# "An outcome evaluation of an adult education and postsecondary alignment program: the Accelerate New Mexico experience"

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| **AUTHORS** | Mario A. Rivera<br>Michael Howland Davis<br>Andrew Feldman<br>Carla Rachkowski |
| **ARTICLE INFO** | Mario A. Rivera, Michael Howland Davis, Andrew Feldman and Carla Rachkowski (2013). An outcome evaluation of an adult education and postsecondary alignment program: the Accelerate New Mexico experience. *Problems and Perspectives in Management*, *11*(4) |
| **RELEASED ON** | Tuesday, 10 December 2013 |
| **JOURNAL** | "Problems and Perspectives in Management" |
| **FOUNDER** | LLC "Consulting Publishing Company "Business Perspectives" |

# SECTION 3. General issues in management

Mario A. Rivera (USA), Michael Howland Davis (USA), Andrew Feldman (USA), Carla Rachkowski (USA)

# An outcome evaluation of an adult education and postsecondary alignment program: the Accelerate New Mexico experience


## Abstract

Accelerate Math Camp, a federally-funded project of the Accelerate Technical Training and Job Placement Program (hereafter Accelerate New Mexico), has been carried out for three consecutive years (2011-2013) in six college campuses in northern New Mexico, in the Southwestern United States. Accelerate Math Camp has uniquely demonstrated statistically significant achievement of learning outcome goals by nontraditional students striving to enter or reenter a very competitive job market in STEM (Science, Technology, Engineering, and Math) related fields. Most remarkably, students of all backgrounds – men, women, racial and ethnic minorities, and majority students – have fared equally well in the 2013 Accelerate Math Camp. The program evaluation here reported found exceptionally positive results across the six program sites for student participants fitting every socio-demographic profile.

This finding runs counter to the vast majority of published evaluations of similar programs – in the United States and Europe alike. These tend to show ambiguous learning outcomes at best, along with lower levels of accomplishment for women and minority students, both of whom are historically underrepresented in STEM fields. What limited findings of success may be reported occasionally in the academic and practitioner literature very often lack statistical rigor, and therefore generalizability and replicability. The present study runs counter to this trend, reporting historically unique, demonstrable success for this initiative, and providing a replicable model for aligned postsecondary education and employability programs.


**Keywords:** adult basic education, employability training, postsecondary/labor market alignment, nontraditional students, diversity, empirical modeling, online learning, intelligent tutors (in computer-based, online education), remedial mathematics education, program evaluation.
**JEL Classification:** L30, I20.

## Introduction

The Accelerate New Mexico (NM) Math Camp is a collaborative partnership among six public Northern New Mexico colleges and the Regional Development Corporation (RDC), based in Española, New Mexico, U.S.A. Accelerate Math Camp is a core component of a federally-funded employability training/retraining program managed by the RDC. The RDC's success in managing these kinds of initiatives, in the context of local economic development, is itself a factor in the increasing success of the Math Camp as it has progressed through three program years – 2011, 2012, and 2013. The RDC was selected by the International Economic Development Council for its award for excellence in 2012, an indication both of the RDC's commitment to transformational programming and its capacity for success in such efforts.

The key goals of the Accelerate partnership just described are to increase the number of nontraditional and underrepresented minority student graduates in STEM fields at northern New Mexico's two and four-year postsecondary institutions, providing participants with effective employability training and support and comprehensive job placement services (Accelerate NM, 2012). The program engages student participants with four key interventions and resources: the Accelerate Math Camp, Career Technical Advisors, Professional Readiness Events, and Internships with local and regional employers (which sometimes lead to permanent jobs).

Accelerate Math Camp is – literally – an instance of an accelerated (or compressed) math program that allows students to move through multiple remedial mathematics courses in a single summer semester so they can begin career-related coursework, in many instances expected to lead to technical or professional degrees in STEM fields. The Math Camp is an instance (as the name suggests) of the application of acceleration strategies in adult, nontraditional student preparation for college or technical school, relying on hybrid (live and online) course designs.

A robotics curriculum (using Carnegie Mellon Robotics Academy LEGO Mindstorms, Ihme, 2013) has been fitted to the math content of the widely adopted ALEKS online courseware (of McGraw Hill Education), complementing ALEKS, grounding it in hands-on practice, and successfully promoting student collaboration in problem-solving. The ALEKS acronym stands for "Assessment and Learning in Knowledge Spaces" (ALEKS Corporation, 2013).

In 2013 Accelerate's lead consultant for the robotics course created supplementary math exercises to accompany robotics activities and led training for instructors in the new combined robotics/adjunct math curriculum before the launch of the 2013 Math Camp. These efforts, a culmination of decisions taken is 2012, have created a singular synergy between the new courseware – ALEKS – and hands-on robotics lab activities. The success of Math Camp in 2013 is in part due to this concerted, coordinated curriculum – instructor and student reactions have been uniformly positive, in contrast to uneven course and instructor evaluation feedback in 2012.

## 1. Program need

Cartnal (1999), Quinn (2003) and many other researchers in the United States and Europe have found that these kinds of transitioning programs have not met with clear-cut success among adult learners trying to re-enter the job market or otherwise transition to postsecondary education, especially in STEM fields (see also Leinbach, Pountney and Etchells, 2002). When there are claims of success, these tend to be anecdotal rather than supported by robust analysis.

While a labor market transition program, Accelerate is also an instance of a diversity recruitment program addressing educational access and retention for underrepresented minority as well as nontraditional students. Such diversity programs commonly use integrated program strategies that include intensive recruitment, financial aid, specialized instruction, and intensive advising and academic support (Teitelbaum, 2011). Again, however, neither the academic nor practitioner literature provides real evidence of sustained success for these kinds of endeavors.

The Accelerate program covers Math Camp tuition and pays a stipend for student attendance and participation in the program and associated events. The stipend serves to offset some lost or foregone employment income for certain students. Student participants are assigned Technical Career Advisors who provide them academic advisement and also help them navigate their educational institutions. Advisors conduct professional readiness events, secure internships, and provide job placement services in what is a fairly typical employability training program.

Ibarra (2001) notes that while employability re/training initiatives may play an important role in facilitating minority success, most of these do not address "…the content and methods of delivering education to all kinds of students, which is the actual business of education within these [transitioning programs]" (p. 8). However, the Accelerate Math Camp is fundamentally different in the way that curriculum and curricular delivery are tailored to its diverse students.

Contrary to the expectations established in both the academic and practitioner research literatures, Accelerate Math Camp has demonstrated success in reaching ethnically-, culturally-, and gender-diverse students, strengthening their content-mastery and self-efficacy in math, particularly introductory and intermediate algebra. While the Math Camp's pre-tests show the customary breakdown by demographic background, with minority and female students faring much less well than their majority counterparts, post-test results for the 2013 show that these same students either meet or exceed the learning outcomes of their majority (white, male) peers. To the authors' knowledge, given established research on the subject, this is the first time that such math learning outcomes have been found and demonstrated empirically for the kind of student population just described. These findings are summarized in the sections that follow.

## 2. The 2013 evaluation approach

The 2013 evaluation of the Accelerate Math Camp reported in this study relied on reflexive controls in the form of cross-site and longitudinal (year-to-year) program impact comparisons, complementing statistical analysis with observational research, focus groups and interviews, document review, and research synthesis in a mixed-methods evaluation design (Creswell, 2009; Glaser & Strauss, 1967; Guest, Bunce & Johnson, 2006). Evaluation design in 2013 included a quasi-experimental pre-test/post-test assessment of mathematics achievement and (through use of the standard ABE pre/post math attitude survey) measures of attitudes toward and self-efficacy in mathematics (Xin & Kishor, 1997). Since randomized assignment was neither possible nor desirable in this instance, the six campus cohorts served as comparison sites for one another, approximating a quasi-experiment with cross-site comparisons (Posavac, 2011; Rossi, Lipsey, & Freeman, 2004; Singleton, Jr. & Straits, 2010; Babbie, 2013).

The quantitative analysis provided in this essay for 2013 is substantially improved over a similar one undertaken in 2012 because it controls for confounding and moderating socio-demographic factors that are common to educational programs (ethnicity, gender, socioeconomic status, and age often emerge as constraining factors in this regard). The 2013 evaluation also improves on its predecessor in incorporating and analyzing the effects of embedded features of student measures.

Similarly, consistent with the rationale of the ALEKS courseware and the 2013 Math Camp curriculum, the 2013 evaluation predicates student success on the following interrelated factors: (1) the amount of time working with the online courseware, instructors, and tutors; (2) the developmental relationships students attain with instructors, tutors, and peer mentors; and (3) the concurrent effects of collaborative, contextualized learning. This is accomplished by analyzing ALEKS post-course content-mastery measures as measured against pre-test levels of mathematics mastery. End-of-course evaluations are used to assess student perceptions of teacher and tutor effectiveness, of the pace and format of the ALEKS-based mathematics course, and of the robotics lab curriculum. These student-related measures of program success are gauged against instructor perspectives as gathered in both one-on-one and focus group interviews.

## 3. 2013 data analysis

Data for the 2013 Math Camp evaluation was collected by instructors and compiled by the RDC, under the direction of the Accelerate Program Manager – compilation and systematization of demographic data was an instance of the deliberate incorporation of lessons learned in 2012. Data collection included individual pre-test/post-test results for content mastery in mathematics as assessed in and through the ALEKS courseware, along with pre-test/post-test scores for the Adult Basic Education Survey of Attitudes toward Mathematics (Brewer, 2007). Demographic included student ethnicity, gender, and age. The effects of ethnicity, gender, and age on attitudes toward math, on content mastery and self-efficacy in STEM subjects, and on anticipated success in STEM careers – all well documented in the literature – were to be tested in the 2013 evaluation and are reported here (Cohen & Ibarra, 2005; Ibarra, 2001; Sandia National Laboratories, 1993; Teitelbaum, 2011).

The 2013 evaluation utilizes multivariate regression analysis – specifically two Ordinary Least Squares (OLS) regression models and a multilevel mixed-effect Analysis of Variance (ANOVA) – to both demonstrate the efficacy of the 2013 Math Camp and to examine the effects of the new ALEKS courseware as incorporated in the Math Camp curriculum. As suggested in earlier characterizations of the literature and as summarized in the section that follows, results indicate that the Accelerate Math Camp in 2013 broke new and significant ground with regard to the aggregate achievement levels and content mastery gains of minority and women students.

The 2013 Math Camp cohort is 60% female, which is consistent with postsecondary enrolment rates throughout the United States. The average age of student cohort members is 27 years-old – with the youngest student being 17-years-old and the oldest 54-years-old. The self-reported racial and ethnic make-up of the cohort is as follows: 27 percent – White, 66 percent – Latina/o, 4 percent – Native American, 2 percent – African-American, and 2 percent – Asian. Descriptive statistics for student, instructor, and tutor demographics are given in Table 1.

Table 1. Descriptive statistics

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Age | 55 | 26.76 | 9.43835 | 17 | 54 |
| Pre-test CM | 55 | .220735 | .1958653 | .0057803 | .99 |
| Pre-test CM | 55 | .6358475 | .2463737 | .11 | 1 |
| ABE pre-test | 55 | .4554545 | .2140856 | .11 | .94 |
| ABE post-test | 55 | .3581818 | .2009246 | 0 | .88 |
| Robotics | 55 | 3.612727 | 1.14747 | 1 | 5 |
| Math Camp | 55 | 3.725455 | .9493113 | 1 | 5 |
| Format/pace | | | | | |
| Tutors | 55 | 4.625455 | .6678374 | 3 | 5 |
| Teachers | 55 | 8.68 | 1.846558 | 3 | 10 |
| Time in ALEKS | 55 | 67.44873 | 40.19272 | 7.4 | 193 |
| White: | 27% | | | | |
| Latina/o: | 66% | | | | |
| Native American: | 4% | | | | |
| African-American/Black | 2% | | | | |
| Asian: | 2% | | | | |
| Female: | 60% | | | | |

In 2013 consistently effective instructional use of the ALEKS courseware, coupled with (1) a robotics lab enhanced with supplementary mathematics content and (2) a multi-modal pedagogical approach that combines both structured and unstructured learning activities with extensive tutoring and informal peer mentoring, led to the extraordinarily significant and substantial improvements in math content mastery here noted. There were also very marked and positive changes in attitudes toward mathematics and measures of self-efficacy in math.

It needs to be underscored that these findings are consistent (not substantially or significantly different) across demographics categories – they obtain irrespective of the 2013 cohort's ethnic make-up, gender or age-range. In fact, there are apparent and marginally statistically significant, findings that the cohort's female students performed somewhat better in ALEKS post-tests than did the male students, and minority students fared somewhat better than majority (white) students in the post-tests as well, which defies the extant literature. However, specific demographic-profile effects for Black, American Indian/Native American, and Asian American students are too small to provide a generalizable statistical analysis by themselves.

However, these findings (of higher post-test scores for women and minority students) are dramatic not only because they utterly defy contrary expectations that are well established in research but also because the *pre-test* ALEKS scores did reflect customary expectations of differential measures set along racial and ethnic demographic categories. These findings demonstrate unequivocally that the new, 2013 pedagogical approach to Math Camp worked exceptionally well.

What made the crucial difference was a particular combination of curriculum and courseware, experienced and skilled instruction and instructional support, an effective hands-on approach to mathematics (in the robotics lab), and a contextualized, collaborative approach to learning that markedly reduced – and in fact eliminated – the demographic achievement gap that practitioner and academic research would lead one to expect, especially as to ethnic minorities.

Students in the 2013 Combined Math Camp cohort improved their mathematics content mastery by a shift of more than 2 standard deviations – 22 percent to 64 percent. This finding is extremely significant: $p$ = 0.0001. Table 2 reports a Combined Content Mastery Pre-test |Post-test Paired $t$-test Comparison, accordingly.

Table 2. 2013 Math Camp combined content mastery pre-test/post-test paired $t$-test comparison

| Variable | Obs | Mean | Std. err. | Std. dev. | [95% conf. interval] |
|---|---|---|---|---|---|
| Pre-test CM | 55 | .220735 | .0264105 | .1958653 | .1677852 .2736848 |
| Post-test CM | 55 | .6358475 | .033221 | .2463737 | .5692434 .7024517 |
| Difference | 55 | -.4151125 | .0345783 | .2564394 | -.4844378 -.3457872 |
| Mean (diff) = mean (PREMAST – PSTMAST) | | | $t$ = -12.0050 | | |
| $H_o$: mean (diff) = 0 | | | Degrees of freedom = 54 | | |
| H1: mean (diff) < 0; $H_2$: mean (diff) ≠ 0; $H_3$: mean (diff) > 0 | | | | | |
| Pr($T$ < $t$) = 0.0000; Pr($T \neq t$) =0.0000; Pr($T$ > $t$) = 1.0000 | | | | | |

The Math Camp students also increased their positive attitudes toward mathematics – specifically, increased self-efficacy in math and reduced levels of math anxiety – as measured by the ABE (Brewer, 2007), by half a standard deviation – a reduction of about ten percent. This finding is extremely significant: $p$ = 0.00001 (Table 3).

Table 3. Accelerate NM Math Camp combined ABE pre-test/post-test: paired $t$-test comparison

| Variable | Obs | Mean | Std. err. | Srd. dev. | [95% conf. interval] |
|---|---|---|---|---|---|
| ABE pre-test | 55 | .4554545 | .0288673 | .2140856 | .3975791 .51333 |
| ABE post-test | 55 | .3581818 | .0270927 | .2009246 | .3038643 .4124994 |
| Difference | 55 | .0972727 | .0217616 | .1613881 | .0536434 .1409021 |
| Mean (diff) = mean (ABEPRE – ABEPST) | | | $t$ = 4.4699 | | |
| $H_o$: mean (diff) = 0 | | | Degrees of freedom = 54 | | |
| H1: mean (diff) < 0; $H_2$: mean (diff) ≠ 0; $H_3$: mean (diff) > 0 | | | | | |
| Pr($T$ < $t$) = 1.0000; Pr($T \neq t$) =0.0000; Pr($T$ > $t$) = 0.0000 | | | | | |

The statistical analysis undertaken in this section did not find a significant difference in the pre-/post-test math attitude measures between male and female students, as Table 4 indicates.

Table 4. One-way ANOVA: pre-test ABE/post-test ABE by gender

| Summary of ABE pre-test | | | |
|---|---|---|---|
| Gender | Mean | Std. dev. | Frequency |
| Male | .440909 | .203514 | 22 |
| Female | .465151 | .222426 | 33 |
| Total | .455454 | .214085 | 55 |

Table 4 (cont.). One-way ANOVA: pre-test ABE/post-test ABE by gender

| ANOVA | | | | | |
|---|---|---|---|---|---|
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .007757 | 1 | .007757 | .17 | .6848 |
| Within groups | 2.467206 | 53 | .046551 | | |
| Total | 2.474963 | 54 | .040370 | | |
| Summary of post-test ABE | | | | | |
| Gender | Mean | Std. dev. | Frequency | | |
| Male | .32590909 | .20174617 | 22 | | |
| Female | .37969697 | .20055369 | 33 | | |
| Total | .35818182 | .20092463 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .038189396 | 1 | .038189396 | 0.95 | 0.3354 |
| Within groups | 2.14182885 | 53 | .040411865 | | |
| Total | 2.18001824 | 54 | .040370708 | | |

At this stage of statistical analysis, the data did not show a substantial or statistically significant gender difference in either pre-test content mastery scores or post-test content mastery scores. However, the bottom of Table 5, following, actually shows that female students exited the program with slightly higher levels of content mastery than did male students. While credible, and important, this particular outcome is somewhat less than statistically significant for reasons pertaining to both the effect size and the size of the intervention cohort (*N*).

These unusual results – all evidence of the Math Camp's success in 2013, as measured against customary findings in national and international studies, as already noted, are closely tracked in content mastery outcomes for ethnic minority students; again the discernible result is that of somewhat higher learning outcome measures for these students, who had markedly lower pre-scores than the cohorts as a whole (Table 6). Variance by socio-demographic category is revisited under the Advanced Regression Modeling heading in the section that follows.

Table 5. One-way ANOVA: pre-test content mastery/post-test content mastery by gender

| Summary of content mastery pre-test | | | | | |
|---|---|---|---|---|---|
| Gender | Mean | Std. dev. | Frequency | | |
| Male | .22160843 | .15597056 | 22 | | |
| Female | .22015277 | .22084508 | 33 | | |
| Total | .22073504 | .19586526 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .00002797 | 1 | .00002797 | 0.00 | 0.9788 |
| Within groups | 2.07158474 | 53 | .039086505 | | |
| Total | 2.07161271 | 54 | .038363198 | | |
| Summary of content mastery post-test | | | | | |
| Gender | Mean | Std. dev. | Frequency | | |
| Male | .59196233 | .24119012 | 22 | | |
| Female | .66510429 | .24909576 | 33 | | |
| Total | .6358475 | .24637374 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .070616639 | 1 | .070616639 | 1.17 | 0.2849 |
| Within groups | 3.20718444 | 53 | .060512914 | | |
| Total | 3.27780107 | 54 | .06070002 | | |

Pre-test content mastery scores show extremely significant ($f = 6.81$, $p = 0.0002$) levels of variance that ranged from 30 percent to 99 percent, consistent with the research literature. Post-test content mastery scores point to very striking improvement from pre-test to post-test for minority students. The finding, at this stage, that there is no statistically significant difference in learning outcomes across ethnic groups (where there is customarily a large variance) points to an important program impact (Table 6); this question is revisited under the Advanced Regression Modeling section that follows, where a normalized OLS regression yields more markedly positive and statistically significant outcomes for both the Latina/o minority and female categories.

Table 6. One-way ANOVA: content mastery pre-test/post-test by ethnicity

| Summary of content mastery pre-test | | | | | |
|---|---|---|---|---|---|
| Ethnicity | Mean | Std. dev. | Frequency | | |
| Black | .36567164 | 0 | 1 | | |
| Asian | .99 | 0 | 1 | | |
| Latina/o | .19111108 | .16352953 | 36 | | |
| Native American | .0359641 | 0.4268628 | 2 | | |
| White | .25552188 | .16966845 | 15 | | |
| Total | .22073504 | .19586526 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .730800491 | 4 | .182700123 | 6.81 | 0.0002 |
| Within groups | 1.34081222 | 50 | .026816244 | | |
| Total | 2.07161271 | 54 | .038363198 | | |
| Summary of content mastery post-test | | | | | |
| Ethnicity | Mean | Std. dev. | Frequency | | |
| Black | .60447761 | 0 | 1 | | |
| Asian | 1 | 0 | 1 | | |
| Latina/o | .59654541 | .24838762 | 36 | | |
| Native American | .86599492 | .16199792 | 2 | | |
| White | .6773007 | .23471465 | 15 | | |
| Total | .6358475 | .24637374 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .32090985 | 4 | .080227462 | 1.36 | 0.2623 |
| Within groups | 2.95689122 | 50 | .059137824 | | |
| Total | 3.27780107 | 54 | .06070002 | | |

These statistics do show (predictably, according to the literature) strongly significant, $p = 0.0002$, differences on the content mastery pre-test (pre-camp mathematics mastery) between the minority and majority ethnic groups in the 2013 cohort. However, these differences were not found at all in the post-test content mastery results, where minority students actually scored at or above their majority peers. This very positive finding underscores the importance of continuing research in this Accelerate Math Camp program, because it could well serve as a demonstration program that may substantially reduce the demographic achievement gap in postsecondary adult education in mathematics, if its results can be generalized and its interventions replicated.

One of the drawbacks of this study, as already suggested, however, is that the sample size (cohort size), while substantial in general terms, is still relatively small [$n = 55$ students], as is the effect size, for purposes of statistical analysis. Implementation protocols that would warrant the establishment of Accelerate Math Camp as a best practice in the field would require both reiteration of the Math Camp instructional and evaluation protocols as implemented in 2013 and, if possible, a somewhat larger cohort size in the future. Variations in cohort size across the six participating campuses should also be minimized, for the sake of analytical reliability.

The greatest variation in the 2013 post-test content mastery scores occurred across campuses, rather than within campus cohorts (again, the expected variation of post-test scores by demographic category did not materialize). Cross-site variation may point to some degree of inconsistency in the way that the Accelerate Math Camp pedagogy was implemented from one campus to another in 2013 – although it is also clear that cross-site consistency was much higher in this regard in 2013 than in 2012.

Cross-site findings are provided in the following subsection, using college site acronyms as identifiers rather than the full title of participating colleges. It should be noted, however, that ‘UNM’ in every instance identifies a site that is part of the University of New Mexico system.

**3.1. Cross-site analysis.** One college, NNMC, made highly significant ($t = -6.929$, $p = 0.0062$) gains in content mastery – pre-test 4% and post-test 75%. As was true in 2012, the UNM-LA campus had the most significant ($t = -8.016$, $p = 0.0013$) gains in content mastery (64%) – with a pre-test mean of 17 percent and a post-test mean of 81 percent. This is a very large shift – 5 standard deviations – equivalent to a shift in grades from a grade of 'D' to a 'B' or 'B+.' This is a much larger improvement gain than was found in the 2012 evaluation. Although some of the variance in post-test gains could be attributable to class size, as well as the change to the ALEKS courseware, it is probable that the enhanced robotics curriculum also played a part in these learning outcomes. UNM-LA had the highest and most consistent rating for robotics (mean = 4.5 with std. dev. = .5).

By way of contrast, UNM-Taos had the lowest and least consistent rating for robotics (mean = 2.8714286 with std. dev. = 1.3941794), though it did rank a close second to UNM-LA in student learning outcomes – likely a product of quality of instruction and very high and sustained levels of enthusiasm among its students, who happened to comprise the largest site cohort (at 14 students). Sample size – larger in the case of UNM-Taos than UNM-LA, is also likely to account for the former site's success despite a less sustained and integrated robotics curriculum.

Though the impact of a relatively small cohort size and high pre-test scores must be considered as explanations here, the site with the least movement in student learning outcome gains pre- to post-test was SFCC. The difference between pre-test and post-test scores represents a statistically significant ($t$ = -4.964, $p$ = .0042 with a two-tailed test) gain (30%) in content mastery. However, higher pre-test scores will mean less movement in learning outcomes by the end of a course in any educational program. Quality of instruction and integration of robotics were both high at SFCC, and student gains were commensurate with the comparatively high levels of content mastery that students there enjoyed at the beginning of Math Camp in 2013.

Both LCC and NMHU had higher gains in content mastery than SFCC. At LCC, the difference between pre-test and post-test scores – 33% to 59% – represents a statistically significant ($t$ = -4.45, $p$ = = 0.0006) gain of 44% in content mastery. NMHU had a closely similar level of success. The difference between pre-test and post-test scores was significant ($t$ = -4.9, $p$ = .0002) – pre-test 24% and post-test 45% – representing a gain of 46% in content mastery.

Evaluator observations during site visits suggest explanations for some of these site-specific findings. At LCC, for example, students bonded well, spending very long hours with ALEKS in a computer lab across a hall from their classroom, a space they virtually appropriated and in which they worked closely throughout the summer session. This kind of development is not captured in the statistical analysis but still suggests a reason for large content mastery gains.

Overall, the 2013 Math Camp exhibited much greater and much more consistent gains than did the 2012 counterpart, which points toward key differences in curricula across the two program years. These also owe to a deliberate, across-the-board increase in the instructors' use of pedagogy proven in the 2012 Math Camp that emphasized multi-modal content, sufficiency of contact hours with instructors and tutors, cohort cohesion, and sustained collaborative learning. Table 7 indicates the cross-site variation in pre-test/post-test gains in math content mastery.

Table 7. One-way ANOVA: content mastery pre-test/post-test by campus

| | | | | | |
|---|---|---|---|---|---|
| Summary of content mastery pre-test by campus | | | | | |
| Campus | Mean | Std. dev. | Frequency | | |
| LCC | .33107191 | .20207965 | 11 | | |
| NMHU | .24666667 | .27364384 | 15 | | |
| NNMC | .04198087 | .03120624 | 4 | | |
| SFCC | .28609615 | .13605342 | 6 | | |
| UNM-LA | .17806083 | .10437545 | 5 | | |
| UNM-Taos | .14455939 | .08231034 | 14 | | |
| Total | .22073504 | .19586526 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | $F$ | $p > f$ |
| Between groups | .387791541 | 5 | .077558308 | 2.26 | 0.0633 |
| Within groups | 1.68382117 | 49 | .034363697 | | |
| Total | 2.07161271 | 54 | .038363198 | Bartlett's test for equal vatiances: $\chi^2$ (5) = 25.1612, $p$ = 0.0001 | |
| Summary of content mastery post-test by campus | | | | | |
| Campus | Mean | Std. dev. | Frequency | | |
| LCC | .5936228 | .24051079 | 11 | | |

Table 7 (cont.). One-way ANOVA: content mastery pre-test/post-test by campus

| | | | | | |
|---|---|---|---|---|---|
| Summary of content mastery post-test by campus | | | | | |
| NMHU | .45666667 | .28664729 | 15 | | |
| NNMC | .75144509 | .21571358 | 4 | | |
| SFCC | .69620928 | .1834165 | 6 | | |
| UNM-LA | .81761264 | .15436623 | 5 | | |
| UNM-Taos | .73719019 | .14153109 | 14 | | |
| Total | .6358475 | .24637374 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .32090985 | 4 | .080227462 | 1.36 | 0.2623 |
| Within groups | 2.95689122 | 50 | .059137824 | | |
| Total | 3.27780107 | 54 | .06070002 | Bartlett's test for equal vatiances: $\chi^2$ (5) = 7.0017, $p$ = 0.221 | |

Table 8. One-way ANOVA: ABE pre-test/post-test by campus

| | | | | | |
|---|---|---|---|---|---|
| Summary of ABEPRE | | | | | |
| Campus | Mean | Std. dev. | Frequency | | |
| LCC | .41454546 | .22857662 | 11 | | |
| NMHU | .378 | .18020622 | 15 | | |
| NNMC | .65000001 | .13735598 | 4 | | |
| SFCC | .59000001 | .17320508 | 6 | | |
| UNM-LA | .414 | .31476975 | 5 | | |
| UNM-Taos | .47214287 | .19884972 | 14 | | |
| Total | .45545455 | .21408564 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .380895225 | 5 | .076179045 | 1.78 | 0.1339 |
| Within groups | 2.09406841 | 49 | .04273609 | | |
| Total | 2.47496363 | 54 | .04583266 | Bartlett's test for equal vatiances: $\chi^2$ (5) = 3.4697, $p$ = 0.628 | |
| Summary of ABEPOST | | | | | |
| Campus | Mean | Std. dev. | Frequency | | |
| LCC | .40636364 | .23226161 | 11 | | |
| NMHU | .29066666 | .16524729 | 15 | | |
| NNMC | .53750002 | .18337122 | 4 | | |
| SFCC | .38833334 | .22031039 | 6 | | |
| UNM-LA | .25999999 | .24320772 | 5 | | |
| UNM-Taos | .36357143 | .17574488 | 14 | | |
| Total | .35818182 | .20092463 | 55 | | |
| ANOVA | | | | | |
| Source | SS | df | MS | *F* | *p > f* |
| Between groups | .276590582 | 5 | .055318116 | 1.42 | 0.2323 |
| Within groups | 1.90342766 | 49 | .038845462 | | |
| Total | 2.18001824 | 54 | .040370708 | Bartlett's test for equal vatiances: $\chi^2$ (5) = 2.1254, $p$ = 0.832 | |

Table 9. OLS regression: the standardized value of the content mastery post-test regressed on gender, age, ethnicity, content mastery pre-test, time, ABE post-test, the format/pace of the class, and robotics, tutor, and faculty evaluations

| Source | SS | df | MS | Number of obs. = 55 |
|---|---|---|---|---|
| | | | | $F$(10, 44) = 3.61 |
| Model | 2.04660813 | 10 | .204660813 | Prob. > $F$ = 0.0015 |
| Residual | 2.4953156 | 44 | .056711718 | $R^2$ = 0.4506 |
| | | | | Adj. $R^2$ = 0.3257 |
| Total | 4.54192373 | 54 | .084109699 | Root MSE = .23814 |

Table 9 (cont.). OLS Regression: the standardized value of the content mastery post-test regressed on gender, age, ethnicity, content mastery pre-test, time, ABE post-test, the format/pace of the class, and robotics, tutor, and faculty evaluations

| PSTMAST2 | Coef. | Std. err. | *t* | *P* > \|*t*\| | Beta |
|---|---|---|---|---|---|
| % female | .09352 | .0680673 | 1.37 | 0.176 | .1594443 |
| Age | .0044276 | .0042576 | 1.04 | .0304 | .1440859 |
| ETHDUMVAR | .1211251 | .0745962 | 1.62 | 0.112 | .2268219 |
| PREMAST | .8945397 | .2120502 | 4.22 | 0.000 | .604135 |
| TIME | .0041457 | .0010329 | 4.01 | 0.000 | .5745495 |
| ABEPST | -.4816507 | .1888741 | -2.55 | 0.014 | -.3336893 |
| FmtPace | -.0154066 | .0422125 | -0.36 | 0.717 | -.0504305 |
| Robotics | .0743808 | .0375194 | 1.98 | 0.054 | .2942924 |
| TUTORS | -.1250367 | .0698644 | -1.79 | 0.080 | -.2879289 |
| TEACHERS | -.0215787 | .0231384 | -0.93 | 0.356 | -.1373934 |
| constant | .4465574 | .3337908 | 1.34 | 0.188 | |

## 4. Advanced regression modeling

The preceding analysis provides a good foundation for the empirical confirmation of extraordinarily positive outcomes for the 2013 Accelerate Math Camp. In this section, the evaluation study further probes the role of instructor/student interaction, both program-wide and in relation to the robotics curriculum. Secondly, outcomes by socio-demographic category are also considered further. This final stage of statistical analysis begins with normalization of data.

Some definitions are necessary at this point. In statistics, OLS – ordinary least squares – regression is a generalized linear modeling technique used to estimate unknown parameters in a linear regression model; OLS minimizes the sum of squared vertical distances between data points in a given dataset and the responses predicted by linear approximation. Secondly, it should also be noted as a matter of definition that data normalization has a variety of meanings in statistics: for the regression tables and analysis that follow, normalization refers to a data transformation intended to bring the entire probability distribution of adjusted values into alignment, allowing comparison. In this case, values are normalized to eliminate data skewness.

In the second OLS model (Table 10) below, the data regarding perceived efficacy of teachers, robotics, and format pace was transformed as follows in order to normalize the data. In Table 10, the skew that was present in the raw data has been removed, using a zero-skew linear-logarithmic transformation for these categories of data (teacher, robotics, and format/pace) to normalize it; this transformation increases this regression model's adherence to projective OLS approximation methods. Furthermore, the values for the content mastery in mathematics pre- and post-tests were standardized, as were the values for math attitude/math anxiety. Also in Table 10, the addition of interaction term *teachers/robotics (IR Teach/Robo)* is intended to capture the ability of the instructors to properly use the robotics curriculum, including utilization of the supplementary mathematics content for robotics developed in 2013.

In the first OLS regression model carried out for this analysis, robotics was found to have explanatory significance but teachers and tutors were not, a counterintuitive and inconsistent finding. By modeling teacher/robotics interaction, the second, normalized regression reported in Table 10 indicates (in a much more commonsensical way) that robotics in and of itself is not a significant predictor of success but that *the interaction between teachers and students in and around the robotics curriculum is a highly significant and positive predictive factor*. This result is consistent with the core finding in this evaluation that teacher-student interaction is a highly significant predictor of curricular success, as are (broadly speaking) tutor-student and student-student collaborative interactions. Table 10 presents, the corresponding analysis.

Table 10. Normalized OLS regression model for the 2013 accelerate math camp

| Source | SS | df | MS | Number of obs. = 55 |
|---|---|---|---|---|
| | | | | $F(12, 42) = 4.11$ |
| Model | 2.4537987 | 12 | .204483225 | Prob. > $F$ = 0.0003 |
| Residual | 2.08812502 | 42 | .049717262 | $R^2 = 0.5403$ |
| | | | | Adj. $R^2 = 0.4089$ |
| Total | 4.54192373 | 54 | .084109699 | Root MSE = .22297 |

Table 10 (cont.). Normalized OLS regression model for the 2013 accelerate math camp

| Post-test CM | Coef. | Std. err. | *t* | *P* > \|*t*\| | Beta |
|---|---|---|---|---|---|
| Time | .0034703 | .0009624 | 3.61 | 0.001 | .4809342 |
| Math anxiety | -.5066794 | .1807232 | -2.80 | 0.008 | -.3510294 |
| Tutors | -.1276301 | .0658307 | -1.94 | 0.059 | -.2939008 |
| Teachers | -.2466833 | .0899881 | -2.74 | 0.009 | -1.265623 |
| Format/pace | .1199314 | .129552 | 0.93 | 0.360 | .1234047 |
| Robotics | -.0629403 | .1341989 | -0.47 | 0.641 | -.06899 |
| IR Teach/Robo | .1693502 | .0671072 | 2.52 | 0.015 | 1.143698 |
| Female | .1140865 | .0644065 | 1.77 | 0.084 | .1944918 |
| Age | .0005098 | .0042478 | 0.12 | 0.905 | .0165902 |
| Other ethn. | .23723 | .1404004 | 1.69 | 0.099 | .2143796 |
| Latina/o | .0284586 | .0879261 | 0.32 | 0.748 | .0470912 |
| Pre-test CM | .1313736 | .0366298 | 3.59 | 0.001 | .4529861 |
| Constant | .784706 | .4206112 | 1.87 | 0.069 | |

The coefficients for the Latina/o group as compared to both white and 'other ethnic' groups in the Math Camp cohort suggest that Latina/o students performed relatively better in post-testing. This normalized regression model has far more explanatory power than those models presented in the preceding data analysis section: $R^2$ = .54, adjusted $R^2$ = .41. This is an exceptionally important finding in the context of remedial STEM/employability education and training. This second, normalized regression model is able to explain 54 percent of the outcomes in terms of content mastery and is extremely significant, $p$ = .0003. In plain terms, there is 30,000$^{th}$ of 1 percent chance of these outcomes occurring as a result of mere chance

To repeat: The most significant single finding in the 2013 evaluation is that the combined content mastery results of the 2013 Math Camp program are shown statistically to eliminate and even reverse the ethnic achievement gap commonly found in remedial mathematics education. It also eliminates gender achievement gaps often found in STEM subjects. This outcome is simply unprecedented in any study of remedial STEM education (especially when tied to employability training) found through very extensive literature searches conducted for this study.

The entirety of the final regression model (Table 10) assesses the influence of time the students spent in the ALEKS courseware, attitudes toward math/math anxiety, student interactions with tutors and teachers[1], student evaluations of the format/pace of the class, student perceptions of the efficacy of robotics, and the interaction between student assessments of teachers and of the robotics curriculum. The model controls for gender, ethnicity, age, and pre-course mathematics content mastery. This normalized regression is superior to previous modeling carried out for this evaluation because findings in this second model are much more significant ($F$ = 4.11, $p$ = = 0.0003) and provide much greater explanatory power ($R^2$ = .54, Adj. $R^2$ = .408). As just suggested, furthermore, this second regression model suggests that robotics mediated and facilitated positive student learning outcomes, through reliance on intensive instructor-student interaction around a math-content enhanced robotics curriculum.

This analysis demonstrates that the amount of time spent in the ALEKS courseware and the amount of pre-course mathematics knowledge are the two largest predictors of success in the Accelerate Math Camp. What has also been demonstrated in the 2013 Math Camp is that curricular and pedagogical interventions must be tailored to specific classroom requirements and student needs. Instructors must be able to implement a tailored curriculum that resonates with students, wherever they are situated culturally and in terms of their individual life contexts.

Impacts by socio-demographic category of the Math Camp's dual curricula are further suggested in the following, normalized pre-math camp OLS regression models (Table 11).

Table 11. Accelerate NM 2013 pre-math camp OLS model

| Source | SS | df | MS | Number of obs. = 55 |
|---|---|---|---|---|
| | | | | $F$(5, 49) = 2.19 |
| Model | 9.86883984 | 5 | 1.97376797 | Prob. > $F$ = 0.0702 |
| Residual | 44.1311595 | 49 | .900635908 | $R^2$ = 0.1828 |
| | | | | Adj. $R^2$ = 0.0994 |
| Total | 53.9999993 | 54 | .999999987 | Root MSE = .94902 |

[1] The value set for student evaluations of teachers, format/pace of the class, and robotics was transformed to eliminate skew using a zero-skewness linear logarithmic transformation. The transformation returns the natural logarithm of the variable minus the number of variables or for example: $\ln(x_1 - k)$.

Table 11 (cont.). Accelerate NM 2013 pre-math camp OLS model

| PSTMAST2 | Coef. | Std. err. | *t* | *P* > \|*t*\| | Beta |
|---|---|---|---|---|---|
| Female | .064141 | .2677949 | 0.24 | 0.812 | .0317122 |
| Age | -.0264078 | .0166769 | -1.58 | 0.120 | -.2492322 |
| ABEPRE | -1.047167 | .642728 | -1.63 | 0.110 | -.2241833 |
| Other ethn. | .0763463 | .5610576 | 0.14 | 0.892 | .020009 |
| Latina/o | -.6616283 | .3411482 | -1.94 | 0.058 | -.3175148 |
| Constant | 1.572733 | .6384839 | 2.46 | 0.017 | |

The regression model depicted in Table 11 describes the 2013 Math Camp students' baseline content mastery as well as the pre-intervention effects of age, attitude toward math (math anxiety), gender, and ethnicity on the mathematics content mastery pre-test scores. What is important to note is that Latina/o students have *pre-test* scores that are much lower than the other ethnic groups, and that this effect (while not statistically significant at a 95% confidence interval) is significant at a 90% confidence interval. A further examination (below) of pre-test scores shows significant variance among ethnic groups, with Latina/o (Hispanic) students performing below the 'other'[1] category. Singularly for these Latina/o students, pre-camp content mastery as gauged by pre-test scores is *not* a good predictor of gains in knowledge in the course of Math Camp.

While the finding of very disparate content mastery scores in pre-testing is consistent with the literature, the pre-to post-movement in content mastery (cf. Table 5 and Table 10) is markedly different from expectations in the literature. As previously shown, post-program content mastery scores for female and Latina/o students actually exceed those for the 'other ethnic' as well as white students in the combined Math Camp cohort, an important outcome.

Table 12. Pre-test mathematics content mastery

| Ethnicity | Mean | Std. dev. | Frequency | | |
|---|---|---|---|---|---|
| Hispanic | .19111108 | .16352953 | 36 | | |
| White | ..25552188 | .16966845 | 15 | | |
| Other | .3479085 | .484543 | 4 | | |
| Total | | | | | |
| Source | SS | df | MS | *F* | Prob. > *F* |
| Between groups | .730800491 | 4 | .182700123 | 6.81 | 0.0002 |
| Within groups | 1.34081222 | 50 | .026816244 | | |
| Total | 2.07161271 | 54 | .038363198 | | |

**4.1. Courseware changeover.** The replacement of Cognitive Tutor with ALEKS courseware for Math Camp made a great deal of difference in 2013. This study therefore turns to a comparative assessment of these two well-known, commercial, intelligent-tutoring online courseware systems. CT and ALEKS are widely used for both regular and accelerated instruction in introductory college algebra (under the University of New Mexico course numbering system, MATH 99, 100, and 120).

About half of the Accelerate Math Camp students are aiming to reenter the job market after a period of under- or unemployment and/or a decision to retool for greater competitiveness and employability. The other half are coming to college directly out of high school. Whether there to retool for a job or to transition from high school to college, a typical Math Camp student either anticipates or already has had difficulty satisfactorily completing the common sequence of introductory, intermediate, and college algebra courses required for advancement in technical and professional majors (broadly defined) in two-year and four-year postsecondary institutions.

This difficulty with transition to college math is generalized across age groups and types of students in the United States at present, but is particularly acute among those nontraditional students returning to postsecondary courses of study after a hiatus in the workplace. Moreover, these same students often use up much or all of their financial aid and loans in taking and retaking these bridging courses. The Accelerate Math Camp endeavors to help these students get through some or all of this course sequence, and it does so (as the name suggests) in an accelerated fashion, over an eight-week period. Depending on the college site, student participants either receive college credit for successful completion of the given course sequence or position themselves to do well in a regular-semester offering of the same courses.

Two successive cohorts completed the Accelerate Math Camp in 2012 and 2013, with the 2012 group

[1] The 'other ethnic' category is combined black, Asian and American Indian students. This masks the performance of all three ethnic categories but is necessary to ensure student confidentiality.

using Cognitive Tutor plus robotics and the 2013 one using ALEKS plus robotics. This study now turns to a research synthesis on the relative strengths and weakness, and different theoretical foundations and operational modalities, of the two courseware systems, considering as well how these worked out for the Accelerate NM Math Camp in 2012 and 2013.

## 5. Assessing the cognitive tutor and ALEKS courseware options taken in 2012 and 2013

**5.1. The need for online courseware.** Math skills are found to be essential to successful job performance in an ever-wider array of skilled and semi-skilled jobs, in both technical and non-technical fields, in today's highly competitive employment market. Rigorous research is needed to assess why (1) many curricula implemented in high school and introductory college math classes are falling short of preparing students for success in the technical and STEM labor market, and (2) how this impediment can be overcome in retraining/employability programs such as Accelerate New Mexico.

**5.2. Carnegie learning's cognitive tutor.** Carnegie Learning's Cognitive Tutor (Carnegie Learning, 2011) is reportedly based on Adaptive Control of Thought-Rational (ACT-R) theory, in essence the modeling of human cognition in human-computer interaction (Anderson, 1996). Cognitive Tutor (CT) pioneered applications of ACT-R for online, self-paced instruction. CT assumes that students learn to solve math problems by examining examples of worked solutions, frequently through word problems. CT is premised on the capacity of word problems to add context to abstract math concepts and operations. Word problems contextualize such learning, CT developers say, by linking the abstract with the everyday experience and knowledge base of students (Anderson, 1996).

One difficulty with this set of premises is that real-life learning takes place in a particular cultural context and environment. Students whose lived experience differs from those of the courseware's developers may not – and usually do not – gain from this putative contextualization of learning. Instead, context is likely to obtain from interaction with others of similar cultural backgrounds, and of dissimilar backgrounds, as is found in the Math Camp classroom.

The Cognitive Tutor courseware is said to attempt to incorporate ACT-R as well as collaborative learning theory (Loll, F., Pinkwart, Scheuer & McLaren, 2011). However, in the Accelerate Math Camp experience in the summer of 2012, Cognitive Tutor fell short on these counts. Cognitive Tutor tended to isolate students in front of computer screens in their own learning tracks after the first week or two of instruction. CT was also found by instructors and students to lack user-friendliness, for instance in the use of 'help' prompts, which usually set the student back several steps in the problem-solving sequence and therefore in the course. These shortcomings prompted the changeover to ALEKS for summer 2013. ALEKS had the additional advantage of several years' adoption in the University of New Mexico system, for introductory algebra courses. At two of the six program sites, instructors were already familiar with ALEKS and were able to help those teachers in the remaining sites transition to this new courseware.

**5.3. ALEKS.** ALEKS is an intelligent tutoring system that reportedly builds on Knowledge Space Theory (KST) to imitate an expert teacher in assessing a student's base of subject matter mastery (Doignon & Falmagne, 1985). KST is not really a cognitive theory like ACT-R, but a learning theory. It posits that given a student response to a problem in a certain topic area, inferences can be made about what other questions in that and other topic areas s/he could answer. ALEKS thereby projects branching 'knowledge spaces' cast as learning maps (Falmagne et al., 1990).

These knowledge spaces are depicted by the ALEKS courseware for each user. A testing system weighs a student's prospective fields of math mastery by tracking responses in various categories of the sub-topic involved (for instance, differential equations in Algebra I), so as to provide him or her with the most suitable next set of problems. The outcome is a pie-chart map of what a student has demonstrated s/he is able to do; the pie chart includes prospective problem types that the student is prepared to learn but has yet to master (Falmagne et al., 2006).

In summary, the ALEKS system is based much more on teacher-student (and teacher-group) interaction than is Cognitive Tutor. Of the two, ALEKS is at the same time the more complexly adapted yet more practically grounded intelligent tutor courseware system.

**5.4. Cognitive tutor and ALEKS compared relative to the accelerate Math Camp experience.** The ALEKS courseware assesses students conti-nuously by using equation problems that require free responses much as those found in paper-and-pencil exercises. The first activity is administration of a 20-30 question assessment, or pre-test. ALEKS makes a 'mapping' decision based on both that response set and the student's responses to the previous questions (i.e., his or her knowledge spaces). Upon completion of the pre-test, ALEKS determines what has and has not yet been mastered, representing this outcome in the pie chart. A student may then choose the next topic s/he wishes to address and may begin working on practice problems. When s/he consistently answers specific practice problems correctly, ALEKS determines that the student has mastered the topic. ALEKS updates the student's mastery pie chart accordingly, and the student can then choose the next topic to work on. In the process, the student can access explanations of problems, which may be linked to electronic text material, animations, and solution videos.

Unlike Cognitive Tutor, which regularly "kicks back" students to earlier questions if they make mistakes or ask for help, ALEKS does not immediately or directly penalize a student for using a help prompt (asking for explanation). However, in ALEKS the student does need to follow up a help request by answering three kindred problems in a row correctly before s/he can establish mastery. Once mastery of the subtopic is shown through the correct solution of three consecutive problems, the advancement registers on the individual pie chart. This sequence gives ALEKS a clear advantage over Cognitive Tutor, which is prone to being 'gamed' by students to avoid getting stuck repeating course sections (Baker, Corbett, Koedinger and Wagner, 2004).

ALEKS administers re-assessments periodically. If a student no longer demonstrates mastery of a topic, s/he is returned to the list of available topics in the individualized pie chart. Students can also take 'off-line' tests provided by the instructor in the courseware itself as well as any paper tests the instructor may administer, a process used across Math Camp in 2013. The pie charts, incidentally, become an important source of feedback and encouragement for most students, who can thereby prompt and track their own progress. Reliance in ALEKS on solving equations allows students to collaborate more readily than does Cognitive Tutor, with its reliance on word problems that require strong reading skills on the part of all students involved.

CT allows instructors to build a custom curriculum by selecting topics for each student through tests administered before and after every course unit. Pre-tests and ongoing assessments set the pace for the given course unit. Much like ALEKS, though to a lesser extent, Carnegie attempts to structure questions and provide response options that mimic the problem-solving steps a student would execute on paper. Problems are 'contextualized' and rendered 'collaborative' through three devices: They are based roughly on real-world situations, presented as word problems, and supplemented with interactive examples and hints for problem-solving. As just suggested, however, Math Camp students found progress through CT's units to be very difficult, because the courseware set them back for asking for help.

In the 2012 Math Camp, most students found word problems to be unusually daunting. CT's word problems were culturally inapt, often unrelated to the experience of nontraditional and minority students in Math Camp. Reliance on word problems challenged their reading ability, as well. Most could not move past that barrier even when they could get help translating the word problems from instructors, tutors, or other students. The systems design device in CT of computer-student collaboration (through so-called 'collaborative scripts') fared no better, since students were, if anything, alienated by their interface with the courseware.

As the preceding statistical results sections show, in contrast, every measure of learning outcomes and of student and instructor satisfaction is indicative of strong preference for the ALEKS courseware over Cognitive Tutor. The courseware's devices of (1) moving students into animations of solutions without undue penalization, (2) providing video assistance at their request, and (3) linking students to the electronic text all compensated for the off-putting quality of equations. One observation volunteered by students was that having links open to an entire chapter in the electronic textbook rather than to sections specific to the given equation-problem was an issue for them. However, that reference mechanism is (in all likelihood) the only feasible way for the software linkages between problems and resources to be implemented.

As expected, cost-effectiveness was also distinct benefit of using ALEKS for Math Camp instructors handling homework assignments, both because of the self-paced and the continually-scored features of the courseware. ALEKS fared much better than Cognitive Tutor as a student learning outcomes tracking system and as a course planning and record system. Student course evaluations, instructor interviews, and focus group comments all confirm a level of satisfaction with ALEKS that was lacking in the comparable 2012 experience with Cognitive Tutor.

## 6. Site visit observations, analysis, and concluding reflections

An illustration of how active learning occurred in the program and benefitted minority students comes from an evaluator site visit to one of the participating colleges the last day of Math Camp in summer 2013. A Native American student was being peer-tutored by a Latina student who had completed her ALEKS final assessment. In working through one equation, the Native student asked her peer tutor to take her back to the basics of factoring, even though it appeared from her prior work that she would be able to solve the equation on her own. This was an instance of maximally-contextual learning – learning that was inductive and relationship-based. Here, 'relationship' is taken to refer to both student/peer-tutor interaction and the relationship among the math concepts, or conceptual schemas, involved.

Context is relational (intra- and inter-personal, and experience-based), while relationships (particularly in adult learning) are context-based. Minimally contextual learning models are individualistic, while maximally-contextual ones are collaborative, especially in the sense of reliance on collaborative relationship. Supportive mentoring (which occurred here for both individuals involved, though in a completely unselfconscious way) can provide all of the requisite elements of contextualized learning. This kind of dyadic peer tutoring occurred across all Math Camp sites in 2013, as well as tutoring and mentoring in triads and larger groups.

In all six sites there was extraordinarily successful engagement of the students by the instructors, as well as informal ALEKS consultations and collaborative robotics assembly and deployment activities by students. Interviews with instructors, tutors, and students suggested a high level of motivation and involvement by all of them, as well as mutual engagement.

Mathematical subjects typically covered during a robotics lab session were diameter and circumference, ratios and proportion, unit conversions, means, graphs and tables, translation of these into equations, patterns, scaling, and both direct and indirect linear relationships. The instructors and tutors took students through a thorough review and consideration of the different ways of representing and analyzing mathematical data: tabular representation, graphing, and equations, with a direct translation of one mode to the next.

Transitions from one instructional activity to another were carefully and capably managed by the instructors in all six sites. The impact of robotics was clear, especially as to joint and group problem solving. Site visits adduced evidence that students and instructors were very involved in the robotics assembly and deployment activities, with learning occurring at multiple levels; e.g., peer to peer, as well as from instructor or tutor to student. Student teams which had finished their tasks helped others still working on them, until most students were brought to demonstrate mastery of the integrated mathematics and robotics activities and tests.

Across sites in 2013, there was a successful effort on the part of the instructors to integrate classroom and ALEKS courseware material with lecture, discussion, and robotics activities. The robotics curriculum effectively emphasized experiential, active learning, team-building, and collaborative problem-solving. In comparison with 2012, the integration in 2013 of robotics lessons and mathematical knowledge was much more direct and complete. What became evident was the synergy possible between ALEKS and the robotics curriculum, which made for a high level of math-aware engagement for instructors, tutors, and students. The net effect of the dual ALEKS and robotics curricula on student content mastery and attitude toward mathematics was the exceptional set of learning outcomes reported in this study.

Evaluator conversations with instructors and students indicated a high level of motivation and involvement on the part of both, as well as mutual, informal engagement in collaborative learning by most of the students. In all sites visited, students who had mastered ‘pie chart’ sections in ALEKS turned to help other students with their remaining problems. Across all sites there were high levels of instructor-student and tutor-student interaction, as well as student-to-student collaborative learning. It was common to see the instructor and a student helping another student, or the tutor and student helping a third student, or simply students clustering in groups of three or four and working together. In-class work therefore involved collaborative learning through all possible forms of intensive engagement, most of it informal and fluid in nature.

In an evaluator interview at one of the sites a student indicated how her dual major (English and Psychology) in a Bachelor of University Studies program of study was back on track after long delay. She credited her success to Math Camp and talked enthusiastically at length about the skills of the Camp instructor. She volunteered that she was just nine credit hours short of graduation, and that she expected to graduate within a semester. She had also decided to take a non-required statistics course after Math 120, since that would better equip her in her research and study in the field of psychology. Personal vignettes such as this one filled the evaluator’s site visit notes in 2013, concretizing findings from the eventual statistical analysis.

It is now evident that the adoption and implementation of the two integrated curricula – ALEKS in place of Cognitive Tutor and an enhanced robotics component to Math Camp – represented a major advance over the curricular approach taken in year 2 of the program (2012). Robotics sessions were filled with collaborative activity, sophisticated construction and reconfiguration of the Mindstorms LEGO robots, and hands-on learning. From the instructors’ perspective, ALEKS provided a fairly easy to learn and execute course management system. Moreover, its easier user interface was combined with instructors’ supplementary lessons and intensified tutoring so as to allow students to remain close to their peers in achievement levels in their respective cohorts. They could therefore advance through the course together as a group.

This strong cohort effect helps account for the extraordinary content mastery gains made by students in 2013, as suggested previously in this study. With Cognitive Tutor, students in all but one of the 2012 sites diverged widely in their progress through the online materials, lending to their isolation from one another after the first week or two of the program. Keeping cohorts relatively close together in achievement levels sustains student morale through a very intensive, compressed educational experience, as does the mutuality of purpose and interpersonal bonding that collaborative learning promotes. The contextualization of learning through close collaboration helps breach the cultural gap between students and courseware. Collaborative learning in turn helped connect students of all cultural and demographic backgrounds.

Finally, the Accelerate Math Camp has proven itself in 2013 as a potential *best practices* model for replication, particularly in postsecondary settings engaging nontraditional students in transitions to the labor market. The record of similar programs in the United States and Europe has been mixed at best – in fact, often poor, and generally ambiguous, as noted throughout this study. The foregoing statistical analysis provides unprecedented empirical evidence for program success and points to the need to disseminate the results here conveyed through a number of venues – peer-reviewed publications such as *Problems and Perspectives in Management* and trade publications, for example. Getting the word out about this program could set the stage for its replication, including scaled-up trials in the United States, Europe and elsewhere.

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