Game-based Learning to Enhance Post-secondary Engineering Training Effectiveness

Kevin F. Hulme, Ph.D., CMSP
Motion Simulation Laboratory
University at Buffalo, Buffalo, NY
hulme@buffalo.edu

Aaron Estes, Ph.D.
Department of Mechanical & Aerospace Engineering
University at Buffalo, Buffalo, NY
aaronest@buffalo.edu

Mark Schiferle
Department of Mechanical & Aerospace Engineering
University at Buffalo, Buffalo, NY
ms286@buffalo.edu

Rachel Su Ann Lim
Motion Simulation Laboratory
University at Buffalo, Buffalo, NY
rlim2@buffalo.edu

ABSTRACT

In recent times, Game-based Learning (GBL) and "Gamification" serve as emergent mechanisms for modern-day Training. In accordance with recent literature, knowledge retention and trainee engagement have been shown to be more effective within a Training environment that purposefully exploits active and experiential opportunities for skillset acquisition. The application of GBL within a high-fidelity Simulation, presented in a Live, Virtual, Constructive (LVC)-context, is a novel modern-day framework for STEM/Engineering and Post-secondary Training.

This paper summarizes the development and deployment of GBL Training experiments intended for a Mechanical Engineering college curriculum. Specifically, we have designed two experiments for undergraduate seniors and graduate students who are studying ground-based vehicle dynamics: 1) a Triangular Race Track that institutes and compares "Ghost" vs. "Gauge" GBL-Trainer elements to optimize real-time vehicle performance, and 2) a Skid Pad closed-course proving grounds that visualizes weight-distribution adjustment to optimize vehicle stability towards a (desirable) neutral steer condition. To assess the effectiveness of our Training solutions, quantitative data (e.g., speed, X/Y position) was collected by the Simulator, and likewise, our class cohort (N=70) offered supplementary self-report data (e.g., trainee Learning Styles) relevant to the GBL experience. As a component of our holistic multi-measure evaluation, these data are analyzed to report lessons-learned along with any meaningful correlates.

To conclude this paper, we propose future extensions of our GBL-based Training solution into other Engineering courses. Namely, our framework can be employed in a Junior-level Dynamics course to demonstrate a second-order representation of a vehicle suspension system, and similarly, within the context of another engineering discipline (Aerospace Engineering), short-period flight modes can be actively demonstrated for an Aircraft Dynamics experiment. Likewise, framework extensibility to a portable augmented/mixed reality deployment for other engineering systems (e.g., military/Marine, K-12 and STEM/location-based entertainment) is forecasted.

ABOUT THE AUTHORS

Dr. Kevin F. Hulme is a Senior Research Associate with the School of Engineering and Applied Sciences at the University at Buffalo. His areas of research and teaching interests include the design, development, and deployment of experiential learning and game-based Simulation elements for next-generation Training. He is a Certified Modeling & Simulation Professional (CMSP).

Dr. Aaron Estes is a Teaching Assistant Professor with the Department of Mechanical & Aerospace Engineering at the University at Buffalo. His teaching interests include dynamics and control (for both ground and flight vehicles), and system identification. Likewise, he has instructional and research-based interests in the novel application of high-fidelity Simulator-based Game-Based Learning within engineering higher education.

Mark Schiferle has his B.S. and is currently pursuing his M.S. in the Department of Mechanical Engineering at the University at Buffalo. His primary area of interest includes the novel application of Gamification and Game-based Simulation to improve student training effectiveness in Post-secondary engineering education.

Rachel Su Ann Lim received her B.S and M.S. degrees from the Department of Biomedical Engineering at the University at Buffalo. Her contributions to the Motion Simulation Laboratory involve novel healthcare advancement and simulation analysis as a platform to extract features that encourage game-based simulation.

Game-based Learning to Enhance Post-secondary Engineering Training Effectiveness

Kevin F. Hulme, Ph.D., CMSP
Motion Simulation Laboratory
University at Buffalo, Buffalo, NY
hulme@buffalo.edu

Aaron Estes, Ph.D.
Department of Mechanical & Aerospace Engineering
University at Buffalo, Buffalo, NY
aaronest@buffalo.edu

Mark Schiferle
Department of Mechanical & Aerospace Engineering
University at Buffalo, Buffalo, NY
ms286@buffalo.edu

Rachel Su Ann Lim
Motion Simulation Laboratory
University at Buffalo, Buffalo, NY
rlim2@buffalo.edu

INTRODUCTION AND BROADER IMPACTS

Educators continue to leverage the value of incorporating gaming components into skillset acquisition. Particularly over the last decade, we have witnessed the emergence of *Gamification* (the process of adding game-like elements within a task to encourage participation) and similarly, *Game-based Learning* (GBL), where trainees explore relevant aspects of gaming, often in a collaborative manner, within a learning context designed by the trainer (ETR, 2013; Dsouza, 2016). The four primary components of GBL: Motivation (points/badges), Feedback (status updates), Practice (learning by trying), and Reinforcement (repetition) (Dhruve, 2017) (refer to Figure 1; Dasara, 2016) lend themselves to a Training atmosphere where learners steadily work towards a goal (i.e., "problem solving") (e.g., Bauman, 2012), and immediately observing the consequences as key elements of the Training process. The application of GBL within a high-fidelity Simulation, presented within a Live, Virtual, Constructive (LVC)-context, can serve as an effective mechanism for STEM/Engineering post-secondary Training.

Figure 1 – Primary GBL components

This paper summarizes a series of GBL-based Post-secondary experiments that were conceived, designed, developed, and deployed for a University-based (mechanical) engineering "technical elective" Road Vehicle Dynamics (RVD) course. Our primary intention was to supplement conventional passive course material delivery (i.e., lectures) with hands-on opportunities for enhanced skillset acquisition to improve Training effectiveness. As a portion of our experiments, we collected performance data from a high-fidelity Simulator, supplemented by relevant self-report data collected both pre- and post- experiment. To conclude this paper, we will preview related avenues that will promote extended dialogue for next-generation opportunities in GBL Training. We begin by emphasizing the relevance of this topic to I/ITSEC, and to the prevailing Conference themes for 2019.

TOPIC RELEVANCE TO 2019 CONFERENCE THEMES

The current topic is relevant to the prevailing themes at the 2019 I/ITSEC: "winning the war of *cognition* by pushing *readiness* and lethality boundaries". Certainly, the notion of "cognition" serves as a vital component for the sustained application of game-based learning (GBL) in next-generation Training; practitioners have acknowledged that playing video games offers physiological benefits associated with brain stimulation. GBL tends to drive decision-making, improves cognitive function, and assists with the acquisition of skillsets that are applicable to real life. Ultimately, the use of serious games for Training improves the mental faculties of the trainee, who actively tries to identify alternative approaches to solving different situations directly within the learning process (Jabary, 2019). Likewise, the notion of "readiness" certainly applies to next-generation Training for students (and warfighters). Recent studies in the literature clearly demonstrate that GBL dramatically improves learner engagement and cognition (Jabbar and Felicia, 2015), and improves the likelihood of knowledge retention in present-day Training (e.g., Li et al., 2017). In our targeted Literature Review, we expand on these notions to present a comprehensive synopsis of GBL in Training.

LITERATURE REVIEW: GAME-BASED LEARNING (GBL)

Engineering Education often involves the application of theoretical physics-based models, for which students and trainees require a depth of comprehension to apply these models systematically, and in real-time. As motor vehicle technologies and automation mechanisms continue to mature, it is critical that educators advance techniques for successful and impactful Training. Our continued focus should concentrate not only on individual concept reinforcement, but also, assuring a comprehensive understanding of downstream impacts of the interactions between system factors (i.e., "cause and effect"). In this manner, implementing interactive, participatory educational experiences inside the classroom can positively impact engineering skill development through improved knowledge retention (e.g., Whitney, 2017), and trainees need to cultivate experiences that help them to navigate the real world (e.g., Nagai, 2001; Feisel and Rosa, 2005). Recent research indicates that students who engage in hands-on learning experiences enjoy improved academic performance, and students who participate in game-based projects tend to study more, retain more knowledge, establish meaningful connections between key concepts and demonstrate expanded comprehension of the subject matter (e.g., Coller and Scott, 2009; Coller, 2012).

While previous engineering education research has focused on the implementation of serious play and gamification in education, gaming elements infused with motion simulation affords a more kinesthetic experience (i.e., awareness of position/movement), as opposed to exclusively visual/aural representations afforded by interactive graphs or screen-based video games. Previously (Hulme et al., 2016), the authors leveraged gaming elements and motion simulation to observe the dangers of distractions and task-unrelated thought while driving, deployed for a Transportation Safety course. More recently (Hulme et al., 2018) explored the implementation of GBL, Modeling & motion-based Simulation to allow engineering student trainees to experience a real-world evasive road test maneuver - the ISO 3888-2 Moose Test. This afforded an experiential opportunity to: a) expose dynamics learners to an official/extreme vehicle test maneuver within a high-fidelity Simulator, and b) observe the degree of impact of employing electronic stability control on driver performance at various speeds. Lessons learned from these past Training experiments will be expanded for the current work, where we will apply standard educational outcome assessments to motion simulation as a platform for interactive learning, while using multiple measures to quantify its effectiveness in comparison to traditional pedagogical tools. The GBL experiments (in the context of Road Vehicle Dynamics) are now detailed, and presented with stated emphasis on the associated Training objectives.

ROAD VEHICLE DYNAMICS (RVD) – THE GBL EXPERIMENTS

In this section, we present an overview of the two Post-secondary experiments that were offered for RVD. The ***Triple Curve*** was offered early in the semester as an exploratory Training mechanism by which to be introduced and acclimated to the framework of our Simulator. The ***Skid Pad*** was offered later in the semester after moderate exposure to relevant course theory. For each experiment, salient Training goals are described and highlighted.

Experiment I: Triple Curve - Cornering Strategy with Tire Saturation

The Triple Curve was designed as a racing simulation on a triangular track with three straight segments joined by tight corners. The students are given simple directions: to complete as many legal laps (i.e., no barrier cones struck) as possible within a two-minute window. This task implies that the students maximize their speed, but maintain control of the vehicle during the critical transitions, for which students quickly learn that braking is essential for both speed and control. The conceptual Training link is "tire saturation": the property that tires generate a limited amount of traction before the vehicle skids out. To achieve an optimal lap time, the student needs to accelerate as much as possible, but only within the physical limitations of the tires. This is especially important in corners, where tire traction provides the centripetal force to hold the vehicle in the corner, and the tractional demands increase in proportion to ***the square of the speed of the vehicle***. The length of the straight segments allow students to accelerate to approximately 80 mph before entering each successive corner. However, entering the tight corners at this speed (without smooth braking) will likely result in an undesirable outcome. Therefore, to make it through this track with the fastest speed, students must brake as they enter corners. The simple geometry of the track, by design, requires students to take the same corner over and over again, adjusting their approach with each entry, each time engaging with the physics of tire saturation.

We designed and implemented a series of gaming elements to guide the learner towards their ultimate Training goal - to achieve the greatest number of legal laps (i.e., no cones struck) within the time allowed, and implicitly, an optimal lap time. We programmed the Simulator to collect a series of data, including the X/Y drive path coordinates for each driver (and each driven lap) on their excursion (captured at 30 Hz.) as well as a Score Sheet printout that summarized primary statistics and from the drive excursion (e.g., data relating to total and legal laps, maximum and average speed, and any hazard events such as cone strikes or spinouts). We employed two Training approaches for the Triple Curve experiment. Our "Ghost" trainer was designed with a "follow the leader" strategy in mind. In other words, rather than trying to coach novice Trainees on the technical nuances of the race course, we simply instructed them to refer to the expert (pre-recorded) "Ghost" vehicle that would accompany them on their drive. In this manner, we observed if trainees could achieve effective Training by watching/observing, and without any presentation relating to the actual performance dynamics of the moving vehicle. Refer to Figure 2, which illustrates the Ghost trainer shown in the red vehicle on the right side of the view. We also developed a GBL-based "Gauge" trainer, enabling visualization of technical guidance to observe if certain learners might respond to game-based on-screen overlays that would help them navigate towards optimized performance. These "gauges" include color-coded spheres placed upon the virtual roadway to simultaneously provide indication of the optimal drive line, as well as colors to indicate regions of acceleration (green), braking (red), and transition segments (yellow). Likewise, a vertical gauge was provided (left side of screen) to indicate the maximum tire slip angles encountered during a turn. The green region (low on the gauge) is indicative of overcautious driving; the red region (high on the gauge) is indicative of reckless driving, and the yellow region (middle of gauge) is the "sweet spot" that we were inspiring novice drivers to try to achieve during their turns. Refer to Figure 3, which illustrates the Gauge-Training environment.

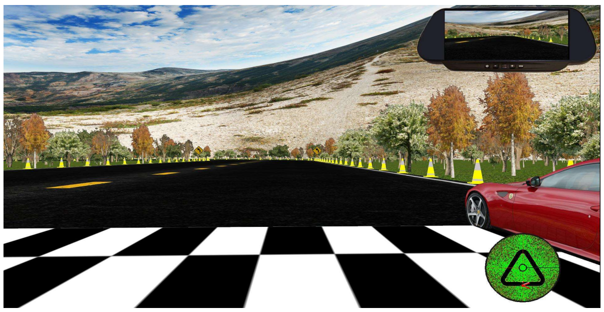

Figure 2 - Triple Curve (GBL "Ghost" Trainer)

Figure 3 - Triple Curve (GBL "Gauge" Trainer)

<u>Experiment II: Skid Pad - Handling of Oversteer and Understeer Vehicles</u>

The Skid Pad interactively teaches students about the understeer and oversteer characteristics of road vehicles, and specifically how these characteristics depend on the longitudinal position of the vehicle's center of gravity (CG). Trainees are afforded a two-minute duration with the goal of achieving the fastest possible lap time. A radius on the skid pad is clearly specified for the students to follow. In addition to being able to steer, brake, and accelerate; the students are able to utilize paddle shifters to the left and right of the steering wheel to adjust the longitudinal CG position of the vehicle. Note that such a feature would be impractical or impossible to experience within a real-world vehicle. Changing the CG position modifies the understeer characteristics of the car, and in-turn, modifies the top speed "potential" of the car while cornering. For optimality, trainees need to modify the CG position towards the "neutral steer" condition. In traditional homework problems, identifying the neutral steer point involves intensive mathematical calculations, while in the simulator, finding neutral steer involves intuitive adjustment of the CG by kinesthetic "feel" to comprehend its resulting impact upon vehicle handling.

Again, we designed and implemented GBL elements to guide the learner towards their ultimate Training goal - optimize the stability of the vehicle towards a desirable neutral steer condition, which typically permits an optimal balance of maximum speed and vehicle control. The GBL elements to guide the trainee are explained as follows:

1) The **<u>steering wheel indicator</u>** provides visual feedback on exactly how much drivers are turning their hands, noting that at neutral steer, trainees are steering LESS (i.e., hands in a fixed-position);
2) The **<u>travel speed gauge</u>** guides drivers towards obtaining their optimum speed on the chosen radius, guided by green/yellow/red color-coding, while the current travel speed is shown digitally to the right of the contour gauge.
3) The **<u>(CG) and tire stiffness distribution meter</u>** guides trainees towards a "balanced" vehicle based upon tire/weight distribution, front-to-rear. The meter tire colors change relative to their individual saturation levels, ranging from 0% (unsaturated; green) to > 6% (saturated/beyond; red), to intermediate (e.g., yellow/orange).
4) The **<u>radar map</u>** displays the current location (and heading) of the driven vehicle relative to the roadway, surrounding cones, and remainder of the GBL virtual world training map.
5) The **<u>heading pathway</u>** lies within the 3D viewport itself, and can be seen a series of colored spheres that guide the driver, and change color in real-time according to compliance: green represents on-center; red indicates far off-center, with intermediate colors (e.g., yellow/orange) indicating partial satisfaction.
6) The **<u>scoring meter</u>** was implemented to provide an overall Gamification "rating" (0-100% scale) based on compliance to speed, heading, and neutral steer proximity. This "rewards" system was instituted to engage and motivate drivers to comply with the goals of the experiment in direct pursuit of its primary Training objective.

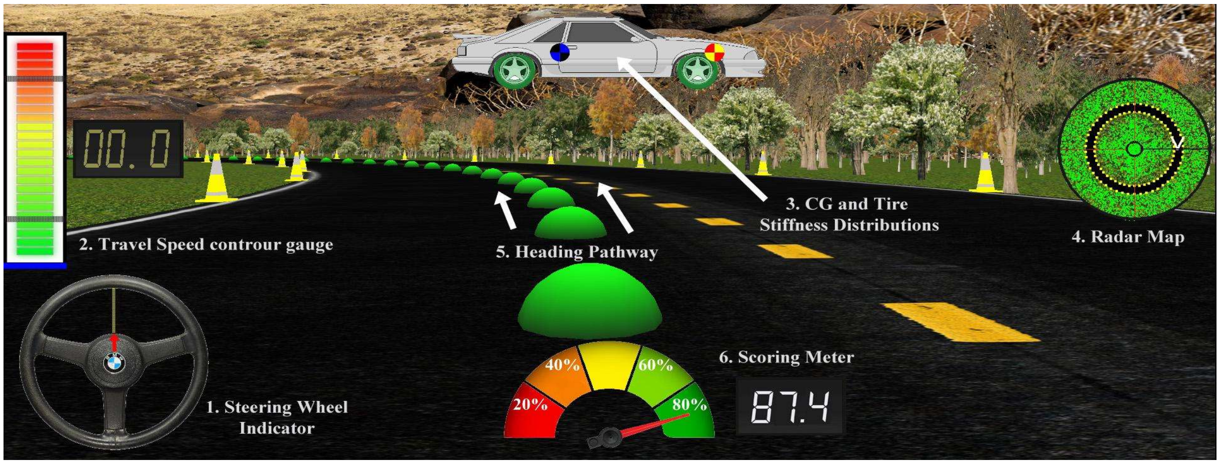

Figure 4 - Skid Pad GBL Trainer (forward view, labelled)

Refer to Figure 4, which illustrates the forward view of the completed Skid Pad GBL Training environment, with all gaming elements depicted and labelled. Prior to a formal presentation of our experimental results, we describe the high-level details of our RVD class cohort as well as a summary of the major features of our high-fidelity driving simulator that was leveraged for both GBL-Training experiments.

COHORT DETAILS AND TRAINING ENVIRONMENT COMPOSITION

The GBL Training exercises have been designed for a Post-secondary course - MAE 454/554: Road Vehicle Dynamics (RVD). The course enrollment was a total of 83 students (22 Grad; 61 Undergrad). Self-report "surveys" (i.e., trainee learning styles) were issued (N=83 completed) that were directly related to the GBL-Training experience offered as a feature element of the RVD course. As students tend to process information in different ways - typically based upon individual preferences (PPC, 2019) – we sought to determine if certain GBL-based Training techniques might be better suited towards certain types of learners. Accordingly, we issued the Index of Learning Styles (Felder and Silverman, 1988; Soloman and Felder, 1999), which explores a four-dimensional learning style model. A series of 44 two-choice questions (i.e., 11 in each of the 4 categories) are issued to determine an indication as to probable strengths and possible tendencies that might lead to challenges and deficiencies in learning/training. The four-dimensions on the scale are: 1) *Active (A) vs. Reflective (B)*: how does a trainee prefer to process information; 2) *Sensing (A) vs. Intuitive (B)*: how does a trainee prefer to take in information; 3) *Visual (A) vs. Verbal (B)*: how does a trainee prefer information to be presented; and 4) *Sequential (A) vs. Global (B)*: how does a trainee prefer to organize information.

The full-cohort results (average/standard deviation) can be viewed in Figure 5. The cohort average was such that the class, taken as a whole, preferred "A"-style learning in all four subcategories (i.e., an "AAAA" sequence). Of the pairs of categories (shown partitioned within the plot), "Visual" was preferred most dominantly over "Verbal" learning; this was followed by "Sensing", which was preferred substantially over "Intuitive" learning; this was followed by "Sequential", which was preferred slightly over "Global" learning; and finally, "Active", was marginally preferred over "Reflective" learning. These Learning Style results will be further explored for our Result Correlations.

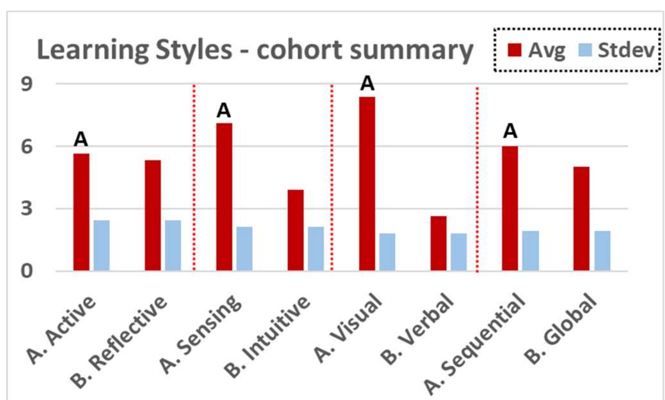

Figure 5 – Index of Learning Styles (*N=83*)

The SimRING Simulator's physical (hardware) environment input system (Human Input Device, or HID) includes a steering wheel (w/ 240 degrees of stroke), pressure-modulated floor pedals (i.e., acceleration and braking), and buttons and paddle shifters that enable real-time, driver in-the-loop input during the simulations. Refer to Figure 6, which presents a driver POV of the HID controls. Dynamics computations include classic ground vehicle models (e.g., Milliken and Milliken, 1995) that implement longitudinal force (i.e., throttle and brake) as model inputs, and compute vehicle velocities, accelerations, and tire forces as outputs. These models include basic tire behavior that allow for hands-on, exploratory Training. Simulator System output manifests itself in three primary forms: a) graphics rendering: a high-definition, surround screen visualization projected upon our large-screen (6 ft. high, 16 ft. diameter) display system (i.e., 11520x1080 composite edge-blended and image-warped screen resolution); b) motion rendering: a 6-DOF 2000E electric motion platform; and c) aural rendering: a 2.1 stereo high-fidelity sound system located around the exterior to the Simulator. Figure 7 depicts a partial-panoramic view of the entire Training environment: the SimRING Simulator (left), and a short-throw projector that displays the forward-only view (i.e., 60 degree FOV) of the driver/passenger for the off-board Training audience. The virtual (software) environment is constructed within the Visual Studio (Windows-based PC) programming environment, using the C/C++ programming language. Input signals are captured from the HID using DirectInput (DirectX); output signals are generated for graphics (OpenGL), Motion (Winsock and Win32 Posix threads), and Sound (OpenAL) using widely-available libraries and functions based upon hybrid elements of C/C++. Preliminary Results from this effort are now featured, including quantitative (Simulator), survey (self-report) and observed correlates.

Figure 6 - HID controls, driver POV

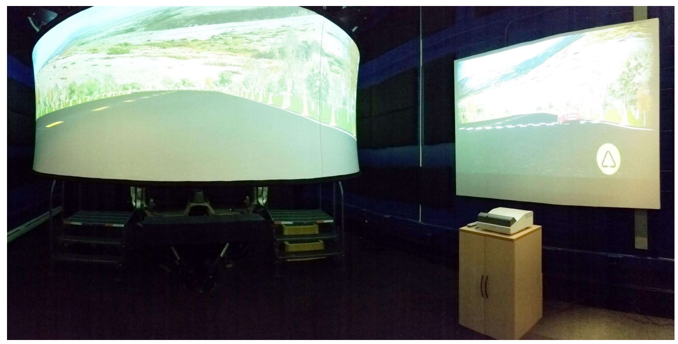

Figure 7 - Simulator Training Environment

EXPERIMENTAL RESULTS & DISCUSSION

In this section, we present an overview of our preliminary results from the implementation of our GBL Training exercises. Here, we present a) quantitative results from the Simulator, b) results from Self Report (both pre- and post-experiment), and c) observed result correlations between these two data forms. Prior to this presentation, we begin with a description of hypotheses that informed what we expected to observe for each experimental condition.

Experimental Hypotheses:

Experiment I – The Triple Curve: We speculated that the ***Ghost Trainer*** (which doesn't afford any rigorous Training scaffolding) would likely impart a greater sense of recklessness for many drivers who would struggle to keep up with the expert driver. We expected to witness more "real-time" learning across a diverse set of driving styles within a more competitive atmosphere; i.e., drivers fighting against another live driver. This might create a greater incentive to "beat the computer", but inherently impart more abruptness in the corners where the Training challenge, ultimately, is to be won or lost. We expected that the ***Gauge Trainer*** would likely assist in navigating novice trainees towards a suggested (optimal) racing line, and would impart a greater sense of consistency with observed driving performance. We expected to see less variability in Training performance, and recognized that there would be more valuable Training feedback to the driver (e.g., trajectory, throttle/brake timings). Likewise, we wondered if too many on-screen GBL elements would serve to distract (rather than enhance) the driver's performance.

Experiment II - Skid Pad: We speculated that the ***CG placement*** would emerge as being the most critical GBL element. However, we recognized that this would require mastery solely "by feel" to achieve optimality, and this will be more challenging than mastering speed/heading. To this end, we predicted that those who score the highest are likely the Trainees who are better "real world" drivers (or, better ***Simulator*** drivers, e.g., natural gamers), who are inherently comfortable driving an oversteer (unstable) vehicle at elevated speeds. Compared to the Triple Curve, trainees are more frequently engaging with learning outcomes, which could be explicitly verified by way of the Scoring tallies, and observed/measured improvement (over time) by way of trainee CG placement.

Quantitative Results collected from the Simulator:

Experiment I – The Triple Curve: For the Triple Curve experiments, we had a total of N=48 driver/passenger combinations; 24 each in the Gauge/Ghost Trainers. To assess quantitative differences in cornering performance, outcomes between the Ghost Trainer and Gauge Trainer Cohorts, we first compare the racing trajectories of each training group to an ideal trajectory generated by an Expert driver. These results are shown in Figure 8; for sake of reference, the average lap times for each cohort (Expert / Gauge/Ghost) are displayed in a similar color-coding within Table 1. The Expert Driver (green) tends to hold an outside lane position in the straight sections, brakes into a tight radius through the apex of each corner, and then transitions again to an outside lane position. The Ghost Trainer (blue) and Gauge Trainer (red) cohorts share similar characteristics to the Expert Driver, however the key difference is the variability of driver behavior at the outlet of each corner, as indicated by the widening of standard deviations. This is indicative of novice trainees (from both cohorts) reaching the tire saturation limits and losing control at the later stages of each corner. This behavior is even more pronounced with the Ghost Trainer Cohort, whose standard deviation bounds easily engulf the Gauge trainer bounds.

	Expert	Gauge Trainer Cohort	Ghost Trainer Cohort
Average Lap Time (s) (±1σ)	24.21 ± 0.80	25.25 ± 2.19	25.41 ± 2.68

Table 1 – Cohort Average Lap Times

This behavior is dissected in greater detail with a G-G diagram (Figure 9) - a traditional means of assessing cornering performance, displaying longitudinal acceleration (i.e., throttling/braking forces) as a function of lateral acceleration (i.e., centripetal forces). The Expert Driver enters the corner and heavily, but smoothly, reduces braking force to approximately -0.22 g's of longitudinal acceleration, as the lateral acceleration obtains a maximum of -1.8 g's. At this point, the brakes are gradually released and the throttle is introduced as the lateral acceleration works back toward zero, and the vehicle begins to straighten out. Notice in Figure 9 that both the Gauge Trainer and Ghost Trainer cohorts employ considerably less deceleration going into the corner than the Expert Driver. The longitudinal acceleration for the Ghost Trainer cohort reaches a minimum of -0.17 g's, and the Gauge Trainer Cohort brakes even less, settling around -0.1 g's. Because both cohorts, on average, brake too little and too late into each corner, they enter the apex with too much speed. As a result, a peak lateral acceleration beyond -1.8 g's is observed, and this pushes the front tires beyond their saturating slip angles. This means that the vehicle can't turn any further (given its current speed and heading angle) with increased attempts at steering. In Figure 9, it is also clear that the contour of the acceleration profile for the Ghost cohort spans a greater range than that observed for the Gauge cohort, indicating larger magnitudes of accelerations, and more aggressive cornering. The greater uniformity of performance across the Gauge cohort can be attributed to the GBL-Training elements that were provided to those drivers: a visible (suggested) racing line, brake/throttle cues, and a tire slip angle heads-up display. While the Ghost Trainer Cohort could deduce a racing line by following the "Ghost" vehicle on the track, this competitor vehicle outpaced most drivers, and quickly left their immediate field of view. Additionally, the implied incentive to "race" the ghost trainer likely encouraged a more aggressive racing strategy, producing the larger variation of behavior we observe within the Ghost Trainer Cohort.

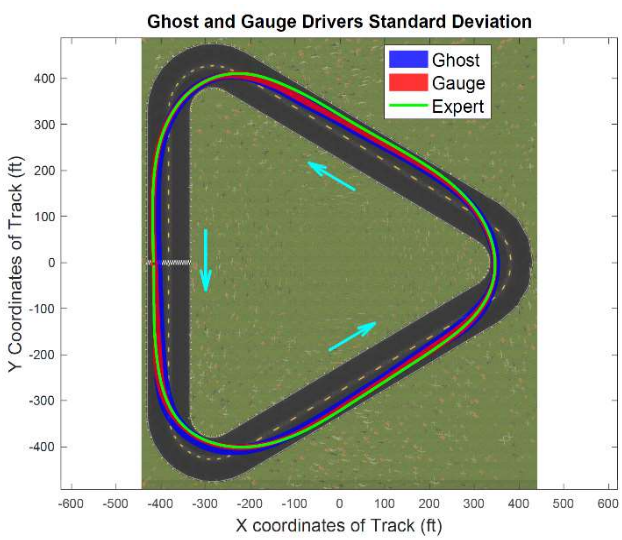

Figure 8 – Ghost Trainer vs. Gauge Trainer Trajectories (± 1σ bounds)

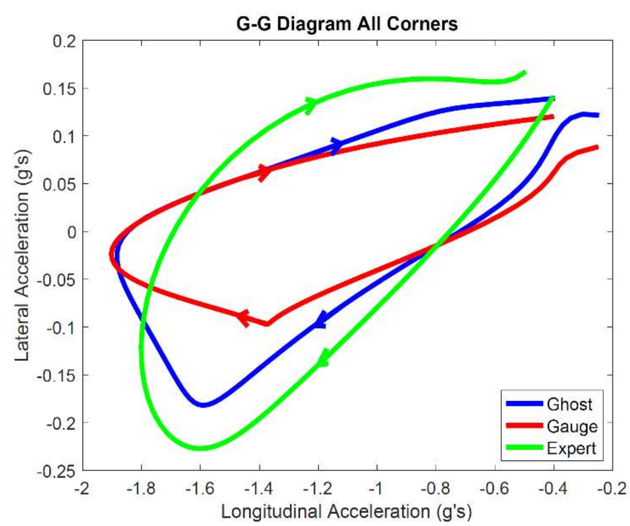

Figure 9 - Ghost Trainer vs. Gauge Trainer G-G Diagram (Averaged from all corners)

Experiment II - Skid Pad:
For the Skid Pad experiment, we had a total of N=44 driver/passenger combinations. This time, rather than introducing multiple variations of the exercise to different students, four cohorts (with approximately 11 driver/passenger combinations per cohort) were tasked with the identical exercise modifying their vehicle's CG toward a neutral steer configuration to complete as many laps as possible on a tight circular track, within a two-minute window. Each vehicle was initially configured as "oversteer" with the CG shifted so far aft that the car was un-drivable at all but low speeds. Typically, an oversteer vehicle will tend to spin nose-in at elevated speeds greater than 30 mph. This encouraged trainees to use paddle shifters mounted on the steering wheel to adjust their CG forward and thus counteract the instability. However, shifting the CG too far forward made the car "understeer"; less sensitive to steering commands and therefore unable to maintain the specified radius at higher (optimized) speeds.

Such an over-adjustment of the CG forced students either to reduce speed, and suffer slower lap times, or once again modify the CG toward an optimized "neutral steer" balance point to achieve and maintain optimal speed. Figure 10 records how the four student cohorts adjusted the CG of their vehicle as a function of time, depicting the ratio of front cornering stiffness to front weight percentage. As this ratio approaches unity, the vehicle approaches the ideal "neutral steer" condition. Therefore, on average, the students modified the vehicle CG toward neutral steer in an exponential fashion. This suggests that trainees consistently engaged with the effect of the CG on the vehicle dynamics throughout the training exercise; making large adjustments early within the allotted experimental timeframe to counteract obvious vehicle performance deficiencies, and subsequently making small compensations later to fine-tune and converge upon more subtle performance gains.

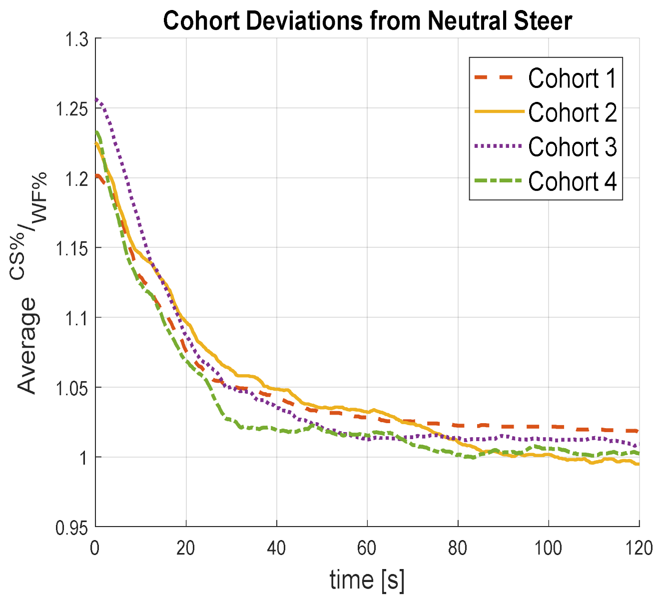

Figure 10 – Average Cohort Deviations (from Neutral Steer)

Result Correlations:
In this final subsection, the authors sought to detect any patterns or correlations between self-reported data related to learning style, and actual (observed and measured) experimental performance upon the driving simulator. Naturally, such information is critical to assist educators in determining how to tailor training content and delivery towards learner preferences and style. Recall (from Figure 5) that a majority of the class cohort, at the very beginning of the semester, stated a preference for Active-Sensing-Visual-Sequential (AAAA) style learning. Due to the physical nature of the GBL-Training environment -- as anchored by a high-fidelity motion-based Simulator -- each of the four authors formed a hypothesis to speculate those learners, among the training cohort, that are the most prone to exhibit elevated training achievement. All four authors agreed on the *first and third* learning categories (in the learning styles sequence) as being Active (A) and Visual (A) for preferred trainees in our environment. *For the second category*: two of us opined that Sensing (A) learners would make the connection between the Simulator and the "real world", while two of us opined that Intuitive (B) learners would better relate to a Simulator as representing an abstraction towards real driving. *For the fourth category*: three of us opined that Global (A) learners might tend to absorb training content somewhat randomly without realizing connections, and then suddenly "getting it", while one of us opined that Sequential (B) learners might tend to perform better within the context of a brand new training exercise, where only partial understanding is achievable within the short duration of the experiment. Hence, we paid particular attention to the Simulator results that were performed by the following learner groups: AAAA (overall preference to entire cohort), and AAAB, ABAA, and ABAB (author hypotheses).

We investigated performance correlations for both the Triple Curve (Experiment I) and the Skid Pad (Experiment II). In Figure 11, we observe the correlation between measured Simulator performance (i.e., cohort-averaged number of legal laps achieved) in the Triple Curve experiment vs. the self-reported preferred learning style of the driver. Note that the learning styles on the X-axis show frequencies parenthetically, totaling 45 drivers who performed the experiment, and for whom we had complete datasets. The plot displays the overall cohort average of Legal Laps achieved (3.695) as a dashed red line. The cohort-averaged preferred learning style (AAAA) is shown as a yellow series, and the author-hypothesized "optimal" learning styles for GBL-Simulator Training (AAAB, ABAB, and ABAA) are shown as red series. Those 10 drivers among the AAAB (Active/Sensing/Visual/Global) learning style displayed a noteworthy tendency for optimal driving performance, while those 5 drivers among the ABAB learning style (i.e., Intuitive in place of Sensing) displayed more moderate performance, and the two drivers among the ABAA learning style (i.e., Intuitive in place of Sensing, and Sequential in place of Global) displayed substandard driving performance.

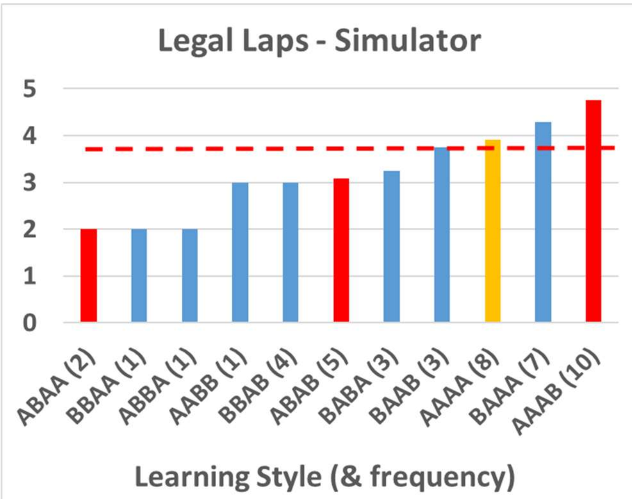

Figure 11 – Experiment I (Triple Curve) correlation

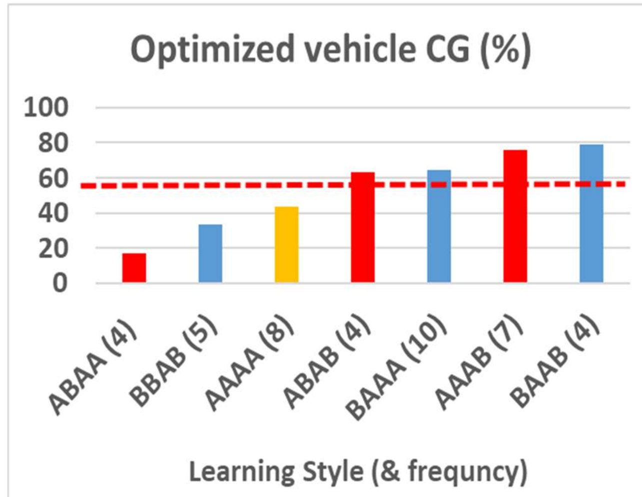

Figure 12 – Experiment II (Skid Pad) correlation

In Figure 12, we plot the correlation between measured Simulator performance (i.e., cohort-averaged percent CG obtained towards 100% neutral steer) in the Skid Pad experiment vs. the self-reported preferred learning style of the driver. Again, the learning styles on the X-axis show frequencies parenthetically, totaling 42 drivers who performed the experiment. Some of these were repeat drivers from Experiment I, and others were not; this accounts for the fact that the frequency of learning styles portrayed in the graph differ from those depicted in Figure 11. The plot displays the overall cohort average of CG optimality (56.3%) as a dashed red line. As with the previous graph, the cohort-averaged preferred learning style (AAAA) is shown as a yellow series, and the author-hypothesized "optimal" learning styles for GBL-Simulator Training (AAAB, ABAB, and ABAA) are shown as red series. And here again, similar trends are observed: those 7 drivers among the AAAB (Active/Sensing/Visual/Global) learning style displayed a noteworthy tendency for optimal driving performance (although, inferior to the four self-reported BAAB for this Experiment), while those four drivers among the ABAB learning style (i.e., Intuitive in place of Sensing) displayed more moderate performance, and the four drivers among the ABAA learning style (i.e., Intuitive in place of Sensing, and Sequential in place of Global) displayed substandard performance.

To conclude our presentation, we now present a targeted summary of valuable lessons learned from this ongoing work. Of these observations, some were offered by the Trainers immediately post-experiment, and others by the actual trainees who endeavored the GBL exercises.

EXPERIMENTAL OBSERVATIONS & LESSONS LEARNED

Finally, in this section, we summarize a series of observations that were detailed immediately post-experiment. Some were noted by the authors of this paper, and others offered by various trainees from the RVD course cohort.

Experiment I – The Triple Curve:

- **FASTEST LAP**. On-screen text innocuously denoting "fastest lap" inadvertently distracted many students from the intended Training purpose of the experiment, which was to try to achieve MANY legal laps instead of one "very fast" lap. Word-of-mouth enticed members of the later cohorts to achieve "bragging rights" for the fastest (single) lap. This notion conflicted with the intended Training goal of the experiment - to master cornering (i.e., smooth straightaway-curve transitions), and achieve as many legal laps as possible within the time period allowed.

- **GAUGE TRAINER**. Numerous students felt that the color-coded racing line feature should adapt (dynamically) to driver behavior rather than serve as a (static) feature primarily intended as a game-based reference "guideline", which was its original design intent. Some drivers thought that the reference spheres were dynamic, and reported that this misconception adversely impacted their performance. Some other drivers attempted to ride the Racing Line too precisely, and this oversight resulted in abrupt corrections and undesirable driver-induced oscillations.
- **GHOST TRAINER**. Numerous students suggested that the Ghost Car adapt to the performance of the previous lap of each driver (dynamically), rather than serve as a full-excursion, static replay of an "expert" Simulator driver, which was its initial design intent. Likewise, drivers astutely requested that the Ghost Car have front and rear brake lights, which would help drivers to better visually comprehend when that vehicle is accelerating and braking amidst the critical cornering segments. Likewise, trainees requested to institute a TRIPLE Ghost Car feature (e.g., 1) expert driver replay; 2) cohort-averaged driver, 3) current driver/previous lap).

<u>Experiment II – The Skid Pad</u>:
At the conclusion of the second Simulator experiment (i.e., the Skid Pad), we issued a brief survey (*N=70 completed*) to query the degree of effectiveness afforded by various aspects of the GBL-based Training. Recall (Figure 4) that these included on-screen indicators that related to travel speed, travel heading (i.e., a "racing line"), CG-placement (weight distribution), a scoring meter, and a steering meter. Refer to Figure 13, which displays average and standard deviation on the left-most segment of the plot. Not surprisingly, the CG-meter was found to be the most useful (on a 5-point Likert scale), followed closely by the heading meter.

Note further that the speed, steering, and scoring meters, respectively, were perceived as being less critical to the Training task. The second segment of the plot queries the impact of driver-on-passenger, and vice-versa. In other words: for those who drove the simulator, was it helpful to have a passenger on-board to assist with "coaching" the GBL-Training elements, and if you were a passenger, were you able to assist the driver during the Training tasks? Both metrics rated nearly equally: close to a 4.0 on a 5-point Likert scale. Finally, the last series on the plot displays Overall satisfaction with the GBL-experiment rated close to the 5-point maximum (and with a small standard deviation) for the entire cohort.

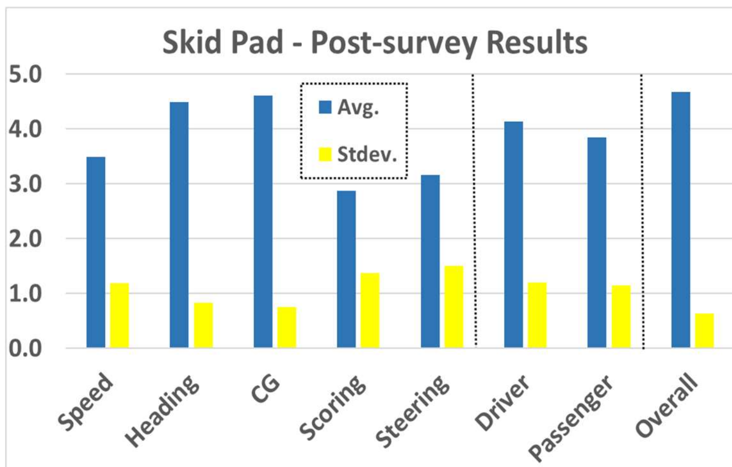

Figure 13 – GBL Element Effectiveness (*N=70*)

Additional anecdotal observations regarding the Skid Pad experiment are briefly listed as follows:

- **CG METER.** Because drivers were (intentionally) made blind to the fore/aft position of the CG relative to the tire stiffness distribution, many didn't realize that they weren't accumulating score at the initial (oversteer) CG position. This absent a priori knowledge would have changed their task prioritization to favor optimizing this feature over the other major subcomponents: speed and heading. In accordance with our Training objective, most trainees in the cohort did a good job with coordinating the front/rear tire colors to achieve neutral steer, and most discovered that this process had to iteratively evolve with elevated vehicle speed.
- **TRAVEL SPEED.** The Trainers realized post-experiment that we over coached trainees on the required caution of a typical Skid Pad experiment. Because of this unintended negative Training, many students achieved maximal speeds in the mid 50's (mph) rather than optimizing the vehicle towards the theoretical optimum of the vehicle (~ 70 mph). In the future, we might consider dynamic metrics such that trainees only score at increasingly elevated speeds as the period of play evolves.
- **STEERING/HEADING.** This GBL element was identified to be useful, but more informative for exterior onlookers to observe than as a real-time Training aide for the driver/passenger pair. A valuable suggestion was made that we introduce a visual/aural counter to denote (in real time) how many guide path spheres have been struck; akin to a "Pac Man" (e.g., Rosenberg, 2018) style of gameplay (e.g., "munching" dots to earn points).

CONCLUSIONS AND NEXT STEPS

In this paper, we have described the design, development, and deployment of a framework for GBL-based Training experiments intended for a Post-secondary Road Vehicle Dynamics (RVD) course. Our primary intention was to supplement traditional course material delivery with experiential, engaging, game-based opportunities for enhanced skillset acquisition to improve Training effectiveness. We collected performance data from a high-fidelity Simulator, supplemented by relevant self-report data relevant to trainee Learning Styles. Highlights from our experimental findings include the following:

Experiment I: Within the Triple Curve, the Ghost trainer inherently encouraged a more aggressive racing strategy. This tended to result in a greater observed uniformity of training performance across the Gauge cohort than the Ghost cohort, largely attributed to the GBL-Training elements that were explicitly provided to the Gauge drivers, as opposed to those that had to be deduced by the Ghost drivers.

- *Result Correlations to Self-reported data*: Those trainees among the most popular learning style (AAAA) performed slightly better than the cohort average, while those drivers among the author-hypothesized "optimal" AAAB (Active/Sensing/Visual/Global) was the highest performing learning style. The trainees among the other author-hypothesized "optimal" learning styles (ABAB, and ABAA) performed "moderately" and "substandard", respectively.

Experiment II: Within the Skid Pad, student cohort-averaged CG ratio adjustment (i.e., from oversteer towards neutral steer) approached unity exponentially, indicating that as intended, trainees consistently engaged with the effect of the CG on the vehicle dynamics throughout the training exercise. Large adjustments were observed initially to counteract obvious vehicle deficiencies, followed by fine-tuning and "optimization" to achieve more subtle performance gains.

- *Result Correlations to Self-reported data*: Those trainees among the most popular learning style (AAAA) performed slightly lower than the cohort average, while those drivers among the author-hypothesized "optimal" AAAB (Active/Sensing/Visual/Global) was the second-highest performing learning style. The trainees among the other author-hypothesized "optimal" learning styles (ABAB, and ABAA) performed "above average" and "substandard", respectively.

The GBL Training framework that has been described in this paper is certainly extensible to other course offerings within a Post-secondary (Mechanical) engineering curriculum. For example, the current team already has aspirations to deploy this framework (Fall, 2019) within a Junior-level Systems Dynamics course. In this context, the GBL-Simulation tools will be adapted to demonstrate a second-order spring-mass-damper representation of a vehicle suspension system. Using these game-based training tools, a "critically damped" vehicle can be converged upon while inducing a bumpy ride (e.g., potholes) within a simulated ground vehicle setting. Similarly, within a more advanced Senior-level course within the context of another engineering discipline (e.g., Aerospace Engineering), Flight modes can be actively demonstrated for an Aircraft Dynamics experiment within our GBL training framework. In this manner, trainees can actively obtain an improved understanding of longitudinal (e.g., Phugoid) vs. lateral (e.g., Dutch Roll) modes of flight motion. Finally, our training framework can be extended to accommodate augmented/mixed reality applications (e.g., a heads-up display interface for next-generation vehicle navigation) for emergent engineering systems (e.g., autonomous vehicles, Flying Cars). Such a Training framework could provide benefit both for young trainees (e.g., K-12 learners and STEM), as well as advanced training applications for warfighters in the military.

ACKNOWLEDGEMENTS

The authors wish to extend their thanks to Moog, Inc. (East Aurora, NY), for generously donating the 2000E motion simulation platform to the School of Engineering and Applied Sciences (SEAS) at the University at Buffalo, and for their ongoing technical and fiscal support. For the past two decades, their motion system has been extensively leveraged to advance Training, experiential learning, and STEM. We would also like to acknowledge Dr. Edward Kasprzak and Mr. Douglas Milliken for their technical consultation regarding vehicle dynamics modeling.

REFERENCES

Bauman, E.B., (2012). "Game-based Learning: A workshop to inform educators and engage contemporary learners", SlideShare, (internet link), https://www.slideshare.net/ebauman/gamebased-learning-a-workshop-to-inform-educators-and-engage-contemporary-learners, May 23, 2012.

Coller, B.D., and Scott, M.J., (2009). "Effectiveness of using a video game to teach a course in mechanical engineering", *Computers & Education*, 53(3), 900-912.

Coller, B.D., (2012). "Preliminary results on using a video game in teaching dynamics", the 119th ASEE Annual Conference and Exposition, San Antonio.

Dasara, Y., (2016). "4 Components of Game-based Learning [Infographic]", CommLabIndia (internet link), https://blog.commlabindia.com/elearning-design/game-based-learning-components-infographic, June 14, 2016.

Dhruve, P., (2017). "Game-Based Learning: Why It Works and Why Implement It", CommLab India (internet link), https://blog.commlabindia.com/elearning-design/game-based-learning-why-it-works, September 6, 2017.

Dsouza, J., (2016). "Based Learning 7: GBL—Game-Based Learning", Medium (internet link), https://medium.com/@johnharrydsouza/based-learning-7-gbl-game-based-learning-123c2a5a5b55, April 5.

EdTechReview (ETR), (2013). "What is GBL (Game-Based Learning)?", (internet link), http://ftp.edtechreview.in/dictionary/298-what-is-game-based-learning, published April 23, 2013.

Feisel, L.D., and Rosa, A.J., (2005). "The role of the laboratory in undergraduate engineering education", *Journal of Engineering Education*, 94(1), 121-130.

Felder, R.M., and Silverman, L.K., (1988). "Learning and Teaching Styles in Engineering Education", *Journal of Engineering Education*, 78(7), 674–68.

Hulme, K.F., Androutselis, T., Eker, U., and, Anastasopoulos, P., (2016). "A Game-based Modeling and Simulation Environment to Examine the Dangers of Task-Unrelated Thought While Driving." MODSIM World Conference, Virginia Beach, VA, April, 2016.

Hulme, K.F, (2018). "Game-based Experiential Learning for Road Vehicle Dynamics Education", Serious Play Conference, Jacobs School of Medicine, Buffalo-Niagara Medical Campus, Buffalo, NY, July, 2018.

Hulme, K.F., Estes, A., Schmid, M., Torres, E., Hendrick, C., and Sivashangaran, S., (2018). "Game-based Proving-grounds Simulation to assess Driving & Learning Preferences", The Interservice/Industry Training, Simulation and Education Conference (I/ITSEC), Orlando, FL, December, 2018.

Jabary, I., (2019). "Game-based Learning Encourages Engagement", Training (online article), https://trainingmag.com/trgmag-article/game-based-learning-encourages-engagement/, Retrieved February 1.

Jabbar, A.I.A., and Felicia, P., (2015). "Gameplay Engagement and Learning in Game-Based Learning: A Systematic Review", Review of Educational Research, December, Vol. 85, No. 4, pp. 740–779.

Jara, C.A., Candelas, F.A., Puente, S.T., and Torres, F. (2011). "Hands-on experiences of undergraduate students in Automatics and Robotics using a virtual and remote laboratory", *Computers & Education*, 57(4), 2451-2461.

Li, K., Hall, M., Bermell-Garcia, P., Alcock, J., Tiwari, A., and Gonzalez-Franco, M., (2017). "Measuring the Learning Effectiveness of Serious Gaming for Training of Complex Manufacturing Tasks", Simulation & Gaming, Vol. 48(6) 770–790.

Milliken, W. F. and Milliken, D. L., (1995). Race Car Vehicle Dynamics, SAE, 1995.

Nagai, K. (2001). "Learning while doing: practical robotics education", *IEEE Robotics & Automation Magazine*, 8(2), 39-43.

The Peak Performance Center (PPC), (2019). "The Index of Learning Styles", (internet link), http://thepeakperformancecenter.com/educational-learning/learning/preferences/learning-styles/felder-silverman/index-of-learning-styles/, Copyright 2019.

Rosenberg, J., (2018). "Pac-Man - A Short History of the Pac-Man Video Game", ThoughtCo., (internet link), https://www.thoughtco.com/pac-man-game-1779412, June 8, 2018.

Soloman, B.A., and Felder, R.M., (1999). "Index of Learning Styles Questionnaire", NC State University (internet link), http://www.engr.ncsu.edu/learningstyles/ilsweb.html

Whitney, K., (2017). "10 Ways Experiential Learning Creates Long-Term Performance Impact", Learning Delivery, https://www.clomedia.com/2017/05/08/10-ways-experiential-learning-creates-long-term-performance-impact/, May 8, 2017.