

Research Note

Gamification of Technology-Mediated Training:
Not All Competitions Are the Same

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Gamification, an application of game design elements to non-gaming contexts, is proposed as a way to add engagement in technology-mediated training programs. Yet there is hardly any information on how to adapt game design elements to improve learning outcomes and promote learner engagement. To address this issue, we focus on a popular game design element, competition, and specifically examine the effects of different competitive structures, i.e., whether a person faces a higher-skilled, lower-skilled or equally-skilled competitor, on learning and engagement. We study a gamified training design for databases, where trainees play a trivia-based mini-game with a competitor after each e-training module. Trainees who faced a lower-skilled competitor reported higher self-efficacy beliefs and better learning outcomes, supporting the effect of peer appraisal, a less examined aspect of social cognitive theory. Yet trainees who faced equally-skilled competitors reported higher levels of engagement, supporting the balance principle of flow theory. Our study findings indicate that no one competitive structure can simultaneously address learning and engagement outcomes. The choice of competitive structures depends on the priority of the outcomes in training. Our findings provide one explanation for the mixed findings on the effect of competitive gamification designs in technology mediated training.

Keywords: gamification; laboratory experiment; social cognitive theory; technology-mediated learning; competition; flow

History: Ritu Agarwal, Senior Editor; Yulin Fang, Associate Editor. This paper was received on August 29, 2014, and was with the authors 7 months for 3 revisions. Published online in *Articles in Advance* April 25, 2016.

"Tell me and I forget, teach me and I may remember, involve me and I learn."

—Benjamin Franklin

Introduction

Training mediated via technology, often referred to as technology-mediated learning (TML), e-learning, and virtual learning, is widely used in business and educational institutions (Alavi and Leidner 2001, Allen and Seaman 2011, Santhanam et al. 2008). Because TML has shown high drop-out rates, gamification designs are proposed as a way to enhance learners' engagement while still supporting learning goals (Greitzer et al. 2007, Gupta and Bostrom 2009, Santhanam et al. 2008, Tay 2010). Gamification is the use of game design elements in non-gaming activities to improve user engagement (Deterding et al. 2011, Kankanhalli et al.

2012, Takahashi 2010). Gamification of TML is about adding a game layer to TML, rather than developing a separate game that integrates learning and gameplay. The added game layer could use game artifacts (e.g., avatars and animations), game mechanics (e.g., leveling-up and competition), and even mini-games (Kapp 2013, Liu et al. 2016, Takahashi 2010, Zaman et al. 2012). While gamification designs are increasingly used in learning environments such as classrooms and Massively Online Open Courses (MOOC; Burke 2012, Domínguez et al. 2013, Goh and Ping 2014), recent reports also highlight the challenges of achieving learning and engagement goals through gamification (Petty and Meulen 2012). Instances have been reported in which game elements could create distractions for learners and even degrade engagement (Young et al. 2012). To address these challenges, recent research

calls for investigations of specific gamification design elements to better design and obtain the benefits of gamification (Deterding et al. 2011, Hamari et al. 2014, Lee and Hammer 2011).

We focus on competition, a popular gamification design element. Competition refers to a contest situation in which two or more parties strive for superiority or victory (Liu et al. 2013). A gamification design with competition lets players compete with one another in a gameful way to enhance learning and engagement. The idea of using competition to enhance learning or engagement is not new. In digital game designs, competition is widely used as an engagement tool to provide challenge, interactivity, and excitement (Demetrovics et al. 2011, Liu et al. 2013, Yee 2006). In classrooms, competition is also leveraged to draw the attention of learners and motivate learning (Cheng et al. 2009, Garcia et al. 2006, Hanus and Fox 2015). Yet researchers also note that competition can create anxiety and impede performance, and caution against using competition in learning settings (Kohn 1992). Given the contrasting views of competition in learning and in games, it is not automatically clear whether competition in gamified TML can simultaneously address learning and engagement goals. Moreover, most existing research contrasts competition with no competition, despite the suggestion that the effect of competition is more nuanced (Epstein and Harackiewicz 1992, Liu et al. 2013). We argue that *competitive structures*, that is, whether an individual faces a higher-skilled, lower-skilled or equally-skilled competitor, matter for learning and engagement goals. Gamified TML provides an excellent opportunity to implement different competitive structures and study their effects on the dual goals of learning and engagement.

We focus on how learning outcomes and engagement differ across competitive structures in a gamified TML design. Competitive structures can be associated with different outcomes depending on the contexts. In economic tournaments, competitive structures can affect contestants' effort or expenditure because contestants must balance between effort expenditure and the likelihood of winning (Baik 2004, Liu et al. 2007). In learning contexts, competitive structures can have implications for TML outcomes such as self-efficacy and learning because they engender different performance feedback and performance expectancies (Compeau et al. 2006, Epstein and Harackiewicz 1992, Moos and Azevedo 2009). Varying competitive structures in gamified TML can also create different challenges that may result in different levels of engagement, an understudied goal in TML literature. In this study, we compare competitive structures on three outcomes, i.e., self-efficacy, learning, and engagement.

Drawing on social cognitive theory and flow theory, we conduct a systematic and theoretically grounded

investigation of competitive structures in gamification designs. We implement different competitive structures in a gamified TML design where trainees play a trivia-based mini-game after each training module to apply what they learn in a fun, competitive environment. This design follows the gamification paradigm because mini-games act as an additional game layer to TML to motivate learning, rather than as a separate game that tightly integrates learning and gameplay.¹ We found that trainees who believed they were matched with a lower-skilled competitor and won their games reported higher self-efficacy beliefs and had better learning outcomes. However, trainees who believed they were matched with an equally-skilled competitor and tied their game reported the highest level of engagement. We discuss the implications of these divergent findings for developing effective gamified TML designs, and for social cognitive theory.

Related Literature

Technology-Mediated Training

Initiated by Alavi and Leidner (2001), a steady stream of information systems (IS) research studies evaluate TML methods for developing information technology (IT) skills (Gupta and Bostrom 2009, 2013; Santhanam et al. 2008; Sasidharan and Santhanam 2006; Wan et al. 2012). Research surveys conclude that, despite considerable progress in the use of TML, problems relating to trainee disinterest persist, and alternative training designs should be investigated to create positive experiences and greater engagement for trainees (Gupta and Bostrom 2009). Interventions to support self-regulation and collaboration of trainees, among others, have been investigated but to our knowledge there are no studies on gamification of TML for IT skills (Gupta and Bostrom 2013, Santhanam et al. 2008).

Game-Based Learning, Simulation Games, and Gamification

Before gamification, researchers and practitioners explored game-inspired learning designs under labels such as virtual immersive learning games, digital-game-based-learning (DGBL), and serious games (de Freitas and Oliver 2006, Susi et al. 2007). These designs aim to provide learning benefits through special-purpose games so that players can learn in a game. To make the game compelling, learning and gameplay must be tightly integrated. For a few topics, such as language and history, designers achieved this lofty goal, but not for others such as science or math (Young

¹ Short and self-contained mini-games are frequently used by game designers to break the monotony and provide bonus experiences. For example, the classic Nintendo game *Zelda* is famously known for including mini-games such as puzzles, fishing, and racing, in its game designs.

et al. 2012). Players tend to focus on gameplay that affords them entertainment value rather than learning. Moreover, these games require substantial investments and frequent updates to keep pace with players (Eck 2006, Susi et al. 2007, Young et al. 2012). Simulation games are another game-inspired design used for a long time in business education (Cronan et al. 2012, de Freitas and Oliver 2006, Faria and Nulsen 1998). Simulation games are special games based on simulating real-world decision scenarios with computer-based symbolic models. Just as DGBL and serious games, simulation games require development of a separate game that integrates learning and gameplay.

Gamification designs call for adding a game layer to non-gaming tasks rather than creating a separate full-fledged game for learning (Deterding et al. 2011, Glover 2013). The additional game layer, which is usually easy to distinguish, can add motivational affordances without taking away from time spent on learning (Kapp 2013, Zaman et al. 2012). Because gamification is an emerging topic, there are few investigations on gamification of TML. Moreover, the limited number of gamification studies have methodological problems, such as a lack of validated psychometric measures, use of singular outcome measurements, and the inability to isolate effects of specific design elements (Domínguez et al. 2013, Hamari et al. 2014).

Competition in Learning vs. Gaming

Competition is leveraged in learning and in games, albeit for different purposes. In the former, it is to improve utilitarian outcomes such as learning, while in the latter, it is to improve hedonic outcomes such as engagement. Prior research shows that introducing competition in the classroom can draw the attention of students (Cheng et al. 2009, Garcia et al. 2006, Hanus and Fox 2015). However, existing evidence suggests that competition can yield positive and negative effects (Reeve and Deci 1996, Tauer and Harackiewicz 2004). When competitive evaluations are emphasized, competition is seen as controlling, reducing learners' intrinsic motivation and creating anxiety (Reeve and Deci 1996, Tauer and Harackiewicz 2004), unless there is an emphasis on mastery (Cheng et al. 2009, Pintrich 2000).

In entertainment settings such as digital games, competition is popular and players may even compete with anonymous others. In games, competition is viewed as a source of challenge that makes games intrinsically motivating (Csikszentmihalyi and Csikszentmihalyi 1975, Malone 1981). Research confirms the role of competition as a source of player motivation and engagement, although there may be individual differences (Demetrovics et al. 2011, Yee 2006).

Although research on competition in gamified learning is emerging, the results are far from clear. In one study, gamified TML produced better results on practical applications of concepts than no gamification, but

worse results on written assignments and participation (Domínguez et al. 2013). In classroom settings, too, gamification designs using competition produced mixed results; some showed improved student motivation and performance (Hanus and Fox 2015), while others did not (Burguillo 2010). Barring a few exceptions (Epstein and Harackiewicz 1992, Liu et al. 2013), most research studies compare scenarios with and without competition, without distinguishing different competitive structures. Because of the mixed findings on competition in learning, it is important to examine the nuances of competitive structures.

Hypotheses Development

We consider a gamified TML design where trainees play a mini-game after completing a learning module. Competition is part of the mini-game as a bonus activity rather than a learning assessment. Trainees experience competitive structures and may play against a higher-, equally- or lower-skilled competitor and receive losing, tie, and winning feedback, respectively. We are interested in the effects of differing competitive structures on learning and engagement outcomes. Because learning outcomes are more utilitarian whereas engagement is more hedonic and experiential, we rely on two different theories. We use social cognitive theory (Bandura 1986), the dominant theory in training research, to develop hypotheses on the effect of competitive structures on self-efficacy beliefs and learning outcomes. Social cognitive theory is rather silent on engagement and other hedonic experiences. These are better described in flow theory, which we apply to study engagement (Agarwal and Karahanna 2000, Csikszentmihalyi and Csikszentmihalyi 1975, Malone 1981). Below we develop research hypotheses on self-efficacy, learning outcomes, and engagement.

Self-Efficacy

One of the most important outcomes of a training program is the learners' self-efficacy (Marcolin et al. 2000, Santhanam et al. 2013, Yi and Jang 2012). As in social cognitive theory, an individual's self-efficacy in a domain is a belief in one's capability to organize and execute the courses of action required to produce given attainments (Bandura 1997, p. 3). It represents an individual's perception of capability to exert control over events of personal relevance, and complements the individual's actual capabilities (Wood and Bandura 1989). Adapting from this general notion of self-efficacy, computer self-efficacy is defined as an individual judgment of one's capability to use a computer (Compeau and Higgins 1995). It is studied as a key outcome in its own right because trainees with high self-efficacy feel confident about their ability to learn a topic, solve problems, and are more persistent (Compeau et al. 2006, Gupta et al. 2010, Johnson and Marakas 2000,

Yi and Davis 2003). In TML environments, self-efficacy for using a computer to learn is most relevant because many trainees have difficulty participating and learning in TML environments (Moos and Azevedo 2009).

As per Bandura (1997), self-efficacy beliefs could develop from several sources of information. Enactive mastery experiences derived from actual performance accomplishments are the strongest source of efficacy because they provide the most direct and authentic evidence of one's abilities. Yet individuals also vicariously form their self-efficacy beliefs, that is, draw inferences about one's capabilities via social comparisons, especially when the uncertainty about one's capabilities is high and there are no absolute measures of adequacy. Most IS training research has so far focused on the effect of observing an expert (such as instructors) performing a task (Compeau et al. 2006, Johnson and Marakas 2000, Yi and Davis 2003). Yet experts may not be the best performance benchmarks for trainees because they have far superior skills. In TML contexts where instructors are often absent, the performance of fellow trainees can be an important source of self-efficacy information because vicarious experiences are most salient when comparison targets are similar to individuals (Bandura 1986, Compeau et al. 2006).

A gamified TML design with competition provides an opportunity for trainees to compare themselves with peer trainees in a gameful context. By comparing performances with peers in a gameful competition, they can infer their own capabilities to learn in TML environments. Bandura (1997) suggested that social comparisons can be used to judge one's self-efficacy: Low relative performance signifies low efficacy whereas high relative performance indicates high efficacy. Trainees who are matched with a lower-skilled competitor find themselves outperforming their peers and get positive relative performance feedback. Thus, they are most likely to improve their self-efficacy beliefs on learning through TML when compared to those in other competitive structures. Hence:

HYPOTHESIS 1. *In gamified TML, trainees matched with a lower-skilled competitor (L) will exhibit higher levels of self-efficacy for learning than those matched with an equally- or higher-skilled competitor (EH).*

Learning Outcomes

While self-efficacy beliefs are important training outcomes in their own right, training designs must also produce tangible learning outcomes. Learning outcomes consist of cognitive and skill-based outcomes (Yi and Davis 2003, Yi and Jang 2012). Cognitive outcomes, also referred to as declarative knowledge, assess the trainee's conceptual understanding of the domain. Skill-based outcomes, also referred to as procedural

knowledge, assess the trainee's ability to apply this knowledge to complete a task (Santhanam et al. 2008).

Learning enhancement may occur during a game competition (as is the goal of many DGBL designs) or after. This study focuses on the latter. A game competition, such as in a mini-game after a learning module, can affect learning outcomes in the next module in two different ways. Positive performance feedback from winning can provide comparative information that enhances trainees' self-efficacy beliefs. Trainees who become more confident in their abilities tend to approach learning tasks with more interest and pay greater attention to the content (Johnson and Marakas 2000, Webster and Hackley 1997, Yi and Davis 2003). Simultaneously, competition allows trainees to form expectancies of success or failure by learning how good their competitors are. Unlike self-efficacy beliefs, which are internally focused and affected by performance outcomes, performance expectancies are externally focused (e.g., affected by competitors' skills) and formed at the onset of competition before the final outcomes are known. As shown by Epstein and Harackiewicz (1992), performance expectancies can influence how individuals approach and experience a task, independent of their self-efficacy beliefs. Those who face an inferior competitor will develop an interest in the task and approach it with greater enthusiasm (Epstein and Harackiewicz 1992, Reeve and Deci 1996, Tauer and Harackiewicz 1999). In our context, trainees who compete with a lower-skilled competitor in the first mini-game will develop an expectancy to win again in the next mini-game; this makes trainees approach the new learning module with enthusiasm and thus achieve better learning outcomes. Hence:

HYPOTHESIS 2. *In gamified TML, trainees matched with a lower-skilled competitor (L) will exhibit higher levels of learning outcomes in the next training module than those matched with an equally- or higher-skilled competitor (EH).*

Engagement

A main goal of gamification is to make an activity engaging (Domínguez et al. 2013). Although the idea of creating engagement by gamification is emerging in the training literature, training researchers generally recognize that trainees must leave the training session with not only knowledge acquisition but also positive experiences. Thus far, the training literature has used a variety of measures such as flow and enjoyment; to our knowledge, there are no standards to assess these hedonic outcomes (Santhanam et al. 2013, Yi and Jang 2012).

In digital games, the experiences of engulfing enjoyment and total immersion are often described using the concept of *flow* because such deep engagement is often accompanied by a loss of sense of time and is pursued for its own sake (Csikszentmihalyi and

Czikszentmihalyi 1975, Keller and Bless 2008, Malone 1981). In IS literature, Agarwal and Karahanna (2000), based on flow theory, further propose *cognitive absorption* to describe a sense of being totally engaged and immersed in one's interactions with an information system. Hence, we use cognitive absorption as a lens to study engagement in gamified TML.

Cognitive absorption is exhibited through several dimensions including temporal dissociation (the inability to register the passage of time while engaged in interaction), focused immersion (the experience of total engagement where other attentional demands are ignored), heightened enjoyment (which captures the pleasurable aspects of the interaction), control (the perception of being in control over the interaction), and curiosity (heightened arousal of cognitive and sensory curiosity). Researchers suggest that appropriate dimensions of cognitive absorption should be used based on the types of hedonic experiences expected in a given context (Lowry et al. 2013, Rutkowski et al. 2007). We choose three dimensions of cognitive absorption, i.e., *enjoyment*, *focused immersion*, and *temporal disassociation*, as measurements for engagement in gamified TML designs. Although control and curiosity also frequently accompany engaging experiences, they are considered sources leading to such experiences (Malone 1981) rather than directly describing engaging experiences.

To establish the relationship between competitive structures and dimensions of cognitive absorption, we rely on the balance principle from the flow literature. According to this literature, one of the precursors to the state of total absorption is the balance between skill and challenge (Csikszentmihalyi 1988, Engeser and Rheinberg 2008). Imbalances between skill and challenge can lead to suboptimal experiences such as boredom and frustration. Extending the balance principle from an individual setting to a dual, competitive setting, we propose that a state of cognitive absorption would also result from a balance between competitors' skills. When a trainee is playing against a competitor of higher skills, the trainee may feel unable to win, experience anxiety, and lose attention. When a trainee competes against a competitor of lower skills, the trainee does not feel challenged and a sense of boredom and apathy may ensue. Only when a trainee plays against an equally-skilled competitor, the suspense of not knowing the final outcome and the challenge of an equally-skilled competitor will keep the trainee immersed. The experiences of cognitive absorption, once initiated by the game competition, can spill over to other parts of the training session, coloring trainees' perception of the entire training experiences. Based on the above, we state our third hypothesis as:

HYPOTHESIS 3. *In gamified TML, trainees matched with an equal-skilled competitor (E) will exhibit higher levels of*

enjoyment, focused immersion, and temporal disassociation than those matched with a lower- or higher-skilled competitor (LH).

Research Method

We develop a TML design where users learn through a series of video-based training modules without instructor intervention. We gamify the TML design so that at the end of each TML module a trainee will be quizzed on the module content but will also play a trivia game against a fellow competitor, based on questions exclusively drawn from the preceding TML module. To test our research hypotheses, we designed a two-phase laboratory experiment, each of which consists of a TML module, a written test for learning outcomes, and a mini-game competition. The goal of the mini-games is not to provide a formal learning assessment, but to provide engaging experiences, performance feedback, and performance expectancies as trainees continue to learn through the TML program. To minimize fatigue, we limited the experiment to two TML modules each followed by a mini-game.

TML Modules and the Mini-Game

The TML content used in the experiment focuses on introductory database management concepts and skills. We recorded two Camtasia video lectures with voice narration for the two TML modules.² TML Module 1 covered basic database concepts, such as the value of databases, the concept of relational databases, and the main activities in the database design. Module 2 covered topics such as database management systems, elements of Microsoft Access, and basic queries with Microsoft Access. Trainees could navigate different subtopics in each module using a menu, and pause, forward or move backward in the video lectures. To avoid confounds, we did not introduce any game feature in the TML modules.

The mini-game used in the experiment was adapted from a Java-based mobile game, "Who Wants to Be a Millionaire?" (hereafter, referred to as the *Millionaire game*). The game mimics the TV game of the same title with features such as (virtual) prizes, (simulated) applause, a 50/50 lifeline, a walk-away option, and background music matched to the intensity of game levels (see A2 for a screenshot of the game).³ We adapted the Millionaire game by adding a competitive

² Refer to the online appendix (available as supplemental material at <http://dx.doi.org/10.1287/isre.2016.0630>) for screenshots of the TML module (A1), the mini-game (A2), the background survey (A3), measurements during the experiment (A4), sample questions for learning outcomes (A5), the grading scheme for problem solving questions (A6), and experimental scripts (A7).

³ "Who Wants to Be a Millionaire?" is a television game show where large cash prizes are offered for correctly answering a series of multiple-choice questions of increasing difficulty. Each question has

element whereby the trainee believed that they were in competitive play with another trainee for maximum scores. To minimize confounds, we simulated the fellow competitor and used manipulation checks to ensure that trainees felt that they were competing with a real person.

Trainees

We used students in a large business course at a large southeastern university as participants in our training study. As an institutional practice, students in this course are required to obtain research experience credits by participating in a research project or writing an essay. We recruited 182 business students, among whom 31% majored in finance, 15% in management, 11% in IS, 34% in non-business majors, and 14% were undecided. Participants ranged in age from 19 to 34; the average age was 21.

Experimental Procedures

We conducted two pilot studies with 50 and 24 trainees, respectively. We refined our experimental procedures, adjusted the length of the TML modules, improved instructions on the game, and revised questions for learning outcomes. In the final design, each TML module lasted 12–15 minutes and the entire experiment took about 90 minutes to complete. The experiment was conducted at a research lab with 16 small cubicles, each of which has a computer, a working space, and a headset. Trainees were blocked in their cubicle and could not look at or talk to another trainee. A proctor blind to the treatments was asked to make notes on any irrelevant behavior, such as falling asleep, web-surfing or studying for an exam.

As shown in Figure 1, trainees first registered online for one of several experiment slots. At this time we collected information on their gender, GPA, academic status, computer experience, prior knowledge on spreadsheets and databases, and individual difference variables, such as goal orientation and trait measure of computer learning self-efficacy (A3).⁴ When they

four possible answers and the player must choose one within a set time limit. Upon answering a question correctly, the contestant wins a certain amount of money and the opportunity to address the next question with greater difficulty and a higher money prize. If a player gets a question wrong, the prize drops to the previous guaranteed amount. After viewing a question, the player can “walk away,” i.e., leave the game with the money already won rather than attempting an answer. Players are given a series of lifelines to aid them with difficult questions, including 50/50, where the computer eliminates two of the incorrect answers, “asking the audience” where the audience is polled and answer statistics are shown to the player, and “phone a friend,” where the player can call a designated friend to get her opinion. We did not implement the “ask the audience” or “phone a friend” feature of the TV version as it was not possible for our setting.

⁴ As in prior TML research (Santhanam et al. 2008), we used both trait measure and state measure of computer learning self-efficacy.

arrived, we gave instructions on how to use the TML modules and the game, and informed them that they would compete with a fellow trainee after each TML module (A7). Trainees played a practice Millionaire game without a competitor for 10 minutes using trivia questions such as “Whose portrait is on the U.S. dime?” After the practice session, they were provided TML Module 1, followed by a learning outcome assessment using a paper and pencil test, which would be used as a baseline control for learning outcomes (A5).⁵ Trainees then proceeded to the first game competition in which we randomly assigned each trainee to one of the three treatment conditions (higher-, equal- or lower-skilled competitor). We simulated the fellow competitor and told trainees that they were randomly paired with a fellow trainee (referred to as “your competitor”) who was simultaneously playing in a different room. A trainee could not see her competitor’s screen but received periodic on-screen performance feedback (e.g., “Your competitor is scoring lower than you.”) and a final outcome report (A7-F). To increase realism, we simulated the completion time of the competitor, and asked trainees who finished a TML module quickly to wait for their competitor (A7-E). After the game competition was over, trainees answered a manipulation check question about their relative performance in the game including an option of “there was no competitor” (A7-G). Trainees then answered questions on our dependent variables, i.e., enjoyment, focused immersion, temporal disassociation, and state measures of computer learning self-efficacy. Next, in Phase 2 of the experiment, they went through TML Module 2 and completed a paper-and-pencil assessment for learning outcomes as another dependent variable. After this, trainees played the game competition for Module 2. Trainees were then debriefed and dismissed.

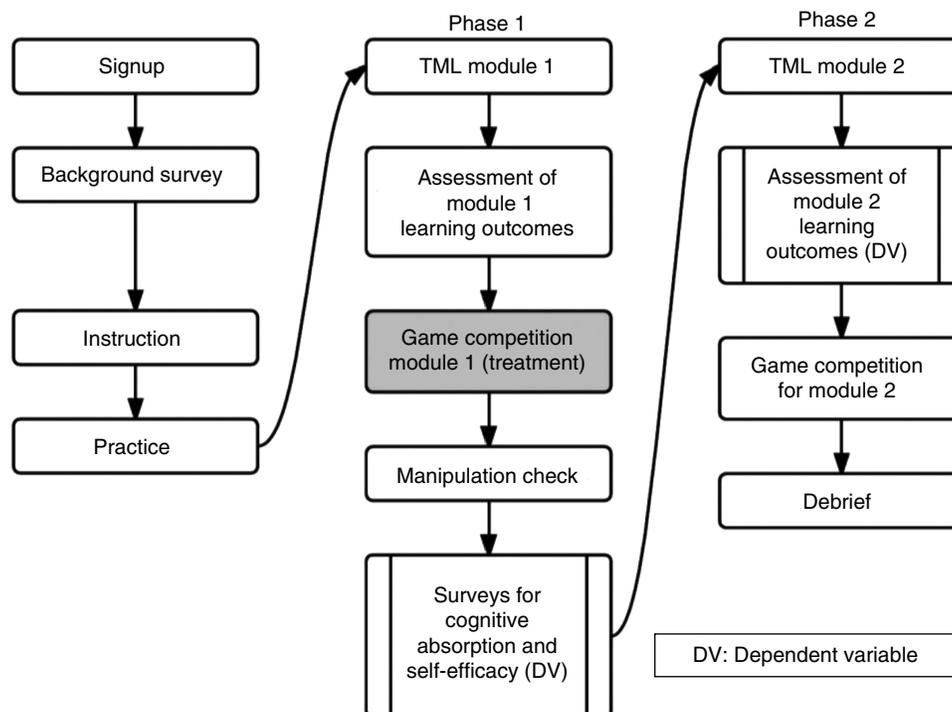
Measurements

We used validated scales to measure reflective constructs on individual differences, including learning orientation, performance orientation (i.e., approach, performance orientation), avoidance (Zweig and Webster 2004), and state and trait measures of computer learning self-efficacy (A4) (Santhanam et al. 2008, Zweig and Webster 2004). For enjoyment, focused immersion, and temporal disassociation, we adapted scales from Agarwal and Karahanna (2000). We measured a trainee’s knowledge level in spreadsheets and databases using

The former captures sustained and consistent characteristics of an individual under different situations, which is used as a control for individual differences; the latter is situation-specific, which serves as a response to our experimental treatments.

⁵ We measured learning outcomes after TML Module 1 primarily to control for individual differences in addition to our background questions on spreadsheet and database knowledge. The learning outcomes as a dependent variable were measured after TML Module 2.

Figure 1 Experimental Procedures



self-reported questions on the scale of low, medium, and high (A3).

Based on prior studies on IS training (Santhanam et al. 2008, Yi and Davis 2003), we developed multiple-choice, short-answer, and problem-solving questions to measure cognitive and skill-based learning outcomes (A5). The multiple-choice and short-answer questions had distinct identifiable objective answers. For problem-solving questions, which entailed subjective grading, we provided two graders with a detailed grading scheme (see A6 for an example) that was developed based on prior studies (Antony and Santhanam 2007) and trained them with test cases. The two graders were well versed in database and blind to treatment conditions. We calculated Cronbach’s alpha, which was greater than 0.90, suggesting a high inter-grader agreement. Finally, two graders met to resolve any discrepancy in their grades. A final consensus on grades was used for data analysis.

Covariates

As shown in Figure 1, we collected information on several control variables including gender, GPA, academic status, computer experience, and self-reported prior knowledge of spreadsheets and databases. We controlled for individual difference variables of goal orientation and the trait variable of computer learning self-efficacy. Using a paper-and-pencil test, we obtained trainees’ learning outcome scores after TML Module 1, and used those scores as a control for each trainee’s prior knowledge. Because the absolute game

performance (as measured by the number of questions answered correctly in the game) may also affect self-efficacy, we also controlled for trainees’ absolute game performance.

Results

Trainees

Among the 182 subjects, eight trainees had incomplete data on key variables, and were dropped. Four other trainees were excluded due to technical problems (e.g., frozen game screen or game performance not logged). Before data analysis, we read the proctor’s notes and removed 12 trainees who failed to follow instructions (e.g., sleeping, texting, bypassing TML modules, and studying for an exam).⁶ We excluded 14 trainees who failed to correctly answer the manipulation check question on whether they had won their competition. In the end, data for 144 trainees remained usable for our analyses.

Table 1 shows descriptive statistics of the trainees by treatment conditions. As shown, no significant difference was detected across treatments in gender, age,

⁶ These students appeared to have come to our study only to obtain research experience credits. Per IRB protocols, we could not ask them to leave. Instead, we relied on the proctor’s notes to remove them to avoid data contamination. We conducted robustness checks by including these records and our results still hold, but to maintain data and experimental integrity, their records were excluded.

Table 1 Descriptive Statistics

	Range	All $n = 144$	L $n = 51$	E $n = 45$	H $n = 48$	ANOVA		KW
						F	p	p
Percentage of males	—	61.8%	60.8%	57.8%	66.7%	0.400	0.671	0.668
Age	19–34	20.99 (1.93)	21.06 (2.27)	20.75 (1.45)	21.15 (1.95)	0.525	0.593	0.646
Academic status (freshman, sophomore, junior)	—	20 90 34	5 35 11	8 27 10	7 28 13	—	0.740*	
GPA	0–4	2.96 (0.48)	3.00 (0.51)	2.92 (0.45)	2.96 (0.49)	0.363	0.696	0.588
Knowledge in databases and spreadsheets	0–4	1.39 (0.97)	1.33 (0.77)	1.33 (1.04)	1.52 (1.09)	0.595	0.553	0.689
Computer usage (hours/day)	1–11	3.43 (1.91)	3.41 (1.87)	3.42 (1.71)	3.46 (2.14)	0.008	0.992	0.789
Gaming experience (hours/day)	0–4	0.85 (0.85)	0.78 (0.66)	0.82 (0.86)	0.94 (1.00)	0.463	0.630	0.946
Learning orientation	1–7	5.84 (0.76)	5.90 (0.81)	5.72 (0.69)	5.90 (0.76)	0.869	0.422	0.285
Performance orientation—approach	1–7	5.66 (0.91)	5.64 (0.96)	5.64 (0.76)	5.71 (1.01)	0.102	0.903	0.870
Performance orientation—avoidance	1–7	3.77 (1.11)	4.00 (1.14)	3.77 (1.14)	3.52 (1.02)	2.346	0.099*	0.141
Computer learning self-efficacy (trait)	1–7	5.48 (0.99)	5.49 (0.96)	5.45 (1.03)	5.50 (0.99)	0.031	0.970	0.999
Absolute game performance	0–12	6.25 (2.22)	6.24 (2.53)	6.48 (1.61)	6.04 (2.38)	0.446	0.641	0.726

Notes. KW shows the results of the Kruskal–Wallis one-way ANOVA. L, E, and H denote lower-, equally-, and higher-skilled competitor, respectively. Standard deviations are shown in parentheses.

*Pearson's Chi-Square test.

* $p < 0.1$.

GPA, knowledge in databases and spreadsheets, academic status, computer use or gaming experience. This suggests a successful random assignment of trainees. The Kruskal–Wallis one-way Analysis of Variance (ANOVA) showed similar results. However, ANOVA showed a marginally significant difference in performance orientation, i.e., avoidance ($p = 0.099$); thus, we included it as a covariate along with other individual characteristics to statistically mitigate their potential confounding effects.

Tests of Validity and Reliability

We used SmartPLS 2.0 M3 to test the measurement properties of our constructs (Ringle et al. 2005). We dropped several items due to low factor loadings on their respective reflective constructs. Items used in the study and their factor loadings are shown in the online appendix (A3 and A4). Table 2 shows the descriptive statistics, number of items, and the CA, CR, and AVE for these reflective constructs and their correlations. The tests of convergent and discriminant validity were satisfied with the measurement items loading together and the square root of the AVE greater than the correlation between the constructs. CA scores were greater than 0.7, suggesting adequate reliability of the scales.

Test of Hypotheses—Self-Efficacy and Learning Outcomes

We conducted Analysis of Covariance (ANCOVA) to examine the treatment effect of competitive structures after controlling for individual differences and prior knowledge. Table 3, Column 1, shows the effects of gamification on self-efficacy (H1). The trait measure of computer learning self-efficacy ($p < 0.001$) and performance orientation, i.e., avoidance ($p = 0.030$), were significant covariates as was game performance ($p = 0.025$). After controlling for these effects, we found that trainees matched with a lower-skilled competitor (i.e., receiving feedback of winning) reported higher levels of self-efficacy beliefs than those matched with an equally- or higher-skilled competitor ($p = 0.047$). We tested the robustness of this finding using bootstrapping with 1,000 samples and obtained similar results. These provided empirical support for H1 that “trainees matched with a lower-skilled competitor will exhibit higher levels of self-efficacy for learning through TML than those matched with an equally- or higher-skilled competitor.”

Columns 2–4 of Table 3 show the effect of gamification on learning outcomes including scores in multiple-choice, short-answer, and problem-solving

Table 2 Correlation Coefficients, Reliability, and Validity

Constructs	Mean (S.D.)	No. of items	CA	CR	AVE	Correlation matrix						
						1	2	3	4	5	6	7
1: Computer learning self-efficacy	5.48 (0.99)	6	0.90	0.93	0.68	0.82						
2: Enjoyment	4.40 (1.40)	4	0.94	0.96	0.85	0.09	0.92					
3: Focused immersion	4.56 (1.06)	4	0.78	0.84	0.58	0.15	0.70	0.76				
4: Temporal dissociation	3.92 (1.45)	3	0.93	0.96	0.88	−0.02	0.69	0.56	0.94			
5: Learning orientation	5.84 (0.76)	7	0.90	0.92	0.64	0.41	0.07	0.15	0.07	0.80		
6: Performance orientation—approach	5.66 (0.91)	5	0.81	0.85	0.55	0.16	0.18	0.18	0.16	0.27	0.74	
7: Performance orientation—avoidance	3.77 (1.11)	6	0.84	0.88	0.56	−0.14	−0.04	−0.06	0.12	−0.26	0.05	0.75

Notes. S.D., Standard deviation; CA, Cronbach's alpha; CR, composite reliability; AVE, average variance extracted; diagonal elements are the square roots of AVE.

questions (H2). As expected, TML Module 1 scores and prior knowledge in databases and spreadsheets were significant covariates. Marginal estimated means, which indicate the central tendency of the dependent variables after controlling for the impact of covariates, were higher for the treatment group. However, only problem solving scores showed statistical significance

($p = 0.037$). Robustness tests using bootstrapping with 1,000 samples yielded similar results. We also analyzed the treatment effect on synthesized learning outcomes obtained through Principal Component Analysis on three scores, and obtained a marginally significant effect ($p = 0.067$). In sum, the results provide partial support for H2 that “trainees matched with lower-skilled

Table 3 ANCOVA Results on Self-Efficacy and Learning Outcomes

Dependent variable	(1)	(2)	(3)	(4)
	H1: Computer learning self-efficacy L > EH	H2: Learning outcomes L > EH		
	Computer learning self-efficacy (state)	Multiple choice	Short answer	Problem solving
Treatment: <i>F</i> -value (<i>p</i> -value)	2.85 (0.047**)	0.54 (0.232)	0.88 (0.175)	3.25 (0.037**)
Covariates: <i>F</i> -value (<i>p</i> -value)				
Gender	1.34 (0.249)	0.11 (0.737)	8.32 (0.005***)	0.35 (0.557)
Knowledge in databases and spreadsheets	0.03 (0.871)	2.77 (0.098*)	2.14 (0.146)	6.53 (0.012**)
Learning orientation	0.36 (0.548)	0.59 (0.445)	0.22 (0.641)	0.10 (0.757)
Performance orientation—approach	1.32 (0.253)	0.93 (0.337)	0.46 (0.501)	0.13 (0.716)
Performance orientation—avoidance	4.84 (0.030**)	0.35 (0.555)	1.48 (0.225)	0.31 (0.577)
Computer learning self-efficacy (trait)	25.58 (0.000***)	6.40 (0.013**)	0.47 (0.494)	0.18 (0.673)
Absolute game performance	5.11 (0.025**)	2.56 (0.112)	4.59 (0.034**)	13.59 (0.000***)
TML1 score—multiple choice		3.91 (0.050*)		
TML1 score—short answer			6.75 (0.010**)	
TML1 score—problem solving				5.24 (0.024**)
Model adjusted <i>R</i> ²	0.221	0.097	0.127	0.185
Marginal estimated means (standard error)				
L (<i>n</i> = 51)	5.49 (0.13)	3.84 (0.14)	11.23 (0.89)	30.34 (1.40)
EH (<i>n</i> = 93)	5.22 (0.09)	3.71 (0.10)	10.19 (0.65)	27.17 (1.03)
E (<i>n</i> = 45)	5.23 (0.13)	3.66 (0.14)	10.25 (0.95)	27.53 (1.52)
H (<i>n</i> = 48)	5.21 (0.13)	3.77 (0.14)	10.13 (0.92)	26.83 (1.46)
Possible range	1–7	0–5	0–20	0–40

Notes. L, Lower-skilled competitor; EH, higher- or equally-skilled competitor. Marginal estimated means and associated SEs show the central tendency and dispersion of the dependent variables after controlling for the impact of covariates.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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Table 4 ANCOVA Results on Enjoyment, Focused Immersion, and Temporal Dissociation

Dependent variable	(1)	(2)	(3)
	H3: Engagement—E > LH		
	Enjoyment	Focused immersion	Temporal dissociation
Treatment: <i>F</i> -value (<i>p</i> -value)	1.82 (0.090*)	1.09 (0.149)	1.69 (0.098*)
Covariates: <i>F</i> -value (<i>p</i> -value)			
Gender	2.72 (0.101)	3.16 (0.078*)	1.53 (0.219)
Knowledge in databases and spreadsheets	3.51 (0.063*)	2.92 (0.090*)	2.38 (0.125)
Learning orientation	0.08 (0.773)	0.19 (0.660)	0.74 (0.392)
Performance orientation—approach	2.62 (0.108)	0.42 (0.520)	1.25 (0.265)
Performance orientation—avoidance	0.41 (0.525)	0.27 (0.604)	1.41 (0.237)
Computer learning self-efficacy (trait)	1.64 (0.202)	2.48 (0.117)	0.01 (0.930)
Absolute game performance	1.63 (0.224)	6.46 (0.012**)	0.52 (0.472)
Model adjusted <i>R</i> ²	0.051	0.073	0.030
Marginal estimated means (standard error)			
E (<i>n</i> = 45)	4.64 (0.21)	4.70 (0.15)	4.15 (0.21)
LH (<i>n</i> = 99)	4.30 (0.14)	4.50 (0.10)	3.81 (0.14)
L (<i>n</i> = 51)	4.60 (0.19)	4.66 (0.14)	4.03 (0.20)
H (<i>n</i> = 48)	3.99 (0.20)	4.34 (0.15)	3.58 (0.21)
Possible range	1–7	1–7	1–7

Notes. E, Equally-skilled competitor; LH, lower- or higher-skilled competitor. Marginal estimated means and associated SEs show the central tendency and dispersion of the dependent variables *after controlling for the impact of covariates*.

p* < 0.10; *p* < 0.05; ****p* < 0.01.

competitors will exhibit higher levels of learning outcomes in the next training module than those matched with an equally- or higher-skilled competitor.”

Table 4 shows the treatment effect of competitive structures on enjoyment, focused immersion, and temporal dissociation (H3). After controlling for covariates, we found that trainees competing with an equally-skilled competitor reported marginally significant higher enjoyment (*p* = 0.090) and temporal dissociation (*p* = 0.098), but not focused immersion. Bootstrapping with 1,000 samples yielded similar results. We also analyzed the treatment effect on a synthesized engagement variable obtained via Principal Component Analysis on enjoyment, focused immersion, and temporal disassociations, and found a significant effect (*p* = 0.073). Overall, we found partial support for H3 that “trainees matched with an equally-skilled competitor will exhibit higher levels of enjoyment, focused immersion, and temporal disassociation than those matched with a lower- or higher-skilled competitor.”

Discussion

Although gamification is suggested as a promising strategy to increase engagement of learners in TML, nuanced analysis is required to understand how to address engagement and learning goals with game designs (Hamari et al. 2014, Liu et al. 2016). Using a gamified TML design with different competitive structures, we show that simultaneously addressing both goals could be inherently challenging. Consistent with social cognitive theory, we find that trainees’

self-efficacy beliefs and learning outcomes were higher when they believed they competed against a lower-skilled competitor, won their games, and received winning performance feedback. Yet, as suggested by the flow theory, engagement in TML was the highest in a more balanced competitive structure. These findings echo the sentiment of researchers that it is important to explicate the effects of each gamification design element and evaluate them on utilitarian and hedonic outcomes.

Theoretical and Practical Implications

Premised on the arguments that competitive structures can alter how trainees approach training tasks, we argued and found support for the idea that the effects of competition on learning outcomes and engagement differ across competitive structures. Because different competitive structures can have distinct effects on player learning, they can contribute to the mixed effects of competition in gamified training studies. In light of the mixed effects of competition in gamification designs (Burguillo 2010, Hamari et al. 2014, Hanus and Fox 2015), our study suggests that future research should report the competitive structures and isolate effects of different competitive structures to allow comparisons across studies.

To address the utilitarian and hedonic goals of gamification, we used two different theories, i.e., social cognitive theory and flow theory, respectively. We found that the two disjoint theory traditions intersect and provide divergent predictions about competitive structures. Specifically, social cognitive theory, which

addresses utilitarian outcomes such as learning and achievements, favors competing with a less able competitor. However, flow theory, which addresses hedonic outcomes such as engagement, calls for a tighter race. Our initial findings reveal the complexity of using competition as a gamification tool, and post intriguing challenges on how to integrate theories for learning and engagement.

By applying social cognitive theory and flow theory in novel contexts, we contribute to each theory tradition. Social cognitive theory predicts that self-efficacy beliefs can be molded by vicarious experiences of observing the performance of others. This has led to extensive research on behavioral modeling and vicarious learning from proficient models (Compeau et al. 2006, Compeau and Higgins 1995, Yi and Davis 2003). We tested a less studied source, i.e., social comparisons among peers through gamified competition. Our findings support the idea that online social settings, such as competitive vicarious experiences, can be a valuable source of self-efficacy beliefs. We also contribute to the flow literature by extending the balance principle to two-person competitive situations by showing that engagement is highest when there is a balance of skills among competitors. Our results hold promise for multiperson extensions where multiple individuals compete individually or in groups.

From a practical perspective our findings suggest that not all competitions are the same and that there may not be a one-size-fits-all competition design. Hence, organizations could optimize gamified training designs based on the priority of their training goals and characteristics of the individuals. For example, in cases where improving trainees' self-efficacy is important, matching trainees with a lower-skilled competitor is the preferred competitive situation. In cases where providing fun and engaging experiences is a priority, trainees could be matched with equally-skilled competitors so that they become more challenged and stay engaged. TML platforms could personalize competition. For example, if the TML platform detects a bored trainee, it may have her compete against a fellow trainee of similar skill. Our design also adds to the emerging research of mitigating the ill effects of competition in learning environments (Cheng et al. 2009, Hanus and Fox 2015): We suggest another approach, that is, to provide competence evaluations as game performance feedback.

Limitations and Future Research

As a study of a new gamified TML design, our research has a few limitations that call for further investigations. Our gamified TML approach should be tested in domains other than database training. Further research is needed using non-student trainees, though students are future employees and an appropriate audience for

gamification. We did not find significant effects on multiple-choice and short-answer questions, perhaps because we had relatively few such questions. We did find support on problem-solving questions, however, which are generally considered the most critical test of learning because they evaluate the depth of understanding (Santhanam and Sein 1994, Yi and Davis 2003). Our effect sizes on learning and engagement were small but stable in additional robustness tests. The small effect sizes may partly reflect our conservative experimental design, which used a simulated competitor to maximize control. Field tests will be worthwhile because they provide more realistic effect sizes.

As one of the first studies on competitive structures in gamification, our study offers a host of opportunities for extensions. Some natural extensions include determining the optimal sequence and transitions of competitive structures, the optimal combination of training and mini-games, and moderating effects of social relations between competitors. Theoretical lens such as social comparison theory could be used to study cases where individuals can choose whether and with whom they want to compete (Dijkstra et al. 2008, Festinger 1954, Garcia et al. 2006). Another extension is to enrich existing game-theoretical models of competition (Kalra and Shi 2001, Liu et al. 2007) by incorporating self-efficacy and engagement.

From a broader IS research perspective, there is now a greater thrust toward building systems that offer hedonic and utilitarian benefits (Lowry et al. 2013, Wu and Lu 2013). Our study directs attention to gamification as a useful design paradigm that addresses both types of benefits. It also highlights that many nuances in gamification design must be addressed with relevant theoretical frameworks. This suggests many opportunities for IS researchers.

Supplemental Material

Supplemental material to this paper is available at <http://dx.doi.org/10.1287/isre.2016.0630>.

Acknowledgments

The authors thank the editors and reviewers for their comments in helping improve the manuscript.

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