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GAMIFIED TECHNOLOGY-MEDIATED LEARNING: THE ROLE OF INDIVIDUAL DIFFERENCES

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Abstract

Researchers and practitioners see significant potential in using gamified technology-mediated learning (TML) systems to engage users and help them to learn. Yet, existing studies on gamified TML indicate inconsistent findings on the value of these systems. Some studies show higher learning outcomes and engagement while others do not; some demonstrate higher learning outcomes but not higher engagement. Therefore, researchers have called for more nuanced analysis including how individual differences interact with game elements. Specifically, we identify and study two individual differences - gender and achievement goals - in competitive gamified TML designs. We find that gender plays an important moderating role – males engage more and learn better in a competitive learning context than females. Achievement goals help explain differences in users' benefits from gamified TML and how users react to competitive contexts. Our findings indicate that gender and achievement goals are important individual differences to consider in designing gamified TML and explaining its outcomes.

Keywords: Gamification, Technology-Mediated Learning, Gender, Achievement Goals, Competition

1 INTRODUCTION

During the past few decades, technology-mediated learning (TML) is used to train users in corporate settings and to educate students. TML refers to an environment in which information technology is used to mediate/support teaching and provide course delivery to large number of users in a cost-effective manner (Allen and Seaman 2011; Gupta and Bostrom 2009; Gupta et al. 2010; Santhanam et al. 2008; Zhang et al. 2004). However, empirical evidence suggests that TML is plagued with low user engagement and high drop-out rates and often fails to deliver anticipated benefits (Greitzer et al. 2007; Gupta and Bostrom 2009; Santhanam et al. 2008). Game-based learning and gamification are proposed as ways to improve user engagement and learning outcomes (de Sousa Borges et al. 2014; Perrotta et al. 2013).

Several studies examine the effects of gamification in learning, particularly in TML, but show mixed results (Domínguez et al. 2013). Hence, researchers suggest that it is important to examine the moderating role of individual difference in the relationship between gamification design elements (e.g., competition) and gamification outcomes (Hamari et al. 2014). As a popular gamification element, competition has received a lot of attention. Many empirical studies have conducted comparisons between competitive vs. non-competitive learning. Advances in information technologies enable the creation of *adjustable/customizable* competitive learning environments, such as by changing the degree of challenge or matching between users (Chen et al. 2012; Cheng et al. 2009; Wilhelmsson 2013). Indeed, a few studies have delineated the impact of different competitive structures (e.g., winning or losing) within a competitive learning and suggested that such competitive structures can be tuned to suit different individual preferences or skill levels (Epstein and Harackiewicz 1992; Liu et al. 2013).

The objective of this study is to scrutinize how individual differences interact with the competition element in gamified TML designs to explain the TML outcomes of learning and engagement. Specifically, we focus on two relevant individual differences, gender and achievement goals, and examine their impact on TML outcomes in a laboratory experiment. We manipulate the competition element of a gamified TML design and highlight how winning and losing can have differential impacts on users' psychological states and behaviors, depending on their gender and achievement goals. Our findings provide insights on why the same competition element in gamified TML can yield different outcomes and hold important implications for the optimal design of gamified TML systems. We next present our research framework, followed by results and discussion.

2 RESEARCH FRAMEWORK

We begin this section by defining gamification, describing its benefits, and highlighting the research gap on the role of individual differences. By reviewing the literature on competition and individual differences in learning, we develop hypotheses on the main effects of competition and individual differences (i.e., gender and achievement goals) and their interaction in affecting engagement and learning outcomes.

2.1 Gamification in Technology-Mediated Learning

First coined in 2008, gamification was described as "the hottest business buzz-word" in 2013 (Deterding et al. 2011; McCormick 2013), but often gets confused with game-based learning or serious games (Burke 2014a; Glover 2013). The latter terms refer to the development and use of full-fledged games for non-entertainment purposes, whereas gamification focuses on the application of game elements in non-game contexts to engage users, motivate action, enhance learning, solve problems, or achieve other organizational goals (Burke 2014a; de Sousa Borges et al. 2014). Examples of these game elements include competition; time pressure; reputation, ranks, and levels; and self-representation with avatars (Reeves and Read 2013). In other words, gamification adds a game layer to TML, instead of developing stand-alone games that support learning.

de Sousa Borges et al. (2014) mapped 26 studies that investigate gamification in educational settings and conclude that well-designed gamification has the potential to engage users, propose challenges, encourage socialization, foster behavioral changes, and improve users' skill and knowledge. But Hamari et al. (2014) survey the broader gamification literature and conclude that much of the "industry chatter" on gamification is based on anecdotes or intuition. Although the gamification market is forecast to be worth $5.5 billion annually by 2018 (Simpson and Jenkins 2015), its rapid growth might be driven partially by "novelty and hype," market confusion, and inflated expectations (Burke 2014a; Burke 2014b). Without appropriate design, most gamification initiatives are expected to fail to meet business objectives, necessitating a systematic research (Gartner 2012).

Gamification deserves attention from IS researchers not only because of its rapid market growth and potential application in corporate training, but also because gamification systems represent the confluence of research on TML, system/game design, technology acceptance, continuous usage intention, and recent investigations of the hedonic nature of novel services (Hamari 2013; Santhanam et al. 2016). Researchers in psychology, education, business, and game design have employed various methodologies to investigate the contributions, limitations, social impacts, and learning outcomes of gamification, as well as users' motivations, perceptions, and cognitive processes. Hamari et al. (2014), who reviewed 24 empirical studies, conclude that gamification research suffers from small sample sizes, lack of control groups or benchmarks, ill-designed experiments, insufficient quantitative analyses, unclear statistical results, and the use of poor psychometric measurements. Such research weaknesses pinpoint the direction for future empirical studies to improve our understanding of gamification, and specifically in gamified TML, where it is seen to have great potential.

To identify the relevant gamification interventions and knowledge gaps in the gamification phenomenon, we adopt the framework proposed in Santhanam et al. (2016). In a gamified information system, user characteristics, game design elements, and task characteristics jointly influence users' intrinsic and extrinsic motivation, which ultimately leads to different experiential and instrumental outcomes. Experiential outcomes refer to desirable psychological experiences, such as aesthetic or sensual pleasure or experiential feelings of engagement, enjoyment, and flow. Instrumental outcomes refer to behavioral outputs, such as system use or improvements in productivity and learning outcomes (Perrotta et al. 2013; Santhanam et al. 2016). This framework stresses the importance of achieving both instrumental goals (e.g. learning outcomes) and experiential qualities (e.g. engagement). The purpose of this research is to scrutinize how individual differences interact with an important game design element, competition, in affecting TML users' engagement and learning outcomes.

2.2 Competition and Learning

Competition is a commonly used game element in designing gamified systems, but from a behavioral perspective, it is a double-edged coin. On one side, competition arouses participants' competitive instincts to achieve performance goals, leading to greater interest, excitement, and engagement/involvement (Cagiltay et al. 2015; Glover 2013; Regueras et al. 2011; Yu 2003). On the other side, ill-designed competition can negatively influence participants' confidence, self-efficacy, attitude towards failure, and interpersonal relationships, resulting in anxiety and diminished empowerment and responsibility for learning (Cagiltay et al. 2015; Chen et al. 2012; Kohn 1992). How to reap the benefits of competition while avoiding its potential harm has been a challenge for decades, especially for educators (Cagiltay et al. 2015; Regueras et al. 2009).

Competitive learning forces social comparisons among users, induces strong negative affect to many losers, and benefits few winners (Ames and Ames 1984; Qin et al. 1995). Yet in game-based designs, competitive elements are seen as an effective and more efficient mechanism to motivate users through intrinsic rewards and competitive engagement (Liu et al. 2013; McGonigal 2011). Mass media also emphasize the benefit of competition, overlooking its potential psychological and behavioral side-effects. For example, a *Wall Street Journal* article indicates that businesses can improve their training through gaming and that "It's all about competition….The games don't have to be that sophisticated as long as they include an essential element: competition" (Totty 2005, p. R6).

Based on prior literature, we hypothesize competition used in gamified TML has a positive effect on engagement and learning outcomes, but acknowledge that given the evidence of competition's negative effect in traditional learning contexts, the opposite may also be true in the new gamified TML contexts.

H1a: Users in competitive gamified TML demonstrate **higher engagement** than those in a non-competitive gamified TML

H1b: Users in competitive gamified TML demonstrate **better learning outcomes** than those in a non-competitive gamified TML

2.3 Individual Differences

The term individual differences refers to factors such as cognitive style, personality profiles, and demographic variables that influence users' beliefs about, attitudes towards, and use of information technology (Agarwal and Prasad 1998; Hamari et al. 2014; Perrotta et al. 2013). Individual differences play an important role in both IS and education research because they may be vital moderators explaining why significant results occur only in certain environments or with only some users (Gupta et al. 2010; Hamari et al. 2014). Moreover, they also help us understand and accommodate users' differences in order to design user-friendly or customized information systems that cater to users' needs or preferences (Santhanam et al. 2016; Zichermann and Cunningham 2011). Although individual differences are found to influence gamification users' attitudes and experiences (Hamari et al. 2014), prior literature still shows a lack of insight into how individual differences directly and indirectly influence psychological and behavioral outcomes. This research focuses on gender and achievement goals in a gamified TML application providing both competitive and non-competitive contexts.

2.3.1 Gender

Unlike games designed for entertainment, TML and gamification for corporate training purposes operate in environments in which gender is an essential concern – learning needs to be accessible by *all* users, not just by groups with specific interests or attributes. As Koivisto and Hamari (2014) note, the gender gap has been shrinking in the use of entertainment games, but little is known about gender's moderating effects in TML and gamification for training purposes. Literature on how men and women deal with competition can be presented from three perspectives – from sociology and economics, from IS and gaming, and from TML and gamification.

The literature in sociology and economics generally concludes that men are more eager to compete, perform better in competitive environments, and respond more positively to an increase in competition, compared to women (Gneezy et al. 2009; Gneezy et al. 2003; Munoz-Merino et al. 2014; Niederle and Vesterlund 2011). Such behavioral differences are likely due to men's greater overconfidence and women's preference to avoid the pressures/anxiety of competition (Niederle and Vesterlund 2011). Furthermore, experimental studies show that women and men perform more poorly in competitive environments when they are in domains in which each is expected to perform more poorly than the other due to stereotyping (e.g., women in math competitions against men and men in writing competitions against women) (van Loo et al. 2013).

The gaming literature suggests that men tend to prefer competitive games and display the need for winning (Hartmann and Klimmt 2006; Lucas and Sherry 2004; Williams et al. 2009). Researchers examine the impact of gender on widely divergent aspects of IS, such as technology usage (Ahuja and Thatcher 2005), technology adoption (Venkatesh and Morris 2000), social networks (Muscanell and Guadagno 2012), and gamification (Koivisto and Hamari 2014). Overall, prior findings suggest that (1) women enjoy and use an information system less than men do, perhaps due to their lower perceived self-efficacy and computer aptitude, as well as higher perceived anxiety (Ahuja and Thatcher 2005; Venkatesh and Morris 2000); (2) women engage more than men when social features are employed

(Haferkamp et al. 2012; Koivisto and Hamari 2014; Muscanell and Guadagno 2012; Williams et al. 2009); (3) women value more highly the feedback they give to and receive from the social community (Koivisto and Hamari 2014); and (4) women perceive gamification as more playful than men (Koivisto and Hamari 2014).

Although studies suggest that men and women do not differ in their TML experience (Astleitner and Steinberg 2005; Lu et al. 2003), gender differences seem prominent in course performance, motivation, study habits, and communication behaviors (Chyung 2007; Gunn et al. 2003; Munoz-Merino et al. 2014; Price 2006; Yukselturk and Bulut 2009). Researchers generally attribute such findings to anxiety level and self-efficacy. Based on the literature and findings above, we focus on the interaction effects of gender on engagement and on learning outcomes by proposing –

H2a: In gamified TML, gender moderates the relationship between competition and **engagement**.

H2b: In gamified TML, gender moderates the relationship between competition and **learning outcomes**.

2.3.2 Achievement Goals

To understand human behavior, researchers have devoted considerable attention to achievement goals in the study of motivation in educational psychology and TML (Harackiewicz et al. 2002; Kaplan and Maehr 2007; Murayama et al. 2011; Santhanam et al. 2008; Zweig and Webster 2004b). Also known as goal orientation, achievement goals represent the purpose of competence-relevant behavior (Maehr 1989). The underlying constructs of achievement goals have evolved over time.

Early research on achievement goals focused on *mastery goals* (goals to develop competence and task mastery) and on *performance goals* (goals to demonstrate competence relative to others) (Ames and Ames 1984). In the 1990s, a second competence-based distinction was added to the theoretical framework to accentuate people's motivation to approach positive outcomes or to avoid negative ones (Elliot and Harackiewicz 1996). Joining the mastery-performance and approach-avoidance distinctions leads to four types of achievement goals – *mastery-approach*; *mastery-avoidance*; *performance-approach*; and *performance-avoidance* (Elliot 1999). Although little follow-up empirical evidence supports the separation of mastery-approach and mastery-avoidance goals, many studies have validated the separation of performance-approach goals (oriented toward gaining the favorable judgment of one's competency from others) and performance-avoidance goals (concerned with avoiding the unfavorable judgment of one's competency from others) (Murayama et al. 2011). The three goal classification is commonly adopted in recent TML and IS research (Santhanam et al. 2008; Zweig and Webster 2004a; Zweig and Webster 2004b). After decades of theoretical development and empirical analyses, achievement goal theory is found robust across different age groups and across countries with widely different cultures (Murayama et al. 2011).

Achievement goal theory is an important foundation in empirical studies of learning, not only because it underlies both engagement and learning outcomes, but also because achievement goals govern the relative importance users place on earning points and rewards versus gaining content mastery (Neietfeld et al. 2014). According to Elliot and Harackiewicz (1996), individuals behaving from mastery goals or from performance-approach goals exhibit intrinsic motivation. Those with high performance-avoidance goals display high engagement in the task to avoid unfavorable judgment from others, but evince decreased intrinsic motivation. Prior literature suggests that learners perform tasks more poorly when driven by extrinsic rewards, especially after the extrinsic reward is removed. What learners need is persistent intrinsic rewards that sustain their pursuit of knowledge or task performance (Deci and Ryan 2000). Such conclusions imply that competition not only triggers engagement (H1a) and improves learning outcomes (H1b), but also leads to different behavioral and psychological outcomes in a competitive learning environment.

Specifically, in a competitive learning environment, users with higher performance-avoidance goals exert more efforts than those with lower performance-avoidance goals to avoid the unfavorable judgment, demonstrating higher engagement and better learning outcomes. Regardless of competition outcomes, better learning outcomes should be observed from learners with high performance-approach goals. Nevertheless, some researchers argue that gamified learning behavior in response to rewards may be an exception, because the game itself may introduce sufficient enjoyment to be intrinsically rewarding, blurring the line between intrinsic and extrinsic motivations (McGonigal 2011). To examine the propositions above, we posit that:

H3a: In gamified TML, users with higher performance-approach goals demonstrate **higher engagement** than those with lower performance-approach goals.

H3b: In gamified TML, users with higher performance-approach goals demonstrate **better learning outcomes** than those with lower performance-approach goals.

H4a: In competitive gamified TML, users with higher performance-avoidance goals demonstrate **higher engagement** than those with lower performance-avoidance goals.

H4b: In competitive gamified TML, users with higher performance-avoidance goals demonstrate **better learning outcomes** than those with lower performance-avoidance goals.

3 RESEARCH METHOD

To examine our hypotheses, we conducted a laboratory experiment with a between-subject design. We manipulated the competition elements by randomly assigning participants to one of three experimental conditions: No-Competition (NC), Competition – Winning (C-Win), and Competition – Losing (C-Lose). We adopted a pretest-posttest design, in which both the pretest and posttest consist of a self-paced TML tutorial video, a paper-and-pencil test to capture learning outcomes, and an online questionnaire to measure participant engagement. Noteworthy is that the purpose of the gamification layer is neither to provide training nor to assess learning outcomes; instead, the gamification layer serves as a way to stimulate participants and provide performance feedback. We perform ANCOVA (Analysis of Covariates) analysis on the experiment data by incorporating both individual differences and competition treatments as independent variables, while controlling pretest variables and other factors as covariates. The following sections show details on research participants, the TML modules, the gamification layer, the experimental procedure, and measurements.

3.1 Research Participants

The laboratory experiment was conducted at the business college of a large southeastern U.S. university. As part of the college's institutional practice, students were required to obtain research experience credits by either participating in one of several available research projects or writing an essay on an approved topic. Regardless of the experiment performance, each participant of our study received full research experience credits and the number of credits granted was not tied to their performance in the study, so as to avoid extraneous incentives. One hundred and sixty-nine students volunteered for this study – 34% female; average age 21.05, ranging from 19 to 34; 20.7% majored in finance, 14.8% in management, 8.9% in IS, 4.2% in other business disciplines, 36.1% non-business majors, and 15.4% undecided.

3.2 TML Modules and Gamification Layer

To simulate the process of corporate training, we used Camtasia Studio to record two narrated, self-paced tutorial videos that cover the basic concepts and skills in database management. TML Module 1 focused on terminology, database concepts, and 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. Participants could navigate different topics using a menu and could control the pace using pause, forward, and backward buttons.

We used Java to design a mini-game that mimicked a famous trivia TV show "Who Wants to be a Millionaire?[1]" as a gamification layer. Such mini-games are frequently used by game designers to break the boredom, while enticing engagement and avoiding distractions (Zaman et al. 2012). All the mini-game questions were exclusively drawn from the content of prior TML tutorial videos. To increase the fun and challenge, the mini-game featured virtual prizes; a 50/50 lifeline; a walk-away option; applause or sound effects after contestants answered correctly or wrongly; and background music matched to the intensity of game levels.

On top of the mini-game, we added simulated competition to the C-Win and C-Lose groups, but not to the NC group. Participants were randomly assigned into an experimental group. Competition was implemented as follows: we first told research participants in C-Win and C-Lose Groups that they had been paired randomly with another participant in a two-part competition. To increase realism, after participants finished a TML learning module, their screen showed a message asking them to wait for their competitor to finish. During mini-game playing, participants could not see their competitor's screen, but received only periodic on-screen messages regarding their competitor's status. For example, participants in the C-Win Group received messages like "Your competitor is scoring lower than you" or "Your competitor is attempting a lower level than you." After the mini-game was completed, a summary page displayed participants' and competitors' scores and the competition results. The mini-game for the NC Group is identical to the original TV show, without competitors, waiting, on-screen messages, and competitive results. Note that there are no financial rewards/penalties associated with winning and losing in the mini-game – this is consistent with many real-world gamification applications that rely on people's intrinsic and social motivations (e.g. the desire to win or to become excellent) rather tangible extrinsic rewards.

3.3 Experimental Procedures

Based on the feedback from and observations on two pilot studies, we shortened the length of the self-paced tutorial videos, clarified research instructions, and adjusted the experimental procedures. The resulting TML learning modules lasted 12 to 15 minutes and the entire experiment took about 90 minutes to complete. The experiment took place at a research lab with 16 cubicles, each of which has a computer, a working space, and a headset. Participants were not allowed to chat with or peek at others.

Figure 1 shows the experimental procedure. Participants' demographics and other trait attributes were collected when they signed up, including their gender and achievement goals. After arriving at the research lab, participants were given the written and oral instructions and then practiced on how to navigate the self-paced tutorial videos and how to play the mini-games, so as to get familiarized with their interfaces. All participants were notified that the content of later mini-game questions would be drawn exclusively from the TML videos. We also informed participants in the C-Win and C-Lose Groups that each would play against the same competitor in the two phases of the experiment, whereas nothing about competition was mentioned to those in the NC Group.

After the practice session, participants were provided TML Module 1, where they watched the first self-paced tutorial video, answered multiple-choice, short-answers, and problems-solving questions on paper to measure their learning outcomes, and filled in an online questionnaire to measure their engagement. The purpose of collecting TML Module 1 measurements is to capture participants' state attributes or prior knowledge *before* the treatment, serving as the baseline/pretest for follow-up statistical analyses.

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[1] "Who Wants to Be a Millionaire?" is a famous TV game show that offers large cash prizes. Contestants answer a series of multiple-choice questions of increasing difficulty within a set time limit. If a contestant answers a question wrong, the cash prize drops to the previous guaranteed prize. To increase fun and uncertainty, contestants can (1) walk away after viewing the question; (2) phone a friend; (3) ask the audience; or (4) choose "50/50", where the computer eliminates two of the incorrect answers.

To enhance the treatment effect, participants then played the mini-games twice with the same predetermined results, based on the experiment groups. In other words, participants in the NC Group saw no competitor, those in the C-Win Group won the mini-games consecutively, and those in the C-Lose Group were defeated twice in a row. Gaming and competition status were clearly shown throughout the playing and were further enhanced in the summary page. To avoid unnecessary confounds due to friendships or rivalry among participants, we simulated the competition and told participants that their anonymous competitor was learning and playing simultaneously in a different room.

To ensure successful installation of treatment effect, we conducted manipulation checks by asking participants whether they just won the game, lost the game, or had no competitor at all – immediately after they saw the result summary. Participants who failed to answer this question correctly were removed from later statistical analyses.

After the manipulation checks, participants were provided TML Module 2, where they watched the second self-paced tutorial video, answered questions on paper to measure their learning outcomes, and filled in the same online questionnaire to measure their engagement. After TML Module 2, we gauged participants' state attributes and learning outcomes, serving as the dependent variables for follow-up statistical analyses. After the posttest measurements, participants played another mini-game, were debriefed and dismissed. The purpose of the second mini-game is to keep pretest and posttest measurements comparable (i.e., participants anticipated a follow up mini-game in both cases). Since all measurements were taken before the second mini-game, it had no other role but fulfilling the expectation. In the debriefing, participants were asked not to discuss the experiment with others. The overall experiment last about 90 minutes.

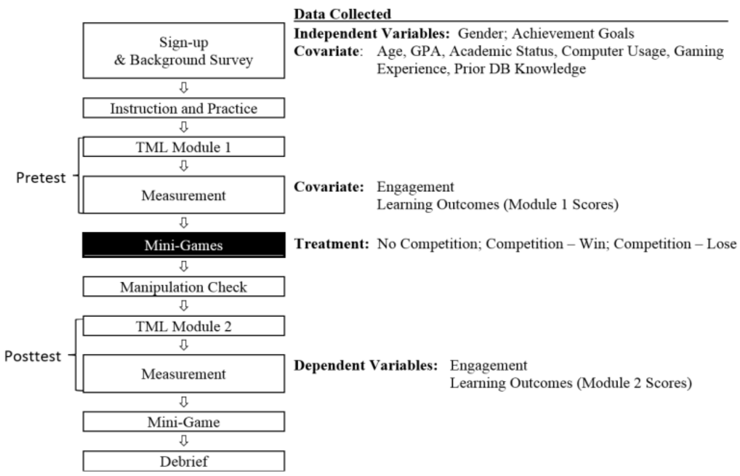

Figure 1 Experimental Procedures

3.4 Measurements

We used a validated scale to measure participants' achievement goals (Zweig and Webster 2004b). Other trait attributes were also collected in the sign-up and background survey, including gender, age, GPA, academic status, computer usage, and gaming experience. We developed a quiz with three multiple-choice questions to determine participants' prior knowledge in databases.

There has not been a consistent definition of engagement in the literature. Depending on the context, engagement has been related to cognitive absorption, attention, and cognitive effort (Liu et al., 2016). Because learning is a highly cognitive activity, an appropriate concept of engagement seems to be mental workload, which is widely used in psychology and IS research (Hart and Staveland 1988; Shen et al. 2012) and found to be significantly correlated with other task engagement measurements (Matthews et al. 2002). There are multiple ways to measure mental workload, including both self-reported questionnaire and psychophysiological recording (e.g., facial expression, eye tracking) (Chen and

Vertegaal 2004; Grafsgaard et al. 2013). We adopted a popular self-reported measurement – NASA-Task Load Index (NASA-TLX), which measure mental and temporal demands, as well as performance, effort, and frustration, as indicators of mental load while performing a task.

Following prior literature (Santhanam et al. 2008; Yi and Davis 2003), we used multiple-choice, short-answer, and problem-solving questions to measure cognitive and skill-based learning outcomes. Great for testing declarative knowledge, multiple-choice and short-answer questions had clear solutions that involved little judgment during grading. We used problem-solving questions to test participants' procedural knowledge and avoided subjectivity and grading biases by having two well-qualified graders, who understood databases but were blind to treatment conditions. They followed a detailed grading scheme and reconciled grading differences, when score inconsistency existed. We also calculated Cronbach's Alpha to ensure inter-grader agreements before performing additional data analyses.

4 RESEARCH RESULTS

4.1 Research Participants

In total, one hundred and sixty-nine students volunteered for this experiment. Three students failed to complete the background survey. Six students were excluded in statistical analyses for failing the manipulation check. To ensure the internal validity of the research, we proctored experiments carefully and removed participants who had serious technical problems, slept through both phases, ignored instructions, completely skipped TML tutorial videos, or gave careless answers with clear patterns (e.g., all the same). One hundred and forty-five records are usable.

Table 1 shows the descriptive statistics for research participants by competition conditions and by gender. ANOVA and Kruskal–Wallis tests on competition conditions suggest no significant difference was detected between NC, C-Win, C-Lose Groups in terms of gender, age, computer usage, or gaming experience, suggesting a successful random assignment. Nevertheless, ANOVA, but not the KW test, shows a marginally significant difference in GPA (p=.08), suggesting the need to include it as a covariate to statistically mitigate its potential confounding effects. One construct of achievement goals, performance-avoidance, demonstrated significant difference in ANOVA and the KW test.

We also group participants by gender to show their differences. ANOVA, but not the KW test, detects a significant difference in age, suggesting the men's greater age dispersion that right-skewed the distribution. Female participants used computers significantly more than males did (p=.09), whereas male participants played significantly more computer games than females did (p=.03). Consistent with prior literature, female participants demonstrated significantly higher performance-avoidance goals than males did (p=.03). These gender-wise differences are consistent with prior literature. Because we are interested in the role of gender, we control significant gender-wise differences by including them as covariates.

4.2 Tests of Measurements

We used Principal Component Analysis (PCA) to reduce the dimensionality of our constructs, including achievement goals and learning outcomes. We dropped a few items of achievement goals due to their low loadings on their respective reflective constructs. Participants' scores on multiple-choice, short-answer, and problem-solving questions in the pretest and posttest are separately synthesized. Their resulting Average Variance Extracted (AVE) are 54.86% and 55.37% respectively, greater than the threshold of acceptance. Note that PCA automatically synthesizes a continuous output that follows standardized distribution. To focus on the measurement of participants' mental workload, we dropped the NASA-TLX item on physical demand – How physically demanding was the task? We followed the tradition and added up the scores on the remaining five items to represent participants' engagement *before* or *after* treatment.

4.3 Tests of Hypothesis – Competition

Hypothesis 1 examines the impact of competition on engagement (H1a) and on learning outcomes (H1b). To test Hypothesis 1, we combined C-Win and C-Lose Groups into a C Group and contrasted it with the NC Group. As shown in Column (1) of Table 2, although participants in the C Group demonstrated slightly higher engagement, no significant difference is detected (p=.336, one-tailed). Nevertheless, as shown in Column (2) of Table 2, comparisons without combining C-Win and C-Lose Groups show an interesting pattern – participants in the C-Lose Group show the highest level of engagement (18.79), followed by the NC Group (17.82), and then by the C-Win Group (16.99). The treatment effect of three groups is significant at p=.072, while the difference between C-Win and C-Lose Groups is statistically significant (p=.022).

The necessity of separating C-Win and C-Lose Groups is further illustrated by the test on learning outcomes (Columns (3) and (4) of Table 2). When combining C-Win and C-Lose, the hypothesis test of C>NC not only shows no statistical difference, but also a wrong direction (p=.585, one-tailed). Decomposing the C Group shows what happened – participants in the C-Win Group demonstrated the best learning outcomes (.196) and those in the C-Lose Group the worst (-.124). Their difference is statistically significant (p=.077).

Overall, the results above provide evidence that although losing the gamified TML competition triggers participants' higher engagement, the learning outcomes do not follow automatically. Engagement and learning outcomes of the NC Group lie between the competition groups, providing an alternative explanation for why the studies of competitive versus non-competitive contexts frequently show inconsistent results. As such, later hypothesis testing will be conducted by keeping the C-Win and C-Lose Groups separated.

4.4 Tests of Hypothesis – Gender

We examine gender's main effect before testing its moderating effect. As shown in Column (2) of Table 2, gender does not show significant main effect engagement (M=18.12; W=17.61; p=.217, one-tailed). Nevertheless, Column (4) of Table 2 suggests that men demonstrate better learning outcomes than women in gamified TML (M=.213; W=-.121; p=.020, one-tailed).

Hypothesis 2 focuses on gender's moderating effect between competition and engagement (H2a) and learning outcomes (H2b). As shown in Table 2, the interaction effect of gender and competition is statistically significant across the board. Additional statistical analyses on the interaction effect indicate that losing the mini-games induces the highest level of engagement in both men and women (M=18.99; W=18.58). When there is no competition, female participants show a high level of engagement (18.47) nearly identical to those who lose the competitions. Female participants reveal the lowest level of engagement (15.76) among all three conditions in the winning games treatment. In contrast, male participants display the lowest engagement (17.16) of the three conditions when there is no competition. Men show a moderate level of engagement when winning the competitions (18.21).

As to learning outcomes, women learn the best when they do not compete (.125), followed by winning the mini-games (-.062) and then by losing the competitions (-.427). Men in the C-Win Group (.453) outperform those in the C-Lose (.179) and the NC (.006) Groups..

In summary, men and women perceive competition and interpret competitive results differently. While competition increases men's engagement level and their learning outcomes, women perform better and engage more without competition. Such results suggest the importance of understanding TML and gamification users' individual differences, so as to avoid the one-size-for-all system that improves some users' performance at the price of reducing others'

	Overall		By Competition						By Gender				
	Range	All (n=145)	NC (n=46)	C-Win (n=50)	C-Lose (n=49)	ANOVA		KW	Male (n=91)	Female (n=54)	ANOVA		KW
						F	p	p			F	p	p
Male Percentage	-	63.0%	58.7%	62.0%	67.3%	0.38	.68	.62	-	-	-	-	-
Age	19-34	21.06 (2.04)	20.83 (1.68)	21.06 (2.29)	21.27 (2.10)	0.55	.58	.40	21.33 (2.32)	20.59 (1.34)	4.53	.04**	.67
GPA	0-4	3.04 (.50)	3.17 (.49)	2.99 (.51)	2.96 (.49)	2.57	.08*	.33	2.99 (0.52)	3.12 (0.47)	2.14	.15	.16
Academic Status													
Freshman		23	11	5	7				15	8			
Sophomore	-	88	24	35	29		.31^		54	34		.91^	
Junior		33	10	10	13				21	12			
Senior		1	1	0	0				1	0			
Prior DB Knowledge	0-3	.83 (.98)	.76 (.97)	.84 (.98)	.88 (1.01)	.17	.84	.79	0.78 (0.95)	0.91 (1.03)	0.57	.45	.51
Computer Usage (hours/day)	1-11	3.43 (2.05)	3.26 (1.87)	3.42 (1.89)	3.61 (2.38)	0.35	.71	.83	3.21 (2.07)	3.81 (1.97)	3.00	.09*	.02**
Gaming Experience (hours/day)	0-5	.89 (.94)	.96 (1.12)	.79 (.66)	.93 (1.00)	0.45	.64	.99	1.02 (0.97)	0.68 (0.85)	4.65	.03**	.01**
Mastery	S.D.	0 (1)	-.05 (1.03)	.00 (1.04)	.03 (0.97)	0.08	.92	.92	0.02 (1.01)	-0.05 (1.01)	0.19	.67	.60
Performance-Approach	S.D.	0 (1)	.03 (.93)	-.01 (.97)	-.02 (1.13)	0.04	.96	.96	0.04 (1.03)	-0.07 (0.97)	0.46	.50	.41
Performance-Avoidance	S.D.	0 (1)	.11 (1.06)	.19 (0.99)	-.32 (0.87)	3.87	.02**	.02**	-0.15 (1.01)	0.23 (0.94)	5.06	.03**	.04**

NC, C-Win, and C-Lose denote No-Competition, Competition-Win, and Competition-Lose, respectively.
* or ** denotes p<.10 or .05; S.D. denotes standardized normal distribution;
Standard deviations are shown in parenthesis; KW shows the results of the Kruskal–Wallis one-way ANOVA.
^ denotes Pearson's Chi-Square test, where senior and junior students were combined to make all cell values ≥5

Table 1 Participant Descriptive Statistics by Conditions and by Gender

4.5 Tests of Hypothesis – Achievement Goals

Hypothesis 3 focuses on the impact of performance-approach goals on engagement (H3a) and learning outcomes (H3b) in gamified TML. As shown in Columns (2) and (4) of Table (2), although performance-approach goal shows no significant impact on engagement (p=.282), participants with higher performance-approach goals demonstrated marginally better learning outcomes than those with lower performance-approach goals (p=0.082), supporting H3b.

Hypothesis 4 scrutinizes the impact of performance-avoidance goals on engagement (H4a) and learning outcomes (H4b). Column (2) of Table 2 shows its significant main effect (p=.001) and interaction effect (p=.020) on engagement. Additional tests on the interaction effect indicate that participants with higher performance-avoidance goals demonstrate significantly higher engagement than those with lower performance-avoidance goals. Losing the competitions triggers the highest levels of engagement, especially for those with high performance-avoidance goals (H=19.46; L=18.11). Expectedly, when there is no competition, participants with higher or lower performance-avoidance goals show similar levels of engagement (H=18.00; L=17.63). However, after winning the competitions, participants with low performance-avoidance goals seem satisfied and reveal the lowest level of engagement (14.64), while those with high performance-avoidance goals still maintain high engagement (19.33). Performance-avoidance goals show neither main nor interaction effect on learning outcomes. Hypothesis 4b is not supported.

	(1)	(2)	(3)	(4)
Dependent Variable	Engagement – Posttest		Learning Outcomes – Posttest	
Independent Variable: F-Value (p-value)				
Competition (C vs. NC)	.181 (.336)		.046 (.585)	
Competition (C-Win, C-Lose, NC)		2.694 (.072*)		1.604 (.205)
Gender	.001 (.971)	.615 (.217)	1.924 (.168)	4.307 (.020**)
Gender * Competition	4.086 (.045**)	3.063 (.050*)	4.656 (.033**)	2.344 (.100*)
Mastery Goal (High vs. Low)	1.103 (.296)	.209 (.649)	.425 (.516)	.047 (.828)
Performance-Approach (H vs. L)	.022 (.883)	1.167 (.282)	3.547 (.062*)	3.067 (.082*)
Performance-Avoidance (H vs. L)	3.448 (.066*)	10.615 (.001***)	1.054 (.306)	1.133 (.289)
Mastery Goal * Competition	.654 (.420)	1.432 (.243)	3.426 (.066*)	2.148 (.121)
Performance-Approach * Competition	2.265 (.135)	1.836 (.164)	2.318 (.130)	.928 (.398)
Performance-Avoidance* Competition	2.565 (.112)	4.035 (.020**)	1.430 (.234)	.511 (.601)
Covariate: F-Value (p-value)				
GPA	3.618 (.059*)	2.254 (.136)	.390 (.533)	.263 (.609)
Age	1.436 (.233)	1.386 (.241)	3.478 (.064*)	3.314 (.071*)
Computer Usage	.000 (.988)	.015 (.902)	13.953 (.000***)	14.600 (.000***)
Gaming Experience	.132 (.717)	.000 (.988)	.866 (.354)	.446 (.506)
Engagement – Pretest	95.820 (.000***)	103.92 (.000***)		
Learning Outcome – Pretest			34.553 (.000***)	31.000 (.000***)
Marginal Estimated Means: Mean (Standard Error)				
NC Group	17.78 (.55)	17.82 (.54)	.065 (.13)	.066 (.13)
C Group	18.07 (.38)		.032 (.09)	
C-Win Group		16.99 (.54)		.196 (.13)
C-Lose Group		18.79 (.56)		-.124 (.13)
Model Adjusted R^2	.425	.448	.275	.275

***, **, *: p <0.01, <.05, <.10, respectively. C denotes competitive context (i.e., C-Win and C-Lose); NC denotes no competition. Marginal estimated means and associated standard errors show the group-wise central tendency and dispersion of the dependent variables *after controlling for the impact of covariates*.

Table 2 ANCOVA Results

5 CONCLUSIONS

In the era of emerging information technologies, competitions in a TML environment are not necessarily zero-sum; instead, gamification designers can fine-tune the degree of challenge or customize the training interface or process to satisfy various users' need. Understanding how individual difference moderate the relationship between gamification design and TML outcomes becomes an inevitable task. By conducting a laboratory experiment, this research examines how gender and achievement goals interact with the element of competition to affect outcomes of a gamified TML system. In prior IS research, gender is shown to have an impact on use of IS (Venkatesh and Morris 2000). We add that males and females react very differently to the competitive elements in a gamified TML. We find that losing in a competition is the most engaging setting for both females and males, but females engaged more by no competition than by winning, and the opposite is true for males. Relatedly, while winning yields better learning outcomes than losing for both genders, females learn best when there is no competition, but males learn best when there is.

We also find that performance-avoidance goals are a significant predictor of engagement: people with higher performance-avoidance goals show higher levels of engagement in competitive gamified TML. Interestingly, individuals with high performance-avoidance goals are engaged similarly in winning and losing conditions (both more than in the no competition condition), whereas individuals with low performance avoidance goals are engaged by losing and no competition conditions, but not by the winning condition. This suggests that performance avoidance is more useful for predicting how people react to winning, than for losing.

Overall, our findings offer new insights into why competition can have very different effects on engagement and learning outcomes depending on whether one is winning or losing. Our results point to two individual differences, gender and performance avoidance, as potential factors for predicting different effects of competition. Such findings have both theoretical value and design implications on how we can use competitive game elements effectively. Arroyo et al. (2013) conclude that the motivation of girls and boys and their responses to specific aspects of the TML module are dissimilar enough to warrant technology customized to each gender. Wilhelmsson (2013) reaches a similar conclusion. Our results underscore the importance of personalization – for gender and performance-avoidance goals – when using competition in gamified TML.

As with all empirical studies, this research suffers from several limitations as well. First, to avoid fatigue and to focus on the impact of gender and achievement goals on the competition, our experiment contains only two phases with two tutorial videos that last about one hour in total. We have no intent to over-stretch our results or advocate the design of a competitive TML that allows users to constantly win or lose. Instead, we emphasize the delicate impact of individual difference on outcomes and encourage future researchers to explore the long-term effect on engagement and learning outcomes. Second, we chose database management as the subject for TML content. Future research is needed to examine whether our results hold on domains that mandate more practice or with more emphasis on procedural knowledge (e.g., accounting, algebra). Third, although we explicitly discouraged participants' from discussing the experiment details with others, we could not statistically measure the impact of diffusion on the research results. Nevertheless, due to the random assignment, we do not expect the diffusion to systematically bias our results. Lastly, although using student subjects in a laboratory experiment helps maintain internal validity of the study, its external validity requires further examination and replication. As one of the first studies on the interaction between individual difference and competition in gamified technology-mediated learning, this research opens the door to numerous extensions that may help the development and implementation of gamification.

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