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Using Players' Gameplay Action-Decision Profiles to Prescribe Training

Reducing Training Costs with Serious Games Analytics

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***Abstract*— Players' gameplay action-decision data can be used towards profiling as serious games analytics. The insights gained can help support the decisions for performance improvement and as 'prescriptions' for training – e.g., diagnosing who should receive training, how much training will be given, informing the design of the game, and determining the contents for inclusion and exclusion. Data-driven training prescription can help learning organizations save money by mitigating unnecessary training to reduce costs. Players' learning performance in games can be measured in lieu of their behaviors traced *in situ* the training environment. Novice players' action-decision data can first be converted into Course of Actions (COAs) before pairwise similarity comparison against that of the expert(s) to reveal how similar they are to the training goal, or expert/model answer. We identified three Gameplay Action-Decision (GAD) profiles from these gameplay action-decision data and applied them as diagnostics towards prescriptive training.**

Keywords*— *Serious Games Analytics, similarity measures, performance improvement, reducing training cost, training prescription.

I. INTRODUCTION

The first commission to convert an entertainment game into a serious game purposed for training originated in the U.S. Marine Corps [1]. Commandant Krulak's idea was to co-opt computer-based gaming technology into *tools* to improve thinking and decision making skills at a time when training resources became increasingly limited, thus, moving the training sessions from the real world (live training) into a virtual one.

Serious games currently available are varied in their purposes. About 90% of them are educative *message broadcasters* aimed at information dissemination [2],[3], while only less than 10% can be considered as *tools* capable of bringing about *training* – defined by Oxford English Dictionary as 'sustained instruction and practice in an art, profession, occupation, or procedure, with a view to proficiency in it', or *learning* – defined as 'relative permanent change in user-behaviors as a result of interaction with the environment' [4, p.30].

Serious games can answer the higher calling of becoming *tools* for training and learning – particularly in acquiring skills not easily taught in classrooms: such as strategic and analytical thinking, planning and execution, problem solving and decision-making, adapting to rapid change [5], and expertise training [6].

Going forward, serious games need to evolve into *effective tools* for training and learning, if they want to be taken 'seriously' by the training industries. Beyond providing excellent instructions and tutorials (which limit serious games to message broadcasting), serious games can further incorporate performance measurement and reporting, even *diagnostics* to help learning organizations 'prescribe training', such as who should receive training, when to provide training, and how much content should be included or withheld. Such serious games can exist as standalone introductory diagnostic units leading up to the main training contents, or post-sale downloadable content (DLC) for monetization.

A. Understanding Performance Gap

Before any diagnostics for prescribing training can be designed, we first need to determine if there are any performance gap exists and how to measure expertise. *Performance Gap* in instructional design literature [7] can be caused by the combination of three factors: knowledge, resource, or motivation. Only the knowledge gap is bridgeable through training, but not the resource and motivation gaps (Fig. 1).

It may be easier to understand when this is stated in another way: that no amount of good instruction can overcome the problems of a lack of resources in the company and a lack of motivation in the trainees/learners. Trainees who are unwilling or unmotivated to learn should first address their issues before being subjected to more training – else, the training will be ineffective and wasted resources. While gamification has been shown to raise motivation in the players, there is no guarantee that the motivation gap can indeed be bridged as the mechanism still remain unclear.

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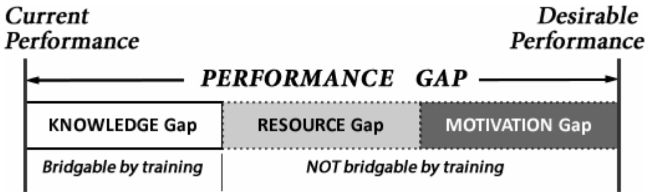


Fig. 1 Performance Gap.

B. *Maximizing the Value of Player Data*

In this paper, we will limit our discussion of training to training using serious games. In order to trace players' gameplay action-decision data *in situ* the serious games environment for performance measurement, telemetric methods are necessary. Telemetry is a common approach used by game designers to beta test game design and balance gameplay as well as network loads [10–12]. Players' data can be traced using telemetry and visualized through heat-mapping to reveal bottlenecks that need fixing or balancing. In serious games, telemetry is much more involved as both learning and gaming events need to be monitored [11]. Some telemetric methods (such as *Information Trails* [12]–[14]) even include performance assessment and reporting capabilities.

Just as the purpose of *Game Analytics* is to 'maximize the value of player data' [15], *Serious Games Analytics* seek to 'maximize the value of player data' for performance measurement, assessment, and improvement [16]. As training can be a very costly endeavor to learning organizations, one of the ways for serious games analytics to maximize value is in helping to reduce the training cost – something that is of interest, even to the U.S. military [1], [17].

Recent reports [18] indicate that one quarter of Global Fortune 500 companies have already adopted serious games for training. As more companies do the same, serious games that can offer insights from analytics for performance prediction [19]–[21] and training prescription will be more valuable to the military, medical, and surgical training industries [22].

C. *Measuring Expertise Levels and Skill Acquisitions*

Serious games for learning organizations that emphasize proficiency of skills acquired (e.g., medical training) must be designed differently from those used for general learning (without the need for measuring proficiency). Serious games designed for these industries must take steps to "ensure the acquisition of required knowledge, skills, and abilities" by the trainees [21, p. 143]; as such, it is particularly important for these games to be useful as *tools* in measuring expertise levels and skill acquisition rates of the trainees.

Dreyfus and Dreyfus [26],[27] described a five-level model of expertise comprising of Novice, Competent, Proficient, Expert, and Master. Figure 2 shows the 5-level expertise model presented as a learning curve with log-log axes to straighten the sigmoidal curve.

Novice workers tend to stick to 'textbook answers' because they are inexperienced and have yet to learn how to properly apply newly acquired knowledge. Competent workers are one level up, and are learning to apply the basic knowledge, skills, and abilities in various job situations. Proficient workers have acquired most of the knowledge, skills, and abilities needed for the job and can work independently most of the time. Proficient workers can often recognize when a mistake has been made and know to self-correct, or find solutions to novel problems independently. 'Leveling up' from one level to another would require repeated, *deliberate practice* [26]–[28] that is severely lacking in traditional classrooms. At a higher level, the Experts and Masters have all gained a wealth of knowledge about the job and are often known to break rules 'on a whim' because they know of tricks and shortcuts not known to the other lower-level workers.

As shown in Fig. 2, only the first three levels can be achievable through *training* (e.g., on-the-job, serious games, or others). The last two levels of Expert and Master are only attainable through long period (years) of deliberate practice and are beyond the scope of this paper. For reference, it can take up to 10 years of deliberate practice to produce a master in a particular discipline.

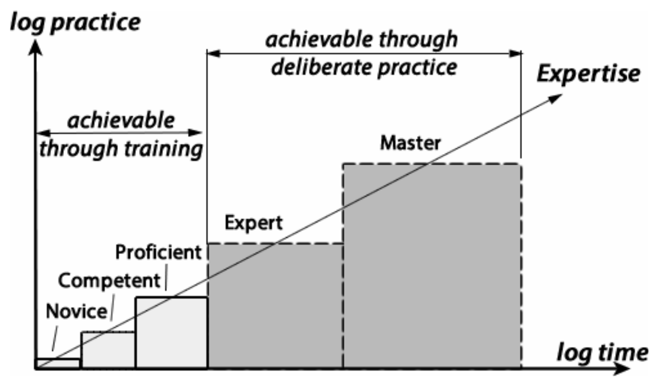


Fig. 2 Effects of training and deliberate practice on levels of expertise.

D. *The Constant Needs for Training*

Unfortunately, as organizations gain Experts through the years, they also lose them through retirement and turnovers. This means organizations must constantly train new hires to replace the lost expertise. For organizations that are looking to replace expertise through training using serious games, we summarize the following observations:

- Most of the workforce in the organization would likely be in the lower levels of Novice, Competent, and Proficient.
- The organization would rarely have an Expert or Master to serve as 'role model'.
- New hires would enter the organization at various level of expertise from absolute Novice to degrees of Proficient.
- Before starting work, new hires need to be trained (at least once) to ensure they have a common understanding of the acceptable level of knowledge or skills.

- Deliberate practice that is severely lacking in face-to-face training can, instead, be achieved through technology-enhanced training (e.g., serious games).
- Trainees' performance and level of expertise can be measured and reported in serious games – using telemetry for data collection and an analytics component for reporting/visualization.
- Trainees' in-game actions and decisions can be measured in lieu of their performance in situ serious games, and later, as insights for predicting performance and prescribing training.

II. Motivation

Many companies rightly issue training when needed because it costs money to train. This partially explains why many companies are reluctant to hire absolute Novices (i.e., fresh graduates with no prior work experience). However, it is important to distinguish excessive, over-, and under-training. In an ideal world, training needs to be thoughtfully prescribed or else it risks becoming indiscriminate and excessive. While *under*-training puts organizations at high risk because workers' mistakes can easily result in liabilities such as lawsuits and insurance claims [31], deliberate *over*-training is necessary for achieving *automaticity* and maintaining adequate performance during high-stress situations [31],[32].

Therefore, organizations that are planning to take serious games 'seriously' need to learn how to prescribe training: to identify *who*, *what*, and *when* to train, or *not* to train – in order to mitigate excessive and under-training. Serious games with in-built capabilities for telemetry and analytics can measure players' gameplay action-decision data and turn them into GAD profiles. These profiles can help Chief Learning Officers prescribe training – in the right amount, to the right people, and at the right time – to reduce overall training costs.

Research in the field of Instructional Design shows that players' *competency* can be observed and demonstrated through their chosen *course of action* (COA) during problem-solving or training [24]. Based on the methodologies outlined in these prior studies [32]–[35], we traced the players' gameplay action-decision data in this study and converted them into COAs for pairwise similarity comparison against that of the expert's (model) answers. Patterns in the data reveal three patterns of problem-solving strategies, or Gameplay Action-Decision (GAD) profiles. In the following sections, we will discuss the implications of these profiles and how they can be applied towards prescribing training.

A. Similarity Measures

Even though similarity measures have gained much popularity in the fields of Computer Science, Engineering, and Data Science, the associated statistical methods remain novel to researchers outside these fields. Converting players' behavioral data into sequential form for similarity comparison and performance measurement as serious games analytics is a particularly new area of research for educational sciences and instructional design.

We will briefly discuss the conversion of navigational action-decisions into COAs for similarity comparison, for the sake of readers who may be unfamiliar with the approach. Details about the various similarity measures and comparisons can be found elsewhere [35]–[37]. For discussion, we will treat all players as Novices in their first round of gameplay as the game would be novel to them at that point in time. As players gain familiarity through repeated practice, their expertise levels should continue to rise through the Competent and Proficient levels. As the last two levels of Expert and Master are not attainable through training, they are excluded from discussion in this paper.

B. Converting Gameplay into Course of Actions

A game world can be arbitrarily divided into a number sections using a grid of some size. Research shows that a very complex game may require special analysis to identify an optimal grid size for serious games analytics [21]. As an example, Fig. 3 shows a 5×5 grid with two navigational paths by one novice and one expert. The Novice's COA can be represented using *stringA* {ABHCIHNIOTY} and the expert's COA can be denoted as *stringB* {ABGMNSY}. Alternative methods include:

- Numeral system, where A=01, B=02, …, Y=25, and
- Cartesian system, where A=(1,1), B=(2,1), …, Y=(5,5).

Once the COAs have been calculated for the entire player corpus, pairwise similarity comparison can be conducted against that of the expert's COA using *similarity measures* – a statistical method to standardize the quantification of (dis)similarities between texts or documents. Similarity measures are rather useful for measurement of performance because the bounds of the index (0 to 1) makes it easy for laymen to understand as a scale of performance (0% to 100%). A value of 1 means the players' COAs is identical to the expert/model answer, whereas 0 means that the players' COAs are at a further distance (or, dissimilar) from the model answer. We limit our analysis to Cosine similarity in this study, but many other alternatives exist and a comparison of various similarity measures on COAs can be found elsewhere [35].

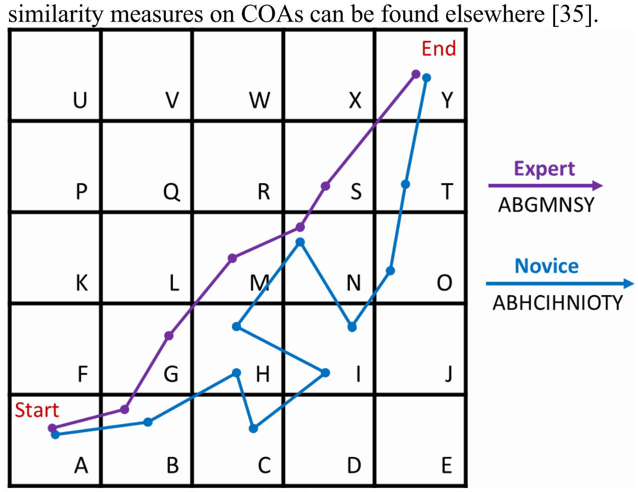


Fig. 3 Converting navigational paths to COA strings.

By applying the similarity concept to the trainable levels of expertise, users with higher scores would be placed near the Proficient zone, while those with low scores would be placed nearer to the Novice zone. The Competent zone would be in the middle (see Fig. 4).

Fig. 4. Similarity index and trainable levels of expertise.

III. Methodology

The study was approved by the Human Subject Review Board of a large mid-Western university and a total of 16 students volunteered for this initial study (first semester). We created an in-house serious game for this study using the Unity3D game engine. The game comprised of a large one-level Maze with a single Escape portal located in a room.

The goal of the game was to search for and locate the portal and to escape through it as fast as possible. There are a total of two *critical paths* [38] (i.e., expert/model answers) from the Start point to the End point: (1) routeA – a longer route with no obstacle, and (2) routeB – a shorter route blocked by a door that can only be opened using a trigger mechanism. The mechanism is made up of a pressure plate that must be stepped on multiple times. Each of the first 8 steps will produce an incremental tone (acoustical hint) that together will form a musical octave, and the last step (No. 9) will unlock the door with an audible click. The seemingly excessive number of steps and lack of instruction on how to unlock the door was designed to separate curious players from the *persistent* players who refused to give up. We expected the players who lacked volition to give up on trying the 'pressure plate' puzzle as only the most inquisitive would succeed.

Both critical paths eventually lead to the End point (room with Exit portal). Players who stepped into the portal were informed about the duration (sec) taken to escape the Maze, and asked if they would like to replay the game to try for a better score. Players could click on the 'YES' button to replay the game, or click on the 'QUIT' button to end the game. Participants could choose to replay the game as many times as they liked to earn 2, 5, or 7 points towards a class assignment. The points were awarded when the best escape time falls below 100, 50, or 38 seconds, respectively. They could terminate the gameplay at any time. The single Expert in this case was the designer of the game and his best records were 38 seconds for routeA and 34 seconds for routeB.

To visualize players' performance in the game, we compared all players COAs pairwise against the expert's COA using Cosine similarity. All statistical analysis and similarity measures were conducted using R [39] and the *stringdist* package [40]. To compensate for the presence of multiple expert routes, we applied the Maximum Similarity Indices (MSI) method. The method and rationale for MSI are fully described in [33] and is applicable to any similarity measures. Further data collection with follow-up findings from cluster analysis is available elsewhere [35].

IV. Findings and Discussions

We plotted the performance improvement (COA similarities) of players against rounds of gameplay. From the players' action-decision data, we were able to differentiate three problem-solving strategies/profiles. The Gameplay Action–Decision (GAD) profiles are: (a) *Fulfillers* (6 players), *Explorers* (4 players), and *Quitters* (6 players). The terms are chosen to best describe players' in-game behaviors and are not meant to be pejorative. Since Experts must provide the model outcomes for both routes, they are, by default, Explorers.

A. Gameplay Action–Decision Profiles

Players in the Fulfillers profile appeared single-minded in that once they have discovered a workable route (be it routeA or routeB), they persist in that singular route until they stopped playing. The plots in Fig. 5 shows Player 1 (left) used mostly routeA (black), and Player 2 (right) used mostly routeB (red) in the game. Fulfillers did not look alternate routes: i.e., Player 1 did not 'discover' routeB, and Player 2 did not find routeA. The performance of Fulfillers is mostly very good, reaching a maximum score at 0.959 (player 14). The amount of time they were willing to spend working on the task seemed dependent on some internal utility function or satisfaction level. This level appeared to differ from person to person, which explains why some individuals pressed on to reach higher scores, while for others, 'enough is enough.'

The four players belonging to the Explorers profiles performed just as well compared to the Fulfiller. In other words, there was no statistical significant difference between the similarity scores of the Fulfillers and Explorers ($p = 0.805$, α-level $= 0.01$). The main difference between the two groups was their problem-solving strategy: Explorers had a 'crisscross' pattern not found in the Fulfillers – compare Fig. 6 with Fig. 5. This crisscross pattern indicated that Explorers switch from one route to another. For instance, Fig. 6 shows the player choosing route B (red higher than black) initially from round 1 to round 9, switching to routeA in round 10 to 12, and then back to routeB again before stopping at round 14.

Such patterns indicated that Explorers would not stop at just one solution, but were willing to explore further to evaluate if a better solution exists. To the player in Fig. 6, routeA obviously did not meet his/her expectations as compared to routeB, which provided the player with high scores in round 8 and 9. Also, the high scores of round 8 did not 'stop' the player from searching for alternate routes. Compared to the Fulfillers, the Explorers seemed interested in searching for potentially better alternative(s), which may or may not lead to better results.

In comparison, the Fulfillers seemed to have less initiative. While both Explorers and Fulfiller clearly self-evaluate to see if they were satisfied with the scores before stopping the game, Explorers evaluated and compared the scores received from multiple routes – a more complex situation. Note that players had no idea how many 'routes' existed in the game. The 'crisscross' in round 1 should be ignored because it is purely 'exploratory' at that point as the game environment is novel to the players.

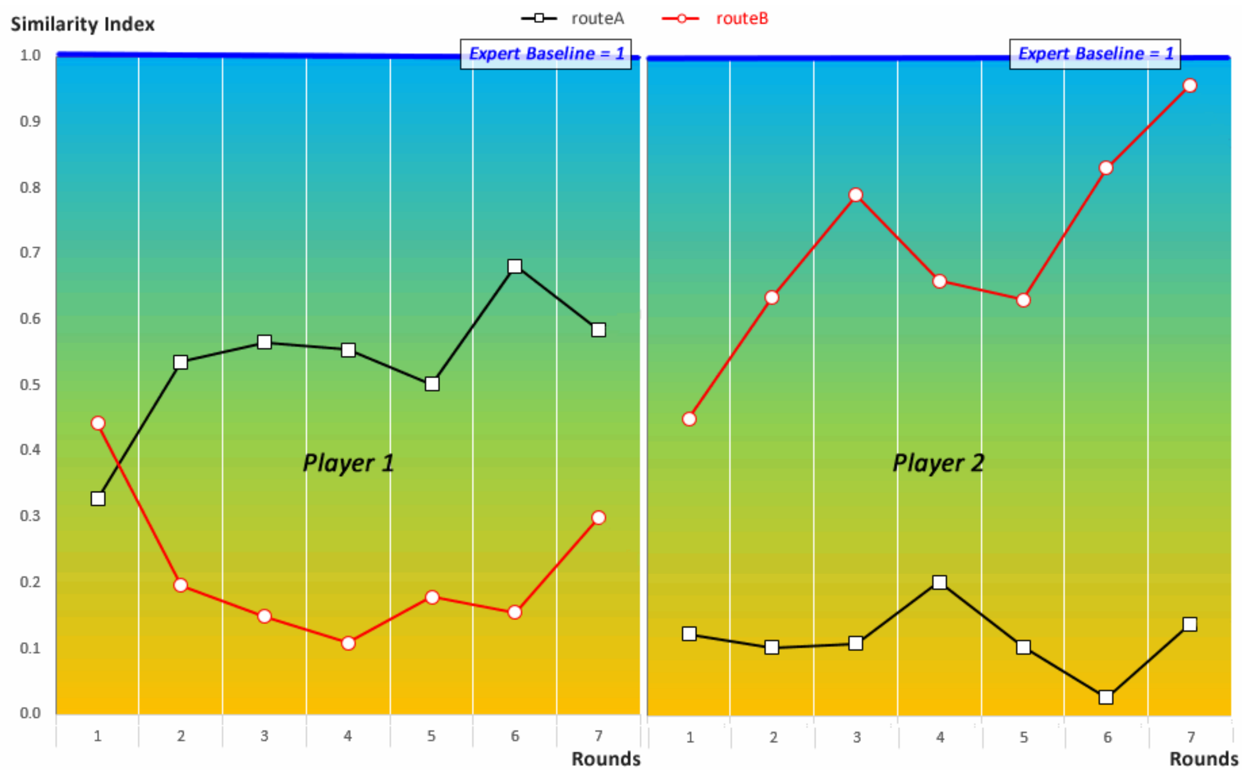


Fig. 5 *Fulfillers* find a working solution and keep using it. (Left) Player 1 uses mostly routeA (black), and (Right) Player 2, mostly routeB (red).

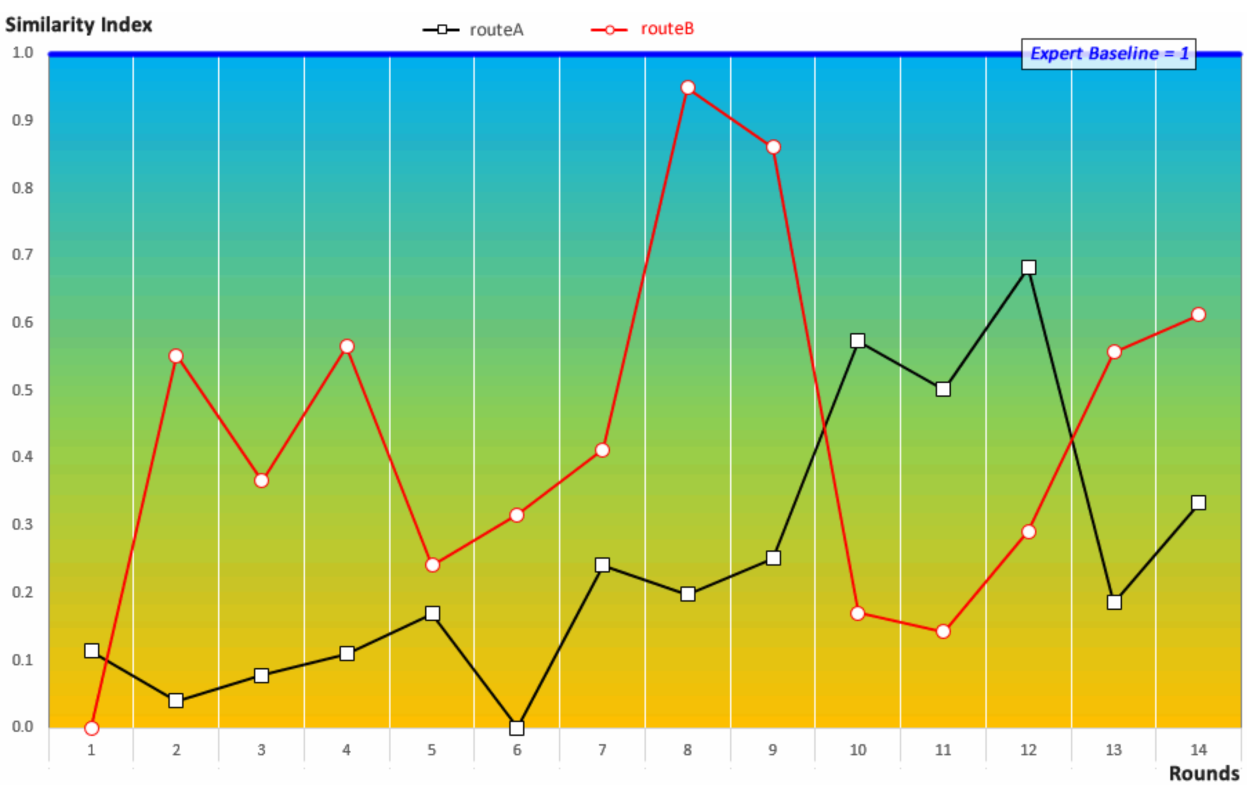


Fig. 6 *Explorers* took initiatives to search for potentially better routes. Their plots show 'crisscross' pattern which indicate they switch from route to route. (In this case, routeA is black and routeB is red).

Lastly, the Quitters profiles comprised of players who 'quit' in less than 5 rounds. They tend to 'abandon' the game, resulting in incomplete rounds. Due to the low number of tries and incomplete rounds, their similarity scores were correspondingly much lower than the other profiles. In Fig. 7, player did not complete round 4, resulting in a much poorer score than round 3. On the whole, Quitters tended to give up too quickly, too early. Some dropped after just 1 round of gameplay.

B. Performance Differences by Profiles

We conducted a simple t-test (α-level = 0.01) to determine how different the three groups were (Fig. 8). We detected a statistically significant difference between Quitters and the two other profiles ($p < 0.0001$ for both cases). There is no detectable statistically significant difference between the Explorers and Fulfillers ($p = 0.805$). Their performance scores are as follows: Quitters ($M = 0.399$, $SD = 0.068$), Fulfillers ($M = 0.794$, $SD = 0.117$), and Explorers ($M = 0.846$, $SD = 0.108$). The highest MSI score (0.959) belonged to a Fulfiller.

Since there are two model answers (critical paths) in this game, we have to measure players' performance using MSI score instead of the regular similarity scores. We ranked the MSI scores for all 16 players (in this first study) and found a kurtosis to the right. This is consistent with the characteristics that Cosine coefficients tends to be on the high side as compared to other similarity coefficients.

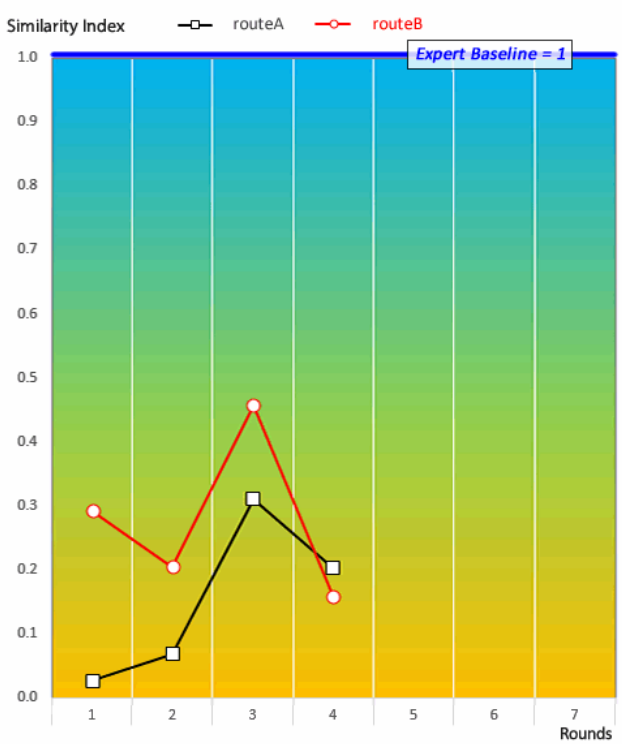


Fig. 7 *Quitters* give up early and tend to remain as Novices despite the opportunity for training.

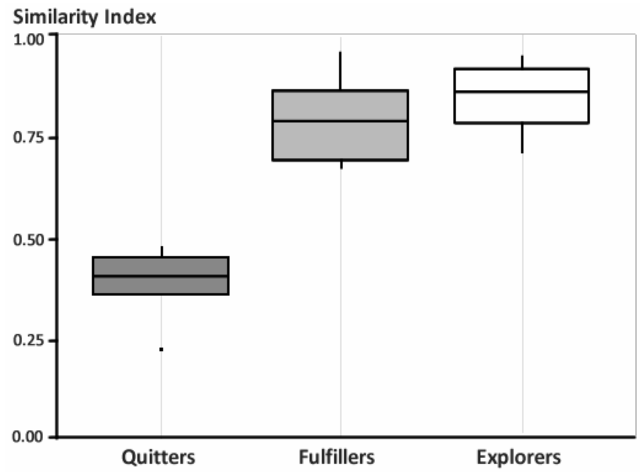


Fig. 8 Boxplot of similarity scores by GAD profile

Based the distributions of the scores, we adjusted the ratios of Novice:Competent:Proficient from the theoretical ratio of 1:1:1 to 3:1:1 to compensate for the kurtosis: i.e., Novice (0–0.6), Competent (0.6–0.8), and Proficient (0.8–1.0) (Fig. 9 and 10). From experience, the placement of these expertise zones – i.e., Novice, Competent, and Proficient, tends to be game dependent. Instead of using specific values to identify the levels of expertise, we recommend the heat map approach to better depict a continuum of expertise for generalization. We plotted a second graph (Fig. 10) showing MSI scores as primary axis and total time of training as secondary axis for each GAD profile.

Interestingly, the graph shows the Explorers to have a much lower total training time than that of the Fulfillers. Recall that there was no statistically significant difference between the performance (MSIs) scores of the Fulfillers and the Explorers. However, the total training duration of Explorers is obviously much shorter than those of the Fulfillers. It would appear that spending some time searching for alternative(s) does pay off. If the Explorers can achieve the same higher scores as the Fulfillers and spend less time training, this makes Explorers a golden profile or strategy to be modeled after to reduce training costs! Future serious games should take this into consideration and include multiple critical paths in the design to help inculcate the Explorer's behavior in the players.

C. Understanding Why Quitters Quit

Every player stopped playing at some point in time but the Quitters seemed to 'give up' much sooner than the others. There is obviously a plethora of reasons as to why players eventually stopped playing. Except, for some unknown reasons, Quitters just resigned to remain as Novices in spite of the opportunities to train for improvement.

From an instructional designer's point of view, the first question to ask would be: Could quitting be due to the poor design or content of the game? This does not seem to be the case as majority of the players went on training for many rounds and achieving better proficiency than the Quitters. A second possibility would be that of motivation. It would do well for stakeholders to conduct follow-up or interviews to ascertain if the quitting is indeed caused by a lack of motivation because the Motivational Gap is not bridgeable by training or instruction. An immediate option to reduce training cost would be to suspend training for the time being as it is ineffective for this group – not until the motivational issues have first been resolved through other non-instructional means.

Based on feedback from the participants in our study, we found 'game motion sickness' to be a plausible reason for quitting. This motion sickness is particularly prominent in first person view and can be exacerbated by immersive environment, such as a large screen TV. About half of the players complained about 'game motion sickness' in our study, likely caused by the 72-in screen TV used in the study. We discovered that it is possible to diminish the discomfort through training; in other words, players experienced less motion sickness as they adjusted to playing the game over several days. Rest and motion sickness medication can also help alleviate the symptoms. In summary, successful identification of the Quitter profile through some kind of diagnostic serious game would be an excellent approach to reduce overall training costs for learning organizations.

D. Do Learning Styles Matter?

For over 30 years, the (mis)concept of learning styles has become entrenched in the learning industry [41]. An entire testing industry has sprung up around learning styles, despite the concept being problematic from an instructional design perspective. If instructional designers must cater to the many learning styles within an organization, instructional software will have to incorporate a large corpus of domain knowledge to facilitate dynamic individualized customization, which is certain to raise production and training costs. Furthermore, organizations may have in-house approaches to training, and the domain knowledge to be included in training materials may contain trade secrets requiring encryption (which escalates costs). High production costs are good news for companies that develop learning software, but are a curse to those who are cognizant of reducing training costs.

Instructional and serious game designers can finally step away from learning styles as recent research has successfully debunked the myth. Not only is there little to no evidence about its effectiveness in learning [42], encouraging students to compensate for their learning styles can be harmful and become a learning weakness [43]. Ineffective training method is just a waste of money, time, and effort [44].

E. Data-Driven Model

Gameplay Action-Decision (GAD) profiling is a data-driven and evidence-based approach to examine the way people make decisions in situ a training habitat. It evaluates what people actually do, given the knowledge they have already accrued (via e-learning, serious games, in-house training programs, etc.). Evidence about what the workforce might do in a certain work situation is crucial for predictive analytics because insights about workers' profiles can alert the human resource department to take steps to correct shortcomings.

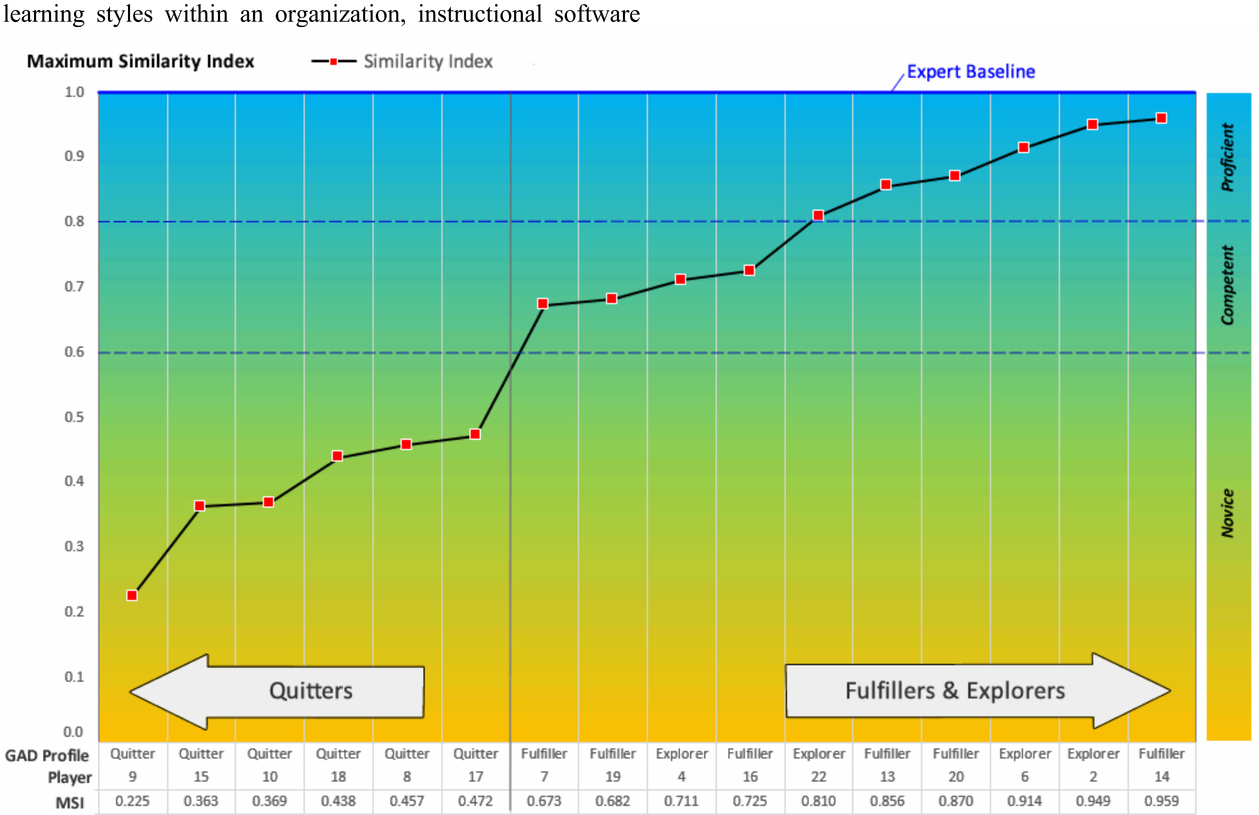
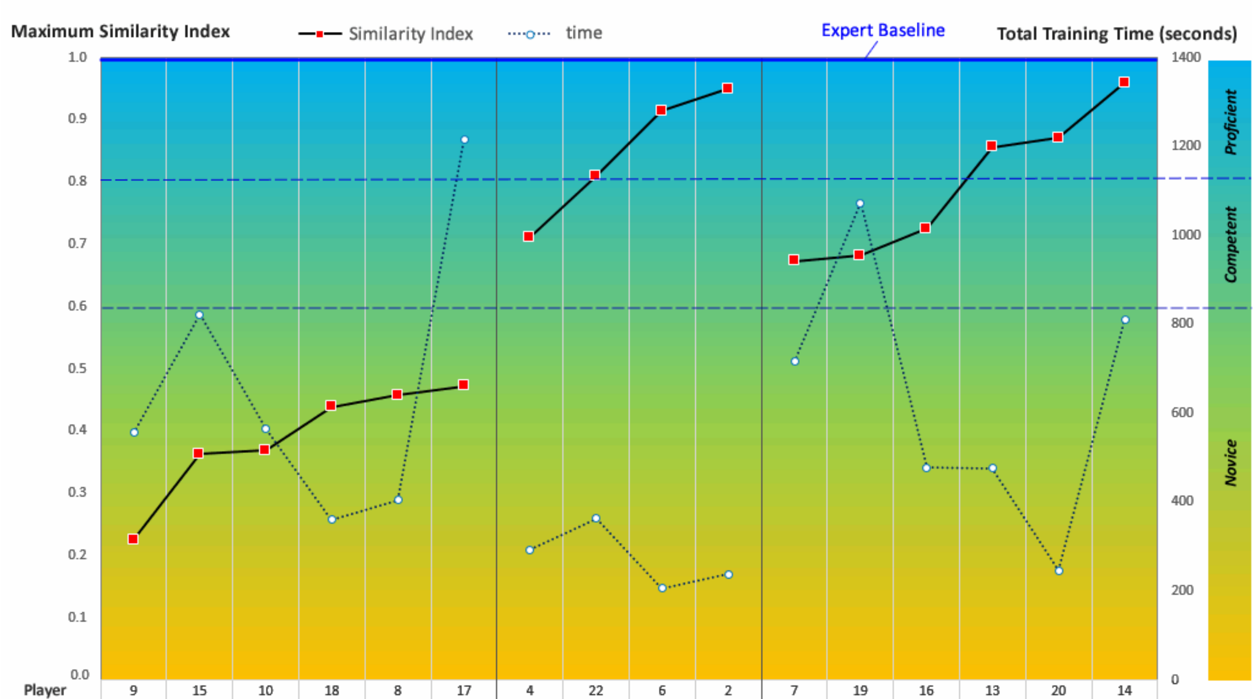


Fig. 9 Players ranked according to Maximum Similarity Indices.



Player	9	15	10	18	8	17	4	22	6	2	7	19	16	13	20	14
GAD Profile	Quitter						Explorer				Fulfiller					
Max Sim Ind	0.225	0.363	0.369	0.438	0.457	0.472	0.711	0.810	0.914	0.949	0.673	0.682	0.725	0.856	0.870	0.959
Max time	556	822	564	361	404	1216	293	363	206	238	716	1073	478	476	246	811

Fig. 10 Maximum Similarity Indices plot by GAD profile by total training time (sec).

Unlike E-learning, which is created specifically to provide instructions anytime, anywhere, game user-interfaces are ineffective for reading large chunks of instructions. Instead, serious games are excellent tools to monitor what players can do in a (simulated) work environment because players can practice repeatedly under various conditions to increase proficiency on the job. Diagnostic serious games can uncover deep-seated beliefs about the workers and enable the organization to be better prepared – e.g., if and when to introduce disaster-preparation training.

F. Future Research

Readers familiar with decision-making styles in Educational psychology literature may notice overlaps between the characteristics of Satisficers and Maximizers [38],[39] and those for the Fulfillers and Explorers. It is unclear at this moment as to how much overlaps exist between the educational psychology and the GAD profiles. Inter-disciplinary collaboration between the two fields will be needed to clarify the relationship and verify this claim.

By default, similarity measures can only compare the sequences of action-decisions. The current process does not take time into consideration. It could be of value to combine COAs similarities, total duration of training required, and changes in expertise levels caused by the serious game training into a single performance score, which can then be factored into calculating the serious game investment returns. Besides the Maximum Similarity Index, other metrics have also been proposed – e.g., Average Similarity Index [35]. Analytics metrics are continually being updated to provide better evidence about the effectiveness of serious games.

V. Conclusions

A. Serious Games as Tools for Analytics

Players' gameplay action-decisions and behaviors can be used to improve workers' performance and predict what they might do through 'what-if' scenarios. Sans the training corpus for game-based instructions, diagnostic serious games should be much smaller and cost less to produce. Since diagnostic games need to be rigorous in their statistical methodologies and analytics approach, an academic-industry alliance is strongly encouraged.

By understanding how players make decisions (during interactive training) in serious games, we can better design the training paths and game events to (re)channel the flow of training. The aim of training prescription is to diagnose how people learn in situ technology-based environments, predict patterns, and prescribe (recommend) training based on the outcome of the diagnosis. Unlike adaptive learning, which is aimed at supporting how people learn (via learning styles), prescriptive training can support, withhold, or even reform old learning habits. Examples of reformative learning include remediation/re-training, habit reformation, and rehabilitation.

B. Player-Behavior Profiling for Performance Improvement

GAD profiles, as an evidence-based and data-driven model, reveal players' problem-solve strategies within serious games environments. Players' data from serious games can be turned into new serious games analytics to help stakeholders reduce training cost through prescriptive training, by helping them identify:

- *Who* and who *Not* to receive training – Besides identifying Explorers and Fulfillers to participate in training, early identification of Quitters with intervention can help to minimize workplace problems and increase overall training effectiveness. Money saved from the training can be rechanneled to other projects, or as gamification incentives to raise external motivation. Unlike training, such actions may actually have a chance in improving Quitters' performance.

- *What* and *How* content should be offered – Because Fulfillers are so single-minded in their approach, they may not be open to explore new routes on their own. The solutions must be somewhat obvious or Fulfillers may miss them altogether. Serious Games can help expose Fulfillers (linear thinkers) to discovery-based learning with multiple critical paths and encourage thinking 'outside the box'. Training programs designed for Fulfillers need to begin with a linear design to ease Fulfiller into the process before gradually including more critical paths. This would be a great way to design Managerial training and prepare them for uncommon, but potentially disastrous work situations (through multiple critical paths).

- *Supportive or Corrective Training* – Serious game designers already know how to encourage gameplay behaviors through gamification. Coaxing players to perform actions that are out of the ordinary, or outside their comfort zone is the first step to stimulate learning. We can implement corrective (targeted) training by first identifying learners' comfort zones for removal through players' action-decision profiling. This approach is can be used to help learners overcome old habits and acquire new knowledge, skills, and abilities. Serious games are great for repetitive 'over-training' for reaching automaticity – going beyond the Proficient level.

- *Stress Training* – "the primary purpose of stress training is to prepare the individuals to maintain effective performance in a high-stress environment" [21, p.143]. Work situations are often stressful and require workers to complete training tasks under time pressure, noisy environments, limited resources, and sleep deprivation. Stress training can help prepare individuals to commit fewer errors during emergencies as repetition enhances familiarity, and builds confidence in the trainees [36],[48]. This is particularly useful for disaster preparations (using serious game). Stress training can reduce costly mistakes made by workers as they are less likely to be caught by surprise and act out of panic.

Besides finding out what kind of training is most needed, organizations can now place workers correctly in the most effective training environment. Future research can possibly inform: which surgeons are prone to stress during surgical operations, which pilots are less fit to perform Trans-Atlantic flights, which soldiers are better suited for training as Reconnaissance, Medics, and others. Reducing training cost is an obvious application for GAD profiles, but it constitutes just one aspect of the Training life-cycle.

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