The Effect of Interdisciplinary Training on Cultivating Graduate Student Innovation Capacities

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Abstract

This study explores the impact of interdisciplinary STEM training on the development of innovation capacities among graduate students in Ph.D. programs. Rooted in constructive-developmental theory and the Inputs-Environments-Outcomes (I-E-O) model, the research assesses how participation in an interdisciplinary program affects students' cognitive, social, and intrapersonal growth. The study uses a longitudinal design and both covariate adjusted and propensity score matched hierarchical blocked regression to evaluate innovation capacity development over time. Results indicate that interdisciplinary training accelerates the development of innovation capacities by roughly one quarter of a standard deviation (β = .27-32) -a very substantial increase. Key innovation benefits are observable in students' creativity, proactivity, and teamwork across diverse fields. These findings highlight the potential of interdisciplinary STEM programs to meet modern scientific and industrial demands for innovative, adaptive researchers, while also underscoring challenges in scaling such programs within traditional academic structures. Implications for program design, student engagement, and the effectiveness of interdisciplinary approaches in higher education are discussed.

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Introduction

Higher education institutions are increasingly focused on equipping students to become innovative thinkers and effective problem solvers. These innovation capacities are essential mechanisms for bridging educational goals and the practical demands of the global market, and for preparing students to navigate the challenges of a connected, dynamic world. These efforts take on special importance in science, technology, engineering, and math (STEM) fields where the interaction between science and industry has long been recognized as a central driver of technological (Kaufmann & Tödtling, 2001) and economic innovation (Atkinson & Mayo, 2010; National Economic Council et al., 2015; National Science Board, 2018).

A central driver of scientific innovation is interaction with diverse others, which has been demonstrated to dramatically increase the novelty and ingenuity of scientific advancements (Hofstra et al., 2020), and leads to more creative solutions to complex, practical problems. In addition to transforming disciplinary cultures to attract, and provide more equitable experiences for scientists who are diverse by way of race, gender, and national status (Museus et al., 2011; National Center for Science and Engineering Statistics (NCSES), 2023; National Science Board, 2019), institutions have increasingly recognized the power of interdisciplinarity for fostering innovation (Jacob, 2015; Wei et al., 2020). Indeed, research demonstrates that innovation in STEM is often catalyzed by cross-disciplinary collaboration in small teams of scientists with complementary skillsets, and who have the explicit support of institutional research and training mechanisms (Heinze et al., 2009).

However, significant gaps exist regarding precisely how, for whom, and in what ways interdisciplinary experiences may benefit students' ability to innovate. Notably, while innovation capacity development has been studied in undergraduates and in mono-disciplinary contexts (Mayhew, Selznick, Zhang, et al., 2021; Selznick, Mayhew, Winkler, et al., 2022; Selznick, Mayhew, Zhang, et al., 2022), little is known regarding its evolution in graduate students -those who will become the next generation of scientific researchers. Furthermore, while it is clear that diverse interactions are associated with the production of scientific innovations (Hofstra et al., 2020), precisely which sorts of interactions spur innovation remains an open question. Finally, innovation is a complex, multifactorial construct that can manifest in many ways (Selznick, 2017; Selznick & Mayhew, 2018), and exactly how interdisciplinary experiences foster growth in which forms of innovation remains unexamined. Resultantly, institutional support for innovation development via interdisciplinarity remains fraught, imprecise, and based upon untested assumptions. These concerns are intensified by the novelty, and complexity of interdisciplinary science programs, and the notable dearth of rigorous research linking program elements to student outcomes (Ryser et al., 2009; Herro et al. 2017; Gao et al., 2020). This study therefore seeks to address the critical research question: How does participation in an interdisciplinary STEM Ph.D. program affect students' development of innovation capacities?

Conceptual Framework

This paper employs Kegan's (1982; 1994) constructive developmental theory of adult psychological and epistemological evolution. In this theory, Neo-Piagetian psychologist Kegan's fourth plateau aligns well with our research purpose. The fourth plateau, self-authorship, allows an individual to navigate between various social-cognitive systems, surpassing the need to meet social expectations and allowing one to critique the systems in which one is embedded (see also Baxter Magolda, 2008). As first-year STEM Ph.D. students, they need to adapt themselves to a new environment and develop their professional capabilities to address cutting-edge research questions.

Kegan's (2018) theoretical model defined three lines of human development: cognitive, social, and intrapersonal. The cognitive line focuses on how individuals think, reason, and make meaning of the world around them. Kegan posits that individuals progress from simpler ways of understanding reality to more complex and nuanced cognitive approaches. The social line of development pertains to how individuals relate to others and navigate interpersonal relationships. Kegan suggests that individuals evolve from a self-centered perspective to a more relational and empathetic orientation. Finally, the intrapersonal line of development concerns individuals' relationship with themselves, including their self-awareness, self-concept, and sense of identity. Kegan proposes that individuals move from an externalized sense of self that is defined by external expectations and societal norms towards an internalized sense of self characterized by self-authorship and self-awareness. This progression involves developing a coherent sense of identity, autonomy, and self-reflection. These lines represent different modes of development in terms of how individuals understand and interact with the world, with themselves, and with others. Several studies have applied Kegan's theory in STEM education (e.g. Sheffield et al, 2017). In this case, we utilized Kegan's theory as a foundation to design the outcomes and programmatic elements of an interdisciplinary Ph.D. program.

Additionally, Astin's (1991) Input-Environment-Outcome (I-E-O) model has been identified as a framework to explain students' engagement in higher education and the developmental outcomes of said engagement. This model suggests that students' initial characteristics interact with both distinctive features of their educational experience (termed "bridge measures", these include constructs like the composition of one's graduate cohort) and distinctive features of the educational environment (such as specific courses or co-curricular programs attended) to predict educational outcomes. In this longitudinal study, we applied students' pre-test and demographic variables as our inputs, thus controlling for the initial state of students' innovation capacities. We then evaluate the developmental influence of initial and continuing environmental characteristics such as involvement in the interdisciplinary program (or treatment), and taking innovation, entrepreneurship, or creativity-focused courses.

Review of the Literature

Innovation capacities

Drawing from foundations in both economic (Baumol, 2004, 2010) and educational theory (Mars, 2013), innovation is defined as "the process of generating and executing contextually beneficial new ideas" (Selznick, 2017, p. 2). Innovation capacities, then, are a set of self-perceptions, skills, and abilities that individuals can acquire to actively engage in the innovation process (Selznick & Mayhew 2018). Contrary to the belief that innovativeness is an innate characteristic, recent research suggests that certain aspects of innovation are teachable and learnable (e.g., Mayhew, Selznick, Zhang, et al., 2021). This active area of research emphasizes the role of students who, through involvement in both the formal college curriculum and extracurricular activities, can nurture, enhance, and apply their innovation capacities to create positive changes in their environment.

Several interventions, pedagogical techniques, and educational environments have been demonstrated to enhance innovation capacity development. For example, several studies have indicated that theoretically-derived, short-term, low cost interventions are effective at boosting innovation development in undergraduate populations (Mayhew et al., 2019; Mayhew, Selznick, Zhang, et al., 2021). Similarly, curricular practices provide a potential avenue for development, with interaction with faculty predicting growth among undergraduates who identify as women (Selznick, Mayhew, Zhang, et al., 2022). Several studies have identified practices that encourage students to make connections between different bodies of knowledge (Selznick, Dahl, et al., 2021), between their studies and real-life experiences (Bock et al., 2020; Selznick, Mayhew, Winkler, et al., 2022), or between their classroom learning and their self-concept (Selznick, Mayhew, Zhang, et al., 2022) are predictive of growth in innovation capacities. Finally, institutional affordances may contribute to innovation capacity development; specifically by providing physical spaces for invention and exploration (Bock et al., 2020), and by partnering with local and regional stakeholders eager to support and make use of innovations (Selznick, Mayhew, et al., 2021). Despite these research advances, Mayhew (2019) highlights the lack of knowledge regarding innovation capacities in the graduate population. This is concerning, as there is a recognized need for graduate programs to cultivate innovative, well-rounded researchers who can translate their disciplinary knowledge to meet the needs of industry (Lenhart et al., 2022).

Interdisciplinarity

While competing definitions of interdisciplinarity and related terms abound in the theoretical and typological literature (Borrego & Newswander, 2010; Lattuca et al., 2004; McCulloch, 2012), the *sine qua non* of an interdisciplinary education involves the active integration of different fields of knowledge, each with their own epistemologies, perspectives, and theoretical underpinnings (Klein, 2017). This form of education has experienced a meteoric rise in popularity in institutions of higher education over the last two decades (Jacob, 2015; Jacobs & Frickel, 2009; Lyall et al., 2015; Wei et al., 2020) as universities seek to address increasingly complex and socially-embedded challenges. However, while advocates of interdisciplinary education cite its potential to address unique challenges, and to produce singularly innovative, critical, daring scientists, interdisciplinary programs present profound challenges to institutions, educational programs, faculty, and students.

Interdisciplinarity poses several distinct challenges. First, it directly works against mono-disciplinary departmental structures, which have long been considered “the essential and irreplaceable building blocks of American universities” (Abbott, 2001, p. 128). Resultantly, institutions often struggle to valorize or support interdisciplinary research efforts using existing systems and structures (Golde & Gallagher, 1999). Furthermore, academic incentive systems (i.e., promotion and tenure, prestige) have a difficult time evaluating the impact of interdisciplinary work, often leading to reduced career performance for interdisciplinary scholars (Tobi, 2014; Van Hartesveldt & Giordan, 2008). Interdisciplinary scholars also consistently receive less funding than their peers (Bromham et al., 2016; Konig & Gorman, 2017) and have more difficulty publishing their work in high-impact (often mono-disciplinary) journals (Rafols et al., 2012). Faculty report that interdisciplinary research is more cognitively and epistemologically demanding (Krohn, 2017), and that establishing common ground and unified vision on an interdisciplinary team often slows the rate of research (Defila & di Giulio, 2017). Students engaged in interdisciplinary studies at the graduate level often perceive it as risky, with unpredictable effects on their career trajectories (Dooling et al., 2017; Graybill et al., 2006). Finally, interdisciplinary socialization, advisory, and mentoring processes present students and faculty with a highly complex network of competing norms that can be difficult to navigate (Boden et al., 2011; Hibbert et al., 2014; Strengers, 2014; Vanstone et al., 2013).

To counterbalance these considerable challenges, advocates of interdisciplinary learning highlight unique social and educational benefits of the practice. Broad interdisciplinary approaches are recognized as the only research methods capable of addressing highly complex, embedded, “wicked” problems (like decarbonizing energy production systems, addressing pandemics, etc.) that require novel, innovative, multiperspectival solutions (Boradkar, 2017; Pohl et al., 2017). Interdisciplinary research also plays a key role in driving innovation and maintaining competitiveness in advanced and keystone industries (Van Hartesveldt & Giordan, 2008). However, the question remains: does interdisciplinary training result in more innovative, competent researchers?

As stated by Lattuca and colleagues “few studies at the postsecondary level provide systematic and methodologically robust assessments of the effects of interdisciplinary study on college students’ learning and development” (Lattuca et al., 2017, p. 338), and none have examined its effects on students’ innovativeness. However, as noted by Morse et al.'s (2007) programmatic case study, there is considerable reason to hypothesize that interdisciplinary training promotes innovation capacity development by strengthening similar core competencies. Specifically, successful interdisciplinarians must exhibit creativity, flexibility, comfort with risk, problem-solving abilities, strong communication skills, and the ability to rally diverse others around a shared vision -all necessary traits for innovators (Selznick, 2017). Scholars (Pacheco et al., 2020; Rhoten et al., 2009) have further suggested that the multiplicity of perspective gained by moving between disciplinary and interdisciplinary understandings may prompt research innovation and creative thinking. Prior literature has demonstrated that racial, cultural, and gender diversity in team science contexts allow scientists to better conceptualize and address complex problems (Sulik et al., 2021), and that interactions across lines of difference generates more innovative scientific research (Hofstra et al., 2020). These processes may transfer to cross-disciplinary difference as well; interdisciplinary teams, while they may produce research more slowly than monodisciplinary peers, tend to produce research that has much stronger impact (Okamura, 2019). Interdisciplinary education also enhances students' ability to communicate and coordinate with profoundly diverse others (Thompson, 2009) -a skill that is both durable (Cummings & Kiesler, 2008) and necessary in the increasingly multicultural context of contemporary science. Finally, the limited empirical research examining the effects of interdisciplinary learning on student competence presents a mixed picture. There is strong theoretical support for such studies leading to deeper critical thinking, creativity, and nuanced understandings (Lattuca et al., 2004). These notions are partially borne out by Ivanitskaya et al. (2002) who reported interdisciplinary students had more advanced epistemologies, deeper critical thinking, better metacognition, and deeper comprehension of alternative perspectives than similar mono-disciplinary peers. However, Lattuca et al. (2017) found no evidence that interdisciplinarity enhanced critical thinking or students' need for cognition -though this may be due to ceiling effects as students who select into interdisciplinary programs initiate their studies with very strong abilities in these areas. Therefore, while there is considerable theoretical reason to believe that interdisciplinarity will boost innovation, the scant and contradictory empirical findings in the research literature provide few answers and fewer insights.

Methods

This study uses longitudinal data from an ongoing mixed-methods study exploring the effectiveness of a convergent research training program designed to help students develop innovative capabilities, collaborate across disciplines, and achieve learning outcomes important to the decarbonized energy industry. Before covering our design, it is important to first provide an overview of the program context.

Program Context

The interdisciplinary Ph.D. program was designed to generate an innovation ecosystem that brought together transdisciplinary teams of faculty, trainees, and external industry and regulatory partners to develop cost-effective, resilient decarbonized energy technologies (Cai & Ahmad, 2023). The program learning objectives were designed in collaboration with the needs of electrical industry stakeholders, including nine businesses, a research organization, and a regulatory agency. Of the 10 program objectives, two focus on developing innovation skills, asking student to: innovate and adapt to find solutions to difficult and ever-changing challenges of sustainable energy and to design forward-thinking solutions related to sustainable energy.

The program was sponsored by the National Science Foundation NSF Research Traineeship program that is designed to support the development of interdisciplinary research scientists working in research areas that are considered a national priority. The program convened ten core faculty from a broad range of disciplines, including: integrated systems engineering; civil, environmental, and geodesic engineering; public policy; agricultural, environmental, and developmental economics; computer science and engineering; electrical engineering; geography; materials science; and education and human ecology. Non-core senior personnel included faculty from the fields of sustainable supply chains; environmental and energy law; engineering education; energy impacts sociology; techno-economic analysis; biofuels; behavior and decision-making; and energy and sustainability.

The Ph.D. program takes five years to complete. In the first year, the students attend a two-week level-setting summer bootcamp in which they were introduced to key faculty members and were given a problem- and team-based sustainable energy challenge to solve by the end of the two-week period. This problem used data from the core research of core faculty members. The pedagogical structure encouraged students to rapidly analyze, innovate, prototype, and test their solutions to be successful. In the students' second year, they return to the bootcamp where they act as near-peer mentors to the entering cohort of students. Students maintain these near-peer mentors throughout their time in the program. They are also assigned an academic faculty mentor, and an external mentor from the energy industry.

After completing the level-setting bootcamp, students take a series of courses throughout fall, spring, and summer terms that last three years. These include a mandatory foundational course taught by program faculty, each of whom are given a two-week period to introduce their field to the students in an applied manner. Students take five elective courses each of which must be drawn from a different thematic area, including: energy-systems modeling; information systems; energy policy, regulation, and economics; energy-business modeling; and energy technology, components, and sub-systems. In the spring of the third year, students must complete a capstone course and project in which they develop an innovative solution to a current energy problem. The students may engage in their dissertation research full-time in the remaining two years of the program.

The program also involved students in three co-curricular experiences. The first, a student community of practice and engagement (SCOPE) consisted of weekly meetings in which prominent members of the energy industry, regulatory bodies, or research organizations spoke with students regarding their career paths and present opportunities. The second consisted of a research exposition, held annually, in which students presented the results of their ongoing research to one another, to program faculty, and to external stakeholders. The exposition included presentations by external partners, networking opportunities, and a poster competition. Finally, every spring program students participate in a week-long, interdisciplinary, team-based innovation competition. This competition addresses a current problem defined by an industry partner. Students gain practical experience in team-based innovation to provide solutions that support the needs of the company sponsoring the innovation competition.

The program was designed to support advancement along all three of Kegan's (2009) developmental lines. Cognitively, the students were challenged to continuously reconsider their epistemological commitments and their framing of decarbonized energy challenges through constant exposure to and deep interaction with challenging interdisciplinary curriculum and through mentorship from academic, industry, and near-peer sources. Intrapersonally, students were encouraged to see themselves as innovators through participation in the level setting bootcamp, the regular innovation challenges, and the capstone project. The social and communicative elements of students' innovation capacities were developed via regularly engaging in interdisciplinary team science in the bootcamp, the research exposition, the team-based innovation challenges, and the student community of practice and engagement. Development along each of these lines may therefore be tentatively ascribed to the action of their associated programmatic elements.

Sample

The survey was deployed once in the late summer/early fall and again in the late spring/early summer of each academic year from 2020 to 2024. Survey participation was limited to students who were beginning their first year of Ph.D. studies at a large, Midwestern, research-intensive university. To facilitate an effective comparative analysis, the design of this study involved an experimental group drawn from Ph.D. trainees in the STEM interdisciplinary training program and a broader control group of Ph.D. students who were not in the training program at the same institution. Experimental students were incentivized to participate in the surveys through $25 gift cards. Control students were incentivized to participate by being entered in a raffle for four $100 gift cards per academic year. The experimental group population consisted of 24 Ph.D. trainees from the interdisciplinary program, of whom 19 consented and completed the full research process for this study.

To evaluate whether participation in an interdisciplinary STEM Ph.D. program affected the development of student's innovation capacities when controlling for demographic factors and previous educational experiences, two complementary analytical approaches – longitudinal hierarchical blocked regression and propensity score matching – were used. This process was chosen to ensure the robustness of central findings to analytical variation (Pascarella et al., 2013). Specifically, hierarchical regression's flexible model structure allowed for a better understanding of the mediating or moderating effects of predictors, as well as better evaluating the impact of continuous variables and time-varying covariates -features that make it especially useful in assessing longitudinal change (Cohen et al., 2003).

In order to achieve more parity between the numbers represented in the control and treatment groups, we used propensity score matching methods (Austin, 2011; Benedetto et al., 2018), an analytic process that maximized available statistical power and reduced the dependence of findings on modeling choices. However, the propensity score matching process itself can be complex, may reduce sample size, and is reliant on the assumption that unobserved variables that are uncorrelated with any observed matching variable do not deeply influence the estimates.

For this reason, and following the recommendation of Pascarella et al. (2013), we used these two approaches – control group comparison via research design and control group comparison via analytic matching – to speak to the effects of participation in our interdisciplinary program on innovation capacities. Such a dual-pronged approach been used extensively in longitudinal research and the evaluation of interventions and programs (Heckman et al., 1997; Imbens & Wooldridge, 2009). We turn now to a description of each.

Full Control Group

The first control group population was composed of all other first-year Ph.D. students enrolled at the same university but who did not participate in the interdisciplinary program. From this population, 127 students completed the entire research process, and constituted the full control group of this study. This full control group was used for the longitudinal hierarchical blocked regression analysis. Differences between the experimental and full control group were accounted for through both longitudinal design and via including an extensive suite of control variables suggested by prior research and this study's theoretical framework.

Propensity Score Matched Control Group

The second control group was constructed via propensity score matching. Propensity score matching is a statistical process designed to identify students in a control condition who were equally likely to have chosen to participate in the experimental condition (Caliendo & Kopeinig, 2008; Grunwald & Mayhew, 2008). This matched control group allowed the research team to isolate and evaluate the unique contributions of the interdisciplinary program to innovation capacities in a more rigorous manner, with convergent findings from each sample further supporting claims of efficacy and providing a more robust range of effect size estimates. For this reason, we position the propensity score approach as a sensitivity analysis, one designed to ensure findings from the full control group design hold across analytic contexts.

To create a control group with sample sizes similar to the treatment, the research team used a set of 11 observed covariates to estimate each students' probability of enrolling in the experimental program. These variables were chosen due to their demonstrated influences on the outcomes and experiences of STEM students (Museus et al., 2011; National Academies of Sciences Engineering and Medicine, 2018; National Center for Science and Engineering Statistics (NCSES), 2023) and graduate students (Bahnson et al., 2022; Love Stowell et al., 2015; O'Meara et al., 2017), and innovators (Martín et al., 2017; Mayhew, Selznick, Zhang, et al., 2021; Selznick, Mayhew, Winkler, et al., 2022; Selznick, Mayhew, Zhang, et al., 2022) and included race/ethnicity, gender identification, first-generation status, age, international student status, transfer student status, family income, political inclination, cohort year, and presence of an immediate family member who created a new product or started a new business. As no students who identified as Latinx or Middle Eastern, as non-binary, or as a transfer student were present in the experimental group, all students with these characteristics were removed from the pool of potential matched control students.

A nearest-neighbor matching process was then used to match each member of the experimental group with a comparable member of the control group (Caliendo & Kopeinig, 2008). All propensity score matching procedures were conducted with the psmatch2 package in Stata v.17 (Leuven & Sianesi, 2003). Subsequently, the quality of the matching procedure and balance of each covariate was evaluated via a series of t-tests (Zhang et al., 2019). No covariate imbalances were detected with the exception of first-generation status which was marginally significant ($p = .05$) with greater first-generation representation in the control group ($M_{experimental} = .21$, $M_{control} = .53$). Select sample characteristics are presented in Table 1, with the full set of characteristics presented in Table A1 in the appendix.

Table 1

Gender and Race/Ethnicity Characteristics of Quantitative Samples

Characteristic	Experimental Group (*n* = 19)		Full Control Group (*n* = 127)		Matched Control Group (*n* = 12)	
	n	%	*n*	%	*n*	%
Racial/Ethnic Identity						
Black/African American	4	21	8	6	2	17
American Indian/ Alaskan Native	0	0	0	0	0	0
Arab, Middle Eastern, or Persian	0	0	2	2	0	0
All Asian	4	21	30	24	1	8
All Latinx	0	0	8	6	0	0
Native Hawaiian or Pacific Islander	0	0	0	0	0	0
White/Caucasian	11	58	68	54	7	58
Multiracial	2	11	8	6	1	8
Other ethnicity or prefer not to respond	0	0	3	2	1	8
Gender Identity						
Man	15	79	51	40	6	50
Woman	6	32	71	56	6	50
Another gender or prefer not to respond	0	0	5	4	0	0

Note. Due to rounding, numbers may not add up to 100%.

Measures

Innovation Capacities

The primary measure used for this study was Innovations Capacities Scale (ICS). The ICS a is a theoretically derived and empirically validated survey instrument that is designed to assess students' innovation capacities (Selznick, 2017; Selznick & Mayhew, 2018). This scale was developed by drawing on latent trait theory (Embretson & Reise, 2000) and is conceptually grounded in both Ajzen's (2002) theory of planned behavior, and in Kegan's (2009) constructive-developmental theory of domains of development. Furthermore, the ICS has demonstrated validity across widely divergent educational and cultural contexts and is therefore well-suited to assess the innovation capacities of students from strongly diverse backgrounds and underrepresented minorities (Mayhew, Simonoff, Baumol, Selznick, & Vassallo, 2016). The innovation capacities scores are second–order factor scores calculated from nine conditioned constructs: three for interpersonal (networking, persuasive communication, teamwork across difference), three for intrapersonal (intrinsic motivation, proactivity, innovation self-concept), and three for cognitive (creative cognition, intention to innovate, and risk taking/tolerance) scales.

In this study, our dependent variables are the overall innovation capacity score and its constituent sub-scores. Each subconstruct was measured via 4-6 items on a 5-point Likert-type agreement scale. Cronbach's *a* and McDonald's ω values for the full scale and each subscale are presented in Table 2, alongside a sample item (Hayes & Coutts, 2020). The full scale and its validation argument may be found in Selznick and Mayhew (2018). After cleaning, all scale scores were converted to factor scores with an ordinary least squares regression method due to the superior accuracy of these scores in small sample sizes when compared to Bartlett's factor scores (DiStefano et al., 2009).

Table 2
Sample Items and Reliability of Innovation Capacities Scale

Construct and Sample Item	Mean	SD	Min	Max	α	ω
Overall Innovation Capacity						
Beginning of academic year	0	.94	-2.34	2.08	.85	.85
End of academic year	0	0.94	-2.56	1.99	.86	.87
Motivation						
I can persist towards achieving long-term goals, even after setbacks						
Beginning of academic year		0.85	-2.49	1.25	.71	.72
End of academic year		0.90	-2.76	1.31	.80	.80
Innovation Self-Concept						
I can come up with creative ideas that will benefit myself and others						
Beginning of academic year		0.94	-2.26	1.43	.77	.77
End of academic year		0.96	-2.50	1.52	.81	.82
Proactivity						
I can initiate actions that will allow me to positively change a situation for myself						
Beginning of academic year		0.88	-3.25	1.33	.71	.72
End of academic year		0.88	-3.13	1.34	.75	.75

Persuasiveness					
I can persuade others to support my point of view					
Beginning of academic year	0.91	-2.70	1.80	.79	.79
End of academic year	0.94	-3.21	1.70	.84	.84
Networking Ability					
I can turn a new relationship into a closer friendship					
Beginning of academic year	0.94	-2.04	1.56	.83	.84
End of academic year	0.94	-2.26	1.40	.86	.87
Teamwork Ability					
I can work as part of a group with people who have different skillsets than my own					
Beginning of academic year	0.90	-2.53	1.19	.81	.81
End of academic year	0.92	-3.42	1.14	.83	.83
Risk Tolerance					
I can challenge a faculty member's suggestions for how to solve a problem					
Beginning of academic year	0.94	-2.63	1.94	.88	.88
End of academic year	0.96	-2.73	1.62	.90	.90
Intention to Innovate					
I enjoy being asked to come up with new ideas					
Beginning of academic year	0.90	-2.68	1.49	.80	.79
End of academic year	0.92	-3.57	1.43	.82	.82
Creativity					
I am skilled at identifying new opportunities (such as a new product or service, or a more effective process)					
Beginning of academic year	0.88	-2.67	1.75	.74	.74
End of academic year	0.91	-2.78	1.60	.80	.81

Sociodemographics

Student gender identity was assessed through a single item with response options of 'Man', 'Woman', 'Nonbinary', 'Other', and 'Prefer not to respond'. Student race/ethnicity was assessed through a 'check all that apply' item with the response options listed in Table 1. Students who expressed multiple racial/ethnic identities were aggregated into a single 'multiracial' category. Student races were then converted to effect codes as these simplify interpretation by comparing each categorical mean to the overall mean. Furthermore, they avoid ideologically privileging a particular racial experience as the reference to which others should be compared (see Mayhew & Simonoff, 2015b, 2015a).

One open-entry item measured student birth month and year which was used to derive student age at time of entrance to their Ph.D. program. A single item assessed student's estimates of their family's income over the last year with responses including 'Less than $25,000', '$25,000 - $49,999', '$50,000 - $74,999', '$75,000 - $99,999', '$100,000 - $124,999', '$125,000 - $149,000', '$150,000 - $174,999', '$175,000 - $199,999', and '$200,000 or more'. These responses were coded ordinally from 1 – 9. Two items assessed the highest level of formal education achieved by the students' father/male guardian and mother/female guardian, respectively. Response options included 'elementary school or less', 'some high school', 'high school diploma', 'some college', 'college degree', 'some graduate school', 'graduate or professional degree', and 'prefer not to answer'. Students who responded to both questions with 'high school diploma' or lower were dummy-coded as first-generation college students. Student political inclinations were assessed at Time 1 with a single item stating "I identify politically as." Response options ranged from 'very conservative' to 'very liberal' on a 5-point scale with 'moderate' as a midpoint and a 'prefer not to answer' option. These responses were ordinally coded with higher numbers indicating a more liberal identification; prefer not to answer responses were treated as missing data. Finally, two dummy-coded items assessed whether or not a member of the students' family had ever started a new business or nonprofit organization, or had ever invented a new product, service, or process.

Bridge variables

Student Ph.D. entrance cohort was assessed by year of response to the survey and was dummy coded with year four as the reference group. Two items assessed transfer and international student status and dummy coded with non-transfer domestic students as the reference group.

Environmental variables

Three dummy-coded items assessed whether or not students had, during their Ph.D. studies, taken a course focused on innovation, entrepreneurship, or creativity. Finally, participation in the interdisciplinary STEM Ph.D. training program (treatment) was determined via information from the university registrar. Descriptive statistics for all covariates are reported in Table A1 in the appendix and bivariate correlations are reported in Table A2.

Analyses

The research team employed hierarchical blocked multiple regression techniques to investigate the effects of interdisciplinary program participation on the development of innovation capacities and its constituent subdomains (see Appendix B) and to illuminate the environmental and experiential factors that promote or impede this development (Cohen et al., 2003; Keith, 2019). Following Mayhew et al.'s (2016) effect size interpretation guidelines for higher education research, standardized regression coefficients (β) of 0.6 were considered small, .12 as medium, and .20 as large (p.20; c.f. Hill et al., 2008; Kraft, 2020).

Through the use of propensity score matching techniques, we included a sensitivity analysis designed to address selection effects to some degree and create a control group with sample size similarities with the treatment group, who, in this case, included doctoral students who participated in the interdisciplinary STEM training program.

Full Control Group Analyses

This analysis compared the experimental group to the full control sample. Our focal variable was participation in an interdisciplinary STEM training program, or "treatment". Following Astin's I-E-O model (1991) our input variables (Model 1) included student innovation capacities at the beginning of the program, sociodemographic variables including race (effect coded), gender identity, age, first generation status, family income and whether a student's family member had either invented a new product or started a new business. Bridge variables (Model 2) included student's cohort year, transfer student status, international student status, and political inclination. Finally, environmental/experiential variables (Model 3) included having taken courses on creativity, entrepreneurship, or innovation over the past four years.

Sensitivity Analysis: Propensity Score Matched Control Group Analyses

This analysis compared the full experimental group to their propensity score matched counterparts in the control group. As previously, treatment was the focal variable. Due to matching on input and bridge covariates, Model 1 consisted only of treatment and innovation capacities at the beginning of the program, while Model 2 added experiential variables accounting for taking courses on creativity, entrepreneurship, or innovation.

Results

Descriptive and exploratory analyses indicated no continuous variables with skewness greater than |2| or kurtosis greater than 7, demonstrating appropriateness for multiple regression analyses (Cohen et al., 2003). Furthermore, item-item correlations did not exceed .65, indicating a lack of multicollinearity between covariates (Table A2). Finally, visual inspection of variable distributions revealed no bimodalities or concerning departures from multivariate normality.

Overall Innovation Capacity Development

The significant results of the hierarchical regression modeling of overall innovation capacity development are presented in Table 5 with full results in Table A3. Model 1 explained 50% of the overall variance in developmental rates. The model indicated that participation in the interdisciplinary STEM program predicted significantly accelerated development of one's overall innovation capacities with a very large effect ($\beta = .32$). Furthermore, identifying as a first-generation student predicted significantly accelerated development of innovation capacities in all models with a medium effect ($\beta = .13 - .14$). Exposure to the interdisciplinary Ph.D. training program continued to have a significant positive impact on innovation capacity development in Model 2, which persisted in explaining 50% of the outcome variability. Finally, the positive treatment effects remained both large ($\beta = .32$) and significant in Model 3, which accounted for no additional variability in students' innovation capacities at the end of the semester. Notably, taking specific courses designed to enhance creativity or innovation, or to prepare one to be an entrepreneur had no significant effects whatsoever on the development of innovation capacity. Introducing these variables reduced the final variance explained to 49%.

Table 5

Developmental Predictors of Overall Innovation Capacity in Full Sample

Variable	Model 1					Model 2					Model 3				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.59*** **	**.07**	**.46**	**.72**	**.60**	**.58*** **	**.07**	**.44**	**.71**	**.59**	**.55*** **	**.07**	**.41**	**.69**	**.56**
Treatment	**.84*** **	**.18**	**.49**	**1.20**	**.32**	**.84*** **	**.19**	**.47**	**1.21**	**.32**	**.83*** **	**.21**	**.43**	**1.24**	**.32**
Other Inputs															
Age	.06	.08	-.10	.21	.05	.05	.08	-.12	.21	.04	.05	.09	-.12	.22	.04
Family Income	.01	.03	-.05	.07	.02	.01	.03	-.05	.07	.03	.01	.03	-.05	.07	.02
First Generation Status	**.27***	**.14**	**-.02**	**.55**	**.13**	**.28***	**.16**	**-.02**	**.59**	**.13**	**.29***	**.16**	**-.02**	**.60**	**.14**
Family New Product	.05	.22	-.38	.48	.02	.11	.22	-.33	.55	.04	.12	.23	-.33	.56	.04
Family New Business	-.19	.13	-.45	.07	-.10	-.18	.13	-.45	.08	-.10	-.16	.14	-.44	.11	-.09
Bridge Effects															
Cohort 1						**-.32***	**.19**	**-.69**	**.05**	**-.16**	-.29	.19	-.67	.09	-.15
Cohort 2						-.04	.20	-.45	.36	-.02	-.05	.21	-.46	.35	-.03
Cohort 3						-.12	.21	-.52	.29	-.05	-.12	.21	-.53	.30	-.05
Transfer Student						.24	.20	-.16	.64	.08	.26	.20	-.15	.66	.09
International Student						-.19	.22	-.63	.25	-.09	-.19	.23	-.64	.26	-.09
Political Leaning						-.05	.07	-.19	.09	-.05	-.07	.07	-.21	.07	-.07
Environmental Effects															
Creativity course											.30	.23	-.15	.75	.13
Entrepreneurship course											-.07	.30	-.66	.51	-.02
Innovation course											-.12	.25	-.61	.37	-.05
Model metrics															
Adjusted R2	**.50**					**.50**					**.49**				
Root MSE	.66					.66					.66				

Note: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$. Significant relationships are bolded. No gender orientations or races/ethnicities exhibited significant relationships with the outcome in any model and are omitted in this table for clarity. See Table A3 for full results.

Hierarchical regressions comparing the propensity score-matched control group to the experimental group produced similar effects with regard to the treatment variable. Specifically, the impact of enrolling in the interdisciplinary Ph.D. program was again quite a large increase (β = .27) in the average degree of innovation capacity development. These findings also suggested that participation in entrepreneurship courses significantly accelerate innovation development (β = .27) -an effect that did not appear in the full control group model. Model results are presented in Table 6.

Table 6

Developmental Predictors of Overall Innovation Capacity in Propensity Score Matched Sample

Variable	Model 1					Model 2				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.55*** **	**.12**	**.31**	**.79**	**.65**	**.39*** **	**.12**	**.15**	**.63**	**.46**
Treatment	**.72*** **	**.25**	**.22**	**1.23**	**.41**	**.48** **	**.23**	**0**	**.97**	**.27**
Environmental Effects										
Creativity course						.53	.34	-.16	1.23	.31
Entrepreneurship course						**.68** **	**.33**	**.01**	**1.36**	**.27**
Innovation course						-.04	.31	-.68	.59	-.03
Model metrics										
Adjusted R2	.47					.66				
Root MSE	.63					.59				

Note: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$

Collectively, these data indicate that enrollment in an interdisciplinary Ph.D. program may positively impact the development of students' overall innovation capacities. This effect may be driven by the program's influence on the development of student proactivity and creativity. Further, these data reveal the potential of entrepreneurship and creativity courses for the development of specific innovation capacities. Results of subdomain analyses are presented in Appendix B.

Limitations

While the multiple methodologies of the present study suggest convergent results regarding the efficacy of the interdisciplinary program on promoting innovation capacity development, the study nonetheless has several limitations secondary to its sampling, design, and contextual features. Regarding sampling, while the control sample was sizable, the number of experimental cases were limited due to the lower-than-expected student enrollment in the novel Ph.D. program. This challenge was compounded by attrition (n = 5) in the experimental cases, which both reduced the statistical power necessary to detect real effects and raises the question of whether those experimental students who continued to participate in the research study were significantly different from their peers who did not. This cannot be determined by the present study; however, strong predictors of research participation (trait agreeableness, age, gender, and socioeconomic status) have not been observed to correlate with innovation capacity in prior research (Selznick, 2017; Selznick & Mayhew, 2018).

Regarding study design and analysis, while the present study reveals inter-group differences in inter-person change over time due to program participation, it cannot specify which elements of the experimental program are most responsible for accelerating innovation development. Such development may be due to extensive mentorship structures (academic, industry, and near-peer), interdisciplinary pluralism, transdisciplinary team science activities, co-curricular engagement, or the emergent properties of these experiences in concert (Selznick et al., 2024). Further research is required to measure the unique contributions of these programmatic elements.

Analytically, it is notable that the propensity score matched model did not include Latinx, Middle-Eastern, non-binary, or transfer students as these identities were not present in the experimental group -consequently nothing can be said regarding how students who hold these identity narratives may differentially respond to the experimental program compared to similar peers in nonexperimental Ph.D. programs. This is especially challenging as prior examinations (Mayhew, Selznick, McChesney, et al., 2021) suggest transfer students may, in general, be more innovative than non-transfer students. Furthermore, while an extensive set of covariates were used in the propensity score matching process, the propensity model is sensitive to specification parameters, and unobserved variables may have influenced student propensity to participate in the experimental program.

Finally, it must be noted that the study occurred during the COVID-19 pandemic. Students faced unusual environmental stresses that may have promoted or interfered with their ability to innovate under these conditions, and academic programs responded heterogeneously to online learning and distancing procedures, which may have influenced their subsequent effects on student innovation capacity development.

Discussion, Implications, and Conclusion

Interdisciplinary STEM training effectively develops innovative students, regardless of their sociodemographic characteristics, international student status, and prior academic achievement. These findings converge with previous research demonstrating that “innovation…is for everyone,” (Selznick, Mayhew, Zhang, et al., 2022, p. 578) and presents a uniquely equitable avenue for evolving research, scientific, and workplace needs (Andersen, 2016; DeHart, 2017; Lenhart et al., 2022). Given the urgent need among the scientific community for sustained innovation in research, technology, and enterprise (Atkinson & Mayo, 2010), and for adaptation to increasingly diverse and team-focused environments (Daily & Eugene, 2013), interdisciplinary STEM training offers institutions of higher education considerable opportunities.

These results also highlight several challenges for IHEs: why are innovation- and creativity-focused curriculum so ineffective in fostering real innovation skills, and how can they be improved? Does STEM interdisciplinary training lack sufficient focus on the “soft skills” of working across difference and empathetically persuading others -and what does this imply for developing sustainable, diverse research teams? How can policymakers and stakeholders effectively establish interdisciplinary STEM programs across mono-disciplinary departments and colleges? And how can current STEM faculty leverage interdisciplinary perspectives to promote the innovativeness of their current students?

While we are unable to answer all these questions, our results offer several pathways forward for research, theory and practice that can advance inform these important inquiries. First, as concerns research, our scholarship (e.g., Mayhew et al., 2012; Mayhew et al., 2021) has long been interested in investigating both innovation-specific experiences (i.e., what works to develop innovators?) and the subsequent assessment of such engagement (i.e., how do we know that it worked?). Yet, for too long, one or both of these areas have failed to attract substantial attention. In that vein, we continue to encourage studies such as ours that seek to more meaningfully explore innovation capacity development, whether using our own or similar quantitative measures, delving qualitatively into one or more dimensions of these developmental experiences, or leveraging mixed methods insights in service of educational and social betterment (Mertens, 2024).

Theoretically, this study holds fascinating parallels for development at the meeting place of team science practice, doctoral education, and self-authorship. Building on our own previous work (e.g., Selznick et al., 2021, 2023) and others (e.g., Wagner, 2012), we continue to speculate that self-authorship in the innovation space can and should be more sufficiently theorized. As our findings demonstrate, interventions that allow students to develop comprehensive and layered understandings (self-, social, and cognitive) of themselves as innovators really can make a difference in capacity building. We hope further efforts will continue to more fully consider what it means to be a self-authored innovator in the space of doctoral STEM education and, ideally, across collegiate teaching and learning environments.

Finally, this study serves as an important reminder that intentionality and good teaching matter – yes, even at the doctoral level. To the first, we spotlight this model as a robust indication that approaches exercising inter-, multi-, and/or transdisciplinary rise and fall on the extent to which these paradigms are delivered intentionally (Lattuca et al., 2017). It is not enough to bring together faculty and students across disciplines. When creating and implementing these programs, care must be paid to ensuring that all disciplines are leveraged to promote high quality and synergistic learning experiences. Relatedly, of course, this involves faculty who are committed to realizing the full benefits of these distinctive learning spaces (Selznick et al., 2023), and who strive to ensure that such spaces ‘foster collisions’ (O’Meara & Culpepper, 2019) in a spirit more aligned with perspectives of learning as an interdependent partnership (Baxter Magolda, 2004).

In closing, while the ‘debate’ as to whether innovators are born or made has become more artifice than anything, questions persist regarding *how* (e.g., through what pedagogies and practices), *when* (e.g., undergraduate/graduate, initially or toward the end of programs), and *toward what* measurable ends (e.g., product/service vs. capacities-based approach) when considering developing innovators through higher education. This study has shed light on some of these questions, and hopefully provides evidence that can be incorporated into future training and development programs. It can also serve as a powerful reminder that one question needing no additional explanation is *why* we need to conduct this work. Confronting the contemporary global landscape of uncertainty and volatility, it is simply no longer enough to train scientists and hope they become innovators; instead, scientific training must be responsible for supporting doctoral students on their long-term progressions toward innovation self-authorship and intentionally emphasize such development as integral – not ancillary – to scientific training.

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Online Only Appendices

Appendix A: Ancillary Tables

Table A1

Full Sample Demographic Characteristics

Characteristic	Experimental Group (*n* = 19)		Full Control Group (*n* = 127)		Matched Control Group (*n* = 12)	
	n	%	*n*	%	*n*	%
Racial/Ethnic Identity						
Black/African American	4	21	8	6	2	17
American Indian/ Alaskan Native	0	0	0	0	0	0
Arab, Middle Eastern, or Persian	0	0	2	2	0	0
All Asian	4	21	30	24	1	8
All Latinx	0	0	8	6	0	0
Native Hawaiian or Pacific Islander	0	0	0	0	0	0
White/Caucasian	11	58	68	54	7	58
Multiracial	2	11	8	6	1	8
Other ethnicity or prefer not to respond	0	0	3	2	1	8
Gender Identity						
Man	15	79	51	40	6	50
Woman	6	32	71	56	6	50
Another gender or prefer not to respond	0	0	5	4	0	0
Estimated Family Income						
Less than $25,000	5	26	16	12	3	25
$25,000 - $49,999	3	16	34	25	0	0
$50,000 - $74,999	4	21	19	14	3	25
$75,000 - $99,999	0	0	18	13	2	17
$100,000 - $124,999	2	11	12	9	2	17
$125,000 - $149,000	2	11	3	2	1	8
$150,000 - $174,999	1	5	3	2	1	8
$175,000 - $199,999	0	0	5	4	0	0
$200,000 or more	2	11	8	6	0	0
Age						
20-21	0	0	8	6	1	8
22-25	9	47	63	50	6	50
26-30	6	32	34	27	3	25
31+	4	21	22	17	2	17
First Generation Status						
First generation	4	21	36	28	5	42
Continuing generation	15	79	90	71	7	58
Family Member Started New Business						
Yes	9	47	56	44	7	58
No	10	53	71	56	5	42
Family Member Invented New Product						
Yes	3	16	16	13	3	25
No	16	84	111	87	9	75
Cohort						
Cohort 1	5	26	41	32	2	17
Cohort 2	4	25	32	25	3	25
Cohort 3	3	16	35	28	4	33
Cohort 4	7	37	19	15	3	25
Transfer Student Status						
Transfer	0	0	17	13	0	0
Non-transfer	19	100	110	87	12	100
International Student Status						
International student	6	32	38	30	3	25

Domestic student	13	68	89	70	9	75
Political Leaning						
Very conservative	0	0	2	2	1	8
Conservative	1	5	9	7	1	8
Moderate	7	37	32	25	2	17
Liberal	6	32	48	38	5	42
Very liberal	5	26	33	26	3	25
Prefer not to answer	0	0	3	2	0	0
Taken a Creativity Course						
Yes	9	47	21	17	4	33
No	10	52	106	83	8	67
Taken an Entrepreneurship Course						
Yes	4	21	5	4	0	0
No	15	79	122	96	12	100
Taken an Innovation Course						
Yes	11	58	14	11	4	33
No	8	42	113	89	8	67

Note: Percents may not total 100 due to rounding.

Table A2

Construct Bivariate Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Initial Overall Innovation Capacities										
(2) Initial Motivation	0.70***									
(3) Initial Inn. Self-Concept	0.83***	0.53***								
(4) Initial Proactivity	0.62***	0.39***	0.48***							
(5) Initial Persuasiveness	0.59***	0.39***	0.36***	0.42***						
(6) Initial Networking Ability	0.39***	0.27***	0.21**	0.31***	0.22**					
(7) Initial Teamwork Ability	0.48***	0.31***	0.31***	0.40***	0.26***	0.32***				
(8) Initial Risk Tolerance	0.43***	0.26**	0.30***	0.19*	0.38***	0.09	0.22**			
(9) Initial Intention to Innovate	0.85***	0.49***	0.64***	0.36***	0.39***	0.25**	0.27***	0.35***		
(10) Initial Creativity	0.84***	0.40***	0.60***	0.48***	0.43***	0.31***	0.33***	0.22**	0.67***	
(11) Final Overall Innovation Capacities	0.65***	0.51***	0.53***	0.45***	0.42***	0.31***	0.33***	0.42***	0.53***	0.46***
(12) Final Motivation	0.47***	0.62***	0.43***	0.33***	0.28***	0.21**	0.18**	0.25**	0.32***	0.25**
(13) Final Inn. Self-Concept	0.56***	0.42***	0.53***	0.28***	0.26***	0.26***	0.24**	0.32***	0.48***	0.41***
(14) Final Proactivity	0.48***	0.37***	0.32***	0.45***	0.43***	0.21**	0.30***	0.34***	0.36***	0.34***
(15) Final Persuasiveness	0.41***	0.29***	0.24**	0.24**	0.53***	0.18**	0.23**	0.36***	0.34***	0.28***
(16) Final Networking Ability	0.40***	0.32***	0.25**	0.29***	0.23**	0.75***	0.21**	0.16	0.26***	0.34***
(17) Final Teamwork Ability	0.33***	0.20*	0.26**	0.25**	0.14	0.24**	0.50***	0.28***	0.19**	0.25**
(18) Final Risk Tolerance	0.25**	0.13	0.20*	0.21**	0.21*	0.13	0.18**	0.57***	0.18**	0.14
(19) Final Intention to Innovate	0.57***	0.35***	0.52***	0.34***	0.27***	0.16	0.18**	0.34***	0.57***	0.41***
(20) Final Creativity	0.51***	0.39***	0.41***	0.41***	0.31***	0.14	0.19**	0.16	0.45***	0.44***
(21) Gender: Woman	0.03	0.11	-0.03	0.05	0.11	0.04	0.17**	-0.23**	-0.05	0.02
(22) Gender: Man	-0.04	-0.07	0.01	0.01	-0.14	-0.05	-0.19**	0.14	0.06	-0.05
(23) Gender: Nonbinary	0.02	-0.08	0.02	-0.29***	-0.06	0.09	0.03	0.12	0.05	0.12
(24) Race: Black	0.15	0.12	0.11	0.12	0.13	0.20**	0.22**	0.07	0.08	0.15
(25) Race: Asian	-0.08	-0.20*	-0.04	-0.13	-0.16	-0.01	-0.17*	-0.09	0.04	-0.01
(26) Race: Latinx	0.04	0.06	0.07	0.01	0.08	-0.06	0.08	0.00	0.01	-0.02
(27) Race: Middle Eastern	-0.18*	-0.20**	-0.12	-0.11	-0.13	0.01	-0.01	-0.13	-0.12	-0.16
(28) Race: White	0.06	0.16	-0.03	0.10	0.19*	-0.07	-0.06	0.11	-0.02	0.00

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(29) Race: Other	-0.04	-0.02**	-0.07	-0.02	-0.19*	0.00	0.11	-0.10	-0.05	0.04
(30) Race: Multiracial	-0.10	-0.05*	0.02	-0.10	-0.23*	-0.02	-0.01	-0.11	-0.10	-0.09
(31) Age	0.03	0.05	-0.07	0.20*	-0.03	0.01	-0.03	0.05	0.04	0.07
(32) Family Income	-0.05	-0.04*	-0.04	-0.08	-0.01	-0.11	-0.03	0.00	-0.02	-0.06
(33) Father’s Ed. Level	-0.05	-0.12	-0.09	-0.10	0.06	0.05	-0.19**	0.01	-0.07	-0.06
(34) Mother’s Ed. Level	-0.13	-0.19**	-0.12	-0.19*	0.03	-0.06	-0.34***	0.01	-0.09	-0.07
(35) Political Leaning	-0.04	-0.12	-0.03	-0.03	0.06	-0.05	0.01	0.09	-0.10	-0.04
(36) Family New Business	-0.05	-0.11	0.07	-0.06	-0.09	-0.11	-0.06	0.02	-0.02	0.04
(37) Family New Product	0.10	0.05	0.18*	0.04	0.00	0.01	0.02	0.04	0.07	0.13
(38) Cohort 1	-0.06	-0.08	-0.02	-0.04	0.06	-0.12	0.00	0.03	-0.02	-0.07
(39) Cohort 2	0.18*	0.12	0.11	0.04	0.08	0.19**	0.15	0.16*	0.10	0.18*
(40) Cohort 3	-0.08	-0.03	-0.03	0.04	0.01	-0.12	-0.06	-0.11	-0.12	-0.10
(41) Cohort 4	-0.04	-0.01	-0.07	-0.04	-0.16*	0.07	-0.10	-0.09	0.05	0.00
(42) Transfer Student	0.03	0.02	-0.01	0.04	0.03	0.05	0.05	0.06	0.05	-0.01
(43) International Student	-0.08	-0.10	0.01	-0.08	-0.16	-0.06	-0.06	-0.08	0.02	-0.03
(44) Innovation Course	0.10	0.03	0.09	0.05	0.00	-0.06	0.01	0.01	0.15	0.14
(45) Entrepreneur Course	0.15	0.10	0.10	0.12	0.00	0.06	0.14	0.04	0.14	0.13
(46) Creativity Course	0.22**	0.13	0.18*	0.07	0.17*	-0.02	0.07	0.27***	0.23**	0.19*
(47) Treatment	0.02	-0.04	0.07	0.02	-0.04	-0.04	-0.15	0.01	0.10	0.05

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(12) Final Motivation	0.74***										
(13) Final Inn. Self-Concept	0.82***	0.56***									
(14) Final Proactivity	0.88***	0.62***	0.63***								
(15) Final Persuasiveness	0.62***	0.37***	0.41***	0.58***							
(16) Final Networking Ability	0.44***	0.31***	0.33***	0.30***	0.29***						
(17) Final Teamwork Ability	0.45***	0.19**	0.30***	0.36***	0.20*	0.27***					
(18) Final Risk Tolerance	0.46***	0.25**	0.28***	0.31***	0.40***	0.29***	0.18**				

(19) Final Intention to Innovate	0.79***	0.48***	0.65***	0.56***	0.33***	0.24**	0.34***	0.35***			
(20) Final Creativity	0.71***	0.44***	0.44***	0.53***	0.37***	0.30***	0.29***	0.32***	0.61***		
(21) Gender: Woman	-0.06	0.06	-0.11	-0.03	-0.06	-0.03	0.12	-0.32***	-0.11	0.08	
(22) Gender: Man	0.05	-0.07	0.07	0.03	0.07	0.05	-0.15	0.27***	0.13	-0.03	-0.93***
(23) Gender: Nonbinary	-0.07	0.01	0.07	-0.06	-0.18*	-0.02	0.04	0.05	-0.09	-0.25**	-0.16
(24) Race: Black	0.22**	0.08	0.11	0.23**	0.15	0.20*	0.18*	0.18*	0.15	0.15	-0.16
(25) Race: Asian	-0.04	-0.07	-0.07	-0.08	-0.13	-0.03	-0.07	0.00	0.06	0.07	0.01
(26) Race: Latinx	0.00	0.00	0.06	-0.03	-0.07	-0.10	0.00	-0.07	0.04	0.01	0.11
(27) Race: Middle Eastern	-0.18*	-0.16*	-0.14	-0.17*	-0.10	-0.11	-0.07	-0.04	-0.12	-0.13	-0.12
(28) Race: White	-0.01	0.14	-0.06	0.04	0.15	-0.04	-0.11	0.00	-0.13	-0.06	0.11
(29) Race: Other	-0.04	-0.09	-0.01	-0.05	0.02	0.02	-0.01	-0.03	0.00	-0.05	0.08
(30) Race: Multiracial	-0.06	-0.11	0.08	-0.12	-0.19*	0.08	0.17*	-0.05	0.02	-0.11	-0.07
(31) Age	0.09	0.08	0.02	0.15	0.01	0.09	-0.06	0.06	0.07	0.08	0.02
(32) Family Income	-0.08	-0.02	-0.07	-0.10	0.01	-0.07	-0.11	-0.09	-0.01	-0.08	0.13
(33) Father's Ed. Level	-0.14	-0.18*	-0.12	-0.19*	-0.11	-0.02	-0.12	-0.06	-0.07	-0.03	0.01
(34) Mother's Ed. Level	-0.17*	-0.15	-0.08	-0.19*	-0.12	-0.08	-0.19*	-0.04	-0.09	-0.12	0.02
(35) Political Leaning	-0.05	-0.02	-0.09	0.00	0.01	-0.06	-0.14	0.20*	-0.05	-0.08	0.10
(36) Family New Business	0.05	0.02	0.14	0.05	-0.06	-0.04	0.09	-0.02	0.02	0.04	0.02
(37) Family New Product	0.03	0.02	0.08	-0.01	0.08	-0.04	0.04	0.07	0.01	0.01	0.02
(38) Cohort 1	-0.15	-0.14	-0.18*	-0.09	0.00	-0.09	-0.09	-0.04	-0.15	-0.10	-0.13
(39) Cohort 2	0.12	0.17*	0.10	0.06	0.11	0.15	0.07	0.15	0.09	-0.03	0.01

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(40) Cohort 3	-0.04	-0.03	0.00	-0.01	-0.17*	-0.10	0.10	-0.14	-0.01	-0.02	0.08
(41) Cohort 4	0.10	0.01	0.11	0.05	0.08	0.06	-0.08	0.05	0.09	0.19**	0.05
(42) Transfer Student	0.02	-0.06	0.03	0.01	-0.04	0.06	0.03	0.04	0.05	0.02	0.01
(43) International Student	-0.06	-0.13	-0.05	-0.09	-0.17*	-0.06	-0.14	0.04	0.09	0.07	-0.16
(44) Innovation Course	0.18*	0.05	0.15	0.11	0.15	0.11	0.03	0.12	0.24**	0.16	0.05
(45) Entrepreneur Course	0.16*	0.02	0.13	0.08	0.21*	0.17*	0.01	0.25**	0.15	0.27***	-0.04
(46) Creativity Course	0.28***	0.12	0.29***	0.21**	0.32***	0.14	0.01	0.25**	0.24**	0.18*	-0.07

(47) Treatment	0.32***	0.17*	0.23***	0.25**	0.20**	0.12	0.14	0.16**	0.34***	0.29***	-0.19**

Variables	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
(23) Gender: Nonbinary	-0.13										
(24) Race: Black	0.18*	-0.04									
(25) Race: Asian	-0.01	0.10	-0.16*								
(26) Race: Latinx	-0.09	-0.04	-0.07	-0.13							
(27) Race: Middle Eastern	0.13	-0.02	-0.04	-0.06	-0.03						
(28) Race: White	-0.14	-0.01	-0.32	-0.58***	-0.26**	-0.13					
(29) Race: Other	-0.07	-0.01	-0.02	-0.05	-0.02	-0.01	-0.09				
(30) Race: Multiracial	0.08	-0.04	-0.08	-0.15	-0.06	-0.03	-0.29***	-0.02			
(31) Age	0.01	-0.01	0.18*	0.11	0.16	-0.08	-0.22**	0.14	-0.02		
(32) Family Income	-0.12	-0.03	-0.16	-0.22**	-0.14	-0.03	0.35***	-	0.02	-0.14	
(33) Father's Ed. Level	-0.02	-0.05	-0.02	-0.02	-0.24**	-0.10	0.15	0.00	0.08	-0.28***	0.19*
(34) Mother's Ed. Level	-0.08	0.09	-0.18*	-0.14	-0.08	-0.08	0.31***	-0.08	0.03	-0.24**	0.29***
(35) Political Leaning	-0.15	0.13	-0.06	-0.04	-0.03	0.02	0.06	0.18*	0.01	-0.03	0.06
(36) Family New Business	-0.03	0.06	-0.09	0.13	-0.03	-0.01	-0.01	0.07	-0.14	-0.12	-0.13
(37) Family New Product	0.04	-0.05	0.12	0.03	0.01	0.05	-0.09	-0.21*	0.03	0.01	-0.26**
(38) Cohort 1	0.15	-0.06	-0.04	-0.06	0.03	-0.08	0.03	-0.06	0.05	-0.17*	0.18*
(39) Cohort 2	0.00	0.09	0.06	-0.09	0.07	0.07	-0.01	-0.05	0.04	0.14	0.00
(40) Cohort 3	-0.11	-0.01	-0.01	0.11	-0.08	0.06	-0.03	-0.05	-0.04	0.07	-0.16
(41) Cohort 4	-0.06	-0.02	-0.01	0.04	-0.03	-0.05	0.00	0.18*	-0.05	-0.04	-0.03
(42) Transfer Student	0.02	-0.05	-0.11	0.01	0.01	-0.04	0.04	-0.03	0.07	-0.07	-0.04
(43) International Student	0.18*	0.06	0.02	0.62***	0.17*	0.18*	-0.65***	0.13	-0.06	0.25**	-0.39***
(44) Innovation Course	-0.02	-0.07	-0.01	0.04	-0.03	-0.05	-0.03	0.18*	0.02	0.07	0.06
(45) Entrepreneur Course	0.06	-0.04	0.24**	-0.01	-0.06	-0.03	-0.10	-0.02	0.04	0.00	-0.04
(46) Creativity Course	0.07	-0.03	0.03	-0.08	-0.05	-0.06	0.08	0.16	-0.01	0.03	0.07
(47) Treatment	0.22**	-0.06	0.16*	-0.04	-0.10	-0.05	-0.01	-0.03	0.05	0.05	-0.01

Variables	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)	(43)
(34) Mother's Ed. Level	0.60***										
(35) Political Leaning	-0.12	-0.07*									
(36) Family New Business	-0.13	-0.09	0.04								
(37) Family New Product	-0.19*	-0.21*	0.02	0.29***							
(38) Cohort 1	0.10	0.14	-0.08	-0.10	-0.20*						
(39) Cohort 2	-0.18*	-0.15	0.00	0.09	0.22**	-0.39***					
(40) Cohort 3	-0.06	0.00	-0.18*	0.00	-0.03	-0.41***	-0.34***				
(41) Cohort 4	0.15	0.00	0.30***	0.02	0.03	-0.32***	-0.26***	-0.28***			
(42) Transfer Student	0.04	0.02	-0.01	-0.07	-0.04	0.12	-0.16**	0.03	0.00		
(43) International Student	-0.18*	-0.27***	-0.04	0.05	0.00	-0.01	-0.10	0.11	0.00	0.13	
(44) Innovation Course	-0.02	-0.02	0.10	0.02	-0.08	-0.16*	0.03	-0.03	0.21*	-0.11	0.12
(45) Entrepreneur Course	0.01	-0.06	0.01	-0.17*	0.02	-0.11	0.05	-0.09	0.18*	0.09	0.14
(46) Creativity Course	-0.07	-0.04	0.19	0.05	0.06	-0.17*	0.10	-0.04	0.16	-0.08	0.02
(47) Treatment	0.09	-0.06	-0.02	0.01	-0.07	-0.03	-0.05	-0.07	0.17*	-0.15	0.03

Variables	(44)	(45)	(46)
(45) Entrepreneur Course	0.33***		
(46) Creativity Course	0.64***	0.36***	
(47) Treatment	0.42***	0.22**	0.27***

Table A3

Developmental Predictors of Overall Innovation Capacity in Full Sample

Variable	Model 1					Model 2					Model 3				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.59*** **	**.07**	**.46**	**.72**	**.60**	**.58*** **	**.07**	**.44**	**.71**	**.59**	**.55*** **	**.07**	**.41**	**.69**	**.56**
Treatment	**.84*** **	**.18**	**.49**	**1.20**	**.32**	**.84*** **	**.19**	**.47**	**1.21**	**.32**	**.83*** **	**.21**	**.43**	**1.24**	**.32**
Gender															
Nonbinary	.57	.37	-.16	1.29	.11	.58	.38	-.18	1.34	.11	.58	.39	-.18	1.35	.11
Woman	-.04	.13	-.30	.22	-.02	-.09	.14	-.36	.18	-.05	-.05	.14	-.33	.23	-.03
Race															
Black	.24	.24	-.23	.70	.07	.22	.24	-.26	.70	.07	.25	.25	-.24	.75	.08
Asian	.12	.18	-.23	.47	.06	.18	.20	-.21	.57	.08	.18	.20	-.21	.57	.08
Latinx	.01	.27	-.52	.54	.00	.09	.27	-.45	.63	.02	.08	.28	-.47	.63	.02
Middle Eastern	-.51	.43	-1.36	.34	-.08	-.48	.46	-1.40	.44	-.08	-.45	.47	-1.38	.48	-.08
White	-.05	.16	-.36	.26	-.03	-.14	.18	-.48	.21	-.08	-.17	.18	-.52	.19	-.09
Multiracial	.00	.24	-.47	.47	-.00	-.07	.24	-.55	.42	-.02	-.09	.25	-.58	.40	-.03
Prefer not to respond	.20	.60	-.229	.701	.09	.19	.63	-.36	.18	.09	.19	.63	-1.05	1.44	.09
Other Inputs															
Age	.06	.08	-.10	.21	.05	.05	.08	-.12	.21	.04	.05	.09	-.12	.22	.04
Family Income	.01	.03	-.05	.07	.02	.01	.03	-.05	.07	.03	.01	.03	-.05	.07	.02
First Generation Status	**.27***	**.14**	**-.02**	**.55**	**.13**	**.28***	**.16**	**-.02**	**.59**	**.13**	**.29***	**.16**	**-.02**	**.60**	**.14**
Family New Product	.05	.22	-.38	.48	.02	.11	.22	-.33	.55	.04	.12	.23	-.33	.56	.04
Family New Business	-.19	.13	-.45	.07	-.10	-.18	.13	-.45	.08	-.10	-.16	.14	-.44	.11	-.09
Bridge Effects															
Cohort 1						**-.32***	**.19**	**-.69**	**.05**	**-.16**	-.29	.19	-.67	.09	-.15
Cohort 2						-.04	.20	-.45	.36	-.02	-.05	.21	-.46	.35	-.03
Cohort 3						-.12	.21	-.52	.29	-.05	-.12	.21	-.53	.30	-.05
Transfer Student						.24	.20	-.16	.64	.08	.26	.20	-.15	.66	.09
International Student						-.19	.22	-.63	.25	-.09	-.19	.23	-.64	.26	-.09
Political Leaning						-.05	.07	-.19	.09	-.05	-.07	.07	-.21	.07	-.07
Environmental Effects															
Creativity course											.30	.23	-.15	.75	.13
Entrepreneurship course											-.07	.30	-.66	.51	-.02
Innovation course											-.12	.25	-.61	.37	-.05
Model metrics															
Adjusted R2	.50					.50					.49				
Root MSE	.66					.66					.66				

Note: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$. Significant relationships are bolded.

Appendix B: Subdomain Analyses

Table B1

Developmental Predictors of Intrapersonal Domains of Innovation Capacity in Full Sample

Variable	Motivation Model 3					Innovation Self-Concept Model 3					Proactivity Model 3				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.66*****	**.09**	**.49**	**.83**	**.62**	**.45*****	**.07**	**.31**	**.60**	**.45**	**.35*****	**.09**	**.18**	**.53**	**.34**
Treatment	**.70*****	**.22**	**.27**	**1.12**	**.27**	**.60*****	**.23**	**.16**	**1.05**	**.22**	**.70*****	**.23**	**.24**	**1.15**	**.28**
Gender															
Nonbinary	.58	.40	-.21	1.37	.11	**1.02****	**.43**	**.18**	**1.86**	**.18**	.41	.43	-.45	1.27	.08
Woman	.04	.14	-.25	.32	.02	-.06	.15	-.36	.24	-.03	.06	.15	-.25	.37	.03
Race															
Black	.03	.24	-.45	.502	.01	-.16	.25	-.66	.35	-.05	.41	.25	-.09	.90	.15
Asian	.35	.185	-.02	.716	.17	-.13	.22	-.55	.30	-.06	.11	.20	-.29	.50	.05
Latinx	-.03	.278	-.58	.523	-.01	.19	.31	-.42	.80	.05	-.10	.30	-.69	.50	-.03
Middle Eastern	-.10	.487	-1.06	.868	-.02	-.50	.52	-1.52	.53	-.08	-.60	.51	-1.61	.42	-.12
White	.00	.186	-.37	.372	.00	**-.41****	**.20**	**-.80**	**-.02**	**-.22**	-.12	.19	-.50	.27	-.07
Multiracial	-.17	.251	-.67	.331	-.05	.06	.27	-.48	.60	.02	-.33	.27	-.87	.21	-.11
Prefer not to respond	-.09	.48	-1.03	.86	-.04	.94	.70	-.44	2.32	.42	.62	.52	-.41	1.64	.31
Other Inputs															
Age	.05	.08	-.12	.21	.05	.08	.09	-.09	.26	.08	.08	.09	-.11	.26	.07
Family Income	.01	.03	-.05	.07	.03	.01	.03	-.05	.08	.03	-.03	.04	-.10	.05	-.07
First Generation Status	.18	.16	-.13	.50	.09	**.29***	**.16**	**-.04**	**.61**	**.13***	.18	.17	-.16	.52	.09
Family New Product	.11	.23	-.35	.57	.04	.21	.25	-.28	.70	.07	.16	.25	-.33	.65	.06
Family New Business	-.12	.14	-.39	.16	-.06	**-.29****	**.15**	**-.58**	**.00**	**-.15**	-.09	.15	-.39	.20	-.05
Bridge Effects															
Cohort 1	-.05	.20	-.45	.35	-.03	**-.47****	**.22**	**-.89**	**-.04**	**-.22**	-.07	.22	-.50	.36	-.38
Cohort 2	.21	.21	-.20	.63	.10	-.16	.22	-.60	.29	-.07	.03	.23	-.42	.48	.02
Cohort 3	.15	.21	-.28	.57	.07	-.18	.23	-.63	.27	-.08	-.03	.23	-.49	.43	-.01
Transfer Student	-.01	.21	-.42	.40	-.00	**.50****	**.22**	**.07**	**.93**	**.17**	.29	.22	-.15	.73	.11
International Student	-.20	.23	-.66	.26	-.10	-.34	.25	-.82	.15	-.16	-.28	.25	-.77	.21	-.14
Political Leaning	.07	.07	-.07	.21	.07	**-.19****	**.07**	**-.33**	**-.04**	**-.19**	-.01	.08	-.17	.14	-.01
Environmental Effects															
Creativity course	.21	.24	-.26	.68	.10	**.53****	**.24**	**.05**	**1.01**	**.22**	**.54****	**.25**	**.05**	**1.03**	**.25**
Entrepreneurship course	-.24	.31	-.85	.37	-.06	-.07	.31	-.69	.54	-.02	-.37	.32	-1.00	.26	-.11
Innovation course	-.26	.26	-.78	.26	-.11	-.14	.27	-.68	.39	-.06	-.19	.28	-.74	.35	-.08
Model metrics															
Adjusted R2	.38					.41					.25				
Root MSE	.70					.74					.76				

Note: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$. Significant relationships are bolded.

Table B2

Developmental Predictors of Intrapersonal Domains of Innovation Capacity in Propensity Score Matched Sample

Variable	Motivation Model 2					Innovation Self-Concept Model 2					Proactivity Model 2				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.45****	**.18**	**.07**	**.82**	**.47**	**.50*****	**.15**	**.19**	**.81**	**.47**	**.25****	**.09**	**.06**	**.44**	**.34**
Treatment	.29	.29	-.32	.89	.20	**.43**	**.32**	**-.24**	**1.09**	**.19**	**.38****	**.18**	**.01**	**.75**	**.27**
Environmental Effects															
Creativity course	.17	.39	-.63	.97	.11	**1.26****	**.46**	**.31**	**2.20**	**.56**	**.58****	**.26**	**.05**	**1.11**	**.42**
Entrepreneurship course	.11	.400	-.71	.93	.05	.37	.46	-.58	1.32	.11	.27	.27	-.27	.82	.13
Innovation course	.05	.38	-.73	.84	.04	-.63	.44	-1.54	.28	-.29	.13	.25	-.39	.65	.10
Model metrics															
Adjusted R2	.11					.50					.55				
Root MSE	.68					.79					.46				

Note: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$. Significant relationships are bolded.

Table B3

Developmental Predictors of Social Domains of Innovation Capacity in Full Sample

Variable	Persuasiveness Model 3					Networking Ability Model 3					Teamwork Ability Model 3				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.54*****	**.08**	**.38**	**.71**	**.55**	**.78*****	**.06**	**.65**	**.90**	**.77**	**.54*****	**.09**	**.36**	**.71**	**.52**
Treatment	**.46****	**.21**	**.05**	**.88**	**.18**	-.01	.18	-.37	.36	.00	**.66*****	**.22**	**.22**	**1.10**	**.26**
Gender															
Nonbinary	.35	.40	-.44	1.14	.07	-.20	.34	-.87	.48	-.04	.54	.41	-.27	1.35	.10
Woman	-.28*	.14	-.56	.01	-.15*	-.09	.12	-.33	.16	-.05	.07	.15	-.22	.37	.04
Race															
Black	-.18	.24	-.65	.30	-.06	.10	.21	-.32	.50	.03	.07	.24	-.42	.55	.02
Asian	.28	.18	-.08	.64	.13	.15	.16	-.16	.47	.07	.18	.19	-.19	.56	.09
Latinx	-.20	.27	-.74	.34	-.06	-.10	.24	-.57	.37	-.03	.12	.28	-.44	.68	.03
Middle Eastern	.02	.47	-.91	.95	.00	-.37	.40	-1.16	.43	-.07	-.12	.48	-1.08	.83	-.02
White	-.05	.18	-.40	.30	-.03	.21	.15	-.09	.51	.12	-.26	.18	-.62	.11	-.15
Multiracial	**-.44***	**.26**	**-.96**	**.07**	**-.14**	**.58*****	**.21**	**.16**	**1.01**	**.18**	**.55****	**.26**	**.04**	**1.05**	**.17**
Prefer not to respond	.57	.48	-.38	1.51	.28	-.58	.40	-1.38	.23	-.27	-.54	.48	-1.50	.42	-.26
Other Inputs															
Age	.02	.09	-.15	.19	.02	**.15****	**.07**	**.00**	**.29**	**.13**	-.07	.09	-.24	.10	-.07
Family Income	.00	.03	-.06	.06	-.01	-.01	.03	-.06	.05	-.01	-.04	.03	-.10	.03	-.09
First Generation Status	**.33****	**.16**	**.02**	**.64**	**.16**	.02	.13	-.25	.28	.01	.16	.17	-.17	.50	.08
Family New Product	-.38	.23	-.83	.08	-.13	.13	.19	-.25	.52	.05	-.05	.23	-.51	.41	-.02
Family New Business	.11	.14	-.17	.38	.06	**-.22***	**.12**	**-.46**	**.02**	**-.12**	-.18	.14	-.46	.10	-.10
Bridge Effects															

Cohort 1	-.17	.20	-.57	.24	-.09	.12	.17	-.22	.46	.06	-.08	.21	-.49	.33	-.04
Cohort 2	-.12	.21	-.54	.31	-.06	-.03	.18	-.39	.32	-.02	-.06	.22	-.49	.37	-.03
Cohort 3	**-.45****	**.22**	**-.87**	**-.02**	**-.21**	-.07	.18	-.44	.29	-.03	.11	.22	-.32	.54	.05
Transfer Student	.04	.21	-.37	.46	.02	-.02	.18	-.37	.33	-.01	.27	.21	-.15	.69	.10
International Student	**-.43***	**.23**	**-.88**	**.01**	**-.22**	-.17	.20	-.56	.22	-.08	**-.60***	**.23**	**-1.07**	**-.14**	**-.30**
Political Leaning	**-.12***	**.07**	**-.26**	**.02**	**-.13**	-.03	.06	-.15	.09	-.04	**-.18***	**.07**	**-.32**	**-.04**	**-.20**
Environmental Effects															
Creativity course	.07	.24	-.40	.54	.03	.18	.20	-.21	.57	.08	-.06	.24	-.54	.41	-.03
Entrepreneurship course	**.52***	**.29**	**-.06**	**1.10**	**.14**	**.48***	**.26**	**-.03**	**.99**	**.13**	-.37	.31	-.99	.25	-.10
Innovation course	.19	.25	-.31	.69	.08	.05	.22	-.38	.48	.02	.03	.27	-.50	.55	.01
Model metrics															
Adjusted R2	.43					.58						.37			
Root MSE	.69					.60						.71			

Note: * indicates *p* < .05, ** indicates *p* < .01, *** indicates *p* < .001. Significant relationships are bolded.

Table B4

Developmental Predictors of Social Domains of Innovation Capacity in Propensity Score Matched Sample

Variable	Persuasiveness Model 2					Networking Ability Model 2					Teamwork Ability Model 2				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.49*****	**.14**	**.20**	**.78**	**.48**	**.58*****	**.11**	**.36**	**.81**	**.65**	.18	.16	-.15	.50	.26
Treatment	.28	.27	-.28	.85	.14	-.31	.20	-.72	.09	-.20	.11	.31	-.53	.75	.08
Environmental Effects															
Creativity course	.05	.40	-.77	.86	.02	.14	.27	-.41	.69	.09	-.15	.38	-.94	.63	-.12
Entrepreneurship course	**1.25*****	**.41**	**.41**	**2.10**	**.44**	**.64****	**.29**	**.04**	**1.24**	**.29**	.33	.42	-.53	1.19	.17
Innovation course	.47	.38	-.31	1.26	.25	.20	.26	-.34	.74	.13	.09	.39	-.70	.89	.08
Model metrics											.06				
Adjusted R2	.50					.62					.68				
Root MSE	.69					.47									

Note: * indicates *p* < .05, ** indicates *p* < .01, *** indicates *p* < .001. Significant relationships are bolded.

Table B5

Developmental Predictors of Cognitive Domains of Innovation Capacity in Full Sample

Variable	Risk Tolerance Model 3					Intention to Innovate Model 3					Creativity Model 3				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.53*****	**.09**	**.36**	**.69**	**.52**	**.52*****	**.08**	**.37**	**.67**	**.51**	**.42*****	**.08**	**.28**	**.57**	**.43**
Treatment	.09	.23	-.36	.55	.03	**.70*****	**.22**	**.26**	**1.14**	**.26**	**.76*****	**.21**	**.34**	**1.18**	**.30**
Gender															
Nonbinary	.11	.45	-.77	1.00	.02	.44	.41	-.38	1.26	.08	.08	.40	-.71	.86	.01
Woman	**-.40****	**.16**	**-.70**	**-.09**	**-.21**	-.18	.15	-.47	.12	-.09	.21	.14	-.07	.49	.12

Race															
Black	.31	.26	-.20	.82	.10	.30	.24	-.18	.77	.10	.09	.23	-.37	.55	.03
Asian	**.35***	**.20**	**-.04**	**.74**	**.16**	.17	.19	-.21	.55	.08	.20	.18	-.16	.56	.10
Latinx	.19	.30	-.40	.78	.05	.39	.29	-.18	.96	.11	.26	.28	-.29	.80	.08
Middle Eastern	.26	.51	-.75	1.27	.05	-.74	.49	-1.71	.24	-.14	-.30	.47	-1.24	.64	-.06
White	.21	.19	-.17	.59	.12	-.11	.18	-.48	.25	-.07	-.03	.18	-.38	.32	-.02
Multiracial	-.03	.27	-.57	.51	-.01	.21	.26	-.31	.73	.06	-.40	.25	-.90	.09	-.13
Prefer not to respond	**-1.29****	**.51**	**-2.31**	**-.27**	**-.59**	-.21	.50	-1.20	.77	-.10	.17	.47	-.77	1.11	.09
Other Inputs															
Age	-.03	.09	-.21	.15	-.03	-.05	.09	-.22	.13	-.04	.02	.08	-.14	.18	.02
Family Income	-.01	.03	-.08	.06	-.03	**.06***	**.03**	**.00**	**.13**	**.15**	.03	.03	-.03	.09	.08
First Generation Status	.16	.17	-.18	.49	.07	.18	.16	-.14	.50	.09	.17	.15	-.13	.48	.09
Family New Product	-.25	.24	-.74	.23	-.08	-.02	.24	-.49	.46	-.01	.01	.23	-.44	.46	.00
Family New Business	.03	.15	-.27	.32	.01	-.09	.15	-.38	.20	-.05	-.16	.14	-.43	.11	-.09
Bridge Effects															
Cohort 1	-.09	.22	-.52	.34	-.05	-.31	.21	-.72	.10	-.15	**-.46***	**.20**	**-.86**	**-.07**	**-.25**
Cohort 2	.04	.23	-.41	.50	.02	.15	.22	-.28	.58	.07	-.40	.21	-.81	.02	-.20
Cohort 3	-.21	.23	-.66	.24	-.10	.17	.22	-.28	.61	.08	-.28	.21	-.70	.14	-.14
Transfer Student	.12	.22	-.32	.56	.04	.31	.22	-.12	.73	.11	.21	.20	-.19	.62	.08
International Student	-.05	.25	-.53	.44	-.02	.18	.24	-.29	.65	.09	.18	.23	-.27	.62	.09
Political Leaning	**.12***	**.07**	**-.02**	**.27**	**.13**	.02	.07	-.13	.16	.02	-.08	.07	-.22	.06	-.09
Environmental Effects															
Creativity course	-.21	.26	-.72	.31	-.09	-.13	.24	-.61	.35	-.06	.15	.23	-.30	.61	.07
Entrepreneurship course	**.80****	**.32**	**.17**	**1.44**	**.21**	-.21	.31	-.81	.40	-.06	.49	.29	-.09	1.07	.14
Innovation course	.13	.28	-.42	.67	.05	.26	.26	-.26	.78	.11	-.26	.25	-.76	.24	-.11
Model metrics															
Adjusted R2	.39					.39					.36				
Root MSE	.75					.73					.70				

Note: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$. Significant relationships are bolded.

Table B6

Developmental Predictors of Cognitive Domains of Innovation Capacity in Propensity Score Matched Sample

Variable	Risk Tolerance Model 2					Intention to Innovate Model 2					Creativity Model 2				
	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β	Coef.	S.E.	L.B.	U.B.	β
Initial Innovation Capacity	**.63*****	**.18**	**.27**	**1.00**	**.52**	**.46****	**.18**	**.10**	**.82**	**.48**	**.26***	**.15**	**-.05**	**.56**	**.28**
Treatment	.22	.28	-.35	.79	.12	.42	.27	-.14	.97	.25	**.66****	**.27**	**.09**	**1.22**	**.36**
Environmental Effects															
Creativity course	.08	.41	-.77	.92	.04	.26	.43	-.62	1.13	.15	.34	.40	-.48	1.17	.19
Entrepreneurship course	**1.38*****	**.40**	**.55**	**2.20**	**.51**	.27	.38	-.51	1.05	.11	**.83****	**.40**	**.02**	**1.65**	**.31**
Innovation course	-.35	.38	-1.14	.45	-.19	.12	.37	-.64	.87	.07	.03	.38	-.75	.81	.02
Model metrics															
Adjusted R2	.47					.39					.43				

Root MSE	.68	.65	.68

Note: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$. Significant relationships are bolded.