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Cluster Analysis of Hong Kong Students' Self-Regulated Learning in Contextualized Multimodal Language Learning

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ABSTRACT: This study investigated how English learners complete multimodal formative quizzes. Participants included 17,950 students enrolled in a mandatory English for Academic Purposes course at a university in Hong Kong. We retrieved data from Blackboard, a learning management system, and conducted a two-step cluster analysis to examine student self-regulated learning (SRL) profiles with the quizzes. We first identified five clusters of learners with distinctively different self-regulated learning patterns. Then, we performed a multivariate analysis of variance (MANOVA) to further explore their differences in SRL, in terms of start day, days started before deadline, differences in scores between first and last attempt, and scores in language learning activities. Our findings echoed those of previous studies on the relationship between self-regulated learning and academic success. This research enables us to better understand the needs of EAP students in Hong Kong.

Keywords: Cluster analysis, English for Academic Purposes, Multimodal, Formative, Quizzes

1. Introduction

Digital multimodal language learning (e.g., audio, videos, cartoons, infographics) is becoming an integral component of English language teaching (ELT) (Jiang & Ren, 2021; Kohnke & Jarvis, 2022). The benefits of multimodality in ELT include heightened semiotic awareness, multiple modes of input, and enhanced communicative competence (Hafner & Miller, 2011; Shin & Cimasko, 2008). In English for Academic Purposes (EAP) courses in Hong Kong, multimodal language learning is used to facilitate second-language acquisition (Hafner & Pun, 2020; Kohnke et al., 2021). By aligning technology, second-language pedagogy (Chapelle & Sauro, 2017), and multimodality (Yeh, 2018), teachers can develop authentic, engaging formative assessments that foster independent language learning (Park et al., 2016).

Formative assessments such as quizzes are integral to monitoring the knowledge and skills of second-language learners (Gardner, 2012; Hinkelman, 2018). Online formative assessment is defined as the use of technological tools to support the process of "gathering and analysing information about student learning by teachers…" (Pachler et al., 2010, p. 716). In higher education, this is usually done by designing useful online activities that can provide feedback to learners on their learning progress. Using automated multimodal quizzes in an EAP program allows students to self-assess while simultaneously requiring them to employ a variety of online learning strategies (Wandler & Imbriale, 2017). Self-regulation skills are a critical variable for success at language learning (Dörnyei, 2005; Tseng et al., 2006). Studies have reported the importance of self-regulation in blended learning environments (Artino, 2007; Broadbent, 2017), though none have focused on multiple semesters of a large EAP course.

Although previous studies have reported on learners' behaviors regarding in-class quizzes (Ross et al., 2018) and multimodality (Kohnke et al., 2022), EAP learners' SRL with multimodal quizzes remains underexplored. Moreover, learning-analytics-based studies that aim to generate actionable insights have not been common in EAP SRL research. Understanding students' self-regulation profiles is important for better developing course policies to target specific types of SRL profiles. Therefore, this study examined students' SRL regarding multimodal quizzes. Using a two-step cluster analysis, we explored the self-regulation profiles of 17,950 students who had taken an EAP course between 2012 and 2019, focusing on how they accessed the online multimodal language-learning content.

2. Literature review

2.1. Multimodality in language learning

One common definition of multimodality is “the use of several semiotic modes in the design of a semiotic product or event… in which these modes are combined… [to] reinforce each other…and fulfil complementary role[s]” (Kress & van Leeuwen, 2001, p. 20). This definition suggests that multimodality combines multiple input methods, such as text, sound, and/or video. The belief that multimodality benefits learning originated from the insight, gained from dual coding theory, that learning can be better facilitated if the information is processed in both spoken and written modes (Paivio, 1986). Earlier research (before the advent of computer-assisted technology) on multimodality in language learning focused on how multimodality can expose learners to diverse ways of communicating and making meaning (Hampel & Hauck, 2006), involving the use of non-computer-assisted multimodality, such as visual, verbal, and other means (Kendrick et al., 2006). However, multimodal language learning research within a non-technological context is still prevalent, using storybooks with pictures and audio input (Tragant & Pellicer-Sánchez, 2019) or videos with text subtitles (Peters, 2019; Pujadas & Muñoz, 2019). This line of research clearly illustrates the benefits of multimodality well before the era of computer-assisted language learning.

Since the advent of research on computer-assisted language learning, research on multimodality is now equally, if not more, interested in how combinations of videos, audios, texts, and online interactive resources can enhance language learning in a computer-assisted environment. For example, Marcel (2020) explored the use of augmented reality (AR) and virtual reality (VR) as a multimodal approach to language learning. They found that learners gained vocabulary through a contextualized multimodality experience. White et al. (2021) explored the use of videoconferencing tools in language learning and found that besides the video and audio inputs provided by the tools, the photo-sharing function created more possibilities for language learning, as learners were not only stimulated by the audio and video footage of the teacher but also by photos shared during the session. Other studies have been conducted on multimodal feedback on language learning, such as those by Wilkie and Liefeith (2020) and Martin (2020). These studies all demonstrate that multimodal resources offering sound, image, text, and animation yield opportunities for effective and dynamic learning.

While these studies establish the effectiveness of multimodality in language learning, they explore the use of multimodality over shorter periods (e.g., a semester and a year); in fact, many studies have examined the effectiveness of multimodal interventions within a course for no more than a year (e.g., Marcel, 2020; Mauricio & Genuino, 2020; White et al., 2021; Wilkie & Liefeith, 2020). This suggests a need for research on multimodal learning over a more prolonged period.

2.2. Multimodality in higher education

In higher education, multimodality is often introduced with various blended-learning input methods through learning management systems (LMS). An LMS provides avenues for multimodal blended learning using tools such as videos, pages, discussion forums, and quizzes (Cole et al., 2021; Coskuncay & Ozkan, 2013). These modalities complement each other in enhancing the learning experience. Studies have found that, overall, students learning in blended classes perform better than those in face-to-face-only classes (Garrison & Vaughan, 2013; Ross & Gage, 2006; Porter et al., 2016; Owston & York, 2018). Among multimodal tools, recent studies have illustrated the positive effects of online quizzes that include multimodal elements (Cook & Babon, 2017; Gamage et al., 2019). It is therefore crucial to examine the potential of these multimodal elements in online quizzes so that teachers can determine the type of multimodal activities that will best support the pedagogical process (Lamy, 2012).

Research on online quizzes suggest that they allow the monitoring of progress and provide timely feedback to support learning (Nicole & Macfarlane-Dick, 2006). Automated online quizzes can be particularly helpful for second-language learners, allowing them to self-assess and take action to address weaknesses (independently or with the help of instructors or peers). While most students consider online quizzes non-threatening (Gardner, 2012), some will not complete them unless they believe the quizzes will make a substantial difference in their ability to succeed in a course. Accordingly, teachers tend to encourage completion by assigning a small percentage of the course grade to each quiz (Padilla-Walker, 2006). To maximize second-language learning, learners need to attempt the quizzes repeatedly. Such quizzes have been found to increase student enthusiasm, achievement levels, and self-regulation (McLaughlin & Yan, 2017). However, research using clustering with multimodal online formative quizzes has been limited in the EAP context.

2.3. Online self-regulated learning

According to Zimmerman (1990), all learners self-regulate to a certain degree. Self-regulated learning (SRL), which entails being systematic in one's learning (Zimmerman & Schunk, 2011), is an important indicator of effectiveness in a face-to-face learning environment (Boekaerts, 1999). Self-regulation involves being active and goal-directed and displaying self-control, motivation, and cognition in performing academic tasks (Pintrich, 1995). These traits are equally important in the online learning environment, where learners have a high degree of autonomy and little teacher presence (Lehmann et al., 2014). Previous studies have found SRL to be an important predictor of learner achievement (Broadbent & Poon, 2015; Kuo et al., 2013) and success in online studies (Bol & Garner, 2001; Cho & Heron, 2015). Students exhibiting successful SRL will set learning goals, plan tasks, and monitor their progress even when facing academically challenging tasks (Broadbent & Poon, 2015; Cho & Cho, 2017). Confidence is also an important factor in SRL, as confident students participate online more strategically (Cho & Jonassen, 2009) and are more likely to set goals and to monitor and adjust their learning processes (Cho & Cho, 2017). A positive attitude is indispensable for engagement in SRL processes (Pintrich, 2004; Zimmerman & Schunk, 2011).

Furthermore, task value (i.e., the perceived value of starting and completing a task) greatly influences SRL. Learners who place a high task value on academic work set clear goals, monitor their learning systematically, and adopt strategies to accomplish their goals (Cho & Shen, 2013; Lawanto et al., 2014). Cho and Heron (2015) found that students who received a passing grade in an online course showed higher task value and motivation than non-passing students. Learners who are less skillful at SRL often fail to set learning goals and demonstrate low confidence in their learning and the learning process. They tend to blame their performance on the instructor or materials. Self-efficacy impacts task choice, effort, persistence, and achievement (Schunk & Pajares, 2002). Students with positive self-efficacy tend to perform better in online courses (Wang et al., 2013). This correlation between SRL and online academic success, which is supported by previous studies (Azevedo & Hadwin, 2005), indicates a need to provide SRL support to all students. To this end, Hill and Hannafin (2001) suggested four types of support: (i) help in prioritizing information, (ii) metacognitive support (e.g., asking questions that help students reflect), (iii) help with resources (e.g., assistance in locating appropriate learning tools), and (iv) multiple options for completing a task.

2.4. Person-centered approach to SRL

Due to the complex nature of SRL, scholars advocate a "person-centered" approach to SRL that explores whether there can be subgroups of learners with distinct SRL behaviors and whether these sub-groups differ in important external criteria (Broadbent & Fuller-Tyszkiewicz, 2018, p. 1437). Person-centered investigation of SRL provides useful insights to course designers on how specific strategies and course policies can be adopted by teachers to promote SRL. With the emergence of data available on online systems, more studies prefer the use of trace data to examine students' SRL, rather than self-reported SRL. One major challenge of using trace data is the measurement of SRL, because there is no single measure that can fully represent all SRL (Winne & Perry, 2000). Also, while some SRL indicators can be observed in the environment (e.g., performance), many SRL indicators can only be inferred (Winne & Perry, 2000). For example, trace data can show some students accessing materials earlier than other students, but one can only infer that the students who access materials early do so to plan their study. There are likely to be challenges in operationalizing SRL variables based on student behavioral traces.

To identify typologies in SRL / adopt a person-centered approach, most studies adopt cluster analysis, according to a recent review (Elsayed et al., 2019). Cluster analysis is an exploratory analysis that attempts to divide samples into groups so that the degree of association for variables within a group is minimal and for other groups is maximal (Antonenko et al., 2012). While some literature considers cluster analysis to be like factor analysis, cluster analysis can also be viewed as a way of visualizing different groups of samples in a large data set (Antonenko et al., 2012). Unlike traditional inferential statistics that requires testing of assumption, cluster analysis can be conducted based on the types of data. For example, k-mean clustering adopted in this study, is defined as non-hierarchical in nature and can take continuous or nominal data but the number of clusters needed to be determined (Antonenko et al., 2012). Recent SRL studies with cluster analysis usually begin by establishing the number of clusters using methods such as the Elbow methods (Yuan & Yang, 2019), followed by an examination of the clusters. The analysis is usually concluded by examining the differences between clusters regarding some external variables. See Ng et al. (2016) and Broadbent and Fuller-Tyszkiewicz (2018) for SRL studies and Guo et al. (2022) and Stenlund et al. (2018) for other educational studies. These studies, especially the SRL studies, can successfully identify and discuss clusters in terms of SRL and other external variables (e.g., course outcomes).

While these studies paint a vivid picture of how SRL profiles can enhance teachers' and course designers' understanding and enable them to develop targeted strategies for students, not enough person-centered SRL studies have been conducted in the EAP context, and more specifically with contextualized multimodal learning. Therefore, this study aims to examine the SRL profiles of students in completing contextualized multimodal quizzes.

3. Methodology

To understand and optimize learning, this study adopted a learning-analytics approach (Ferguson, 2012) to collect and analyze data on students' SRL behaviors with multimodal content. Data were retrieved from the LMS, and a two-step cluster analysis was conducted to identify student SRL profiles. Ethical clearance was obtained, and the learning data were retrieved after a formal data request was made as stipulated by the data governance framework of the research site.

3.1. Context

The study used data gathered from students taking a 13-week EAP course at a university in Hong Kong. The course was launched in 2012 when a 4-year undergraduate curriculum was introduced in Hong Kong. It is a mandatory English course in the undergraduate curriculum, with an annual enrolment of 2,500 to 3,000 students.

The course is standardized across cohorts in terms of course assessments, grading descriptors, and marker training procedures. While its teachers have flexibility in delivering class activities and may provide additional class materials, the course notes, assessments, grading criteria, descriptors, and multimodal quiz requirements were comparable across the cohorts and classes included in this study. The course is assessed through two essays and one presentation. Grading criteria include content development (e.g., in essays), organization (including source incorporation), language (including style), and referencing skills. These three assessment categories determine the overall course grade, which is reduced by a penalty if students fail to complete the multimodal quiz requirements.

3.2. Multimodal learning package

The multimodal learning package (MLP) is composed of numerous activities hosted on Blackboard, the university's LMS. In earlier cohorts (2012–2014), there were more than 15 activities each semester, but the activities were re-grouped to 13 from 2015 onwards. The activities cover four areas: academic style, genre knowledge, referencing, and academic presentation skills. Each activity contains multimodal content (e.g., videos, podcasts, reading, and infographics) and is followed by an online formative quiz with around 20 questions. As a formative assessment, students will know the correct answers of the quiz after submission so that they can know how well they did, i.e., their learning progress. The activities are designed to supplement the content taught in class (see the Appendix for details). For example, after the discussion of academic style during class in Week 1, students are expected to complete an activity on academic style as the "Session 1" activity.

The MLP was designed by experienced in-house teachers and was first piloted in 2011. After the initial pilot run, enhancements were made in preparation for full implementation in 2012. The MLP was reviewed every semester through the regular quality assurance mechanism of the university, and minor adjustments were made (e.g., correction of typos, reshooting the videos) throughout the years. Numerous past studies have been conducted with the MLP (see authors), thus ensuring the validity of the MLP as a learning tool and an assessment instrument.

The MLP was designed to contextualize language learning to foster an effective learning climate and allow learners to control their learning progress. The content of the activities is assessed through assignments (see the Appendix). Teachers are expected to check the progress of students through the LMS. If students are not performing well on some quizzes, teachers will offer supplementary activities to help students better grasp the content. For example, if students in some classes do not perform well in the MLP activities on academic style, teachers will always arrange more activities on academic style. As a common practice, many teachers review the performance of MLP before major assessments so that they can design some relevant revision activities before major assessments. Students are required to earn an overall score of at least 50% based on all the online quizzes.

Failure to achieve this score results in a penalty that ranges from a half- to full-grade deduction from the final grade.

3.3. Participants

This study included 17,950 students who were enrolled in a mandatory EAP course in a Hong Kong university at any point between the 2012 fall semester and the 2018 winter semester (i.e., seven academic years and 14 cohorts). The data for 2019, 2020, and 2021 were not included because class delivery was affected by social unrest and the pandemic in Hong Kong. Summer-semester students (around 30 to 60 students each year) were also not included, as the student behavioral pattern for the 7-week summer schedule was different than that observed in the other cohorts. Aside from these exceptions, this study was designed to include all students who have taken the course since its inception.

Admission to the course requires a band score of 5.48–5.56 in IELTS (International English Language Testing System) or equivalent and no prior formal training in academic literacy. Students taking this course include those in Applied Science, Business, Health, Social Sciences, and Engineering. No other demographical information was available with the data from the Learning Management System. Table 1 shows the number of students in each cohort.

Table 1. Number of students in cohorts

Semester	Number of students
2012/2013 Fall	1,730
2012/2013 Winter	397
2013/2014 Fall	1,792
2013/2014 Winter	790
2014/2015 Fall	1,695
2014/2015 Winter	620
2015/2016 Fall	2,039
2015/2016 Winter	962
2016/2017 Fall	1,867
2016/2017 Winter	884
2017/2018 Fall	1,641
2017/2018 Winter	695
2018/2019 Fall	2,246
2018/2019 Winter	592
Total	17,950

3.4. Measures

There is no simple way to operationalize self-regulated learning (Winne, 2010; Veenman et al., 2006; Rovers et al., 2019) because there is no direct measure of students' underlying mental processes. However, the adopted measures below are considered to correspond to SRL behaviors (Li et al, 2020). Still, this study considers course-based variables adopted in other studies to identify different phases of SRL (e.g., Hadwin et al., 2004; Li et al., 2020; Quic et al., 2020). In the current study, eight variables were included in the cluster analysis and further analysis to measure SRL behaviors in contextualized language learning (Table 2). It is important to note that due to the context sensitivity of SRL (Winne & Hadwin 1998), these measures were included based on how the contextualized multimodal learning was designed, and they aim to provide a generalized understanding of SRL.

The goal of this study is to identify SRL profiles and thus allow teachers and course designers to facilitate SRL based on students' SRL profiles. The results of analysis should allow teachers to take action with multimodal language learning SRL patterns. Therefore, outcome measures (i.e., course grades) were not used for cluster analysis.

Table 2. Details of measures

SRL categories	Measures	Definition	Range (before re-scaling)	Justification
Clustered measures				
Performance	Overall Course/Final Grade	Final grade in the course	0–4.5	Course Outcome
Planning	Start Day	Number of days after the start of the term that a student first submitted an MLP quiz	-2.03–96.49 (negative = starting before the term begins)	Study in Advance: suggested by Li et al. (2020)
	nth Day Before Deadline for First Attempt	Number of days before the deadline that a student first submitted an MLP quiz	-6.19–89.50 (negative = submitting a quiz after the deadline)	
	Duration	Number of days between submitting the first attempt and last attempts	0–96.45	Time between first submission and deadline adopted by Quick et al. (2020)
Performance Monitoring	Differences in Attempt Score	Difference in scores between the first and last attempt	-4.43–6.53 (negative = lower score on the last than the first attempt)	Progression of tasks suggested by Hadwin et al. (2004)
	Score in Academic Style Activities	Average score in Academic Style Activities	0–1.0	Direct outcome measure of the MLP activities
	Score in Referencing Activities	Average score in Referencing Activities	0–1.0	
	Score in Genre Activities	Average score in Genre Activities	0–1.0	
	Score in Academic Presentation Activities	Average score in Academic Presentation Activities	0–1.0	
Measures not clustered				
Performance on Assessments	Content Development	Sum of assessment scores—content development domain	0–12.5	Outcome measures correspond to MLP activities
	Organisation	Sum of assessment scores—organization domain	0–8.5	
	Language	Sum of assessment scores—language domain	0–16	
	Referencing	Sum of assessment scores—referencing domain	0–8.5	

3.5. Data processing and preparation

After retrieving the data from the learning management system, the research team processed them for cluster analysis. Students who did not complete any assessments were removed. These were not uncommon; they belonged to students who were deregistered from the course and/or the university but remained on the course list. Next, all data values were standardized (i.e., Z score) as is the common practice in cluster analysis (Sarma & Vardhan, 2018). Because cluster analysis is sensitive to outliers, the outliers were then removed. Around 2,000 data points were removed from the 14 semesters of data.

3.6. Data analysis

The objective of this study is to identify profiles and patterns of learners' SRL with no pre-existing assumptions or expected profile. Therefore, cluster analysis was adopted. Cluster analysis is an exploratory technique and should not be treated as an "outcome practice" for hypothesis testing (Sarma & Vardhan, 2018). Using the final data set, the number of clusters was determined using the "elbow method," identifying the dipping/changing point from the Total Sum of Within Squares (Bholowalia & Kumar, 2014). After that, the k-means cluster analysis was conducted with R (version 4.0.3). Then, the overall average of the silhouette values was examined as an indicator of cohesion and separation (Hao et al., 2021). This measure can range from -1 to 1. A positive measure is desirable.

After completing the cluster analysis, a MANOVA (with IBM SPSS Statistics 27) was used to explore the differences between clusters, using the cluster groups as the grouping variables and the SRL behaviors and performance variables as dependent variables. It is important to note that MANOVA was used only to explore the extent of the between-cluster differences across the indicators, as the indicators were expected to be different after being clustered. This aligns with the methods used in another SRL study (Ng et al., 2016; Broadbent & Fuller-Tyszkiewicz, 2018). The alpha value was set at 0.05.

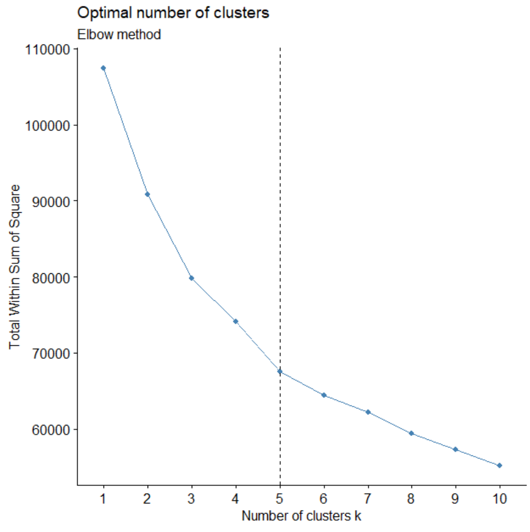
4. Results

The objective of this study was to explore students' SRL behaviors. Cluster analysis was first adopted with the elbow method to find the optimal number of clusters, followed by the k-means clustering technique and then MANOVA to determine if indicators of SRL differed among the clusters. The characteristics of the clusters (i.e., profiles) were then described and discussed.

4.1. Step 1 – Optimal number of clusters and k-means clustering

To determine the optimal number of clusters, the elbow method was adopted. This method is based on the Total Sum of Within Squares and can be represented graphically. Figure 1 shows that four clusters are the optimal number.

Figure 1. Optimal number of clusters with elbow method



Five clusters were subsequently formulated (see Table 3 for the descriptive statistics). While there is no consensus on a fit index for cluster analysis, and most measures were used for comparisons, silhouette values were used to assess indicate the adequacy of the cluster analysis. The average of the silhouette measures was 0.14, which suggested that clustering was still desirable (Hao et al., 2021). Appendix 2 presents a Radar chart as a visualizations of all clusters.

Table 3. Descriptive statistics for clusters

	Cluster 1 (*n* = 3974)		Cluster 2 (*n* = 2127)		Cluster 3 (*n* = 2324)		Cluster 4 (*n* = 4876)		Cluster 5 (*n* = 2713)	
Clustered measures										
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Overall course grade	0.00	0.84	-0.43	0.82	0.30	0.85	0.30	0.84	0.09	0.80
Start day	-0.60	0.56	0.78	0.89	-0.62	0.45	-0.42	0.68	1.22	0.47
Nth Day before Deadline for First Attempt	-0.36	0.59	-0.48	0.58	1.62	0.65	0.15	0.77	-0.66	0.48
Duration	0.38	0.62	0.02	0.93	-0.72	0.90	0.73	0.64	-0.95	0.75
Differences in Attempt Score	-0.10	0.51	0.12	0.81	0.00	0.78	-0.08	0.64	-0.35	0.54
Score in Academic Style Activities	0.28	0.56	-0.41	0.89	0.14	0.77	0.34	0.64	0.22	0.70
Score in Referencing Activities	0.26	0.55	-0.29	0.81	0.24	0.56	0.30	0.60	0.27	0.52
Score in Genre Activities	-0.07	0.85	-1.02	0.95	0.09	0.73	0.58	0.59	0.29	0.60
Score in Academic Presentation Activities	-0.89	0.44	0.44	0.70	-0.52	0.96	0.93	0.34	-0.31	0.98
Measures not clustered										
Content development	-0.04	0.91	-0.35	0.90	0.25	0.88	0.23	0.91	0.06	0.89
Organisation	-0.04	0.92	-0.39	0.90	0.23	0.92	0.24	0.94	0.06	0.91
Language	-0.02	0.90	-0.31	0.91	0.14	0.99	0.16	0.95	0.09	0.91
Referencing	0.02	0.90	-0.42	0.90	0.29	0.90	0.25	0.91	-0.02	0.93

4.2. Step 2 – Exploration of SRL profiles

MANOVA was conducted to explore further the differences and similarities across the four clusters. Dependent variables included all the SRL indicators used in clustering, along with the content development, organization, language, referencing, and presentation assessment outcomes. MANOVA was in no way a validation of the clusters, as clustering is an exploratory technique for identifying patterns, not an outcome process for testing hypotheses (Sarma & Vardhan, 2018). However, MANOVA is useful for exploring the differences across clusters. DiFrancesca et al. (2016) used MANOVA similarly as a follow-up technique in their SRL study.

There was a statistically significant difference in all SRL indicators and assessments outcomes based on clusters, $F(52, 61958.23) = 1565.77$, $p < .05$; Wilk's $\Lambda = 0.039$, partial $\eta^2 = .56$. Further univariate ANOVA indicated significant main effect of clusters on all indicators and outcomes. Table 4 shows the univariate ANOVA results. For the descriptive statistics of the clusters, see Table 3.

The purpose of this study was to identify how EAP learners use SRL in regard to multimodal formative quizzes in a large EAP course at a higher education institution in Hong Kong. Our data, based on descriptive statistics, revealed two major findings. First, the students fell into five clusters: two groups that performed well while exhibiting different SRL behaviors; two groups that performed at par while exhibiting different SRL behaviors; and one group that performed poorly and exhibited few SRL behaviors. Second, we found that the identification of five clusters of students and their behaviors in completing the multimodal formative quizzes confirmed the importance of SRL (e.g., goal setting, time-management) (see Dörnyei & Ryan, 2015) in language learning. See Table 5 for a summary of the results.

Table 4. Follow-up ANOVA for clustered and un-clustered variables

	df	*F* value	Partial eta squared
Clustered measures			
Overall course grade	4	229.03*	0.08
Start day	4	2107.03*	0.58
Nth day before deadline for first attempt	4	2112.06*	0.56
Duration	4	1678.31*	0.43
Differences in attempts	4	72.88*	0.04
Scores in academic style activities	4	225.62*	0.11
Scores in referencing activities	4	149.57*	0.09
Score in genre activities	4	991.05*	0.31
Score in academic presentation activities	4	2152.31*	0.55
Measures not clustered			
Content development	4	191.54*	0.05
Organization	4	199.48*	0.05
Language	4	108.58*	0.03
Referencing	4	243.25*	0.06

Note. $^{*}p < .05$.

Table 5. Summary of cluster characteristics

Categories (indicators)	Cluster 1 (n = 3974)	Cluster 2 (n = 2127)	Cluster 3 (n = 2324)	Cluster 4 (n = 4876)	Cluster 5 (n = 2713)
Course performance	At par	Poor performance	Good performance	Good performance	At par
Planning					
Start day	Started early	Started late	Started early	Started later / not the earliest	Started late
Nth day before deadline for first attempt	Started shortly before the deadline	Started shortly before the deadline	Started shortly before the deadline		Started shortly before the deadline
Performance monitoring					
Scores on activities	Above mean on most activities, except the last one	Below mean on most activities, except the last one	Above mean scores on most activities, except the last	Above mean on most activities	Above mean on most activities, except the last one
Differences between attempts		Improved between attempts			Did not improve much between attempts
Duration	Spent more time	At par	Spent less time	Spent more time	Spent less time

5. Discussion

5.1. Five types of SRL behaviors

We identified five clusters of students who differed distinctly in their SRL behaviors in completing the multimodal formative quizzes. The EAP students in Cluster 3 and Cluster 4 earned the highest grades on the quizzes, and those in Cluster 2 received the lowest scores. Students in Cluster 4 and Cluster 5 performed at par (i.e., close to 0 for standardized score).

As the results for the students in Cluster 3 and Cluster 4 demonstrate, there was a correlation between success aided by starting the quizzes well before the deadline and taking the multimodal quizzes seriously (i.e., obtaining above-average scores on most quizzes). In these two clusters, students may start later or early and may spend less time or more time on quizzes. The grades of the students in Cluster 1 and Cluster 5 were slightly lower than those in Cluster 3 and Cluster 4. Students in these clusters began the quizzes shortly before the deadline but demonstrated positive SRL behaviors by taking the quizzes seriously (i.e., obtaining above-average marks in their first attempt at most quizzes). The main difference between these two clusters (i.e., good performance and at-par performance) lay in the matter of how long before the deadline the students began their quizzes. Students who performed well began their multimodal quizzes well before the deadline, but students who performed at par began only shortly before the deadline. It is important to note that students in these four clusters, achieving at least at-par performance if not better, took the multimodal quizzes seriously. This finding supports the argument that students who display self-regulatory behaviors are more prone to monitoring and adjusting their learning processes (Cho & Cho, 2017). It also accords with Azevedo and Hadwin's (2005) observation that there is a strong correlation between SRL and academic success. This study, however, finds that the SRL behavior that matters is how long before a deadline students begin and whether they monitor their learning.

The students in Cluster 2 demonstrated poor skills in SRL, beginning their activities late and close to the deadlines. Although their activity scores were below the mean for almost all quizzes, they did not monitor their progress or improve their scores. These students did not perform well on course assessments. Thus, this group of students did not take advantage of the multimodal formative online quizzes to obtain ongoing and timely feedback on their learning (see more discussion from Nicole and Macfarlane-Dick, 2006 on how students can take more responsibility in their learning). By completing formative quizzes, EAP students can discover their weaknesses and take steps to mitigate them before summative assessments take place. Formative quizzes are also important tools for teachers to monitor students' understanding of language concepts (Gardner, 2012; Hinkelman, 2018). As the results indicated, Cluster 2 students did not use the quizzes to revise and consolidate knowledge. Nor did the quizzes develop SRL, contrary to McLaughlin and Yan's (2017) who found that such quizzes can improve SRL of students. Because of their lack of SRL behaviors and poor performance, the individuals in Cluster 2 could be classified as unsuccessful students (Gerami & Baighlou, 2011).

The students in Cluster 5 demonstrated a pragmatic form of SRL by doing just enough. This group began the quizzes later and performed well in the first few activities. Then, their performance declined, and they did not improve much between attempts at the quizzes. However, their course assessments were right at par. This may suggest that they did not demonstrate enough SRL to do better, but it could also signify that their SRL skills were outstanding. Students in this group could have planned well, putting in enough effort on the earlier activities to stop doing activities later. They may have allocated only enough time and effort to complete the quizzes, thus displaying outstanding SRL. Although the Cluster 5 students performed at par in the course, they demonstrated as few SRL behaviors as the Cluster 2 students. They were reluctant to make an effort to learn and could be classified as passive students (Zimmerman & Schunk, 2011).

While good mastery of SRL was strongly related to course outcomes in the contextualized language course, we observed only more obvious links between SRL and some assessment components (i.e., content development and referencing), but not other assessment components (i.e., organization and referencing). One possible explanation is that SRL reflects the overall effort put into the course (Cho & Heron, 2015), and this can only be revealed by certain assessment components. For example, content development assessment focuses on the research that students have conducted for their essays (e.g., searching for sources, reading, and developing strong arguments). The more effort students expend on content development, the better the grade they will achieve, which should, to a great extent, reflect the effort students put in for MLP activities. The same applies to conventions that require students to prepare in-text citations and the reference list carefully; these require students to make efforts to check style guides to ensure that their citations are correct (e.g., formatting and punctuation).

In contrast, some assessment components (i.e., organization and language) may not accurately reflect the content and effort put into MLP activities. For example, academic style is included in the MLP activities and in language assessments, but the effort put into the use of varied and accurate language, which is central to language assessment, is not reflected in MLP activities. In the same vein, the assessment of organization is related to subtle genre knowledge and rhetorical skills. While there are MLP activities addressing genre knowledge, such as organizational structure of essays, students can easily acquire such genre knowledge by referring to essay samples or class notes regardless of their performance in MLP activities. Students may perform well because they can write logically when they complete the assessment; therefore, effort and content in MLP genre and activities may not be strong indicators. More investigations into the correlation between MLP SRL, contextualized language learning, and overall assessment performance should be performed.

6. Conclusion

This study provides insights into the relationship between students' SRL and performance through an analysis of data from multimodal formative quizzes. The results revealed correlations between SRL and academic performance, planning, and performance monitoring. It showed that students who start well before deadlines and take formative quizzes seriously will perform best. This study also shows five different profiles of students when they complete formative online quizzes. Based on our findings, we recommend that educators develop personalized instructions for each cluster of students to motivate, stimulate, and foster SRL. This should improve course performance. Having access to learner analytics allows educators to adjust blended, multimodal formative quizzes to meet the needs and interests of specific student cohorts (Ferguson, 2012). As educators, we need to understand and address EAP students' needs to improve the flexibility and efficiency of their blended learning experiences.

6.1. Limitations and future studies

Several limitations of this study should be noted. Although this study provides evidence of a relationship between SRL and strong academic performance, all of the respondents came from one university, thus limiting the generalizability of our findings. In addition, clustering is an exploratory technique; it is not designed to assess outcomes (e.g., hypothesis testing). Also, model adequacy measures indicated that the cluster structure was weak. These limit the validity of claims made about SRL behaviors.

We propose several topics for future study. Researchers could focus on gathering rich information by using both a questionnaire and interviews to complement the objective quiz data. Such qualitative data might provide insight into students' perceptions of the interfaces and designs of the multimodal formative quizzes and their levels and sources of motivation. It could also suggest ways that the quality of the quizzes could be enhanced using the features of LMS platforms. Finally, research in educational settings beyond Asia could shed more light on the relationships among SRL, multimodal formative quizzes, and strong course performance. We hope that the findings of this study serve to remind educators that EAP students need to develop strong SRL skills and engage seriously in multimodal contextualized language learning to succeed in their studies.

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Appendix 1 – Examples of Multimodal Learning Package (MLP)

<table>
<tr><th>List of 13 Quizzes</th><th>Categories</th><th>Examples of Multimodal Content</th><th>Examples of Formative Quiz</th><th>Corresponding Assessment Criteria</th></tr>
<tr><td>Session 1 “Academic Style”</td><td>Academic Style</td><td>Website [URL for institution removed]: Screenshot to be displayed for peer review; link to be displayed in the final publication


Tentativity

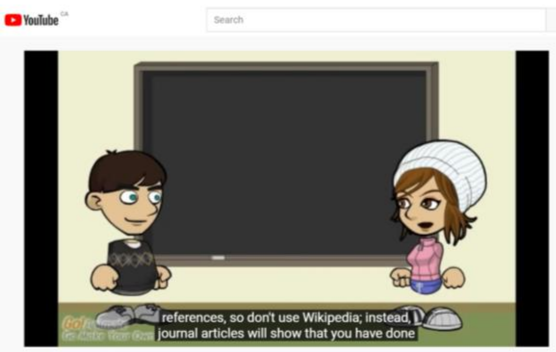
Home » CILL » EAP » EAP book » Tentativity Academic writing argument is rarely expressed in strongly positive language. To express an idea or finding in such a way would leave the writer open to attack by critical readers. To avoid making strong claims and expressing subjective opinions, academic writers use **tentative** rather then **assertive** language.. Compare the tentative and assertive language in the table below.

Tentative expression	Assertive expression
One could argue that the overall standard of English in Hong Kong has improved	The overall standard of English in Hong Kong has clearly improved.

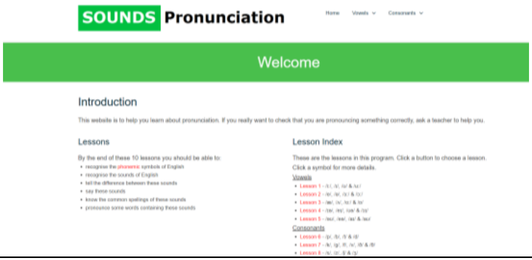
Modal verbs such as *could*, *may* and *might* are common in academic writing because they help writers express uncertainty or tentativeness. Also common are the verbs *appear to* and *seem to*, as well as adverbs of probability: *perhaps, possibly, probably, likely, unlikely*.

Of course, depending on viewpoint and the available evidence, a writer can express greater or lesser degrees of certainty. Look at the examples in the table below.

1. Positive and assertive:	Clearly, then, Hong Kong student's standard of written Chinese is declining.
2. Suggesting likelihood:	The evidence seems to suggest that Hong Kong student's standard of written Chinese is declining.
3. Expressing less likelihood:	It may/might/could be the case that Hong Kong student's standard of written

Infographics for Academic style</td><td>Drag and Drop activity, on definitions of academic style issues (e.g., contraction)</td><td>Language (All writing assessments)</td></tr>
<tr><td>Session 2 “Referencing”
Session 4 “Integrating Sources”</td><td>Referencing</td><td>Youtube [name of institution removed]: Screenshot to be displayed for peer review; link to be displayed in the final publication

</td><td>MC questions on content presented in the videos</td><td>Referencing (All writing assessments)</td></tr>
<tr><td>Session 3 “Reading Academic Articles”
Session 5 “Essay Writing (1)”
Session 6 “Essay Writing (2)”
Session 7 “Fact vs Opinion”
Session 8 “‘For’ &</td><td>Genre Knowledge</td><td>Youtube [name of institution removed]

</td><td>MC questions, on facts presented in videos, problems with Introduction paragraph, flow of an Introduction paragraph</td><td>Content Development / Organization (All writing assessments)</td></tr>
</table>

‘Against’ Essays” Session 9 “Editing your Work”				
Session 10 “Academic Presentations” Session 11 “Visual Aids” Session 12 “Effective Presentation Delivery” Session 13 “Presentations”	Presentation Skills	Youtube [name of institution removed]  Pronunciation Website hosted on by the institution: Screenshot to be displayed for peer review; link to be displayed in the final publication 	Labelling activity, on how to create interest	All criteria for Presentation assessment

Appendix 2 – Visualization of Five Clusters