ONLINE APPENDICES

Appendix A. Brief Review of Online Learning and Gamification

Table A1. Review of Empirical Studies on Online Learning in the Basket of Eight Journals over the Past Five Years (full references provided at the end of the appendices)

Paper	Research Context	Theoretical Framework	Research Methods	Main Findings
Piccoli et al. (2020)	Online learning for massified education (e.g., massive open online courses (MOOCs) and virtual learning environments)	Intervention theory	Design science method with three iterations to develop a socio-technical artifact that offers a solution to the general problem of providing performance feedback at scale to 310 users	The design of effective and efficient feedback systems for digital skill mastery is an important area of research. The artifact is scalable to a large number of learners, provides near-real-time, valid, and reliable feedback, and has a positive impact on learners' behaviors and engagement.
Huang et al. (2021)	Counteracting procrastination in MOOCs and online learning management systems (LMS)	Temporal motivation theory	Randomized field experiment in a leading MOOC platform in China with calls to action (CTA) interventions delivered in the form of both emails and on-platform notifications	To alleviate the high levels of procrastination by learners in MOOCs, the study used different types of CTA interventions that prompt the completion and submission of course assignments. Descriptive norm interventions that communicate peer assignment completion rates lead to higher probabilities of completion and shorter time to completion. Several moderators were identified.
Hull et al. (2019)	Problem-based learning for information systems management education	Cognitive load theory, cognitive evaluation theory, constructivist learning theory, and social cognitive theory	Development of a three-act series of narrative animated videos that provide training to students	Narrative animated videos are a form of self-determined learning that feature immersive, story-based content. Their use can intrinsically motivate users to process materials to completion,

			and educators to counteract the threat of spear phishing	enhance cognitive and behavioral outcomes, and facilitate team-based learning and self-regulated learning modes for problem-based learning.
Kwak et al. (2019)	Gamified team-based training and learning	Motivational consistency theories and elaboration likelihood model of persuasion	Lab experiment with 232 students (78 teams) in an integrated business process team setting using enterprise resource planning simulation games (ERPsim)	Team-based gamification elements (e.g., leaderboard and team rank) and social groups (team cohesion) play important roles in human information processing in the context of team-based gamified training. It was found that a leaderboard for team cohesion had a positive effect on team performance. Team cohesion positively moderated the relationship between utilitarian perceptions and attitude and negatively moderated the relationship between hedonic perceptions and attitude.
Santhanam et al. (2016)	Technology-mediated learning and training	Social cognitive theory and flow theory	Two-phased laboratory experiment with 182 business university students	No one single competition structure can simultaneously address both learning and engagement outcomes. Trainees who faced lower-skilled competitors developed higher self-efficacy beliefs and better learning outcomes, while trainees who faced equally skilled competitors reported higher levels of engagement.

Table A2. Literature Review of Empirical Studies on Gamification in Non-Learning Contexts in the Basket of Eight Journals over the Past Five Years

Paper	**Research Context**	**Theoretical Framework**	**Research Methods**	**Main Findings**
Chen et al. (2018)	Knowledge sharing using votes and badges	Dynamics of motivation and contribution	Data analysis of 2,147 users from SuperUser.com	Three types of motivating mechanisms (i.e., reciprocity, peer recognition, and self-image) transition users across various latent states (i.e., low, medium, and high) in

				online communities’ voluntary motivation. Reciprocity is only effective in transitioning users from a low to medium motivation state. Peer recognition can boost all users to higher states. Self-image can move users from a low/medium state to a high state but has no effect if a user is already in a high state.
Goes et al. (2016)	Knowledge sharing using reward points and incentive hierarchies	Goal-setting theory and drive-reduction theory	Regression discontinuity design with a random sample of 2,000 users with at least one reward point from StackOverflow.com	Hierarchical incentives may motivate users to contribute more before they reach their goals. User contribution levels drop significantly when the goals are met. The positive effect of hierarchical incentives on users is temporary and increasingly smaller for higher ranks.
Khansa et al. (2015)	Knowledge sharing based on membership level	Goal setting theory	Data analysis (eight weeks) of 2,920 users with public profiles who asked questions on Yahoo! Answers in the past six months	Active online participation is primarily driven by artifacts (e.g., incentives), membership (e.g., levels of membership and tenure), and habits (e.g., past behaviors). Incentives may represent an artificial mechanism that can manipulate goal-setting processes.
Holzer et al. (2020)	Knowledge sharing using game-like features	N/A	Design science approach to develop gamified knowledge management systems for Doctors without Borders	Feedback gamification on users’ perceptions of their sociometric status and behavior can increase individuals’ engagement and altruistic knowledge sharing in the knowledge management system.
Silic and Lowry (2020)	Security training using points, medals, and a leaderboard	Flow theory	Design science research with a six-month field study involving 420 participants who took part in gamified security training	Gamified security training can lead to an improved ability to efficaciously respond to actual phishing attempts.
James et al. (2019)	Exercise using gamification	Goal content theory, self-determination theory, and theory of affordances	Survey study of 619 users recruited from Amazon Mechanical Turk that used fitness technology in the past	Users with intrinsic exercise goals (e.g., enjoyment and competence) are more likely to use the data management features of fitness technology. Users with body-focused extrinsic exercise goals are more likely to use data management features and less likely to use

				social interaction features. Users with social extrinsic goals are more likely to use both exercise control and social interaction features.
Huang et al. (2019)	Video game engagement	Theories of customer engagement and player motivation	Hidden Markov model with two-stage data-analytic modelling on 1,309 randomly sampled gamers' playing histories over 29 months	People with different levels of engagement (i.e., low, medium, and high) respond differently to motivations (e.g., effectance and need for a challenge). Developing a matching algorithm that learns a gamer's current engagement state can maximize gamer game-play volume and frequency by 4–8%, leading to a significant revenue gain for the game company.
Fang et al. (2019)	Social game engagement	Behavioral contagion theory	Data analysis of a social game dataset (RoyalSword) provided by Tencent.com (daily data of 86,022 players in 1 month)	The cohesion effect of players' direct connections in a social gaming network positively affected their willingness to pay. The effect of pure friends was stronger than that of Simmelian-ties.
Bellman and Murray (2018)	Design of an IS interface with feedback on task performance	Feedback intervention theory	Online experiment involving an online game with four types of feedback (i.e., no, positive, neutral, and negative feedback) and two types of interface usage (i.e., 1 and 3 competitor trials) with 482 users	Positive and negative feedback can affect the enjoyment of the hedonic use of IS. Normative feedback, which compares task performance with others', can distract users from learning by excessively focusing on self-concept.

Table A3. Examples of the Positive and Negative Outcomes of Gamified Learning in Relevant Journals over the Past Five Years

Paper	**Research Context and Theoretical Framework**	**Research Methods**	**Main Findings**
Positive Aspects of Gamification			
Park et al. (2019)	Development of a gamified e-learning system called GAMESIT using Malone's theory of intrinsically	Design science and laboratory experiment involving 81 university students	With GAMESIT, learners can enhance learning outcomes (e.g., knowledge comprehension and task performance) and engagement when compared to a non-gamified e-learning system.

	motivating instruction		
Landers et al. (2017)	A study of the impact of leaderboards on employees' task performance with the use of goal-setting theory	Laboratory experiment involving 240 university participants	The addition of leaderboards can improve task performance. However, individual goal commitment moderates the success of leaderboards. If individuals do not believe that the leaderboard is worthwhile or appropriate, it is unlikely to affect their task performance.
Cheong et al. (2014)	A study of students' perception of game elements (e.g., points, leaderboards, profiles, teams, progress bars, and badges)	Survey study of 51 undergraduate IT students to obtain their perceptions of game elements	Students think positively about the usefulness of all game elements in making a gamified system more enjoyable. The progress bar received the highest minimum rating. Leaderboards and badges had the two highest average ratings.
de-Marcos et al. (2016)	A comparison of game-like and social approach gamification on learning performance based on the meaningful gamification framework	Field experiment in a 10-week undergraduate blended course called "Qualification for ICT Users" involving 379 first-year students	Competition reward-based gamification serves as an extrinsic motivator and boosts learning performance when learning objectives and learning activities are carefully aligned with the instrument. Social gamification returns better results in terms of immediacy across various evaluation items.
Krause et al. (2015)	A study of student retention in online education with a comparison of gamification and gamification with social elements	Controlled laboratory experiment involving 213 students majoring in psychology or computer science	With a gamified interface, students show a 25% increase in retention period and 23% higher average scores. Social gamification amplifies the statistics even further with a 50% increase in retention period and 40% higher average scores.
Tenório et al. (2016)	Development of a gamified peer assessment model with game elements such as badges, points, medals, and rankings	Two experiments (30 users) using the proposed gamified peer assessment model within an intelligent tutoring system called MeuTutor.	The average grades given by students in the gamified peer assessment model were equivalent to those given by experts but the time and cost were greatly reduced. Gamification can positively influence the quality and quantity of students' essay assessments.
Tsay et al. (2018)	A study of technology-mediated gamification with the use of self-determination theory and organismic integration theory	Design science and field study in an undergraduate personal and professional development course with 136 students	The course performance was better in a gamified environment than in a non-gamified environment. Engagement in online learning activities was positively related to course performance.

Haug et al. (2014)	A study of open badges to promote learners' activities in MOOCs through the use of self-determination theory and cognitive evaluation theory	Case study of MOOC participants (1,451 participants) using questionnaires and the data analysis of log files	Although learner activities in the MOOC decreased over time, the decrease was smaller among participants who aimed to achieve an open badge or certificate of attendance.
Negative Aspects or Mixed Effects of Gamification			
Kyewski and Krämer (2018)	A study of the impact of badges on students' online learning motivation and performance with the help of cognitive evaluation theory and social comparison theory	Survey study of 126 students who participated in a field study on an online seminar course in a German university	Badges have less impact on students' motivation and learning performance. Badges that are only visible to the focal students seem to be evaluated more positively than badges that can be viewed by the peers, suggesting that badges do not enable social comparison.
Hanus and Fox (2015)	A study of gamification on classroom learning with the help of cognitive evaluation theory and social comparison theory	Longitudinal study with four surveys separated by four weeks untill the end of a semester (71 university students completed all surveys)	A gamified system with special reward features had negative effects on students. Students were less motivated, empowered, and satisfied over time and the gamified course reduced intrinsic motivation, which led to poorer final exam grades.
Christy and Fox (2014)	A study of the effects of leaderboards on females' math performance in a virtual classroom with the use of social comparison theory	A field study of 80 female undergraduate students	Leaderboards evoked social comparisons and academic identification among female students. However, female participants performed more poorly in the female majority leaderboard condition than those in the male majority condition.
Hakulinen et al. (2015)	A study of achievement badges on students' learning performance with the use of cognitive evaluation theory	Randomized online experiment with 281 university students in a data structure and algorithm course	Collecting achievement badges did not affect final grades. However, exercise points in the experiment had a positive relationship with grades.
Hakulinen and Auvinen (2014)	A study of gamification on students' learning behavior with the use of achievement goal orientation theory	Field experiment with 278 students in a data structure and algorithm course	There was no statistically significant difference in the learning behavior across groups with different goal orientations regarding badges. However, students' attitudes toward badges varied. Students who reported high motivation toward badges had higher mastery-intrinsic, mastery-extrinsic, and

			performance-approach orientations. However, not all high-performing students were motivated by badges.
van Roy and Zaman (2018)	A study of the effects of need-supporting gamification on students' learning motivation in an online learning environment with the use of self-determination theory	Four survey studies over a 15-week period with 40 students who interacted with need-supporting game elements in Google+ communities for a university course	The affordances of individual game elements influenced the motivational effects of gamification. The motivational impact of gamification was person-specific.
Mekler et al. (2017)	A study of gamification on students' motivation and task performance with the use of self-determination theory, achievement goal theory, and causality orientation theory	2 (causality orientations, namely, autonomy and control orientations) by 4 (game conditions: points, leaderboards, levels, and no game elements) online experiment on an image annotation task with 273 participants recruited via email from a university database	Compared to the control condition, game elements did not significantly affect competence and intrinsic motivation regardless of participants' causality orientations. However, participants' performance did not mirror their intrinsic motivations and game elements (e.g., points, levels, and leaderboards) and may act as an extrinsic incentive while promoting performance quantity.

Appendix B. Screenshots of Online Course on KEEP

Figure B1 General Introduction of KEEP to students

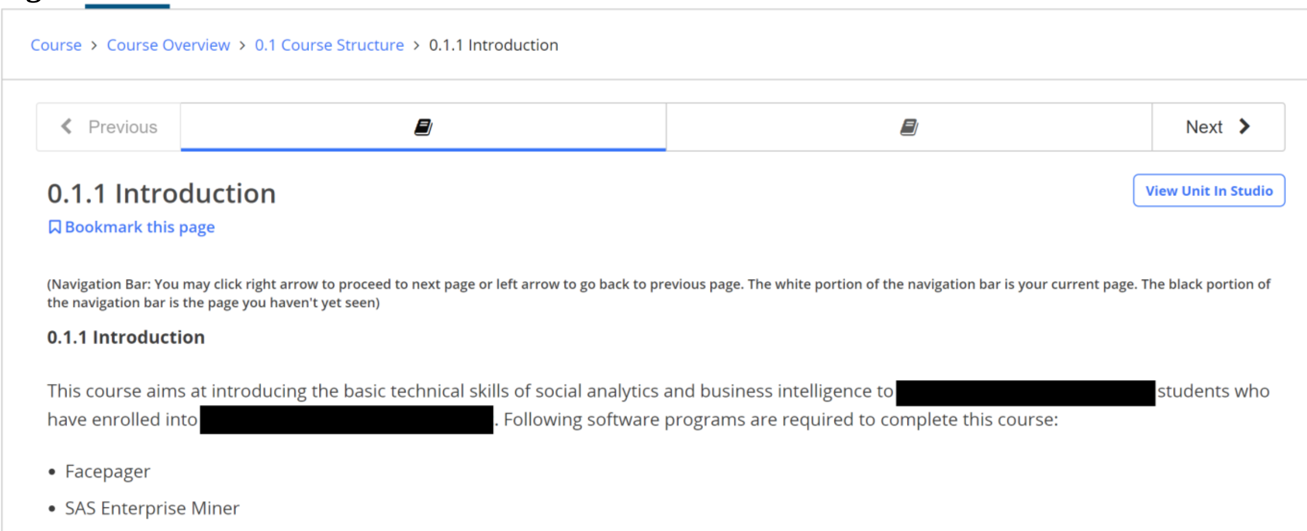


Figure B2 Planning Learning Activities

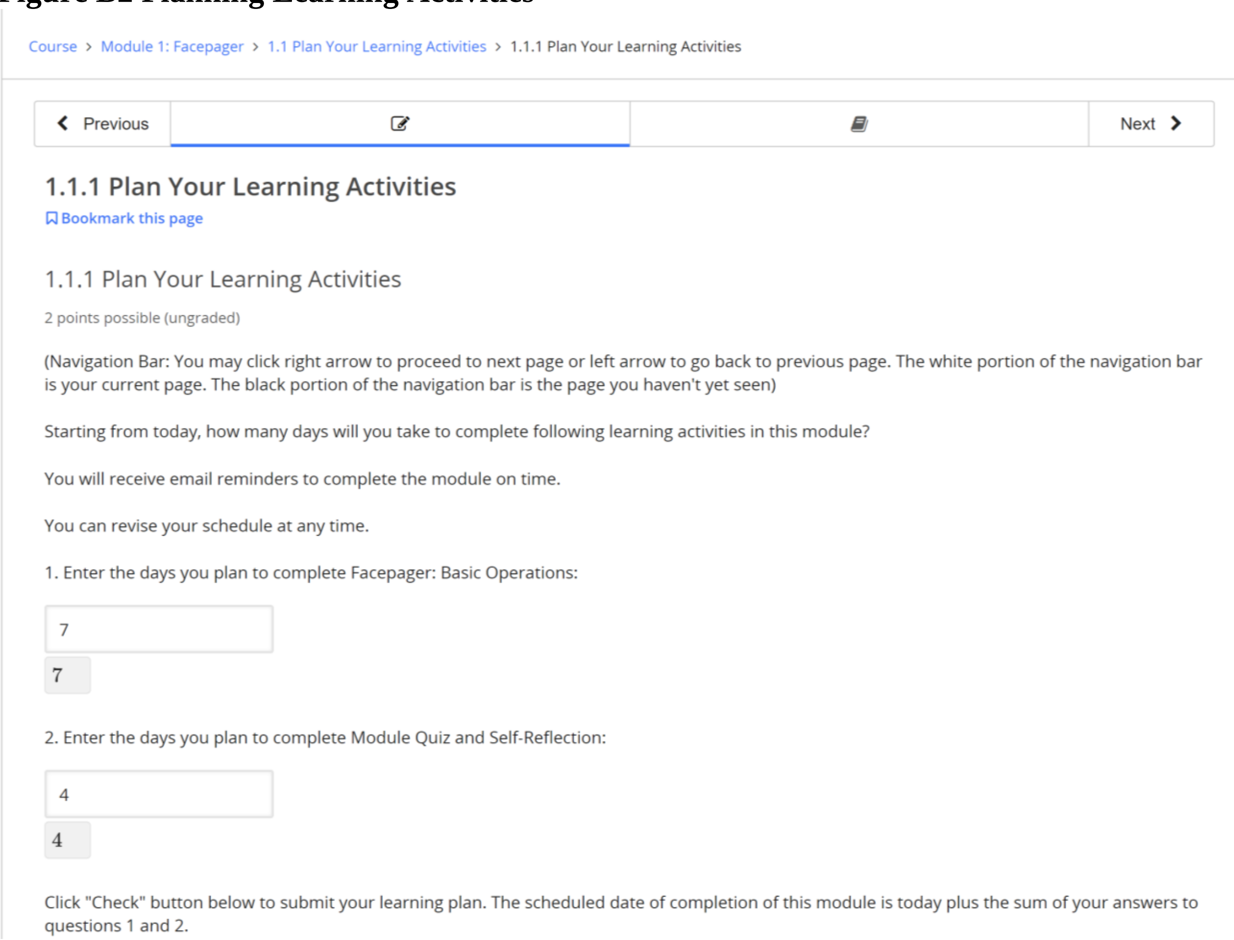


Figure B3 Reading and Posting Questions on a Learning Forum

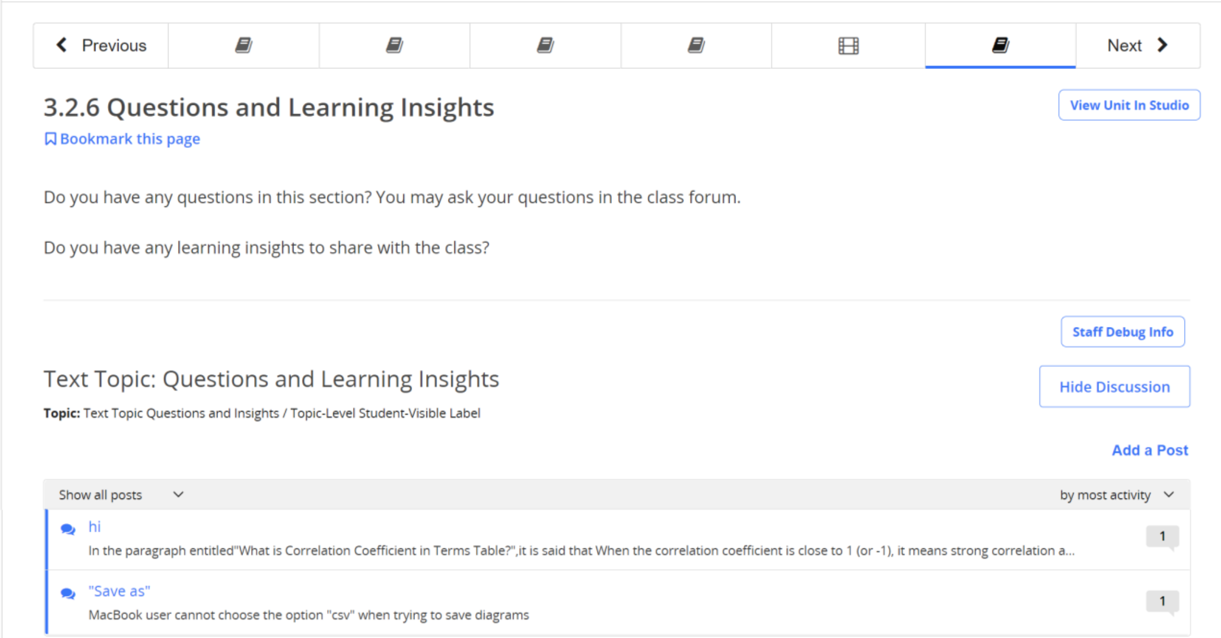


Figure B4 Reading and Initiating Discussions on a Learning Forum

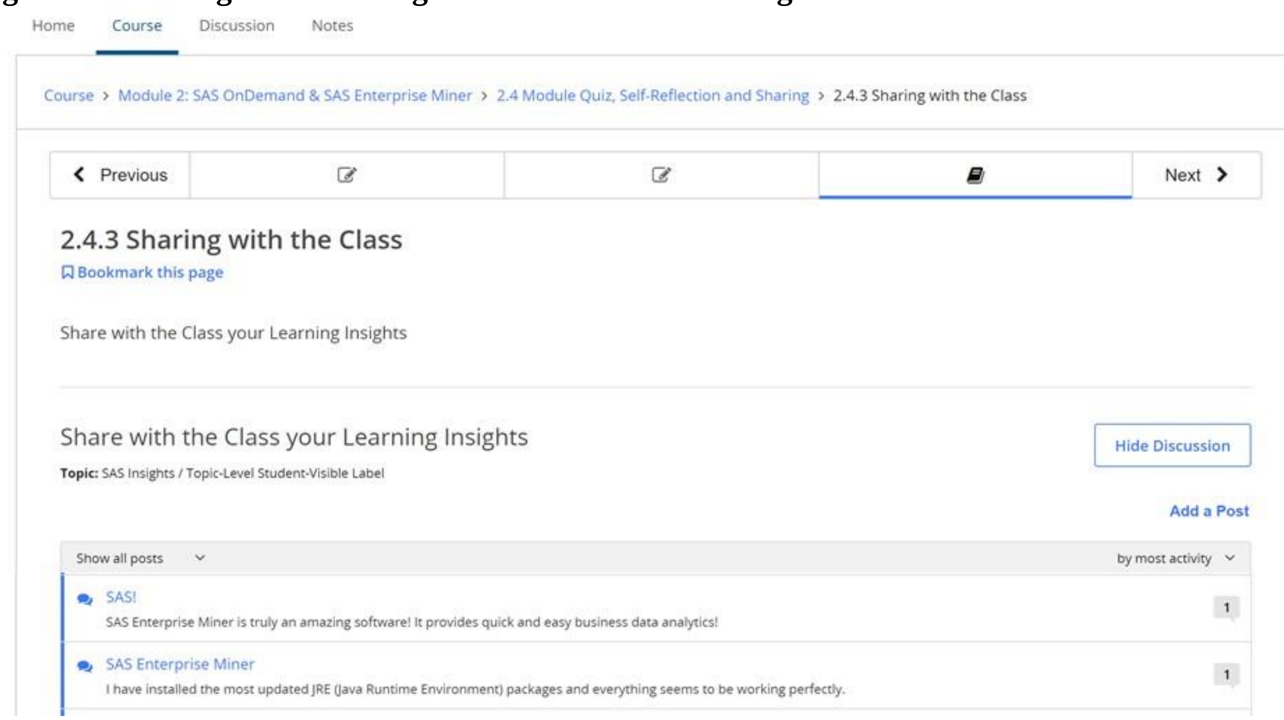


Figure B5 Sample Learning Materials

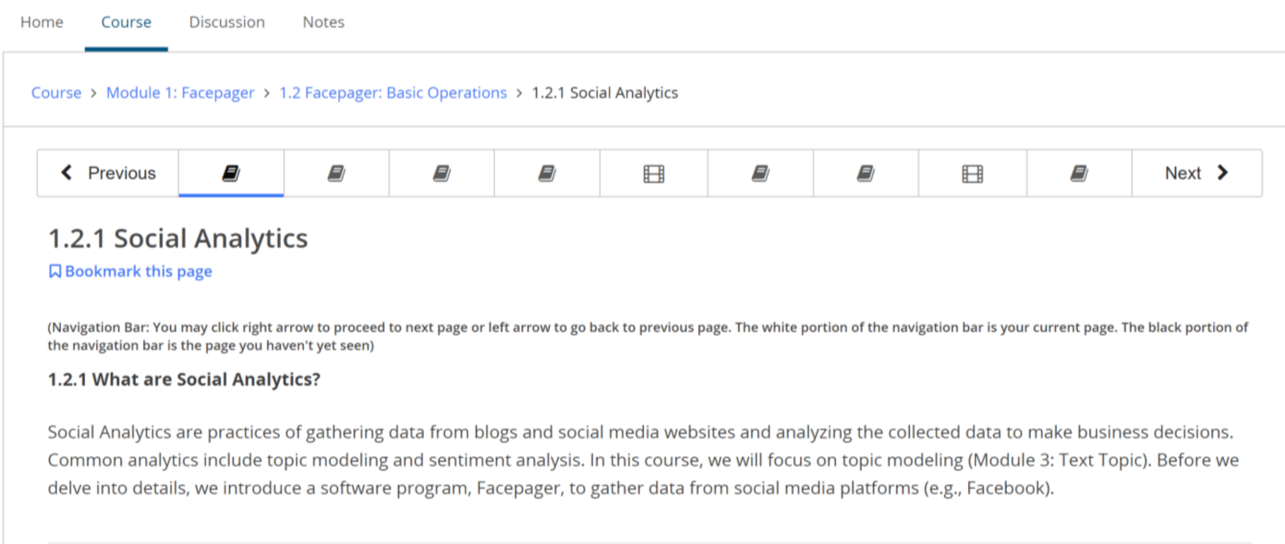


Figure B6 Sample Tutorial Video

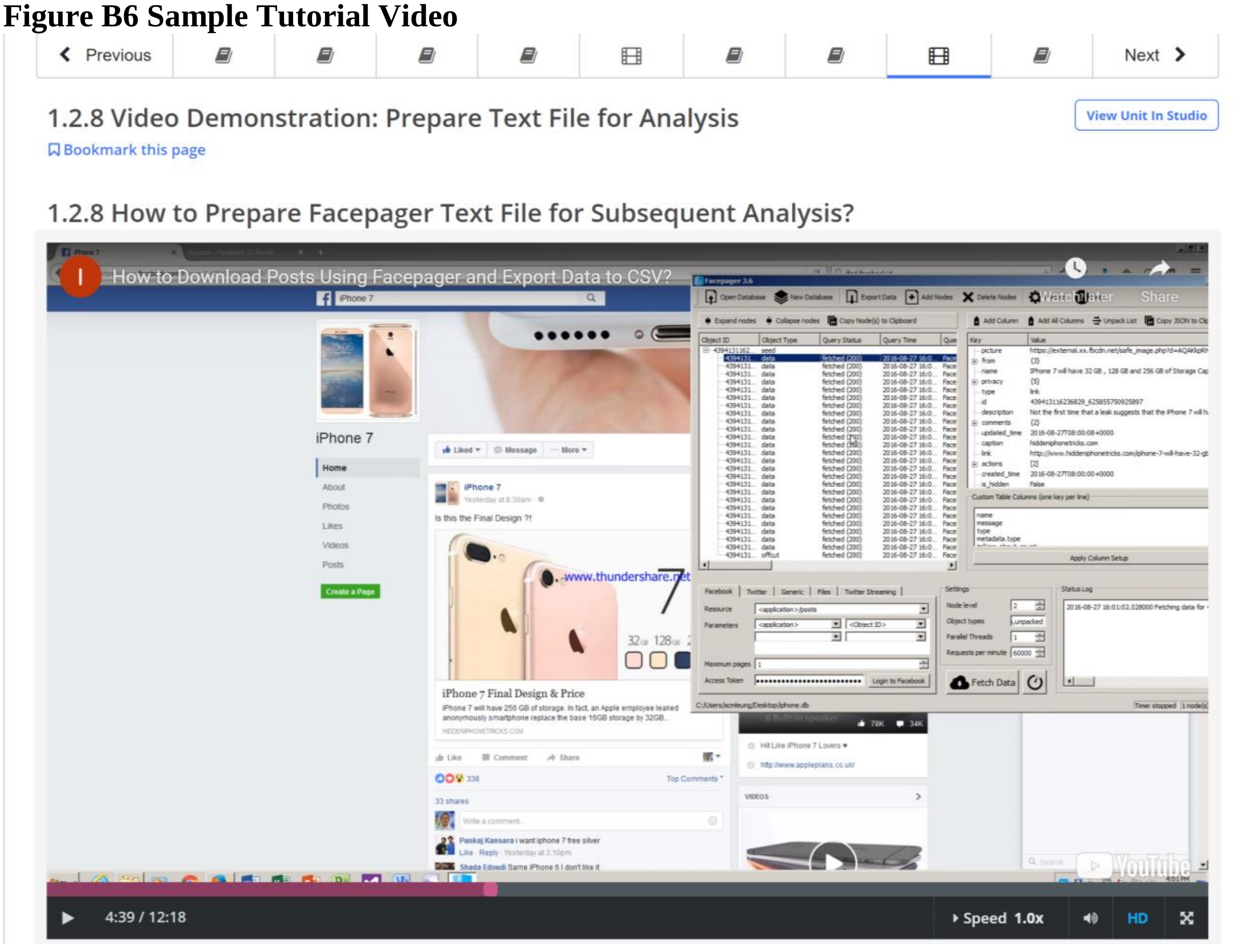


Figure B7 Sample Module Quiz

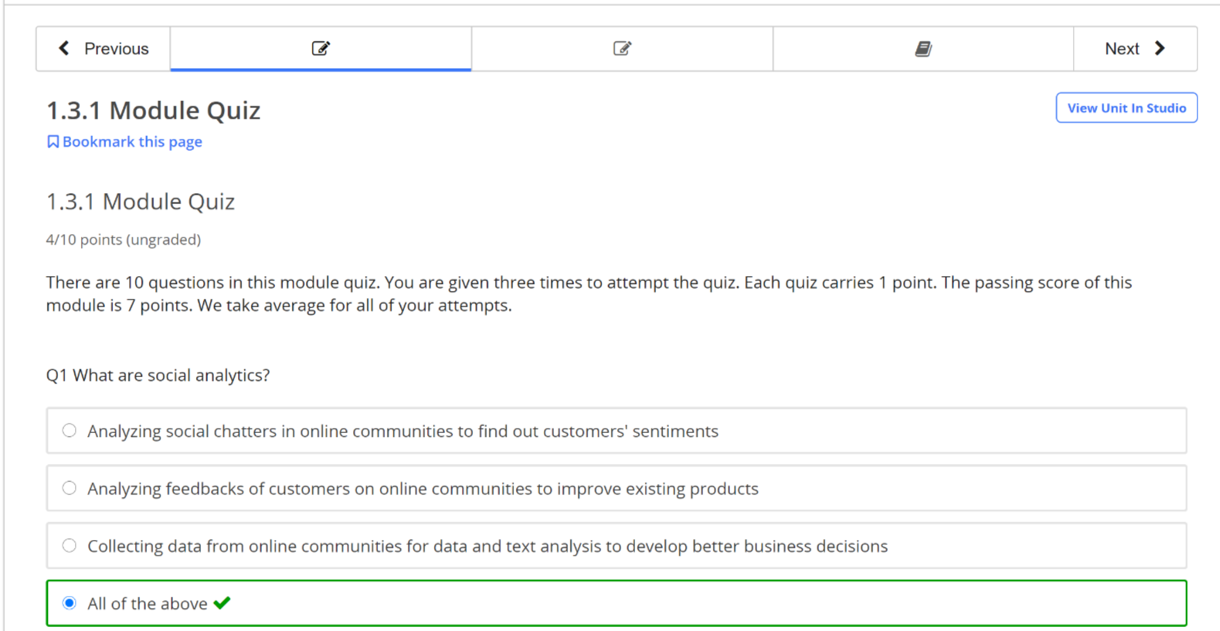


Figure B8 Note Taking

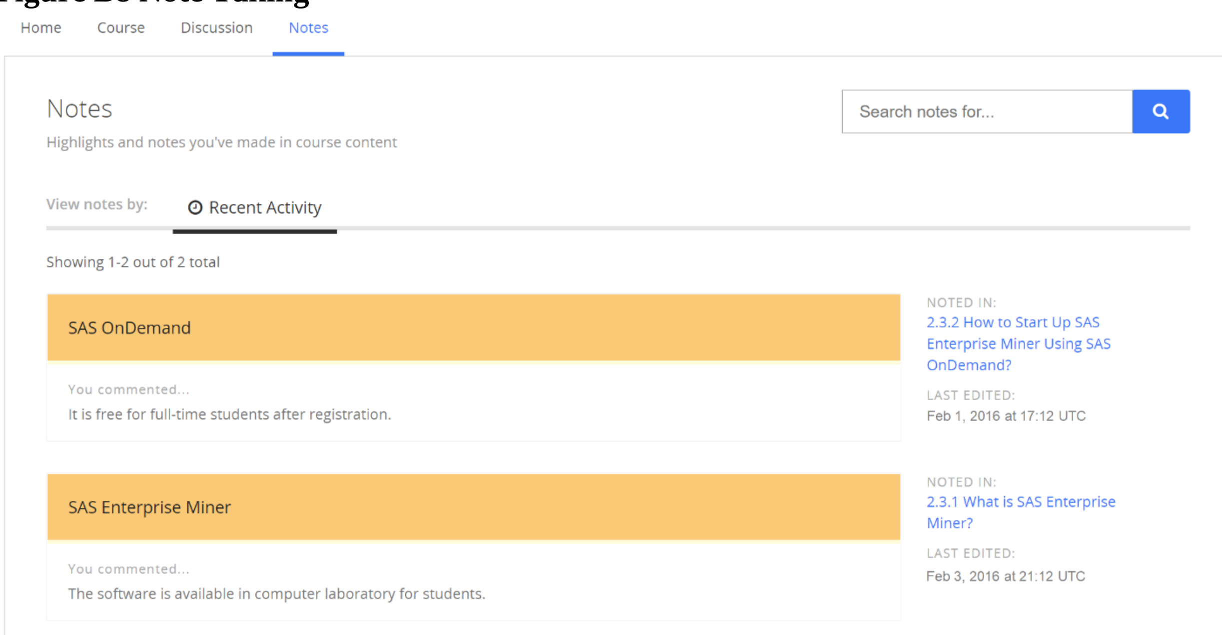


Figure B9 Note Editing

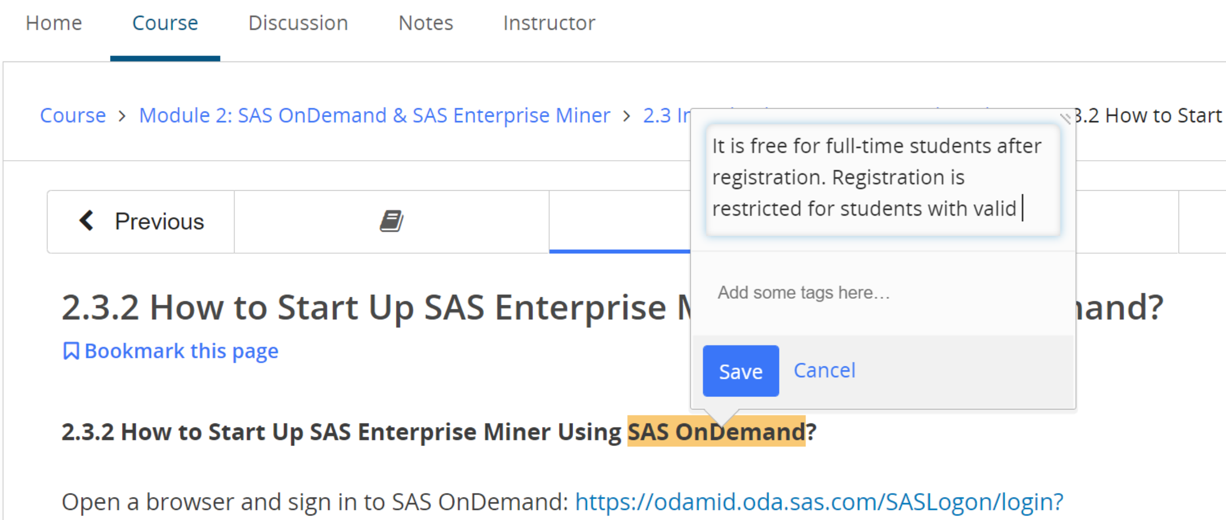
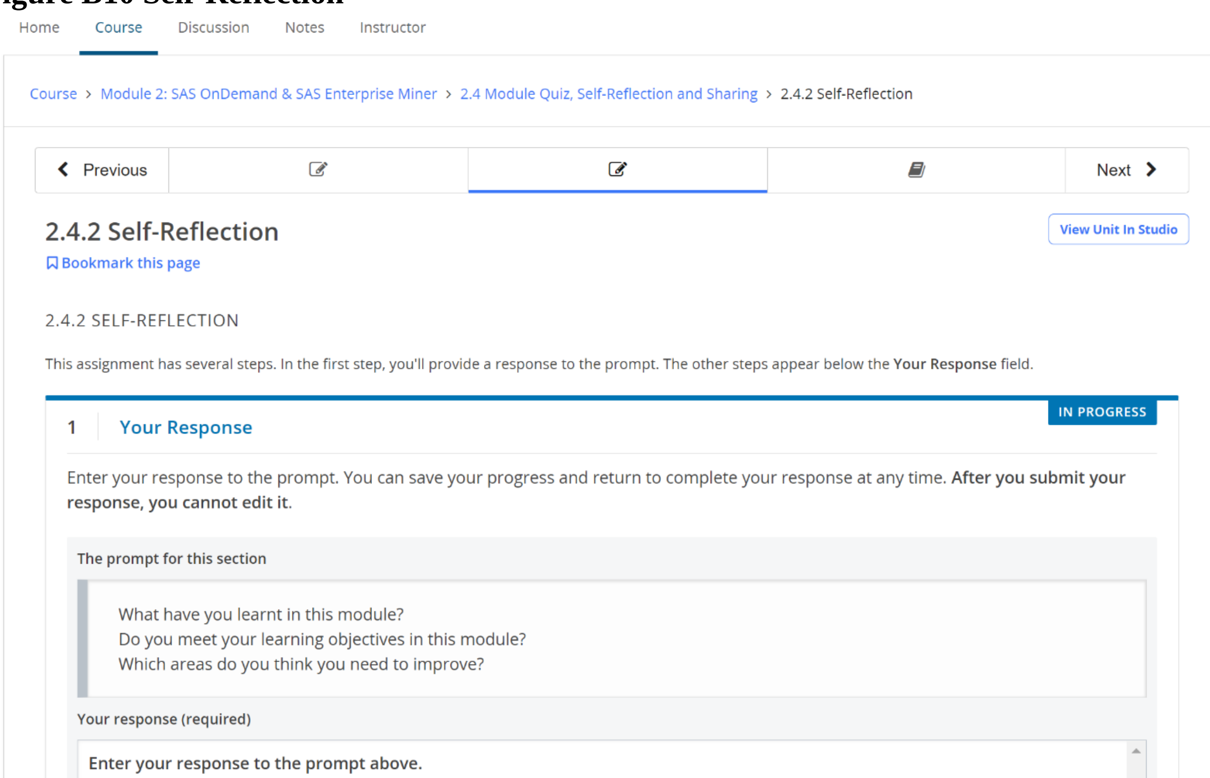


Figure B10 Self-Reflection



Appendix C. Samples of Gamified Performance Feedback

Figure C1 Example of Gamified Performance Feedback with Positive Personal Comparison

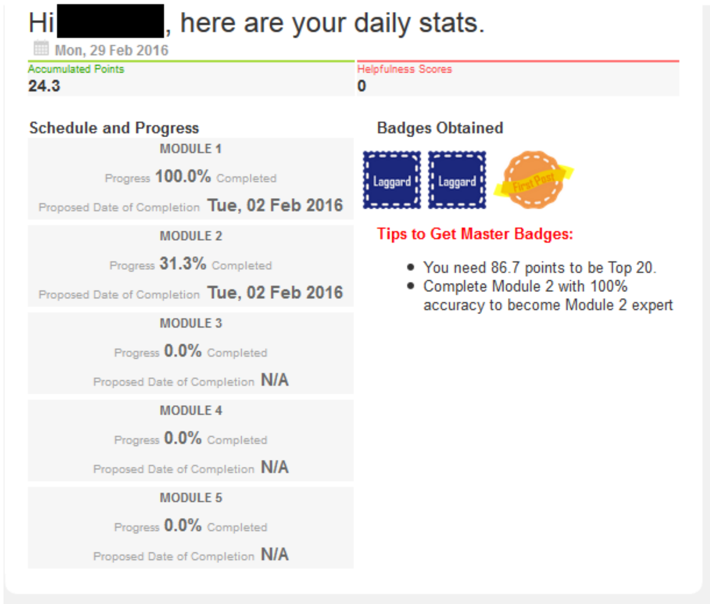
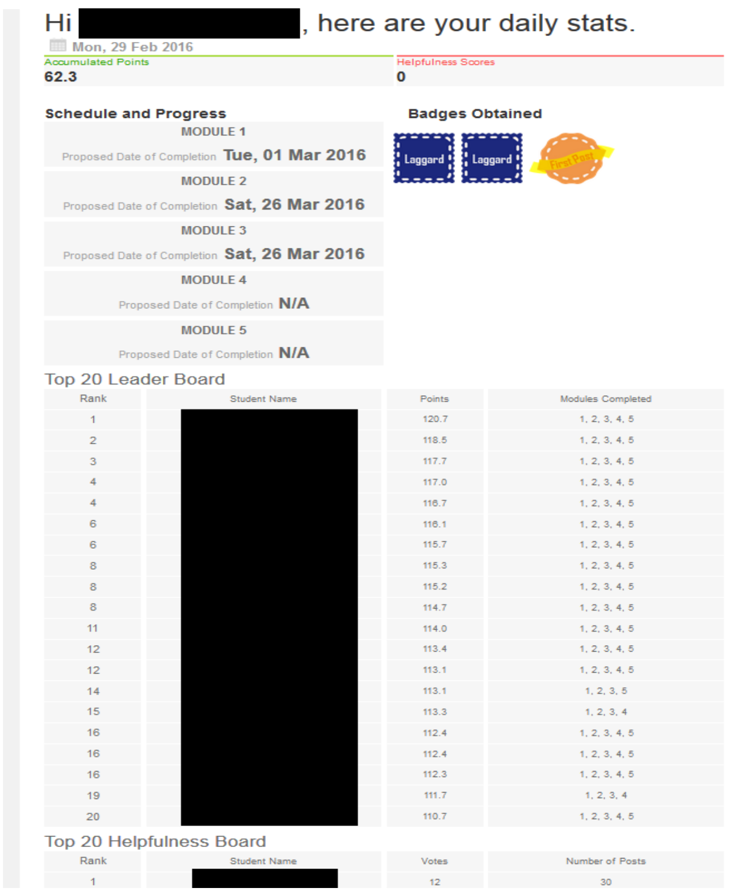


Figure C2. Example of Gamified Performance Feedback with Positive Social Comparison



Rank	Student Name	Points	Modules Completed
1	[redacted]	120.7	1, 2, 3, 4, 5
2		118.5	1, 2, 3, 4, 5
3		117.7	1, 2, 3, 4, 5
4		117.0	1, 2, 3, 4, 5
4		116.7	1, 2, 3, 4, 5
6		116.1	1, 2, 3, 4, 5
6		115.7	1, 2, 3, 4, 5
8		115.3	1, 2, 3, 4, 5
8		115.2	1, 2, 3, 4, 5
8		114.7	1, 2, 3, 4, 5
11		114.0	1, 2, 3, 4, 5
12		113.4	1, 2, 3, 4, 5
12		113.1	1, 2, 3, 4, 5
14		113.1	1, 2, 3, 5
15		113.3	1, 2, 3, 4
16		112.4	1, 2, 3, 4, 5
16		112.4	1, 2, 3, 4, 5
16		112.3	1, 2, 3, 4, 5
19		111.7	1, 2, 3, 4
20		110.7	1, 2, 3, 4, 5

Top 20 Helpfulness Board

Rank	Student Name	Votes	Number of Posts
1	[redacted]	12	30

Figure C3. Example of Gamified Performance Feedback with Negative Personal Comparison

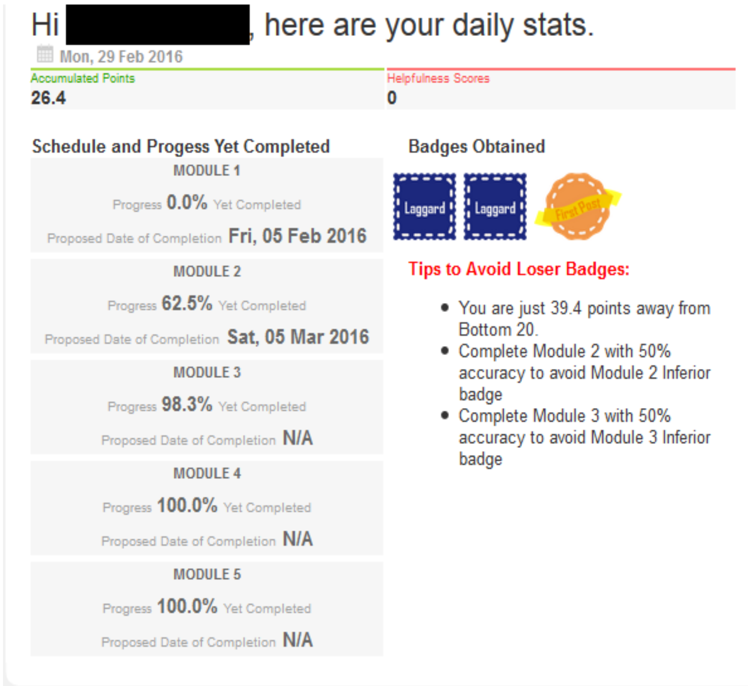


Figure C4. Example of Gamified Performance Feedback with Negative Social Comparison

Figure C5. Example of Control Group without Gamified Performance Feedback

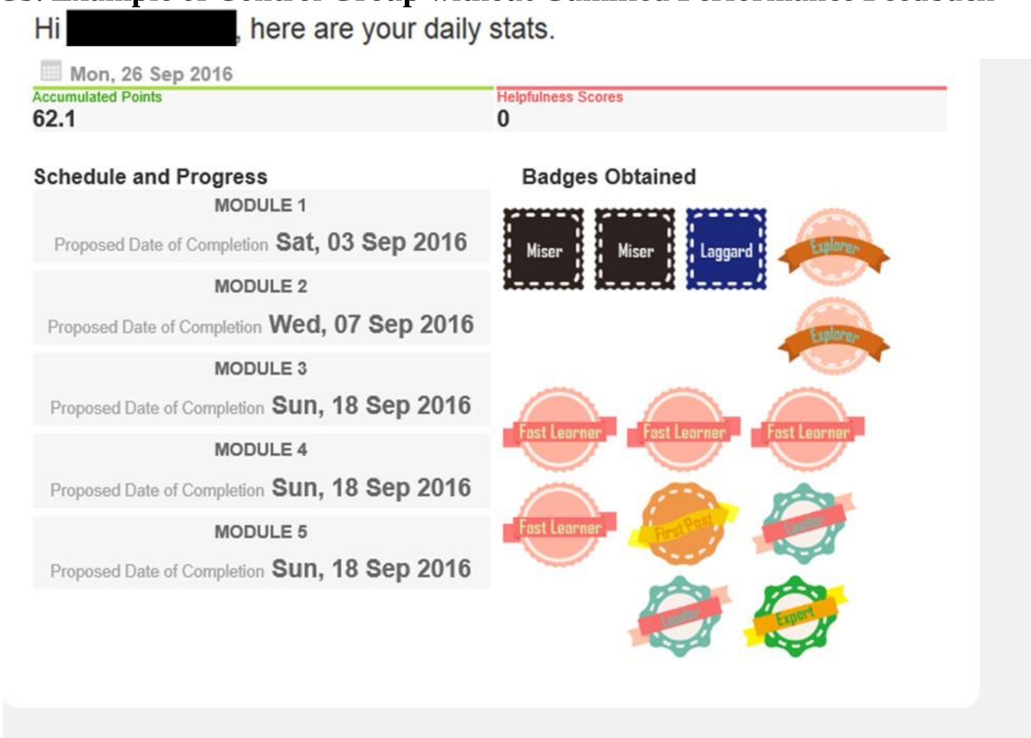
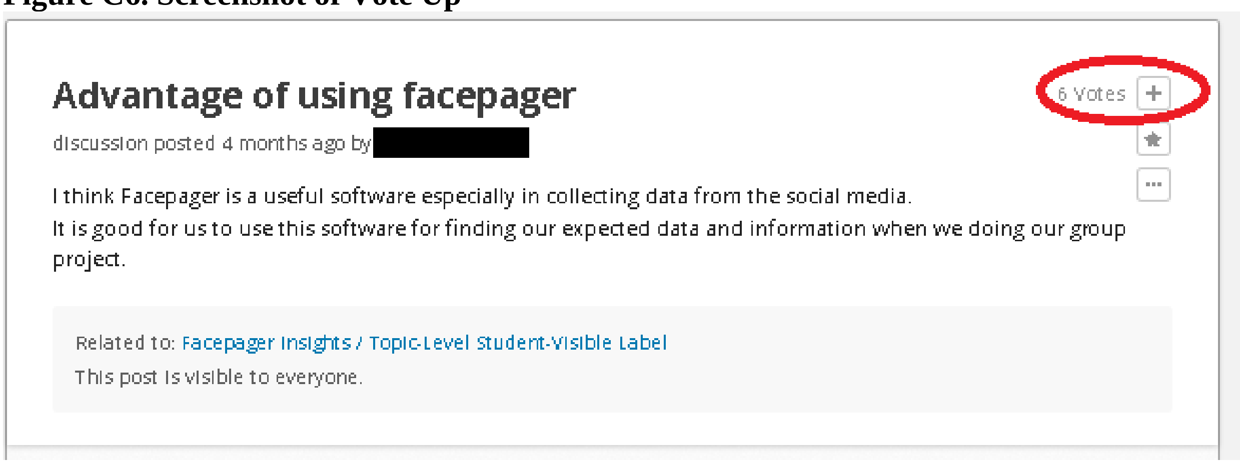


Figure C6. Screenshot of Vote Up



Appendix D. Pre-experiment Learning Orientation, Background Survey and Knowledge Test

This questionnaire aims to know more about your learning goal and general knowledge of information management. It is a part of teaching and learning project supported by **[Teaching and Learning Grant Anonymized]** for the benefits of **[Course Name Anonymized]**. By participating in this questionnaire, you will get 1% bonus on top of your coursework and exam in this course. Please answer all questions. Some questions may test your knowledge on some future course topics. There is no penalty for incorrect answers. Don't worry!

Answer questions 1-14 with following options:
(A): Strongly disagree; (B): Disagree; (C): Neutral; (D): Agree; (E): Strongly agree

(1) It's important to me that I learn a lot of new concepts this year.
(2) It's important to me that I thoroughly understand my class work.
(3) It's important to me that I improve my skills this year.
(4) It's important to me that other students in my class think I am good at my class work.
(5) It's important to me that I look smart compared to others in my class.
(6) It's important to me that I don't look stupid in class.
(7) It's important to me that my teacher doesn't think that I know less than others in class.
(8) The sun rises from the west.
(9) One of my learning goals in class is to learn as much as I can.
(10) One of my learning goals is to master a lot of new skills this year.
(11) One of my learning goals is to show others that I'm good at my class work.
(12) One of my learning goals is to show others that class work is easy for me.
(13) One of my learning goals is to look smart in comparison to the other students in my class.
(14) One of my learning goals is to keep others from thinking I'm not smart in class.
(15) One of my learning goals in class is to avoid looking like I have trouble doing the work.

Select appropriate answer for following questions.

(16) Do you know Facepager?
(A) No. (B) Yes, I have heard of it but never use it. (C) Yes, I have used it before but not very familiar with it. (D) Yes, I am familiar with it and know basic operations.

(17) Do you know SAS Enterprise Miner?
(A) No. (B) Yes, I have heard of it but never use it. (C) Yes, I have used it before but not very familiar with it. (D) Yes, I am familiar with it and know basic operations.

(18) What is business intelligence?
(A) Use robots to mimic human intelligence and automate some manual tasks.
(B) Use IT to communicate with other project team members and use collective intelligence to develop better corporate strategies.
(C) Use enterprise databases to store corporate data for subsequent analysis; the databases represent collective intelligence of a corporation.
(D) Use past data to predict for the future trend so as to make better business decisions.

(19) What are social analytics?
(A) Collect and analyze social media platform data so as to understand preferences of online users.
(B) Investigate how social media change the attitudes of customers to a brand.
(C) Use data mining approach to find out how likely a social media user will buy a product.
(D) Use collective wisdom obtained from social media to predict for future trends.

(20) _________ is a technique to derive meaningful patterns from words.
(A) Data mining; (B) Text mining; (C) Cluster analysis; (D) Association detection

(21) ________ is a technique to find out common themes among online user communications.
(A) Data mining; (B) Text Topic analysis; (C) Sentiment analysis; (D) Association detection

(22) What is sentiment analysis?
(A) It is a type of text mining to analyze the general perception of customers to a product/service based on their online reviews.
(B) It is a type of data mining to find out the loyalty of customers to a brand.
(C) It is a type of association detection that links the mood of a user to the usage of a product/service.
(D) It is a type of cluster analysis that groups users with similar comments together.

(23) What kind of analysis is suitable to find out how likely a customer will purchase Product A if he/she has already purchased Product B?

(A) Text Mining; (B) Social analytics; (C) Association detection; (D) Cluster analysis

(24) In marketing, managers are interested to group similar customers with similar background together. It is also known as customer profiling. How do you identify customers with similar background?

(A) Cluster analysis; (B) Association detection; (C) Text Mining; (D) Sentiment analysis

Demographic Information

(25) What is your gender?

(A) Female; (B) Male

(26) How do you evaluate your computer/IT skill?

(A) I know nothing about computer/IT. (B) I know a little about computer/IT. (C) My knowledge on computer/IT is fair. (D) My knowledge on computer/IT is above average. (E) I am an expert in computer/IT.

(27) What is 3×11?

(A) 14; (B) 21; (C) 28; (D) 30; (E) 33

(28) What is your age?

(A) 18 and below; (B) 19 – 20; (C) 21 – 22; (D) 23 – 25; (E) 26 and above

(29) What is your academic background in secondary school?

(A) Arts and Humanities; (B) Business; (C) Science and Mathematics; (D) Others

Appendix E Post-experiment Knowledge and Performance Test

Name: ______________________________ Student ID: ___________________________

Instructions:

1. Write down your name and student ID on this question paper
2. There are 11 questions in this test
3. You are given 40 minutes to finish the test.
4. You are required to input your answers to **Canvas**
5. You may access the Internet throughout the test
6. No communication (e.g., email, instant messaging, phone, and talking) is allowed throughout the test
7. Please use Facepager and SAS Enterprise Miner in the computer laboratory. SAS OnDemand is not allowed.
8. Unless you have technical problems (e.g., computer malfunction), your instructor will not answer any questions related to the test
9. When time is up, your instructor will collect all your question papers
10. You will get 1% bonus (on top of your coursework and exam) by participating in this test. Top performers will also receive a $50 Haagen-Dazs coupon.

Test Version A

Q1) What is your test version? (0%)

A. Version A; B. Version B; C. Version C; D. Version D; E. Version E

Knowledge Test

Q2) ____________ is an analysis that finds out common themes of discussion among online chatters in a social community. (5%)

A. Text Topic Analysis; B. Sentiment Analysis; C. Business Intelligence; D. Social Analytics; E. Text Mining

Q3) In text topic analysis, ____________ is a step to identify words according to their parts of speech. (5%)

Q4) SAS OnDemand is a type of __________ services that allow users to access software provided by SAS (e.g., SAS Enterprise Miner) without installing it in their computer. (5%)

A. Data Mining; B. Text Topic; C. Text Mining; D. Cloud; E. Social analytics and business intelligence

Q5) When you use “Export Data” function in Facepager, the default column delimiter of the exported file is in which of the following formats? (5%)

A. Tab; B. Space; C. Comma; D. Semi-colon; E. Period

Q6) Which of the following statement is true with regard to “terms” table after running Text Topic analysis using SAS Enterprise Miner? (5%)

A. The numeric number in “terms” table indicates the relative importance of a text topic.

B. The magnitude but not the sign of the numeric number in “terms” table is the most important indicator of the importance of relationship between a word and a text topic.

C. If the numeric number in “terms” table is close to 1, it means that a word is not likely to appear in a text topic

D. The numeric number in “terms” table can range from 0 to 1.

E. If the numeric number in “terms” table is close to zero, it means that there is no relationship between a word and a topic

Performance Test

Q7) What is the Facebook ID of [University Community Anonymized]?
https://www.facebook.com/[anonymized]/?ref=br_rs (5%)

Q8) Extract 1 page of Facebook posts and comments from the Facebook community in Q7 and prepare a CSV file that is **ready** for text topic analysis. Please keep columns of Name and Message and save your file as a new CSV file. Upload the CSV file to Canvas. (25%)

Q9) Download file with movie review data from Canvas -> Modules -> Week 7 Tutorial -> data1.csv. Conduct Topic Model Analysis using the file. Which topic is the most common? (Write down the components of the topic **NOT** topic ID) (25%)

Q10) Which topic has the lowest correlation coefficient with the term “+good” (Adj)? (Write down the components of the topic **NOT** topic ID) (5%)

Q11) What are the managerial implications based on your answer in Q10? (Short answers only. Don’t write an essay.) (15%)

--End--

Appendix F. Goal Orientations and Validity Tests

Goal orientations are commonly studied in educational psychology research (e.g., Elliot et al. 2011; Reeve 2013; Turner et al. 2002; Wolters and Daugherty 2007). To measure goal orientations, we originally used five, five, and four questions for mastery, performance-approach, and performance-avoidance goal orientations, respectively, based on Midgley et al. (2000)'s measures of adaptive learning. Due to a lack of discriminant validity, we removed two questions related to performance-approach goal orientation and two questions related to performance-avoidance goal orientation (see Table F1 for the remaining questions). Since the three learning orientation constructs are reflective rather than formative, the corresponding measurement items are reflections rather than constituent components of the constructs (Petter et al. 2007). Previous IS studies have suggested that it is acceptable to remove some measurement items that do not establish convergent and discriminant validity (Straub et al. 2004). Santhanam et al. (2008) also removed certain measurement items related to learning orientation measures due to a lack of discriminant validity.

We took the average of its respective measurement items for each goal orientation (i.e., mastery, performance-approach, and performance-avoidance orientations). Each goal orientation is represented by a continuous number ranging from 1 (low) to 5 (high). Notably, some participants may possess multiple goal orientations. Many previous studies (e.g., Linnenbrink 2005; Midgley et al. 2001) have investigated the existence of multiple goal orientaitons. Some studies (e.g., Daniels et al. 2008; Luo et al. 2011; Tapola and Niemivirta 2008) even conducted cluster analyses to identify different combinations. In the present research, we allowed for the co-existence of multiple goal orientations rather than fixing participants to a unique one. Although it is rare for some strange combinations of goal orientaitons to exist, previous research (e.g., Meece and Holt 1993; Wan et al. 2012) has shown such occurrences among the three goal orientations.

Table F1 presents the final measurement items and corresponding validity tests of the three goal orientations.

Table F1. Internal Consistency and Convergent and Discriminant Validity Testing

Items	Measures (1: Strongly disagree; 5 Strongly agree)	Latent Factor	1	2	3
M1	It's important to me that I learn a lot of new concepts this year.	Mastery Orientation Cronbach's Alpha = 0.89 AVE = 0.70	**0.83**	0.12	0.28
M2	It's important to me that I thoroughly understand my classwork.		**0.81**	0.00	0.36
M3	It's important to me that I improve my skills this year.		**0.86**	0.06	0.34
M4	One of my learning goals in class is to learn as much as I can.		**0.84**	0.19	0.27
M5	One of my learning goals is to master a lot of new skills this year.		**0.84**	0.27	0.18
P1	One of my learning goals is to show others that I'm good at my classwork.	Performance Orientation Cronbach's Alpha = 0.83 AVE = 0.74	0.28	**0.83**	0.46
P2	One of my learning goals is to show others that classwork is easy for me.		0.06	**0.90**	0.33
P3	One of my learning goals is to look smart in comparison to the other students in my class.		0.11	**0.85**	0.51
A1	It's important to me that I don't look stupid in class.	Avoidance Goal Orientation Cronbach's Alpha = 0.71	0.30	0.42	**0.89**
A2	It's important to me that my teacher doesn't think that I know less than others in my class.		0.30	0.48	**0.85**

		AVE = 0.75			

Appendix G. Propensity Score Matching, Demographics, and Correlation Matrix

Following previous studies (e.g., Burtch et al. 2018; Rishika et al. 2013), we conducted propensity score matching (PSM) between participants in the treatment and control groups to ensure that the demographics and pre-experiment knowledge test scores were similar across groups. We ran a logit model to determine the propensity scores of being in the treatment group for each individual. Notably, we had 419 participants in the treatment group and 341 participants in the control group, for a total of 760 participants. The result of the logit model is shown in Table G1. We then matched each participant in the treatment group with a participant in the control group. After PSM, the ratio of participants in the treatment to those in the matched control groups was 1:1. We present the similarity of the treatment and control groups after PSM in terms of the propensity score in a box plot (Figure G1) and a smooth histogram (Figure G2). The Kolmogorov-Smirnov (KS) test also showed that the distributions of propensity score in the treatment and matched control groups were similar, with a *p*-value of 0.756. We further split the treatment group into four subgroups based on the gamified performance feedback. The pairwise comparisons of the treatment and control groups before (Panel A) and after (Panel B) PSM are presented in Table G2. As shown in Panel A of Table G2, before PSM, the treatment and control groups were not always the same in demographics and pre-experiment knowledge test scores. However, as shown in Panel B of Table G2, the participants across the treatment and matched control groups were similar after PSM. F-test statistics could not reject the null hypothesis that the means across the treatment and matched control groups were the same. Table G3 presents the correlation matrix.

Table G1. Logit Model Result

Independent Variables	Coefficient Estimate [95% confidence interval] (Standard Error)
Mastery Goal Orientation [1, 5]	-0.6094*** [-0.9057, -0.3132] (0.1512)
Performance-Approach Goal Orientation [1, 5]	0.5685*** [0.3081, 0.8288] (0.1328)
Performance-Avoidance Goal Orientation [1, 5]	-0.4229** [-0.7036, -0.1421] (0.1432)
Male (0: female; 1: male)	-0.7840*** [-1.1171, -0.4509] (0.1699)
IT Skill (1: I know nothing about computers/IT; 5: I am expert in computers/IT)	-0.2195* [-0.4315, -0.0075] (0.1082)
Age (1: 18 and below; 2: 19-20 years old; 3: 21-22 years old; 4: 23-24 years old; 5: 26 years old or above)	0.4603** [0.1714, 0.7491] (0.1474)
Pre-experiment Knowledge Test (*PreTest*) [0, 7]	-0.2203*** [-0.3343, -0.1063] (0.0582)
Transfer	1.4074***

(0: freshman; 1: non-freshman)	[0.8220, 1.9927] (0.2986)
Technical Major (0: no; 1: yes)	-0.3078 [-1.1916, 0.5759] (0.4509)
Cumulative Grade Point Average before Experiment (*CGPA*) [0, 4.3]	0.6305** [0.2595, 1.0015] (0.1893)
Arts, Business, and Humanities Background in Secondary School (0: no; 1:yes)	-0.1799 [-0.7405, 0.3807] (0.2860)
Science and Mathematics Background in Secondary School (0: no; 1:yes)	0.1668 [-0.4466, 0.7802] (0.3130)
Constant	1.3427 [-0.4499, 3.1353] (0.9146)
N	760
Adj. Pseudo R^2	0.15

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%

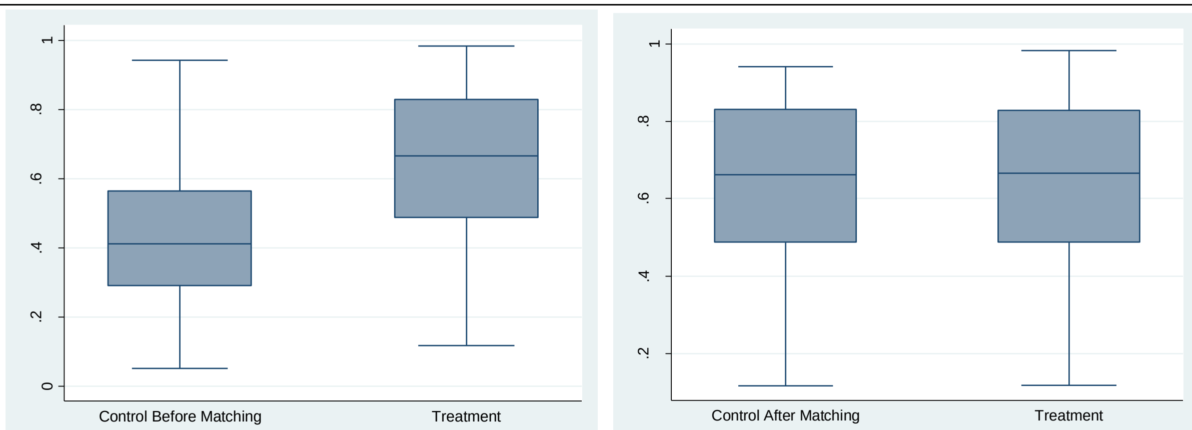


Figure G1. Box Plots of Propensity Score Before and After Matching

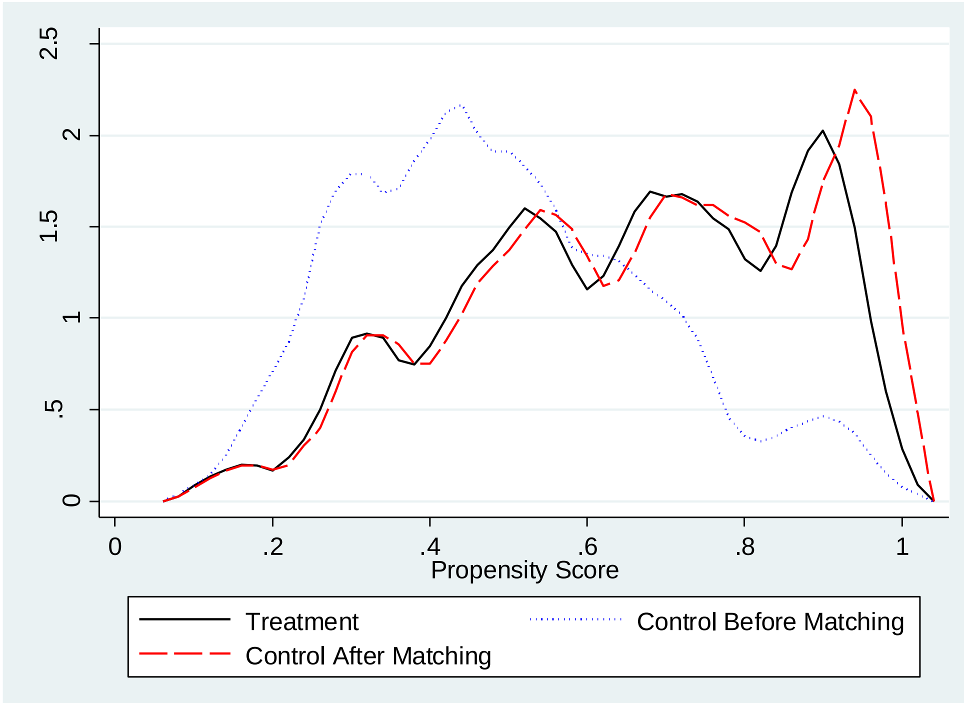


Figure G2. Smooth Histogram Plots of Propensity Score Distributions of Treatment and Control Groups Before and After PSM

Table G2. Comparison of Demographics Across Groups						
Panel A: Comparison of Demographics Across Groups Before PSM						
Groups / Demographics	Positive Personal Comparison Treatment (N=97)	Positive Social Comparison Treatment (N=106)	Negative Personal Comparison Treatment (N=110)	Negative Social Comparison Treatment (N=106)	Control Before Matching (N=341)	ANOVA F-Test Statistic (p-value) #
Mastery Goal Orientation [1, 5]	4.09 (0.90)	4.05 (0.70)	4.10 (0.80)	4.11 (0.76)	4.32 (0.44)	5.89 (0.00)
Performance-Approach Goal Orientation [1, 5]	3.19 (0.73)	3.19 (0.83)	3.20 (0.81)	3.15 (0.88)	3.06 (0.70)	1.25 (0.29)
Performance-Avoidance Goal Orientation [1, 5]	3.66 (0.75)	3.67 (0.73)	3.60 (0.87)	3.63 (0.80)	3.77 (0.64)	1.69 (0.15)
Male (0: female; 1: male)	0.34 (0.48)	0.39 (0.49)	0.39 (0.49)	0.42 (0.50)	0.54 (0.50)	4.79 (0.00)
IT Skill (1: I know nothing about computers/IT; 5: I am expert in computers/IT)	2.53 (0.88)	2.38 (0.88)	2.38 (0.78)	2.52 (0.77)	2.62 (0.74)	3.1 (0.02)
Age (1: 18 and below; 2: 19-20 years old; 3: 21-22 years old; 4: 23-24 years old; 5: 26 years old or above)	1.72 (0.75)	1.75 (0.72)	1.79 (0.73)	1.84 (0.74)	1.42 (0.67)	12.43 (0.00)
Pre-experiment Knowledge Test (*PreTest*) [0, 7]	2.71 (1.34)	2.69 (1.35)	2.81 (1.46)	2.74 (1.38)	3.13 (1.53)	3.58 (0.01)

Transfer (0: freshman; 1: non-freshman)	0.30 (0.46)	0.30 (0.46)	0.33 (0.47)	0.38 (0.49)	0.09 (0.28)	17.66 (0.00)
Technical Major (0: no; 1: yes)	0.07 (0.26)	0.09 (0.29)	0.06 (0.25)	0.08 (0.27)	0.03 (0.18)	1.97 (0.10)
Cumulative Grade Point Average before Experiment (*CGPA*) [0, 4.3]	3.07 (0.49)	3.00 (0.46)	3.03 (0.46)	3.01 (0.55)	2.95 (0.38)	1.65 (0.16)
Arts, Business, and Humanities Background in Secondary School (0: no; 1:yes)	0.57 (0.50)	0.65 (0.48)	0.65 (0.48)	0.63 (0.48)	0.67 (0.47)	0.99 (0.41)
Science and Mathematics Background in Secondary School (0: no; 1:yes)	0.33 (0.47)	0.23 (0.42)	0.27 (0.45)	0.26 (0.44)	0.22 (0.42)	1.34 (0.25)
Other Academic Background in Secondary School (0: no; 1: yes)	0.10 (0.31)	0.12 (0.33)	0.07 (0.26)	0.10 (0.31)	0.10 (0.30)	0.38 (0.82)
Panel B: Comparison of Demographics Across Groups After PSM						
Groups Demographics	Positive Personal Comparison Treatment (N=97)	Positive Social Comparison Treatment (N=106)	Negative Personal Comparison Treatment (N=110)	Negative Social Comparison Treatment (N=106)	Control After Matching (N=419)	ANOVA F-Test Statistic (p-value) #
Mastery Goal Orientation [1, 5]	4.09 (0.90)	4.05 (0.70)	4.10 (0.80)	4.11 (0.76)	4.21 (0.48)	1.86 (0.12)
Performance-Approach Goal Orientation [1, 5]	3.19 (0.73)	3.19 (0.83)	3.20 (0.81)	3.15 (0.88)	3.18 (0.64)	0.07 (0.99)

Performance-Avoidance Goal Orientation [1, 5]	3.66 (0.75)	3.67 (0.73)	3.60 (0.87)	3.63 (0.80)	3.68 (0.57)	0.36 (0.84)
Male (0: female; 1: male)	0.34 (0.48)	0.39 (0.49)	0.39 (0.49)	0.42 (0.50)	0.40 (0.49)	0.39 (0.82)
IT Skill (1: I know nothing about computers/IT; 5: I am expert in computers/IT)	2.53 (0.88)	2.38 (0.88)	2.38 (0.78)	2.52 (0.77)	2.39 (0.77)	1.1 (0.35)
Age (1: 18 and below; 2: 19-20 years old; 3: 21-22 years old; 4: 23-24 years old; 5: 26 years old or above)	1.72 (0.75)	1.75 (0.72)	1.79 (0.73)	1.84 (0.74)	1.88 (1.01)	0.94 (0.44)
Pre-experiment Knowledge Test (*PreTest*) [0, 7]	2.71 (1.34)	2.69 (1.35)	2.81 (1.46)	2.74 (1.38)	2.82 (1.38)	0.3 (0.88)
Transfer (0: freshman; 1: non-freshman)	0.30 (0.46)	0.30 (0.46)	0.33 (0.47)	0.38 (0.49)	0.36 (0.48)	0.65 (0.63)
Technical Major (0: no; 1: yes)	0.07 (0.26)	0.09 (0.29)	0.06 (0.25)	0.08 (0.27)	0.09 (0.29)	0.36 (0.84)
Cumulative Grade Point Average before Experiment (*CGPA*) [0, 4.3]	3.07 (0.49)	3.00 (0.46)	3.03 (0.46)	3.01 (0.55)	3.03 (0.34)	0.34 (0.85)
Arts, Business, and Humanities Background in Secondary School (0: no; 1:yes)	0.57 (0.50)	0.65 (0.48)	0.65 (0.48)	0.63 (0.48)	0.60 (0.49)	0.65 (0.63)

Science and Mathematics Background in Secondary School (0: no; 1:yes)	0.33 (0.47)	0.23 (0.42)	0.27 (0.45)	0.26 (0.44)	0.25 (0.43)	0.84 (0.50)
Other Academic Background in Secondary School (0: no; 1: yes)	0.10 (0.31)	0.12 (0.33)	0.07 (0.26)	0.10 (0.31)	0.15 (0.35)	1.32 (0.26)

Note: Numbers without parentheses are average and numbers with parentheses are standard deviation in the four treatment and control groups.

Numbers are F-test statistics and numbers in parentheses are p-value. For Panel B, apart from ANOVA tests, we also perform pairwise comparison across groups by Tukey’s HSD (honestly significant difference) post-hoc analyses. The results show that the individual differences of group average are not statistically significant after PSM.

Table G3. Pearson’s Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) *SRL*	1														
(2) *Male*	-0.13	1													
(3) *IT_Skill*	0.01	0.15	1												
(4) *Age*	-0.04	0.16	0.11	1											
(5) *PreTest*	0.11	0.09	0.16	0.20	1										
(6) *Transfer*	-0.05	0.15	0.06	0.66	0.17	1									
(7) *Technical Major*	0.02	0.05	0.08	0.20	0.01	0.40	1								
(8) *CGPA*	0.28	-0.09	-0.03	-0.12	0.07	-0.07	0.09	1							
(9) Arts, Business, and Humanities Background in Secondary School	-0.09	-0.13	0.05	-0.05	-0.08	-0.12	-0.24	-0.12	1						
(10) Science and Mathematics Background in Secondary School	0.11	0.15	-0.01	-0.01	0.08	0.07	0.07	0.08	-0.75	1					
(11) *Positive Personal Comparison*	0.08	-0.04	0.05	-0.04	-0.02	-0.03	-0.02	0.03	-0.04	0.06	1				
(12) *Positive Social Comparison*	0.02	-0.01	-0.02	-0.03	-0.02	-0.03	0.01	-0.02	0.03	-0.03	-0.14	1			
(13) *Negative Personal Comparison*	0.08	0.00	-0.02	-0.02	0.01	-0.01	-0.03	0.00	0.03	0.01	-0.14	-0.15	1		
(14) *Negative Social Comparison*	0.02	0.02	0.05	0.01	-0.01	0.03	-0.01	-0.02	0.01	0.00	-0.14	-0.14	-0.15	1	
(15) *Mastery*	0.20	-0.01	0.05	0.05	0.08	-0.04	-0.01	0.14	-0.07	0.13	-0.03	-0.06	-0.03	-0.02	1
(16) *Performance-Approach*	-0.01	-0.02	0.05	-0.03	-0.05	-0.11	-0.06	-0.04	0.16	-0.12	0.00	0.00	0.01	-0.02	0.21
(17) *Performance-Avoidance*	0.03	0.02	0.00	-0.03	0.01	-0.09	-0.16	0.04	-0.01	0.10	0.00	0.01	-0.04	-0.01	0.37
(18) *Positive Personal Comparison x Mastery*	0.03	0.01	-0.03	-0.02	-0.03	-0.07	-0.03	0.02	-0.02	0.02	-0.06	0.01	0.01	0.01	0.47
(19) *Positive Social Comparison x Mastery*	0.08	0.05	0.01	0.00	-0.04	0.01	0.01	0.08	-0.02	0.06	0.02	-0.13	0.02	0.02	0.38
(20) *Negative Personal Comparison x Mastery*	0.09	-0.04	0.04	-0.03	-0.02	-0.04	-0.04	0.06	0.00	0.00	0.01	0.01	-0.06	0.01	0.44
(21) *Negative Social Comparison x Mastery*	0.12	-0.05	0.02	0.03	0.03	0.01	0.05	0.11	-0.02	0.04	0.01	0.01	0.01	-0.04	0.41
(22) *Positive Personal Comparison x Performance-Approach*	-0.01	0.01	0.03	0.01	-0.05	0.06	-0.02	0.01	-0.03	0.02	0.01	0.00	0.00	0.00	0.08
(23) *Positive Social Comparison x Performance-Approach*	0.09	0.05	0.03	-0.05	-0.02	0.00	-0.02	-0.01	0.10	-0.04	0.00	0.01	0.00	0.00	0.13
(24) *Negative Personal Comparison x Performance-Approach*	0.04	0.00	0.04	-0.01	-0.02	-0.01	0.02	-0.03	0.01	-0.01	0.00	0.00	0.02	0.00	0.15
(25) *Negative Social Comparison x Performance-Approach*	0.02	-0.04	0.01	-0.01	-0.04	-0.03	-0.01	0.02	0.02	-0.01	0.00	0.00	0.01	-0.03	0.08
(26) *Positive Personal Comparison x Performance-Avoidance*	0.08	0.01	0.01	-0.04	-0.03	0.03	-0.03	0.04	-0.03	0.03	0.01	0.00	0.00	0.00	0.19
(27) *Positive Social Comparison x Performance-Avoidance*	0.04	0.05	0.02	0.01	-0.01	0.00	-0.04	0.04	0.05	-0.03	0.00	0.01	0.00	0.00	0.15
(28) *Negative Personal Comparison x Performance-Avoidance*	0.02	0.02	0.03	-0.02	-0.06	-0.02	0.00	0.00	-0.03	0.03	0.01	0.01	-0.07	0.01	0.20

(29) *Negative Social x Performance-Avoidance*	0.02	-0.04	0.06	0.02	0.00	0.00	0.03	0.06	-0.02	0.06	0.00	0.00	0.00	-0.03	0.12
	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	
(16) *Performance-Approach*	1														
(17) *Performance-Avoidance*	0.55	1													
(18) *Positive Personal Comparison x Mastery*	0.06	0.15	1												
(19) *Positive Social Comparison x Mastery*	0.13	0.15	0.00	1											
(20) *Negative Personal Comparison x Mastery*	0.13	0.20	0.00	0.00	1										
(21) *Negative Social Comparison x Mastery*	0.08	0.12	0.00	0.00	0.00	1									
(22) *Positive Personal Comparison x Performance-Approach*	0.34	0.19	0.17	0.00	0.00	0.00	1								
(23) *Positive Social Comparison x Performance-Approach*	0.40	0.21	0.00	0.33	0.00	0.00	0.00	1							
(24) *Negative Personal Comparison x Performance-Approach*	0.40	0.28	0.00	0.00	0.34	0.00	0.00	0.00	1						
(25) *Negative Social Comparison x Performance-Approach*	0.43	0.23	0.00	0.00	0.00	0.20	0.00	0.00	0.00	1					
(26) *Positive Personal Comparison x Performance-Avoidance*	0.18	0.37	0.42	0.00	0.00	0.00	0.52	0.00	0.00	0.00	1				
(27) *Positive Social Comparison x Performance-Avoidance*	0.23	0.38	0.00	0.41	0.00	0.00	0.00	0.56	0.00	0.00	0.00	1			
(28) *Negative Personal Comparison x Performance-Avoidance*	0.25	0.46	0.00	0.00	0.44	0.00	0.00	0.00	0.62	0.00	0.00	0.00	1		
(29) *Negative Social x Performance-Avoidance*	0.24	0.41	0.00	0.00	0.00	0.30	0.00	0.00	0.00	0.56	0.00	0.00	0.00	1	

Appendix H. Manipulation Check of Treatment Effectiveness

Table H1. Manipulation Check across Groups								
Manipulation Check Questions	Groups	Positive Personal Comparison Treatment (N=97)	Positive Social Comparison Treatment (N=106)	Negative Personal Comparison Treatment (N=110)	Negative Social Comparison Treatment (N=106)	Control (N=419)	ANOVA Test Statistic (p-value) #
PP1: The daily emails remind me of the modules and sub-modules I have completed.	Average of PP1 to PP3	3.64 (0.70)	2.43 (0.65)	2.33 (0.62)	2.39 (0.69)	2.68 (0.60)	72.76 (0.00)
PP2: The daily emails give me advice for receiving more master badges.							
PP3: The daily emails give me suggestions on how to receive more cumulative points.							
PS1: The daily emails show how good students perform on the learning platform.	Average of PS1 to PS3	2.30 (0.68)	3.66 (0.69)	2.35 (0.63)	2.40 (0.66)	2.76 (0.72)	72.09 (0.00)
PS2: The daily emails make me feel smart when I know that I perform better than most of my classmates.							
PS3: The daily emails make my classmates feel that I am good at my classwork when I perform well.							
NP1: The daily emails remind me of the modules and sub-modules I have not yet completed.	Average of NP1 to NP3	2.29 (0.57)	2.41 (0.63)	3.61 (0.74)	2.35 (0.66)	2.60 (0.72)	69.14 (0.00)
NP2: The daily emails give me advice on how to avoid loser badges.							
NP3: The daily emails give me suggestions on how to avoid							

penalty scores.							
NS1: The daily emails show how bad students perform on the learning platform. NS2: The daily emails make me feel that I have trouble doing my classwork when I know that I perform worse than most of my classmates. NS3: The daily emails make my classmates feel that I learn less than them when I perform badly.	Average of NS1 to NS3	2.27 (0.64)	2.32 (0.65)	2.37 (0.65)	3.65 (0.71)	2.72 (0.73)	72.85 (0.00)

Note: The manipulation check questions are scored using a five-point Likert scale to determine whether respondents agree with specific statements stated in the questions (1:strongly disagree; 5: strongly agree). Numbers without parentheses in the above table are averages, while numbers in parentheses are standard deviations in the four treatment and control groups.

We performed Tukey HSD post-hoc analyses after ANOVA tests and the results show that Positive Personal Comparison Treatment group is significantly different from other groups in the average of PP1 to PP3; Positive Social Comparison Treatment group is significantly different from other groups in the average PS1 to PS3; Negative Personal Comparison Treatment is significantly different from other groups in the average of NP1 to NP3; Negative Social Comparison Treatment group is significantly different from other groups in the average of NS1 to NS3.

Appendix I. Analyses of the Impact of Goal Orientations and Gamified Performance Feedback on SRL Engagement and Pace to Complete a Module with SRL

Table I1. The Impact of Goal Orientations and Gamified Performance Feedback on SRL Engagement				
	Dependent Variable: SRL Engagement			
Independent Variables: Goal Orientations, Gamified Performance Feedback, and Interaction Terms	**(1)**	**(2)**	**(3)**	**(4)**
Positive Personal Comparison	0.2467** [0.0844, 0.4089] (0.0826)		0.2767** [0.1107, 0.4427] (0.0846)	0.2668** [0.1078, 0.4258] (0.0810)
Positive Social Comparison	0.1591 [-0.0219, 0.3401] (0.0922)		0.1909* [0.0115, 0.3702] (0.0914)	0.1865* [0.0067, 0.3663] (0.0916)
Negative Personal Comparison	0.2691** [0.0849, 0.4533] (0.0938)		0.2894** [0.1079, 0.4708] (0.0924)	0.2921** [0.1124, 0.4718] (0.0915)
Negative Social Comparison	0.1626 [-0.0120, 0.3372] (0.0889)		0.1799* [0.0101, 0.3497] (0.0865)	0.1903* [0.0207, 0.3599] (0.0864)
Mastery		0.2108*** [0.1115, 0.3101] (0.0506)	0.2283*** [0.1308, 0.3258] (0.0497)	0.3475*** [0.1528, 0.5423] (0.0992)
Performance-Approach		0.0091 [-0.0804, 0.0986] (0.0456)	0.0033 [-0.0850, 0.0916] (0.0450)	-0.1135 [-0.2359, 0.0089] (0.0623)
Performance-Avoidance		-0.0697 [-0.1695, 0.0301] (0.0508)	-0.0642 [-0.1631, 0.0347] (0.0504)	-0.1877* [-0.3340, -0.0414] (0.0746)
Positive Personal Comparison x Mastery				-0.3797** [-0.6454, -0.1140] (0.1354)
Positive Social Comparison x Mastery				-0.1924 [-0.4925, 0.1077] (0.1529)

Negative Personal Comparison x Mastery				-0.1534 [-0.4504, 0.1437] (0.1513)
Negative Social Comparison x Mastery				-0.0555 [-0.3198, 0.2087] (0.1346)
Positive Personal Comparison x Performance-Approach				-0.0671 [-0.3296, 0.1953] (0.1337)
Positive Social Comparison x Performance-Approach				0.4264** [0.1826, 0.6702] (0.1242)
Negative Personal Comparison x Performance-Approach				0.2061 [-0.1024, 0.5147] (0.1572)
Negative Social Comparison x Performance-Approach				0.1498 [-0.0708, 0.3704] (0.1124)
Positive Personal Comparison x Performance-Avoidance				0.5436*** [0.2945, 0.7926] (0.1269)
Positive Social Comparison x Performance-Avoidance				0.0450 [-0.2547, 0.3447] (0.1527)
Negative Personal Comparison x Performance-Avoidance				0.1468 [-0.0988, 0.3925] (0.1252)
Negative Social Comparison x Performance-Avoidance				0.0726 [-0.2499, 0.3950] (0.1643)
Constant##	-1.7980*** [-2.3509, -1.2452] (0.2817)	-2.1585*** [-2.8180, -1.4990] (0.3360)	-2.3117*** [-2.9639, -1.6596] (0.3322)	-1.9463*** [-2.8908, -1.0017] (0.4812)
With control variables#				
N	838	838	838	838
Adj. R^2	0.12	0.12	0.14	0.16
Max VIF	2.59	2.61	2.62	5.1

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%

Some control variables are significant. *Male* is negative and significant at 0.001 with coefficient estimates ranging from -0.2180 to -0.2058 in columns (1) to (4). *Pre-experiment Knowledge Test* is positive and significant at 0.05 with coefficient estimates ranging from 0.0522 to 0.0593 in Models (1) to (4). CGPA is positive and significant at 0.001 with coefficient estimates ranging from 0.4425 to 0.4953 in Models (1) to (4).
The constant term of (1) represents the average SRL engagement of participants in the control group; the constant term of (2) represents the average SRL engagement of participants with the lowest mastery, performance-approach, and performance-avoidance goal orientations; the constant terms of (3) and (4) represent the average SRL engagement of participants with the lowest mastery, performance-approach, and performance-avoidance goal orientations in the control group.

Table I2. The Impact of Goal Orientations and Gamified Performance Feedback on Pace to Complete a Module with SRL

	Dependent Variable: Pace to Complete a Module with SRL			
Independent Variables: Goal Orientations, Gamified Performance Feedback, and Interaction Terms	**(1)**	**(2)**	**(3)**	**(4)**
Positive Personal Comparison	0.4991** [0.1301, 0.8680] (0.1883)		0.5272** [0.1622, 0.8923] (0.1862)	0.5425** [0.1691, 0.9160] (0.1905)
Positive Social Comparison	0.2947 [-0.0767, 0.6661] (0.1895)		0.3393 [-0.0285, 0.7071] (0.1877)	0.3625 [-0.0141, 0.7391] (0.1922)
Negative Personal Comparison	0.5528** [0.1878, 0.9178] (0.1862)		0.5948** [0.2325, 0.9571] (0.1848)	0.6096** [0.2397, 0.9796] (0.1888)
Negative Social Comparison	0.2237 [-0.1507, 0.5982] (0.1910)		0.2272 [-0.1431, 0.5974] (0.1889)	0.2637 [-0.1145, 0.6420] (0.1930)
Mastery		0.2455** [0.0814, 0.4095] (0.0837)	0.2570** [0.0958, 0.4182] (0.0822)	0.4028* [0.0841, 0.7215] (0.1626)
Performance-Approach		0.0328 [-0.1190, 0.1846] (0.0774)	0.0179 [-0.1318, 0.1677] (0.0764)	-0.0787 [-0.3493, 0.1920] (0.1381)
Performance-Avoidance		-0.0265 [-0.1924, 0.1395] (0.0847)	-0.0053 [-0.1691, 0.1584] (0.0836)	-0.1487 [-0.4587, 0.1613] (0.1582)
Positive Personal Comparison				**-0.4722***

x Mastery				**[-0.9236, -0.0207] (0.2303)**
Positive Social Comparison x Mastery				-0.1641 [-0.6947, 0.3664] (0.2707)
Negative Personal Comparison x Mastery				-0.0391 [-0.5205, 0.4422] (0.2456)
Negative Social Comparison x Mastery				-0.2586 [-0.7514, 0.2342] (0.2514)
Positive Personal Comparison x Performance-Approach				-0.1131 [-0.5611, 0.3350] (0.2286)
Positive Social Comparison x Performance-Approach				**0.5395* [0.0568, 1.0221] (0.2462)**
Negative Personal Comparison x Performance-Approach				0.1528 [-0.2920, 0.5976] (0.2270)
Negative Social Comparison x Performance-Approach				0.0655 [-0.3832, 0.5141] (0.2289)
Positive Personal Comparison x Performance-Avoidance				**0.5247* [0.0191, 1.0303] (0.2580)**
Positive Social Comparison x Performance-Avoidance				0.0160 [-0.5248, 0.5568] (0.2759)
Negative Personal Comparison x Performance-Avoidance				0.1784 [-0.2875, 0.6444] (0.2377)
Negative Social Comparison x Performance-Avoidance				0.1169 [-0.3882, 0.6220] (0.2577)
Theta	0.1028	0.1444	0.0981	0.1036

	(0.0477)	(0.0593)	(0.0460)	(0.0485)
With control variables##				
N	838	838	838	838
Chi^2	67.12	63.79	78.84	94.37
Max VIF	2.59	2.61	2.62	4.55

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%; Numbers are coefficient estimates; numbers in square parentheses are 95% confidence interval; numbers in parenthesis are robust standard error.

Some control variables are significant. *Male* is negative and significant at 0.05 with coefficient estimates ranging from -0.2329 to -0.2033 in columns (1) to (4). *Senior* is positive and significant at 5% with a coefficient estimate of 0.2818 in column (3). CGPA is positive and significant at 0.001 with coefficient estimates ranging from 0.7364 to 0.7891 across column (1) to (4).

Appendix J. *A Priori* Test, Tests of Model Assumptions, and Analyses of Model Fit

To determine the optimal sample size, we conducted an *a priori* test using G*Power software (version 3.1.9.7). We followed Cohen (1988) and specified the effect size (f^2) to be 0.35 for a large f^2 in regression. We took a standard Type I error probability of 0.05 (i.e., α) and a power (i.e., $1 - \beta$) of 0.95. Since we had 30 independent variables, the total sample size for the regression model was 126 (please see Figure J1 for details).

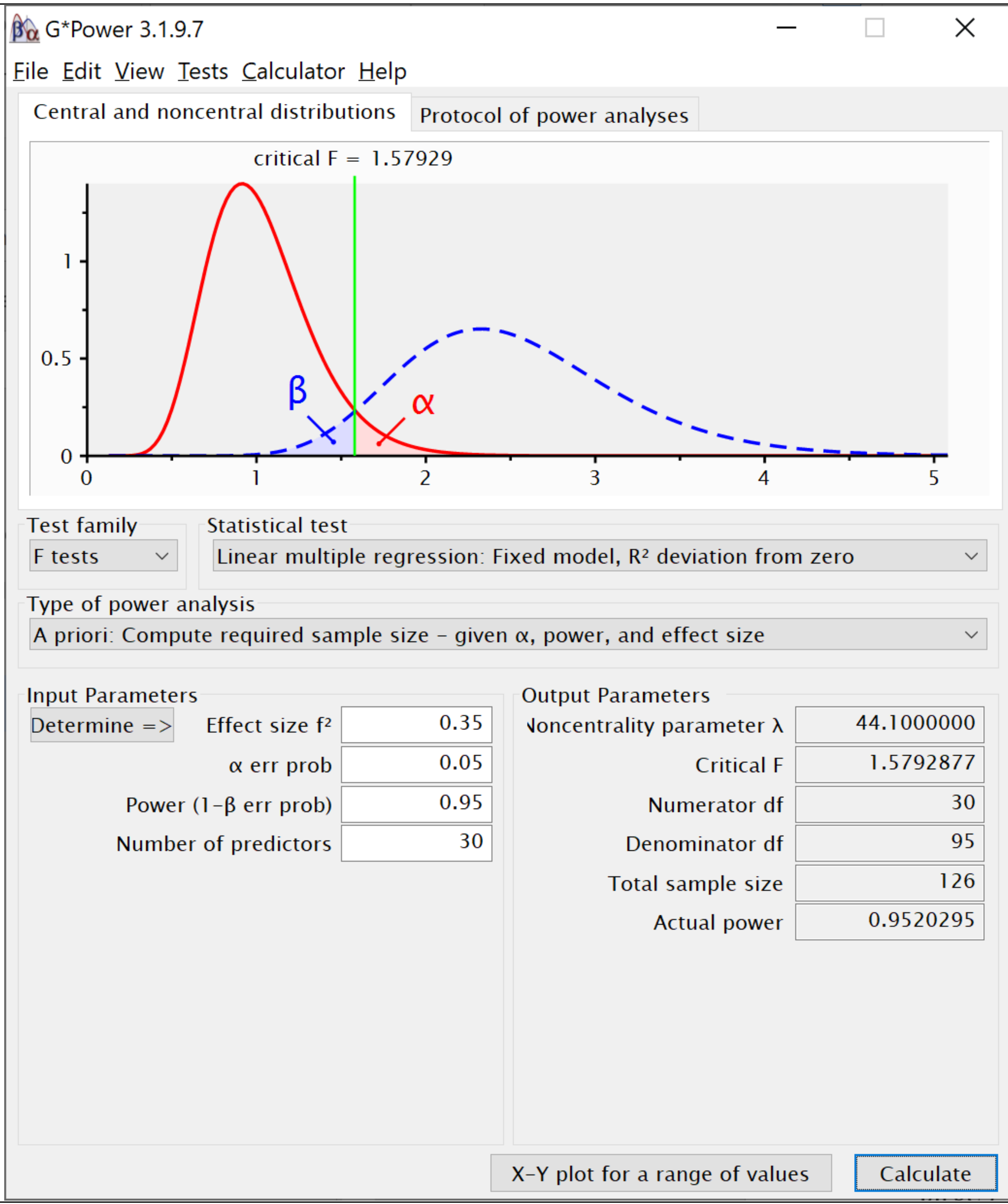
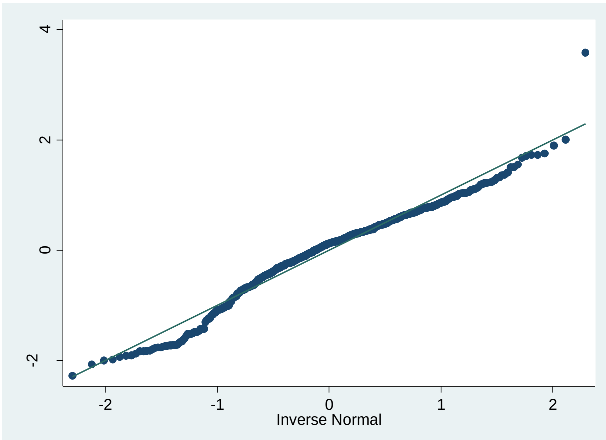


Figure J1 ***A Priori*** **Analysis**

After running the main research models, we also examined the model assumptions and model fit of equations (1) (SRL engagement model) and (2) (learning efficiency model). Concerning the SRL engagement model, we tested the normality and homoscedasticity assumptions of OLS. As shown in Figure J2(a), the quantile-to-quantile (Q-Q) plot shows that the residuals of the regression nearly fall on a straight line; therefore, the normality assumption is valid. Figure J2(b) presents the residual plot in which residuals are almost random, which suggests that the homoscedasticity assumption is also valid.



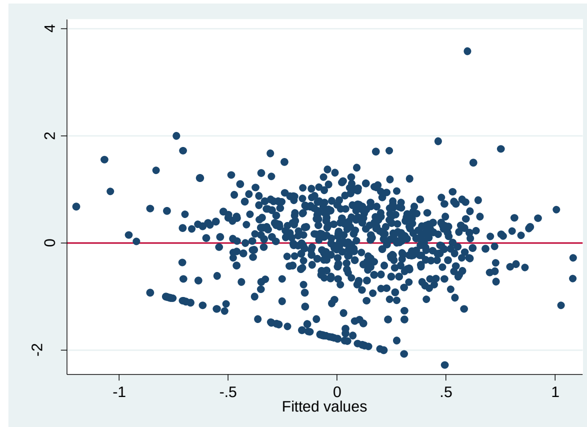
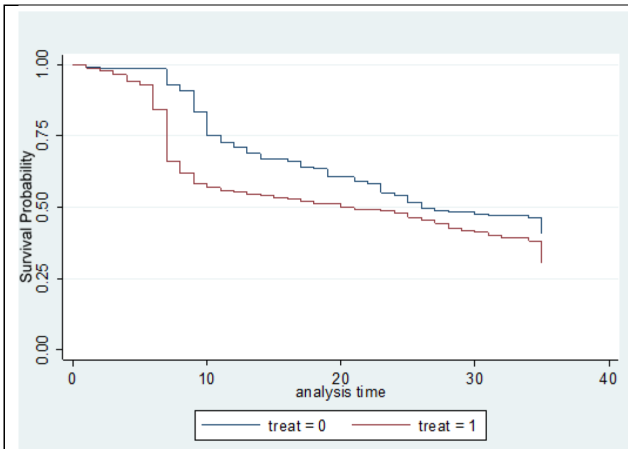


Figure J2 (a) Quantile-to-Quantile Plot (left) (b) Residual Plot (right)

The main assumption of the learning efficiency model is proportional hazards. J3(a) shows a Kaplan-Meier plot. The treatment and control lines are roughly parallel, which do not show divergence or crossing over analysis time; therefore, the proportional hazard assumption is valid. Furthermore, J3(b) shows that most of the Cox-Snell residuals fall on the straight line of the Nelson-Aalen cumulative hazard, which suggests a good model fit. Notably, it is natural to have some deviations on the right side of the Cox-Snell residual plot.



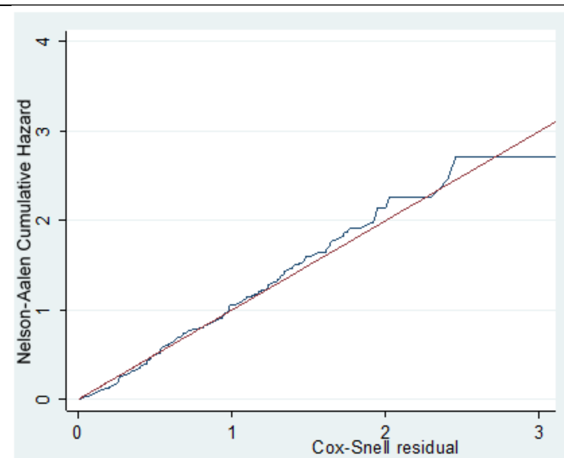


Figure J3 (a) Kaplan-Meier Plot (left) (b) Cox-Snell Residual Plot (right)

Appendix K. Mediation Test of SRL on Test Performance

To evaluate the mediation effect of SRL on knowledge (Panel A) and performance tests (Panel B), we followed Baron and Kenny (1986)'s steps to demonstrate the existence of such a mediating effect, as well as the bootstrapping method of Preacher and Hayes (2008) to quantify the indirect effect of the match between gamified performance feedback and goal orientation on learning outcomes (as measured by knowledge and performance test scores) via SRL.

Following the steps of Baron and Kenny (1986), we first showed that the mediating variable *SRL* was a strong explanatory variable of learning performance in both knowledge and performance tests. The coefficient estimate of *SRL* was positive and significant (β=1.5905, $p<0.001$ in Column (1) of Panel A in Table K1; β=5.7157, $p<0.001$ in Column (1) of Panel B in Table K1) in both knowledge and performance test models. Second, we established that some of our explanatory variables (e.g., *Mastery*, *Positive Personal Comparison* × *Mastery*, *Positive Social Comparison* × *Mastery*, and *Negative Social Comparison* × *Mastery*) were significant explanatory variables of learning performance in both knowledge and performance tests without the mediating variable SRL (Columns 2–4 of Panels A and B in Table K1). Third, we established that our explanatory variables (e.g., *Positive Personal Comparison, Positive Social Comparison, Negative Personal Comparison, Negative Social Comparison, Mastery, Performance-Avoidance, Positive Personal Comparison* × *Mastery, Positive Social Comparison* × *Performance-Approach, and Positive Personal Comparison* × *Performance-Avoidance*) were significant variables that explain the mediator of SRL engagement as shown in Table 4. Fourth, we investigated whether the presence of the mediating variable SRL deteriorated the previously significant explanatory variables in the second step and whether the mediating factor remained significant at the same time. As shown in Column (5) of Panels A and B in Table K1, the mediating factor, SRL, was positive and significant in both learning performance models (β=1.6428, $p<0.001$ in Column (5) of Panel A in Table K1; β=5.6689, $p<0.001$ in Colum (5) of Panel B in Table K1). Simultaneously, variables like *Positive Personal Comparison* × *Mastery* underwent a sharp decline in significance for the regression models with *SRL*. In Panel A of Table K1, the test statistic of *Positive Personal Comparison* × *Mastery* in Column (5) (i.e., a regression model with *SRL*) was -4.17 (i.e., -3.7264/0.8941), which was smaller in magnitude than that of *Positive Personal Comparison* × *Mastery* in Column (4) (i.e., regression model without *SRL*) with a value of -4.74 (i.e., -4.4305/0.9347). In Panel B of Table K1, the test statistic of *Positive Personal Comparison* × *Mastery* in Column (5) (i.e., a regression model with *SRL*) was -1.88 (i.e., -6.1419/3.2699), which was smaller in magnitude than that of *Positive Personal Comparison* × *Mastery* in Column (4) (i.e., a regression model without *SRL*) with a value of -2.39 (i.e., -8.5715/3.5934).These results provide support for the mediation role of SRL.

Furthermore, we quantified the mediation effect of SRL by using the bootstrapping method of Preacher and Hayes (2008), which has been applied in various IS studies (e.g., Hildebrand et al. (2013) and Hong and Pavlou (2014)). We used the Stata codes (https://stats.idre.ucla.edu/stata/faq/how-can-i-do-moderated-mediation-in-stata/) to implement the method. Consistent with our main findings, the indirect effects of *Positive Personal Comparison* × *Mastery* on learning performance via SRL were negative and significant (β=-0.7041, $p<0.01$ in Column 6 of Panel A of Table K1; β=-2.4296, $p<0.01$ in Column 6 of Panel B in Table K1), while those of *Positive Social Comparison* × *Performance-Approach* (β=0.7267, $p<0.01$ in Column 6 of Panel A of Table K1; β=2.5077, $p<0.01$ in Column 6 of Panel B in Table K1) and *Positive Personal Comparison* × *Performance-Avoidance* (β=0.9115, $p<0.01$ in Column 6 of Panel A in Table K1; β=3.1453, $p<0.01$ in Column 6 of Panel B in Table K1) were positive and significant, as shown in Columns 6 of Panels A and B in Table K1. These results provide strong support for H4, which states that *SRL* mediates the influence of the match between gamified performance feedback and goal orientation on learning outcomes.

Table K1. The Mediation Test of SRL on Test Performance Panel A: Knowledge Test						
	Dependent Variable: Knowledge Test					
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6) Bootstrapping Model
<u>SRL</u>	1.5905*** [1.1108, 2.0701] (0.2444)				1.6428*** [1.1572, 2.1284] (0.2474)	
Positive Personal Comparison		-1.1055 [-2.3695, 0.1585] (0.6440)		-0.7685 [-2.0408, 0.5038] (0.6482)	-1.2376 [-2.4790, 0.0038] (0.6324)	0.4691** [0.1484, 0.7898] (0.1636)
Positive Social Comparison		-2.7824*** [-3.9929, -1.5719] (0.6167)		-2.3838*** [-3.5830, -1.1845] (0.6110)	-2.7139*** [-3.9170, -1.5108] (0.6129)	0.3301* [0.0084, 0.6519] (0.1642)
Negative Personal Comparison		-1.5627* [-2.8496, -0.2757] (0.6556)		-1.3084* [-2.5611, -0.0557] (0.6382)	-1.8044** [-3.0371, -0.5716] (0.6280)	0.4960** [0.1637, 0.8283] (0.1695)
Negative Social Comparison		-1.7106** [-2.8478, -0.5734] (0.5794)		-1.4866** [-2.5901, -0.3830] (0.5622)	-1.8292** [-2.9102, -0.7482] (0.5507)	0.3426* [0.0438, 0.6414] (0.1524)
Mastery			1.1601** [0.4927, 1.8274] (0.3400)	4.1394*** [2.7871, 5.4917] (0.6889)	3.5149*** [2.2348, 4.7950] (0.6521)	0.6245** [0.2505, 0.9985] (0.1908)
Performance-Approach			0.2576 [-0.4387, 0.9539] (0.3547)	0.6755 [-0.4106, 1.7617] (0.5533)	0.8782 [-0.2143, 1.9708] (0.5566)	-0.2027 [-0.4209, 0.0155] (0.1113)
Performance-Avoidance			0.3546 [-0.4203, 1.1296] (0.3948)	0.1892 [-1.2168, 1.5952] (0.7163)	0.5268 [-0.8735, 1.9271] (0.7134)	-0.3376* [-0.6076, -0.0675] (0.1378)
<u>Positive Personal Comparison x Mastery</u>				-4.4305*** [-6.2653, -2.5957] (0.9347)	-3.7264*** [-5.4815, -1.9713] (0.8941)	-0.7041** [-1.2085, -0.1997] (0.2573)
Positive Social Comparison x				-3.2552** [-5.3392, -1.1712] (1.0617)	-2.8476** [-4.8451, -0.8501] (1.0176)	-0.4075 [-0.9091, 0.0941] (0.2559)

Mastery						
Negative Personal Comparison x Mastery				-4.0639*** [-5.9330, -2.1948] (0.9522)	-3.7596*** [-5.5885, -1.9306] (0.9318)	-0.3043 [-0.8226, 0.2140] (0.2644)
Negative Social Comparison x Mastery				-4.6945*** [-6.4878, -2.9013] (0.9136)	-4.5301*** [-6.2599, -2.8003] (0.8812)	-0.1644 [-0.6230, 0.2942] (0.2340)
Positive Personal Comparison x Performance-Approach				-1.0102 [-3.0275, 1.0070] (1.0277)	-0.9258 [-2.9005, 1.0489] (1.0060)	-0.0844 [-0.5429, 0.3740] (0.2339)
Positive Social Comparison x Performance -Approach				0.7086 [-0.9889, 2.4060] (0.8647)	-0.0181 [-1.7372, 1.7009] (0.8758)	0.7267** [0.2498, 1.2036] (0.2433)
Negative Personal Comparison x Performance-Approach				-0.0422 [-2.1373, 2.0529] (1.0673)	-0.3856 [-2.5024, 1.7311] (1.0784)	0.3434 [-0.1709, 0.8578] (0.2624)
Negative Social Comparison x Performance-Approach				-1.8995* [-3.6163, -0.1826] (0.8746)	-2.2057* [-3.9303, -0.4812] (0.8786)	0.3062 [-0.0848, 0.6973] (0.1995)
Positive Personal Comparison x Performance -Avoidance				1.2680 [-1.2119, 3.7479] (1.2634)	0.3565 [-2.0689, 2.7820] (1.2356)	0.9115** [0.3910, 1.4319] (0.2655)

Positive Social Comparison x Performance-Avoidance				-1.0417 [-3.2172, 1.1338] (1.1083)	-1.1673 [-3.2772, 0.9426] (1.0749)	0.1256 [-0.3715, 0.6226] (0.2536)
Negative Personal Comparison x Performance-Avoidance				-0.4068 [-2.6547, 1.8411] (1.1452)	-0.6908 [-2.9456, 1.5640] (1.1487)	0.2840 [-0.1510, 0.7190] (0.2219)
Negative Social Comparison x Performance-Avoidance				1.1641 [-0.8033, 3.1314] (1.0023)	1.0272 [-1.0371, 3.0915] (1.0517)	0.1369 [-0.4146, 0.6884] (0.2814)
Constant	0.0371 [-3.4793, 3.5534] (1.7915)	-1.7465 [-5.2795, 1.7865] (1.7999)	-8.2104*** [-12.5384, -3.8825] (2.2049)	-19.7963*** [-25.6684, -13.9243] (2.9915)	-16.4942*** [-22.2521, -10.7364] (2.9333)	
With control variables and test versions[#]						
N	838	838	838	838	838	838
Adj. R^2	0.22	0.20	0.20	0.25	0.28	
Max VIF	2.67	2.69	2.70	5.22	5.26	

Panel B: Performance Test						
	Dependent Variable: Performance Test					
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6) Bootstrapping Model
SRL	5.7157*** [4.4092, 7.0222] (0.6656)				5.6689*** [4.3204, 7.0174] (0.6870)	
Positive Personal Comparison		-1.2993 [-5.5510, 2.9525] (2.1661)		-0.5352 [-4.7949, 3.7245] (2.1701)	-2.1539 [-6.1008, 1.7929] (2.0107)	1.6187** [0.5922, 2.6452] (0.5237)
Positive Social		-2.3439 [-5.9839, 1.2961]		-1.9112 [-5.5977, 1.7752]	-3.0505 [-6.6287, 0.5277]	1.1393* [0.0311, 2.2474]

Comparison		(1.8544)		(1.8780)	(1.8229)	(0.5654)
Negative Personal Comparison		1.3743 [-2.4853, 5.2338] (1.9663)		2.2408 [-1.6192, 6.1008] (1.9665)	0.5293 [-3.1532, 4.2118] (1.8760)	1.7115** [0.6002, 2.8229] (0.5670)
Negative Social Comparison		-2.8029 [-6.6206, 1.0149] (1.9450)		-2.4148 [-6.1763, 1.3467] (1.9163)	-3.5971 [-7.3523, 0.1581] (1.9131)	1.1823* [0.1487, 2.2158] (0.5273)
Mastery			2.9693** [0.7451, 5.1935] (1.1331)	9.1424*** [5.4470, 12.8378] (1.8826)	6.9874*** [3.4249, 10.5499] (1.8149)	2.1550** [0.8804, 3.4296] (0.6503)
Performance-Approach			-0.0946 [-2.3197, 2.1305] (1.1336)	-0.0314 [-3.3676, 3.3047] (1.6996)	0.6681 [-2.6445, 3.9807] (1.6876)	-0.6995 [-1.4247, 0.0257] (0.3700)
Performance-Avoidance			-0.2042 [-2.6640, 2.2556] (1.2532)	-0.5351 [-4.7974, 3.7272] (2.1714)	0.6297 [-3.6273, 4.8867] (2.1687)	-1.1648* [-2.0967, -0.2330] (0.4754)
Positive Personal Comparison x Mastery				-8.5715* [-15.6251, -1.5179] (3.5934)	-6.1419 [-12.5605, 0.2767] (3.2699)	-2.4296** [-4.1451, -0.7141] (0.8753)
Positive Social Comparison x Mastery				-11.1359*** [-16.2030, -6.0688] (2.5814)	-9.7297*** [-14.6118, -4.8476] (2.4872)	-1.4062 [-3.2642, 0.4518] (0.9480)
Negative Personal Comparison x Mastery				-4.3964 [-10.3045, 1.5116] (3.0098)	-3.3462 [-9.2598, 2.5673] (3.0126)	-1.0502 [-2.8416, 0.7411] (0.9140)
Negative Social Comparison x Mastery				-11.0492*** [-16.6606, -5.4377] (2.8587)	-10.4818*** [-16.1168, -4.8467] (2.8708)	-0.5674 [-2.1277, 0.9929] (0.7961)
Positive Personal Comparison x Performance-				-0.1498 [-7.8294, 7.5298] (3.9123)	0.1416 [-7.1452, 7.4284] (3.7122)	-0.2914 [-1.8011, 1.2184] (0.7703)

Approach						
Positive Social Comparison x Performance -Approach				3.0656 [-3.4819, 9.6131] (3.3356)	0.5579 [-5.8405, 6.9564] (3.2597)	2.5077** [0.9662, 4.0492] (0.7865)
Negative Personal Comparison x Performance-Approach				-0.6456 [-6.6054, 5.3142] (3.0362)	-1.8307 [-7.6822, 4.0207] (2.9810)	1.1851 [-0.5119, 2.8821] (0.8658)
Negative Social Comparison x Performance-Approach				-1.6674 [-8.0091, 4.6742] (3.2307)	-2.7242 [-9.1166, 3.6682] (3.2566)	1.0567 [-0.2369, 2.3503] (0.6600)
Positive Personal Comparison x Performance -Avoidance				-0.2020 [-8.7734, 8.3695] (4.3667)	-3.3472 [-11.5277, 4.8332] (4.1675)	3.1453** [1.3607, 4.9298] (0.9105)
Positive Social Comparison x Performance-Avoidance				0.7319 [-6.3424, 7.8061] (3.6039)	0.2986 [-6.3952, 6.9924] (3.4101)	0.4333 [-1.2381, 2.1047] (0.8528)
Negative Personal Comparison x Performance-Avoidance				1.3382 [-5.0366, 7.7130] (3.2476)	0.3581 [-5.8860, 6.6022] (3.1810)	0.9801 [-0.5661, 2.5262] (0.7889)
Negative Social x Performance-				-0.3255 [-7.4954, 6.8444] (3.6527)	-0.7978 [-8.3157, 6.7202] (3.8300)	0.4723 [-1.3922, 2.3367] (0.9513)

Avoidance						
Constant	-1.9279 [-12.9692, 9.1134] (5.6251)	-10.8895 [-22.5695, 0.7905] (5.9505)	-20.0432** [-33.0553, -7.0311] (6.6292)	-43.1727*** [-62.4751, -23.8703] (9.8336)	-31.7780** [-50.5925, -12.9635] (9.5849)	
With control variables and test versions##						
N	838	838	838	838	838	838
Adj. R^2	0.25	0.20	0.21	0.22	0.26	
Max VIF	2.67	2.69	2.70	5.22	5.26	

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%; Numbers are coefficient estimates; numbers in square parentheses are 95% confidence interval; numbers in parenthesis are robust standard error.

Among various control variables, *Male* is negative and significant at 0.01 with coefficient estimates ranging from -1.8067 to -1.3453 across columns (1) to (5). *IT Skill* is positive and significant at 0.001 with coefficient estimates ranging from 0.9459 to 1.0677 across columns (1) to (5). *Pre-experiment Knowledge Test* is positive and significant at 0.05 with coefficient estimates ranging from 0.3349 to 0.5864 across columns (1) to (5). *Technical Major* is positive and significant at 0.001 with coefficient estimates ranging from 3.6918 to 4.0311 across columns (1) to (5). *CGPA* is positive and significant at 0.001 with coefficient estimates ranging from 2.4881 to 3.4048 across columns (1) to (5).

Among various control variables, *Male* is positive and significant at 0.05 with coefficient estimates of 2.6290 and 2.7811 in columns (1) and (5), respectively. *IT Skill* is positive and significant at 0.05 with coefficient estimates ranging from 2.0997 to 2.3253 across columns (1) to (5). *Age* is negative and significant at 0.05 with coefficient estimates ranging from -2.5781 to -1.8814 across columns (1) to (5). *Pre-experiment Knowledge Test* is positive and significant at 0.05 with coefficient estimates ranging from 1.0634 to 1.6984 across columns (1) to (5). *Technical Major* is positive and significant at 0.01 with coefficient estimates ranging from 8.2663 to 8.9735 across columns (1) to (5). *CGPA* is positive and significant at 0.001 with coefficient estimates ranging from 10.0337 to 12.8789 across columns (1) to (5).

Appendix L. Additional Analysis Results

We report the regression results without control variables in Tables L1 (The Impact of Global Orientations and Gamified Performance Feedback on SRL) and L2 (The Impact of SRL on Test Performance). We also included interaction term one at a time. These results are presented in Tables L3 (The Impact of Goal Orientations and Gamified Performance Feedback on SRL Engagement) and L4 (The Impact of Goal Orientations and Gamified Performance Feedback on Pace to Complete a Module with SRL). We report other learning outcomes in Table L5 (The Impact of SRL on Course Performance).

Table L1. The Impact of Goal Orientations and Gamified Performance Feedback on SRL

	Dependent Variables	
Independent Variables: Goal Orientations, Gamified Performance Feedback, and Interaction Terms	**SRL Engagement**	**Pace to Complete a Module with SRL**
Positive Personal Comparison	0.3092*** [0.1361, 0.4824] (0.0882)	0.5654** [0.1760, 0.9548] (0.1987)
Positive Social Comparison	0.1822 [-0.0036, 0.3679] (0.0946)	0.3935+ [-0.0001, 0.7871] (0.2008)
Negative Personal Comparison	0.3064** [0.1247, 0.4882] (0.0926)	0.5887** [0.2019, 0.9755] (0.1973)
Negative Social Comparison	0.1811* [0.0060, 0.3562] (0.0892)	0.2742 [-0.1194, 0.6678] (0.2008)
Mastery	0.4490*** [0.2590, 0.6390] (0.0968)	0.5103** [0.2140, 0.8066] (0.1512)
Performance-Approach	-0.1417* [-0.2618, -0.0216] (0.0612)	-0.0724 [-0.3219, 0.1771] (0.1273)
Performance-Avoidance	-0.1633* [-0.3069, -0.0197] (0.0732)	-0.2462+ [-0.5349, 0.0425] (0.1473)
Positive Personal Comparison x Mastery	-0.4602** [-0.7320, -0.1884] (0.1385)	-0.6493** [-1.0842, -0.2143] (0.2219)
Positive Social Comparison x Mastery	-0.2324 [-0.5402, 0.0755] (0.1568)	-0.1440 [-0.6781, 0.3901] (0.2725)
Negative Personal Comparison x Mastery	-0.1765 [-0.4877, 0.1347] (0.1585)	0.0035 [-0.4631, 0.4700] (0.2380)
Negative Social Comparison x Mastery	-0.0543 [-0.3467, 0.2382] (0.1490)	-0.2414 [-0.7386, 0.2559] (0.2537)
Positive Personal Comparison x Performance-Approach	-0.0849 [-0.3612, 0.1915] (0.1408)	-0.0974 [-0.5240, 0.3293] (0.2177)

<u>Positive Social Comparison x Performance-Approach</u>	0.3866** [0.1365, 0.6367] (0.1274)	0.4448+ [-0.0256, 0.9153] (0.2400)
Negative Personal Comparison x Performance-Approach	0.1951 [-0.1306, 0.5208] (0.1659)	0.0453 [-0.3900, 0.4807] (0.2221)
Negative Social Comparison x Performance-Approach	0.1525 [-0.0620, 0.3669] (0.1093)	0.0117 [-0.4272, 0.4505] (0.2239)
<u>Positive Personal Comparison x Performance-Avoidance</u>	0.5437*** [0.2828, 0.8046] (0.1329)	0.6595** [0.1662, 1.1529] (0.2517)
Positive Social Comparison x Performance-Avoidance	0.0356 [-0.2743, 0.3455] (0.1579)	0.1073 [-0.4143, 0.6290] (0.2661)
Negative Personal Comparison x Performance-Avoidance	0.1016 [-0.1701, 0.3732] (0.1384)	0.1892 [-0.2566, 0.6351] (0.2275)
Negative Social Comparison x Performance-Avoidance	0.1045 [-0.2331, 0.4422] (0.1720)	0.3260 [-0.1598, 0.8117] (0.2478)
Constant / Theta	Constant: -0.9419* [-1.6813, -0.2025] (0.3767)	Theta: 0.1273 (0.0534)
<u>Without</u> any control variables		
N	838	838
Model Fit	*Adj.* R^2=0.08	*Chi*^{2}=49.49

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%

Table L2. The Impact of SRL on Test Performance

	(1) Knowledge Test	(2) Performance Test
<u>SRL</u>	2.2111*** [1.7444, 2.6777] (0.2378)	7.7607*** [6.4738, 9.0475] (0.6556)
Constant	12.9654*** [12.5517, 13.3791] (0.2108)	24.8473*** [23.5680, 26.1265] (0.6517)
<u>Without</u> any control variables[#] and test versions		
N	838	838
Adj. R^2	0.08	0.10

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%

Table L3. The Impact of Goal Orientations and Gamified Performance Feedback on SRL Engagement			
	Dependent Variable: SRL Engagement		
Independent Variables: Goal Orientations, Gamified Performance Feedback, and Interaction Terms	**(1)**	**(2)**	**(3)**
Positive Personal Comparison	0.2721** [0.1077, 0.4366] (0.0838)	0.2762** [0.1104, 0.4421] (0.0845)	0.2741** [0.1112, 0.4370] (0.0830)
Positive Social Comparison	0.1963* [0.0164, 0.3762] (0.0916)	0.1886* [0.0129, 0.3643] (0.0895)	0.1895* [0.0097, 0.3693] (0.0916)
Negative Personal Comparison	0.2940** [0.1125, 0.4756] (0.0925)	0.2912** [0.1088, 0.4736] (0.0929)	0.2854** [0.1033, 0.4676] (0.0928)
Negative Social Comparison	0.1838* [0.0143, 0.3533] (0.0864)	0.1795* [0.0097, 0.3494] (0.0865)	0.1785* [0.0087, 0.3483] (0.0865)
Mastery	0.2682*** [0.1594, 0.3769] (0.0554)	0.2192*** [0.1221, 0.3164] (0.0495)	0.2208*** [0.1221, 0.3196] (0.0503)
Performance-Approach	-0.0009 [-0.0884, 0.0865] (0.0445)	-0.0473 [-0.1403, 0.0457] (0.0474)	0.0060 [-0.0822, 0.0941] (0.0449)
Performance-Avoidance	-0.0635 [-0.1619, 0.0350] (0.0502)	-0.0584 [-0.1566, 0.0399] (0.0501)	-0.0954^{+} [-0.2010, 0.0103] (0.0538)
Positive Personal Comparison x Mastery	-0.1722^{+} [-0.3727, 0.0283] (0.1022)		
Positive Social Comparison x Performance-Approach		0.3012** [0.1033, 0.4991] (0.1008)	
Positive Personal Comparison x Performance-Avoidance			0.2239* [0.0218, 0.4259] (0.1029)
Constant	-2.4324*** [-3.1110, -1.7538] (0.3457)	-2.1239*** [-2.7856, -1.4621] (0.3371)	-2.1891*** [-2.8531, -1.5252] (0.3382)
With control variables			
N	838	838	838
Adj. R^2	0.14	0.14	0.14

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%, $^{+}$ Significant at 10%

Table L4. The Impact of Goal Orientations and Gamified Performance Feedback on Pace to Complete a Module with SRL			
	Dependent Variable: Pace to Complete a Module with SRL		
Independent Variables: Goal Orientations, Gamified Performance Feedback, and Interaction Terms	**(1)**	**(2)**	**(3)**
Positive Personal Comparison	0.5444** [0.1761, 0.9127] (0.1879)	0.5314** [0.1678, 0.8949] (0.1855)	0.5208** [0.1546, 0.8870] (0.1869)
Positive Social Comparison	0.3513^{+} [-0.0190, 0.7216] (0.1889)	0.3355^{+} [-0.0325, 0.7035] (0.1877)	0.3400^{+} [-0.0285, 0.7086] (0.1880)
Negative Personal Comparison	0.6057** [0.2410, 0.9704] (0.1861)	0.5929** [0.2320, 0.9538] (0.1841)	0.5896** [0.2262, 0.9529] (0.1854)
Negative Social Comparison	0.2324 [-0.1401, 0.6048] (0.1900)	0.2339 [-0.1348, 0.6026] (0.1881)	0.2274 [-0.1434, 0.5983] (0.1892)
Mastery	0.3280*** [0.1443, 0.5117] (0.0937)	0.2411** [0.0794, 0.4029] (0.0825)	0.2577** [0.0952, 0.4202] (0.0829)
Performance-Approach	0.0094 [-0.1406, 0.1594] (0.0765)	-0.0499 [-0.2088, 0.1090] (0.0811)	0.0186 [-0.1309, 0.1680] (0.0763)
Performance-Avoidance	-0.0053 [-0.1699, 0.1592] (0.0840)	-0.0008 [-0.1652, 0.1636] (0.0839)	-0.0348 [-0.2087, 0.1392] (0.0887)
Positive Personal Comparison x Mastery	-0.2931^{+} [-0.6318, 0.0455] (0.1728)		
Positive Social Comparison x Performance-Approach		0.4400* [0.0895, 0.7906] (0.1789)	
Positive Personal Comparison x Performance-Avoidance			0.1834 [-0.1910, 0.5578] (0.1910)
Theta	0.1008*** (0.0469)	0.0963*** (0.0457)	0.0989*** (0.0463)
With control variables			
N	838	838	838
Chi^2	80.61	85.12	80.05

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%, $^{+}$ Significant at 10%

Table L5. The Impact of SRL on Course Performance

	(1) Examination Scores	(2) Course GPA
SRL	3.0201*** [1.5214, 4.5188] (0.7635)	0.0571* [0.0009, 0.1133] (0.0286)
Constant	6.1432 [-6.6643, 18.9506] (6.5249)	0.4164 [-0.0753, 0.9081] (0.2505)
With control variables and test versions		
N	838	838
Adj. R^2	0.20	0.41

***Significant at 0.1%, ** Significant at 1%, * Significant at 5%

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