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The Effect of Self-Regulated Learning in Online Professional Training

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ABSTRACT

With the rapid expansion of mobile, blended, and seamless learning, researchers claim two factors, lack of self-discipline and poor time management, adversely impact learning performance. In online educational environments, reduced social interactions and low engagement levels generate high dropout rates. Self-regulated learning (SRL), the individual ability to check progress toward a goal and manage learning behavior, appears critical to adult online learning success. Clickstream data can observe, record, and evaluate patterns of users' real-time learning behavior in an online learning environment. Linking clickstream data with performance outcomes allows researchers to assess online learning behaviors and academic performance. The guiding research question was: Are students who apply SLR strategies more likely to demonstrate mastery of knowledge and skills in a self-directed e-learning context? Clickstream data and performance measures were analyzed to explore whether task and cognitive conditions influence how SLR strategies are applied in online training.

KEYWORDS

Adult Learning, Asynchronous Online Learning, eLearning, Self-Regulated Learning (SRL)

INTRODUCTION

Accompanying the rapid expansion of blended and online learning in professional and educational environments, researchers claim two factors adversely impact formal and informal learning processes and typically lower performance: (1) lack of academic motivation, and (2) poor time management for task completion (Berestova et al., 2022). Looking specifically at self-directed e-learning (SDEL) for job training, two effects - reduced social interactions and lower levels of engagement - generate higher dropout rates (Kim et al., 2012; Muilenburg & deBerge, 2007; de Freitas et al., 2015; Macfadyen & Dawson, 2010). To meet performance goals, adults who engage with online learning should monitor and control their learning processes by creating, monitoring, and adjusting their learning behaviors (Dabbagh & Kitsantas, 2004; Roll & Winne, 2015). Self-regulated learning (SRL) strategies can assist learners to check their progress toward a goal and manage their learning to achieve higher performance (Broadbent & Poon, 2015). Over the past decade, researchers have relied on data from

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self-report surveys to identify students with low SRL skills (Broadbent & Poon, 2015; Winne, 2010), while acknowledging limitations such as inaccuracy, subjectivity (Brown, 2017; Miller, 2016) and bias (Ganda & Boruchovitch, 2018).

Over the past 20 years, limited scholarship has synthesized how adults select SRL strategies to monitor and enhance their online performance or how SRL influences their learning experience in the context of self-directed e-learning (SDEL) (Kim & Frick, 2011; Kim et al., 2019). More recently, a few scholars have explored SRL strategies that a user may apply to promote their academic performance in computer-based learning environments (Leggett et al., 2013; Zheng, 2016). For example, some instructors deliberately modified a course design to assist students to manage their time more effectively. Others allowed students to set their own deadlines and suggested that students schedule their study time. Yet others encouraged students to plan a specific process to efficiently complete activities (Baker et al., 2019; Baker et al., 2016; Sitzmann and Johnson, 2012). In all, inconsistent findings suggest that individual circumstances beyond the learning environment may influence whether facilitating time management skills enhances performance across an entire course (Ariely & Wertenbroch, 2002; Burger et al., 2011; Levy & Ramim, 2013). Conflicting recommendations from these studies may be attributed to biases from self-reported data or contextual variations across programs and students.

In response to these constraints, we selected an innovative methodology to ascertain how individuals apply self-regulated learning strategies for improved task performance in a self-directed e-learning context. Clickstream data are information collected about a user that can be applied to observe, measure, and analyze recorded and real-time learning behaviors in a learning management system (LMS). Linking click-stream data with performance outcomes means researchers can create a more comprehensive assessment of learning behaviors and determine how this may impact academic performance in an online learning experience. We asked the following research question: Are students who apply SRL strategies more likely to demonstrate mastery in knowledge and skills in a self-directed e-Learning context?

While there is a growing number of studies that rely on clickstream data to trace and analyze learning behaviors in an LMS, typically researchers still apply improved algorithms to evaluate the performance of predictive models. Rarely do these studies provide details about the influence of contextual factors that are required to interpret clickstream data in meaningful ways (Baker et al., 2020). In this current study, clickstream data were linked to each participant and tracked to analyze how patterns of learning behavior influenced task completion for professional training in a self-directed e-learning environment where there were no peer learners or a regularly available instructor. The 16-week asynchronous online training, known as the Intensive Pedagogical Training Institute (IPTI), provided the context to investigate the use of self-regulated learning strategies by adult learners to master professional knowledge and skills. The training is designed as the first step to prepare teachers by attaining an Ohio Alternative Resident Educator License.

BACKGROUND

Professionals operate in settings where profound social and technological changes are fundamentally altering the nature of work (Dall'Alba, 2009). Conventional approaches for delivering professional training are less impactful, particularly in situations where they do not target dimensions of professional learning considered essential for productivity in a contemporary workplace (Littlejohn & Margaryan, 2013). For example, in the field of education, professional learning can grow educators' pedagogical content knowledge and skills when sustained over time through in person, blended, or virtual learning communities (Darling-Hammond et al., 2009). In this context, an adult learner takes responsibility for their learning by determining their needs, setting goals, identifying resources, implementing a plan to meet their goals, and evaluating the outcomes.

Exploring SRL From a Metacognitive Perspective Theoretical Framework

The Winne and Hadwin model of self-regulated learning (SRL) (Winne & Perry, 2000; Butler & Winne, 1995; Winne, 1996) provides the theoretical framework for this study. SRL is a metacognitively guided behavior that enables individuals to adaptively regulate their use of cognitive tactics and strategies in the face of a task (Winne, 1996). The model includes four phases (Winne, 2011): (1) *task definition* - the learner generates an understanding of the task to be performed; (2) *goal setting and planning* - the learner generates goals and a plan to achieve these; (3) *study tactics and strategies* – the learner's use of the actions needed to reach those goals; and (4) *metacognitively adapting studying* – this occurs once the focal processes are completed and the learner adopts long-term changes in their motivation, beliefs and strategies for future learning. These four phases operate recursively in a feedback loop, allowing a learner to adjust their behavior and avoid mistakes from the previous phase. In each phase, there are five facets that influence task performance: conditions, operation, product, evaluation, and standards (COPES) (Winne & Hadwin, 1998).

Self-regulated learning is conceptualized as a 'recycling' process, starting with cognitive architecture and task definition (Phase 1), followed by the creation of learning goals that direct the best plan to successfully complete tasks (Phase 2). This leads to enacting strategies for learning (Phase 3). The products of learning, including the overall product accuracy informs the participant about their learning needs and other factors, such as efficacy and time management. If the product does not fit the standard, then additional learning operations can modify the existing conditions, for example setting aside more time for studying. Lastly, after engaging with a learning event, participants may choose long-term alterations to the beliefs, motivation, and strategies that make up SRL (Phase 4). These changes can include the addition or deletion of conditions or operations, as well as minor (tuning) and major (restructuring) changes to the ways that conditions cue operations for the learner (Winne, 2001).

Self-Regulated Learning in Online Contexts

A unique characteristic of e-learning is the pedagogical shift from instructor-centered recitation to learner-centered teaching that encourages learners to interact with content in a nonlinear manner (Dillon & Greene, 2003; Garrison, 2003; Man et al., 2019). In general, online learning allows participants to check internal and external resources and subsequently explore dynamic and non-linear navigation operations with hyperlinks (Jacobson & Archodidou, 2000; Jonassen et al., 1995; Maslova et al., 2020). When prompted to self-direct their learning behavior, individuals are more likely to regulate their engagement in an e-learning environment (Dabbagh & Kitsantas, 2004; Elfaki et al., 2019; Logan et al., 2017). Consequently, the design of online learning environments plays a role in enhancing learning experiences.

Using self-determination theory as a theoretical construct, researchers claim that an individual needs an elevated level of self-regulated learning to meet their formative learning benchmarks in an online learning environment (Dabbagh & Kitsantas, 2004; Ferrer et al., 2020; Hartley & Bendixen, 2001; You & Kang, 2014). Other empirical evidence from analyses of performance in online coursework suggests that self-regulation factors significantly correlate with final course grades. Moreover, metacognitive regulation and course satisfaction have been shown to be positively correlated (Puzziferro, 2008; Yukselturk & Bulut, 2007). In an online learning environment, self-regulated learning plays a significant role in achieving academic success, as learners cannot interact directly with instructors in a timely manner. In summary, participants who can self-regulate are more likely to attain academic learning outcomes in e-learning environments (Kim et al., 2019).

SRL Measurement Methods Based on Self-Reported Survey Data

Over the past 20 years, while refining methodologies, researchers have continued to explore new instruments and measurement methods that elicit empirical evidence of self-regulated learning in offline or online learning environments (Chen, 2020; Kim et al., 2019; Puzziferro, 2008; Saint et al., 2022; Winne et al., 2002). Researchers often use survey-based methods that instruct participants to respond to several Likert scale statements to either predict their learning behavior in a forthcoming course or recall their behavior in a recently completed course (Li et al., 2020). The *Motivation Strategies For Learning Survey (MSLQ)* (Pintrich et al., 1993) and *Learning and Study Strategies Inventory (LSSI)* (Weinstein & Palmer, 1990; Weinstein et al., 1987) are examples of frequently used instruments for offline data collection. A significant body of research, however, has applied these instruments to capture student self-regulated behaviors in various online learning contexts. (Artino Jr & Stephens, 2009; Cho & Shen, 2013; Wang et al., 2013). The *MSLQ* was created from a general cognitive perspective of motivation and learning strategies with a participant represented as an active processor of information whose beliefs and cognations are important coordinators of instructional input (Pintrich et al., 1993). A strength of the *MSLQ* is that it connects self-regulated learning and motivation, providing a more comprehensive view of a participant's learning strategies (Roth et al., 2016; Honicke & Broadbent, 2016). The *LASSI* is a self-reporting instrument designed to assess students' awareness about and use of learning and study strategies (Weinstein & Palmer, 1990; Weinstein et al.,1987). The purpose of this instrument is assisting students to develop an awareness of the strengths and weaknesses in their studying. The *LASSI* measures the learning processes in two categories: study skills and self-regulation. Study skills include information processing, selecting main ideas, and test strategies focusing on anxiety, attitude, and motivation. Self-regulation includes concentration, self-testing, study aids, and time management. Also, there are several studies using the *LASSI* to measure self-regulation in learning (Dembo, 2001; Downing et al., 2008).

Despite ample self-reported evidence, findings show mixed and/or contradictory results in the relationships between self-regulated learning and academic outcomes in online contexts. Some researchers report significant and positive relationships (Chang, 2007; Cho & Shen, 2013; Puzziferro, 2008), while others find no significant correlations between academic outcomes and self-reported measures of self-regulated learning (Cicchinelli et al., 2018; Pardo, Han, & Ellis, 2016) and subscales such as time management (Bruso & Stefaniak, 2016; Klingsieck et al, 2012) and effort regulation (Dunnigan, 2018). A plausible explanation is that the validity of the SRL instruments for traditional in-person courses (Pardo et al., 2016) may not be valid for online courses (Barnard et al., 2009).

Limitations of self-report surveys also relate to accuracy and reliability of results. For example, Veenman (2011) showed participants' self-regulation strategies differed from their actual self-regulation behavior. When students respond to survey questions, they rely on subjective, sometimes distorted memories (Ericsson & Simon, 1993) and may present inaccurate perceptions of self-regulated activities (Winne et al., 2002; Winne & Perry, 2000; Zimmerman, 2000). This can lead to a nebulous association between research hypotheses and self-reported data (Greene & Azevedo, 2010; Hadwin et al., 2007). Additionally, aggregated memories lack significant contextual features (e.g., the nature of the task or resources available) and may profoundly influence self-regulated behaviors (Gilbert & Wilson, 2007). Previous studies found that participants tend to underestimate the difficulties of applying self-regulated learning behaviors and overestimate their skills at the onset of a training (Matuga, 2009). Predicting SRL behaviors challenges students who have limited or no experience with online learning because such predictions often rely on past experiences within a face-to-face classroom context that differs from an e-learning environment (Alghamdi,2020; Lee &Tsai, 2011; Winne, 2005).

Using Click-Stream Data to Measure SRL

While offering basic functions for teaching and learning online, including delivering learning materials (e.g., lecture videos and course materials), managing learning activities (e.g., assignments, and discussions), and supporting assessments (e.g., exams and essays), learning management systems (LMS) such as eThink, Blackboard and Canvas can capture and record learner behavior in computer-supported learning. Click-stream data provides detailed, frequent, and unobtrusive records of users' click behavior in online environments such as logging into the learning platform, watching video lectures, browsing course materials, examining resources, and submitting assignments. Researchers can analyze these behaviors from the perspective of individual cognition, i.e., making sense of the learning experience and metacognitive acts, i.e., an awareness and understanding of one's own thought processes and therefore provide promising opportunities for tracing and measuring self-regulated learning (Winne, 2010).

By linking trace and automated log data of participant activity, Winne and Hadwin first advocated the use of clickstream data to assess how self-regulated learning scaffolding impacts performance in computer-supported learning environments (Winne et al., 2010; Winne & Hadwin, 2013). Trace data from earlier studies (Winne, 1982; Winne & Perry, 2000) reveal insights for studying both temporal and sequential analysis of self-regulated learning (Malmberg et al., 2013; Panadero et al., 2015b; Winne et al. 2011). Winne and Hadwin advocate that click-stream data have several advantages over self- reported data as measures of self-regulated learning in online learning environments. First, click-stream data are digital records of individual action. Therefore, learning behaviors are assessed more objectively, accurately, and comprehensively than self-reported data that are based on unreliable and decontextualized memories (Winne, 2010). Second, clickstream data are unobtrusive and do not require attention or effort as data collection happens without interrupting the learning process. In contrast, self-report data may encourage students to reflect on their behavior and therefore bias results in an unpredictable manner (Greene & Azevedo, 2010). Third, unlike self-reported data, clickstream data focuses on the process of self-regulated learning such that we can understand how personal and environmental factors influence self-regulated learning behaviors. Last, clickstream data provide timely, frequent, and large-scale measures of student behavior, usually not feasible with self-reporting data. Consequently, a growing body of scholarship reports analyses of clickstream data from LMSs on students' use of self-regulated learning strategies (Baker et al., 2018; Cicchinelli et al., 2018; Crossley et al., 2016; Winne et al., 2002).

METHODOLOGY

Research Design

For this study, we adopted the Winne and Hadwin model of self-regulated learning (and its four phases) to analyze learning behaviors in an e-learning environment from an information-processing perspective. In each phase, participants engaged with a set of tasks within an online learning experience that generated an interaction between conditions, operations, products, evaluations, and standards (known as COPES). Notably, regarding instrument use in future studies of online self-regulated learning, scholars advocate the unobtrusive and automatic method of learning analytics to provide a perspective other than participants' self-reported, perceived self-regulation (Chen, 2020; Saint et al., 2022). In response, for the purpose of data definition, the number of clicks associated with each learning task were collated from the automated raw LMS logs. Next, a procedure of data preprocessing transformed the learning behavior of individuals into sequences. Then, we conducted an analysis of variance (ANOVA) and applied a sequential data clustering technique (Valsamidis et al., 2021) to classify participants into discrete groups based on outcomes of behavior clustering and overlaid a self-organized map technique to visualize these clusters. Last, we examined the sequence of clicks presented by the plot to interpret representations of the four phases of self-regulated learning theorized by Winne and Hadwin.

Specifically, data collated from the LMS included: (1) trace and automated log data, a record of participant online activities; (2) performance data defined as the score for each assignment; and (3) survey data that included feedback from students. We qualitatively coded the automated logs into trace data as participant online SRL behavior. We applied descriptive statistics and the sequential clustering method to explore different SRL patterns and associated statistical elements. Then we used an ANOVA and the Kruskal–Wallis one-way analysis of variance test to compare participant performance and satisfaction across different clusters. We built a Random Forest model using SRL variables to predict performance and noted which variables played a significant role. Lastly, we applied correlation analysis to check the relationship between behavior, performance, and feedback.

Intensive Pedagogical Training Institute Context

Participants in this study were registered for the Intensive Pedagogical Training Institute (IPTI), a 16-week online teacher preparation experience that provides instruction through three mastery-based content modules in the principles of teaching and learning, including topics related to student development, formative and summative assessment processes, curriculum planning, and classroom management. The training, with its 15 assignments, follows an asynchronous model of delivery, available 24/7, allowing participants to complete and submit assignments at their own pace. Communication with the instructor and technical support for each participant is through email and an online messaging system. As necessary, the instructor provides constructive feedback with the expectation of mastery of content. Each assignment pairs with a rubric that identifies the assignment components and a range of performance for each component (see Table 1). A participant must score a minimum of 80% proficiency for each assignment to successfully complete the IPTI. If an assignment does not initially meet the 80% proficient criteria, participants may revise and resubmit until the 80% threshold is met. IPTI requires each participant to complete a 25-hour field experience concurrently and includes experiences such as observing school-age students, actively participating, and engaging with instructional practice. Participants submit a Field Experience Log and a Field Experience Portfolio before the end of the course.

The eThink Education LMS that delivers the IPTI constitutes a partnership of two open-source LMS solutions, Moodle and Totara Learn. Primarily, industry uses eThink Education for new hire onboarding, employee professional development, and external client/vendor training, among other uses.

Unlike how traditional LMS are structured for academic purposes, eThink has unique features that are customized for specific learning paths based on job descriptions and/or task performance.

Table 1. IPTI structure

Modules	Lessons	Assignments
Teaching as a Profession	1. Introduction 2. Overview of Teaching in Ohio 3. A Profession Framed by Standards 4. Legal and Ethical Issues in Education 5. District and School Organization	1. Self-Assessment Reflection 2. Goal Setting Tool 3. Standards Alignment Table 4. Statement of Professional Responsibility 5. Teacher Interview
Student Development and Learning	1. Introduction 2. Learning Theory and Student Learning 3. Adolescent Development 4. Diversity Learners 5. Exceptionalities and Learning	1. Personalized Learning SWOT 2. Student Case Study 3. Culturally Responsive Teaching Plan 4. IEP Accommodation Analysis
Essentials of Teaching Practice	1. Content Area Review 2. Curriculum Development 3. Teaching Methods 4. Assessing Student Learning 5. Unit Plan Construction 6. Classroom Management	1. Individual Lesson Plan Detailed Lesson Plan with Differentiation 2. Lesson Assessment Collection 3. 10-Lesson Unit Plan 4. Classroom Management Plan 5. Final Reflection
Field Experience	1. Instruction 2. Direction for field experience	1. Planning and Preparation 2. The Classroom Environment 3. Instruction 4. Professional Responsibilities

DATA DESCRIPTION

Automated Log Data

The 275 participants were sampled from the total population of IPTI completers during a one-year period. July 1, 2020 - June 30, 2021. Participant data from assignment completion comprised log data from the database, containing 72 columns and over 5 million records.

Performance Data

Academic performance data contain participant scores in 15 course assignments, 4 field assignments and other required submissions. Each participant was assigned a score based on the rubric for each assignment. One grader was responsible for evaluating assignments with each score based on the same criteria.

Label Log Data with SRL Phrase Tags

Three content modules comprise the online IPTI professional training. We classified procedures into seven categories based on function: (1) instruction, (2) rubric, (3) resources, (4) lecture, (5) assignments, (6) feedback, and (7) others. Based on the Winne and Hadwin model, we used five labels to code different activities on each page. These tags reflect the function of each page in the course design: (1) conditions, (2) operations, (3) products, (4) evaluations, and (5) standards (see Table 2).

FINDINGS

From extant scholarship, we know multiple factors can affect learning performance in online training. Findings from recent studies (highlighted earlier) suggest that an individual's skill to self-regulate their learning behaviors undergirds metacognitive successes in an asynchronous context. In this study, we identified six variables as discrete parameters to categorize learning behaviors, and to subsequently explain the degree of self-regulation exhibited by a participant during the training: (1) active days, (2) lecture viewing frequency, (3) assignments per submission, (4) interval between two submissions, (5) last submission time, and (6) the orderliness of submission. A multiple regression model was used to detect if these variables significantly predicted students' final performance measures as assignment scores. The Winne and Hadwin model of self-regulated learning (and its four phases) was applied to interpret the findings: (1) *task definition* - the learner generates an understanding of the task to be performed; (2) *goal setting and planning* - the learner generates goals and a plan to achieve these; (3) *study tactics and strategies* – the learner's use of the actions needed to reach those goals; and (4) *metacognitively adapting studying*.

Table 2. Code labels

Labels	Description
Conditions (C)	Resources available to a person and the constraints inherent to a task or environment
Operations (O)	The cognitive processes, tactics and strategies used by the student referred to as SMART -Searching, Monitoring, Assembling, Rehearsing and Translating- (Winne, 2001)
Products (P)	The information created by operations
Evaluations (E)	Feedback about the fit between products and standards that are either generated internally by the student or provided by external sources
Standards (S)	Monitored criteria against products (Winne and Hadwin, 1998; Greene and Azevedo, 2007)

Mastery Performance

Performance mastery by each IPTI registrant is benchmarked by a cut-off mark for the 15 individual assignments. Each assignment pairs with a rubric that identifies the assignment components and a range of skill for each component. Participants must attain a minimum of 80 percent score on each assignment to demonstrate mastery of content and skills. If an assignment is not assessed to meet or exceed the acceptable 80 percent threshold, then a participant may revise and resubmit until mastery is demonstrated. When assignment scores were initially aggregated the distribution of the scores was so highly concentrated that the mean of the original scores was 94.90 with a standard deviation of 2.69 and a range of scores between 87.5 and 100. These descriptive statistics rendered it difficult to discriminate learning behaviors between participants who met mastery on the first attempt and those who attempted more than once to demonstrate the 80 percent mastery threshold. To address this problem, we corrected the original scores by penalizing each rejected assignment five points which generated a mean of corrected scores as 76.78, a standard deviation of 15.33, and a range from 21.5 to 100. This correction generated results that reflected the performance of participants more realistically than the original computation procedure (see Table 3).

Multiple Regression Model Results

The fitted multiple regression model (see Table 4) was significant ($F(6,260) = 20.134$, $p<0.001$), with R-squared equal to 0.317 suggesting that about 32% of the variance within the assignment scores are explained by the model. Each selected factor was statistically significant except the orderliness.

Table 3. Descriptive statistics and correlation

	Mean	SD	1	2	3	4	5	6	7
1. Final grade	76.78	15.33	-	-	-	-	-	-	-
2. Active Days	35.04	12.31	.004	-	-	-	-	-	-
3. Lecture viewing frequency	13.64	5.92	-.145	.687	-	-	-	-	-
4. Assignments per Submission	1.34	.36	-.212	-.691	-.406	-	-	-	-
5. Interval Between Submissions	3.40	1.88	-.375	.628	.259	-.591	-	-	-
6. Last Submission	78.29	31.94	-.027	.586	.247	-.445	.687	-	-
7. Orderliness	.22	.23	-.082	-.086	-.010	.184	-.117	.049	-

Table 4. Regression analysis summary

Predictor	b	beta	T	p
(intercept)	73.977		62.805	.000
Active Days	-.390	-.204	-1.971	.05
Lecture viewing frequency	-.791	-.201	-2.756	.006
Assignments per Submission	-13.442	-.205	-2.770	.006
Interval Between Submissions	7.920	.673	8.071	.000
Last Submission	-.244	-.333	-4.525	.000
Orderliness	-1.732	-.017	-.329	.742

Note: R2 adjusted = 0.301

Active Days

The activity level of learning recorded by 275 IPTI participants was evaluated across the 16-week period (105 days) to complete the training. 'Active' indicates how many days a participant logged into the asynchronous training and made at least one click. The mean for active days was 35.04 with a standard deviation of 12.31. We found a positive relationship between the number of active days and the total number of days associated with completion of the training. For example, a participant who completed the training within 10 days and spent 10 active days averaged at least 15 clicks per day. A participant who completed the training in 105 days spent 60 active days and averaged between 2.5 to 7.5 clicks/active day. The latter participant profile indicates more consistent time with learning materials over a longer period of engagement. There was more variation in the click average at the beginning and towards the end of the training than in the middle (see Figure 1).

The variable, 'active days' was a significant predictor (B = -.39, p=0.05) of improved performance. An increase of one (1) active day decreased an assignment score by 0.39 point, i.e., less concentrated time spent on an assignment resulted in lower performance. While the result may appear contrary to the accepted belief that spending more time (captured as the number of clicks) on learning leads to better outcomes, spending extended time with fewer clicks promoted learning.

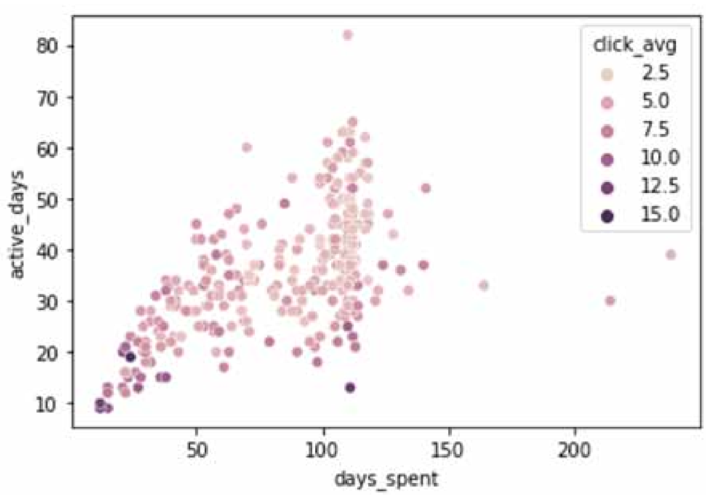
Lecture Viewing Frequency

The three IPTI content modules embed training lectures into multiple content pages. Clickstream data record the second variable, lecture viewing frequency for each participant, including how many times a participant clicked on these same pages and viewed and re-viewed each lecture. The mean lecture viewing frequency was 13.64 with a standard deviation of 5.92. Results from the regression model indicate that the variable, lecture viewing frequency is a significant predictor (B = -0.791, p<0.05) of performance. With an increase of 1 click on the lecture page, an assignment score decreased by 0.79 that suggests the frequency of lecture viewing has a small negative effect on an individuals' score.

Assignments per Submission

A learning analytic procedure, step plots, was applied to visualize how the third variable, 'assignments per submission' may influence performance. We explored how participants may adopt differing strategies for assignment submission and analyzed patterns of submission behavior. Participants who submitted

Figure 1. Days spent and active days to complete the training

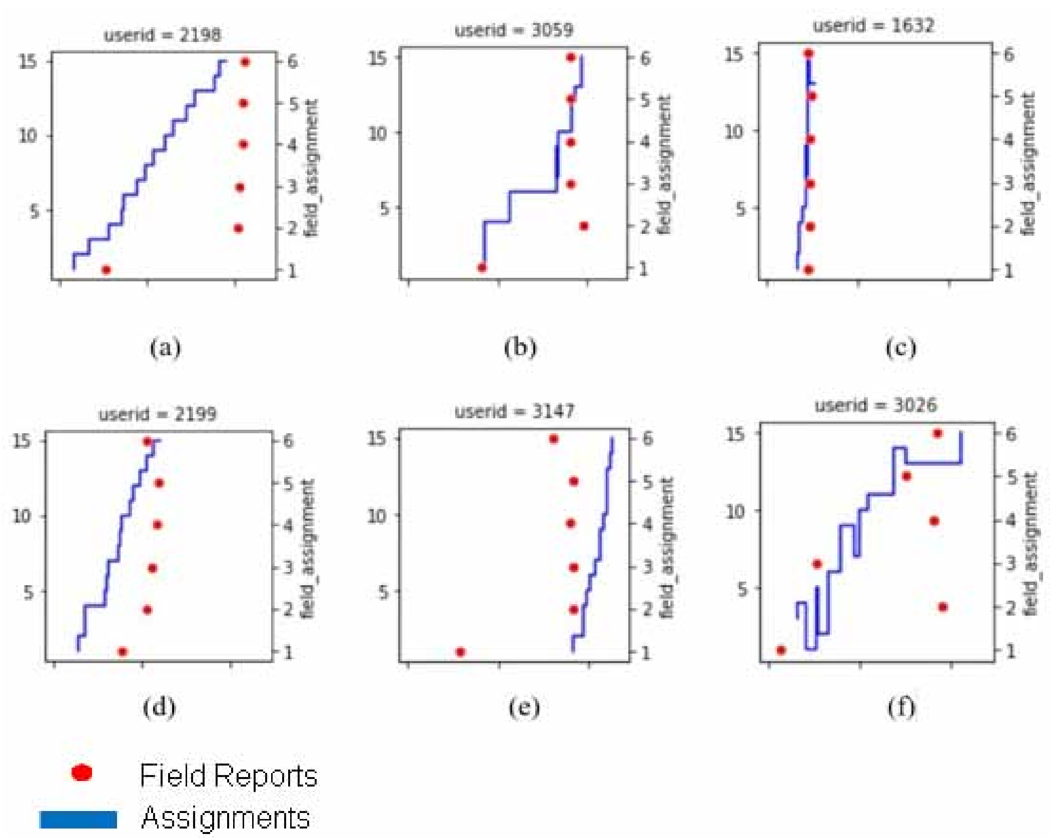


one or two assignments at any given time and maintained a consistent rate of submission reflect constant small jumps across time on the step plot (Figure 2. (a)). In contrast, participants who submitted multiple assignments per unit of time showed fewer and higher jumps in the step plot (see Figure 2. (b)). The mean of assignments per submission is 1.34 with a standard deviation of 0.36. Subsequently, this third variable 'assignment per submission' was also a significant predictor (B = 13.44, p <0.01) for performance, with our model suggesting a 13.44 decrease in the final performance score when the submission per time increased by more than one unit and was therefore a significant influence. Submitting multiple submissions at any given time lowered the participant's performance scores.

Interval Between Submissions

The fourth variable was defined as 'interval between submission' and was introduced into our model to evaluate whether variation in the interval between submissions impacts performance mastery. Some participants submitted assignments with high frequency over a brief period that generated a steep step (Figure 2. (c)), while others maintained more consistent intervals between submissions that were visualized in the step plot as regular stairs (Figure 2. (a)). Yet other participants in this study displayed more nuanced submission patterns that presented as a mix of these two patterns, noting long pauses about the mid-point of the training middle and then active engagement before the deadline for completion. When participants offer an inconsistent approach for monitoring their learning process such a variegated pattern suggests an ebb and flow of self-regulated learning strategies. The mean interval between submissions was 3.40 with a standard deviation of 1.88.

Figure 2. Assignment submission patterns



The interval between submissions was a positive and significant predictor of performance mastery (B = 7.92, $p < .001$) and accounted for the greatest unique variance ($sr^2 = .13$) and the largest proportion of remaining variance after controlling for all other variables ($pr^2 = .17$).

This finding indicated that for every one-day increase in the submission interval, a 7.92 increase in the final score was predicted, when holding other variables constant. In summary, a participant who submitted assignments with regularity over the 16-week period led to a higher performance score.

Last Submission

The fifth variable, 'last submission', provided insight into a participant's degree of self-regulation skill. Researchers suggest that one indication of self-regulation ability rests in timely submission of products, i.e., if a participant submits an assignment late or up against a deadline, then this suggests a lower level of self-regulation. The time stamp of the last submission by an IPTI participant indicates closeness to the assignment completion deadline. When initial enrolment was activated, some participants worked steadily to complete the course in a short period (see Figure 2. (d)). Others waited before submitting assignments and bumped up against the end of training (see Figure 2. (e)). The mean of the last submission time was 78.29 with a standard deviation of 31.94. According to the regression, the last submission is a significant predictor (B = -0.244, $p < 0.001$) suggesting that for each late day for the last submission, the final performance score decreases by 0.244 points. Late assignment submission negatively impacted performance.

Orderliness

The final variable, 'orderliness' indicated the order pattern of assignment completion within a content module that an IPTI participant selected. While the three modules must be completed in order, a participant can determine the order of assignment completion within each module. Results report that most students completed the assignments in a predetermined order (see Figure 2. (a)), but some students oscillate within the module as visualized in the step plot (see Figure 2. (f)). We used permutation entropy to evaluate the orderliness of submissions. For example, the permutation entropy of [1,2,3,4,5] was 0, and the permutation entropy of [2,1,4,3,5] was 0.36. The mean of permutation entropy was 0.22 with a standard deviation of 0.23. The results show that the orderliness was the only non-significant predictor in this model ($p = 0.74$) suggesting that the order of submission within modules has no significant influence on the final performance score.

To interpret the results, we applied the four phases of self-regulated learning modelled by the Winne and Hadwin theoretical framework. In their first phase, *task definition*, the learner generates an understanding of the task to be performed. We introduced two variables, 'active days' and 'lecture viewing frequency' to ascertain how *task definition* may impact participant performance. We report that spending extended time with fewer clicks over more active days compared to the training period promoted performance. Further, we found that greater exposure to viewing lectures may not lead to better performance and could negatively impact performance. According to Winne and Hadwin (1998), in phase two *goal setting and planning* a learner generates goals and a plan to achieve performance outcomes. Analyses of the variable, 'assignments per submission' affirmed that submitting more than two submissions at any given time lowered performance scores. The next variables, 'interval between submission' and 'last submission' aligned with phase three and described participants' use of *tactics and strategies* to attain learning goals. We found that participants who submitted assignments with regularity over the 16-week period led to a higher performance score. Last, the variable, 'orderliness' tested the degree of self-regulated learning in the phase, *metacognitively adapting studying*. We report that the order of assignment submission within each content modules did not influence the performance.

In summary, we claim that longer intervals between submissions, fewer assignments submitted each time, and earlier final submissions lead to better performance. On the contrary, submitting assignments too quickly or conducting multiple tasks concurrently or submitting as the end of training approaches can lower performance.

CONCLUSION

The purpose of this study was to use clickstream data from a 16-week-long online training to investigate self-regulated learning strategies among participants. Key findings translate to specific actions. First, spending time browsing content (more clicks) was not an effective strategy for performance mastery when compared to extended and concentrated engagement with content (fewer clicks). Second, the number of assignments submitted at any given time has a greater negative effect on performance, i.e., participants who focus on one task at a time are more likely to attain better performance, while students who complete multiple tasks concurrently receive lower scores and consequently do not initially meet the 80% passing threshold. Third, consistent intervals between assignment submission have a positive effect on grade which suggests participants who spend regular time preparing their response for each assignment are more likely to perform better. Submitting assignments too frequently over a brief period may lead to unsatisfactory performance. Fourth, assignments submitted close to the end of training were of lower quality, and such action negatively impacted final scores. Last, participants who completed the assignments within each content module in order did not receive an advantage compared to those who completed the assignments randomly.

Learning that delivers self-paced training offers academically positive experiences for participants whose self-regulated learning skills can enhance performance. For participants who demonstrate a lower level of self-regulated learning, too much flexibility of content delivery can lead to poor planning, chaotic pacing, and delays that culminate in lesser performance. To enhance performance mastery, a roadmap can propose a learning schedule with guiding times for assignment completion and submission. A second recommendation relates to the use of the LMS monitoring system to understand participants' online learning behavior. If a participant submits multiple assessments in a brief period, or more than two assignments at a time, or is inactive for an extended period, or is trending to submit assignments to close to the training end, then the online learning system can prompt participants to adjust their learning progress to enhance performance mastery.

We acknowledge some limitations of this study that include the linear design of the training and inadequate integration of video content which did not allow for a more complete understanding of how participants harness their self-regulation learning skills. Additionally, clickstream log data did not provide direct measures of participants' time on assignments as the number of clicks served as a proxy for time spent on learning contents. While clickstream data provided deeper understanding of participants' online learning behaviors, these are not sufficient to provide more complete explanations. Last, it is important to acknowledge that this study was conducted during the COVID-19 pandemic which disrupted personal and work lives. The influence of the pandemic on participant's learning behavior is still unclear and therefore limits our claims from the results.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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