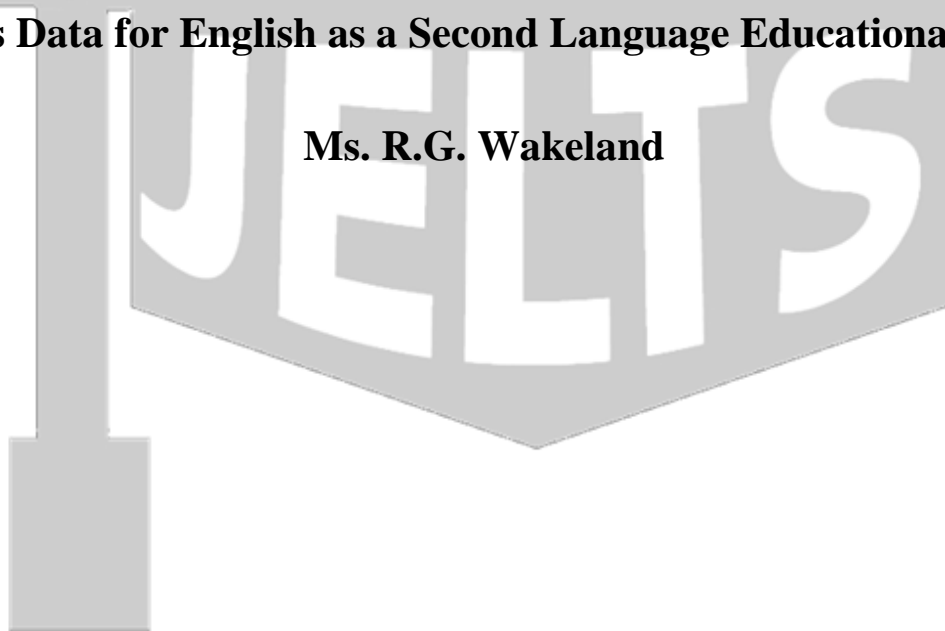




International Journal of English Learning and Teaching Skills

**Anonymous Data for English as a Second Language Educational Assessment**

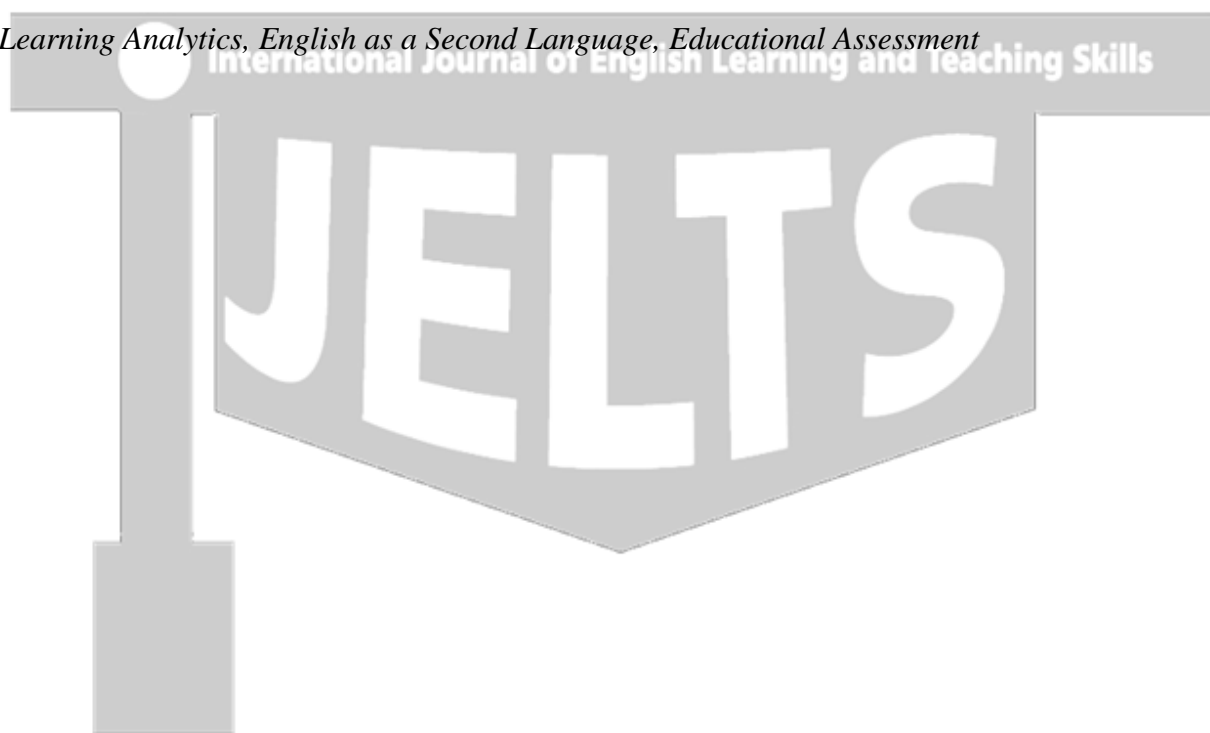
**Ms. R.G. Wakeland**



**Abstract**

*Anonymous demographic and course attendance data from both credit and non-credit English as a second language (ESL) courses at a community college in the USA formed the basis to compare the two. Derived from public information obtained from students, this data served to gauge the success of both individual courses as well as the college's goals for student success. Course efficiency was measured as a ratio between faculty number and student attendance hours. Functioning to comply with funding requirements, the data also showed the differences between the two course types. This method had relevance for curriculum choice, funding, and both individual course as well as overall program evaluation. The literature review placed the comparison on a timeline of data used in educational assessment from 1961 grant reports to 21st century learning analytics. Included are suggestions for future applications.*

**Keywords:** *Learning Analytics, English as a Second Language, Educational Assessment*



## **Introduction**

Using public data from Allan Hancock College (AHC), a community college in California, United States of America (USA), characteristics of non-credit and credit English as a second language (ESL) students and course efficiency were compared. Encompassing 2012-2017 academic years, this data analysis fit in the continuum anonymous data application among ESL classes since 1961. Contemporary research subsequently was enhanced with computerized data, and algorithmic conclusions. Data collection segued into 21st century method of learning analytics, which applied data to assessment. Overall conclusions showed more equal gender enrollment and higher efficiency among non-credit courses. Summer courses in both courses shared the same lower enrollment and efficiency rates. Overall evaluation for both course types concluded in an increase in enrollment through time. Literature models for involvement and permission from students suggested anonymous data could expand relevancy with the addition of student involvement.

## **DESCRIPTION OF THE PROGRAM**

Allan Hancock College is a two year publicly funded college in Santa Maria, California. During the time frame of the data, annual enrollment of noncredit students averaged around 1100, while credit students averaged around 480. These figures represented headcounts, or individual students enrolled each semester. Curriculum consisted of mainstream publishers, written according by Central European Frame of Reference (CEFR) levels (Council of Europe, 2001).

Credit and noncredit ESL courses were distinguished via location of classes. Credit courses were typically held in the AHC buildings in classrooms sized for small classes. The college branches served students in neighboring Lompoc and Santa Ynez valley. Available classroom space ranged from meeting rooms to elementary through high school classrooms and cafeterias.

## **DATA**

Data were collected via a public records request to the college. All student data remained anonymous, and permitted under the law. In USA, the federal educational records privacy act (FERPA), 20 U.S.C. §1232g, 34 CFR Part 99, precluded public access to student educational records without students' permission. Thusly, this anonymous data did not comprise educational records.

College data collection facilitated reporting to the funding source, the California state community colleges Chancellor's Office, for both credit and noncredit ESL course funding. These courses required number of student hours in class for California residents (positive attendance), California code of regulations title 5, §§ 58003 et seq., 58003.1(d), (e), (g); 58006, 58160; California education code §§ 84757(a), 84760.5. These were converted to full time equivalent students (FTES), the basis for reimbursement to colleges. Both credit and noncredit ESL courses were funded at a gradually increasing rate per FTES from 2013-2017, exhibiting an approximate 13% rise. The chancellor also approved the college noncredit ESL certificates in 2010, 2016 and 2017. (Chancellor's Office, 2017b).

## **LITERATURE REVIEW**

Government accountability formed one purpose of quantitative evaluation. To evaluate its adult migrant education courses (including English), the Australian government compiled data on students and courses. Data included student demographics, learning objectives, hours of teaching, and assessment tools utilized. Here, data analysis contributed to the case specific evaluation method. Conclusions criticized the government for inadequate funds compared to the quantity of students, and found that women and students with limited education represented the direst need. (Blesing, 1981).

In USA, this case specific evaluation model combined with quantitative data collection, as well. A 1997 USA

federal government funded programs required a data analysis. A total of 476 literacy and family centered education programs in 11 states focused on migrant education and provided the basis for program evaluation. (Tao & Arriola 1997). English literacy courses given at public libraries also were accountable to government funding agencies, and utilized anonymous data. The standard report form encompassed student demographics and statistics, course learning objectives, hours of teaching, training for instructors, and teachers' assessment tools. (Maravilla, 1998; Hunt 1993).

At the USA federal level, education program evaluation began in 1963, when methodologies included formative and summative evaluation, data collection, empirical bases, and population needs. Via impetus provided by the no child left behind initiative in 2005, these same methods were applied to ESL, and English as a foreign language (EFL) language endeavors. Targeted goals were how to meet needs of minority and indigenous people, and how to incorporate empirical tests into overall evaluation (Minor, 2016).

ESL evaluation methods spanning 1961-2016 comprised a metadata report. Here, a trait-based measurement method dominated between 1961-2003. The present study approximated this method, via inclusion of course efficiency, gender, age, ethnic identity, and course type. The interactionist method, measuring skills, context, and performance goals, developed beginning in 1996 and persists today. This study here involved aspects of this method via contexts such as credit/non-credit, and class efficiency, plus certificates and attendance (Purpura, 2016).

In a review of ESL evaluation methods between 2006-2016, Norris (2016) sorted objectives and applicability ranging from curriculum to accountability. He also engaged the issue of cultural bias by reviewers. He cited compensating methods to implement during the analysis. As a model, he supported the New Zealand government assessment of its education efforts, including teaching English, among the indigenous Maori. Maori themselves were involved in the evaluation, which incorporated collecting quantitative data (Norris,

2016).

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Sharing similarities with the present study, San Francisco City College collected quantitative data in a seven year longitudinal study comparing ESL credit and non-credit courses. Tracking 38,095 non-credit and 6,666 credit students over 7 years, it evaluated persistence, learning gains, and transition to credit studies. This led to conclusions, for example, that credit ESL enrollment increased by 26%, while non-credit enrollment decreased by 9% (Spurling et al., 2008).

A two semester ESL course sponsored by a non-profit organization utilized student demographic data and course completion rates, as well as pre-test and post-tests, towards its self-evaluation. Participants (35) were recruited from parents and guardians of USA Head Start students (federally funded low income preschool). Curriculum was relevant to parenting and child development. Data collected included gender, age, country of origin, family income, number of children, and age of children, attendance rates, and persistence rates based on completion of both semesters. (Sommer et al., 2018).

Conclusions manifested high (83% and 70%) completion rates for each semester. However, completion rate for both semesters reached only 46%. These rates were high compared to national community based ESL programs (attendance=50% and completion=25-30%). Conclusions suggested, among others, that a single semester program should be developed. (Sommer et al., 2018).

Beyond ESL courses, data collection factored into the broader education context. Scientific and evidence-based educational assessment, compiling input and data from stakeholders and their communities, was recently adopted by the United Nations Educational Scientific and Cultural Organization (UNESCO). Driven by the impetus to synthesize theory and pragmatics, articulated goals aimed to provide bases for policy and needs assessment (Duraiappah, 2021). AHC shares these goals, as in 2017, the Chancellor adopted evidence-based assessment and placement for noncredit students, in response to legislation mandating same (Chancellor's

Office 2017c).

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AHC and UNESCO's recommendations both segue into and comport with the educational assessment parameters of learning analytics. Generated by 21st century burgeoning digital explosion, this method arose 10 years ago. In a United Kingdom (UK) study, demographic data, together with student engagement statistics, and course-specific data, at the college level functioned via learning analytics in an attempt to predict exam outcome, but with little success. (Tomasevic, 2020).

Statistical analyses (e.g. demographics and academic history) predicted which students would be the most at-risk for dropping out and facilitated support for these students early on to connect them with resources (Banks & Dohy, 2019). Academic performance, demographics, and trace data from online courses and social media of 149,672 college students engendered learning analytics to quantify achievement gaps (Nguyen et al., 2020).

Broughan and Prinsloo (2020) contextualized learning analytics' goals, motivations, and methods within Freire's philosophy and pragmatics. As Freire pre-dated learning analytics, their inquiry focused on data's potential to facilitate student centered assessment. As Freire posited that student centric education propelled transformation, could data satisfy this parameter for both student and institutional assessment? Given the milieu of demographic, student engagement, exam, assignment, online courses, and behavioral data, the authors concluded a Freire implementation would invite student participation in and incorporate students at all stages of learning analytics (2020).

## **DISCUSSION**

At Allan Hancock College, non-credit ESL courses were funded within the state Chancellor of Education's basic adult education budget. As such, the state required reports of student hours in class, on an annual basis. Funding to the college derived from these numbers (FTES). Teachers recorded student hourly attendance, and

submitted reports to the administration. Anonymous quantitative data was then compiled for each class taught. (Chancellor's Office, 2017b). As teachers' names associated with specific classes were public information, this allowed their names to be linked to course efficiency and size data. This could be accomplished by comparing records of faculty assigned to each course, by semester. See Figures 6,7.

Age, gender, ethnic self-identity, and certificate or other accomplishment data were compiled from students' application forms, but separated from their names. The certificate completion comprised a recent addition, as it was only recently demanded by the Chancellor's Office. Persistence was not tracked in non-credit courses. Thus, data within the realm of accomplishment among non-credit students was limited to the certificates.

However, both credit and non-credit courses were evaluated for efficiency, FTES divided by number of full time faculty hours (FTEF). This derived from attendance quantity in any given class. This data, approximately 1100 noncredit students each year, and 480 credit students each year, met the standard of reliability based on quantity. See the San Francisco longitudinal study concluding same, (Spurling et al., 2008).

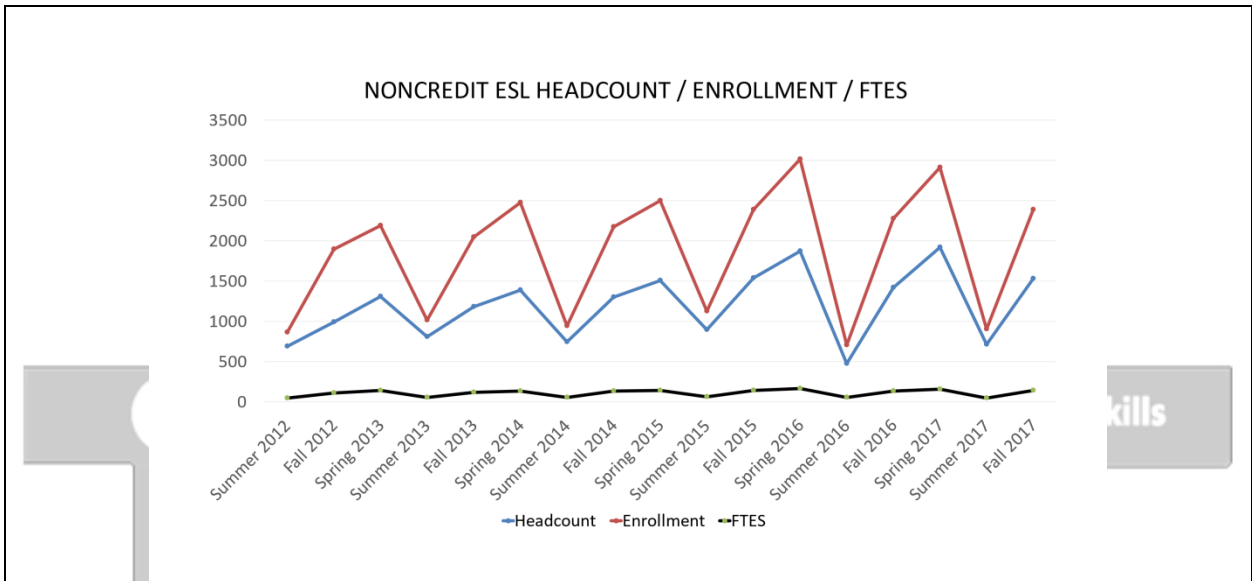
## **COMPARISONS**

Starting with an overview of enrollment and attendance, the headcount, enrollment and full time equivalent student data (FTES) indicate differences between the two types as well as relationships within each type. The full time equivalent student data derived from the attendance records of instructors. The credit students attended class more frequently than the non-credit students, according to the associated gaps between FTES and enrollment. See Figures 1,2. Here, headcount represented individual students, while enrollment indicated the number of courses students matriculated. Student presence in class by the hour was reflected in FTES.

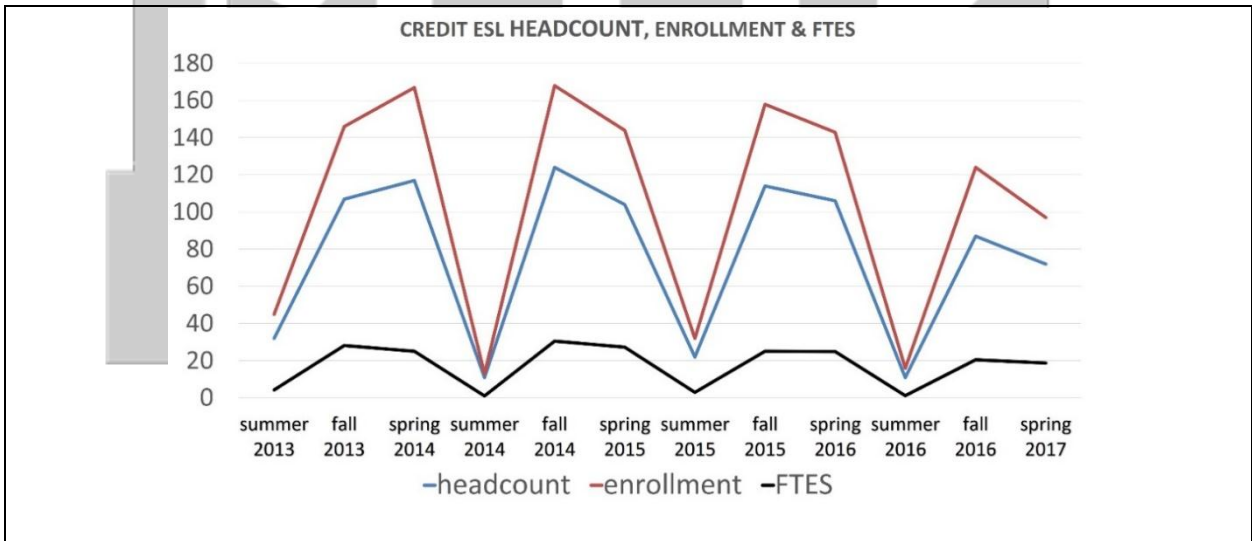
The non-credit students took an average of 2 courses each, and their attendance comprised 100 full time students out of 2,200-3,000 enrollment. Whereas the credit students took about 1.27 courses each, comprising



an average of 25 full time students out of enrollment of about 150. For both, enrollment was lower but the attendance rate was higher in the summer. Figures 1,2. (Broughan & Prinsloo, 2020). 9



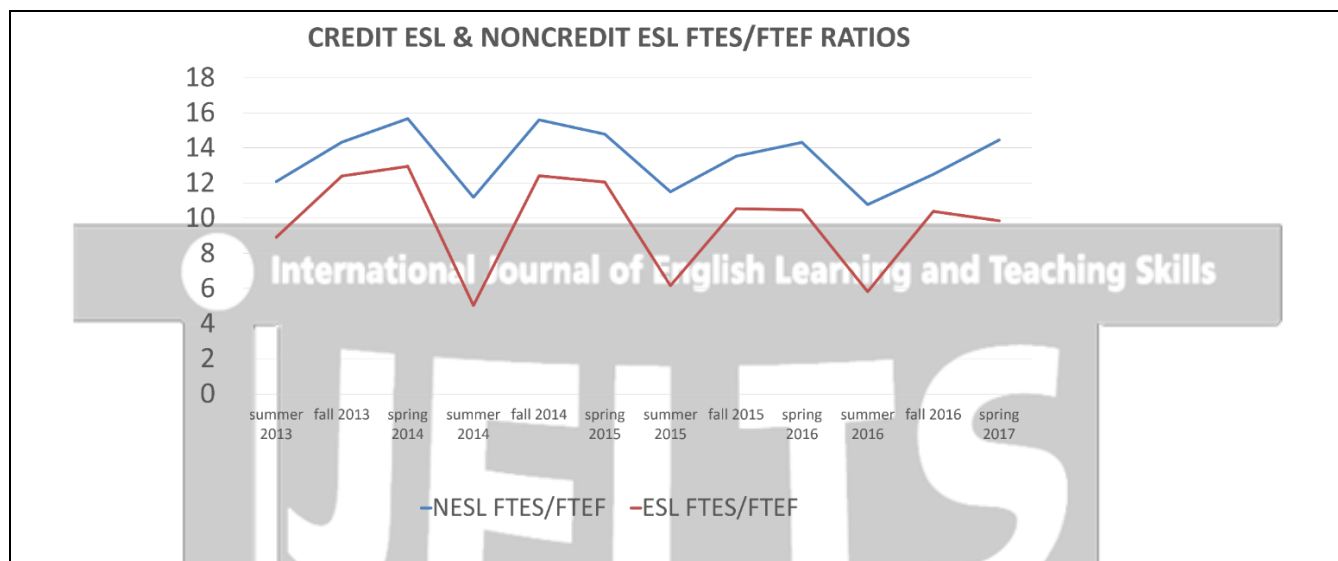
1. Allan Hancock College, non-credit English as a second language student data, 2012-2017



2. Allan Hancock College, credit English as a second language student data, 2013-2017

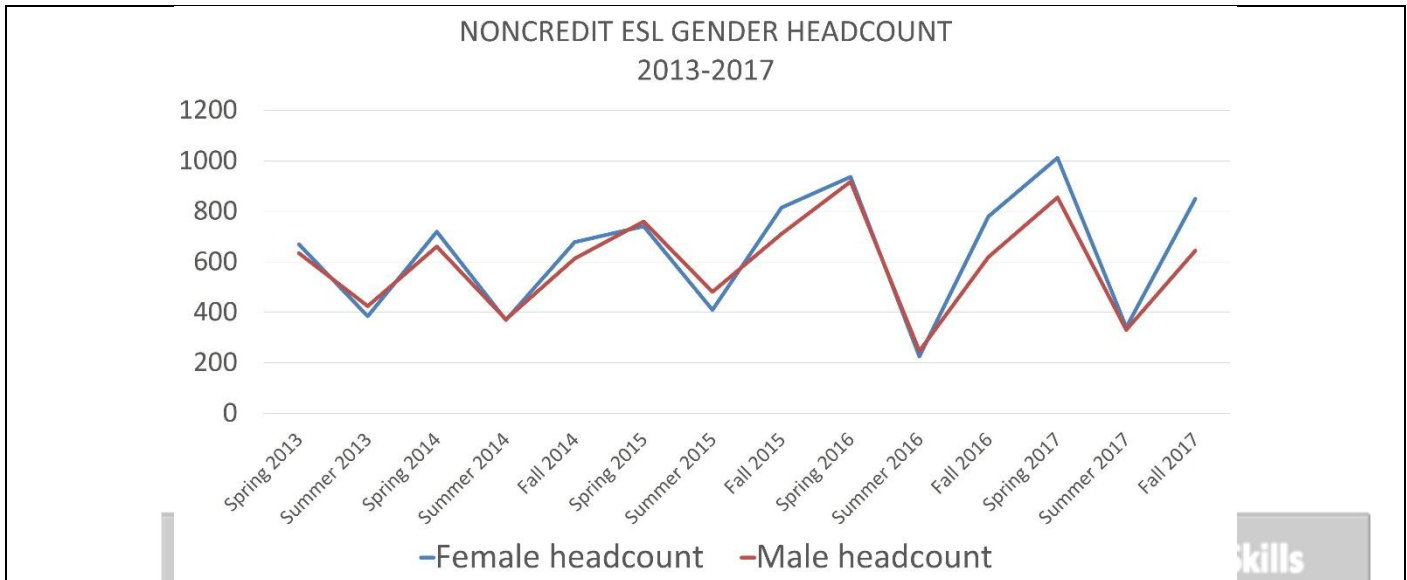
However, despite their relative lower attendance rate, the non-credit courses had a higher efficiency ratio, calculated by FTES/FTEF. This means there were more students attending each non-credit class, as there was consistently only one instructor per class. See Figure 3. This, together with the enrollment figures, Figures 1,2,

showed that a higher number of non-credit students signed up for the class, but attended at a lower rate compared to the credit students. Likewise, this indicated non-credit instructors taught more students. Overall program analysis results that, except for summer courses, enrollment and headcounts increased from 2013 to 2017.

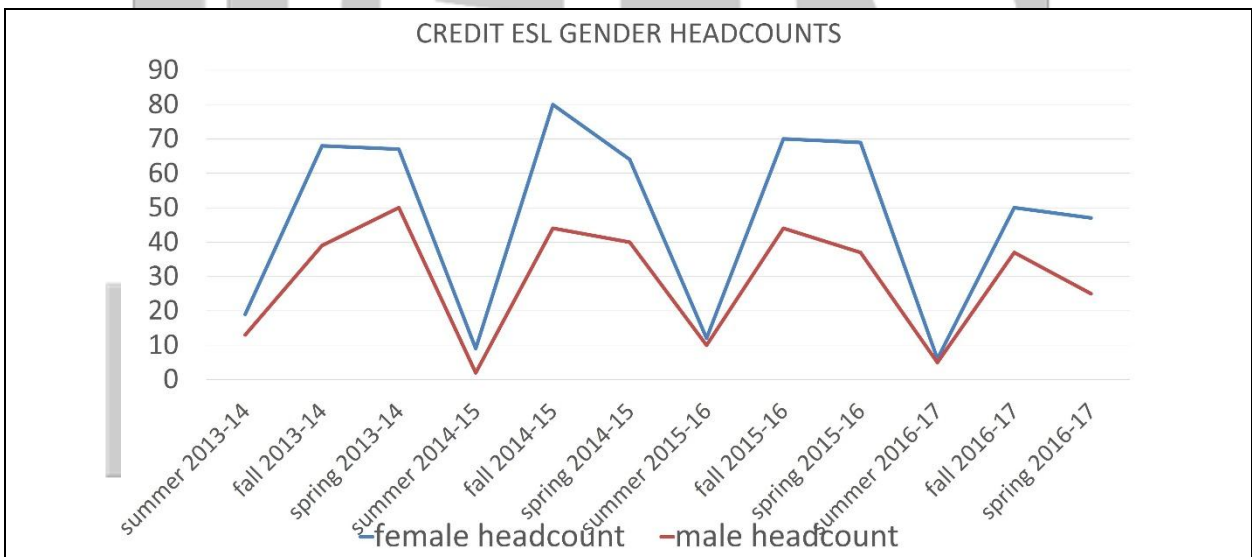


3. Allan Hancock College, credit and non-credit English as a second language student data, 2012-2017

Headcount equaled total individual students enrolled. Each student was counted once regardless of number of courses enrolled in. As noted above in Figures 1 and 2, noncredit students took an average of two courses each, while credit student enrolled in about 1.27. Comparing headcounts by gender, noncredit course counts were closer than those in credit courses. For noncredit students, genders matched in number until fall 2016 semester. At this time, except for summer, about 20% more female than male students enrolled, Figure 4. Credit students, except for summer classes, enrolled more female students during the entire time span, and at larger differences, Figure 5.



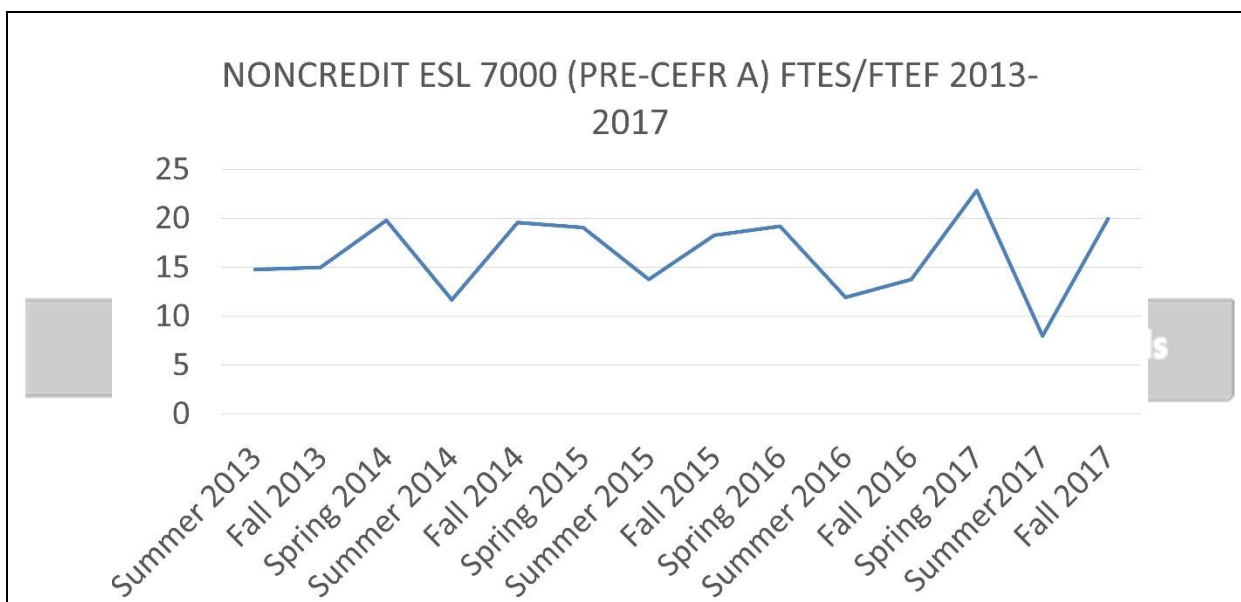
4. Allan Hancock College, noncredit English as a second language student data, 2013-2017, individual and female students numbers compared



5. Allan Hancock College, credit English as a second language student data, 2013-2017, enrollment numbers of individuals according to gender

In addition to discovering efficiency, enrollment, attendance and gender, the data also facilitated evaluation of each class. Thereby, all classes could be compared in various configurations. Data could be sorted by semester, or any other selected time frame. Courses could be compiled by teachers, as well. As course numbers specify pre-A through C levels, this could also result in comparison of these levels, or courses within each level. In

addition, graphs could be plotted showing relative size and efficiency. Data output comprised two forms. One consisted of line chart, as shown below, Figure 6. These indicated the typical low points in summer, with an overall rise toward the end of the time sequence.



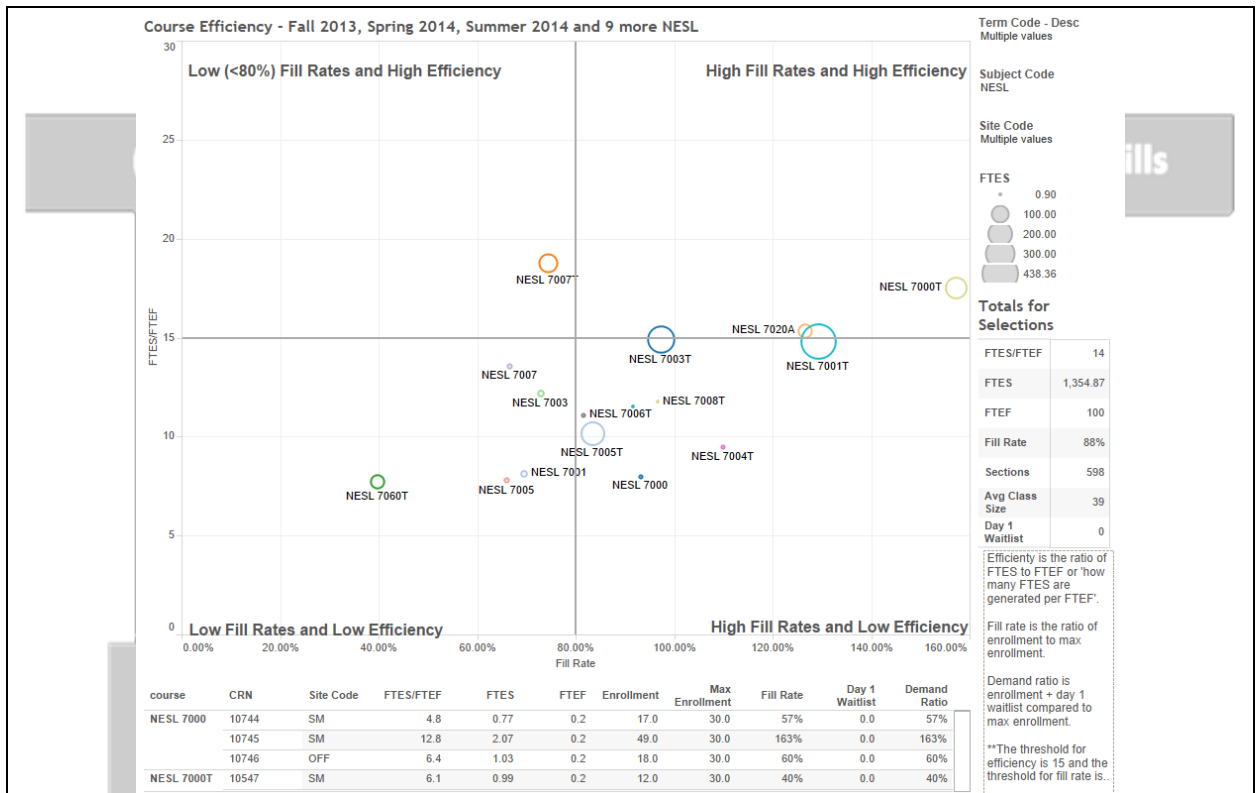
6. Allan Hancock College, noncredit English as a second language efficiency ratios, course pre-CEFR A level)

The other form of chart, an algorithm produced dot on a graph, portrayed fill rates for each course, Figures 6,7. Fill rates represented ratio of actual enrollment to maximum allowed enrollment. In addition, in this same graph, efficiency rates, or how many FTES were generated per FTEF appeared as well. This standardized comparison between credit and non-credit courses. Typically, credit courses were held in smaller sized college classrooms, compared to the school or community based noncredit courses with larger rooms allowing for larger enrollment. Figure 6 symbolized noncredit courses, fall, summer and spring semesters 2013-2017 inclusive.

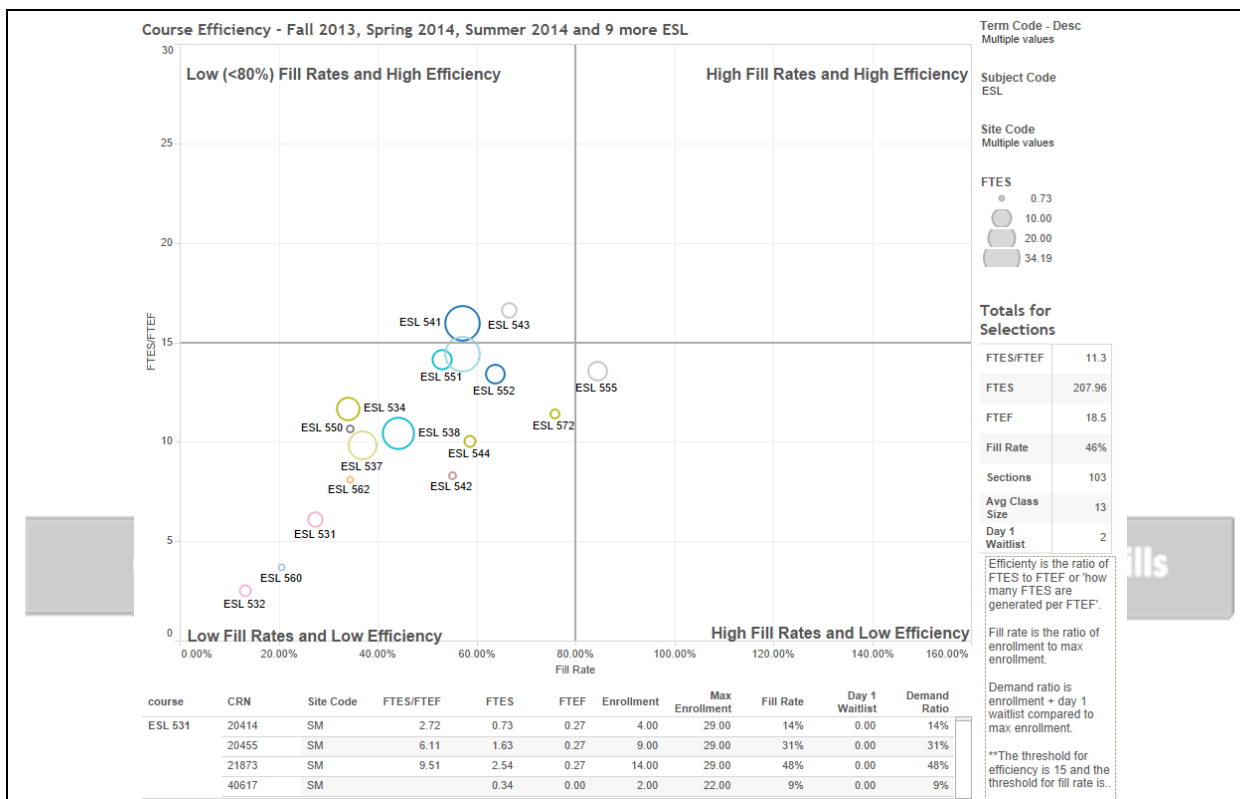
In viewing the database from which this chart was downloaded as provided by AHC office of institutional effectiveness, data for all courses appears at the bottom, via the scroll down arrow. However, when converted to a saved image, only the first few lines remained visible. Nevertheless, the complete data also resided in the

spreadsheets in the data published online with this article.

The formula for Figures 7 and 8 was contained in the dataset uploaded and published with this article online. The graphs here were generated by the college, and separated credit and noncredit courses. However, the data sets allowed for combination likewise of credit and noncredit courses on the same graph via the application of the formula by statisticians.



7. Allan Hancock College, noncredit English as a second language courses by number, ncy ratios and course size, fall, spring, and summer semesters, 2013-2017



8. Allan Hancock College, credit English as a second language courses by number, efficiency and course size, fall, spring, and summer semesters, 2013-2017

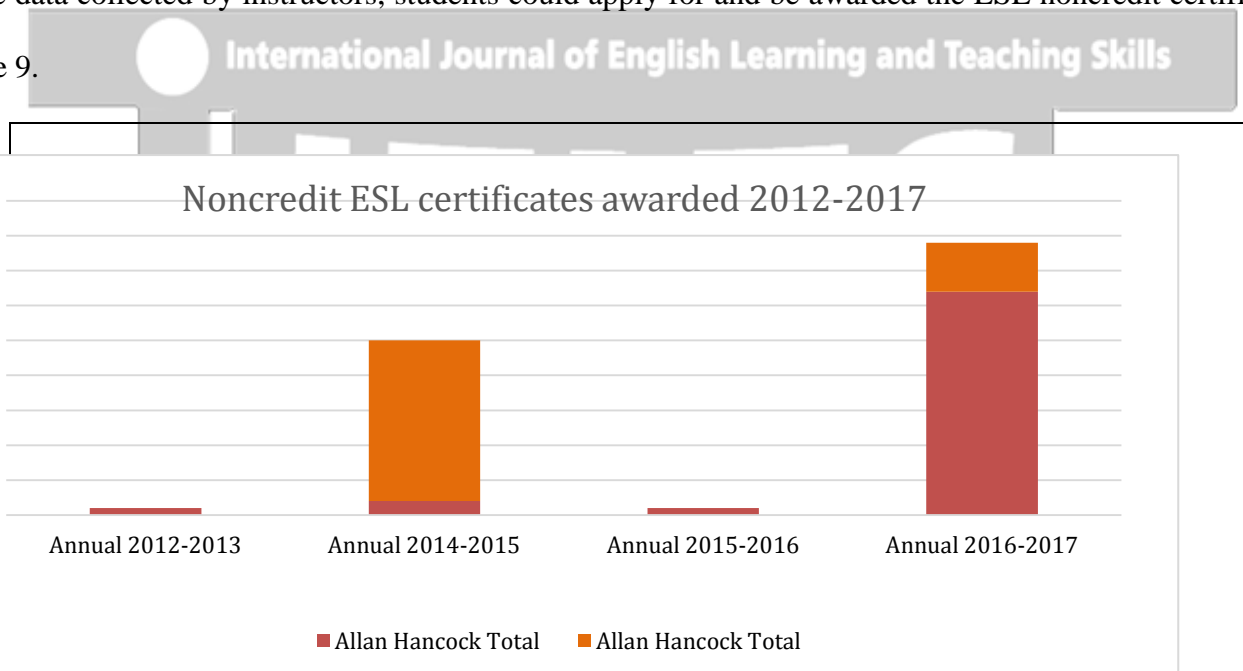
As Figure 8 indicated credit course data for the same semesters, these formed bases for comparison to the noncredit courses in Figure 7. Whereas the fill rates between the two were comparable, the credit courses clustered lower in efficiency ratios. Thus this sort and number crunching provided the possibility for overall program evaluation and comparison. As noted above with the line charts, any number of combinations, including tracking courses by number throughout time, were possible via this data.

Anonymous data facilitated as well compilation of statistics on success of credit and noncredit students both. While the credit student data judged perseverance based on associate degrees, certificates and transfer to four year colleges (Figure 10), no such measurement applied to noncredit students. Therefore, no direct comparison can be made. However, Figures 8 and 9 provide graphic indications for each distinct criteria and data sets. The college noncredit certificate requirements and parameters had been approved according to the Chancellor’s

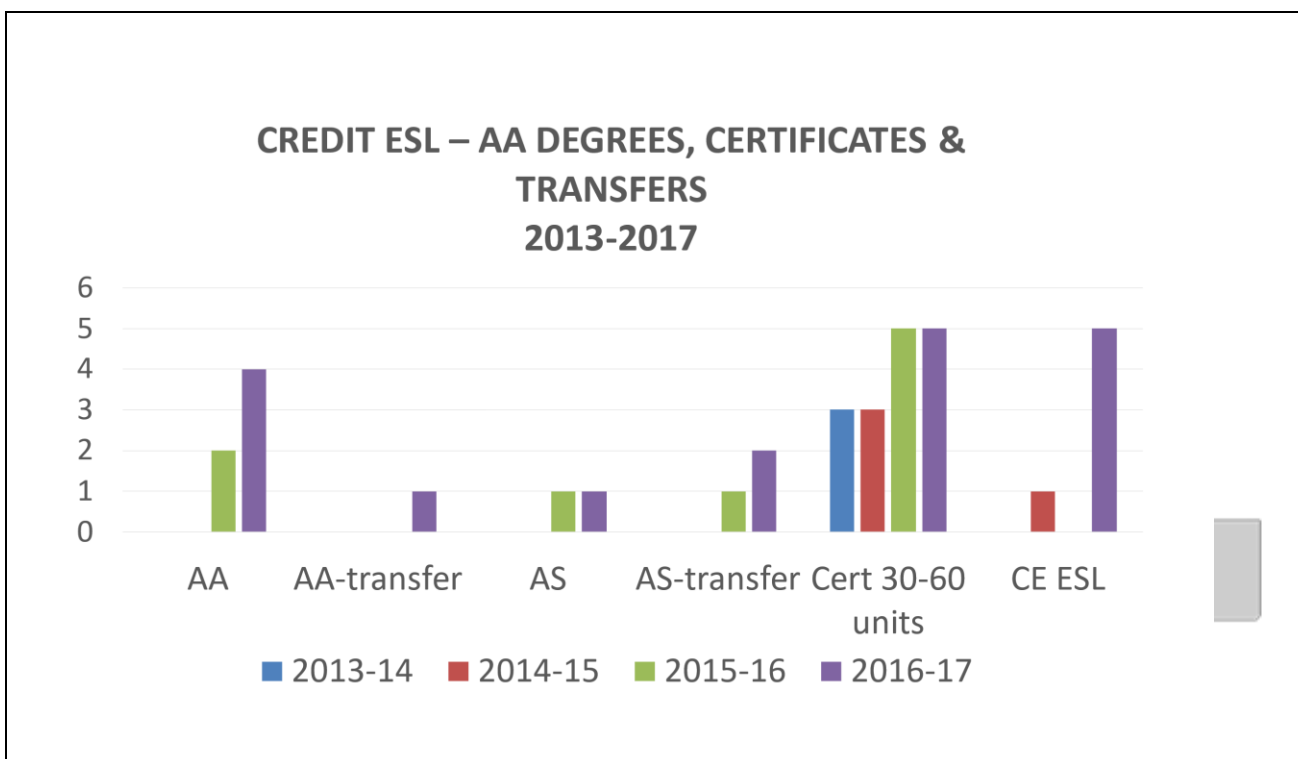
guidelines from 2010-2017. These included a minimum of 75% attendance in every course (Chancellor’s Office, 2017b).

Indeed, the Chancellor’s Office provided motivation for this certificate via emphasis on noncredit progress. (Chancellor’s Office, 2017b). In 2016, the Chancellor’s California Community College Curriculum Committee (5c) (2016) investigated implementation of a pseudo grading system for noncredit courses. However, such evaluation grades were not implemented during the time of this data (2012-2017). Utilizing the hourly class attendance data collected by instructors, students could apply for and be awarded the ESL noncredit certificate.

See Figure 9.



9. Allan Hancock College, noncredit English as a second language student certificate awards, 2017 (Chancellor’s Office, 2017a)



10. Allan Hancock College, credit English as a second language student success, 2012-2017  
Chancellor's Office, 2017a)

## CONCLUSION

Increase in total student enrollment, gender equity in noncredit courses, higher attendance rates in credit courses, and noncredit instructors' greater student load all derived from this data. Adding student involvement, student permissions, and population needs and placement, beyond anonymous data, would implement Freire's concepts. This iteration of learning analytics as applied by vanguard studies aimed at data in closer proximity to the student, and engaging student ownership of data. As well, the results of the measurements were directly funneled to individual students in the form of tutoring, and other interventions. Thus, implementation of these methods at AHC would fulfill both the Chancellor's Office directives and Freirean learning analytics.



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