Individualized Data - The Missing Link of True Training Effectiveness & Capability Sustainment

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ABSTRACT

We have already witnessed how the applications of technological advancements have provided increases in learning outcomes for all learner types. For example, we have seen higher levels of motivation and engagement through the adoption of immersive technologies; more readily available relevant data through advancements such as xAPI; greater, more rapidly available understanding of learner outcomes with applications of Artificial Intelligence (AI), and increased capabilities to rapidly gather, analyze, and process all of this data through new computational capabilities. However, an understanding of overall learner outcomes is just the beginning—technology will continue to become an increasingly integrated part of our lives, and with it, a previously unimaginable quantity of individualized data will be available at the point of need.

With this individualized data, we need to look not only to track learner outcomes—but track, analyze, and *understand* how effective different approaches to learning are, at the *individual* level. In this presentation we will discuss; the relationship between competency acquisition and the probability of successful performance; the effect that training methods which focus on near/far transference, metacognition, and individual preferences have on skill acquisition and the time spent training; and the role that 'Big Data', AI, and advancements in cloud-computing will play in the delivery of training to learners in a way that maximizes its effectiveness for *that learner*. Further, we will discuss the challenges surrounding the full realization of data-application as a means of paving the way for adaptations in training—training that *by design* results in better outcomes in less time.

ABOUT THE AUTHOR

Jenna Tuck, Director for 4C Strategies North America, has spent the past 12 years acquiring and honing her skills in the development of advanced solutions serving the Defense sector's evolving needs to embrace new technologies as an imperative for competitive advantage. Embracing the core values of innovation, education, and evolution—Jenna is deeply passionate about—and commits significant effort to—the technological improvements in education; STEM initiatives; and the application of data-driven insights as a means of increasing war-fighter readiness.

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TECHNOLOGY AND THE GOVERNANCE OF LEARNING

Technology has—and always will—play[ed] a key role in the governance of learning, with observable correlations throughout history between significant evolutions and transitions in learning structures, and key technological innovations. Technology, broadly defined as "the application of scientific knowledge to the practical aims of human life" (Britannica, 2022), has had a pervasive effect on all aspects of human life—to include *what* we learn, *why* we need to learn, as well as *how* we are able to learn. Take for example the invention of the printing-press, which not only resulted in the ability to mass-produce books, academic works, and articles, but also diagrams and charts—effectively democratizing the access of information and drastically transforming the availability of learning methodologies—is thought to of paved the way for higher education (McLuhan, 1962).

In recent years we have borne witness to advancements in technology which have already transformed learning structures through novel approaches, with increasingly favorable training results for all learner types—such as advancements like Experience Application Programming Interface (xAPI), and the increased utilization of Artificial Intelligence (AI). However, gathering mass amounts of data to retro-actively review training outcomes is only providing us with the answer to 'how well did we do?' Advancements in AI, the Internet of Things (IoT), and cloud and quantum computing are making *more* data, more *persistently(consistently) available* than was previously imaginable. Applying these capabilities in the right way, we need to answer the question "how can we do better?" and increase our competitive edge by training *smarter*, achieving better results in less time, and making better decisions faster. In order to do that with any degree of success, and without significant wasted time—we first need to establish; what we are training for; how we measure success; whether we are using the right methods of training to obtain that success; and what *actually affects* our ability to obtain that success. Once these are understood, we will be able to ascertain what data is actually relevant, and how we apply that data to overcome factors that affect success and generate training that *by design* results in the best possible outcomes, in the least possible time.

HOW DO WE MEASURE SUCCESS?

There is "considerable confusion about exactly what constitutes a learning outcome and how (or if) it is distinguished from learning objectives or competencies" (Hartel & Foegeding, 2006). These terms are often used interchangeably, however the nuanced differences between mean that discussions surrounding them may be unclear. These terms are at the heart of this discussion, and so we will define them here for the purposes of setting a baseline.

Learning Objectives could be defined as the broad description of the overall goal(s) of the training, for example 'This course will teach learners to drive a car'. On the other hand, Learning Outcomes are specific, measurable results of the training or what the learner should be able to *do* after completing the training, for example: 'Park car without hitting barrier cones.' Competency on the other hand "is a cluster of highly interrelated attributes, including knowledge, skills, and abilities (KSAs)" (SHRM,2021), that the learner *should possess after completing the training* (and is often comprised of *multiple* outcomes). Using the same example, the resulting competency would be "ability to safely drive a car in accordance with traffic rules."

Competency vs. Performance

With a baseline understanding of Competency—it is easy to grasp why organizations are so heavily focused on achievement of competencies, seeing as ultimately the ability for an individual to successfully perform a particular task or grouping of individual tasks in a *real-world setting* is the inherent goal of military training.

However, herein lies 'the rub'. Generally, competencies are measured based on whether or not an individual has successfully completed a training task, completed some sort of assessment of the completion of that training task, or—as defined by Kevin Owen—"as a vectored state of human capability and probability; in other words, a state of what one can do now and a probability of how one will perform in the immediate future"(Owen, 2021). Thus, competency assessments are a strong evaluation tool to determine 'readiness', but they are not always indicative of *performance*. Competencies are a *probability* of successful performance, which is determined through successful completion of specific tasks/courses/assessments etc. It is therefore safe to extrapolate that the aim of training is to result in the highest *probability* of successful performance, and the challenge then lies in determining how to achieve the highest probability of performance, in the least amount of time/cost.

Multiple literary reviews of current competency-based models generally agree that to gain a higher probability of successful performance, the learner must not only have measurable learning outcomes, and achievement of competencies—but also significant practice. Described another way, whilst an individual may have achieved a competency—***unless this competency is paired with an understanding of experiential data or observed capabilities—it does not necessary correlate to the highest confidence in their ability to perform in real world settings.***

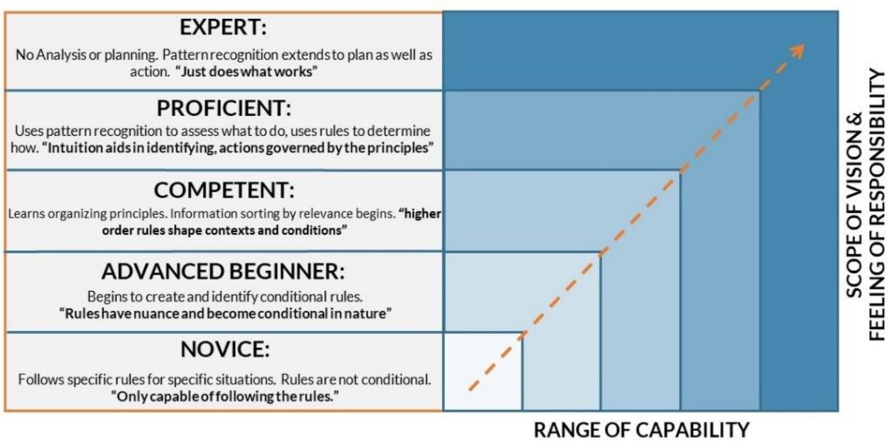

Figure 1. Dreyfus Model of Skill Acquisition

Take for example the Dreyfus Model of Skill Acquisition (Dreyfus, 1998) (figure 1.) The Dreyfus Model charts competence as a mere 'milestone' towards higher levels of skill acquisition. Competency is explained as the individual having an understanding of the rules/principles of the tasks, but not the *depth* of recollection, recognition, or decision-making capabilities necessary to perform in instances outside of those which are identical to trained materials (Dreyfus, 1998).

Another way to look at competence as an indicator of performance was proposed by Martin Broadwell in 1969, and later updated by Noel Burch (Adams, 2015). The 'Four Stages of Competence' (figure 2.) model asserts that when acquiring a skill there are four stages that the learner must traverse, from; *unconscious incompetence* – 'I don't know what I don't know'; to *conscious incompetence* – 'I know I don't know this, and I need to learn'; followed by *conscious competence* – 'I know this, but I need to think through the knowledge before performing'; and finally to *unconscious competence* – 'I know this so deeply it is automatic.'

Drawing similarities between both models, in light of this discussion: whilst competency—if effectively assessed—can provide a level of probability that *successful performance* will occur, increasing the probability of successful *performance* comes not from increased repetitions of the same training, but from training experiences that result in *deeper* cognitive understanding if not just what to do, but why it is done that way, and how it could/couldn't be done differently. Who hasn't heard the term 'we learn from our mistakes'?

The next section of this discussion focuses on *how* this deeper understanding—and thus *greater* probability of performance can be achieved through a shift in training focus and/or methodologies.

ARE WE USING THE RIGHT METHODOLOGIES TO OBTAIN SUCCESS?

Historically training initiatives have been very procedural in nature. A specific set of information is provided via instruction, the information is memorized, an assessment is completed—much like a production line. Individuals are processed through a factory progressing linearly from one 'stop' to the next. A quality assurance check is completed after each 'stop', and they continue to each pre-defined station until they have visited each stop and completed one final 'check' before being sent out into the world—just as thousands have done before them. But as technological capabilities continue to expand and fields of study have become increasingly interdisciplinary, the sequential, routine approach to training no longer results in the level of proficiency, cognitive reasoning, or problem-solving capabilities at are representative of today's performance needs. For example, according to a study completed by the U.S. Office of Personnel Management (OMP), a mere 10-20% of training is applied in the workplace (Training Transfer - Training and Development Policy Wiki, n.d.).

For training to meet the ever-evolving requirements of operations, there must be a greater focus on the acquisition of skills that can be applied in real-world situations. Further, by utilizing training that *also* focuses on the development of 'soft skills' such as problem solving, strategic development, critical thinking, and collaboration—the training would result in learners that not only acquire competency—but learners that are *more apt to acquire deeper understanding and learn more rapidly.* in conjunction, these would be assumed to result in a greater probability of performance in less time spent training.

This deflection from 'how it has always been done' requires us to alter *how* we think about training, and view training not as a means to obtain a particular competency or skill—but instead as 'part of a whole'. The thought is that—in addition to the development of competency—each training would also reinforce the continual development of the individual's cognitive knowledge, and overall capabilities to perform in real world situations. In the following subsections we discuss a few of the most significant shifts associated with this way of thinking.

Retention vs. Transference – So What?

Retention has long been a focus of training development with the understanding that increased retention—or the ability for learners to recall, remember, and/or perform a particular learned task, skill, or knowledge after a length of time—as an indicator of successful training. Transfer on the other hand measures success as a person who acquires some knowledge or skill in a formal or structured situation like a classroom, or a training situation, and is then able to *transfer* this knowledge and skills to application in real-life situations. (Frederica, 2021). Further, the *extent* to which learners can transfer previously learned skills to applications unrelated to the initial training determines how *near* or *far* the transference is. Near transference for example occurs when a learned skill/knowledge is applied in a real-life situation very similar (or identical) to the trained skill, whereas far-transference occurs when a previously learned skill is successfully applied to real-life situations that are dissimilar to that which was learned. Whilst retention of a procedure may be an important indicator of a learned skill, transference—and more specifically far transference—would be indicative of an ability to understand not only a procedure, but also provide critical thinking, decision making, and problem-solving capabilities surrounding the completion of said procedure.

Given that the ability to apply learned knowledge in different areas would result in a deeper understanding of the task at hand, as well as aid in successful completion of *future* training, we can reasonably conclude that training/learning which results in far transference—or the ability to apply learned fundamentals to a multitude of situations—would result in a greater probability of successful performance in less time than training which only provides near-transference.

Pedagogy vs. Andragogy

Since the works of Jean Piaget, often seen as the 'Father of Modern Pedagogy', pedagogy has been a fundamental pillar in the approach to instructional content/learning. And just as is the case with most learning methodologies, approaches to pedagogy have undergone their own transformations and evolutions with the emergence of new technologies, research-findings, and imperial data. However, it is important to note that pedagogical approaches are rooted in the teaching of children. Children and Adults can generally be expected to have large differences in motivators, level of pre-existing knowledge, what engages them, etc. and so the theory of Andragogy—or the teaching of adults, was developed in the 1970's to define approaches to learning that are more closely aligned to characteristics associated with engaging, motivating, and teaching adults (*The Andragogy Approach: Knowles' Adult Learning Theory Principles*, 2021).

Andragogy "refers to the methods and approaches used in adult education and is directed towards self-actualization, gaining experience, and problem-solving" (ELM Learning, 2022). Most importantly for this discussion, comparative to pedagogical approaches (table 1.), the andragogical approach to learning places a greater focus on metacognitive skills, problem solving, and cognitive reflection that would align more closely with far-transference skills, and a deeper 'unconscious competency.'

Table 1. Comparison: Pedagogy and Andragogy (Findsen & Formosa, 2011)

	Pedagogy	**Andragogy**
Learner	*Dependent.* Teacher directs what, when, how a subject is learned, and tests what has been learned	*Self-Directing and independent.* The task of the teacher is to encourage and nurture learning.
Experience	*Of little value.* Teacher experience and texts is what matters. Hence, teaching methods are didactic	*A rich experience used as a resource.* Teaching methods include discussion, problem solving etc.
Readiness	*People learn what society expects them to.* The curriculum is standardized.	*People learn what they need to know.* Learning programs are organized around life application.
Orientation	*Acquisition of subject matter.* Curriculum organized by the subjects under focus	*Learning based on experiences.* People are performance-centered in their learning.
Motivation	*External Factors.* Examples include parents, fear of failure, etc.	*Internal factors.* Examples include self-esteem, quality of life, recognition etc.

The Introduction of Metacognitive Knowledge

In the mid 1940's Benjamin S. Bloom initiated a group of educational professionals from all over the United States with the purpose of attempting to define a framework of educational objectives which universities could use to measure test results against a standardized set of educational objectives. These efforts resulted in the publishing of 'The Taxonomy of Educational Objectives,' which outlined the six (6) categories of the cognitive domain as; knowledge, comprehension, application, analysis, synthesis, and evaluation (Krathwohl, 2002). These categories were understood to be linear in nature with each preceding category serving as the basis for the subsequent. The category of knowledge served as the foundation, and all categories above knowledge were classified as 'skills and abilities' (McDaniel, 2022). Subsequently in 2001, a revision of 'Blooms Taxonomy' was introduced by a group of psychologists, experts, and researchers to include Linda Anderson and David Krathwohl. This revised taxonomy made a number of changes to more closely align the taxonomy to recent findings, however for the purposes of this discussion we will focus on the changes to the foundational category: knowledge.

The 'Original Taxonomy' consisted of three sub-categories of knowledge: factual, conceptual and procedural. And whilst the 'Revised Taxonomy' renamed *Knowledge* to *Remember,* it maintained "the substance of the subcategories of Knowledge in the original framework" (Krathwohl, 2002), but was reorganized to recognize the distinctions of cognitive psychology that had developed since the original framework was devised (Krathwohl, 2002). The most significant evolution of the revised taxonomy came in the form of adding "A fourth, and new category, Metacognitive Knowledge" (Krathwohl, 2002). Metacognitive knowledge—whilst largely unknown when the original taxonomy was developed—has become an increasingly important subject of discussion, and includes strategic knowledge, self-knowledge, and knowledge on cognitive tasks (McDaniel, 2022). Metacognitive knowledge put simply, can be defined as 'learning how you learn' with the ability for learners to understand how they learn best, develop increased self-awareness, gain a deeper cognitive understanding of what they are learning, and how to best adapt and *apply* what they have learned to real-world situations.

A similar shift has resulted from the works of Rand Spiro who pioneered the "Cognitive Flexibility Theory." Spiro asserts that "the old linear, more mechanistic, single-perspective approaches" to training are based in routine, but life seldom follows routine, and this is where a significant deficiency lies between what is trained, and what is needed to perform the increasingly inter-twined requirements of real-world applications. Cognitive Flexibility Theory, focuses not on dictating what, or how to think – but on providing learners with the "the kind of knowledge they can make connections with and use as a tool for solving and dealing with new problems and situations" and "preparing people to select, adapt, and combine knowledge and experience in new ways to deal with situations that are different than the ones they have encountered before" (Spiro, 2002).

In terms of increasing the probability of performance, metacognitive knowledge and cognitive flexibility provides for increased far-transference and is more closely aligned to the individual-centric andragogical methodologies. It can therefore be concluded that in addition to a focus on the acquisition of knowledge in the original subcategories—factual, conceptual, and procedural—the additional training which also focused on the acquisition of metacognitive knowledge would result in an ability for learners to obtain knowledge faster, and at a deeper level.

WHAT AFFECTS THE ABILITY TO OBTAIN 'SUCCESS'?

As if the transition from; instructor centric to student centric; pedagogy to andragogy; retention to transference; and a 'what/when/how' focus to a 'why/why not/what if' focus weren't enough, the addition of entirely new *modalities* of training (such as eXtended Realities (XR)) have resulted in further transitions in not only the approach to learning, but also how we measure and understand the *effectiveness* of that training.

In recent years we have seen the rapid emergence of innovative technologies that have provided a unique ability to train learners safely and effectively in realistic environments reflective of complex, hazardous, or inaccessible conditions. These immersive offerings have not only made it possible to 'train the untrainable,' but they have also enabled more complex social-interactions, role playing, and the ability to *design* experiences coupled with a focus on exploration, discover, and learner autonomy (De Freitas et al. 2010). The significant departure from traditional approaches to learning in these new "experiential learning circumstances within designed virtual and hybrid spaces", gave rise to the need for a new method to evaluate the "efficacy, benefits, and challenges of learning in these new ways (De Freitas et al. 2010)." As it relates to the general transition to a more learner-centric, metacognitive approach to learning, the suggestion that this use new approach—if done effectively—provides a "greater emphasis on learner control, engagement, learner-generated content, and peer-supported communities" would most certainly result in a greater focus on the attributes which we have identified as being drivers of *increasing the probability of positive performance.*

Four-Dimensional Framework	
Learner Specifics • Profile • Role • Competencies	**Pedagogy** • Associative • Cognitive • Social/Situative
Representation • Fidelity • Interactivity • Immersion	**Context** • Environment • Access to Learning • Support Resources

Figure 3. Four-Dimensional Framework (De Freitas et al. 2010)

Further, asserting that these new experiences essentially create a new cross-disciplinary and non-linear approach to learning that cannot reasonably be evaluated using traditional methodologies, De Freitas et al. outlined the factors which play a role in the effectiveness of immersive experiences as a training modality in what is referred to as the "Four-dimensional Framework" (Figure 3).

This Four-Dimensional Framework has become a heavily utilized tool for determining the effectiveness of new-age training such as serious games, and immersive simulations. Each dimension takes into account multiple sub-categories, which independently play a role in whether or not the training could be deemed effective—but also as an assessment of the combination of all characteristics. Most notably as it relates to this discussion, the higher the; presence of associative and cognitive pedagogy (or andragogy); and/or level of interactivity and immersion - the more effective the training is expected to be. *Similarly, increased levels of cognitive, immersive, or learner-led experiences will result in better outcomes in less time – and by extension, greater probability of successful performance.*

Individual Preferences = Individual Results

This discussion asserts that a greater focus on individual, learner-centric methodologies will ultimately result in an individual that not only achieves competencies through an observed completion of pre-defined tasks/objectives—but has a far greater ability to; solve complex problems; apply fundamental theories to a multitude of cross-functional disciplines; and apply this knowledge to real-world situations—and thus have a far greater probability of successfully *performing* in operational environments. However, what we have yet to discuss – and which is of paramount importance is the *role* that the individual plays in how effective training is or is not!

The Four-Dimensional Framework for example concludes that learner specifics such as; individual profile—to include individual preferences; role of the learner—to include individual learning pathways; and competencies—to include transferable knowledge from previous trainings—make up a significant portion of how effective a particular training plan (or approach) will be for that learner. Delving further into how learner specifics affect learning, but for all modalities, as opposed to in relation to immersive training—we look to the recent 2021 works for Frank Ritter. Combining recent findings from "work in the Applied Cognitive Science Lab," with assertions from a wide range of publications dated between 2018 and 2021, Ritter provides an outline of the various learner attributes which will influence learning (Ritter, 2021) (table 2).

Table 2. Learner Factors Influencing Learning (Ritter, 2021)

Learner Factors Influencing Learning
●Gender ●Working Memory ●Physical Strength ●Previous Knowledge ●Emotional aspects ●Interests ●Physiology: e.g., sleep ●Motivation ●Team Variables

Whilst the list of learner attributes which will affect the effectiveness of any particular training for an individual (table 3) gives pause for a discussion in and of itself, most notable for *this* discussion are; *Previous Knowledge,* "which can influence what can be learned and how well it will be retained"; *Interests;* and "*Cognitive Capabilities*, for example, working memory capacity" (Ritter, 2021). These factors as they relate to skill acquisition and the value of overall training outcomes will be discussed herein. Additionally, the ways that AI and data analysis can aid in decreasing the effects of these factors will be discussed in later sections.

Previous Knowledge

Inclusion of previous knowledge as a factor which influences how effective training is at providing positive outcomes further supports the conclusion that training which focuses on; experiential learning; obtaining skills that can be easily transferred and applied to real-world situations; and results in greater metacognitive knowledge will result in subsequent training becoming exponentially more effective—resulting in learners achieving proficient and expert-level abilities (Dreyfus, 1998), and a higher probability of positive performance, in less time than a learner that has completed training which resulted in less transferable (previous) knowledge.

Interests

Individual interests, to include individual preferences (not to be confused with learning preferences) lies at the heart of engaging and motivating learners, but it is also one of the most difficult attributes to evaluate, define, or predict. The complexity surrounding interests lies in the fact that interests are developed (and change) over-time and are generally formed at least in part by; experiences unique to the individual, social connections, and socio-economic demographics (Bardina et al., 2020). Furthermore, research has shown that "the technology and media used by children during their formative years has an influence on learning preferences" (Dede, 2009)—meaning that all else equal, one individual may have an interest in immersive trainings while the other refuses to engage in immersive training, based on nothing more than their use—and lack of use (respectively)—with immersive technologies during their childhood(s).

Cognitive Capabilities

Perhaps an the most sensitive—but possibly the most critical—factor which will influences learning can be seen in cognitive capabilities. Cognitive capabilities has long been a topic for debate, but Cognitive Ability (as a degree to which one could be deemed to possess the capability) is defined by the American Psychological Association as: "the skills involved in performing the tasks associated with perception, learning, memory, understanding, awareness, reasoning, judgment, intuition, and language" (APA Dictionary of Psychology, 2022)—skills which are generally understood to be based on brain function, and are often referred to as 'fluid intelligence.'

First proposed by Raymond B. Cattell in 1963, and further defined in 1987, *Fluid Intelligence* is closely related to functionality of the temporal lobe, frontal lobe, and cerebellum and is responsible for "the capacity to think speedily and reason flexibly in order to solve new problems" (Perera, 2020), comprehension, strategy development, and learning ability. Comparatively, Cattell asserted that Crystalized Intelligence is responsible for "the ability to utilize skills and knowledge acquired via prior learning", and "recalling of pre-existing information as well as skills" (Perera, 2020).

Additionally, "until recently, it was widely held that fluid intelligence is static, largely determined by genetic factors, and therefore, could not be altered. However, some research has suggested that fluid intelligence can be improved" (Perera, 2020)—and although it is important to note that improving of fluid intelligence is far more complex than the improvement of other learner attributes such as crystalized intelligence, physiology, or physical strength, the importance of cognitive capabilities on a learner's successful outcome cannot be overstated. The importance of fluid intelligence further supports the need to develop training which focuses not just on competency, but on performance by way of metacognitive abilities.

OVERCOMING FACTORS THAT AFFECT SUCCESS

We have probably all heard the old saying "a chain is only as strong as its weakest link," and whilst cliché, this idiom is a perfect representation of the training between echelons. Whilst it is understood that team dynamics, and inter-echelon synergy deserves its own unique training focus, ultimately if changes in the method of training results in a greater probability of successful performance at the individual level, then by default the probability of successful performance of the *overall* cohort whether that is at the squad, or battalion level also increases. What's more, by focusing on training that produces more transferable skills, metacognitive knowledge, and cognitive flexibility—thus increasing the collaborative, problem-solving, and critical-thinking skills of each individual—we would also expect to see the greater team dynamics as a byproduct.

Having established that increased value of individual learning results in an increased overall value of training, we need to re-address the 'Troublesome Three' of the aforementioned individual attributes that influence learning—and more importantly, how the application of data-driven insights stands to aid in decreasing their impact, resulting in improved training outcomes in less time.

Previous Knowledge

Decreasing the impact of previous knowledge is the simplest of the 'Troublesome Three.' Tracking the experiential data of a learner and using this information to cross reference it with data such as; recorded simulation data, key events during training, assessment results, and competencies achieved, is already well within the realm of the possible, and can provide insights such as; what training has been completed and what increased level of experience this training resulted in. Furthermore, by tracking *each individual* and then applying AI into these data outputs, with increased 'data points' over time, AI-driven results would provide an understanding of *how long* it generally takes an individual to reach a certain level of performance, what a general rate of increased ability is with each course, and which training courses result in the most transferrable knowledge to subsequent courses—and are thus the most effective at decreasing the impact of previous knowledge. For the purposes of comprehension, we will discuss a highly simplified example of how this may work in application (table 3.). A minimal number of participants are used in this 'example' for the sake of ease of understanding, recognizing that it would take a significantly higher quantity of participants before outcomes would provide insight of value/reliability.

Assumptions:

1. 'Results' are combination of experiential data, simulation data, and/or assessment data. The value ranges from 0-100% of 'competency achieved, with 0% meaning no measurable competency, and 100% meaning the learner has achieved full competency.

2. 'Training' columns represent the training experiences that the learner had. In this example all learners follow the same training pathway, with Learner B and C experienced a *different* training from all other learners in training 3.

Table 3. Learner Factors Influencing Learning (Ritter, 2021)

Learner	Pre-Training	Training 1	Results	Training 2	Results	Training 3	Results	Training 4	Results
A	0%	Beginner 1	10%	Intro 1	20%	Intrmdt. 1	30%	Adv.1	40%
B	1%	Beginner 1	11%	Intro 1	21%	Intrmdt. 1b	41%	Adv.1	51%
C	1%	Beginner 1	10%	Intro 1	19%	Intrmdt. 1b	37%	Adv.1	46%
D	2%	Beginner 1	12%	Intro 1	22%	Intrmdt. 1	32%	Adv.1	42%
E	1%	Beginner 1	13%	Intro 1	25%	Intrmdt. 1	37%	Adv.1	49%

Findings:

1. Learners A, D, and E: The *rate* of increase in measurement of competency *per training* was the same for all trainings. (A=10% increase per training, D= 10% increase per training, E=12% increase per training)
2. Learners B, C: The *rate* of increase *per training* in measurement of competency was the same for all trainings 1, 2, or 4. (B = 10% increase per training, C = 9% increase per training)
3. Learners B, C: The rate of increase in measurement of competency *per training* doubled for training Intrmdt. 1b compared to all other trainings completed.

Conclusion: The training experience of Intrmdt.1b results in significantly higher levels of transferable knowledge than Intrmdt. 1

Whilst simple, this example is representative of the sort of insights that the use of data-tracking during training management provides—and the decision-making support it would provide. In this example for instance, a decision to remove Intrmdt 1. and replace it with Intrmdt. 1b would have a high probability of decreasing the time it takes for learners to reach 100% competency. What's more, the technological capabilities associated with this solution are fully available *today*, to include AI-driven evaluations, automated assessments, and Natural Language Processors in support of generating recommendations for proficiency ratings.

Interests

The interests of individual learners are so closely intertwined with their individuality that predictions based on known data points such as age, sex, marital status etc. would produce wildly inconsistent results. But take for example the power of algorithms seen in use by social media, search engines, and the likes, and it becomes apparent that with enough of the *right* data, applied in the *right way*, it is fully possible to create a unique profile of individual learners that is reflective of their individuality. If we were to apply this thinking to our approach to training, it would involve the tracking of experiential data (such as xAPI) for learners across all modalities, disciplines, and training types, and using this data to understand *which* modality, subject, or type of training results in the greatest enjoyment or engagement for *that learner*. Armed with this information, and the growing focus on training content that can be accessed in multiple modalities, it would be reasonable to think that content would be accessed in a way that is dynamically generated at the point of need for *each individual*, based on their 'individual profile.' And whilst decreasing the effects of individual interest on the effectiveness of training may not be fully viable today, by beginning to track the relevant data *now* we begin the arduous task of generating the quantity and quality of data that would be necessary to produce the sort of 'individual profiles' that we are discussing.

Cognitive Capabilities

Cognitive capabilities and fluid intelligence are undeniably a factor in how quickly an individual learner will be able to acquire knowledge, skills, competencies – and ultimately obtain the highest probability of performance in the least amount of time. Outside of cognitive-based testing, the types of data that would be used to track 'Previous Knowledge' would also be relevant to provide *indicators* of the capabilities of individuals. For instance, using the same example (table 3), a review of the data would show that—outside of Training 3—all learners except for C and E gained 10% competency per training, whereas Learner C only gained 9% per training, and Learner E gained 12%. Again, recognizing that this is oversimplified – if all else where equal, this data would indicate that Learner C and Learner E have lower and greater (respectively) cognitive capabilities than their peers. How this data would be utilized—if at all—is part of a much larger discussion but is discussed briefly in the following section.

BIG DATA – THE LONG POLE IN THE TENT

Simply put, 'Big Data' is data that is available in greater variety, with greater speed, and greater granularity and it has become a topic of immense discussion as advancements in everything from edge computing to micro-servers have made the collection, analysis and distribution of data more viable, and cost/time effective than ever before. The ability for us to track individual user data, measure the effectiveness of training, and ultimately train individuals more effectively, and in less time is *heavily* reliant on having the necessary data to inform the approach. For example, it is one thing to *say* that learners trained with a focus on metacognitive knowledge will have a higher rate of transference and higher probability of successful performance—it is another thing entirely to track experiential data that enables the automated assessment and evaluation of learners at the individual level and generates with a high degree of certainty what the probability of performance is. The fact is that all of the advanced capabilities that are currently available or will *become* available are reliant on access to—and use of—relevant, reliable data. Given the lengths to which the challenges associated with data access/use continue to be discussed, we will not discuss all of the unique challenges. Instead, we herein highlight some of the most significant challenges associated with big data in the context of using it in support of training initiatives as outlined in this paper.

1. **Too Much of a Good Thing:** Believe it or not, there is such a thing as 'too much' data. A significant amount of time and resources is put into tracking an excessive amount of data, but without the labor force, or strategic forethought to filter the data in a way that results in *usable* data, then it is just 'data for the sake of data.' Instead, if data collection was done for a specific purpose—though it may result in a lesser quantity of the data, it would be of greater quality in terms of its ability to be applied and provide actionable insights.
2. **Security Concerns:** From a training perspective this concern is more focused on access to military-relevant data. Cyber security is of paramount importance, but until we are able to find a way to more rapidly provide access to relevant data that is *not* sensitive in nature, government and military organizations will have far less opportunities to benefit from the solutions that are so readily available on the commercial marketplace.
3. **Data Quality:** Especially when it comes to legacy data, there lakes upon lakes of training-relevant data that could provide insights from historical training outcomes to support the foundation of AI applications for current and future training initiatives. However, in many cases the data is entirely unusable due to hierarchal inconsistencies, incomplete data, or simply the lack of knowledge that the data even exists. Whilst significant funding is being spent on the development of AI-driven solutions, if even a small portion of this funding was applied to 'cleaning' some of the existing data it would more than likely result in greater success in AI-focused projects given that it would provide substantial data points that can be used to further refine relevant algorithms.
4. **Are We Ready to Hear What the Data Has to Say?** Data driven findings regarding training hold the power to significantly increase the competitive edge of our military—if we objectively follow the findings without regard for the social, political—or possibly even ethical—implications. What happens if the data inexplicably asserts that the process for training x skill which has been used for 20 years is less than half as effective than a process that emerged 6 months ago? Or that Individual X who would otherwise have been eligible for a particular MOS, does not have the metacognitive capabilities to succeed in this position without significant oversight or additional training (thus greater cost/time expenditure) and so they are not eligible to pursue their chosen path? The entrepreneurial spirit of the US is a fundamental piece of our identity and drives the views that; with enough practice you can be anything you want to be, and if you work hard enough anything is possible. But what happens when the data concludes that no matter how hard Individual A trains, they may never have the necessary skill set/character traits to succeed in a military organization? Ultimately, our adversaries have little qualms in precluding particular individuals based on their level of excellence —and so we could expect if the US took this same approach, we would see an increase in our 'competitive edge,'—but is it worth the cost? Until this question can be answered, it may continue to be a challenge

CONCLUSION:

The approach to training has always undergone evolution as a result of technological advancements, just as advancements surrounding the viability and utility of data are now poised to transform training methodologies once more. By overcoming the challenges surrounding *how* we move forward in the use of data, we are able to develop and integrate *purposeful* AI models to help truly understand *which* methods of training are/are not effective at focusing on the development of both competencies *and* transferable skills at the *individual level*. Ultimately, through *autonomous* predictions and assessments of how *best* to develop a force that has a far *deeper* understanding of tasks, and a conscious development of critical thinking abilities—we stand to see a force that achieves the greatest probability of successful performance in real-world situations in significantly less time.

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