Instr Sci (2009) 37:129–149
DOI 10.1007/s11251-007-9039-0

Online learning: Learner characteristics and their approaches to managing learning

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Received: 28 November 2006 / Accepted: 17 October 2007 / Published online: 9 November 2007

Abstract Using cluster analysis this study investigated the characteristics of learning strategies learners use in online courses with one-on-one mentoring. Three distinct approaches were identified: "Mastery oriented", "Task focused" and "Minimalist in effort". Despite the widespread concern that students will have difficulty managing their time in online courses with high level of student freedom, this study found that the vast majority of learners were very effective in their learning strategies. The findings speak well for the potential of distance education environments to provide high quality self-paced learning, accommodating different learning strategies, which is difficult to do in group-paced courses. We further explored how these approaches relate to and interact with, participants' background and their levels of satisfaction and self reported learning.

Keywords Learning strategies · Online learning · Online professional development · Distance education · Learner characteristics · Cluster analysis · Problem based learning

Introduction

Curriculum offerings for distance learners have grown tremendously over the last decade where, for some universities, the online offerings rival those delivered in the classroom (e.g., Allen and Seaman 2004; Duffy and Kirkley 2004a). Universities are increasingly finding distance education attractive since they can increase enrollments without increasing their physical plant requirements and they can reach out to audiences that would not otherwise be able to attend post-secondary education or who would normally not attend that particular institution (Moore and Anderson 2003). For many students, the online environment provides their only avenue to post secondary education. These are students who are time restricted by work requirements (e.g., teachers seeking additional degrees or

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professional development), cannot afford the residential or commuting costs, or who are house bound with children, with a disability, or other constraints.

Many students are also attracted to online DE because of the freedom and flexibility in organizing their learning activities and the opportunity to work from any place. However, Bonk (2002), Parker (1999) and others have found high drop out rates in online courses suggesting that this freedom also presents problems. Lawless and Kulikowich (1996), found that while many students flourish with the freedom online environments provide, many flounder, becoming confused and even apathetic. While their learning environment involved shorter online learning activities, their findings suggests that the ability to manage the learning demands that comes with the freedom of online DE is a key issue to success, and it is reasonable to expect that longer courses would increase the chances of learners having problems managing the freedom this environments provide. Skills at managing learning are at two levels. First, there is the broader issue of scheduling time for learning. Many residential students cannot manage their time for academic work even with the fixed class time and the campus as a reminder. The flexibility of DE, with no fixed time to be in class or other cues to say, “time to learn”, brings an even greater need to be able to manage that flexibility.

The second management issue is managing the learning process. Learning online is different from face-to-face learning not because they differ at the level of cognitive processes or the strategies important to learning, but because of contextual differences in constraints, affordances, and goals (Duffy and Kirkley 2004a). It is not just devoting time to a course. We expect students to read, reflect, write, discuss, etc. We expect them to use all or most of the course resources, to overview the course, and to take learning seriously. Nonetheless, as the Lawless and Kulikowich (1996) study suggests, with the lack of constraints many students are unable to effectively manage their learning activities and make effective use of resources in the open online environment.

In our research, we seek to understand how the constraints, affordances, and goals in distance learning impact student work patterns. In this study, our primary goal is to identify types of learners, based on their patterns of work in an authentic online learning environment: professional development courses teachers choose to enroll in. We also relate the work strategies to reported learning, testing our inferences about the work patterns. Finally, we relate the demographic characters of the learners to the work patterns. If there are distinctive patterns and we can relate these to a successful online learning experience, then we can also begin to investigate how to foster successful approaches to online learning through specific advising and facilitation strategies as well as course instructional design.

The patterns of work in an online environment can be determined at least in part through the analysis of online activity. Complex log-files (click-stream data), along with other forms of data, allow us to paint a rich description of what learners do while working online. The basic click stream data can be analyzed to provide structural measures (patterns of student activity) and temporal measures (when and for how long students do something online). Following the “footprints” they leave when working online aids us in inferring learning strategies.

Assumptions are made when interpreting click stream data. For example, if a learner opens a document we assume the learner is making an effort to read it, if a message is open we assume it is being read. However, we make similar assumptions in face to face environments. For example, if our students are watching a video in class we assume they are focused on what they are watching and if a book is open in front of them and they are looking at it, we assume they are reading. Therefore, the assumptions we make about what online learners do when they click on something are not distant from those we make when working in campus based courses. Click- stream data may even offer some advantages since we do know what resources students select to use and how long they have them open before they go and click on something else.

There is a reasonable body of recent experimental work demonstrating the effectiveness of analyzing click-stream data to identify profiles of individuals completing tasks in hypermedia environments (Barab et al. 1997; Barab et al. 1996a, b; Barab et al. 1999; Ford and Chen 2000; Hall et al. 2000; Lawless and Kulikowich 1996). For example, Barab et al. (1997) presented students with a campus Kiosk and gave students tasks of finding information. Using cluster analysis to analyze click stream data of the types of pages examined and the depth of those pages in the hypermedia system, they were able to identify four types of users according to the way they navigate in the kiosk:

- Model users: compliant and earnest, pick the simplest task, fewer deviations
- Disenchanted volunteers: rebellious and impatient, explored very little
- Feature explorers: feature oriented and confused, use help screens, lowest self-efficacy
- Cyber cartographers: curious, goal directed, longer time, deepest levels, highest self-efficacy

Lawless and Kulikowich (1996) also used cluster analysis, but this time to examine the click stream data of students in an experimental learning task that required participants to learn about general psychology theories using a hypertext tutorial. They identified three profiles in their analysis:

- Knowledge seekers: focused on information based cards, used more time on available content resources
- Feature Explorers: exploring the "terrain" and attracted by special features rather than focusing on the available information
- Apathetic hypertext users: spent little time in hypertext and information cards, followed a linear pattern and explored few features

Lawless and Kulikowich (1998) and Ford and Chen (2000) have sought to relate individual differences among learners to navigational patterns. For example, Lawless and Kulikowich (1998) in a replication of the 1996 study mentioned above, examined the relationship of cognitive and affective variables, especially domain knowledge and interest, to the different profiles. While domain knowledge is knowledge related to a specific field of study (e.g., education, psychology, chemistry) (Alexander 1992), individual interest is the interest learners may exhibit in a specific domain or content area regardless of their knowledge of that domain (Hidi and Baird 1988). Their findings, in addition to confirming the hypertext navigation profiles previously identified, indicated that domain knowledge has a significant effect on navigation performance. For example, those with high domain knowledge showed less interest in exploring the hypertext (Apathetic Users); while those with low domain knowledge seemed to be more attracted to the technology based features rather than to the content and thus were labeled as Feature Explorers. Those who had a moderate amount of domain knowledge in psychology represented the learners with the highest use of information cards (Knowledge Seekers).

Ford and Chen (2000) studied the behavior and performance of 65 graduate students using a hypermedia-based tutorial and examined cognitive style, prior experience, motivation, age, and gender in relation to their performance. Field-dependent and independent cognitive styles were linked to differences in navigation strategies, and levels of prior experience were linked to quantitative differences in both navigation behavior and learning performance. While field-dependent learners adopted a more random use of the material, using fewer features and focusing on lower levels of content, field-independent learners tend to use the index, spent a higher proportion of time studying deeper levels of content, and explored the section that introduced techniques to use the tutorial.

It is important to note that it only makes sense to study online DE profiles within a flexible environment in which learners have the freedom to make enough decisions about their work so clearly distinguishable approaches may emerge. A fixed linear environment with a strictly defined set of required readings and sequence of activities would most probably leave very little space for different learning profiles to emerge.

The studies we have reviewed offered a flexible environment, but they were conducted mainly over brief experiences, most of them in an experimental context where the learner interacted with the environment over a relatively short period of time and with an instructional task assigned by the researchers. Additionally, the majority of the studies used information search tasks rather than learning tasks. Our goal is to extend this work to authentic, distance learning environments. Even within traditional DE courses, students typically have considerable freedom with topics or weeks of the course, and have access to a range of learning and communication resources to use in completing task assignments. As distance learning grows, we are seeing an increasing number of courses and programs that offer (or impose upon) students much greater freedom through extensive use of learner centered problem solving and self-study approaches (Duffy and Kirkley 2004b). In the Learning to Teach with Technology (LTTS), the online program we will examine in this research (Duffy et al. 2006; Wise et al. 2004), the courses are self-paced and follow a *guided problem solving* approach, permitting students to use the approach that is comfortable in their learning. They can plow through systematically, jump around, procrastinate and then rush through it, or be thoughtful and systematic.

We were interested in the impact of prior knowledge of on the online learning strategies. Of particular interest was prior knowledge of inquiry teaching practices and the use of technology in teaching. We assessed this by asking the teachers to rate their prior knowledge of inquiry and technology based teaching on a 5 points Likert scale. We acknowledge this is a measure of perceived previous knowledge, but since these are common terms, specially in the participants' field, and they are professionals, there is no reason to suspect the teachers are not reasonable judges of their "previous knowledge".

We did not ask the teachers about their interest in these topics or in the course, but we assume it to be high since participants were voluntarily enrolled in a professional development activity, selecting one course with more than 50 options, and they completed the learning experience.

Our focus was on identifying profiles of student approaches to online learning. We purposely do not use the terms "cognitive style" or "learning style" since we are focusing on strategies of work that can evolve and change over time and in different contexts, showing what we consider to be different situational approaches to managing learning in online environments rather than learning styles as they are generally understood. In this process we measured cardinal (where they go), structural (patterns of activity) and temporal (when and for how long) variables. We also examined characteristics of learners across profiles that could be relevant to identifying work patterns and relevant to considering the design of DE and support of learners. Finally, the learners' perceptions of course quality, specific course components, perceived learning, previous knowledge, and expected transfer to the classroom where also examined in relation to the different profiles.

Method

Learning environment

The study examined the learning activities of individuals who enrolled in and completed a course in LTTS (http://ltts.indiana.edu). LTTS is an online teacher professional development curriculum that has a catalogue of 60 courses all of which are problem-centered and self-paced. Courses are short (between 25 and 30 h); entirely webs based, self-paced, individually mentored, and address technology integration in learner-centered teaching.

A course begins with the presentation of a curriculum problem and a proposal as to how to address that problem. For example, a curriculum problem might begin with how students are overwhelmed with the number and types of resources they find when they are asked to use the internet and evaluate resources as they explore a topic. The proposed solution is to develop a "WebQuest" (Dodge 1995, 1998): an inquiry based teaching strategy in which students are confronted with a task or "quest" that ask them to use a network of rich yet constrained set of online resources defined by the teacher, in order to complete the quest that is aligned with the learning objectives. In this example, the learner's task is to develop a WebQuest lesson plan for her particular classroom. The lesson plan must be pedagogically sound, following the basic principles of learner centered instruction (APA Work Group of the Board of Educational Affairs 1997; McCombs and Whisler 1997) and address curriculum standards, all appropriate for her particular class. This is a guided problem-centered learning environment in that there are 4–7 activities that a learner must complete in moving from curriculum problem to lesson plan. The activities are all related to developing that lesson plan and providing justification in terms of learner-centered principles and curriculum standards.

For each activity, LTTS provides a description of the task and what must be submitted, guidance for how to approach the task, and links to learning resources (primarily links to other web sites relevant to the task) to support the work. The courses have a rich array of learning resources since many of the courses must support learners representing a wide range of grade levels and subject matter areas. When students enroll in an LTTS course they are welcomed by a mentor, an experienced teacher, who provides guidance and encouragement to the student and seeks to establish rapport and familiarity. The primary contact between mentor and learner is in the context of the learner's submission of work on the problem. In providing feedback to the learner, the mentor may provide suggestions on redesign of the work, ask for clarification or elaboration, or suggest particular resources. A discussion of that feedback may follow and the student may resubmit work. All discussion occurs through an internal email system that is the main mean of communication between facilitator and student. Since learners submit their work using the LTTS Workbook, not the messenger tool, the bulk of the exchanged messages are the feedback messages from the facilitator in response to each learner submission. Student messages outside the workbook environment are reduced to a minimum. Facilitator messages offer personalized feedback and guidance for the course activities and in that sense they are critical to the LTTS pedagogical design. Facilitator messages are often long and rich in content and students often go back to them as they review their work and progress in the course. Thus, the time learners spent posting a message and the time spent reading each facilitator message (often more than once), is an index of reflection upon facilitator feedback and guidance.

Learners have complete freedom of movement in the course. From the very beginning they have access to all course activities and learning resources, including the final assessments. There is no requirement for a sequential submission for the course activities.

LTTS courses are offered for continuing education units or for one graduate credit. Students pay an enrollment fee and additional tuition if they request graduate credit.

Participants

The participants were 59 individuals who completed at least one LTTS course between November 2002 and April 2004. They completed a total 101 courses, but only the data from the first course in which each person was enrolled was used. The group of participants selected and completed 20 different courses during the study including language arts, math, science, social studies and cross discipline courses.

Participants were regular LTTS enrollees, who paid \$75–\$100 to enroll in the course. Pre-service teachers who also completed courses during this period were excluded from the sample because, unlike regular participants, they took LTTS courses as a requirement for a regular semester based face-to-face course.

Prior to the student's enrollment in their first course they complete an online voluntary registration form requesting voluntary demographic information including age, gender, location, position, and teaching experience. Participants reported their occupations as: teacher (73%), school administration or support staff (12%), graduate student (8%) and professions unrelated to school (7%). Among those who were teachers and school personnel, 24 reported working in elementary schools, 11 in middle schools and 15 in high schools. Reported teaching experience was as follows: 9 (15.3%) no teaching experience, 14 (23.7%) 1–5 years, 14 (23.7%) 6–10, and 22 (37.3%) more than 10 years of experience.

Forty-eight participants were female and 11 male, which is consistent with the gender proportion among school personnel (Department of Education, 2003). The age distribution for the 54 participants who reported age was: 1 participant under 25 years, 24 (40.7%) between ages 26 and 35, 15 (25.4%) between ages 36 and 45, and 14 (23.8%) over 45 years of age. Participants were located in 13 different US states and one other country.

Indices of learning activities

The objects to which a learner can go include the course problem page, course activity pages, learning resources that are part of an activity, work submissions within an activity, reading or writing a mail message, and course assessments. In an online environment it is possible to record the stream of student mouse clicks on links in the course. Thus, through an analysis of this click stream data we are able to identify each of course object a student went to, the time the student went to it, the object from which the student came, and when the student moved to the next object. While there are dozens of indices of learning activity that could be developed from these measures, in the cluster analysis approach used in this study, the number of variables that can be examined is limited by the number of participant data sets. Therefore we defined eight variables judged as relevant to the course design, and that would reflect learners' management of the freedom and flexibility provided in the online self-paced environment, as well as their commitment to the course work. Four measures provided a picture of how students approached the course overall:

Total time online: total number of minutes spent online during the course. This is the sum of all time in all learning sessions. Determining when a session ended is difficult because there is no formal log off process in LTTS—and even if there was, users are not accustomed to logging off of web based applications. We sought to determine a reasonable index of when a session ended by using two criteria. First, we looked at the frequency distribution of the time between clicks to determine when the frequency of time between clicks tended to fall off. The distribution indicated that until a 30 min interval there was a reasonable consistent frequency. After 30 min, however, the frequencies decreased and were much more sporadic. Therefore we chose a 30 min interval with no clicks as the indicator that a session had ended. Those 30 min were then subtracted from the session time. However, we presume that the learner did not simply quit with that last click before the 30 min silent interval, but rather worked for a while longer, albeit without clicks. Therefore as a second criterion, we looked at what the last click was on (e.g., a learning resource) and then looked at the average time the learner spent on that type of item (learning resources.) This mean time was then added back into the session length as well as to other measures involving that item, e.g., the total time and mean time spent on resources).

Course duration: number of calendar days from the first course activity to completion of the course. This measure was used to index whether students concentrated their learning or spread it over time, and is especially relevant in a self-paced environment.

Total sessions: number of sessions used to complete the course. As described for Total Time Online, a session was defined from entering the course after a login to a period of 30 min without course activity. This measure indexed the learner's frequency of working online.

Average inter-session interval: the average number of days between logins was used along with duration of the course to index the concentration of work.

In addition to these measures of amount and concentration of work, four measures examined the student study strategy within the course.

Proportion of time on learning resources: time on a learning resource was measured from the time when the resource was first engaged until the time of the next click onto another course object. Since different courses have different numbers of available learning resources, the proportion of time spent on learning resources relative to Total Online Time was used to index the extent to which learning from the resources were a focus of the students' attention.

Proportion of learning resources accessed: the ratio of the learning resources accessed to the total number of learning resources was calculated. The total number of learning resources in the 20 courses ranged from 27 to 81 with an average of 41. This measure further indexed the degree to which the students focused on learning.

Exploration: the number of times a learner moved between activities beyond what would be expected by a linear path through the course. This measure was used to index the which the participant was a linear learner, simply progressing through the course from start to finish versus reviewing the course and perhaps even working on different parts of the course as they appear interesting and useful. Following a total linear path through the course activities would yield an Exploration score of zero.

Proportion of time in messenger: time in the mail system was measured from the time when the Messenger icon was clicked on until another course object, outside of mail, was clicked on. The proportion of time in Messenger was calculated relative to Total Online Time. Since the course feedback and interaction with the mentor occurs through Messenger, this measure was used to index the extent to which the participant focused on feedback—either reading the feedback or responding to it.

In addition to the eight variables used in the cluster analysis two other click-stream variables were measured and used in order to further examine the behaviors of the cluster members: number of messages sent to the facilitator and number of times each facilitator message was read.

Student evaluations

After completing the course, students completed a 15 item survey asking about their course experience and their evaluation of the course. Fourteen of the items were five-choice Likert scale questions asking for degree of agreement with statements that focused on:

Satisfaction: a measure of overall satisfaction with the course was based on six questions that asked students if they would recommend the course, if the course activities were engaging, if the facilitation was helpful to their learning, if the course activities were relevant to their learning goals, if the difficulty was appropriate, and to rate the overall quality of the course.

Learning and transfer: four items asked students to rate their perceived learning (one item) and expected transfer to the classroom (three items).

Previous experience: students were asked to report their previous experience with technology integration (one item) and inquiry learning (one item), the two instructional goals common to the courses.

Group learning preference: a single item asked students the degree to which they preferred learning with other students. The self-paced, individualized learning and mentoring is core to the LTTS course and thus this measure was used to index preference for the LTTS approach to learning. If students preferred learning in groups, we might expect them to be frustrated with LTTS and either minimize their learning efforts or have difficulty with the freedom of the self paced environment.

Procedure

Participants completed the registration survey. Sometime after that, each learner independently enrolled in a course selecting it from the available LTTS course catalogue (35–50 different courses available during the study period). Students paid an enrollment fee and if graduate credit was desired, they also paid tuition for one graduate credit. Once enrolled, the course is listed in the student's personal work area and can be entered at anytime after logging into LTTS. Data recording began when a student first entered the course and continued until course completion.

Four LTTS trained mentors did the facilitation with each student assigned one mentor. Within 24 h after enrolling in the course, the facilitator sent a welcome message which also served to encourage the student to begin work. While course messages were stored within LTTS, the student received an email indicating that there was a message and could click through from the message to LTTS. Once enrolled, the learners had 12 weeks (84 days) to complete the course, working entirely at their own pace, completing the course activities and receiving feedback from the mentor for each submission. Work was submitted after each activity and feedback was provided. That feedback could lead to a resubmission of the work by the participant and another feedback. After the final course product was submitted, the learner completed a self-assessment and the course evaluation.

Results and discussion

Cluster analysis

Click stream data were collected for all participants until they completed the course. Following Barab et al. (1997) we used Ward's (1963) hierarchical cluster analysis to identify "naturally" occurring groups of students that, according to their online performance, were taking distinctive learning approaches in the online environment. Cluster analysis is a statistical exploratory tool used to classify or sort cases into groups, previously unknown or not evident. Participants are grouped based on the similarity of their composite scores, in our case according to their behavior on the eight course activity variables. Ward's procedure has shown to effectively recover the underlying structure of the data (Alexander et al. 1995).

The square Euclidean distance model was used to calculate the distance between clusters. As suggested by Aldenderfer and Blashfield (1984), all scores entered into the cluster analysis were standardized so as to assure common variability among the different scales. A cluster analysis yields many levels of clustering. A skree plot (Lawless and Kulikowich 1996), along with a determination of the meaningfulness of the clusters was used to determine the optimum number of clusters. In the skree plot, which converts a dendrogram to a profile curve, we looked for an extreme inflection point reflecting a meaningful change in between group variability. The number of groups before that inflection point was used to define the optimum number of groups.

An examination of the skree plot in Fig. 1 indicates that when the coefficient drops below 300, between a three and four cluster solution, the skree plot starts to level off indicating a reduced variability between clusters. By convention (Lawless and Kulikowich 1996), the change in slope, i.e., the reduction of variability, as indicated by the arrow, was used to determine that three separate clusters is an optimum solution. Further, an examination of those clusters, described below, suggests that the three groups reflect meaningful differences in online learning strategies

To confirm that an optimum cluster solution was obtained, each of the eight variables was compared across the three clusters. The intent was to use a series of ANOVA's for the comparisons, but a visual inspection of the histograms of the data suggested that a number of the distributions had a large deviation from normal. Shapiro-Wilks tests for normality indicated that a quarter of the 24 distributions (each variable for each cluster) deviated significantly from normal and several other distributions approached significance. While

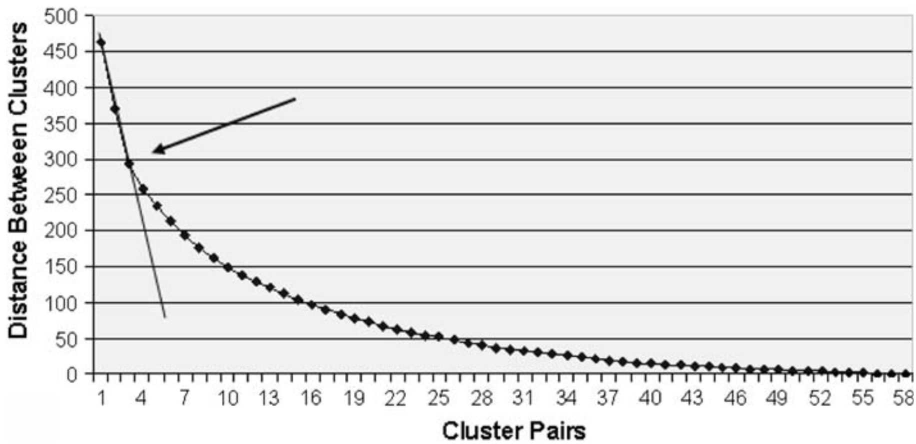

Fig. 1 Scree-plot used to determine number of meaningful clusters. Note: The arrow points when between-clusters variability stops being meaningful to suggest separate clusters, supporting the identification of three different groups

the ANOVA is robust with regard to the assumption of normality, with the number of significant deviations it was decided to take a conservative approach and use a non-parametric Kruskal-Wallis one-way ANOVA to analyze the data with cluster membership as the independent variable.

A separate analysis was conducted for each of the eight navigational variables. As seen in Table 1 the analyses yielded significant differences for all but one of the eight variables. The analysis failed to detect a significant difference between group medians only for Proportion of Time spent on messenger. The results support the existence of significantly different learning approaches based on the cluster analyses.

Subsequent Mann-Whitney U pairwise comparisons were used to determine significance between pairs of clusters. As seen in Table 2, each of the three possible pairings of clusters yielded significant differences on at least four of the dependent measures. Further, those significant differences involved both time management and learning management variables.

Table 1 Results of K-Wallis tests for each clustering variable

Variable/value	χ^2 Statistic	Degrees of freedom	Asymptotic significance
Total time online	22.660	2	.000
Course duration	29.275	2	.000
Total sessions	30.448	2	.000
Average inter-session interval	30.495	2	.000
Proportion of time on learning resources	13.292	2	.001
Proportion of learning resources accessed	22.322	2	.000
Exploration	20.817	2	.000
Proportion of time in messenger	2.356	2	.308

Table 2 Results of Mann-Whitney U tests for clustering variables by cluster pairs

	Clusters 1 and 2		Clusters 1 and 3		Clusters 2 and 3	
	Mann-Whitney U	Asymptotic significance (2-tailed)	Mann-Whitney U	Asymptotic significance (2-tailed)	Mann-Whitney U	Asymptotic significance (2-tailed)
Total time online	138.00	.03	13.00*	.000	30.00**	.015
Course duration	2.00*	.00	168.00	.542	3.00*	.000
Total sessions	44.50*	.00	19.00*	.000	64.50	.691
Average inter-session interval	37.00*	.000	58.00*	.000	3.00*	.000
Proportion of time in learning resources	199.00	.508	55.50*	.000	23.00*	.004
Proportion of learning resources used	192.00	.410	10.50*	.000	14.50*	.000
Exploration	91.50*	.002	44.00*	.000	38.00	.055
Proportion of time in messenger	165.00	.147	157.50	.373	68.50	.865

*$p < .01$, **$p < .05$

Online learning approaches

An examination of the results in Tables 2 and 3 suggests that the three clusters represent distinctive approaches to online learning. The means and variability for each cluster is presented in Table 3. However, to more easily see the relative position of each cluster on each variable, standardized means are graphically represented in Fig. 2. The means were calculated by first converting each participants score on a variable to a z score based on the scores of all the subjects. Then, the mean z score for the subset of participants in a particular cluster was calculated. Thus, the graph in Fig. 2 reflects on average how many standard deviations above or below the mean of zero the members of a cluster are for each variable. The data suggest that the three clusters may be interpreted to reflect three approaches to learning as described below.

Cluster 1: Mastery oriented or "Self-driven" approach. Cluster 1 is the largest cluster with 35 learners representing 59.3% of the study sample. This group is formed by those students with the highest number of work sessions ($M = 55.86$, SD = 17.05) and the highest online time with an average of 7.07 h (SD = 2.13), the latter being more than twice that of Cluster 3 and almost 25% more than Cluster 2. They also had the largest number of calendar days spent on the course ($M = 71.20$, SD = 14.37), but an intermediate work interval, logging in on average more than five times a week. Thus we see this cluster reflecting a high level of effort in the course; while the time between sessions was intermediate, they had far more sessions then the other clusters working across a longer period of time.

The strategy for working within a course suggests that there was not only a high level of effort, but that the effort was also learning focused. Cluster 1 showed the highest number of transitions between course activities ($M = 27.17$, SD = 15.07), being twice the number of transitions of Cluster 2 and more than three times that of Cluster 3. They also showed the highest proportion of learning resources used ($M = 48.97$, SD = 15.83), using on average almost half of the resources available, while those in Cluster 3 used only 16% of them. Consistent with this, these learners also spent a high proportion of course time (22.3%) on learning resources, being again more than twice the proportion of time spent by learners in Cluster 3. Finally, an analysis of message usage indicated that learners in Clusters 1 and 2 read messages more frequently than did students in Cluster 3 ($M = 1.7$, 1.7, and 1.4 respectively; $\chi^2(2, N = 59) = 6{,}588$, $p < .037$).

In sum these learners explore the course often, spend a large proportion of time in the learning resources and look at half of the resources available. All of these reflect a very learning oriented approach. This along with the amount of time spent in the course suggests that this cluster reflects students who are committed to the course and self-driven in their work, both suggesting a commitment to mastery.

Cluster 2: Task focused or "Get it done" approach. The second cluster accounted for 22% of the study sample ($n = 13$). This cluster reflects an overall lower level of effort in the course as compared to the Mastery Cluster but generally higher than Cluster 3. Members of this cluster have an intermediate number of work sessions ($M = 30.54$, SD = 11.37), and an intermediate total hours online ($M = 5.42$ h, SD = 2.30). However, they have the lowest number of calendar days invested in the course ($M = 17.92$, SD = 10.19) and the shortest time between logins with less than a day on average ($M = 14.68$ h, SD = 7.22) between logins. Thus they worked frequently and regularly, logging in very often, but spending only the necessary time on the course, without spreading it over many days or work sessions. They are focused on their work, completing the course as soon as possible, spending in average less than three weeks to finish, out of 12 weeks available

Table 3 Mean scores and standard deviations for each dependent variable by cluster

Cluster means and SD		Total time online	Course duration	Total sessions	Average inter-session interval	Proportion of time in learning resources	Proportion of learning resources used	Exploration	Proportion of time in messenger
Cluster 1: Mastery $n = 35$	Mean (SD)	7.07 (2.13)	71.20 (14.37)	55.86 (17.05)	35.61 (13.76)	22.13 (9.77)	48.97 (15.83)	27.17 (15.07)	12.85 (6.19)
Cluster 2: Task $n = 19$	Mean (SD)	5.42 (2.30)	17.92 (10.19)	30.54 (11.37)	14.68 (7.22)	25.56 (14.72)	45.71 (23.80)	14.00 (4.86)	16.61 (8.79)
Cluster 3: Minimalist $n = 16$	Mean (SD)	3.20 (1.30)	65.45 (19.87)	28.64 (8.48)	62.42 (21.60)	9.60 (7.31)	16.25 (11.51)	8.82 (5.96)	16.30 (9.89)

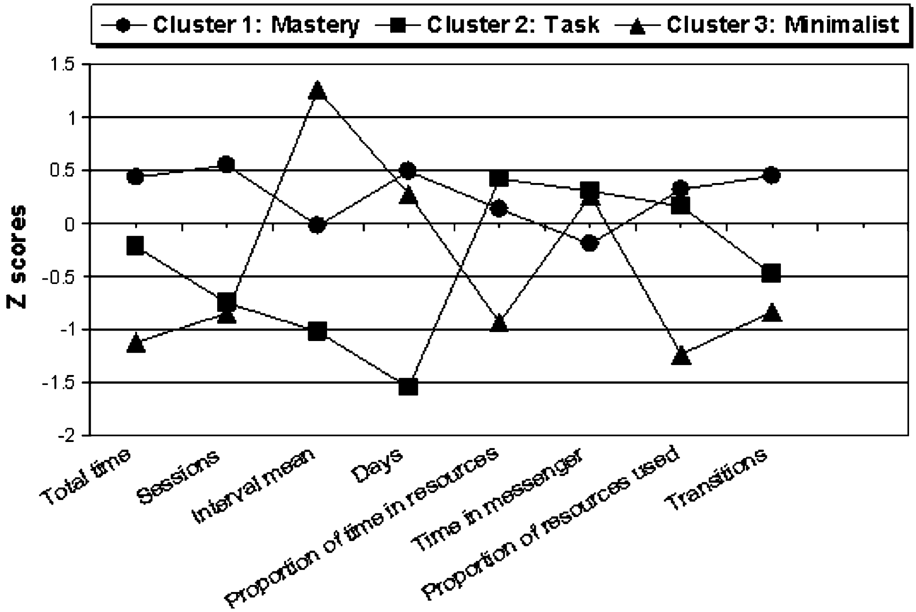

Fig. 2 Standardized means of the three clusters on the eight online activity variables

While Cluster 2 represents a lower and more concentrated work level than the Mastery Oriented, Cluster 1, the two clusters are reasonably similar in their approach to studying within the course. Like Cluster 1, members of this cluster tended to explore the course with an average of 14 transitions. They are also similar to Cluster 1 in the proportion of learning resources used (45.71%) and they spent even a greater proportion of their time (25.56%) exploring the learning resources.

In sum, these learners seem to be in a hurry to complete the course, concentrating their time and not spending nearly the time online that we find with Cluster 1. However, they reflect positive study strategies comparable to Cluster 1, exploring the course and making good use of learning resources. They are committed to the course but bound by their focus on completing the task: they have a task focused approach.

Cluster 3: Minimalist in effort or "Procrastinator" approach. Members of the third cluster (n = 11 or 18.7% of the study sample) used on average a high number of calendar days to complete the course (M = 65.45, SD = 19.87), comparable to those in the mastery oriented approach, but despite this they had the lowest number of work sessions (M = 28.64, SD = 8.48), comparable to those in the task oriented approach, and by far the lowest total online time (M = 3.20, SD = 1.30). Thus, their sessions were short and they spread their work over time, having by far the highest inter-session interval with an average of more than two and a half days between sessions.

In addition to a lower level and less concentrated effort on the course, the use of course materials by members of Cluster 3 is not reflective of a commitment to learning. They used by far the lowest proportion of learning resources, less than 17%, and spent less than 10% of their total course time on this critical activity. Furthermore, they had a low number of "jumps" or transitions between course activities (M = 8.82, SD = 5.96), being less than a third of the number of transitions of Cluster 1 and about half the transitions of Cluster 2.

Finally, as noted previously, they returned to the facilitators messages less often than students in the other two clusters. (M = 1.40 vs. 1.7 for Clusters 1 and 2, SD = 0.19).

In sum, Cluster 3 shows the shortest and most distributed amount of time on the course suggesting a weak commitment to the course. They seem to be in no hurry to complete the course, tend to spread their work over time, with not very frequent logins and no regularity of work. This lack of commitment is further supported by their practices within the course that included a linear path through the course and a focus on the task or activities rather than the learning resources. Overall, members of Cluster 3 reflect a minimal commitment to the course.

End of course evaluation

We next examined whether learners who took different approaches in learning perceived and judged their online experience as different and if these perceptions shed light on the characteristics of the different approaches.

Satisfaction: Chronbach alpha calculated on the five satisfaction items indicated a high level of internal consistency (α = .93). However, students tended to rate their satisfaction high, (see Table 4) with an overall mean of 4.17 and a median of 4.33 on a scale of 5.0. To correct the negative skew arising from this ceiling effect, we subtracted all values from the highest value plus 1, and performed a square root transformation. However, a Shapiro-Wilks test indicated that the data were still highly skewed ($p < .002$). Therefore the non-parametric, Kruskal-Wallis one way ANOVA was used to compare the satisfaction of the three groups. While the Mastery and Task Oriented groups tended to be more satisfied (see Table 4), the analysis failed to detect a significant difference between group medians, $\chi^2(2, N = 59) = 9.71$, $p < .615$.

Learning and transfer: Self-reported learning was assessed through a single item, "I learned a lot in this course". The median and mean ratings showed a ceiling effect in the scores (Table 5). A square root transformation failed to reduce the negative skewness (Shapiro-Wilks $p < .001$). Thus, the scores dictated the use of the non-parametric,

Table 4 Median (mean) and interquartile range score for course satisfaction (Likert scale 1 = SD 5 = SA)

Approach	Median (mean)	Interquartile range
Cluster 1: Mastery (n = 35)	4.33 (4.17)	3.83, 4.83
Cluster 2: Task (n = 13)	4.33 (4.38)	4.00, 4.83
Cluster 3: Minimalist (n = 11)	4.00 (3.94)	3.00, 4.83
Total (N = 59)	4.33 (4.17)	3.83, 4.83

Table 5 Median and interquartile range score for self reported learning (Likert scale 1 = SD 5 = SA)

Approach	Median (mean)	Interquartile range
Cluster 1: Mastery (n = 35)	4 (4.20)	4.00, 5.00
Cluster 2: Task (n = 13)	5 (4.46)	4.17, 5.00
Cluster 3: Minimalist (n = 11)	4 (3.72)	3.33, 5.00
Total (N = 59)	4 (4.16)	4.00, 5.00

Table 6 Median and interquartile range score for ability to transfer (Likert scale 1 = SD 5 = SA)

Approach	Median (mean)	Interquartile range
Cluster 1: Mastery (n = 35)	4.40 (4.67)	4.00, 5.00
Cluster 2: Task (n = 13)	4.54 (4.67)	4.00, 5.00
Cluster 3: Minimalist (n = 11)	4.12 (4.00)	2.00, 5.00
Total (N = 59)	4.38 (4.67)	4.00, 5.00

Kruskal-Wallis one way ANOVA, which failed to yield a significant differences, $\chi^2(2, N = 59) = 2.77$, $p > .05$.

Transfer was assessed through three items with a .90 Chronbach alpha for internal consistency. The medians and means of the composite scores (Table 6) showed a skewness due to the ceiling effect that was not adequately reduced by a square root transformation. (Shapiro-Wilks test, $p < .001$). A Kruskal-Wallis one way ANOVA failed to detect any significant differences $\chi^2(2, N = 59) = 2.15$, $p > .05$.

Students in all clusters rated their learning and the expectation for transfer to the classroom very high with the Mastery and Task Oriented Clusters rating them somewhat higher. However, as with Satisfaction, no statistically significant differences were detected between groups.

Preference for a cohort: A single question asked participants the degree to which they preferred working with a group, so that a rating of 5 indicated strong preference for learning with a cohort while a rating of 1 indicated a preference for individual learning. A weighted means, one way ANOVA of the mean scores yielded a significant main effect of Clusters, $F(2, 56) = 4.14$, $p < .03$. With a score of 3.0 indicating no preference, participants in the Minimalist Cluster indicated a preference for working with a group $M = 3.45$ (SD = 1.21), while the Task oriented cluster indicated a preference for individual work $M = 2.08$ (SD = 0.86), and the Mastery group was near the mid-point, still with a preference for working individually ($M = 2.57$ (1.26). A Tukey post-hoc comparison indicated that those in the minimalist oriented group had a significantly higher mean score when asked about their preference for working with a cohort ($p < .05$) compared to the other two clusters. These data suggest that at least one reason for poor online working of the Minimalist oriented cluster, despite their interest, is a dependence on a cohort of students. This may reflect a motivational need or a preference for the greater structure and guidance that occurs with a grouped paced course. One would expect task-oriented learners to prefer working alone as it allows them to be efficient in their effort.

Learner background

Age and Teaching experience: Table 7 presents the learners' mean age and mean years of teaching experience for each cluster. Separate one-way ANOVAs of mean Age and Teaching Experience yielded a significant effect of Teaching Experience ($F(2, 50) = 5.71$, $p < .01$). The Age effect failed to reach significance ($F(2, 51) = 1.57$, $p > .05$.) A Tukey post-hoc comparison indicated that those in the Mastery Oriented group had significantly higher previous teaching experience compared to those in the Task Oriented group $p < .05$). Post-hoc comparisons with the minimalist group failed to reach significance.

These data suggest that the experienced teachers focused more on mastery while less experienced teachers needed to "get the job done" (task oriented).

Table 7 Mean score (and SD) in years for age and teaching experience by cluster

	Cluster 1: Mastery	Cluster 2: Task	Cluster 3: Minimalist	Total
Age[a]	40.31 (10.92)	34.62 (6.60)	37.78 (9.71)	38.52 (9.98)
Teaching experience[b]	13.27 (7.24)**	5.96 (4.46)	8.09 (7.93)	10.54 (7.48)

**Significant at $p < .01$

[a] Five participants did not respond to this question

[b] Six participants did not respond to this question

Table 8 Mean and standard deviation score for previous domain knowledge (Likert scale 1 = SD 5 = SA)

Approach	Technology integration	Experience with inquiry learning
Cluster 1: Mastery (n = 35)	3.23 (1.31)	3.26 (1.24)
Cluster 2: Task (n = 13)	3.15 (1.07)	3.54 (0.88)
Cluster 3: Minimalist (n = 11)	3.82 (0.98)	3.73 (0.79)
Total (N = 59)	3.32 (1.21)	3.41 (1.10)

Course domain knowledge: Two questions asked if learners felt they already knew a lot about strategies for using technology in the classroom and about learner centered teaching strategies like inquiry learning (Table 8). Separate one way ANOVA's with Clusters as the independent variable failed to yield significant difference on reported experience with technology integration ($F(2, 56) = 1.16$, $p > .05$) or experience with inquiry learning ($F(2, 56) = 0.88$, $p > .05$).

General discussion and conclusions

In this study, we sought to characterize the online learning strategies of teachers enrolled in professional development courses for continuing education credit. Further, we sought to understand the characteristics that distinguish different types of online learners. The findings identified three approaches to online learning: Mastery oriented, Task focused, and Minimalist in effort. Two broad characteristics distinguish these three groups: the level of engagement in the course and the strategies for working within the course. Both Mastery and Task oriented groups took what can be interpreted as an active and serious approach to their work within the course. They spent a large proportion of their time (about 25%) on the learning resources and looked at a high proportion (almost 50%) of those resources. Further, they tended to explore the course rather than progressing through it linearly. What distinguishes these two groups is the amount and distribution of time spent on the course. The Task oriented group tended to spend less overall time on the course and concentrate that time in a narrower window of calendar time. Hence, while serious learners, this appears to be a task to be completed and they look to work efficiently at the task.

We also found that the Mastery oriented teachers had significantly more teaching experience than the Task oriented teachers. We suspect that this greater experience had two potential consequences that may account for the differences between Mastery and Task oriented teachers. First, with more experience, the teachers have more of their work prepared and hence can spend more time in learning. In contrast, the less experienced teachers typically have considerable work to do in preparing lessons and tests and grading work. Thus, they need to be efficient in getting what they need from the course. Additionally, it may be that the more experienced teachers have greater background knowledge and this provides the framework or basis for exploring more deeply. Of course, these inferences need further testing. Indeed, we did not find a significant difference in self-reported knowledge, but the teaching experience can be thought of as providing a broader and less subjective measure of knowledge.

The Minimalist group spent the least amount of time online and did not have a learning orientation while they were online. The little time they did spend was distributed over more than 2 months on average. They moved linearly through the course and spent less than 10% of their time on the resources, looking at only 16% of them. Bonk (2003), describes one of the "myths" of online learning to be the perception that "online courses are easy" and DE practitioners often discuss learners who expect the DE experience to be not very demanding (e.g., Carnwell 2000). This may characterize the expectations of our Minimalist group. Indeed, in open comments on the course evaluation some LTTS learners express this view in asking: "Why is this course so demanding if it is online?" However, we found that the vast majority of learners were, in fact, committed to learning and were willing to put in the effort.

Our data suggests that the problem with the minimalist students may rest with this learning environment. That is, in a post course survey, significantly more minimalist students indicated they preferred working in groups rather than the self-paced, individually mentored approach of LTTS. This suggests that the Minimalist students may need more motivational support or structure provided by a group paced course in order to gain maximum learning benefit. This could be due to the motivational effect of other teachers as well as the guidance they provide or it could be due to the increased course structure and guidance necessitated by a group paced environment.

Seemingly all three approaches can be relatively successful; all learners in the three clusters completed the courses and all but one (a minimalist learner) obtained a passing grade. Even learners taking a minimalist approach do reasonably good work sufficient to pass the course and move on with their objectives. However, those taking the minimalist approach seem to struggle more to manage their online learning experience and they seem less willing to put effort in the courses. Additionally, while the analysis of the evaluation measure yielded significant effects for only one measure (preference for cohort work), in all evaluation measures minimalist learners are less satisfied with the course experience, and report lower learning and ability to transfer.

The current findings differ from previous research in several ways. First, apathetic learners, or Minimalists in our terms, was the largest cluster in prior research, with the smallest cluster consisting of the mastery oriented learners (e.g., Lawless and Kulikowich 1996). Here we find just the opposite. The Mastery students represented 59% of the learners and the task oriented represent another 22%. Only 19% did not take a learning orientation. A second contrast is that while we identify a cluster as task oriented learners, the prior research found a group of "explorers" (Lawless and Kulikowich 1996) or "cyber cartographers" (Barab et al. (1997) individuals more interested in the technology than in learning. Thus the proportion of "learners" in these other studies was considerably lower than what we found. While we found 81% engaged learners, as indicated earlier in Table 2, three prior laboratory studies found between 21% and 34% active learners (see Table 9). This is an important distinction for a couple of reasons. First, our findings do suggest that the online environment is a very viable learning environment in which the majority of students put in significant effort. In contrast, the earlier studies would suggest that online learning environments are educationally impoverished.

Table 9 Proportion of participants classified as "learning oriented" across four studies

	N	Learners (%)	Inattentive participants (%)[a]
Current study	59	81	19
Lawless and Kulikowich (1998)	56	34	69
Lawless and Kulikowich (1996)	42	21	79
Barab et al. (1997)	66	33	67

[a] Includes clusters characterized as represented apathetic, explorers, or other characterizations not reflecting a focus on leaning

Second, the findings suggest the ecological validity of the learning environment is an important factor in studying online learning. Our students were teachers who voluntarily enrolled in one credit courses as part of their professional development initiative. While some may be enrolled simply to fulfill a requirement, the courses are nonetheless professionally relevant to these students and the students has a wide variety of choices to find a course that was most relevant to their needs. Therefore, most of our learners can be expected to be engaged, and in fact they were able to complete an extended online course. In contrast, the prior research involved experimental studies were students were recruited as "participants". Thus while we find 81% engaged learners, as indicated earlier in Table 2, three prior laboratory studies found between 21% and 34% active learners (Table 9). It could be argue that the difference is due to the pool of participants, the resources used, or the domain of study, but even if this is the case, all those aspects are finally part of the essence of the learning environment, including an authentic task and resources designed for spontaneously engaged participants, characteristics that might have made the difference by helping the learner to focus on the learning task.

The findings do suggest that how the student works online may be a good index of their commitment to learning. Additional research could usefully use interviews or surveys to validate our inference that the degree of linearity and the use of learning resources can serve as early indicators of learning goals. If validated, this data can be used to prompt counseling intervention.

Lawless and Kulikowich (1998) proposed that students with a medium amount of subject matter knowledge would have the greatest tendency toward mastery learning—these are students who knew something about the subject thus indicating an interest, but not enough to be bored. As discussed above, that is inconsistent with our findings that the mastery students had the greatest amount of background experience. While there was not a significant difference in reported knowledge, the direction of the relationship also suggested the mastery students had more knowledge of the specific teaching issues. We suspect that Lawless and Kulikowich are perhaps too general in referring to subject matter knowledge separate from context. Certainly even experts continue to learn in their area of expertise and are not bored by those opportunities. Indeed, the proper reference should likely be to the particular learning resources rather than the subject matter in general.

We acknowledge that in our study the measure of previous knowledge is self reported (perceived knowledge), and that there is no substitute for a knowledge test, which simply was not feasible in the context of this study, but since these are common terms, specially in the participants' field, and they are professionals, we consider that teachers are reasonable judges of their "previous knowledge". Additionally, participants reported their teaching experience in years, which since the main domain knowledge in all courses is teaching, this also give as a sense of their previous knowledge. Thus, we think the comparison is reasonable, and we would argue that the central role of subject matter knowledge in their studies is due to the artificial learning environment. Lawless and Kulikowih (1998) argue that apathetic users are less motivated to navigate content pages because they already possess high amounts of domain knowledge, and users who have a lower amount of domain knowledge are seduced away from pertinent material by special site features. This being the case, we argue that an authentic and more challenging environment would make the difference, thus the fixed experimental setting, with no tutoring, which does not allow them to reach their personal learning goals, is affecting their performance.

LTTS is a self-paced learning environment with one-to-one mentoring. Students move at their own pace as they complete 5–7 activities. While the mentoring assures individual attention and support, it requires motivated students who can manage their own time allocation and learning activities. Our data suggests that the problem with the minimalist students may rest with this learning environment. That is, in a post course survey, the minimalist students indicated they preferred working in groups. This may reflect any one of at least three reasons for preferring groups. First, it may be a preference for a larger community in which to share stories. Second, a group may be needed to provide motivation and direction. Finally, the group necessitates a paced course with regularly scheduled assignment and this may be needed to help provide structure.

There has been a concern that students will have difficulty managing their time and learning resources in online learning environments (Bonk et al. 2004). The design of the LTTS courses with the high level of student freedom would certainly be an environment where we would expect such problems to appear. Yet, we have found that the vast majority of learners are very effective in their learning strategies with fewer than 20% exhibiting a level of inability to manage their learning in terms of time expenditure as well as learning activities. Thus these data speak well for the potential of DE environments to provide high quality learning experiences. Indeed, the LTTS environment accommodated learners interested in working on the task seriously but efficiently as well as learners who wanted to spend more time on particular resources and perhaps probe issues in depth, something that is difficult to do in group paced courses. Additional research is needed to confirm our inferences about the relationship of knowledge and mastery learning—and the moderating effect of the authenticity of the environment. We used a self-report measure of knowledge as well as years of teaching experience which is a secondary measure. Thus, future research should measure knowledge more directly, but at the same time look at the impact of knowledge in relationship to the authenticity or relevance of the learning requirement.

Additional research is also needed to further assess the factors that lead students to take a minimalist approach to learning. Of course this is much broader issues and one that everyone wishes could be solved. However, in this particular context of a professional development environment, the Minimalist students' reported preference for group paced learning rather than individual mentoring in a self-paced environment, suggests these students may simply need more guidance, e.g., a learning plan, defined deadlines, or other cues to prompt them to work in the course, or if they would benefit from a community to exchange stories and set group commitments. Of course, there are going to be some learners who simply will not be engaged, often for reasons external to the course—but again, happily, we found few of those in the LTTS courses.

There are two important limitations of this study that should be addressed in future research. First, we only have self-reports of learning and transfer and there was a ceiling effect on those measures. All of the students reported a high amount of satisfaction, learning, and expectation of being able to transfer the learning to the classroom. In recent work (Osman ans Duffy 2006) we found that about three quarters of LTTS students, interviewed at least 6 months after completing the course, do report that the LTTS lesson they developed was used in their classroom or otherwise impacted how they teach. However, we do not have data on actual learning. Students take different courses, reflecting their learning needs, and thus assessment is not straight forward. However, we are developing a rubric that can be applied across courses to assess the degree to which the lesson plan the teacher develops is learner-centered (Wise et al. 2004). Future research should use a more direct measure of learning.

The second limitation is that we are only looking at online activities. Student reports suggest that almost 60% of their learning is online. We simply do not know what the students are doing in the offline environment. While there is no reason to suspect the offline behavior would differ from the online behavior, it would be valuable to have students keep log books to record their offline learning activities or, alternatively, to interview them weekly throughout the course.

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