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Uncovering student learning profiles with a video annotation tool: Reflective learning with and without instructional norms

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Introduction

Higher education institutions are increasingly adopting blended or digital learning strategies to better meet the demands and expectations of prospective students (Garrison & Kanuka, 2004; Gosper, Malfroy, & McKenzie, 2013; Graham, Woodfield, & Harrison, 2013). At the same, there is a growing evidence base demonstrating the impact of blended learning on student learning performance[1]. In essence, blended learning approaches are seen to better promote academic performance and higher order learning outcomes when compared to more traditional and fully online modes of instruction (Al-Qahtani & Higgins, 2013; Chen, Lambert, & Guidry, 2010; Torrisi-Steele & Drew, 2013). While blended learning offers much potential to meet the challenges associated with a shifting education landscape driven in part by changing student expectations, competing demands on student time, as well as learning and teaching quality, there remain questions regarding how students engage with such technologies to specifically support their learning strategies and approaches (Lust, Elen, & Clarebout, 2013; Lust, Vandewaetere, Ceulemans, Elen, & Clarebout, 2011). Although there are a number of learning tools available for facilitating blended learning (e.g. blogs,

[1] For the purpose of the study presented in this paper, we have adopted Garrison and Vaughan's (2008) definition of blended learning as the “integration of thoughtfully selected and complementary face-to-face and online approaches and technologies” (p. 148).

wikis, and discussion forums), one particular technology that has gained in momentum in blended learning settings is the use of video-based learning techniques (Giannakos, Chorianopoulos, & Chrisochoides, 2014). While in some blended learning models, students are asked to watch a lecture video prior to coming to a face-to-face session, in other learning settings, students are asked to watch video recordings of their own presentations or performances and provide reflective comments on their perceived strengths and weaknesses. This study focuses on the latter whereby students reflect on their video recorded performance. A video annotation tool is used to facilitate students' reflective practice and promote self-regulated learning proficiency as they watch the video recordings of the own performances. The primary aim of this study was to investigate how students engage with the video recordings and video annotation tool in a blended learning setting. The findings from the study have important implications for future course design when integrating videos as an instructional medium.

Students' Engagement with Technology

At present, the learning management system (LMS) is one of the most commonly adopted technologies for supporting course delivery in higher education today. The LMS is essentially an aggregation of differing tools that support the provision of content as well as student collaborations such as discussion forums or self-reflection and assessment tools. Despite the vast number of learning technologies accessible for the contemporary student cohort, not all students avail themselves of these tools or engage them in a manner that effectively supports their learning process (Lust et al., 2013, 2011; Yen & Lee, 2011). Drawing on the earlier work of Winne (2006), Lust and colleagues (2013) pose two inter-connected reasons why students' choose not to engage with an educational technology – internal and external conditions. Broadly speaking, the first relates to the low proficiency of students' self-regulated learning. Essentially, students' self-regulated skills are largely insufficient to enable them to identify when to engage with a particular technology in order to support their learning (Lust et al., 2013). This premise was well demonstrated in their study investigating student's engagement with the various tools available in a LMS in an undergraduate course.

Through cluster analyses, Lust and colleagues (2013, 2011) aimed to identify patterns in students' use of learning tools across two sequential phases of a single course offered in a blended learning model. The course design consisted of series of lectures that was complemented by the LMS and teacher support (instructor and tutors). The first phase of the course focused on factual and comprehension of concepts while the second phase related to the application of these learned concepts. Lust et al. (2013, 2011) noted that based on the frequency and duration of tool use and the types of tools adopted (e.g. lower order vs. higher order learning) three clusters of students emerged in the first phase of the course instruction. Namely: *no-users, intensive users,* and *selective users*. In the second phase of the study a fourth cluster emerged, termed *limited users*. The authors noted that the students in cluster one (the no-users) had a significantly lower level of engagement with the learning tools than the students in cluster two (the intensive users) and in cluster three (the selective users).

The intensive users were frequent users of multiple tools within the LMS, particularly the practice quizzes. The selective users, in phase one, were more exploratory in their engagement of the various tools opting primarily for basic information and scaffolding type tools. However, for phase two, this particular cluster strategically accessed the video lectures and attended face-to-face support sessions showing signs of goal-orientation. Finally, the *limited users*, a cluster emerging only in the second phase of the course, used the online learning tools significantly less than both the *intensive* and *selective* users and focused most of their effort in attending face-to-face lecturers and learning support sessions. Temporal analyses over the duration of phases one and two revealed that most students across all three clusters (identified in phase one) transitioned into the *limited users* cluster during phase two. This suggests that the students perceived their adopted tool use for phase one was no longer applicable given the altered course conditions in phase two. This shift in tool selection and engagement shows signs of student self-regulation and agency towards their learning (Winne, 2006). While students are active agents in their learning process, the choices they make are influenced by both internal and external conditions. The work of Lust and colleagues (2013, 2011) illustrates that the internal conditions, such as metacognitive awareness, motivation, and prior knowledge, affect student tool choice and application of these tools for learning. These choices are based on an individual's past experience and capacity to relate to the external conditions associated with the course such as level of academic guidance and support alongside the driving instructional context (e.g. learning activities, formative and summative assessment tasks).

The discussion of internal conditions (self-regulated learning) influencing tool choice and engagement segues to the second factor proposed by Lust colleagues, that is, the instructor norms (i.e., external conditions). Research in factors influencing students' use of a LMS has shown that instructor norms can impact upon students' decisions to engage or not engage with an educational technology (McGill & Klobas, 2009). For instance, if students are aware that the instructor of the course perceives that the use of a particular technology is beneficial for their learning there is a corresponding increase in the use of that particular technology among the student cohort. This notion resonates with Perkins (1985) who posited that students do not always engage with the learning opportunities presented or features of technology if they are not fully aware of the gains they will achieve from it. Further, the role of external conditions or factors such as assessment and feedback can also influence student learning (Hattie & Timperley, 2007) and in particular, ongoing and timely feedback specific to students' performance can promote meta-cognitive awareness and encourage students (Gibbs & Simpson, 2004). While there is much literature on the influence of assessment design and feedback in general, to date there has been limited research investigating the role such external factors play on students' self-regulation of learning or agency in terms of the choice and use of video technologies incorporated to support their study. In particular, the effect of the interplay between internal and external conditions on students' adoption of video technology across multiple courses involving different instructional conditions and pedagogical approaches is limited. Hence, this study aims to address this gap in the literature by conducting cluster analysis on students' use of a video annotation tool that was adopted across four courses. The subsequent cluster analyses are based on the different instructional conditions encountered in the various courses. In this case, the presence or absence of external conditions namely, graded self-reflection annotations.

Video Annotation Software

The integration of video content into online and blended courses is rapidly becoming the norm for higher education (Yousef, Chatti, & Schroeder, 2014) with an increasing number of video annotation software seeking to make the simple transmission of video and audio content a more collaborative and dynamic process (Cross, Bayyapunedi, Ravindran, Cutrell, & Thies, 2014). For example, Aubert, Prié, and Canellas (2014) discuss various uses of video annotation in e-learning contexts, particularly massive open and online courses (MOOCs) that provide opportunities for students to annotate lecture videos or their own recordings (e.g. self-reflection) individually or collaboratively. The development of, and research associated with, these web-based video annotation technologies has been available over the past several years. For instance, one of the initial video annotation tools, the Microsoft Research Annotation System (MRAS) was designed to aid student engagement through the use of note-taking (time-stamped annotations) while viewing video content. An early experimental study using MRAS demonstrated that students had preference towards using the annotation tool with video content over more traditional note-taking within a live lecture context (Bargeron, Gupta, Grudin, & Sanocki, 1999). More recently, the Media Annotation Tool (MAT) has the additional features of a structured annotation learning cycle whereby students can annotate a form of media, see their peers' and teachers' comments, and then provide final reflective notes (Colasante & Fenn, 2009). A pilot case study incorporating the use of MAT was undertaken with pre-service teachers specializing in physical education who were requested to complete the annotation learning cycle by viewing videos of their own teaching scenarios and those of their peers' in order to enhance critical reflection in a collaborative manner (Colasante, 2011). Survey, interview, and observational data revealed that the majority of students valued the peer and teacher feedback features of MAT and that the media annotations are effective for enhancing student learning. Similarly, Rich and Hannafin (2008) reported on a variety of video annotation tools being used by pre-service teachers, in particular to reflect on their teaching practice and refine their skills. Hence, while video annotation software is not a novel technology and the above and similar studies (Bargeron et al., 1999; Colasante, 2011; Magenheim, Reinhardt, Roth, Moi, & Engbring, 2010) have shown that students perceive video annotation technologies to be valuable for their learning and reflective practice, they have relied heavily on self-report data rather than more automated logged data that can be derived from the student's actual use of the technology. While self-reported data can shed light on how students' perceive technologies (e.g., typically to understand perceived usefulness and ease of use), the methodology is subject to social desirability bias where students may provide a desired response rather than the most accurate response (Beretvas, Meyers, & Leite, 2002; Gonyea, 2005). Furthermore, a reliance on students' recall of previous behaviour with a specific technology can lead to the collection of inaccurate data about the activities taken by learners while using the technology (Winne & Jamieson-Noel, 2002). Moreover, due to individual differences (e.g., metacognitive skills and motivation), students tend to approach their learning differently (Winne, 2013). However, the identification of these strategies is questionable due to the abovementioned potential inaccuracies associated with self-reported data.

In contrast, learning analytics and data mining techniques are applied to extract users' actual behavioral data with technologies. Hence, learning analytics and educational data mining can provide more objective data of a student's actual use of technologies in lieu of the individuals recall of their activity (Greller & Drachsler, 2012). However, the use of data from students' interactions with videos and associated tools (e.g. video annotation software) to analyze their use and engagement with videos is still at an early stage with few studies leveraging such data to understand students' actual experiences (Giannakos, Chorianopoulos, & Chrisochoides, 2015). For example, in a study investigating students' note-taking behavior while watching lecture videos, Mu (2010) analysed the logged data captured through students interactions with the specific technology. This data was used to analyse the length and frequency of students' notes. A further example using data mining techniques for analyzing student use of video can be found in the work of Brooks, Epp, Logan, and Greer (2011). These researchers applied various data mining methods to analyse objective data from students' engagement with lecture videos to discover patterns in students' use of the recordings. Using k-means clustering, Brooks et al. (2011) revealed five types of student engagement with video lectures: *minimal active learners* who rarely access the videos; *high activity learners* who watch a portion of each lecture video on a weekly basis; *deferred learners* who began to access the videos towards the second half of the semester; and two clusters of *just-in-time learners* who accessed the videos either only a week prior to the midterm exam or the week of the midterm exam. By extending the studies by Mu (2010) and Brooks et al.'s (2011), this paper advances the research in video analytics to specifically explore students' use of video annotation software for reflective purposes in differing instructional conditions (graded vs. non graded) to identify patterns in students' learning behaviour.

Learning Technology Usage Profiles

Derived from the research noted above, it would appear that student engagement with a technology can be classified around particular learning profiles. For example, Lust et al. (2013) identified four clusters (profiles) of student use with the LMS. Similarly, Brooks et al. (2011) also noted four clusters based on student engagement with lecture videos. In a further study undertaken by Phillips, Maor, Preston, and Cumming-Potvin (2012) also investigating student use of lecture video recordings, multiple user profiles were defined based on patterns of student engagement with the various recordings. In this case, the profiles ranged from the low level access of non-users and random users through to frequently accessed profiles such as high-achieving and conscientious users. Essentially, these studies suggest there is potential for logged data derived from student interactions with technologies, to provide a measure of self-regulated learning proficiency and the impact of external conditions on learning behavior and tool adoption. To date, there have been few studies that have aimed *to investigate the interaction between the usage profiles and the instructional conditions (external conditions) of a course of study.* This study aims to address these deficits by examining the profiles of students based on the data available from their use of a video annotation tool when exposed to differing instructional conditions. Moreover, the study looks at the effects of usage profiles on academic achievement of the students. This is an important issue to investigate since self-regulated learning skills are recognized as important for academic achievement (Pintrich & de Groot, 1990).

Research Questions

1. What are the main learning profiles that emerge from the use of video annotation software?

2. Do different instructional methods influence the development of the learning profiles identified based on student engagement or use of video annotation software?

3. What is the effect of the learning profiles that emerge from the use of video annotation software on students' academic achievement?

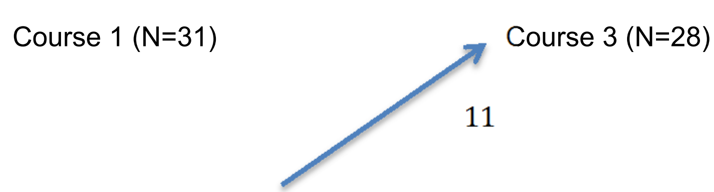
Method

Setting and Sample

A case study approach was deemed the most appropriate research design given that the data were collected from a single disciplinary area (performing arts) in one higher education institution in North America (Eisenhardt, 1989) and the researchers lacked any control over the behaviours of the students and instead investigated learning and engagement within the natural context of the course (Yin, 2009). Following institutional ethics approval, secondary log data from all courses that used a locally-hosted video annotation tool called the Collaborative Lecture Annotation System (CLAS), in the 2012-2013 academic year were extracted. At this time, all potentially identifiable information such as username or student number were transformed using a randomly generated code to ensure student and instructor privacy. The secondary data extracted from the log files only contained information relating to student and instructor interactions with the video annotation tool. Hence, the conditions for ethics approval required that the teaching context and approach for each course was inferred from the secondary data collected involving the adoption of CLAS. Initial observation of the data revealed that students in four of the courses used the tool for self-reflection purposes (e.g. students described their performance and noted goals for improvement), and that of these four courses, two incorporated graded assessment of the student annotations as observed in the feedback text provided by the instructors. Hence, the research team concluded that for two of the courses, the use of the video annotation tool was not graded and hence, any student use was optional and supplemental to the course. However, for the remaining two courses, the reflective annotation activity was a graded component of the course in which the students received instructional feedback on their reflections, offering them guidance on how to improve their subsequent reflections. The CLAS tool was developed by the institution at which the study was conducted. The CLAS tool was used predominantly for the first time during the particular academic year

(2012-2013) and the students in this study did not have any prior experience with the tool.

The participating courses in the study were situated in the performing arts discipline and consistently involved students' self-reflective annotations or comments on their own performance. The study was restricted to the analysis of the use of CLAS within the four performing arts courses. This decision was informed by the unique feature of the video annotation tool affording students opportunity to make time-stamped and general annotations on their individual performance recordings (detailed below). Time and date stamps of the recorded data further showed that two of the courses were offered in the first semester of the year and two other courses offered in the subsequent semester. The data also revealed that a proportion of the student cohort was enrolled in one of the courses in the first semester and then progressed to one of two courses offered in the subsequent semester. The randomly generated IDs for the students also revealed that for one of the courses (Course 1) all students posted annotations to the same set of videos. However, for the other three courses, each student posted annotations to an individual video. Hence, it can be inferred that for Course 1, students could see each other's annotations and were annotating a group performance. Conversely, for the other three courses, the students annotated their own performance only and were therefore unlikely to have shared their reflective posts with their peers. Furthermore, since the research team did not have any control as to how the video annotation tool was used by the students nor how it was integrated into the curriculum, such as a graded component or non-graded, the study had the characteristics of a natural experiment (Dunning, 2012). Figure 1 below shows the pedagogical context and the progression of courses.



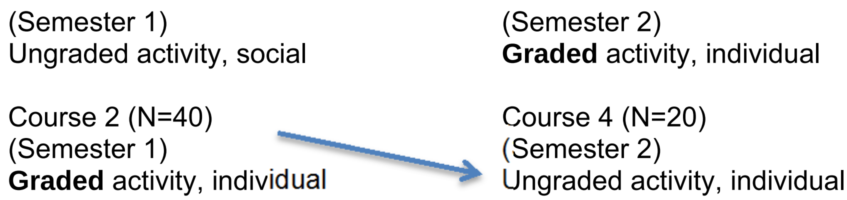


Fig. 1
Pedagogical approach and progression of students between the undergraduate courses included in the study

Learning environment – video annotation tool

At the higher education institution where this study occurred, a locally-hosted video annotation tool, CLAS, was available for enhancing students' experience of watching recorded lectures, performances, or presentations by posting time-stamped annotations and general comments for reflective practice or self-study while viewing the recordings to develop their metacognitive skills (Authors, 2012; Authors 2013). Since the tool was locally hosted, students' interactivity with the tool, or 'mouse-click' trace data, was captured and stored in the database. CLAS allowed instructors to provide access to videos to students only enrolled in their course and to restrict students from directly downloading the videos. This feature ensures that any student and instructor activity with a video via CLAS can be recorded and stored. Various types of data were captured, such as the number of times students made, edited, or deleted an annotation, the use of various types of video playing functions (e.g., play, pause, forward, and rewind), and the time a user made their first and latest annotation. These types of data, analysed collectively, can be used to provide insight into students' learning profiles when using video annotation tools. Figure 2 illustrates the various features of the video annotation tool.

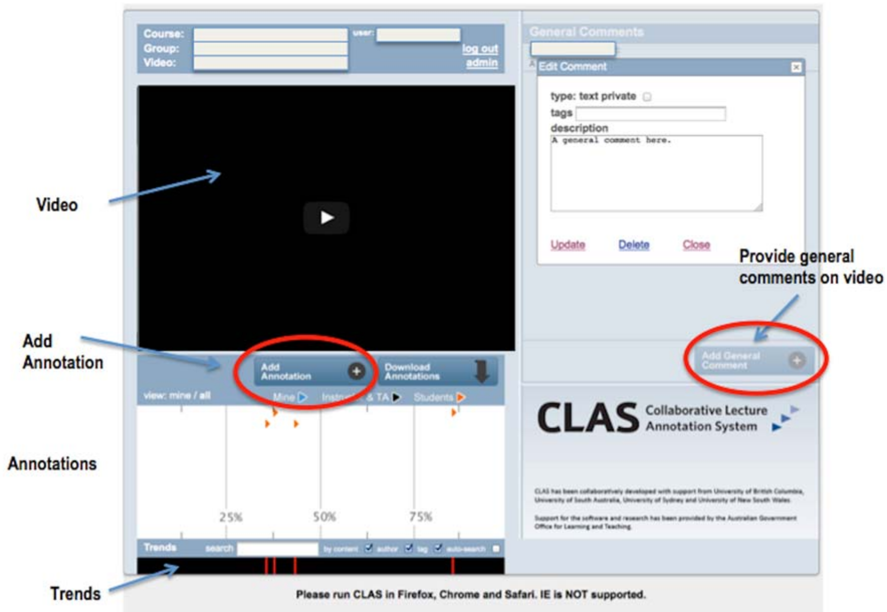


Fig. 2

A screenshot of the interface of CLAS, the video annotation software used in the study

Variables

Of the various clickstream data captured by the video annotation tool, 12 particular variables, derived from the trace data logged by the video annotation tool, were selected to represent students' interaction with the tool and the different ways they can choose to engage with this particular technology. The analysis of the engagement data provides further insight into student learning profiles. The following five variables measure the students viewing patterns based on how they interact with the video control buttons. Such viewing patterns can show whether students choose to view videos non-stop or spend time rewinding or fast-forward to reach particular points in the video as well as how much of the videos they view.

- *Fast-forward:* The total number of times forwarding each video.
- *Rewind:* The total number of times rewinding each video.
- *Non-stop:* The total number of times activating the play button for the entire duration of a video without transitioning to another function.

- *Pause:* Total number of times pausing a video.
- *Time watched:* Total amount of time each video has played. This variable, however, has the limitation of only capturing data based on students' mouse-clicks with the play button. While students may 'play' a video, it is not known for certain whether they actually viewed the video or were engaging with something else while the video played in background.

The following six variables relate to students use of the annotation functions in the video annotation tool. The main additional feature of using the video annotation tool rather than viewing the videos in any other video streaming player, is the capability the tool provides for making time-stamped annotations while viewing the video that can be revisited later.

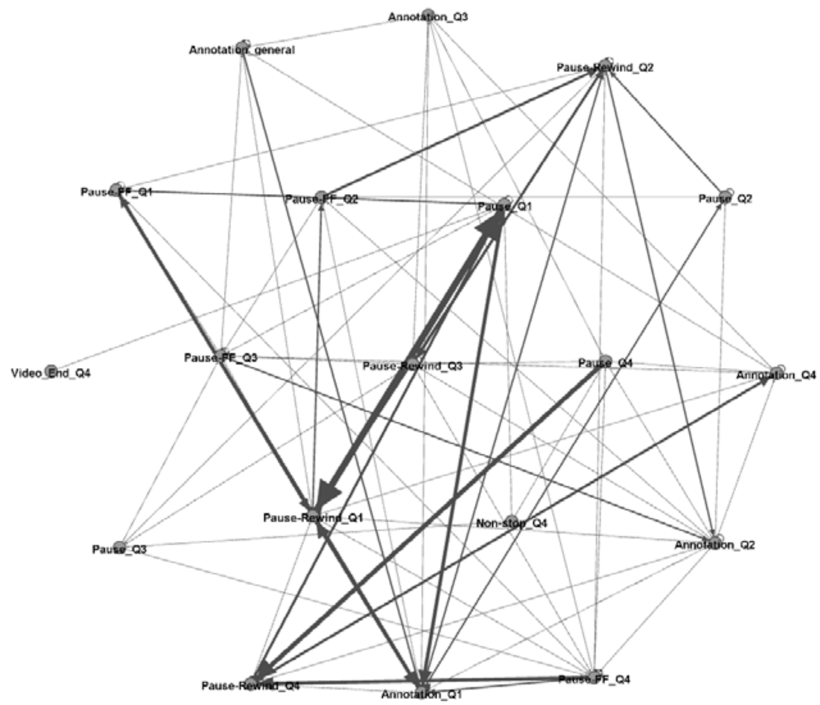
- *Annotations total:* Total number of annotations students make in each video.
- *Annotations edited:* Total number of times students edit annotations in a video. This measure shows whether students write an annotation and later go back and make a change or leave their annotation as it is.
- *Annotations deleted:* Total number of annotations students delete in each video. This measure shows if students return to an annotation and select to delete it.
- *Videos annotated:* Total number of videos students make at least one annotation on.
- *Earliest annotation added:* The earliest date and time each student made their first annotation from the time that the video was available to them. This measure represents whether the students waited a long time before making their first annotation (the main feature of the tool and requirement

for some of the students) or whether students made their first annotation right away.

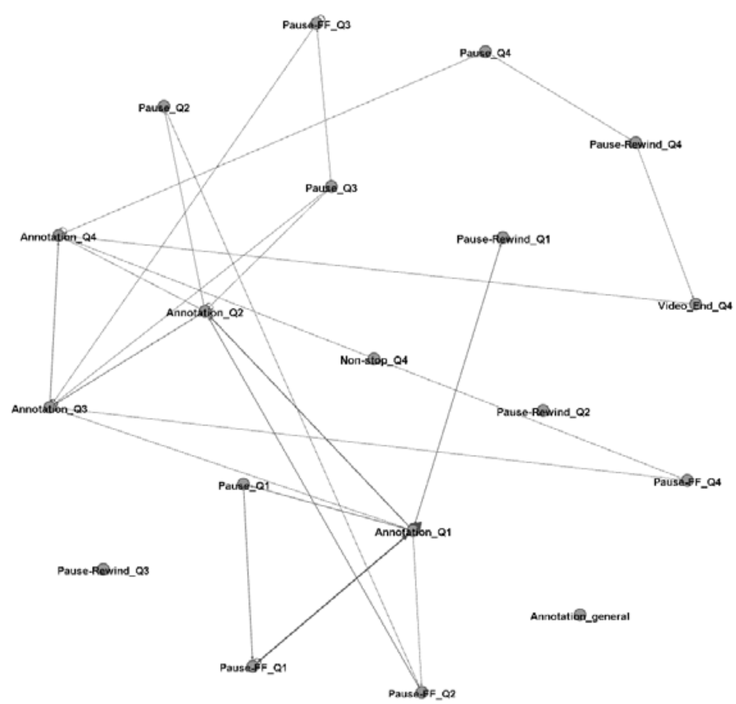
- *Latest annotation added:* The length of time from when the video was first available to the time the last annotation was made by the student. This variable, along with the *earliest annotation added,* shows whether students were engaged with the activity of annotating the video during a long period of time (i.e. if they made their initial annotation soon after the video was available and their last annotation at a considerably later time) or if their initial and final annotations were close in time.

Transition graphs were constructed for each student in each course of the study. These graphs were used to gain a holistic view into the learning strategies adopted by the students. Transition graphs were created from a contingency matrix in which rows and columns were all events logged by the video annotation tool. The rows denoted the start and the columns the end nodes of the transition edges. To create a transition edge from event A to event B, number one was written in the matrix cell intersecting row A and column B. There was a sequential increase in the number in that cell for any future appearance of the edge from event A to event B. To capture the temporal nature of video and reflect on the differences in temporal distribution of different events captured by trace data (Authors, 2014), events were associated with temporal quartiles of videos they belonged too (e.g., create annotation in quartile one, or pause in quartile two).

Density of the transition graphs was the final and 12th variable that was calculated for each student in each course of the study. This variable shows the extent to which students clicked on subsequent different functions within the video annotation tool or the number of transitions they accumulate. The overall network density is measured by considering all possible transitions between features of the video annotation tool based on the total possible transitions across all students (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). The more functions a student clicked on, and the greater the number of transitions they had, the larger the network density and metacognitive monitoring. As posited by Hadwin et al. (2007), greater graph density of students' activity shows that they are experimenting with different learning strategies, and thus, have a higher level of metacognitive monitoring activity. In contrast, a lower graph density illustrates that the student has already selected key strategies to aid their learning process. Hence, as the network density declines, there is parallel assumption that the students' metacognitive monitoring and self-regulated learning also declines. Figure 3 illustrates two network graphs. The network graph at the top (a) shows an example of a student with many transitions in the tool and hence more density while the network graph on the bottom (b) shows an example where there are fewer transitions. The density measure represents whether students tended to click on many different functions while engaging with the video annotation tool or had decided to use a few key features.



a)



b)

Fig. 3

Examples of transitions graphs of two students enrolled in course 2 (a) and course 4 (b) of the study, respectively.

Finally, the students' grades from the four courses were used to gauge the effect of the learning profiles on academic achievement.

Data Analysis Method

This study applied Ward's (1963) hierarchical cluster method as it can effectively uncover the underlying data structure without human intervention or having to interpret or rely on self-reported data (Alexander, Jetton, & Kulikowich, 1995). Clickstream data of students' use of the video annotation tool and the density of the transition graphs, specifically the 12 variables noted in the previous section, were used to identify clusters of student user behaviour. To account for different scales, all data were standardized. The dendrogram in Figure 4 illustrates the results of the hierarchical cluster analysis revealing four clusters. Each line at the bottom of the diagram represents a student. Students merge with other students or groups to form larger groups. The height of the merged line represents the dissimilarity between groups. A four-cluster solution minimizes intergroup dissimilarity and maximizes intragroup dissimilarity.

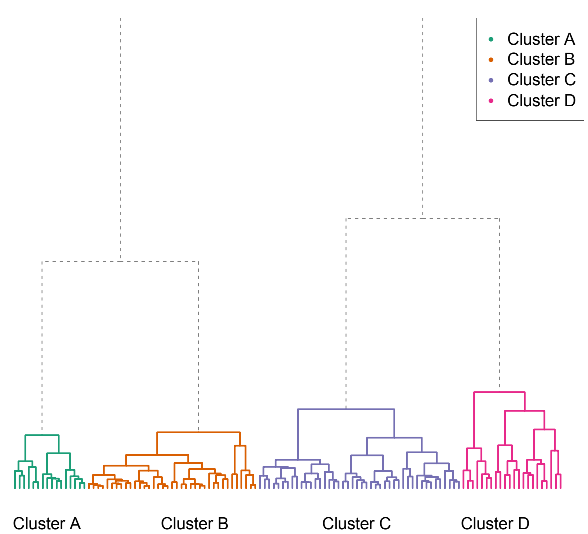


Fig. 4

Dendrogram illustrating results of the hierarchical cluster analysis

Consistent with del Valle and Duffy (2009), to confirm whether four clusters is an accurate number, each of the 12 variables were compared across the four clusters. Levene's test for homogeneity of variance was undertaken to determine if variances in the different clusters are equal. In cases where the assumption of homogeneity of variance is not violated, one way ANOVAs were conducted. Where Levene's test resulted in a significant difference from homogeneity, the non-parametric Kruskal-Wallis ANOVA was applied. The ANOVAs and Kruskal-Wallis ANOVA tests identified significant differences for all 12 variables. Subsequent post-hoc tests (Tukey HSD and Mann-Whitney U pair-wise comparisons) with the Holm-Bonferroni adjustment (to control for Type 1 error rate due to multiple comparisons) revealed the significant differences between pairs of clusters. To account for the differences between the four courses, the comparisons between the identified clusters were performed within each of the four courses.

Results

The cluster analysis identified a four-cluster solution as the most optimal and meaningful for interpretation as illustrated in the dendrogram (Figure 4). The distances of any additional clusters were too close to individual cases and thus would unnecessarily over-fit the data. For the purpose of interpreting the differences between the clusters and due to the non-normal distribution of the data, medians along with the 25^{th} and 75^{th} percentiles are shown in Table 1 and followed by Figure 5 illustrates the differences between the clusters based on centred mean values (i.e. z-scores) of the 12 video annotation software usage variables.

Table 1

The Descriptive Statistics (medians and 25^{th} and 75^{th} percentiles; 1^{st} and 3^{rd} quartiles) of the 12 Usage Variables

	Cluster A (N=37)		Cluster B (N=44)		Cluster C (N=16)		Cluster D (N=22)	
Variable	Med	Q1, Q3	Med	Q1, Q3	Med	Q1, Q3	Med	Q1, Q3
Videos annotated	3.00	2.00, 3.00	4.00	4.00, 5.00	4.00	3.00, 4.75	4.00	4.00, 5.00
Total annotations	11.00	8.00, 18.00	73.00	58.00, 95.00	53.50	36.00, 62.50	65.50	54.50, 95.25
Annotations deleted	0.00	0.00, 1.00	2.00	1.00, 4.00	0.00	0.00, 1.00	22.00	6.00, 38.25
Annotations edited	0.00	0.00, 2.00	3.50	0.00, 6.00	0.00	0.00, 2.00	36.50	0.04, 2.28
Time watched	1535.00	1022.00, 2294.00	4387.50	3465.50, 5789.50	1018.00	312.50, 3690.25	11201.50	8327.50, 13066.00
Pause	19.00	7.00, 37.00	97.00	70.25, 127.50	19.50	8.25, 37.75	180.50	106.75, 292.00
Non stop	0.00	0.00,1.00	2.00	1.00, 4.00	0.00	0.00, 1.75	6.50	3.00, 12.00
Rewind	12.00	2.00, 27.00	32.00	20.00, 54.50	7.00	0.75, 15.50	110.00	76.50, 189.75
Fast forward	3.00	0.00, 6.00	22.00	15.75, 35.00	7.50	0.75, 10.75	37.50	12.00, 53.00
Density	0.16	0.13, 0.19	0.25	0.22, 0.28	0.09	0.05, 0.15	0.31	0.27, 0.34
Earliest annotation	4683.00	3171.00, 5530.00	3474.00	1994.50, 5230.50	8786.00	6471.00, 10371.00	3989.50	2985.25, 6376.75
Latest annotation	8603.00	5729.00, 8770.00	10645.00	8851.25, 19249.75	41114.00	27647.75, 58399.75	11139.50	9264.75, 19572.25

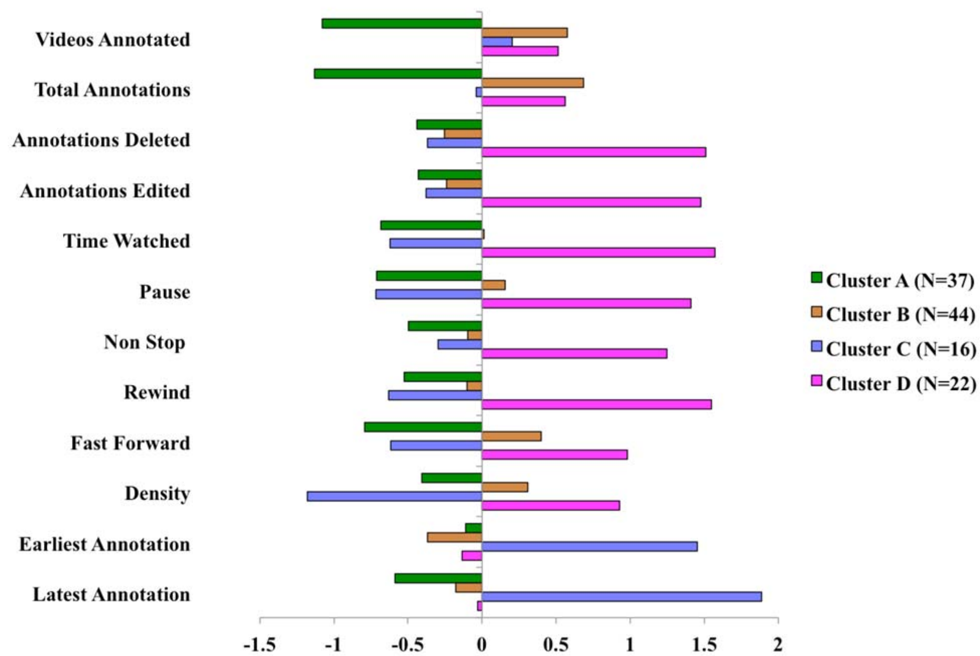


Fig. 5

Comparison of the four clusters based on the centered mean values (i.e., z-scores) of the 12 variables used in the study

The results of the ANOVA and Kruskal-Wallis ANOVA tests (as appropriate given the results of the Levene's tests) revealed significant differences for all 12 variables. While the ANOVA tests showed that there were significant differences present between clusters on the 12 variables, pair-wise comparisons with the Holm-Bonferroni adjustment revealed where these differences are present amongst the pairs of clusters.

Table 2

Pair-wise Comparison between Clusters by using Tukey HSD Test and Mann–Whitney U (MW) as Post-hoc Tests of ANOVA and Kruskal-Wallis ANOVA, Respectively

Variables	Test statistics	Clusters A (Minimalists) and B (Task-Focused)	Clusters A (Minimalists) and C (Disenchanted)	Clusters A (Minimalists) and D (Intensive Users)	Clusters B (Task-Focused) and C (Disenchanted)	Clusters B (Task-Focused) and D (Intensive Users)	Clusters C (Disenchanted) and D (Intensive Users)
Videos annotated (Tukey)	F(3)=45.20, p < .001	*	*	*			
Annotations Total (MW)	H(3)=78.61, p < .001	*	*	*			
Annotations Deleted (MW)	H(3)=54.95, p < .001	*		*		*	*
Annotations Edited (MW)	H(3)=55.38, p < .001	*		*		*	*
Time Watched (MW)	H(3)=79.07, p < .001	*		*	*	*	*
Pause (MW)	H(3)=76.15, p < .001	*		*	*	*	*
Non-Stop (MW)	H(3)=42.28, p < .001	*		*		*	*
Rewind (MW)	H(3)=64.48, p < .001	*		*	*	*	*
Fast Forward (MW)	H(3)=67.20, p < .001	*		*	*		*
Density (Tukey)	F(3)=29.63, p < .001	*	*	*	*	*	*
Earliest annotation (Tukey)	F(3)=20.04, p < .001		*		*		*
Latest annotation (MW)	H(3)=60.66, p < .001	*	*	*	*		*
Grades (MW)	H(3)=30.65, p < .001	*	*				*

Note: * denotes significance at <0.05

Table 2 shows that for all six possible pairings of clusters, significant differences were observed for the majority of the variables. However, for the density measure in particular, there were significant differences for all six cluster pairings. The significant differences amongst the pairs involved both variables related to students' viewing of the videos and their use of the annotation functions. Table 3 presents the results of the comparison of the students' overall grades between the clusters with the comparisons within the four individual courses.

Table 3

Summary of the Comparison of Grades between the Clusters with Comparisons within the Four Courses

Cluster	Course 1 N, M (SD)	Course 2† N, M (SD)	Course 3‡ N, M (SD)	Course 4¥ N, M (SD)
A (minimalists)	29, 93.41 (3.55)	2, 69.00 (4.24)	-	2, 86.00 (0.00)
B (task-focused)	-	21, 88.71 (5.13)	19, 86.05 (4.40)	4, 83.50 (3.70)
C (disenchanted)	-	4, 79.00 (7.87)	-	12, 82.25 (6.03)
D (intensive)	-	13, 87.00 (10.31)	9, 90.11 (2.85)	-
Total	29, 93.41 (3.55)	40, 86.20 (6.69)	28, 87.36 (4.36)	18, 82.94 (5.24)

Legend: N – number of students, M – mean value, SD – standard deviation value. Grades for two cases in both Course 1 and Course 4 were missing (and thus, the difference between the numbers in the table and Fig. 6.

† Course 1 - H (3) = 9.22, p=.027. Significant differences between Cluster A and Cluster B, between Cluster A and Cluster D, between Cluster B and Cluster C, and between Cluster C and Cluster D.

‡ Course 3 – H(1)=5.05, p=.024.

¥ Course 4 – H(2)=1.34, p=.511.

In the following section we discuss the significant differences amongst the clusters and how these findings can be interpreted to explain the four types of observed learning profiles.

Interpretation and Discussion of Clusters – Research Question 1

The results of post-hoc tests presented in Table 2 and the centred means illustrated in Figure 5 help identify patterns in students' engagement with various features of the video annotation tool across all four courses in this study regardless of the instructional design (graded and ungraded use of the video annotation tool). These analyses were used to answer the first research question that investigated profiles of users of a video annotation software for reflective learning. Specifically, differentiating characteristics of each cluster are observed, interpreted, and labeled below. Table 4 summarises the differences and interpretations between the clusters.

Cluster A: Minimalists

Cluster A represents the second largest number of students (n = 37 or 32% of the study sample). Compared with the students in the remaining three clusters, this cluster had significantly fewer annotations and videos annotated overall. The annotations, in particular, are designed to help students reflect on and self-regulate their skills when viewing videos of their own performance. Hence, it is of particular interest that this fairly large group of students made a very limited number of annotations. Further, the students in this cluster had significantly lower use of the video viewing features as well compared with clusters B and D. However, this cluster had significantly higher density of the transition graphs than those in cluster C. This may be due to social sharing whereby the students in this particular cluster were predominantly in the course where annotations were based on a group performance (research question #2 discussed in the next section). The sharing of annotations may promote high levels of metacognitive monitoring leading to higher density in transitions. This suggests that although the students in this first cluster have minimal engagement with the video viewing functions and overall fewer annotations, their transition from one feature to the next is more extensive than the students in cluster C who may not have been sharing their annotations with their peers and hence, had lower metacognitive monitoring. This finding resonates with Hadwin et al. (2007) who posited that students who have lower graph density have specific studying or learning behaviour while those who have higher graph density have not yet confirmed their learning strategies and are trying different tactics showing signs of greater self-regulated learning and metacognitive monitoring. The higher levels of metacognitive monitoring are important, as according to Azevedo, Moos, Greene, Winters, and Cromley (2008) they associated with an increase of feeling of knowing, judgment of learning, and monitoring of progress toward goals. However, due to the overall minimal engagement, this first cluster of students are considered the *minimalists*, based loosely on del Valle and Duffy’s (2009) third cluster of students who exhibited limited engagement with online resources, infrequent logins, and minimum commitment to their learning much like Lust et al.'s (2013) *no-users* and Brooks et al.'s (2011) *minimal active learners*.

Cluster B: Task-Focused

Cluster B represents the majority of the students (n=44 or 37%) in the study. The students in cluster B produced the highest amount of video annotations and annotated the highest number of videos compared with all other clusters. In particular, cluster B showed significantly more video annotations than in cluster A and significantly more videos annotated than in cluster A. Similarly, the students in cluster B had significantly higher engagement with the video viewing functions than students in clusters A and C. However, the students in cluster B used the video features significantly less than those in cluster D with the exception of fast-forwarding. In particular, they viewed significantly less of the videos (*time-watched*) and showed patterns of less *non-stop* viewing yet had the highest amount of annotations. Hence, their behaviour can be interpreted as displaying a task-focused approach whereby the students use the video annotation tool to the extent they require in order to reflect on their performance and make the necessary time-stamped and general annotations. Furthermore, the density of transitions between functions is significantly higher for the students in this cluster compared with clusters A and C illustrating a higher element of metacognitive monitoring as they experimented with different learning strategies to achieve their outcomes (Hadwin et al., 2007). Overall, due to the highest use of the key feature of the video annotation tool, making annotations, and the greater engagement with the video viewing functions and density, the group of students in this cluster are classified as *task-focused.* The classification, *task-focused,* is based loosely on del Valle and Duffy's (2009) second cluster of students who were described to have a *get it done* approach. The task-focused group also resonates with Cleave, Edelson, and Beckwith's (1993) cluster of *dominators* who were focused and goal-oriented, and Lust et al.'s (2013) *selective users* that are described as strategically accessing video lectures in a goal directed way.

Cluster C: Disenchanted

Cluster C represents the smallest number of students (n=16 or 13% of the study sample) and shows a behavioural pattern of significantly less interaction with the video viewing features than clusters B and D yet significantly more annotations in total and videos annotated in total than cluster A, the *minimalist* cluster. While the students in this cluster appear to be the first to annotate a video once it was available, and subsequently the last to post a final annotation as well, there was limited sustained effort compared to students in clusters B and D. Further, the graph density of this cluster is significantly lower than that of all other clusters contributing to the characterization of the lack of continuous or sustained effort in using various features of the tool, and thus, lower level of metacognitive monitoring. The lower graph density of this group of students illustrates that they have likely identified their learning strategy and do not need to experiment how they transition between different features of the tool (Hadwin et al., 2007). While the students in cluster C clearly engaged with the video annotation tool more so than the *minimalist* cluster and were first to try the annotation functionality than students in other clusters, they revealed a pattern of surface engagement rather than a deep engagement with the tool. Adapting Barab, Bowdish, and Lawless' (1997) cluster description of *disenchanted users* as those who glanced at various features, but did not explore most in depth, the term applies to cluster C in this study as the students who tried most of the functionality but without any sustained effort or depth. The emergence of this particular cluster verifies Brooks et al.'s (2011) hypothesis that a *disillusioned* group of students would initially access a video lecture tool and gradually decline their use due to a perception that the tool does not effectively support their learning.

Cluster D: Intensive

Cluster D represents the second lowest number of students (n=22 or 18.5% of the study sample) and is comprised of students exhibiting behaviours that can be interpreted as putting in the most amount of effort or self-driven approach. The students in this particular cluster revealed significantly higher use of all video viewing features (except for *fast-forwarding*) than all other clusters. In particular, they watched significantly more of the videos (*time-watched)* and engaged in more non-stop viewing than all other clusters. Although they did not have the highest amount of annotations or videos annotated than the *task-oriented* (cluster B), they were close behind and had a significantly higher number of annotations than the *minimalists* (cluster A). Due to their extensive use of all functions in the video annotation tool, this fourth cluster is classified as the *intensive* students as adapted from Lust et al.'s (2013) cluster of students who accessed many, if not all available learning tools frequently and intensively. This fourth cluster also exhibited significantly higher density measures than all other clusters as the students transitioned from one feature to the next. This suggests that this cluster had the highest level of metacognitive monitoring activity (Hadwin et al., 2007). Likewise, this cluster is also similar to Barab et al.'s (1997) *cyber cartographers* cluster as those who are goal-oriented, commit time to have deep engagement, and demonstrate self-efficacy. Table 4 summarises the four user profiles of video annotation for each cluster, as discussed above.

Table 4

Summary of the Four Profiles of Users of Video Annotation Software

Cluster	Profile
Minimalists (Cluster A)	Minimal engagement overall with all features based on: • Significantly lower use of all video features compared with clusters B and D • Significantly lower amount of annotations and videos annotated than ALL other clusters • Significantly more density than cluster C only and relatively low metacognitive monitoring activity
Task Focused (Cluster B)	On-task, based on: • significantly higher amount of use of all video viewing features compared with cluster A and C but significantly less than cluster D (except fast forward) • highest amount of total annotations and videos annotated than other clusters but significantly higher than cluster A • significantly higher density of transitions between features compared with clusters A and C, but not much less than cluster D.
Disenchanted (Cluster C)	Tried all features, earliest to annotate a video but overall no sustained engagement based on: • Significantly more videos annotated and total annotations compared with cluster A only • No significant difference with cluster A (although slightly more use) with respect to use of video view features nor deleting or editing annotations • Significantly less use of video viewing features than clusters B and D • Significantly earliest and latest annotation posting • Significantly lowest density of transitions between features compared with ALL other clusters (i.e., low metacognitive monitoring)
Intensive (Cluster D)	High-effort, self-driven approach based on: • significantly higher amount of use of most video viewing features (exception of fast forwarding) compared to ALL clusters • significantly higher density of transitions compared to ALL clusters (i.e., highest metacognitive monitoring) • significantly higher number of annotations than cluster A.

Discussion of Behavioural Patterns in Different Courses – Research Questions 2 & 3

The four clusters emerging from the hierarchical cluster analysis in this study reveal distinct types of interaction with the video annotation tool and, therefore, different learning profiles. However, as noted earlier, there were variations in the instructional design of the four courses. Two of the courses included graded general comment annotations and two courses were designed with an optional and ungraded use of the tool. Longitudinal analysis of the results revealed that some of the students in the graded two courses continued on to a subsequent course where the annotation activity and use was completely optional. An analysis of the profiles described in Table 4 for the four clusters could lead to the hypothesis that the *minimalists* or *disenchanted* users as mostly in courses where the use of the tool is optional unlike the other two clusters who exhibited a far greater number of annotations and videos annotated. A cross-tabulation of the four clusters against the four courses helps identify the behavioural patterns most dominant in order to answer the second research question that investigated whether different instructional methods influence learner profiles based on their use of a video annotation software. Figure 6 illustrates the cross-tabulation and reveals the spread of students in each cluster across the four courses.

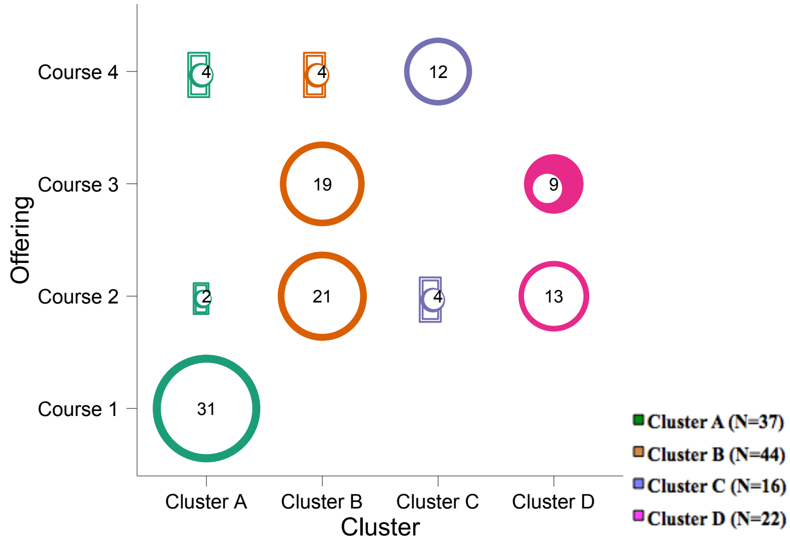


Fig. 6

Cross-tabulation of clusters and courses: cluster A – minimalists; cluster B – task-focused; cluster C – disenchanted; and cluster D – intensive.

As Figure 6 demonstrates, a large portion of the students in cluster A, the *minimalists,* were enrolled in Course 1 where the use of the video annotation tool was optional and ungraded with a small number enrolled in Course 4 where the use of the video annotation tool was also optional. Similarly, the majority of students associated with cluster C, the *disenchanted,* were also enrolled in Course 4. Hence, the pattern arising confirms the hypothesis that the majority of the *minimalists* and *disenchanted profiles* were enrolled in courses where the use of the video annotation tool was entirely voluntary. The only difference being that the students in Course 4 included those who had previously taken Course 2 where the use of the video annotation tool was required and general comment annotations graded. However, since the students in Course 4 included students who had previously taken a course where annotating and commenting on videos was a required activity, there was a higher proportion of *disenchanted* students (cluster C) in Course 4 than *minimalists* (cluster A). There are two significant differences between these two clusters. The first concerns the greater number of annotations and videos annotated by the *disenchanted* students than the *minimalists.* This may be due to the students in Course 4 becoming more accustomed to annotating their videos or beginning to appreciate how the activity enhances their learning and self-regulation skills due to their prior experience in Course 2. This could also be a result of students in Course 1 being conscious that their peers may view their annotations since they all annotated the same videos unlike the students in the other courses and were, therefore, more carefully monitoring their annotations leading to a fewer number. The second concerns the higher graph density exhibited by the *minimalists.* This may be attributed to the majority of *minimalists* in Course 1 where they did not have prior experience with CLAS. Based on Hadwin et al.'s (2007) earlier work, *minimalists* may have been trialing different learning strategies, although minimally, leading to a greater graph density as they accessed different features.

While the required video annotation activities in Course 2 may have contributed to more *disenchanted* students in the later course than *minimalists,* Figure 6 illustrates that only four *task-focused* students (Cluster B) and none of the *intensive* students (Cluster D) were enrolled in the final course. The majority of the *task-focused* students (Cluster B) were almost equally spread across courses 2 and 3 while all of the *intensive* students (Cluster D) were spread across these same two courses. Hence, a distinct and expected pattern emerges where by the students who engaged with the functions of the video annotation tool the most were enrolled in the courses where the general annotations were graded and the activity was a required component of the curriculum. In other words, they exhibited behaviours consistent with staying on task, self-driven, and making the most use of the features available within the video annotation tool. This is not surprising since their use of the video annotation tool was graded in Courses 2 and 3.

However, the main conclusion from the cross-tabulation lies in the lack of *intensive* students and very few *task-focused* students in Course 4 despite their previous use of the video annotation tool in Course 2 when it was graded.

While the study did not explore the intentions beneath students' engagement with the video annotation tool or lack thereof, there are a number of possible reasons or hypotheses for why students in Course 4 largely fall within Cluster C, the *disenchanted* and, minimally, Cluster A, the *minimalists*. One possible explanation may be that despite the students in Course 4 having some experience with the use of graded video annotations, the intrinsic motivation and self-regulated learning skills to identify when viewing and annotating videos of their previous performances enhances their learning experience still requires further development. While the students who fall in the *disenchanted* cluster may have begun to develop these skills more so than those who fall in the *minimalist* cluster, more external regulation and instructors acknowledging the usefulness of the tool, instructional norms (McGill & Klobas, 2009) are required. In other words, experience in one prior course with graded use of a video annotation system is not sufficient for students to appreciate the full value of viewing and annotating one's own recorded performance. Instead, students require more scaffolding and external motivating factors (e.g. assessed or graded activities) to encourage their use of the educational technologies (Lust et al., 2011; Perkins, 1985).

As shown in Table 3, statistically significant differences in grades between the clusters were revealed in Courses 2 and 3, in which the use of video annotation software was a graded activity. Specifically, in Course 2, the grades of the students in clusters A (*minimalists*) and C and (*disenchanted*) were significantly lower than those of the students in clusters B (*task-focused*) and D (*intensive*). In Course 3, the *intensive* students (cluster D) had significantly higher grades than *task-focused* students (cluster B). These findings reinforce the importance of the patterns of students' technology engagement particularly in courses in which tasks with the technology are graded. Moreover, the reasons linked to the differences in self-regulated skills between the different clusters, as discussed above, are probable explanations for the differences in the academic achievement as well. Future research should also account for individual differences (e.g. motivation or metacognitive awareness) – representative of internal conditions as per Winne's (2006) model of self-regulated learning – when investigating the effects of learning profiles on academic achievement.

Implications for Practice

The findings in this study have several implications for pedagogical practice, namely blended learning course design integrating video annotation technologies for enhancing students' reflective practice. Although there are studies on the use of video annotation tools to aid students' reflections on their own performance in pre-service teacher education programs (Colasante, 2011; Magenheim et al., 2010) and in medical education (Hulsman, Harmsen, & Fabriek, 2009), the studies have relied heavily on self-reports rather than data collected from students actual use of video annotation software. Further, these studies have not specifically explored patterns in students' learning profiles about learning strategies they used when using a video annotation tool under different instructional methods. Hence, the emerging use profiles of *intensive* and *task-oriented* clusters of students appearing more in courses where annotations are graded and, in particular, more *disenchanted* students in a course with ungraded annotations despite having previously enrolled in a course with graded annotations shows that students are slowly moving towards self-regulating their learning. Since their level of use continues to be relatively limited, the study shows that students will need more than one course where they are incentivized through the use of assessment (e.g. grades associated with their annotations) to engage with the video annotation tool to further develop their self-regulated skills (Lust et al., 2013) and awareness of the learning opportunities it presents (Perkins, 1985). Hence, when developing a blended learning curriculum educators need to consider that one course with graded use of a video annotation tool may not be sufficient in developing and sustaining students' appreciation of the reflective exercise. Rather, educators should design a program of courses whereby the tool is introduced with a set of extrinsic motivators (e.g., grades) linked via a series of courses with gradual movement towards more optional use of the tool in order to support and scaffold students' understanding of how using a video annotation can enhance their learning experience. This concept of incentivizing effort is well noted in the literature related to intrinsic and extrinsic motivation of learners. For instance, Cerasoli, Nicklin, and Ford (2014) undertook a meta-analysis of motivation research to identify the relationship between extrinsic and intrinsic motivation on student learning performance. The authors demonstrated that extrinsic motivation or the use of incentives were significant predictors of the quantity of performance for individual students. However, quality was best predicted by student interest or intrinsic motivation. Similarly, in the present study we suggest that the use of grades is applied as incentive to promote use and activity of the video annotation tool while students develop sufficient self-regulatory skills in the direct application of the tool to aid their learning. Research in self-determination theory also well notes the use of incentives or extrinsic motivation can be used to promote student intrinsic motivation (Koestner, Ryan, Bernieri, & Holt, 1984; Ryan, Mims, & Koestner, 1983).

Implications for Research

While the study provides insight into the learning profiles of students when using a video annotation tool, and the differences observed when the pedagogical approach is more formative than summative, there are four primary limitations that future research can address. First, as the research design was a case study focusing on the use of a video annotation system in a single institution where the courses that used the tool for self-reflection purposes were in the performing arts discipline only, the findings cannot be widely generalized to other disciplines or settings. Future studies exploring students' learning profiles when using a video annotation tool for reflective practice in other disciplines and institutions are required to support or refute the findings in this study. Second, future studies could include a triangulation of cluster analysis of use profiles and cross-tabulation of students enrolled in courses where the video annotation activity is graded vs ungraded with students' performance (i.e. overall grades) in order to better understand the characteristics of the clusters and whether various learning profiles correlate with better overall course performance. Third, since this study focused only on students' trace data based on their interactions with the video annotation tool, future research capturing students' intentions either through surveys or interviews behind the way they used the tool will help to explain the observed learning profiles. Finally, experimental studies where students have greater opportunities to engage with a video annotation tool when annotations are graded prior to having the option to use it will help reveal the extent that extrinsic motivation is required prior to students developing their own intrinsic motivation and self-regulated approach to their reflective learning.

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