Quantitative Measures for Assessing Learning Centers: An Agenda and Exploration

Kevin Berkopes and Stacey Abshire
Indiana University-Purdue University Indianapolis

Abstract

The national trend of requiring all college students to engage with tertiary-level mathematics has created the need to rethink how students can be supported at this level. Current trends in higher education show a decreased reliance on remedial developmental education courses and expanded reliance on learning centers. It is important to look at student participation and learning in the context of these supportive resources. This research paper explores first-generation college student usage of a mathematics learning center at a large Midwestern university and launches a research agenda to explore rigorous analytical methods of understanding the impact of learning centers.

Ongoing efforts to increase and broaden college attainment have drawn new attention to services for undergraduates, particularly in their transition to first-year studies in STEM courses. A consortium of seven leading higher education organizations recently called for new attention and investment in strategies that help students succeed in challenging lower-division courses (Charles A. Dana Center, 2012). Central to this call is decreased reliance on non-credit remedial developmental education courses and expanded reliance on second access programs such as Supplemental Instruction (SI) and learning centers. These programs typically involve cross-departmental collaborations that provide additional access to course content, usually via peer mentoring and tutoring from vetted undergraduate students. For the purpose of this paper, we focus our efforts on the utilization of tertiary mathematics learning centers. This choice is multi-faceted but primarily due to learning centers' proposed viability for centralizing campus resources. Theoretically, these centers provide a robust, campus-vetted second access to content to support the initial access gained by students in lecture.

Our research group recognizes the widespread literature reporting student difficulties with the transition from secondary mathematics to tertiary mathematics (De Guzmán, Hodgson, Robert, & Villani, 1998; Gueudet, 2008). We are also invested in the literature that suggests that students largely blame the nature, design, and implementation of the formal mathematics lecture for many of their negative interactions with mathematical content (Yusof & Tall, 1998). We find this blame is an oversimplification of a very complex issue but do empathize with students' struggles, as we ourselves have struggled in our own studies of mathematics. We do recognize the formal lecture, in its current form, as problematic, but we do not believe that replacing or reforming the implementation of lecture is the most pragmatic approach to this complex issue. Some factors contributing to students' views of lecture are obvious, namely that lecturers rarely are instructed in practical teaching methodology, and research often takes precedence over lecturing (Mamona-Downs & Downs, 2008). Other cognitive science factors could contribute to the complexity of scaling the widespread reform to the tertiary lecture, such as mathematicians' content knowledge for teaching (Ball, Thames, & Phelps, 2008; Davis & Renert, 2013; Freudenthal, 1983); different orientations to the nature of the discipline and teaching of mathematics (Ernest, 1985; Renert & Davis, 2010); and mathematicians' perception of the disconnect of Educational Mathematics literature for helping them cope with the work demands of the tertiary lecture (Sfard, 1998). One final note is that decades-old efforts to reform tertiary mathematics lectures have resulted in little consistent, widespread impact on students' experiences with the content (Mamona-Downs & Downs, 2008). We turn then to learning centers and their culture for supporting cross-campus partnerships to scale a university's ability to improve students' interactions with robust mathematical content.

Context

Learning centers have a long history in higher education dating back to the colonial times (Carpenter & Johnson, 1991). Literature suggests that these centers often have been synonymous with remediation and traditionally provide services for computer-assisted learning, assessment, advisement, and counseling (Perin, 2004; Rubin, 1991; Stern, 2001). We as researchers recognize this rich history and intend to contribute to it by the open-access learning center design that we employ at our large Midwestern university. This model positions our learning centers as Learning Commons (LC), or collective academic centers designed to create collaborative spaces. We position these centers to heighten the collision of ideas requisite of high-quality learning and act as a support for the work done in lecture (Davis, 2008; Davis & Sumara, 2008; Varela, Thompson, & Rosch, 1991). The implementation of the LC model at our institution has increased our student traffic at our learning centers from 18,000 student visits per academic year to more than 80,000 student visits per academic year. While we qualify this as a success for the model, we are intrigued to know more about the quantitative impact to our campus in the context of student success and return on investment. We endeavor, as part of our Hunter Boylan Research Scholarship from the National College Learning Center Association (NCLCA), to research and produce sound statistical analysis techniques that will help us, and other institutions of higher education, provide rigorous quantitative analytics as complementary to qualitative methods.

Objectives

For the purposes of this research study, we recognize the complexity of the endeavor that we wish to pursue. To our knowledge, showing the impact of the LC design on our campus in the context of student success and return on investment would require a widespread agreement on what these factors mean. It would also necessitate finding rigorous quantitative methods without violating ethical standards for social sciences research. Despite these complexities, we do believe that there are meaningful quantitative techniques that can be applied ethically to these types of data sets, which will produce useful information for telling the story of a learning center's place in higher education. We therefore position this research paper as a device to share our intended agenda and provide a small piece of our research group's initial findings.

Thus, we propose that an important initial analysis should be of the attendance and usage rates of students of specific cohorts. This analysis will provide insights into how our students are using the LC model learning center on our campus and if this matches with current literature on student cohorts and usage statistics. For this research report, we focus on the student cohort of first-generation, first-time freshmen (FGFF). This student population is considered in literature to be a high-risk cohort because of low retention and persistence rates (Choy, 2001; Ishitani, 2006; Lohfink & Paulsen, 2005; Nunez 1998; Pratt & Skaggs, 1989). Even more importantly, this cohort has been shown to have lower academic preparation, which can lead to lower success rates in their transition to tertiary mathematics courses and avoidance of STEM majors (Chen, 2013; Gayles & Ampaw, 2011; Stebleton & Soria, 2012; U.S. Department of Education, 2005). We start from the literature-based assumption that students of this cohort utilize campus resources at lower rates compared to the continuing generation student population group. We begin with the following research questions to guide our inquiry into this cohort and their usage statistics for the learning centers on our campus:

1. What are the first-time freshmen (FF) usage statistics for the Mathematics Assistance Center (MAC) for the Fall 2014 semester?
2. What are the first-generation, first-time freshmen (FGFF) and continuing generation, first-time freshmen (CGFF) usage statistics for the Mathematics Assistance Center (MAC) for the Fall 2014 semester?
3. How do the usage statistics of continuing generation, first-time freshmen (CGFF) compare to first-generation, first-time freshmen (FGFF) for the Mathematics Assistance Center (MAC) for the Fall 2014 semester?

Literature Review

First Generation (FG) College Students

Literature suggests that there are several workable definitions for FG college students. A meta-analysis of definitions provided us with an understanding that differences are contingent upon the amount of college completed by a student's parents or guardians. At our institution, we define FG students as individuals from families in which neither the student's father nor mother attended college (M. Hansen, personal communication, October 26, 2015). Though our research uses this definition, it is important to recognize that the definition of a FG college student varies among higher education literature. Specifically, some definitions refer to parent(s) or guardian(s) attending college, yet others are more restrictive and require that the parent(s) or guardian(s) graduate with a degree (Ward, Siegel, & Davenport, 2012). This cohort is a large subset of the all-undergraduate student enrollees. More precisely, 2011-2012 census data showed that roughly 34% of undergraduate students have parents whose highest level of education is a high school diploma or less (U.S. Department of Education, 2014, p. 101). These students are navigating the complexity of higher education as the first representatives of their families. This limits the support that families can provide these students, such as understanding how to "…adapt to changing academic and social expectations" (Ward, Siegel, & Davenport, 2012, p. 20).

Terenzini, Springer, Yaeger, Pascarella, and Nora (1996) conducted a longitudinal study, as a part of the National Study of Student Learning (NSSL), which demonstrated that the college experiences and success rates for FG college students are different in fundamental ways from their continuing generation peer students. NSSL results suggested that FG students have factors limiting their ability to interact collectively with the content of their courses. For example, FG students were found to spend significantly less time-on-task with academic content, and they have a higher rate of working off-campus, non-academic-focused jobs (Terenzini et al., 1996). Recent studies find consistent conclusions to these decades-old findings. For example, Stebleton and Soria (2012) studied perceived barriers between FG students and continuing generation students.

They found that FG students experienced more job responsibilities, family responsibilities, weak mathematics and literacy skills, as well as higher rates of stress-related depression and anxiety while engaged with their academic work.

The aforementioned factors link to a concerning theme that FG students have a higher risk of attrition (Choy, 2001; Ishitani, 2006; Lohfink & Paulsen, 2005; Nunez, 1998; Pratt & Skaggs, 1989); lack of persistence (Lohfink & Paulsen, 2005); lower rates of campus social integration (Nunez, 1998); and also have overall lower high school GPA and test scores compared to their peers (Atherton, 2014). Literature therefore suggests that this cohort of students encounters greater challenges in persisting to graduation than their continuing generation peers.

University-sponsored Academic and Social Integration

Research suggests that reasonable levels of social and academic-centered campus support can provide positive gains in influencing students' persistence and success in undergraduate study (Bank, Slavings, & Biddle, 1990; Callahan, 2008; Liu & Liu, 2000). However, positive gains are not linked to institutions offering the services alone. It is important to understand the equity in access to the services by different cohorts of students. For example, Engle and Tinto (2008) found differences within the FG student cohort. FG students, who are also identified as low-income students, are less likely than their peers to utilize supportive resources on campus or study together. The logical conclusion is that campuses can provide resources; but if the FG students, for complex social-cultural reasons, are not utilizing the resources, then the intervention is inconsequential for those students. Therefore, we intend to contribute to this body of knowledge by better understanding the utilization of our learning center by first-year, FG students. The analysis of student utilization rates can tell us more about the ability of a campus-supported resource, like our LC modeled centers, to positively influence the retention and success rates of undergraduate students.

Methodology

Participants

The participants of this study are members of the Fall 2014 freshman class at a large Midwestern urban university campus. There are 3,584 students in this cohort, and all data was collected through a partnership with Institutional Research and Decision Support (IRDS).

Data Collection

For this exploratory analysis, we looked at the characteristics listed in Table 1 in the Appendix. Data collection and tracking mechanisms necessitated the cleaning of the data. For a full description of the tracking data cleaning methodology, please see the notes in the Appendix.

Data Analysis

After the data collection and cleaning phase, we sorted the data for analysis by filtering observations by TOT_MATH_HRS>0 to determine the FGFF college students and CGFF students who enrolled in at least one mathematics course. This statistical data is considered categorical data, or variables that can be assigned to particular groups (categories). To obtain the likelihood that differences between categories arose by chance or another factor, we chose to utilize the Pearson Chi-Square test. This would allow us to test the hypothesis that there is a difference between the FGFF and CGFF cohorts of students in terms of their usage statistics for the MAC.

Our second analysis was done through a cross-comparison between the means of average time per visit of the FGFF and CGFF student cohorts. For this analysis, we chose to utilize an independent sample *t*-test for verifying the equality of the mean average time per visit of the FGFF and CGFF student populations.

Results

The purpose of our analysis was first to answer the question of what are the first-time freshmen (FF) usage statistics for the MAC for the Fall 2014 semester? As mentioned in the methods section, the FF Fall 2014 cohort at our institution consisted of 3,584 students, of which 2,840 students enrolled in at least one mathematics course. Of this 2,840, 1,526 attended the MAC at least once. This reveals that 53.7% of first-time freshmen enrolled in at least one mathematics course visited the MAC at least once. The average time per visit for these participants was 1.12 hours (SD= .55). The average number of visits during the semester was 8.88 (SD= 10.98) for those who attended the MAC at least once. The distribution for the average time per visit appeared to be roughly normally distributed (see figure 1 in the Appendix).

For the second research question we intended to investigate the first-generation, first-time freshmen (FGFF) and continuing generation, first-time freshman (CGFF) usage statistics for the MAC for the Fall 2014 semester. For FGFF, 979 students enrolled in at least one mathematics course in the Fall 2014 semester. Of this group, 520 or 53.1% attended the MAC at least once. The average time per visit for these participants was 1.15 hours (SD= .60). The average number of visits was 7.93 (SD= 9.98). Parsing the data further, we found that there were 1,861 CGFF who took at least one mathematics course. Of those, 1,006, or 54.1% visited the MAC at least once. The average time per visit was 1.11 hours (SD= .52). The average number of visits was 9.38 (SD= 11.44).

Next we intended to compare usage statistics between CGFF and FGFF for the MAC for the Fall 2014 semester. Using the Pearson chi-Square test (χ^2 (1)= .23, p= .63), we can conclude that there is not a significant difference in the proportion of students in the FGFF and CGFF cohorts who attended the MAC at least once. Through using the t-test for equality of means (t(1524)= -1.28, p= .2), we found that there is no statistical difference in the average time per visit for FGFF students and CGFF students.

We can conclude that there is not a significant statistical difference in the usage statistics between the two cohorts. The results from the t-test for equality of means and the Pearson chi-square test permits us to conclude that there is a high likelihood that the differences between the data sets is by chance. The results of our analysis are summarized in the tables in the Appendix.

Discussion

Our results indicate that the MAC usage by FGFF and CGFF students does not differ significantly. This differs from previous studies that have documented FGFF students as less inclined to utilize support services on campuses and therefore limiting the impact those resources can make on the students' educational experiences. This initial finding is promising, as it may support the conclusion that the open-access learning center design, on our campus, is promoting student usage from various cohorts at the same rates. These preliminary findings suggest that our center, for the Fall 2014 academic semester, decreased the inequities between student cohorts established in research literature. Further longitudinal research will be necessary to validate these findings. It is worth noting that nearly half of the students who took a mathematics course on our campus did not utilize our learning center. Therefore, our findings are limited; we can only conclude for now that the attendance rates for the Fall 2014 semester at our center did not differ by first-generation student status. As next steps, we intend to analyze a three-year longitudinal study of the visitation data to enhance our ability to make claims about this trend and further validate it as a contradiction to previously established research.

The Research Agenda

We are intrigued to further investigate how to best quantitatively analyze the impact of learning centers on student retention, learning, and academic achievement in the context of mathematics. Our hope is to provide our colleagues with an easily accessible quantitative analytics package to help tell the story of the impact of their programs.

Our initial research into this agenda suggests a complexity of interaction inherent in learning that renders certain quantitative analyses as incomplete or at best inadequate. Literature suggests that these processes can be defined as sequential processes (e.g., student-to-student interactions, student-to-teacher interactions, etc.). Explicit examples of this can be found in Chiu and colleagues' work from the last decade (Chiu, 2004; Chiu & Khoo, 2003, 2005). Chiu and Khoo (2005) warn researchers engaged with this work that there are inherent difficulties in trying to quantify complex social and academic interactions. The complexity relates to how researchers can reliably define social and learning situations, because the researcher acts as a filter for understanding what is happening in the social situation. Researchers continue to develop their capabilities for working with complex data sets, such as the data we are proposing for this research study and future work. Methodologies that we have used in our own preliminary research and that have been used in existing literature (Chiu, 2004; Chiu & Khoo, 2003, 2005) include but are not limited to:

- Conditional Probabilities
- Sequential Analysis
- Pre-post comparison examinations
- Logit
- Comparisons of metrics (e.g., Drop-Fail-Withdrawal [[DFW]] rates for courses)
- Dynamic Multi-level Analysis (DMA)

Chiu and Khoo (2005) give a cross-comparison between many of these techniques that will act as the basis of our research group's own preliminary analysis. We intend to find the most rigorous statistical analysis methods accepted by researchers in this field to examine the impact of learning centers.

Despite the complexity of this endeavor, we are passionate about fully understanding how to show the impact of student success and return on investment in a rigorous quantitative manner. We intend to be forthright with all of our findings. This includes reporting ethical dilemmas and results that potentially point to the inability for quantitative research to capture the essence of learning center impact on students, should those results emerge from the data. This will enable the learning assistance community to refine our services and allocate resources effectively. This will help us do the work that we all strive to do, which is to better understand how to provide high-quality academic experiences for all students who attend our institutions.

References

Atherton, M. C. (2014). Academic preparedness of first-generation college students: Different perspectives. *Journal of College Student Development, 55*(8), 824-829.

Ball, D. L., Thames, M. H., & Phelps, G. (2008). Content knowledge for teaching: What makes it special? *Journal for Teacher Education, 59,* 389-407.

Bank, B. J., Slavings, R. L., & Biddle, B. J. (1990). Effects of peer, faculty, and parental influences on students' persistence. *Sociology of Education, 63*(3), 208-225.

Callahan, K. M. (2008). Academic-centered peer interactions and retention in undergraduate mathematics programs. *Journal of College Student Retention: Research, Theory and Practice, 10*(3), 361-389.

Carpenter, K., & Johnson, L. (1991). Program organization. In R. F Flippo & D. C. Caverly (Eds.), *College reading & study strategy programs* (pp. 31-33). Newark, DE: International Reading Association.

Charles A. Dana Center. (2012). *Core principles for transforming remedial education: A joint statement.* Retrieved from http://www.completecollege.org/docs/Remediation_Joint_Statement-Embargo.pdf

Chen, X. (2013). STEM attrition: College students' paths into and out of STEM fields [NCES 2014- 001]. Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Retrieved from http://files.eric.ed.gov/fulltext/ED544470.pdf

Chiu, M. M. (2004). Adapting teacher interventions to student needs during cooperative learning: How to improve student problem solving and time on-task. *American Educational Research Journal, 41*(2), 365-399.

Chiu, M. M., & Khoo, L. (2003). Rudeness and status effects during group problem solving: Do they bias evaluations and reduce the likelihood of correct solutions? *Journal of Educational Psychology, 95*(3), 506.

Chiu, M. M., & Khoo, L. (2005). A new method for analyzing sequential processes dynamic multilevel analysis. *Small Group Research, 36*(5), 600-631.

Choy, S. (2001). Students whose parents did not go to college: Postsecondary access, persistence, and attainment. *Findings from the Condition of Education,* 2001. Retreived from http://nces.ed.gov/pubs2001/2001072_Essay.pdf

Davis, B. (2008). Complexity and education: Vital simultaneities. *Educational Philosophy and Theory, 40*(1), 50-65.

Davis, B., & Renert, M. (2013). Profound understanding of emergent mathematics: Broadening the construct of teachers' disciplinary knowledge. *Educational Studies in Mathematics, 82,* 245-265.

Davis, B., & Sumara, D. (2008). Complexity as a theory of education. *Transnational Curriculum Inquiry, 5*(2), 33-44.

De Guzmán, M., Hodgson, B. R., Robert, A., & Villani, V. (1998). *Difficulties in the passage from secondary to tertiary education.* Paper presented at the proceedings of the International Congress of Mathematicians, Berlin, Germany.

Engle, J., & Tinto, V. (2008). Moving beyond access: College success for low-income, first-generation students. *Pell Institute for the Study of Opportunity in Higher Education*. Retrieved from http://files.eric.ed.gov/fulltext/ED504448.pdf

Ernest, P. (1985). The philosophy of mathematics and mathematics education. *International Journal for Mathematics Education in Science and Technology, 16*(5), 603-612.

Freudenthal, H. (1983). *Didactical phenomenology of mathematical structures.* Boston, MA: D. Reidel.

Gayles, J. G., & Ampaw, F. D. (2011). Gender matters: An examination of differential effects of the college experience on degree attainment in STEM. *New Directions for Institutional Research, 152,* 19–25.

Gueudet, G. (2008). Investigating the secondary–tertiary transition. *Educational Studies in Mathematics, 67*(3), 237-254.

Ishitani, T. T. (2006). Studying attrition and degree completion behavior among first-generation college students in the United States. *Journal of Higher Education, 77*(5), 861-885.

Liu, R., & Liu, E. (2000). Institutional Integration: An Analysis of Tinto's Theory. Paper presented at the Annual Forum of the Association for Institutional Research, Cincinnati, OH. Retrieved from http://files.eric.ed.gov/fulltext/ED445629.pdf

Lohfink, M. M., & Paulsen, M. B. (2005). Comparing the determinants of persistence for first generation and continuing-generation students. *Journal of College Student Development, 46*(4), 409-428.

Mamona-Downs, J., & Downs, M. (2008). Advanced mathematical thinking and the role of mathematical structure. In L. English (Ed.), *Handbook of international research in mathematics education* (pp. 154-175). New York, NY: Routledge.

Nunez, A. M. (1998). First-generation students: A longitudinal analysis of educational and early labor market outcomes. Paper presented at the ASHE Annual Meeting, Miami, FL. Retrieved from http://files.eric.ed.gov/fulltext/ED427599.pdf

Perin, D. (2004). Remediation beyond developmental education: The use of learning assistance centers to increase academic preparedness in community colleges. *Community College Journal of Research & Practice, 28*(7), 559-582.

Pratt, P. A., & Skaggs, C. T. (1989). First generation college students: Are they at greater risk for attrition than their peers? *Research in Rural Education, 6*(2), 31-34.

Renert, M., & Davis, B. (2010). Life in mathematics: Evolutionary perspectives on subject matter. In M. Walshaw (Ed.), *Unpacking pedagogy* (pp. 177-199). Charlotte, NC: Information Age Publishing.

Rubin, M. (1991). A glossary of developmental education terms: Compiled by the CRLA Task Force on Professional Language for College Reading and Learning. *Journal of College Reading and Learning, 23*(2), 1-13.

Sfard, A. (1998). A mathematician's view of research in mathematics education: An interview with Shimshon A. Amitsur. In *Mathematics education as a research domain: A search for identity* (pp. 445-458). Dordrecht, Netherlands: Springer.

Stebleton, M., & Soria, K. (2012). Breaking down barriers: Academic obstacles of first generation students at research universities. *The Learning Assistance Review, 17*(2), 7-19.

Stern, S. (2001). Learning assistance centers: Helping students through. *ERIC Digest.* Retreived from http://eric.ed.gov/?id=ED455901

Terenzini, P. T., Springer, L., Yaeger, P. M., Pascarella, E. T., & Nora, A. (1996). First-generation college students: Characteristics, experiences, and cognitive development. *Research in Higher Education, 37*(1), 1-22.

U.S. Department of Education (2005). First-generation students in post-secondary education: A look at their college transcripts. *National Center for Education Statistics.* Retrieved from http://files.eric.ed.gov/fulltext/ED485756.pdf

U.S. Department of Education. (2014). Profile of undergraduate students: 2011-2012 (Web Tables). *National Center for Education Statistics.* Retrieved from http://nces.ed.gov/pubs2015/2015167.pdf

Varela, F., Thompson, E., & Rosch, E. (1991). *The embodied mind: Cognitive science and human experience.* Cambridge, MA: MIT Press.

Ward, L., Siegel, M. J., & Davenport, Z. (2012). *First-generation college students: Understanding and improving the experience from recruitment to commencement.* San Francisco, CA: Jossey-Bass.

Yusof, Y. M., & Tall, D. (1998). Changing attitudes to university mathematics through problem solving. *Educational Studies in Mathematics, 37*(1), 67-82.

Appendix

If a student forgot to sign out of the learning center, the system codes his or her time as zero minutes; consequently, we had ten observations that had unreasonably small average times for multiple visits. To remedy this problem, if a student had more than one visit (MAC_TOT_VISITS >1) and average time per visit less than 10 minutes (MAC_AVG_TIMEPERVISIT < 10), we imputed the mean average time per visit, x=1.11 for the MAC_AVG_TIMEPERVISIT variable.

Table 1

Variables Used in Analysis

Name	**Description**	**Values**
FGEN	First Generation	1=Yes 0=No
TOT_MATH_HRS	Total hours of math taken	Numeric
MAC_PARTIC	Attended MAC at least once	1=Yes 0=No
MAC_TOT_VISITS	Total visits to MAC	Numeric
MAC_TOT_HRS	Total hours in MAC	Numeric
MAC-AVG_TIMEPERVISIT	Average time per visit (total hours divided by total visits)	Numeric

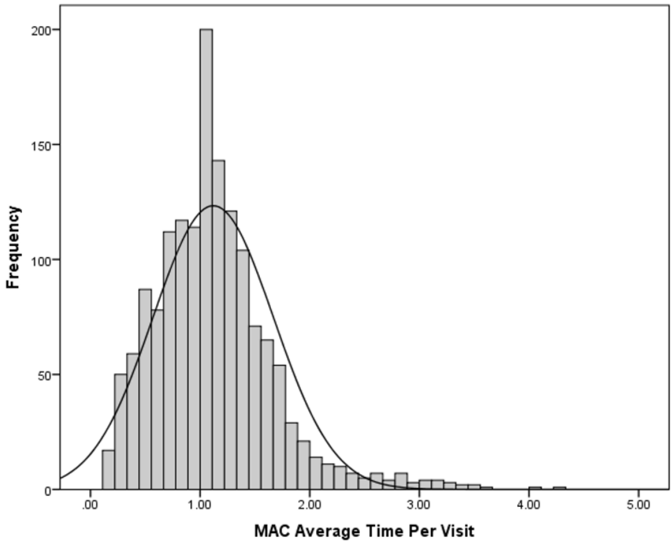

Figure 1. Average time per visit for all freshmen in the Fall 2014 cohort who visited the MAC.

Table 2

Usage Statistics for all Freshmen in the Fall 2014 Cohort

Groups	***n***	***%***	***M***	***SD***
First-Time, Full-Time Freshmen	2840	53.7	1.12	0.55
First Generation, First-Time Freshmen	979	53.1	1.15	0.60
Continuing Generation, First-Time Freshmen	1861	54.1	1.11	0.52

Note. n represents the number of students who enrolled in a math course for the Fall 2014 semester. % represents percent of students enrolled in at least one math course who attended the MAC. M represents the mean average time per visit. The chi-squared result was insignificant between first generation and continuing generation freshmen (χ^2 (1)=.23, *p*=.63), and the independent sample t-test for M (average time per visit) for first generation and continuing generation freshmen was also insignificant (*t*(1524)= -1.28, *p*= .20).

Table 3

Analysis of First-Generation and Continuing-Generation Students

	First-Generation Students	Continuing-Generation Students
Number Enrolled in at Least One Math Course	979	1861
Percent (%) Visited the MAC at Least Once	53.1	54.1
Chi-Square Result Significance	(1)= .23 p= .63	
Average Time Per Visit	1.15	1.11
Standard Deviation	.60	.52
t-Test Result Significance	t= -1.28 p= .2	