ECURE

EXPANDING COURSE-BASED
UNDERGRADUATE RESEARCH
EXPERIENCES PROJECT

COMPREHENSIVE PROJECT REPORT:

FULL PROJECT

(COHORTS ONE THROUGH FOUR, 2020-24)

June 21, 2026

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Introduction

Undergraduate research has been linked to increased student persistence (Gregerman, von Hippel, Jonides & Nagda, 1998; Rodenbusch, Hernandez, Simmons & Dolan, 2016; Jones, Barlow & Villarejo, 2010), improved graduation rates (Rodenbusch, Hernandez, Simmons & Dolan, 2016; Lopatto, 2004; Narayanan, 1999; Russell, Hancock & McCullough, 2007; Willis, Krueger & Kendrick, 2013), increased STEM content mastery (Willis, Krueger & Kendrick, 2013; Lopatto & Tobias, 2010), enhanced science identity (Hunter, Laursen & Seymour, 2007) and research self-efficacy (Adedokun, Bessenbacher, Parker, Kirkham & Burgess, 2013; Carpi, Ronan, Falconer & Lents, 2017). These positive effects of undergraduate research experiences are even more pronounced for students from groups typically underrepresented in STEM (URM) (Gregerman, von Hippel, Jonides & Nagda, 1998; Carpi, Ronan, Falconer & Lents, 2017; Bangera & Brownell, 2014; Chang, Sharkness, Hurtado & Newman, 2014). There is a high demand for undergraduate research experiences at the University of New Mexico (UNM), and at other colleges and universities across the country. However, interest in pursuing STEM disciplines among incoming freshman exceeds the capacity of UNM to provide early curricular or co-curricular full research experiences for undergraduates, despite evidence that such experiences boost student persistence and achievement in STEM disciplines. As a result, early undergraduate research experiences tend to serve students who come to UNM already research-ready, and minimize participation among underrepresented student populations.

To address these challenges, the University of New Mexico is implementing and testing an Expanded Course-Based Undergraduate Research Experience framework (E-CURE) that broadens early participation in undergraduate research and creates more diverse pathways to higher level research engagement. This expanded framework builds upon the traditional Course-Based Undergraduate Research (CURE) model where students engage in full research experiences by adding pre-CURE experiences where students engage in preparatory (PREP) or partial (PARTIAL) research experiences.

ECURE PROJECT GOALS AND OBJECTIVES.

Goal 1. Improve lower to upper division transition rates, retention rates and STEM persistence rates for UNM STEM students through the use of undergraduate research experiences and pathways

Goal 2. Conduct research that addresses gaps in the CURE and Pre-CURE literature, and that informs instructional practices and policies at UNM

Goal 3. Develop an effective metric for measuring critical transitions from LD to UD coursework in STEM disciplines, especially for institutions where students enter with math-sequence delays

Goal 4. Increase the number of students who are introduced to research during their freshman and sophomore years, and increase the diversity of UNM undergraduate researchers by creating a more inclusive research pathway

Goal 5. Strengthen instruction in general education and portal courses through the use of undergraduate research pedagogy and experiences

Goal 6. Strengthen early science identity and science literacy for UNM STEM students, especially for those traditionally underrepresented in STEM professions

Objective 1: Train and support STEM instructors to develop, deliver and assess E-CURE-based sections of STEM general education and portal courses.

Objective 2: Train and support STEM instructors to develop approaches related to undergraduate research, science literacy, research self-efficacy and science identity.

Objective 3: Design and deliver E-CURE-based sections in multiple STEM disciplines.

Objective 4: Measure and improve lower to upper division transition rate for STEM-interested undergraduate students enrolled in E-CURE-based sections; Measure & improve retention, STEM persistence and graduation rates for STEM-interested undergraduate students enrolled in E-CURE-based sections.

Objective 5: Measure and improve science literacy, research self-efficacy and science identity for STEM-interested undergraduate students enrolled in E-CURE sections.

Objective 6: Test, refine and publish E-CURE lower to upper division transition rate metric. Through application on E-CURE redesign outcomes, test efficacy of this transition metric.

Objective 7: Study and report the comparative benefits of pre-CURE and full CURE approaches. Publish and present findings, and utilize findings to inform future instructional practices and academic policies.

ECURE Project Leadership

Table 1. Project Team for Cohort Four (2023-2024)

Rosa Isela Cervantes, Director of El Centro de la Raza.
Pamela Cheek (Co-PI), Associate Provost for Student Success, and Associate Professor of French.
Hua Guo (Co-PI), Distinguished Professor of Physical Chemistry.
Mark Emmons, Associate Dean, University Libraries.
Erik Erhardt (Co-PI), Associate Professor of Statistics.
Charles Fledderman, Associate Dean for Academic Affairs in the School of Engineering.
Cristyn Elder, Associate Professor, Rhetoric and Writing Program, Department of English.
James Halloway (PI), Provost and Executive Vice President.
Aeron Haynie, Executive Director of the Center for Teaching and Learning.
Jason Moore, Assistant Professor of Paleontology, Honors College.
Tim Schroeder, Director UNM Undergraduate Research, Arts and Design Network (URAD).
Vanessa Svihla, Associate Professor of Organization, Information & Learning Sciences, with cross appointment in Chemical & Biological Engineering
Davood Tofighi, Assistant Professor of Psychology.
Assata Zerai, Vice President for Equity and Inclusion;
Lynn Nordstrom, External Evaluator.

Motivating Rationale for ECURE Implementation

UNM is motivated to build upon institutional momentum and recent pilot projects to expand early undergraduate research opportunities, improve lower to upper division transition for STEM students, enrich general education instruction, and strengthen early science identify for STEM students.

Creating New Undergraduate Research Engagements for Early STEM Students.

UNM is a Carnegie-designated Research 1 university, with world-class researchers, facilities and technology, access to three national labs, approximately $120 million in research expenditures annually and 60 NSF Career Awardees since 1995 (UNM Office of the Vice President for Research, 2018). STEM students account for 50% of all first-year students (UNM STEM Collaborative Center, 2018). These students are eager to participate in undergraduate research. In 2017 and 2018 combined, 1,155 students who registered for Freshman Orientation indicated a desire to participate in undergraduate research experiences at UNM. This high demand among early students is consistent with findings in the literature (Mahatmya et al, 2017). However, UNM has few options to offer these students for early engagement. Through curricular and co-curricular options combined, the Office of the Vice President for Research estimates that fewer than 300 freshman and sophomore students participate in research experiences. This is less than 5% of these populations, and only 30% of the known demand among freshmen and sophomores.

Reducing UNM's STEM Equity Gaps.

UNM is a university rich in diversity, with Hispanic students accounting for 49% of undergraduate enrollment, Native American students accounting for 6%, and African American students accounting for 2%. Women account for 56% of undergraduate headcount (UNM Office of Enrollment Management, 2018). Of freshmen interested in STEM degrees, 54% are Hispanic, 5% are Native American and 2% are African American. Forty-seven percent are Pell eligible (low income) and 24% are first-generation students (UNM STEM Collaborative Center, (2018). However, UNM serves one of the poorest states in the nation. New Mexico ranks third in the percentage of population living in poverty (19.1%) (U.S. Census Bureau, 2017) and ranks last in high school graduation rates (69%) (National Center for Educational Statistics, 2017). As a result, while freshman interest in UNM STEM degrees has risen over the past eight years from 39% to 51% (UNM STEM Collaborative Center, 2018), significant equity gaps exist in UNM STEM attainment.

Improving Lower Division to Upper Division Critical Transitions.

At UNM, 53% of freshmen enroll in College Algebra-level math or lower during their first semester, meaning they are still at least three semesters away from Calculus. Only 6% of entering freshmen enroll in Calculus during their first semesters (UNM STEM Collaborative

Center, 2017). This means that many STEM students significantly delay their entry into upper division courses, where calculus is usually pre-requisite. During this delay, many students walk away from their STEM dreams. Thirty-six percent of STEM-interested freshmen drop out of UNM within the first two years, before transitioning to UD coursework. Another 18% switch majors out of STEM in this same period (UNM STEM Collaborative Center, 2018). The University must develop earlier research experiences for lower division students that promote successful retention and transition to upper division courses

Building Upon Pilot Efforts in STEM General Education at UNM.

In 2017, the state of New Mexico passed legislation that mandates general education courses focus on five essential skills (including critical thinking, quantitative literacy and information literacy). This legislation requires New Mexico colleges and universities to document for each general education course the methods used for weaving these focus areas into the curriculum (New Mexico Higher Education Department, 2019). The need to enrich instruction in STEM general education courses is especially compelling. Of the 20 UNM courses with the highest fail rates, 11 are STEM general education courses (UNM Office of Institutional Analytics, 2019). In Spring 2018, the UNM Provost Office established the Academic Affairs General Education Faculty Fellows Program. For this pilot project, Faculty fellows (all of whom teach general education courses) formed communities of practice to develop strategies for incorporating state-mandated general education focus areas into UNM courses. One of these faculty communities focused on Undergraduate Research. Four faculty fellows (including one from chemistry and one from paleontology) developed an *expanded* CURE framework designed specifically for the general education core, including large lecture-based sections.

This framework combines a structured pre-CURE model with the traditional full CURE model. Measuring the relative impact of pre-CURE and full CURE models is crucial to general education courses, where UNM interacts with the vast majority of our STEM undergraduate students. If the pre-CURE model is proven to be effective in producing important student outcomes relative to full CURE, then it offers significant institutional benefits when applied to the general education core. It can: 1) be implemented in large courses, including lecture sections, with minimal financial resources dedicated to teaching assistants or out-of-class research supports; 2) be used by instructors who have minimal research experience, including lecturers and teaching assistants; 3) be used in courses where students have minimal prior math or science competencies; 4) dramatically expand the number of students who can participate in the institution's research mission; 5) minimize self-selection bias in measuring the impact of undergraduate research experiences; and 6) encourage reluctant faculty members to "wade into" undergraduate research experiences, building their confidence towards full CURE implementations.

Strengthening Early Science Identity for STEM Students at UNM.

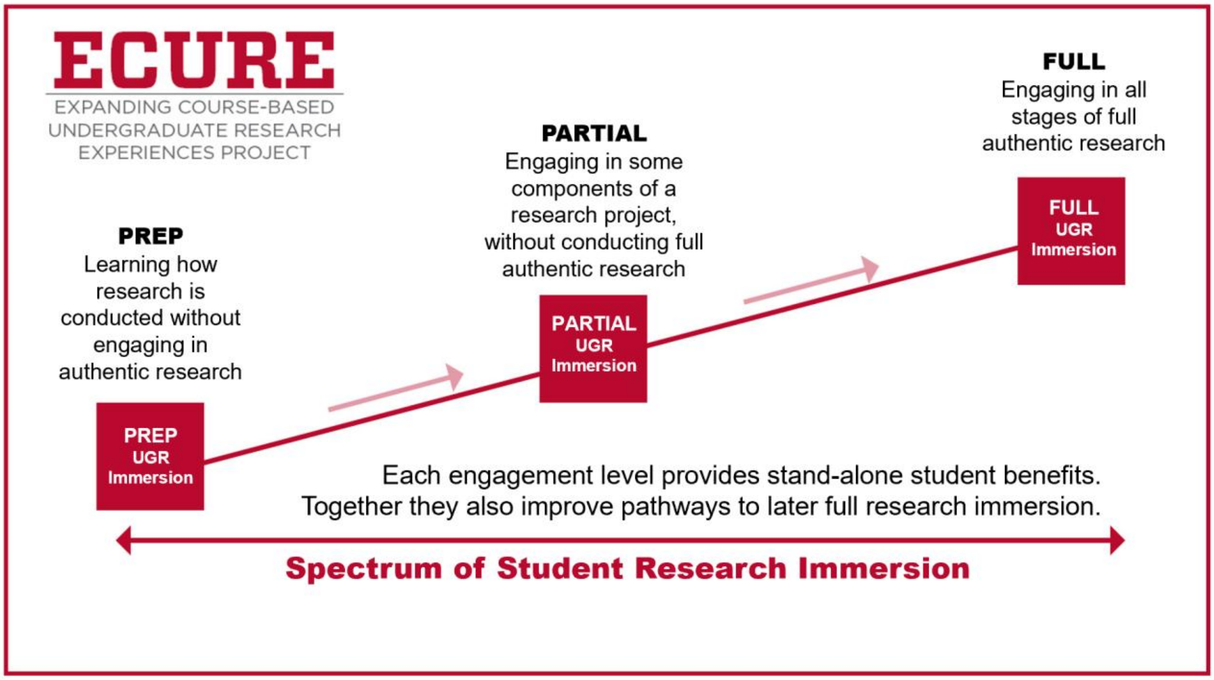
Students who feel they belong to and are a significant part of the university will invest more energy into graduating (Tinto, 1993; Pascarella & Terenzini, 1977; Terenzini & Pascarella, 1977). Teaching science literacy and helping to establish a science identity in their students is a critical task of STEM faculty. In 2014, *Revisiting the STEM Workforce: A Companion to Science and Engineering Indicators* noted that "STEM knowledge and skills enable multiple, dynamic pathways to STEM and non-STEM occupations alike" (Aschbacher & Roth, 2010), stressing the importance of providing STEM experience and enabling science literacy for all students. In addition, the manifestation of a science identity in students has been shown to influence science persistence, which is integral to the retention and graduation of STEM majors (Aschbacher & Roth, 2010; Brickhouse, Lowery & Schultz, 2000; Carlone & Johnson, 2007; Barton & Yang, 2000). Most undergraduates, even those who initially choose to pursue STEM degrees, do not readily identify themselves as being scientists (Hazari, Sadler & Sonnert, 2013). Undergraduate research experiences have been shown to encourage students to realign their individual persona and to take on more of a science identity (Robnett, Chemers & Zurbriggen, 2015; Chemers, Zurbriggen, Syed, Goza & Bearman, 2011; Egan et al, 2013). The establishment of science identity has been directly related to the generation of self-efficacy (Robnett, Chemers & Zurbriggen, 2015; Trujillo & Tanner, 2014). This realization of self-efficacy, or your belief in your ability to succeed, is intensified when your social experience emphasizes your confidence and sense of purpose (Estrada, Woodcock, Hernandez & Schults, 2011; DiBenedetto & Bernbenutty, 2013). Those undergraduates who were high in their identity as a scientist were especially likely to apply to graduate school in a science-related field (Russell, Hancock & McCullough, 2007; Robnett, Chemers & Zurbriggen, 2015) or pursue professional science careers (Hunter, Laursen & Seymour, 2007; Robnett, Chemers & Zurbriggen, 2015). By implementing an undergraduate research framework in general education and portal courses, UNM hopes to promote early science identity among the students who are most likely to leave UNM prior to graduation.

Overview of the ECURE Framework

Course-based undergraduate research experiences positively impact retention, graduation, equity, science identity, and science literacy. In comparison to out-of-class undergraduate research experiences, they provide important additional *institutional* benefits: 1) they are able to engage larger student populations who are not self-selected or pre-selected based on their perceptions of research self-efficacy; 2) they are better equipped to serve working students who cannot afford to engage outside of the classroom; and 3) they do not require the development of large co-curricular research infrastructures. However, the *student* benefits of CUREs (for instance increased science literacy and improved retention/graduation rates) are almost always connected in the literature to full and authentic research experiences, where students complete all stages of research. In STEM, these full experiences are most often implemented in lab sections, or at the upper division level.

An emerging set of literature supports the premise that "pre-CUREs" or "preparatory" research experiences (those that fall short of full or authentic research) may generate similar student outcomes, while also providing more effective pathways to research for early undergraduates. In the literature, Pre-CUREs are loosely defined, and have not been widely studied. The UNM Academic Affairs General Education Faculty Fellows further characterized and defined the pre-CURE model to create an expanded CURE framework designed specifically for general education courses. This expanded framework categorizes pre-CURE into two levels of student immersion in research: preparatory instruction (PREP), and partial research engagement (PARTIAL). When combined with the traditional full CURE model, this framework can be implemented more extensively through the general education core, including in large lecture sections.

Figure 1. ECURE Framework



Course-based Undergraduate Research Experiences (CURE). E-CURE builds upon the foundation of the CURE model. CUREs are defined as "learning experiences where whole classes of students address a research question or problem with unknown outcomes or solutions that are of interest to external stakeholders" (Dolan, 2016). CUREs have been primarily developed for biology and chemistry lab courses (Dolan, 2016), but CUREs have also been implemented in engineering (Moore & Diefes-Dux, 2004; Reeves & Laffey, 1999), geosciences (Ryan, 2014), and physics (Beckham, Simmons, Stovall & Farre, 2016), among many other disciplines. CUREs have been linked to increased content mastery and improved scientific literacy, as well as to increased retention, degree persistence and graduation rates (Rodenbusch, Hernandez, Simmons & Dolan, 2016; Dolan, 2016; Brownell et al, 2015). CUREs and other undergraduate research experiences are considered to be especially useful for women and underrepresented minority students (Gregerman, Lerner, von Hippel, Jonides & Nagda, 1998; Carpi, Ronan, Falconer & Lents, 2017; Bangera & Brownell, 2014; Chang, Sharkness, Hurtado & Newman, 2014). CUREs are backed by an extensive literature, national alliances, reports, professional associations and instructional/administrative resource websites.

CUREs are most often *defined* through the use of essential elements that all must be present for the course to be considered a CURE (see Table 2). In addition to these essential elements, CUREs are sometimes *described* by the instructional mechanisms, activities and/or research practices used in implementation. Examples include "asking questions, building and evaluating models, proposing hypotheses, designing studies, selecting methods, using the tools of science, gathering and analyzing data, identifying meaningful variation, navigating the messiness of real-world data, developing and critiquing interpretations and arguments and communicating findings (Auchincloss et al, 2014)." An example of a CURE might include a class project where students collectively identify a real-world problem, conduct a preliminary literature review, design a research study, collect data, analyze data, and publish or present their findings. CUREs are most commonly utilized in labs courses, upper division courses, and courses with low enrollments.

Table 2. Traditional Full CURE Essential Elements (Auchincloss et al, 2014)

Scientific practices	**Uses generally accepted scientific practices to answer research questions**
Discovery	Generates new knowledge, insights or understanding (focuses on questions where the answers are unknown).
Broadly relevant or important work	Findings are meaningful and important beyond the classroom
Collaboration	Involves teams of researchers working together
Iteration	Builds upon previous research and current knowledge

Pre-CURE. E-CURE expands upon emerging pre-CURE approaches. While the CURE framework has been widely defined and described in the literature, an emerging body of research describes the importance of course-based research experiences that do not meet the standards or definition of traditional CUREs. These experiences are sometimes called Pre-CUREs or undergraduate research pathways. Pre-CUREs are defined as learning about research outside of a full research setting.

In the literature, pre-CUREs are sometimes described as "modular" implementations (Horsch, St. John & Christensen, 2012). Pre-CUREs teach students concepts such as iteration, thinking critically about research, and learning about research methods and experimental design (Mahatmya et al, 2017). These courses provide more tangible connections between lectures and lab or real world applications (Horsch, St. John & Christensen, 2012), contribute to the development of student confidence, and encourage students to participate in research experiences (Mahatmya et al, 2017). Preparatory research experiences also improve pathways to undergraduate research for traditionally underrepresented students (Hurtado, Cabrera, Lin, Arellano & Espinosa, 2009). This is especially true for students who cite lack of research preparedness as the primary barrier to their participation (Mahatmya et al, 2017). Though pre-CUREs are gaining in popularity, and have been linked to improved retention rates (Horsch, St. John & Christensen, 2012), there have been few large multi-disciplinary implementations of pre-CUREs designed to compare outcomes to traditional CUREs.

Structure of the ECURE Project

Building upon an expanded CURE framework developed by UNM's Academic Affairs General Education Faculty Fellows, E-CURE: 1) collects and analyzes course-level data to identify which STEM general education and portal courses could most benefit from pre-CURE and/or full CURE implementations, 2) works with academic administrators to select courses and instructors to incorporate pre-CURE and full CURE into their sections, 3) trains instructors to effectively incorporate pre-CURE and full CURE, 4) assess the relative impacts of pre-CURE and full CURE implementations on student perceptions and behaviors, 5) distributes findings through publications and presentations, and 6) institutionalize pre-CURE and full CURE inclusion in UNM general education and portal courses.

Operationalizing PREP and PARTIAL in the E-CURE Framework.

The UNM Academic Affairs General Education Faculty Fellows characterized and defined the *pre-CURE* approach to create an *expanded* CURE framework designed specifically for general education courses. This structured pre-CURE framework categorizes two entry levels of student immersion in research as preparatory instruction (PREP) and partial research engagement (PARTIAL) This structure is similar to the engagements described by Gentile, Brenner and Stephens, who note that "students can realize the benefits of research at any stage" (Gentile, Brenner & Stephens, 2017). It is anticipated that PREP pre-CURE will produce different student outcomes than PARTIAL pre-CURE, and that both forms of pre-CURE will produce different student outcomes than full-CURE. Our research design will identify & measure the differences in student outcomes for each approach.

In the E-CURE Framework, PREP is defined as teaching students how research is conducted (including explaining the connection of foundational skills to research processes), but *without* actual engagement in research. PREP can be taught in either lecture or active learning environments. In the traditional CURE literature, PREP is specifically and intentionally excluded from the CURE definition/model (Gentile, Brenner & Stephens, 2017; Auchincloss et al, 2014).

<u>E-CURE operationalizes the PREP definition as providing at least ten separate activities, assignments or focused lectures addressing research skills or research-applied foundational skills during the course of an academic term</u>. Examples include teaching students to differentiate between correlation and causation, exploring the value of peer-based literature compared to Wikipedia, developing research questions, practicing data collection techniques, or using MS Excel to determine significance.

In the E-CURE framework, PARTIAL is defined as engaging students in selected components of research, *without* engaging in all of the essential elements of full CUREs. In the literature, PARTIAL is generally excluded from the CURE definition/framework because it does not include all of the essential elements. An example of PARTIAL might an include a class where students are provided a research problem by the instructor (rather than identifying one themselves), are provided a summary of existing knowledge (rather than conducting their own lit reviews), are provided with a research method (rather than selecting their own), are required to collect & analyze data individually, and report their findings to the instructor in a research journal (rather than sharing with research peers). E-CURE operationalizes the PARTIAL definition as engaging students in at least one of the essential CURE element, within a context in which students ask or answer questions to which the answers are unknown. This definition differentiates PARTIAL experiences from cookbook experiments. In order to compare the impact of pre-CUREs to full CUREs, E-CURE also operationalizes the definition of a full CURE as engaging students in a research project that involves all five essential CURE elements.

COURSE ANALYSIS, FELLOWS & PROJECT RECRUITMENT AND SELECTION.

E-CURE followed a process for identifying course redesign projects developed by the UNM STEM Gateway Project (funded by US Department of Education Title V STEM Grant, concluded 2017). This process was both bottom-up and top-down, in order to encourage participation and sustainability. The ECURE Project Director convened an Administrative Workgroup, composed of faculty within the Center for Teaching and Learning, Deans or Associate Deans in Arts & Sciences, Engineering, and Honors, and Department Chairs or Associate Chairs in six STEM disciplines (with preference placed on participation by math, biology, chemistry and physics Chairs). This workgroup reviewed course success data prepared by UNM institutional researchers in order to identify courses most in need of redesigned sections. Workgroup members then recruited and selected instructors to apply for E-CURE Redesign Faculty Fellowships. This targeted approach was used alongside a broader institution-wide call for participation among faculty.

TYPES OF ECURE TEACHING FELLOWSHIPS.

ECURE supported Implementation Fellows and Exploratory Fellows. Implementation Fellows developed and implemented ONE of the three levels of immersion in at least one section of a STEM general education or portal course. Each Implementation Fellow received a $4,000 summer stipend. Exploratory Fellows explored the use of the ECURE framework in their courses by observing their peers' implementation projects, but did not commit to an implementation themselves. Exploratory Fellows were encouraged to apply as Implementation Fellows next year, if they felt this is an appropriate framework for their course(s). Exploratory Fellows received a $1,000 summer stipend. Former Implementation Fellows were also encouraged to apply as Publication Fellows. Publication Fellows were supported in submitting their course project and findings for publication.

FELLOWS RECRUITMENT.

ECURE staff worked with the UNM Provost Office to develop a Request for Participation process in combination with the UNM Student Experience Project (funded by the APLU). This process encouraged faculty to learn about both programs, and to select which of the two best fit their instructional needs. Due to Covid delays, this RFP went out in early May, with a June 5 deadline. We were able to accept/fund 100% of applicants who met our participation requirements.

ECURE Website

ECURE staff created a project website to describe the project, request faculty participants, and link participants to key resources. This site is located at: https://urad.unm.edu/faculty-staff/ecure.html

Faculty Development, ECURE Summer Institute

Cohort Three ECURE Summer Institute Report and Communities of Practice

ECURE Summer Institute (ECSI):. ECSI was offered virtually through the UNM course management system, with four synchronous sessions (three hours each), and the remainder of the institute offered asynchronously through discussion boards and other online tools. This allowed ECSI to meet busy and varied faculty summer schedules. Throughout the length of the ECURE program, ECSI engagement varied from four weeks in the first two years to eight weeks in the third and fourth years. Since ECURE contained elements of both professional development and course redesign work, four weeks did not quite provide instructors enough time to learn, reflect, incorporate, reflect and revise.

ECSI for Cohort Four focused on professional development around the following four primary areas: Course-Based Undergraduate Research (CURE), Culturally Responsive Pedagogy (CRP), effective online instruction (in response to the COVID pandemic); and Active Learning Strategies (ALS). Engagement during ECSI is strategically designed to foster peer-to-peer and fellow-to-instructor dialogue and includes minimal instructor-to-fellow lectures/presentations.

Institute Goals: ECSI learning goals and objectives included:

GOAL 1: Participants will understand and appreciate the differences between directing and carrying out research practices. Upon completion of the institute, participants will be able to:

- Describe high and low agency research practices salient to courses taught
- Identify barriers to students directing research practices
- Plan strategies to surmount these barriers
- Connect research-based outcomes for students who carry out versus direct research practices in terms of content mastery, research efficacy, science literacy, and science identity

GOAL 2: Participants will understand and appreciate asset-based and culturally-responsive teaching (CRT). Upon completion of the institute, participants will be able to:

- Describe specific strategies to build rapport with and show care for students

- Describe ways to identify research skills diverse students bring from their cultural and everyday lives and position them as researchers
- Adapt research-based, CRT strategies for use in their course
- Explain the outcomes of CRT for all students in terms of content mastery, research efficacy, science literacy, and science identity

GOAL 3: Participants will understand and appreciate active learning strategies. Upon completion of the institute, participants will be able to:
- Adapt research-based, active learning strategies for use in their course

GOAL 4: Participants will value faculty learning community. Upon completion of the institute, participants will be able to:
- Explain benefits of participation in a faculty learning community
- Describe strategies for making effective use of a faculty learning community

Facilitators: ECSI was facilitated by the following UNM administrator and faculty:

- Dr. Tim Schroeder, Director, UNM ECURE Program; Director, UNM URAD.
- Dr. Cristyn Elder, Associate Professor and Director, Rhetoric and Composition, Department of English; Director of Writing Across the Curriculum, Center for Teaching and Learning; ECURE Summer Institute Curriculum Development
- Dr. Vanessa Svihla, Associate Professor, Organization, Information & Learning Sciences, with cross appointment in Chemical & Biological Engineering; E-CURE Educational Researcher; ECURE Summer Institute Curriculum Development
- Dr. Jason Moore, Associate Professor, Honors College.

ECURE Impact Assessment

Pre and Post Surveys.

During the Spring and Summer of 2020, ECURE researchers met to review established assessment tools, including the Test of Scientific Literacy Skills, the SURE and CURE surveys, the Colorado Learning Attitudes about Science Survey, the Experimental Design Ability Test, and the Project Ownership Survey. While none of these instruments perfectly fit our needs, most contributed important elements to our assessment goals.

After a careful review of existing CURE surveys, we decided to develop a new pre/post survey that could fit our context well and that followed best practices in survey design (Dillman et al., 2016; McCoach et al., 2013). More specifically, we defined constructs of interest (research identity, cultural compatibility, research self-efficacy, and intent to persist in research). Many of these constructs had well-developed surveys (Davidson et al., 2009; Echohawk et al., 2014; Estrada-Hollenbeck et al., 2011; Hanauer et al., 2016; Robnett et al., 2015; Trujillo & Tanner, 2014), but typically in a specific domain like science or engineering. We adapted these for the broader context of research processes.

Creation of Process to Establish Baseline Student Population.

To develop stronger measures of assessing ECURE impact on student outcomes, UNM researchers developed a method for identifying a comparison student population who did not receive ECURE interventions. In course-based undergraduate research initiatives, baseline populations are often pulled from non-intervention sections of the same course. This option was not available to us, as some of our ECURE courses are only offered in one section per semester, without non-intervention sections to draw from. To solve this challenge, we first developed a list of key student variables (i.e., gender, ethnicity, class standing, college/school, SES). Second, we pulled the course rosters for each of the ECURE sections, and then pulled the data for those key variables for each student. After de-identifying the students, we then utilized statistical matching to identify three UNM students not enrolled in any ECURE section matched to each ECURE-enrolled student. We then surveyed the baseline population using the same survey tool as ECURE students.

This baseline population is also utilized for measuring impact on non-survey outcomes, including college retention, degree persistence, and graduation.

Matching Description and Rationale: In the UNM ECURE trial, we evaluate the educational effects (science literacy, science identity, research self-efficacy, and likelihood to persist) of the levels of the ECURE Framework (Prep, Partial, or Full) by prospectively comparing students with undergraduate research experiences (treatment) to those with "standard" experiences (non-treated, "control"). In our prospective cluster randomized controlled trial, classes of students (clusters) either undergo an ECURE treatment or not, where the treated classes are self-selected by the instructors. While one of the disadvantages of this design compared with an individually randomized controlled trial is that the experiences of individuals within the same group are likely similar, leading to correlated results (Campbell, Melbourne, Altman, 2004), the design is being strengthened by a priori bipartite matching. We perform case-control matching to find, for every treated student, at least one non-treated student with similar ("balanced") observable characteristics against whom the effect of the treatment can be assessed (Rubin, 1973). By matching treated units to similar non-treated units, matching enables a comparison of outcomes among treated and non-treated units to estimate the effect of the treatment reducing selection bias due to confounding (Rubin, 1973; Anderson, Kish, Cornell, 1980; Kupper, et al., 1981).

Increasing the number of controls above the number of cases, up to a ratio of about 4-to-1, is a cost-effective way to improve the study (Grimes and Schulz, 2005); furthermore, the 4-to-1 matching accounts for attrition (lack of participation) from students in the control group. Matching techniques have improved over propensity scores, which has been shown to increase model dependence, bias, inefficiency, and power and is no longer recommended compared to other matching methods (Rosenbaum and Rubin, 1983; King and Nielsen, 2019). We use a multivariate matching technique with automated balance optimization with the "Matching" R Package (Jasjeet, 2011). We use the "GenMatch" function to find the optimal balance using multivariate matching where a genetic search algorithm determines the weight each covariate is given.

As a quality check, we also implement standard methods implemented in the "Match" function and compare the covariate balance before and after matching (using the MatchBalance function). This matching strategy does not make the same strong assumptions that propensity scores and Mahalanobis distance make that covariates have ellipsoidal distributions, but instead searches over a space of distance metrics and finds a better metric. The "GenMatch" function has been shown to have better properties than the usual alternative matching methods both when the ellipsoidal distribution property holds and when it does not (Sekhon 2006a; Diamond and Sekhon 2005). We implemented the GenMatch function genetic algorithm with 4 matches, a population size of 1000, the "pvals" fit function, no ties, with several covariates: current age, gender, ethnicity, college (A&S, Engineering, etc.), academic level (1-4 for freshman-senior), number of transfer credits (coming from another school), number of 100-400 level credits enrolled in at UNM for Fall 2021, number of Fall 2021 STEM General Education credits, Pell Grant receiving status (SES indicator), and number of STEM General Education currently enrolled in at UNM for Fall 2020. Categorical variables were coded using a design matrix with a specified baseline and indicator variables indicating when not the baseline category.

FULL PROJECT FINDINGS

TABLE 4. PARTICIPATION NUMBERS, ALL COHORTS.

	Cohort One Fall 2020 and Spring 2021	Cohort Two Fall 2021 and Spring 2022	Cohort Three Fall 2022 and Spring 2023	Cohort Four Fall 2023 and Spring 2024
Number of ECURE sections	20 (fall) +33 (spring) =53 (total)	60+52=112	71+66=137	80+61=141
Number of students enrolled in all ECURE sections combined	977	2126	2406	2702
Number of students in ECURE sections who completed the Pre survey (beginning of term)	813	1032	1331	1461
Number of students in ECURE sections who completed the Post survey (end of term)	488	392	732	760

Number of control students not enrolled in ECURE sections who completed the Pre survey (beginning of term)	370	655	757	913
Number of control students not in ECURE sections who completed the Post survey (end of term)	297	346	291	428

List of ECURE Course Implementations, All Cohorts Combined*.

- ARCH 302, Architectural Design IV
- ARCH 2125, World Architecture History II
- ARCH 401, Architectural Design V
- BIOC 495 Topics in Biochemistry
- BIOL 1110L, General Biology Lab
- BIOL 1140, Biology for Health Sciences
- BIOL 2110C, Principles of Biology: Cellular and Molecular Lecture and Laboratory
- BIOL 2305, Microbiology for Health Sciences
- BIOL 302C Genes to Genomes: Lecture and Laboratory
- BIOL 401, Topics in Cell and Molecular Biology
- BIOL 406 Topics in Organismal Biology
- BIOL 2410, Genetics
- CHEM 1215L, General Chemistry I for STEM Majors Laboratory
- CHEM 1225L, General Chemistry II for STEM Majors Laboratory
- ECE 203 Circuit Analysis I
- ECON 2110, Macroeconomic Principles
- ECON 2120, Microeconomic Principles
- ENG 180, Seminar: Engineering Honors
- ENVS 320 Environmental Systems
- ENVS 322L, Life & the Earth System
- ENVS 1130, Blue Planet
- FYEX 1110, First Year Seminar
- GEOG 1115, Maps & GIS Science
- GEOG 1160, Home Planet
- GEOG 1160L, Home Planet Lab
- GEOL 1110, Physical Geology
- GEOG 2115, Information Design in Science and Society
- GEOL 2110C, Historical Geology
- LING 2151, Language of Advertising
- MATH 311, Vector Analysis
- MATH 1240, Pre-Calculus
- PHYS 1115, Survey of Physics
- PHYS 1320L, Calculus-based Physics Lab
- POLS 2110, Comparative Politics
- POLS 2140 Introduction to Political Analysis
- PSYCH 2250, Brain and Behavior
- SOC 398 Special Topics in Sociology
- SOC 2120, Intro to Criminal Justice System
- SOC 2315, Dynamics of Prejudice

- SOCI 429, Peers, Groups and Gangs
- SOCI 1110, Introduction to Sociology

*For a list of courses per cohort, please see individual cohort reports.

ECURE Analysis Description and Findings

Analysis Structure and Definitions: Student Data comes from two sources: pre and post ECURE surveys; and student records in Banner. Student populations are primarily: (1) students in ECURE courses/sections (ECURE or TREATMENT); and (2) students not-in ECURE courses/sections who have been matched to ECURE students using demographic and academic variables (CONTROL). Matching variables include race, ethnicity, gender, age, Pell-receiving status, academic standing, and STEM-affiliation, among others.

ECURE students are further subdivided into three categories: (1) students in ECURE courses/sections with "full" research engagement level 21 (FULL); (2) students in ECURE courses/sections with "partial" research engagement (PARTIAL); and (3) students in ECURE courses/sections with "preparatory" research engagement (PREP).

Survey-based data were analyzed using two approaches. First, we compared changes in student responses on the pre and post surveys (GAINS). While this approach provides the most accurate assessment of gains or losses throughout the ECURE semester, it also comes with one primarily limitation. Since response rates for CONTROL students have been lower than desired, the number of these students who have completed both the pre and the post surveys reduces our confidence level in these findings. As a result, we also utilized an "end of term" approach (EOT). EOT allows us to compare end-of-semester perceptions, based only on student responses on the post surveys. Note that EOT does not measure how student perceptions changed over the course of the semester, but rather what students perceived at the end of the semester.

The definition as to whether a specific course should be categorized as STEM was created and interpreted by the ECURE Leadership Team. Generally, if an academic discipline could receive research funding from the National Science Foundation, then it was considered a STEM discipline.

The definition for portal course was also created and interpreted by the ECURE Leadership Team. Generally, a portal course was defined as a course within the academic major that counts towards that major's degree requirements other than as a general elective, and that had no more than two in-major pre-requisites.

FINDINGS: SURVEY RESULTS

To collect data regarding student perceptions, ECURE researchers adapted several existing instruments into a new pre/post survey that could fit the context well and that followed best practices in survey design (Dillman et al., 2016; McCoach et al., 2013). More specifically, UNM defined constructs of interest (research identity, cultural compatibility, research self-efficacy, and intent to persist in research). Many of these constructs had well-developed surveys (Davidson et al., 2009; Echohawk et al., 2014; Estrada-Hollenbeck et al., 2011; Hanauer et al., 2016; Robnett et al., 2015; Trujillo & Tanner, 2014), but typically in a specific domain like science or engineering. UNM adapted these for the broader context of research processes.

The following questions from the pre and post surveys are organized into four groups.

Research Identity

1. **RI1: Self image.** Q14: How important or unimportant is being a researcher to your self image?
2. **RI2: Community.** Q15: How strongly or weakly is your sense of belonging to a community of researchers?
3. **RI3: Researcher right now.** Q16: How much or little do you perceive yourself as a researcher right now?
4. **RI4: Future researcher.** Q17: How much or little do you perceive yourself as a future researcher?

Research Self-Efficacy

1. **RSE1: Use technical skills.** Q19-1: How unconfident or confident are you that you can... use technical skills (use of tools, instruments, and/or techniques of your field of study) to do research?
2. **RSE2: Generate research question.** Q19-2: How unconfident or confident are you that you can... generate a research question to answer?
3. **RSE3: Which data to collect.** Q19-3: How unconfident or confident are you that you can... figure out which data/observations to collect and how to collect them?
4. **RSE4: Explain analysis results.** Q19-4: How unconfident or confident are you that you can... explain the analysis results?
5. **RSE5: Use academic literature.** Q19-5: How unconfident or confident are you that you can... use academic literature to guide your research?
6. **RSE6: Persist in courses w/research.** Q23-2: How strong or weak is your intention to persist in... courses that include research experiences?
7. **RSE7: Persist in research experience.** Q23-3: How strong or weak is your intention to persist in... a research experience, such as a summer program or working in a faculty or national lab?

Behavioral measures

1. **BH1: Retention at least 1 semester.** Remained enrolled at the university for at least one more semester.
2. **BH2: Change in major between STEM/non-STEM.** Change in major either way between STEM of non-STEM groups.
3. **BH4: Grade in course (numeric).** GPA-equivalent grade in course.

Cultural Values

1. **CV1: Doing research compatible with cultural values.** Q18: How compatible or incompatible is... doing research with your cultural values?
2. **CV2: Career in research compatible with cultural values.** Q18: How compatible or incompatible is... a career in research with your cultural values?

We summarize the model results for the Impact on the four areas listed above by Treatment and adjusted for demographic covariates, Engagement type adjusted for demographic covariates, the Instructor experience covariate, and the COVID cohort covariate (Figures X2, X3, and X4). High-level result interpretations are provided.

RESEARCH IDENTITY AND SELF-EFFICACY MEASURES

Results summary

At endpoint (Post), the ECURE Treatment has positive effects for research identity (RI2 and RI3) and research self-efficacy (RSE1, RSE2, RSE3, RSE4, and RSE5). Furthermore, ECURE Engagement Type has increasing impact (RI3, RSE1, RSE2, RSE3, RSE4, and RSE5). The instructor experience had almost no effect. The Cohort (COVID vs not-COVID) had some nuanced effects; RI1, RSE2, RSE3 were reduced only for Females in the COVID cohort, and RI4 was slightly reduced for the COVID cohort. Some general demographic patterns were also observed. Older age groups had higher endpoints, number of undergraduate credits were not associated with outcomes, First-generation students had higher outcomes than "unknown" students (i.e., international students), gender effects were few and not consistent, STEM majors tended to have higher endpoints compared to non-STEM, and Research identity was higher for students of minoritized race.

For Gain (Post - Pre) over the semester, the ECURE Treatment also has positive effects for research identity (RI3) and research self-efficacy (RSE1, RSE2, RSE3, RSE4, and RSE5). ECURE Engagement Type has increasing impact only on RSE2. The instructor experience had almost no effect. The Cohort (COVID vs not-COVID) had no effect. Some general demographic patterns were also observed. Almost no demographics influenced the gain in Research identity. For Research self-efficacy, number of undergraduate credits had some small positive effects, non-STEM majors increased more than STEM majors, though the pattern is reversed for students with higher numbers of undergraduate credits.

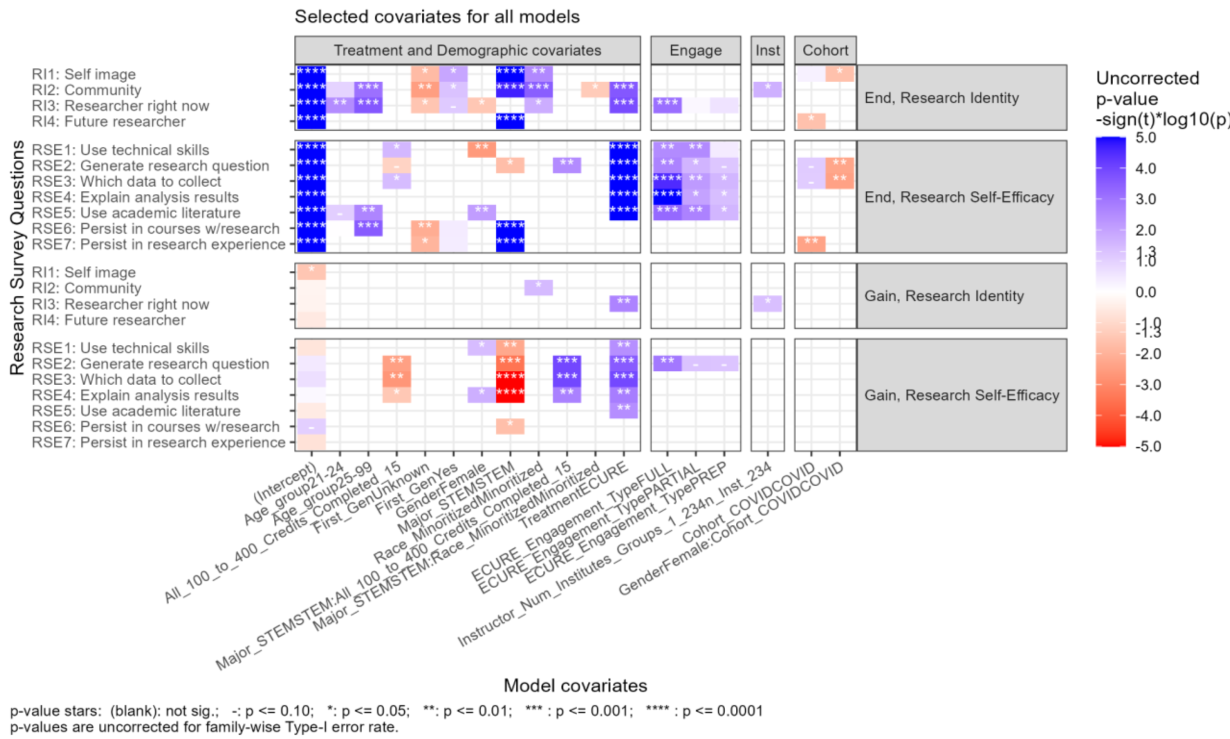


Figure X2. Impact on Research Identity and Self-Efficacy Endpoints and Gains of Treatment and Demographic covariates, Engagement type ("Engage"), Instructor experience ("Inst"), and COVID Cohort ("Cohort"). Each row represents the result of a regression model selection within each column facet; there are four models represented on each row. The "Engage" model included all of the demographic variables as possible covariates but only the Engagement type covariates are reported. The "Inst" model included Gender, Age, and Major as covariates. The "Cohort" model included Gender and Age as covariates. The uncorrected p-values are plotted (log10 scale) with the sign of the model estimate; empty cells indicate that the model covariates was not included in the selected model. Categorical covariate effects represent the difference from the baseline level (included in the model "intercept").

FINDINGS: BEHAVIORAL MEASURES

<u>Results summary</u>

Three behavioral measures were studied: BH1: Retention at least 1 semester, BH2: Change in major between STEM/non-STEM, and BH3: Grade in course (numeric). For all three, there was not an observable ECURE Treatment. The probabilities of BH1 and BH2 are both complex functions of demographic features. The ECURE Engagement Level effect for BH2 and BH3 was unusual in that the second level (PARTIAL) was different from Controls, but the first and third levels (PREP and FULL) were not different from Controls, thus it is likely an effect of a particular type of course and not a general Engagement level. Increased instructor experience led to lower Grades, but this may be due to differing expectations or grading curves across courses. For the two-year COVID cohort, there was a reduced probability of BH1: Retention at least 1 semester, and an increased probability of BH2: Change in major between STEM/non-STEM.

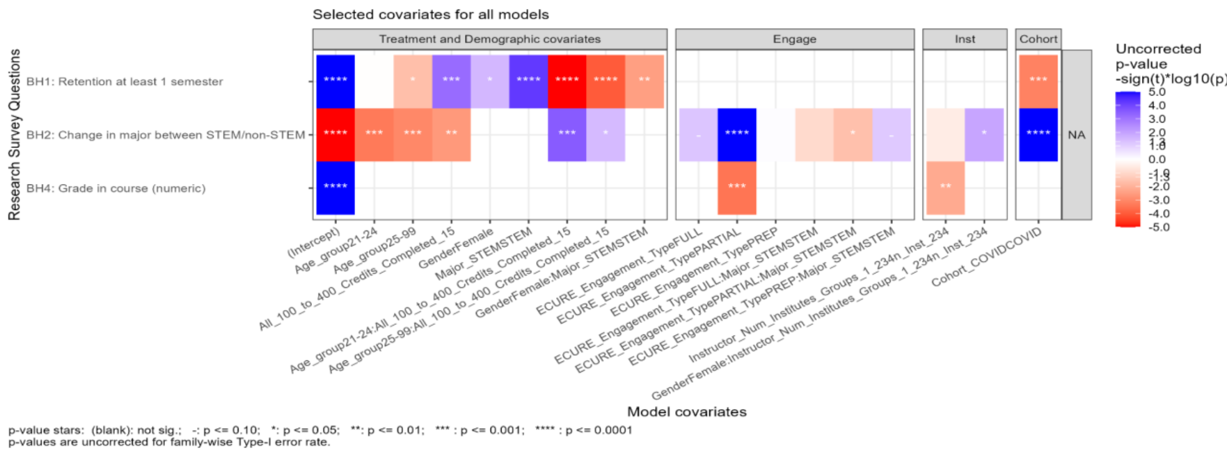


Figure X3. Impact on Behavioral measures of Treatment and Demographic covariates, Engagement type ("Engage"), Instructor experience ("Inst"), and COVID Cohort ("Cohort"). See Figure X2 caption for description.

FINDINGS: CULTURAL MEASURES

Results summary

Two Cultural values measures were studied: CV1: Doing research compatible with cultural values and CV2: Career in research compatible with cultural values.

At endpoint (Post), the ECURE Treatment has positive effects for doing research (CV1), but only for STEM students, and for a career in research (CV2) for all students. However, ECURE Engagement Type, instructor experience, and the Cohort (COVID vs not-COVID) had no observable effects.

For Gain (Post - Pre) over the semester, ECURE Treatment, ECURE Engagement Type, instructor experience, and the Cohort (COVID vs not-COVID) had no observable effects.

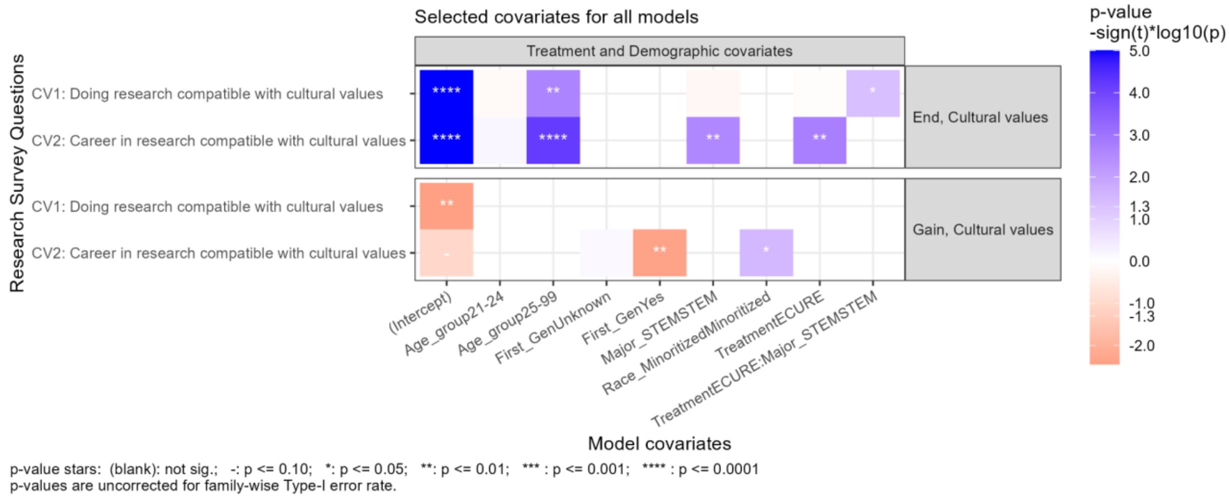


Figure X4. Impact on Cultural values of Treatment and Demographic covariates, Engagement type ("Engage"), Instructor experience ("Inst"), and COVID Cohort ("Cohort"). See Figure X2 caption for description.

AI-Generated Analysis

The following analysis was generated by Claude.ai (Opus 4.8) on June 15, 2026, and was self-checked and aligned to the summary above completed by Dr. Erikson, ECURE Co-PI. It is included here to provide more detail and context.

1. Orientation: How to Read These Figures

Figures 2, 3, and 4 are statistical *heat maps*. They are not pictures of average scores; they are compact visual summaries of a large battery of regression models, with one model fitted for each combination of an outcome (the rows) and a family of explanatory variables (the column blocks). The color of each cell answers a single question: did this variable show a statistically detectable relationship with this outcome, in which direction, and how strong was the evidence? Three conventions govern the reading. First, **direction is encoded by hue**: blue and purple cells indicate a positive relationship (the variable is associated with higher values of the outcome), while red and orange cells indicate a negative relationship. Second, **strength of evidence is encoded by color intensity and by asterisks**: the deeper the color, the smaller the p-value, with the asterisk key running from a single dash (a statistical trend, $p \leq .10$) through one to four asterisks ($p \leq .05$, .01, .001, and .0001, respectively). Third, **a blank cell means the variable was not retained** in the model the analysts selected for that row; it signals an absence of evidence rather than positive evidence of no effect. One caution follows immediately from the color scale: it encodes the *strength of evidence*, not the *size* of the effect. A deep blue cell tells us an association is highly unlikely to be due to chance; it does not, by itself, tell us whether the underlying difference is large or small in practical terms.

Two structural features of the figures deserve emphasis because the rest of this analysis depends on them. The column headers are organized into four model families. The largest, labeled *Treatment and Demographic covariates*, contains the headline contrast between E-CURE participants and matched non-participants (the column "TreatmentECURE") alongside student background characteristics such as age, gender, first-generation status, major, and minoritized status. The *Engage* block is the analytical heart of the project: it decomposes the single treatment into the three levels of research immersion the framework defines — FULL, PARTIAL, and PREP. The *Inst* (instructor experience) and *Cohort* (whether a section was delivered during the COVID-disrupted period) blocks capture two important contextual influences. Reading across a row therefore tells a layered story: first whether the intervention as a whole moved an outcome, and then whether that movement was concentrated in the more research-intensive engagement levels.

Figure 2 additionally stacks two analytic approaches that are easily conflated. The upper bands, labeled *End*, report end-of-term standing — where students sat on each measure at the close of the semester, holding covariates constant. The lower bands, labeled *Gain*, report change from the beginning to the end of the term. The distinction is consequential: an *endpoint* difference can reflect pre-existing differences between groups that survived matching, whereas a *gain* score isolates movement that occurred during the course itself. In the vocabulary of program evaluation, the gain models are the stronger basis for causal claims about the experience, while the endpoint models are more vulnerable to residual selection. Where the two agree — as they do for self-efficacy — confidence rightly rises.

The matched-comparison design strengthens these inferences considerably. Because treated students were paired with up to four demographically and academically similar non-treated students through genetic multivariate matching, the contrasts approximate the logic of the quasi-experimental designs that anchor the strongest CURE outcome studies, most notably the propensity-matched analysis of the Freshman Research Initiative (Rodenbusch, Hernandez, Simmons, & Dolan, 2016). Matching of this kind is widely regarded as a substantial improvement over simple before-and-after comparisons because it reduces the selection bias that otherwise inflates apparent program effects. It does not, however, eliminate three cautions that should temper every reading that follows.

First, the figures display **uncorrected p-values**, as their captions state plainly. With dozens of cells per figure, a handful of single-asterisk results would be expected to surface by chance alone without any reasonable family-wise error correction; the four-asterisk results are far more credible than the marginal ones, and a pattern that repeats across several related rows is more trustworthy than any isolated cell. Second, **differential attrition** is a live concern: post-survey response rates were markedly lower than pre-survey rates, and lower still among control students (Table 4 shows control post-survey counts roughly a third of their pre-survey counts in some cohorts), so the gain-score models in particular rest on a self-selected subset of survey completers. Third, the dose of research here is a **single general-education term**, far shorter and earlier than the multi-semester, upper-division programs behind the most celebrated long-term CURE outcomes. Taken together, these considerations recommend reading the findings below as a coherent and suggestive pattern — a strong basis for institutional decisions and for sharper follow-up analysis — rather than as a set of independently confirmed causal effects.

2. Research Identity and Research Self-Efficacy (Figure 2)

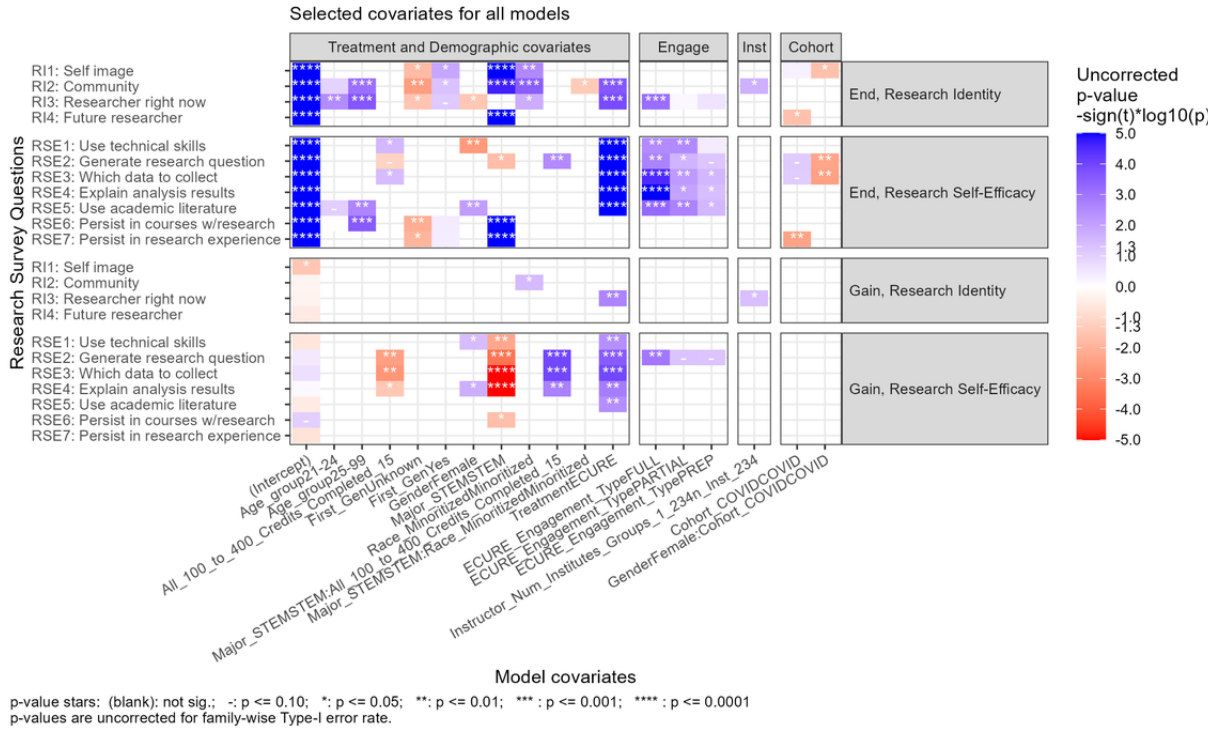


Figure 2. Endpoint and gain models for Research Identity (RI1–RI4) and Research Self-Efficacy (RSE1–RSE7) survey items.

Finding 1. The intervention reliably raised research self-efficacy but moved research identity far less.

The single clearest signal in Figure 2 is the column of strong positive cells under TreatmentECURE for the research self-efficacy items. At the end of the term, E-CURE students reported significantly higher confidence than matched peers across the full self-efficacy battery — using technical skills, generating a research question, deciding which data to collect, explaining analysis results, and using academic literature — with several items at the strongest evidentiary tier ($p \leq .0001$). Crucially, the *gain* models echo the endpoint models: E-CURE participation is associated with positive within-term growth in self-efficacy (generally $p \leq .01$), so the endpoint advantage is not merely a residue of who chose to enroll. By contrast, the four research-identity items respond more selectively: the treatment is positively associated at endpoint with a sense of belonging to a community of researchers (RI2) and with seeing oneself as a researcher in the present (RI3), and RI3 also shows a positive within-term gain, but the remaining identity items and the construct as a whole move far less than self-efficacy does. In the language of higher-education learning theory, the course functioned as a powerful source of *mastery experience* — the most potent of the four inputs to self-efficacy in Bandura's (1997) account — while leaving the slower-forming construct of *science identity* comparatively untouched over a single term.

This dissociation aligns closely with the literature. Research self-efficacy is consistently the most responsive short-term outcome of course-based research, and the assessment frameworks for CUREs treat it as a proximal, readily movable target (Auchincloss et al., 2014; Corwin, Graham, & Dolan, 2015). Identity, by contrast, is theorized and repeatedly observed to consolidate over longer arcs and through repeated participation and recognition by others as a scientist (Hunter, Laursen, & Seymour, 2007; Estrada, Woodcock, Hernandez, & Schultz, 2011). That a one-semester general-education experience produced measurable efficacy gains but not identity shifts is therefore the expected developmental sequence, and it usefully calibrates what any single early course can reasonably be asked to accomplish. It also implies a design principle: if identity gains are a goal, the institution should think in terms of *sequences* of research-bearing courses rather than one-off exposures.

Finding 2. A clear dose-response gradient appeared across engagement levels: FULL > PARTIAL > PREP.

The *Engage* block converts the project's central design question into a visible gradient. For end-of-term self-efficacy, FULL engagement carries the deepest, most significant positive cells (several at $p \leq .001$ to .0001), PARTIAL engagement shows consistently positive but more moderate cells (commonly $p \leq .05$ to .01), and PREP engagement is largely faint or, on several items, only a marginal trend. This ordering is a textbook *dose-response* relationship: the more fully students were immersed in authentic research practice, the larger their confidence gains. The same ranking, though attenuated, is visible in the self-efficacy gain band. Because the three levels are defined by how much of the authentic research cycle students actually perform, the gradient is most naturally read as evidence that *doing* research, not merely encountering it, is the active ingredient.

This is arguably the most consequential finding for the project's stated purpose of comparing pre-CURE and full-CURE models, and it converges strikingly with the most directly comparable study in the recent literature. The multi-institution Malate dehydrogenase CURE Community trial — roughly 1,500 students across nineteen institutions — found that full-semester CUREs produced the largest gains in research-relevant outcomes such as experimental design and career interest, while short modular CUREs produced outcomes that were, for most measures, statistically indistinguishable from traditional control courses (DeChenne-Peters et al., 2023). The E-CURE gradient reproduces that hierarchy in an independent population and across a far broader disciplinary range than biochemistry, which lends the pattern real weight. When two well-matched studies in different contexts recover the same ordering, the inference that depth of engagement drives affective gains becomes considerably more secure.

Finding 3. PREP was not inert: it produced a consistent, modest, positive signal on self-efficacy — detectable about as often as PARTIAL, though weaker in strength.

Across the end-of-term self-efficacy battery, PREP carries a faint but genuine positive cell on the majority of items — generating a research question (RSE2), deciding which data to collect (RSE3), explaining analysis results (RSE4), and using academic literature (RSE5) — and is blank only on using technical skills (RSE1). PARTIAL, by comparison, registers on those same items plus RSE1. Counting the cells in which each lower level shows a detectable positive association with the outcome relative to controls, PREP appears on roughly five of the six items on which PARTIAL appears; and in the within-term gain model for RSE2, the only self-efficacy item with any engagement signal, the PREP and PARTIAL cells are of nearly equal depth. PREP produced a weaker-in-magnitude yet comparably consistent positive signal: it underperforms PARTIAL and FULL in evidential strength while very nearly matching PARTIAL in how often it is detectable at all.

The literature proposes that students can realize the benefits of research at any stage (Gentile, Brenner, & Stephens, 2017) and that preparatory experiences build confidence and lower the barriers to later participation (Mahatmya et al., 2017; Horsch, St. John, & Christensen, 2012). The E-CURE data are broadly consistent with that strand rather than a strict bound upon it: even the preparatory level — teaching how research is conducted without engaging students in doing it — is associated with a small positive shift in research self-efficacy across most of the construct, which is exactly the proximal, readily movable outcome that CURE assessment frameworks treat as the first thing to respond (Auchincloss et al., 2014; Corwin, Graham, & Dolan, 2015) and that authentic and quasi-authentic research experiences reliably raise (Adedokun et al., 2013; Carpi, Ronan, Falconer, & Lents, 2017). Mechanistically this is what Bandura's (1997) account would predict: instruction about research practice delivers vicarious and per suasory efficacy information even in the absence of mastery experience, so a modest, broadly distributed PREP effect is more congruent with theory than a flat null would be.

Finding 4. The COVID-era cohort depressed affective outcomes — an effect concentrated among women.

The *Cohort* block flags the pandemic as a meaningful contextual depressant, but a careful reading shows the effect is more specific than a blanket decline: most of it resides in a *gender-by-cohort interaction* rather than in a uniform cohort shift. Several items — self-image as a researcher (RI1), generating a research question (RSE2), and deciding which data to collect (RSE3) — were depressed specifically for women in the COVID cohort, while only the future-researcher identity item (RI4) shows a general, gender-independent cohort reduction. In evaluation terms, the conditions under which the early sections were delivered attenuated the affective outcomes the intervention was designed to raise, and did so unevenly by gender.

This is consistent with emerging accounts of how emergency remote instruction blunted the hands-on, collaborative, and iterative features that give course-based research its effect — the very dimensions that define a CURE in the first place (Auchincloss et al., 2014), and that cross-disciplinary syntheses have since linked to pandemic-era declines in student interest and sense of competence. The finding also carries an internal-validity warning that should travel with every other result in this report: because the earliest cohorts overlap the COVID period, the program's maturation over time and the lifting of pandemic conditions are partially confounded with cohort. The practical implication is that the treatment estimates are most safely read as *conservative* — that is, likely dampened by the circumstances of the early implementations rather than inflated by them.

Finding 5. STEM majors gained less in self-efficacy than non-STEM majors — a likely ceiling effect, not a racial equity gap.

Within the gain band for self-efficacy, one column carries some of the figure's most intense negative cells (for several items, $p \leq .001$ to $.0001$). That column is the *STEM-major main effect*: over the term, students already majoring in STEM gained *less* in research self-efficacy than non-STEM majors, with the pattern reversing for students who had completed more credits. This is most parsimoniously read as a *ceiling effect* — STEM majors typically begin the term with higher research self-efficacy and therefore have less room to grow — rather than as a deficit produced by the program.

3. Behavioral Outcomes: Retention, Major Change, and Course Grade (Figure 3)

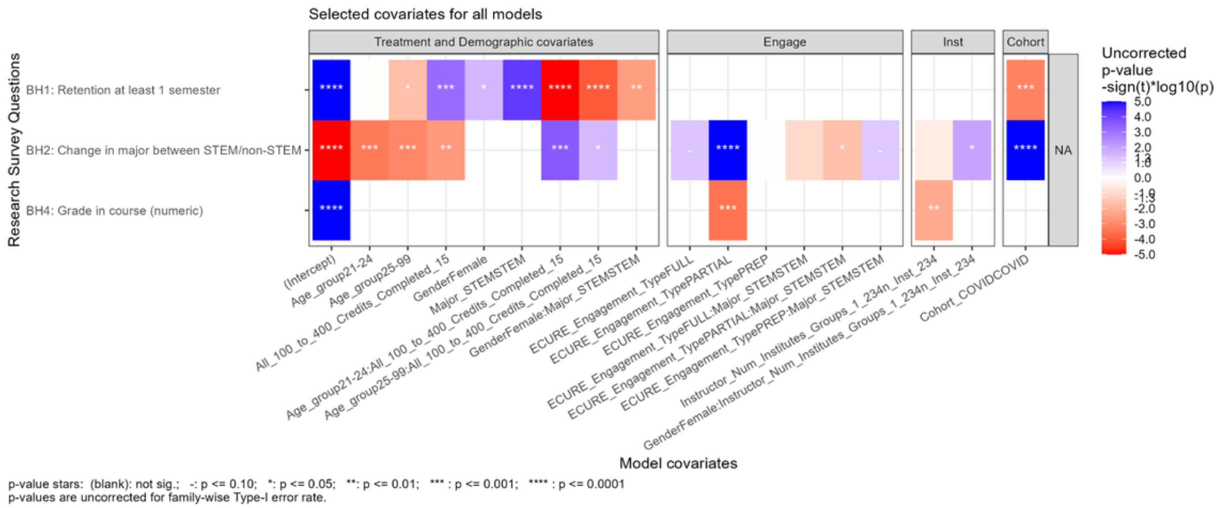


Figure 3. Models for one-semester retention (BH1), change of major between STEM and non-STEM (BH2), and numeric course grade (BH4).

Finding 6. One-semester retention was driven by student characteristics and the pandemic, not by engagement level.

For the retention row, the strong cells lie in the demographic and cohort blocks rather than in the engagement or institution blocks, with the ECURE Treatment absent and never selected in the models. Being female is positively associated with remaining enrolled ($p \le .001$), several background variables register, and the COVID-cohort indicator is significantly negative ($p \le .001$) — the pandemic reduced short-term persistence. Notably, the engagement-type cells for retention are essentially empty or deviating from a dose-response relationship, meaning depth of research immersion was not a selected predictor of whether a student returned the following semester.

At first glance this seems to contradict the signature CURE result that early research participation raises persistence and graduation (Rodenbusch et al., 2016; Gregerman, Lerner, von Hippel, Jonides, & Nagda, 1998). The apparent contradiction largely dissolves once the outcome's timescale is considered. Rodenbusch et al. measured *six-year* graduation following a *three-semester* program; one-semester re-enrollment is a far more proximal and noisier proxy, and it is subject to a *ceiling effect* in a population most of whom would re-enroll the next term regardless of any single course. The most defensible reading is that one general-education term is too short and too early a lever to move a behavioral outcome that, in Tinto's (1993) classic account of student departure, is governed by a broad web of academic and social-integration factors operating well beyond any one classroom. The absence of a retention effect here is thus not evidence against the long-run persistence benefits documented elsewhere; the two simply operate on different horizons.

Finding 7. PARTIAL engagement and the COVID cohort were both associated with movement between STEM and non-STEM majors.

The change-of-major row is among the busiest in Figure 3. PARTIAL engagement shows a strong cell ($p \leq .0001$), the COVID cohort shows a comparably strong cell, and several demographic terms register as well. Because the outcome is coded simply as a change in *either* direction between STEM and non-STEM categories, the *direction* of educational benefit cannot be read from the figure alone: an association with major-switching is consistent both with students migrating *into* STEM (a pathway success, in keeping with the project's recruitment rationale) and with students migrating out of it.

This ambiguity is itself the finding worth reporting honestly, and it is a good illustration of why an aggregated indicator can obscure as much as it reveals. The pre-CURE pathway literature would predict that partial engagement functions as an on-ramp, nudging exploring or undecided students toward STEM commitments (Mahatmya et al., 2017). The competing interpretation — that an authentic but incomplete taste of research helps some students recognize that a STEM path is not for them — is equally plausible *a priori*, and is not necessarily a bad outcome from the student's perspective, since an informed early exit is preferable to a late and costly one. Resolving the question requires the directional breakdown that lies behind this collapsed indicator. A further, structural caution sharpens the reading: the engagement signal here is *non-monotonic* — only the middle level (PARTIAL) differs from controls, while both PREP and FULL do not (deviating from a dose-response relationship) — which strongly suggests the association is driven by one or two particular courses that happened to be taught at the PARTIAL level rather than by partial engagement as a general property. Until both the directional breakdown and the course-level check are produced, the most that can be claimed is that a PARTIAL subset is associated with major mobility, with the welfare sign and the true cause to be determined.

Finding 8. PARTIAL engagement was associated with somewhat lower course grades.

In the course-grade row, PARTIAL engagement carries a significant negative cell ($p \leq .001$), and greater instructor institute experience is likewise negatively associated. Taken at face value, students in partially research-infused sections earned modestly lower grades than their matched comparison peers.

This is less alarming than it first appears and is broadly consistent with the literature. The strongest long-term CURE study found *no* effect on grade-point average even as it documented large graduation benefits (Rodenbusch et al., 2016), implying that course grades and the deeper outcomes of research participation are only loosely coupled. Authentic research also introduces what the learning-sciences literature calls *desirable difficulties* and *productive struggle*: open-ended, ambiguous tasks with genuinely unknown answers raise cognitive demand and can depress conventional grades in the short run even as they build the more durable competencies that grades measure poorly. Recent longitudinal work on CUREs frames exactly this challenge-and-frustration dynamic as an engine of, rather than an obstacle to, sustained interest. A grade decrement is therefore plausibly a marker of added rigor rather than of diminished learning. A structural caveat reinforces the caution: because only the PARTIAL level departs from controls while both PREP and FULL do not, the grade dip is most likely an artifact of the specific courses delivered at that level rather than a property of partial engagement, and it should not be generalized across the engagement gradient. As with every cell in these figures, the uncorrected p-value and the unmeasured variation in grading practices across many different courses and instructors counsel restraint before treating the grade dip as a real cost.

4. Cultural-Values Compatibility (Figure 4)

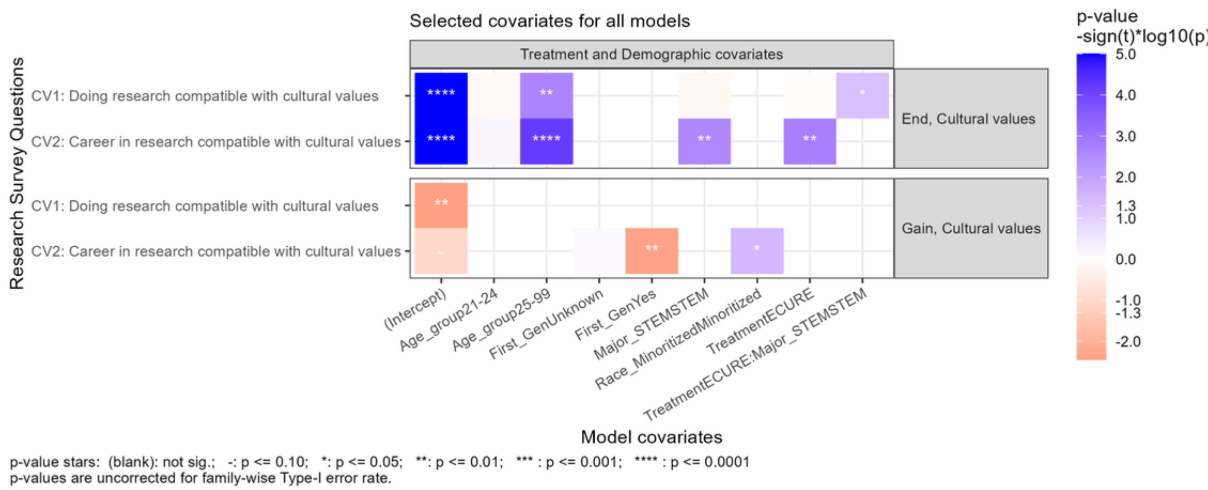


Figure 4. Endpoint and gain models for the perceived compatibility of doing research (CV1) and of a research career (CV2) with students' cultural values.

Finding 9. Valuing research as culturally compatible was tied to STEM-major status and, modestly, to the intervention — but age was the dominant predictor.

At the end of the term, the two compatibility items were most strongly predicted by being an older or returning student (the 25-and-older age band reaches $p \leq .0001$ on the research-career item) and by being a STEM major ($p \leq .01$). The TreatmentECURE term is positively and significantly associated with viewing a research *career* as compatible with one's values ($p \leq .01$), and a positive treatment-by-STEM interaction appears for the doing-research item. In the vocabulary of motivation theory, these items tap the *values* or *internalization* component of integration into a scientific community — the sense that research is not merely something one *can* do but something that *fits* who one is and wants to become.

This maps cleanly onto Estrada et al.'s (2011) influential model, in which self-efficacy, scientific identity, and the internalization of scientific community values jointly predict persistence, and in which values are theorized to consolidate later and most strongly among the more committed. That the strongest predictors here are age and major, with the intervention adding a modest but real positive increment, fits a picture in which a single course can *nudge* but not *manufacture* the sense that research belongs in one's life. Read alongside Findings 1 and 2, this completes a coherent account of the Estrada triad as it responds to a brief early intervention: self-efficacy moves readily, values move modestly, and identity — the most deeply held of the three — barely moves at all within one term.

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