
- For experts, more information is not always better. Experts know what to pay attention to and what not to. Information gathering can be a detrimental technique, because it places unnecessary cognitive demands on working memory and often distracts from an already chosen optimal path based on experience.
- Uncertainty comes more often from an inaccurate framing of information than it does from a lack of information.
- Performance is not improved by simply disseminating existing models, it must include challenges to existing models.
- Training through rote-style learning can reinforce lower level decision models and be harmful to expert operators.

A FUNDAMENTAL MECHANISM OF DEVELOPMENT: DISEQUILIBRATION

Cognitive Equilibrium

As we gain experience in any task domain, we build *schemas*, or, mental models that organize our experience into meaningful perceptions of our environment. These schemata allow us to create expectations for how the world will behave and how our actions influence and are influenced by it. A key feature of this model is that it is "constructivist" insofar as learning is not simply a reaction to environmental stimuli, but rather, an active, constructive process of transforming experiences and updating prior beliefs that "makes the world make sense" (Block, 1982). Jean Piaget, studying the basic mechanisms of cognitive development, argued that humans are motived to learn by a desire to create *cognitive equilibrium* between our expectations based on prior knowledge and our environment (Piaget, 1977). As we move through developmental stages, similar to the stages of expertise, we take on new knowledge about how to operate effectively in the world, and construct more and more sophisticated mental models.

Acting in the world, we are always encountering new information that threatens our prior knowledge. Encountering new or unique information, our first response is to try to *assimilate* it into our existing expectations, thereby confirming and reinforcing our prior schemata. If we are unable to assimilate this new information, we then use a strategy of *accommodation*, in which we adjust our prior schemata to accommodate it, thus expanding our knowledge base. The equilibration process is one in which the individual seeks to modify and refine these cognitive structures to achieve greater equilibrium between our expectations and the environment.

In situations of high uncertainty, or in situations where one encounters information that drastically violates our prior mental models, one experiences a state of *disequilibration*. The process of disequilibration jeopardizes one's ability to create meaningful expectations for how to behave in the world. The more one's mental models are violated, the greater the experience of disequilibration, and the more strategies one has to employ to recover cognitive equilibrium. For Piaget, disequilibration is the primary motivational force driving our trajectory through major developmental stages. The assimilatory response does not engender change, only the process of disequilibration and accommodation offer a mechanism of developmental growth.

Building on Piaget's model, many researchers have updated this initial framework, such as Kolb's "experiential learning" model (Kolb & Kolb, 2005), which expands the set of mental conflicts that must be resolved to achieve equilibrium, and Clark's "predictive processing" model, which refines the neuroscience of expectation and belief updating (Clark, 2013). But the fundamental Piagetian mechanism of change remains the same and, for our purposes in this paper, is key to guiding operators to achieve expert level performance.

Accelerating Expertise

Capturing, storing and transferring expert knowledge and reducing skill fade among experts are among the biggest challenges that high volatility organizations face. A common rule of thumb is that in order to become an expert, 10,000 hours of "deliberate practice" is required. Deliberate practice in this context is defined as "engagement in structured activities created specifically to improve performance in a domain." (Macnamara, Hambrick & Oswald, 2014). The findings are persuasive and backed up with compelling examples: while aptitude plays a role in enhancing expertise, those who get a jump start on completing 10,000 hours are more likely to become top experts in their field than people who are born with natural capabilities or who possess extraordinary genius.

Superficially these findings overturn our assumptions about the role that natural talent and aptitude play in skills development. However, the "10,000 hours rule" applies primarily to structured environments like chess or sports, where success has more predictable rules. Research shows that in these more structured domains, deliberate practice accounts for roughly 20% of the difference between superior achievers and their average colleagues (Macnamara, Hambrick & Oswald, 2014). However, in "other professions," which included computer programmers, pilots, and salespeople, deliberate practice accounted for only 1% of this difference.

In these more unstructured domains, the amount of deliberate practice one completes is not necessarily a strong predictor of success. The results of these studies are especially critical for naturalistic, highly volatile domains, such as war, emergency first-response, and firefighting where rules, goals, and standard practices need to be more fluid to accommodate complexity in rapidly evolving situations. Traditional training methods based on classical knowledge transfer are insufficient and structured training programs that rely on deliberate practice alone will not suffice. As such, developing leading experts in these domains requires not only a large amount of practice, but crucially a different kind of practice.

Cycles of Failure

Based on the Piagetian model, the assimilatory process does not produce change. Thus, to move through developmental stages of expertise, operators cannot simply rehearse scenarios that continuously reinforce existing knowledge. Instead, they must be exposed to situations that violate their prior mental models, leaving them unable to form an interpretation and choose a course of action. In other words, adding new knowledge and practicing standard procedures is insufficient for developing expert level performance. To activate new modes of thinking and behaving (develop new schemas) in response to dynamic environments, old models must first be "unlearned." This is achieved through the disequilibration process by which old, default mental models are recognized as inadequate, creating fertile ground for unlearning and relearning. As such, a purposeful "failure" of the default mental models is essential. Routinely disequilibrating operators through complex scenarios allows them to break down and reorganize mental models to more easily adapt to evolving circumstances, facilitating a transition through the stages of expertise.

In highly structured domains with routine tasks, practicing the same solution over and over increases your performance and differentiates you from others. But in highly volatile domains, given the research outline above on expertise reversal, this kind of routinized practice can actually become a deficit (Kalyuga, Ayres, Chandler & Sweeler, 2003). Understanding how to navigate infrequent events, disruptions and uncertainties is the key ingredient to developing and accelerating expertise. Thus, developing expertise in volatile contexts should not defined by the *number of hours* one spends in deliberate practice, it is defined by the *number of failure cycles* that a person experiences. Learning is accelerated when these challenges induce failure cycles more rapidly. The more failure cycles operators encounter, the more refined and adaptive their solution set becomes.

ACCELERATED LEARNING IN VIRTUAL WORLDS

Providing the right training environment to advance failure cycles and drive learning is often too expensive or too difficult or dangerous to carry out due to real world constraints. As such, accelerating the development of expertise is critical for organizations that must invest heavily in training requirements (Hoffman, et. al., 2014). As training programs have evolved over the years, simulation-based models, also called "serious games" or "immersive learning," have emerged as one of the most promising new methods for learning, training and organizational change (Dalgarno & Lee, 2009; DiBello, Missildine & Struttmann, 2008; DiBello & Missildine, 2010). Simulation-based training allows for a participator process, whereby expertise is not predetermined, rather it is allowed to emerge from situational constraints. Real world, hands on simulations, such as wargames, have been around for a long time, and can be highly effective. But, for example, these kinds of trainings must still account for operator safety, and often, in order to meet the actual training demands of the job, the cost of these environments is often prohibitive. In the last few decades, synthetic virtual environments have helped reduced implementation demands for complex training needs (Alexander, Brunye, Sidman, & Weil, 2005). These synthetic, virtual environments are especially suited for training situations which are impractical, difficult, dangerous or expensive to reproduce in an operational environment (Whitney, Tempby, & Stephens, 2014).

However, not all virtual environments are created equal. To clear up some of the confusion around different types of virtual environments, and why the current wave of virtual reality and virtual worlds have shown so much promise, it's important to outline some distinctions. Generally speaking, a "3D virtual environment" or "immersive virtual environment" (IVE) refers to a single player walkthrough space, unpopulated by other people (avatars). These IVEs are often replications of real world objects and environments that are used to help familiarize people with a task or space, showcase an object or product, or aid in the design or basic knowledge induction of an operating environment. As they have become more realistic and the programming more elaborate, training environments can be gamified to take a single player through pre-determined scenarios with other non-player characters. IVEs have also been used as a general term to encompass all virtual environments, regardless of their characteristics. "Virtual reality" (VR) refers to an immersive experience in a virtual environment using head mounted goggles. Because these VR headsets provide a fully immersive view of a virtual environment, VR is best used for learning and training scenarios that rely on the feeling of presence or "being there" to engender potent somatic responses. Finally, "virtual worlds" (VW) refers to a 3D virtual environment filled with avatars controlled by multiple players who can remotely interact with each other through avatars in a persistent, synchronous virtual environment (Bell, 2004). These multiplayer virtual worlds are best suited to training that requires team interaction to solve more complex problems. The virtual world allows designers to create affordances in an environment, communication mechanisms, and role specific tasks and feedback that challenge teams of people to solve problems together.

Simulations in single-player IVEs have a long history in training, typically focused on *task training simulators* (Blow, 2012). Flight simulators, for example, enable pilots to become familiarized with cockpit controls and rehearse emergency scenarios hundreds of times before they ever step foot in a plane. As computer technology evolved, simulations became more sophisticated and provided increasingly accurate replicas of objects and environments, often aimed at developing specific operational skills. Research has shown many examples in which IVEs have proved to be effective as educational and training environments (Mikropoulos & Natsis, 2011; Seymour, et. al., 2002). Along with other applications, like truck driving simulators and simulated surgeries for medical practitioners, these involve intensive operational capability, targeting hard skills that rely on rote memory and extensive practice to enhance dexterity, accuracy and acuity and reduce error rates (Schout, et.al., 2010). However, they generally still rely on highly structured decision paths with concrete, pre-determined pathways to success. In other words, these types of IVEs are best suited for skills that do not require handling high uncertainty tasks with unpredictable interactions, unknown sources of risk and unreliable outcomes.

The advent of virtual worlds created a new way to simulate complex, multiplayer behaviour. Immersive, multiplayer virtual worlds provide an environment in which users can remotely interact in real time with other users, using voice communication and controlling avatars for rich interactivity. Virtual worlds, which enables persistent, interactive, multiplayer environment allows learning designers to target skills associated with dynamic group interaction, complex decision making, and strategic coordination and communication to achieve a goal. They provide a high-fidelity platform where risks are unpredictable, decision paths are co-created and evolving situations create multiple solutions for success. But, while virtual worlds appear to be an ideal platform to roll out immersive learning programs, many of them have failed. Numerous programs and platforms have shown initial successes but have not been able to demonstrate the transformative value that has been promised.

We argue that two factors are responsible for these failures: First, simulation designers are often overly focused on environmental fidelity. Their primary value proposition has been to create increasingly robust, accurate replications of reality without considering the implications for how this advances the learning process (Hays & Singer, 1998). Second, simulation designers often do not optimize the environment for advanced learning experiences, and, as a result, organizations have often simply imported their existing, rote-style training programs into a virtual world. As such, while virtual worlds have enormous potential to transform learning experiences and accelerate expertise development, without designing the simulation based on a rigorous learning model, this opportunity is often squandered. In addition, many of the unique affordances of the virtual worlds (simulating death, catastrophes, rogue actors, miscommunication, etc.) are underutilized. To achieve optimal accelerated learning using virtual worlds, designers should focus less on customizing the virtual environment to accommodate an existing training program and focus more on how the training program can be designed to take advantage of the full affordances of the virtual environment.

From "Proficiency Assurance" to "Iterative Failure" Using Virtual Worlds

To fully exploit the value of virtual world simulations, learning experience designers need to have a robust understanding of the cognitive demands placed on the target population of learners, and the mechanisms that underlie learning and development for that population. Our goal in this paper has been to outline some fundamental learning models related to accelerated expertise as it applies to learning and training in high uncertainty operating environments. Let's review some of these findings.

In high volatility domains, not only are the training requirements high, but the outcomes can be unreliable. Learning environments must prepare operators not just for procedural knowledge of how to carry out tasks, but for a larger, holistic understanding and awareness of multiple, unpredictable risk factors (Zambok & Klein, 1997). Operators need to know how to flexibly adapt to changing circumstances and even changing goals. They need to be prepared, not just for how to follow protocol, but for how to behave when the protocol breaks down. They need to be trained to remain emotionally regulated under conditions where the outcome is uncertain, and where untested ideas may be the only option available. And, they need to know how to rapidly innovate solutions to unforeseen problems (Weick, 2015).

In many training programs, there is a disproportionate focus on "proficiency assurance." Proficiency assurance involves a "skill and drill" approach to prove that operators can demonstrate task proficiency, comply with standard operating procedures, and respond to routine and non-routine incidents based on appropriate protocols and procedures. However, expert-level operators in high volatility domains must go beyond mere proficiency. If we return to the Dreyfus 5-stage model for a moment, the key shift from "Proficient" to "Expert" is the ability to respond to complexity with intuitive decision making, relying on a recognition-primed, context-driven, holistic approach that does not rely on rules or procedures. Beyond handling challenging situations (known unknowns) experts must demonstrate an ability to manage chaotic situations (unknown unknowns), where worked examples and practiced responses are inadequate. They must be able not just to apply solutions to difficult problems but create innovative solutions to "wicked problems." Thus, to move from proficient to expert, an adaptive learning model must be employed that utilizes *iterative failure* over proficiency assurance, continuously disequilibrating their thinking at increasing levels of complexity

Developing expertise requires exposure to situations that significantly disrupt operators' existing mental models. This helps propel operators to higher levels of expert knowledge through the motivational mechanism of disequilibration as they attempt to resolve discrepant or uncertain sources of information to achieve cognitive equilibrium. Routinely disequilibrating operators through complex scenarios allows them to break down and reorganize mental models to more easily adapt to evolving circumstances. However, based on cognitive load theory, this process is only effective when prior knowledge and working memory capacity is accounted for. Overexposure to disequilibrating scenarios leads to burdensome cognitive demands that can inhibit learning. Once the learning needs are adequately calibrated, accelerating this process propels operators through this developmental process more quickly, which helps organizations overcome time and resource training burdens.

Virtual worlds have enormous potential to act as rehearsal environments in which operators can rapidly experience infrequent, disruptive scenarios in a repeatable and controllable fashion, with exposure to a wide range of scenarios in a compressed time frame. Moreover, virtual worlds have proven to be an effective platform to accelerate skills development along all levels of the expertise continuum. The environment can be simplified and heavily facilitated to accommodate novice learners. Expert learners, on the other hand, can be exposed to situations wherein their intuitive, 'from the gut' reaction (schema) can be challenged and fail. This drives the kind of learning necessary to continuously challenge experts operating high uncertainty contexts. But again, it's important to reiterate: virtual worlds are simply places that facilitate the delivery of immersive learning experiences. The science (and art) of designing high impact learning experiences to different levels of expertise is contingent upon the appropriate method of delivery, the learning model applied, the affordances in the environments that support the learning model, and the degree of facilitation and guidance required at each stage.

FIVE KEY DESIGN ELEMENTS FOR ITERATIVE FAILURE

In our work designing learning experiences in synthetic environments, we have developed a number of design parameters that drive our ability to engineer disequilibration into the learning process for expert operators. These five guiding design parameters below can help transform a synthetic virtual world environment into a meaningful learning experience that exploits the fundamental cognitive mechanisms of development.

Plausibility over realism

As outlined above, people don't simply absorb information directly from their environment, they organize it and interpret it through schemas (mental models). To drive a learning process, it's more important to engage and disrupt the mental model, than to simply present new information. For many virtual simulation designers, the focus is on fidelity, that is, the degree to which the virtual, simulated environment replicates reality. But numerous studies have shown that full fidelity is not necessary to produce adequate learning outcomes, and often full replication is either not feasible or can distract from the learning goals (Hays & Singer, 1998; Stewart, Johnson & Howse, 2008). Research on transfer, that is, the degree to which knowledge acquired in the virtual environment transfers to the real world, shows questions some assumptions on needed similarities between the simulated and real world operating environment. Studies suggest that the "surface elements" (like high fidelity visual features) of the training environment are not as important to effective transfer as "deep structural features" (logical connections and underlying decision-making principles) (Lehman, Lempert, & Nisbett, 1988).

In addition, no matter how realistic they are, synthetic environments will never achieve full realism for any training exercise. What is more important is the degree to which designers can create a sense of "presence," which is the feeling of "being there" in a plausible virtual environment. This is achieved by producing two essential illusions in the virtual environment: the *place illusion*, which is the degree to which you feel transported into a virtual space, and the *plausibility illusion*, which is the degree to which the environment feels credible to the learner and relationships among decision elements make sense (Slater, 2009). To create a place illusion, it is not necessary to replicate all aspects of the environment, only those that are needed to enable action and interaction. Creating a plausibility illusion, designers must not focus too heavily on realism, but replicate essential features of the schema that needs to be activated, disequilibrated and reorganized. To illustrate this point further, think of the difference between a photograph and a caricature. We often look at photographs and say "that doesn't look like me," even though it is a full fidelity, two-dimensional replica of your image. On the other hand, a caricature artist can create a drawing that "looks exactly like me" because it captures the essential features of one's mental model of a person rather than how they actually look. Thus, an important guiding principle is that we design for "plausibility" not "realism." The affordances of the world must contain those elements that activate mental models and are key to framing the decision process, not necessarily presenting everything that would be available in a particular operating environment.

Guided discovery

Experts and novices learn differently, and as the learning needs evolve, learning techniques and environments must flexibly adapt to accommodate these qualitative shifts (LaFrance, 1989; Daley, 1999). While novices benefit greatly from the heavily guided instructional techniques, learners that have some expertise in a domain learn better when they are able to discover solutions to problems on their own, rather than simply practicing a pre-determined procedure (Kalyuga & Renkyl, 2010; Kirschner, Sweller & Clark, 2006). Expert learners need to be exposed to a problem, apply a solution and (if inappropriate) have that solution fail. By repeatedly encountering a problem and devising an undetermined solution, learners experience cycles of failure and reorganization, a previously identified essential component of expertise development.

Guided discovery also helps discard prior beliefs that may not have been serving their goals, and it enhances buy-in and engagement. When users find a solution on their own through trial and error, they are more likely to buy-in to its effectiveness than if they are simply told that it works. It allows them to see what works and what doesn't and engage more fully with the solution. Increasing engagement in the learning process is a key component of retention.

Unpredictable distractions

Often in disaster training scenarios, participants are forewarned about the nature of the emergency scenario. How often have we done a "fire drill," all lined up, told where to go, and simply followed instructions to our exit? Does anyone think these routine fire drills will help us act effectively in the event of an actual fire? Many training programs, while much more robust than simple fire drills, make a similar mistake. The learners are forewarned about the nature of the training and instruction is given as the event unfolds. In real life, operators don't know what event is occurring or when it will occur. In our experience, if the critical feature of the disaster is that it is a disruptive surprise in an otherwise routine day, then the unpredictability of a surprise event is crucial to the learning process. The element of surprise is best engineered by having participants engaged with routine tasks and distracted or misdirected about the nature of the exercise.

Incomplete information

A prominent feature of high uncertainty operating environments is that information is often incomplete and unreliable, sources may be untrustworthy or contradictory, and the meaning of the information may be unclear. Providing participants with unreliable, incomplete or conflicting information heightens complexity during emergency scenarios. More importantly, it reveals the default mental model of the operator. If the operators are able to solve a challenge based on standard emergency procedures, it is difficult to get a sense of the gaps in their mental models. By forcing them to deal with untrustworthy information, assessors get a window into their default patterns.

Risk to every decision

Every decision, even and especially the right ones, must carry some risk (i.e., can lead to a chain of negative consequences). This is especially critical in "guided discovery" learning environments. With minimal instructional guidance from facilitators, learners acquire knowledge by making decisions against the affordances of the environment. Negative and positive consequences of actions "teach" the learner the optimal path. If these decisions do not carry any risk, participants will simply choose the least risky path without being challenged to weigh alternatives. It is especially important that good decisions have risk, which forces the participant to consider options critically.

CONCLUSION

Creating effective learning experiences for expert operators in high uncertainty environments requires going beyond proficiency assurance by inducing a targeted disequilibration of their mental models. Research on cognitive development, expertise, and naturalistic decision-making shows that these learning experiences are most effective when they account for differential instructional needs for learners at different stages in the process. Expertise development can be accelerated more effectively through rapid, iterative failure over routine proficiency assurance. But meeting these kind of training needs for operators in high uncertainty contexts is often cost prohibitive.

New immersive technologies, such as virtual worlds, have shown promise in providing a synthetic, scalable, multiplayer environment that can expose expert operators to scenarios that accelerate the iterative failure process. However, designers have often neglected to take full advantage of what the platform has to offer. Designers have focused disproportionate resources on how the virtual environment can be customized to meet the needs of their training program, rather than how the training program can be transformed by exploiting the unique affordances of the virtual environment. Despite some successes, and promising research demonstrating their potential value, widespread adoption of immersive virtual technologies for training purposes is still very limited and as a result, large scale empirical studies have not been able to adequately examine their effectiveness. Learning experience designers can better exploit their value by applying a learning model through key elements like plausibility, risk, unpredictability, and guided discovery to leverage the affordances of the virtual environment to meet the needs of expert operators.

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