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Procrastination and other learning behavioral types in e-learning and their relationship with learning outcomes

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ABSTRACT

The aims of this longitudinal study were to describe undergraduates' learning behavioral types in e-learning and to investigate their relationship to learning outcomes over an entire semester. In the first part of the study, 441 students at a national university in Japan were analyzed with regard to their visualization of learning progress. Seven distinct types of learning behavior were identified: (1) procrastination, (2) learning habit, (3) random, (4) diminished drive, (5) early bird, (6) chevron, and (7) catch-up. In the second part of this study, data from 226 students were analyzed. The results showed significant relationships between their learning type and ultimate learning outcomes. The students who exhibited the learning habit type scored significantly higher on the test than those students of the procrastination type. The results imply that regulated learning (i.e., forming a learning habit) could increase learning effectiveness and lead to better learning outcomes in e-learning.

1. Introduction

In higher education, over 70% of students postpone the acts that are necessary for them to reach their goals through a behavior known as procrastination (Schouwenburg, Lay, Pychyl, & Ferrari, 2004), with Ellis and Knaus (1977) reporting that up to 95% of students may in fact be procrastinators. Even in online educational settings such as e-learning, procrastination has been viewed as a problematic behavior. Previous research has indicated that procrastination can lead to students failing academic courses and developing physical and psychological problems (Hussain & Sultan, 2010), consequently lowering their satisfaction with their life (Özer & Saçkes, 2011). Many studies have been conducted on procrastination and they have all found a negative correlation between procrastination and learning outcomes (Tan et al., 2008). However, most of these studies have been conducted in a traditional face-to-face educational setting while few have dealt with the online learning setting (Klingsieck, Fries, Horz, & Hofer, 2012).

Rotenstein, Davis, and Tatum (2009) summarized the procrastination measures utilized in the previous research and reported that valid and reliable measures have not yet been established. Most previous studies employed self-reported scales to measure procrastination. This led to Phase 1 of the present study, which was intended to propose a categorization method for learning behavioral types such as procrastination and other hyperbolic patterns, focusing on the e-learning setting and being based on actual learning behavior.

The aims of this study were to describe definite learning types in e-learning, considering timing and progress of learning, and to investigate the relationships between these learning types and the ultimate learning outcomes. Our research project therefore aims to develop a learning support system for e-learning to provide appropriate and customized feedback in a timely manner, based on learners' actual learning types. The study was positioned to match learning types and their necessary support and to determine the appropriate timing for such learning support.

2. Literature review

2.1. Procrastination

Procrastination has been defined as the delay of initiation or of completion of important tasks (Lay, 1986). In previous research,

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Table 1
Unit numbers, item numbers, and learning hours of learning materials.

Section	Part	Category	Task	Unit #	Item #	Required learning hours
Listening	1	Photographs	Dictation	13	130	2
			American English	6	30	2
			Other English	6	30	2
	2	Question–response	Dictation	20	166	2
			American English	9	45	2
			Other English	9	45	2
	3	Conversations	Dictation	20	199	3
			American English	18	90	3
			Other English	18	90	3
	4	Talks	Dictation	11	93	3
			American English	13	47	2
			Other English	13	47	2
Reading	5	Incomplete sentences (short passage)	Practices	20	400	7
	6	incomplete sentences (longer passage)	Practices	10	50	5
	7	Reading comprehension	Fast-reading	10	275	4
			Practices	10	50	3
		Total		206	1787	47

procrastination and its effects have garnered much interest. Most research has found that procrastination has a negative effect on learning performance and can also lead to physical and psychological problems (Hussain & Sultan, 2010). These results were consistent even in longitudinal studies (Tice & Baumeister, 1997). Recently, however, procrastination research has entered a new phase, with some researchers suggesting the positive effects of procrastination. Chu and Choi (2005) for example introduced the new perspective that not all procrastination behaviors may be harmful or have negative consequences. They refer to this positive type of procrastination as active procrastination. They describe active procrastinators as those who prefer to work under pressure and who make deliberate decisions to procrastinate. Choi and Moran (2009) developed a new active procrastination scale and identified four factors of active procrastination: (1) outcome satisfaction, (2) preference for pressure, (3) intentional decision, and (4) ability to meet deadlines. Strunk, Cho, Steele, and Bridges (2013) proposed a 2 × 2 model of procrastination with two dimensions of time-related academic behavior and motivational orientation.

2.2. Measuring procrastination

Concerning instrumentation in the research, self-reported scales such as the Procrastination Assessment Scale—Students (PASS), which was initially proposed by Solomon and Rothblum (1984), and Lay's (1986) scale were employed in many of the previous studies. However, the scales' correlation with actual learning behavior was found to be low in the content analysis by Rotenstein et al. (2009). They summarized the procrastination measures used in previous research in a table (p. 225); most of the research used self-reported scales and analyzed the data with the scales inferentially. Other studies reported a weaker relationship between the Procrastination Scale scores and behavioral measures of procrastination ($r = -.54$ in Tuckman, 1991; $r = -.38$, in Howell, Watson, Powell, & Buro, 2006). Although the correlation seems low, the inferential statistics show the significance. Thus, the categorization method of learning behavioral types based on actual learning records should be further investigated. There is a plausible explanation for the inconsistency in research results between the measurements and actual procrastination. According to Steel's (2007) meta-analysis, actual postponing (state procrastination) is affected by a personal tendency to delay tasks (trait procrastination), and trait procrastination tends to be stable regardless of situations and time durations. If the trait procrastination is relatively constant, these two kinds of procrastination may affect the results of the relationship between scores on scales and actual behavior. Thus, more longitudinal research on the matter should be conducted.

2.3. Dynamic nature of procrastination and modeling

Some researchers challenge the model of learners' academic procrastination. Moon and Illingworth (2005) employed a latent growth curve analysis with actual procrastination behavior, test performance, and self-reported levels of trait procrastination for 303 students. They pointed out that self-reported measures did not predict temporal changes in procrastination and test performance. They also found that both high and low procrastinators followed the same trajectory over time. From our own observation, there seem to be differences as well as similarities between high and low procrastinators' behavioral patterns.

Wäschle, Allgaier, Lachner, Fink and Nückles (2014) focused on the relationship between procrastination and self-efficacy in self-regulated learning cycles through a weekly web-based self-monitoring protocol. In their longitudinal research, they found amplifying feedback loops of low self-efficacy and perceived goal achievement in procrastination. They concluded that students exhibiting low self-efficacy are vulnerable to the undesirable loop of procrastination. The regression results of McElroy and Lubich (2013) showed that a marked delay in making a first class posting could be an alert for possible procrastinators. This implies that a delay in initial activities could be a useful clue in identifying possible procrastinators.

Several indicators of procrastination have been suggested in previous research. However, our research interests are to find appropriate support for learners' needs for all types of learning behaviors. The uniqueness of this study is to identify other learning behavior types besides procrastination in the online educational setting.

2.4. Learning behavioral types for e-learning

e-Learning provides less restrictions on learning as students can learn at any time and in any place. However, the lower constraints of this learning setting necessitate self-regulation by students (Goda, et al., 2013; Lynch & Dembo, 2004; Michinov, Brunot, Bohec, Juhel, & Delaval, 2011) and intrinsic motivation (Wighting, Liu, & Rovai, 2008). Unlike traditional instruction, in e-learning it is easy to accumulate learning logs and records from inside and outside the classroom. This helps researchers to analyze the learning process even when there is a large amount of data. Hung and Zhang (2008) tried to study online learning behavior and activity using the data mining technique on 17,934 server logs. They found that most learning activities were passive, involving just reading or accessing course materials, although collaborations were strongly emphasized during the classes.

Some studies focusing on the online educational setting have also demonstrated that procrastinators experience negative effects in their

Table 2
Learning paces for Weeks 1 to 8 ($N = 441$).

Learning pace	Week 1		Week 2		Week 3		Week 4		Week 5		Week 6		Week 7		Week 8	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Slow	436	98.9	416	94.3	394	89.3	396	89.8	406	92.1	410	93.0	408	92.5	399	90.5
Appropriate	5	1.1	23	5.2	40	9.1	35	7.9	26	5.9	18	4.1	15	3.4	14	3.2
Fast	0	0.0	2	0.5	7	1.6	9	2.0	8	1.8	12	2.7	16	3.6	26	5.9
Task completed	0	0.0	0	0.0	0	0.0	1	0.2	1	0.2	1	0.2	2	0.5	2	0.5

academic performance and grades (McElroy & Lubich, 2013; Tuckman, 2005). However, Klingsieck et al. (2012) postulated that most studies were conducted in a traditional educational setting and that more research should be conducted into the online learning setting.

In order to meet our goal of providing prompt feedback and support to prevent academic procrastination and to instead form preferred learning habits in the online setting, we focused on state procrastination over the course of a whole semester and we investigated other learning behavior types in our longitudinal study.

3. Research methods

Actual learning logs focusing on timing and progress were analyzed to describe feature learning behavioral types in e-learning. There were two key research questions in this study:

Research Question 1: What learning behavioral types exist in e-learning?
Research Question 2: What learning behavioral type corresponds to positive learning performances?

Both parts of this study were examined in order to find answers to these research questions. In Phase 1, the process of determining learning type categories was explained and the characteristics of each type were discussed. In Phase 2, the relationship between learning types and learning outcomes was analyzed.

3.1. Phase 1

3.1.1. Setting and participants

Five mandatory e-learning courses in computer assisted language learning (CALL), with two credits provided to sophomores at a national university in Japan, were employed in this research. The courses were provided to science-related departments and combined face-to-face classroom learning with self-paced e-learning outside of the classroom for 15 weeks. The learning materials employed in this study were *Newton e-Learning TLT Soft*, online drill-and-practice learning materials developed to help students prepare for the TOEIC with a mastery learning approach. The e-Leaning vendor, Newton, Inc., explained that the materials had been designed and developed to allow students with a TOEIC score of less than 450 to reach a score of more than 750 in a short period. The average TOEIC score of freshmen at the university for the last five years ranged from 433.6 to 484.8. Thus, the materials were considered suitable for the sophomore students and were employed in the targeted courses.

The assigned materials had listening and reading sections and included 206 units, with a total of 1787 quiz items (see Table 1). They required approximately 30 to 40 h for completion. The students were asked to complete the assigned materials by the end of the semester.

In the face-to-face classroom, the lessons consisted of two parts: The first part was a dictation of the listening material selected from web-news and reports related to the students' major for 30 min; then, the students studied the e-learning materials at their own pace for about 60 min. In the classroom, students could ask the instructor questions; outside of the classroom, a learning management system, Blackboard, was utilized for interactions between students and the instructor. The instructor was the same for all of the five courses.

A total of 441 students participated in this study. Students from five different departments participated: Science ($n = 56$, 12.70%), Pharmacy ($n = 92$, 20.86%), Computer Science & Electrical Engineering ($n = 104$, 23.58%), Mechanical System Engineering ($n = 104$, 23.58%), and Civil and Environment Engineering ($n = 85$, 19.27%). The number of men and women was 359 (81.41%) and 82 (18.59%), respectively. A convenience sample was selected from the five classes for the science-related departments, and the number of male students was four times that of female students.

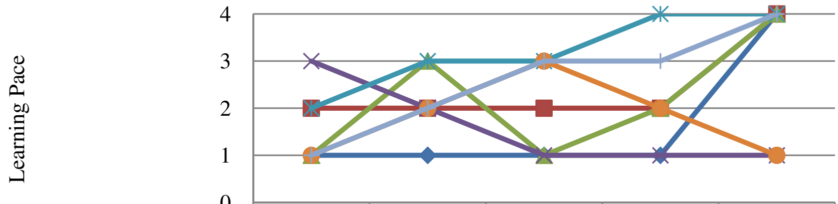
There were 26 dropout students and their departments were: 3 Pharmacy, 11 Computer Science & Electrical Engineering, 8 Mechanical System Engineering, and 4 Civil and Environmental Engineering. The conditions for being classified as a dropout were not joining the course at all and failing to attend the classroom or access the learning materials after the second or third weeks. Six dropout students (23.1%) were reported as taking a leave of absence after the semester. The research focus was to categorize learning types and so the dropout students were categorized as the "other" learning type and removed from further analyses.

3.1.2. Instrument and data collection

For data collection, the e-learning application had a function for administrators to check students' progress over a selected period. The administrators could view a summary of each student's learning progress with the completion rate percentage and hours spent on the learning materials. The weekly completion rates of the learning materials were used to determine actual learning behavior. The completion rates were calculated from the number of learned items for the selected period, divided by the total number of items. Weekly-cumulated completion rates were used to determine the students' learning pace. Since the completion of the learning materials was 100% as a learning progress for 15 weeks, students had to complete about 6.67% (100/15) per week for an appropriate learning pace. There were no sub-deadlines before the end of the semester. The students were expected to learn the

Table 3
Learning paces for Weeks 9 to 15 ($N = 441$).

Learning pace	Week 9		Week 10		Week 11		Week 12		Week 13		Week 14		Week 15	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Slow	387	87.8	386	87.5	382	86.6	363	82.3	366	83.0	366	83.0	37	8.4
Appropriate	30	6.8	24	5.4	31	7.0	47	10.7	42	9.5	46	10.4	0	0.0
Fast	22	5.0	29	6.6	26	5.9	24	5.4	19	4.3	2	0.5	0	0.0
Task completed	2	0.5	2	0.5	2	0.5	7	1.6	14	3.2	27	6.1	404	91.6



	Week 3 Learning Pace	Week 6 Learning Pace	Week 9 Learning Pace	Week 12 Learning Pace	Week 15 Learning Pace
Learning Type 1a	1	1	1	1	4
Learning Type 2	2	2	2	2	4
Learning Type 3	1	3	1	2	4
Learning Type 4	3	2	1	1	1
Learning Type 5	2	3	3	4	4
Learning Type 6	1	2	3	2	1
Learning Type 7	1	2	3	3	4

Fig. 1. Examples of learning behavioral type categorization. Learning pace 1 indicates "slow"; 2, "appropriate"; 3, "fast"; and 4, "completion".

materials in a self-regulated manner, but they had the opportunity to learn and plan for the next week in the weekly face-to-face classroom lessons and to compare their learning progress against that of their classmates.

The weekly actual completion rates were categorized under four labels: three learning paces (appropriate, fast, and slow) and full completion. The learning pace with the appropriate completion rate for the week, plus or minus 5%, was labeled as appropriate, more than 5% above the rate was labeled as fast, and more than 5% below the rate was labeled as slow. This range of 10% was decided on by the researchers, who have more than ten years of teaching experience. Weekly labels for 15 weeks for each student were used to determine a learning behavior pattern.

3.1.3. Analyses for learning behavioral type categorization

In order to find an answer to Research Question 1, 15 weeks' worth of learning behaviors was analyzed and categorized into seven learning types. A description of this study's attempts to find salient learning types follows.

One hundred and ten patterns were found from the combinations of three learning types and a full completion for 15 weeks (4^{15} patterns). There were still too many patterns to determine salient features for students in online learning. Then, the completion rates for three-week periods were used for the data analysis. From the observations of five three-week completion rates, 59 patterns were observed out of 1024 (4^5). The patterns were visualized with line plots, and similar shapes were grouped. Then, the patterns were organized into seven types following careful discussion among the researchers.

Table 4
Learning types and their ratio of task completion.

	Learning behavioral type	Total		Task completed		Not completed	
		n	%	*n*	%	*n*	%
1	Procrastination	305	69.16%	300	98.36%	5	1.64%
2	Learning habit	20	4.54%	20	100.00%	0	0.00%
3	Random	7	1.59%	7	100.00%	0	0.00%
4	Diminished drive	24	5.44%	21	87.50%	3	12.50%
5	Early bird	7	1.59%	7	100.00%	0	0.00%
6	Chevron	30	6.80%	27	90.00%	3	10.00%
7	Catch-up	22	4.99%	22	100.00%	0	0.00%
–	Other	26	5.90%	0	0.00%	26	100.00%
	Total	441	100%	404	91.61%	37	8.39%

3.1.4. Results

Tables 2 and 3 show the number of students and percentages for each learning pace label for the 15 weeks in order to present the overall tendency of learning behaviors. Table 2 shows the learning paces in the first half of the semester: more than 90% of students' learning paces were labeled as "slow" up to Week 8. Then, closer to the end of the semester, the percentage of appropriate learning paces increased. The task completion rate jumped from 6.12% to 91.61% in the last week, although 37 students (8.39%) did not complete the assigned tasks by the deadline, as shown in Table 3.

The seven learning behavioral types identified were as follows: (1) procrastination, (2) learning habit, (3) random, (4) diminished drive, (5) early bird, (6) chevron, and (7) catch-up. Fig. 1 illustrates three examples of visualized line plots and learning behavioral types. The first example is for Learning Type (1a) (procrastination with task-completion). The learning paces for Weeks 3, 6, 9, and 12 were 1, or "slow." In Week 15, the learning pace reached 4 (task completion). The second example, for Type (2), shows that all learning paces up to Week 12 were 2 "appropriate"; this type was labeled as learning habit. The last example was categorized as Learning Type (4), diminished

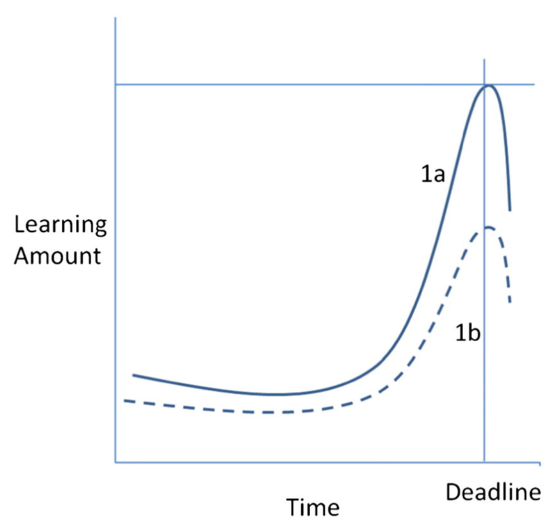


Fig. 2. Learning Type (1): Procrastination; (1a): Procrastination with task completion by the deadline, (1b): Procrastination with task incompletion by the deadline.

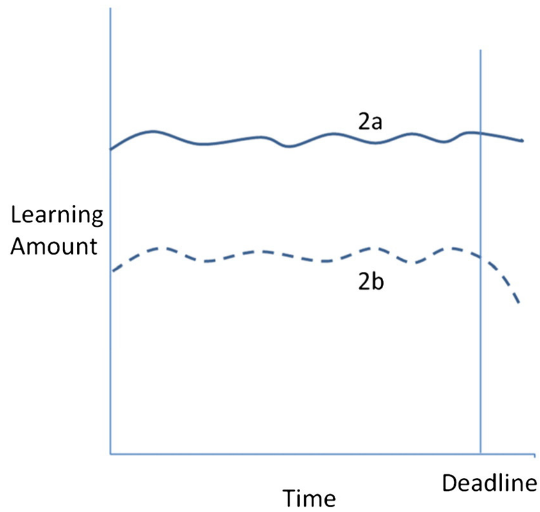


Fig. 3. Learning Type (2): Learning habit; (2a): Learning habit with larger learning amount, (2b): Learning habit with appropriate learning amount.

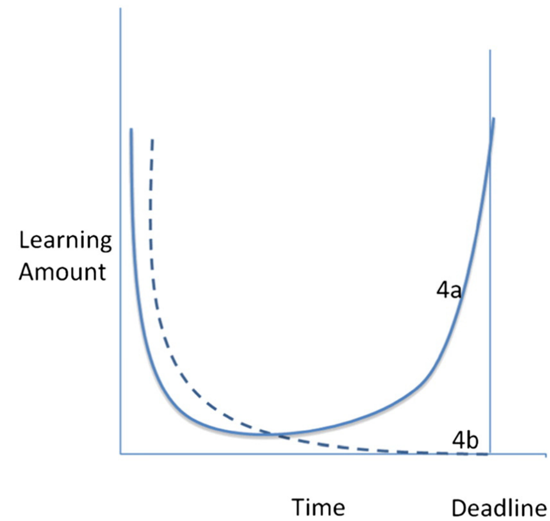


Fig. 5. Learning Type (4): Diminished drive. (4a): U-shape, (4b): Easy quitter.

drive, with an appropriate learning pace in Week 3, but "slow" learning paces in the other weeks.

3.1.5. Descriptions of the seven learning behavioral types

The characteristics of the following seven learning behavioral types will be discussed based on the results of our analyses and observations: (1) procrastination, (2) learning habit, (3) random, (4) diminished drive, (5) early bird, (6) chevron, and (7) catch-up. Table 4 summarizes the learning types and their ratio of the task completion. Theoretically, Learning Types (1), (3), (4), and (6) should be further categorized into two subtypes each in relation to task completion, although, as shown in Table 4, Learning Type (3) does not feature students with task incompletion. Learning Type (2) also has two subtypes, according to learning amount for each learning time. The subtypes will be introduced in this section.

There is another type, the "other" type discussed above, under which 26 students were categorized. These students either did not access the learning materials at all or accessed the online learning materials once, for a short period, and did not access them after that. They either dropped out or withdrew from the course. Since the course was mandatory, those who did not begin the course should be analyzed from other perspectives, not learning behaviors. Thus, we labeled them as "other" and ceased further analysis in Phase 2.

(1) Procrastination ($n = 305$, 69.16%, see Fig. 2)
In this type, students tend to procrastinate on a task or action until the last minute. They put in a last spurt right before the deadline. This type might be either considered as sluggards or as efficient, based on their level of intention, self-regulation, and meta-cognition.

(1a) Procrastination with task completion by the deadline: Students of this type should have good meta-cognition and self-regulation.

(1b) Procrastination with task incompletion by the deadline: In this type, students' meta-cognition does not work well. They may miscalculate the time required to complete a task and/or may not be able to predict an unusual event during their last spurt.

(2) Learning habit ($n = 20$, 4.54%, see Fig. 3)
In this type, students might have high self-regulation and motivation. They form their learning habits, and their learning could be effective in bringing about higher learning outcomes (i.e., better understanding and retention). This type could be further categorized into two subtypes (2a and 2b), according to their learning amount for each time period.

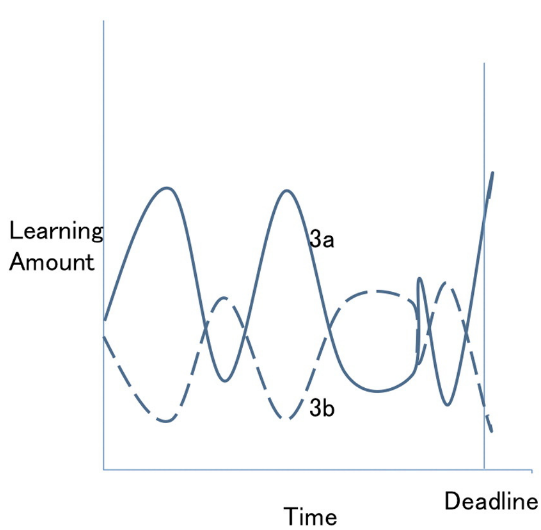


Fig. 4. Learning Type (3): Random. (3a): Random with task completion by the deadline, (3b): Random and dropout.

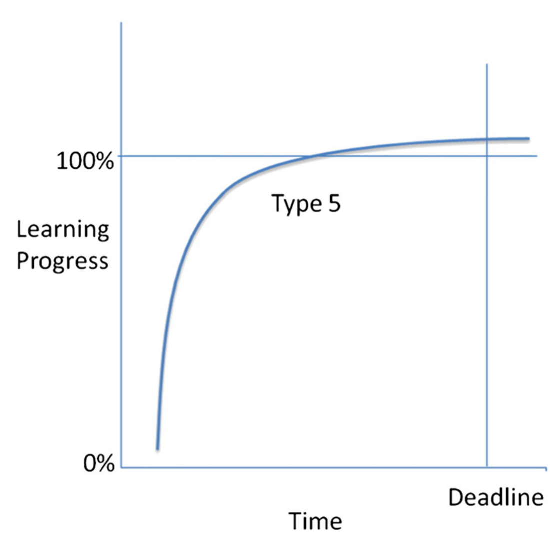


Fig. 6. Learning Type (5): Early bird.

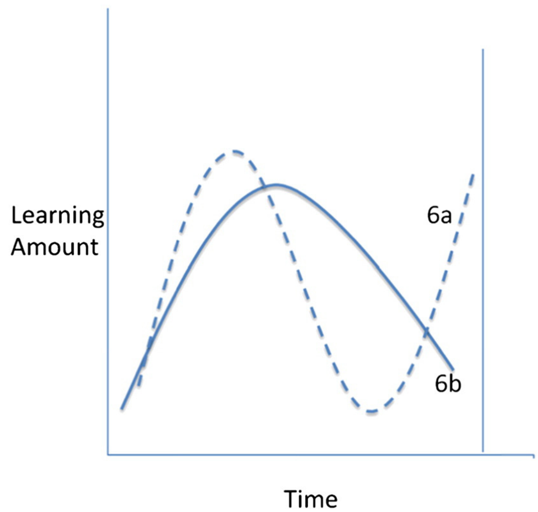


Fig. 7. Learning Type (6): Chevron. (6a): Chevron with task completion by the deadline, (6b): Chevron and dropout.

(2a) Learning habit with larger learning amount: In this type, individuals might exhibit learning-goal orientation (Dweck, 1986). They might seek "to increase their competence, to understand, or to master something new" (Dweck, 1986, p. 1040) regardless of the required task or assignment as a course requirement.

(2b) Learning habit with appropriate learning amount: These individuals regularly study the appropriate learning amount for each learning period, by calculating the required learning amount from the total learning amount divided by the learning duration. Their learning goal should be strongly affected by the required task or assignment.

(3) Random ($n = 7$, 1.59%, see Fig. 4)
Learning behavior that does not have a definite tendency is categorized as this type. Students of this type might be affected by mood or by external variables such as part-time jobs, club activities, and instructional design (quiz or test) of a targeted course or other courses. This type is also categorized into two subtypes regarding task completion.

(3a) Random with task completion by the deadline: Learning progress is irregular, but the required task is completed within the learning period.

(3b) Random and dropout: These students study irregularly and drop out sometime during the course.

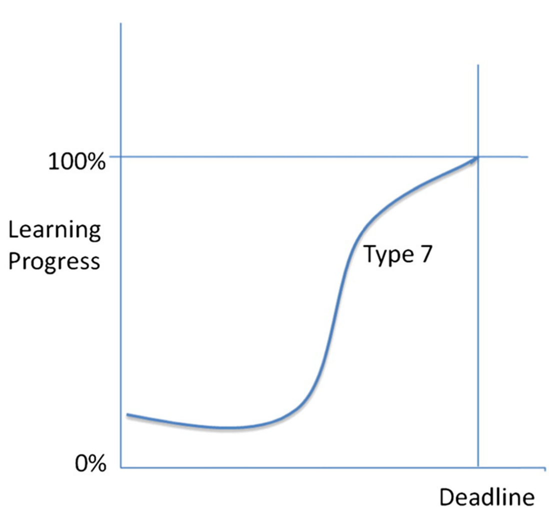


Fig. 8. Learning Type (7): catch-up.

Table 5
Ratio of learning types in Phase 1 and Phase 2.

	Learning type	Phase 2		Phase 1	
		n	%	n	%
1	Procrastination	145	64.16%	305	69.16%
2	Learning habit	9	3.98%	20	4.54%
3	Random	4	1.77%	7	1.59%
4	Diminished drive	20	8.85%	24	5.44%
5	Early bird	3	1.33%	7	1.59%
6	Chevron	19	8.41%	30	6.80%
7	Catch-up	13	5.75%	22	4.99%
–	Other	13	5.75%	26	5.90%
		226	100.00%	441	100.00%

(4) Diminished drive ($n = 24$, 5.44%, see Fig. 5)
The diminished drive type students tend to start with a great amount of learning, but gradually slow down their learning pace. The type can be divided into the following two subtypes:

(4a) U-shape: These students lose learning progress toward the middle of the semester, but increase their learning amount closer to the deadline. Although they may not be able to sustain their motivation, they can regulate their learning and they have good meta-cognition to complete the required task by the deadline.

(4b) Easy quitter: These students have a good learning rate in the beginning, but their learning rate decreases toward the middle of the learning period, and they finally drop out of the course.

(5) Early bird ($n = 7$, 1.59%, see Fig. 6)
Students of this type complete the assigned task far before the deadline. They might have a careful and conscientious temperament. Individuals of this type might also have a performance–goal orientation (Dweck, 1986) to prevent their receiving negative judgments.

(6) Chevron ($n = 30$, 6.80%, see Fig. 7)
The lines of this type are in a mountain-like shape when it comes to learning amount visualization. There are two subtypes in relation to task completion.

(6a) Chevron with task completion by the deadline: In the middle of the learning period, their learning amount increases. Then, they may slow down their learning pace after they become confident about their completion of the task. Eventually, they complete the task right before the deadline. Students of this type can, in a sense, regulate their own learning.

(6b) Chevron and dropping out: Students of this type increase their learning in the middle, but their efforts do not last and they cannot complete the required task, eventually dropping out of the course.

(7) Catch-up ($n = 22$, 4.99%, see Fig. 8).
At first, catch-up type students have a slower learning pace, but in the middle of the learning period, they increase their learning amount and gradually catch up to the appropriate learning pace.

3.2. Phase 2

The purpose of Phase 2 was to investigate the relationship between the learning behavioral types identified in Phase 1 and learning performances. In Phase 2, the scores of the TOEIC-IP were employed as learning performance indicators.

3.2.1. Setting and participants

The participants and learning materials were the same as in Phase 1. Data from 226 students out of 441 were considered for further analysis with the TOEIC-IP scores. The 226 participants were from three departments that participated in this study: Pharmacy ($n = 77$, 34.07%), Computer Science and Electrical Engineering ($n = 84$, 37.17%), and Civil and

Table 6
Learning types and learning outcomes.

	Learning behavioral types	*n*	*M*	*SD*	*SE*	95% CI		Min.	Max.
						Lowest	Highest		
1	Procrastination	145	432.48	94.671	7.862	416.94	448.02	245	680
2	Learning habit	9	582.78	130.770	43.590	482.26	683.30	400	810
3	Random	4	497.50	146.771	73.385	263.95	731.05	345	640
4	Diminished drive	20	488.75	65.792	14.712	457.96	519.54	340	610
5	Early bird	3	516.67	90.738	52.387	291.26	742.07	420	600
6	Chevron	19	516.05	66.324	15.216	484.09	548.02	380	645
7	Catch-up	13	500.38	87.689	24.321	447.39	553.37	360	645
–	Other	13	478.08	126.170	34.993	401.83	554.32	325	780
	Total	226	459.27	101.445	6.748	445.97	472.57	245	810

Environment Engineering ($n = 65$, 28.76%). The ratio of learning types in Phase 1 and Phase 2 is compared in Table 5. The chi-square was not significant for the ratio of learning types in Phase 1 as expected value and those in Phase 2 as observed value ($\chi^2(7, N = 226) = 5.12, p = .65$). This implies that the learning type ratio in Phase 2 may represent those in Phase 1.

3.2.2. Data analyses and results

Table 6 summarizes the descriptive statistics of the TOEIC-IP scores and learning types. Among the 226 participants, 13 students were categorized as the “other” type. As mentioned earlier, the other type was unique and should be analyzed using different methods than actual learning time and progress. Thus, the 13 students' data was removed from the data of the 226 participants, and data from the remaining 213 students' was further analyzed.

In order to investigate the effect of different learning types on learning outcomes, ANOVA was conducted. The results showed significant differences among the learning types ($F = 5.78, p < .01$). The results of Tukey's post hoc test are shown in Table 7. There are significant differences between Learning Types (1) (procrastination) and (2) (learning habit) (mean difference $= -150.30, p < .01$), and between Learning Types (1) (procrastination) and (6) (chevron) (mean difference $= -83.57, p < .01$).

Table 7
Tukey's post hoc test results.

Learning type (I)	Learning type (J)	Mean dif. (I − J)	*SE*	*p*	95% CI	
1	2**	−150.30	32.52	0.00	−249.82	−50.77
	3	−65.02	47.98	0.88	−211.85	81.82
	4	−56.27	22.58	0.20	−125.37	12.84
	5	−84.18	55.21	0.79	−253.17	84.80
	6**	−83.57	23.09	0.01	−154.25	−12.89
	7	−67.90	27.40	0.21	−151.78	15.97
2	3	85.28	56.88	0.81	−88.81	259.37
	4	94.03	37.99	0.21	−22.26	210.31
	5	66.11	63.10	0.97	−127.03	259.25
	6	66.73	38.30	0.66	−50.50	183.95
	7	82.39	41.05	0.48	−43.23	208.02
3	4	8.75	51.85	1.00	−149.93	167.43
	5	−19.17	72.29	1.00	−240.43	202.10
	6	−18.55	52.07	1.00	−177.93	140.82
	7	−2.88	54.12	1.00	−168.53	162.76
4	5	−27.92	58.61	1.00	−207.28	151.45
	6	−27.30	30.32	0.99	−120.11	65.51
	7	−11.63	33.72	1.00	−114.85	91.58
5	6	0.61	58.81	1.00	−179.37	180.60
	7	16.28	60.63	1.00	−169.28	201.84
6	7	15.67	34.07	1.00	−88.61	119.94

Note. Learning types: (1), procrastination; (2), learning habit; (3), random; (4), diminished drive; (5), early bird; (6), chevron; and (7), catch-up.
** $p < .01$.

4. Discussion and future implications

This research comprised two phases whose research purposes, respectively, were as follows: (1) categorization of students' self-paced learning behavior and (2) relationship between categorized behaviors and learning outcomes. These purposes were reflected in the research questions: (1) What learning behavioral types exist in e-learning? and (2) What learning behavioral type corresponds to positive learning performances?

4.1. Categorization of learning behavior types

In Phase 1, to identify learning behavioral types for e-learning, individuals' learning paces for 15 weeks were visualized and grouped with similar plots. The visualization of actual learning behaviors led to the identification of seven learning types: (1) procrastination (69.16%), (2) learning habit (4.54%), (3) random (1.59%), (4) diminished drive (5.44%), (5) early bird (1.59%), (6) chevron (6.80%), and (7) catch-up (4.99%). The results show similar ratios of procrastinators to those in previous research, which is about 70% (Schouwenburg et al., 2004). In general, procrastination has negative effects on academic performance and emotions. Therefore procrastination may lead to dropouts or to the loss of social credits. On the other hand, among the 69.16% active procrastinators (Chu & Choi, 2005), some may have high self-regulated learning strategies (Wolters, 2003). In order to determine the necessary support and feedback in the learning process as a final project goal, the procrastinators should be further categorized according to their needs.

Out of 441 participants, 37 students (8.39%) could not complete the assigned task by the deadline. Types (1b), (4b), and (6b) may need support related to time and resource management skills and/or metacognitive skills, since they may lack self-regulation and be unable to properly reflect on their learning.

4.2. Behavioral types and learning performance

Phase 2 tested the relationship between learning behavioral types based on the Phase 1 categorization and learning performance, or TOEIC-IP scores. The results showed significant differences between the learning types. The post hoc tests indicated a significant difference between Learning Types (1) and (2) and Learning Types (1) and (6). This implies that the learning habit type and the chevron type scored significantly higher than the procrastination type on the TOEIC-IP. This result supports the widely accepted belief that a learning habit of constant learning is most effective. Based on these results, it is reasonable to provide feedback and support for e-learning to encourage students to form a learning habit. As discussed in the section on the features of each learning type in Phase 1, goal orientation may affect students' learning behavior. To encourage students to learn for themselves and not simply for course credits or scores, we could provide support to help them establish mastery goal orientation (Dweck, 1986). This could help students establish positive and active inclinations toward long-life learning.

Procrastination is caused by a lack of self-control and self-regulation (Schouwenburg et al., 2004; Wolters, 2003), and so successful online learners therefore have effective and efficient self-regulated strategies (Goda, et al., 2013; Lynch & Dembo, 2004; Michinov et al., 2011). Self-regulated learning involves factors of cognition, meta-cognition, affection, help seeking, and resource management (Wolters, Pintrich, & Karabenic, 2003).

4.3. Implications for future research

In future research, the categorization method used in this study should be examined and validated in different online contexts. The levels of the learning material might affect learners' behaviors such as work avoidance or postponing. In this study, the target level of the learning materials was selected fit to the overall students' level, but it should be necessary to consider each individual student's performance level in order to accurately investigate how the relevant learning materials' level affects his or her learning behavior.

The learning types should also be tested in relation to other variables such as learning quality, classroom performance, self-regulated learning, motivation, and so on, to provide appropriate support for individuals in e-learning.

4.4. Limitations

There are several research limitations. First, the e-learning materials used in this research were developed for those learning English as a foreign language. Therefore subject matter and cultural context might affect the results of the study. Language acquisition requires continuous practice to master, and this subject feature may influence the relationship between learning behavioral types and learning performance. Second, the data of actual learning was collected from a mandatory course. The nature of courses, mandatory or elective, might affect learners' motivation and decision-making. In future research, these limitations should be considered, and more evidence-based research with actual learning behaviors in e-learning should be conducted.

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