How a Cornerstone Course Impacts Self-Efficacy and Entrepreneurial Skills

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Work in progress: How a Cornerstone Course Impacts Self-efficacy and Entrepreneurship

Introduction

Engineers have emerged as pivotal players in technological innovation in the past decade by founding or actively participating in entrepreneurial ventures [1]. Consequently, policy initiatives have increasingly supported integrating entrepreneurship programs within engineering education [2]. Economic shifts and an evolving job market for graduates have heightened the demand for engineers with an entrepreneurial mindset, which is defined as the cognitive adaptability that preceeds entrepreneurial behaviors for acting on opportunities, learning from failures, and creating economic and social value through problem-solving [6]. Such a mindset needs to be complemented with skills that include creativity, critical thinking, and collaboration[3, 6], along with an improved self-efficacy to conduct different entrepreneurial tasks, that is, the person's belief of being capable [4].

Prior studies have shown that students who received entrepreneurial training reported higher levels of entrepreneurial self-efficacy [2], and were much more likely to engage with hands-on experiences were they are expected to learn how to navigate complex technological landscapes and spearhead the development of solutions to significant technological challenges on both local and global scales [5]. To achieve this later objective, engineering programs have implemented practical experiences based on project- and team-based learning [6]. Cornerstone courses are first-year courses that aim to introduce students to engineering from an early stage in their studies [7]. They are usually taught using a project-based approach, inviting students to solve real-world problems [8]. Project-based courses encourage teamwork [9], creativity [10], and critical thinking [8]. To our knowledge, cornerstones are underexplored as an entrepreneurial learning experience, although it could lay the foundations for developing favorable attitudes and behaviors for entrepreneurship. This research aims to comprehend how a cornerstone course contributes to the entrepreneur mindset by developing student self-efficacy to undertake different tasks related to entrepreneurship and innovation.

Methods

This Work-In-Progress addresses the following research question: *How does a cornerstone course contribute to developing an entrepreneurial mindset by enhancing student self-efficacy in undertaking various tasks related to entrepreneurship and innovation?* To answer this research question, we conducted a quantitative study in a cornerstone course taught every semester in a highly selective engineering school in Chile. During the first semester of their first year, 800 civil engineering students take this Cornerstone as a core curriculum course. During the second semester of their first year, 250 students who will pursue a Major in Civil Engineering in a Bachelor's in Science program take the course. This course is part of the core curriculum for students pursuing a Major in Civil Engineering. The course context and summary is in Appendix A.

To evaluate students' entrepreneurship-related self-efficacy, a questionnaire based on the scale developed by Cooper and Lucas (2007) [11] was used. The scale consisted of items rated on a 10-point scale. Data were collected from 2019 to 2024, with surveys administered at the beginning and end of each semester. Students received the questionnaire via email and participated voluntarily, yielding 4,309 responses (39.11% response rate out of 11,017 expected responses). Additional details are provided in Appendix B.

Data analysis was carried out in R [12]. Using Exploratory Factor Analysis (EFA) [13], we identified the latent dimensions within the self-efficacy scale, employing minimum residual as the factor extraction method and applying an oblimin rotation to account for correlations among latent factors.

To determine the statistical significance of differences between various comparison groups, we performed one-way analysis of variance (one-way ANOVA) [14]. Separate analyses were performed for each latent dimension obtained in the EFA, treating them as dependent variables. Each analysis simultaneously incorporated three grouping variables: pre-post course (this is application timing: beginning/end of the course), program (engineering/science bachelor), and year (2019-2024). This approach enabled us to control cross-effects and isolate the specific impact of each comparison group on the latent dimensions. Subsequently, Tukey's Honest Significant Differences (THSD) [15] post-hoc tests were employed to identify which specific pairs of comparison exhibited statistically significant differences in their mean values. In all tests, the null hypothesis (H_0) assumed that there were no mean differences, while the alternative hypothesis (H_1) stated that there were such differences. A *p*-value less than 0.05 led to the rejection of the null hypothesis (H_0), indicating statistical significance.

Results

Table 1 shows the fit indices for the three-factor solution obtained (MR1, MR2, and MR3), which together explain 56% of the variance in the original variables. This result supports the adequacy of the factor structure for the data. The sum of squared loadings (SS Loadings) indicates that MR2 (2.25) accounts for the highest factor contribution, followed by MR1 (1.51) and MR3 (1.31).

Table 1: Exploratory factor analysis fit indices

	MR1	MR2	MR3
SS Loadings	1.51	2.25	1.31
Proportion var	0.17	0.25	0.15
Cumulative var	0.17	0.42	0.56
Proportion explained	0.30	0.44	0.26
Cumulative proportion	0.30	0.74	1.00

Table 2 presents the factor loadings matrix, which allows for the interpretation of the latent factors. For MR1, the items that load is 'Present a problem and its solution orally in Spanish' (.80), 'Find a solution consistent with the problem being addressed' (.66), and 'Work as a team on a common project' (.36), so we interpret that factor as 'collaborative problem-solving'. For MR2, the main factor loadings are from the items ‘Solve a real problem using a design centered on its users’ (.84), ‘Design a prototype of a new product or service that addresses the needs of a user’ (.78), and ‘Recognize a good opportunity to generate a new product or service in a real-world context’ (.56), so we interpret that factor as ‘solution development’. Finally, in MR3, the items that load are ‘Learn topics not taught in classes on my own’ (.77), ‘Study a technology and discover a new practical use for it’ (.49), and ‘Draw conclusions from information obtained from different sources’ (.37), it is interpreted as ‘autonomous learning and critical thinking’.

Table 2: Factor loadings matrix

Item	MR1	MR2	MR3	Communality	Complexity
Present a problem and its solution orally in Spanish.	0.80			0.59	1.06
Find a solution consistent with the problem being addressed.	0.66			0.62	1.34
Work as a team on a common project.	0.36			0.41	2.29
Solve a real problem using a design centered on its users.		0.84		0.72	1.01
Design a prototype of a new product or service that addresses a user's needs.		0.78		0.62	1.03
Recognize a good opportunity to generate a new product or service in a real-world context.		0.56		0.54	1.24
Learn topics not taught in classes on my own.			0.77	0.56	1.00
Study a technology and discover a new practical use for it.		0.35	0.49	0.58	1.80
Draw conclusions from information obtained from different sources.			0.37	0.45	2.38

Table 3 presents the results of the ANOVA for latent variable ‘Collaborative Problem-Solving’, indicating that all effects are statistically significant ($p << 0.01$). THSD post-hoc tests reveal that scores at the end of the semester (post) are significantly higher than at the beginning (pre). Additionally, science bachelor students outperform engineering students. For further details, see Appendix C.

Table 3: One-way ANOVA results for ‘Collaborative problem-solving’ by Program, Pre-Post, and Year

Comparison variable	Degrees of freedom	Sum of squares	Mean square	*F* statistic	*p*-value
Program*	1	6.13	6.13	11.56	0.00
Pre-post**	1	73.45	73.45	138.48	0.00
Year***	5	956.75	191.351	360.79	0.00
Residuals	4281	2270.50	0.53		

Notes: * Program refers to engineering or Science bachelor. ** Pre-post indicates the timing of the survey administration (at the beginning or the end of the semester). *** Year ranges from 2019 to 2024.

Concerning the ANOVA for the latent dimension ‘Solution development’ dimension (see Table 4), there are statistically significant differences according to the program and the time when the survey was applied (both p-values << 0.01). According to THSD post-hoc tests, scores improve from the start (pre) to the end (post) of the semester. Likewise, students in science bachelor programs attain higher scores than those in engineering (see Appendix C).

Table 4: One-way ANOVA results for ‘Solution Development’ by Program, Pre-Post, and Year

Comparison variable	Degrees of freedom	Sum of squares	Mean square	*F* statistic	*p*-value
Program*	1	27.89	27.89	32.81	0.00
Pre-post**	1	10.64	10.64	12.52	0.00
Year***	5	8.56	1.71	2.02	0.07
Residuals	4281	3638.28	0.85		

Notes as in Table 3

Unlike the previous dimensions, ANOVA for ‘Autonomous Learning and Critical Thinking’ latent dimension (see Table 5), only shows statistically significant differences according to the year the survey was applied (p-value << 0.01). THSD post-hoc tests suggest that students who enrolled in 2024 have slightly higher scores than students who enrolled in previous years (see Appendix C).

Table 5: One-way ANOVA results for ‘Autonomous learning and critical thinking’ by Program, Pre-Post, and Year

Comparison variable	Degrees of freedom	Sum of squares	Mean square	*F* statistic	*p*-value
Program*	1	0.42	0.42	0.56	0.45
Pre-post**	1	0.48	0.48	0.65	0.42
Year***	5	18.28	3.66	4.96	0.00
Residuals	4281	3154.59	0.74		

Notes as in Table 3

Discussion and Limitations

This WIP illustrates how a cornerstone course can contribute to developing entrepreneurial self-efficacy, particularly related to student self-confidence for collaborative problem-solving and solution development. According to the ANOVA analysis, the pre-post differences in student scores are statistically significant for the variables related to collaborative problem-solving and solution development. This combines entrepreneurial skills that have already been highlighted by prior literature as relevant [6], [8].

The differences by program may suggest that Science Bachelor students who take the course in their second semester have likely had other learning opportunities to develop skills such as collaborative problem-solving and solution development. Regardless of this potential explanation of these differences, it may be interesting for future work to deepen our understanding of how entrepreneurship education impacts engineering students in contrast to other degrees.

Still, according to the moment the survey was applied, the cornerstone course has a significant effect on students' self-efficacy related to ‘Solution development’ and ‘Autonomous learning and critical thinking,' which is robust when controlled for year and program. Further work is needed to understand why students in the 2024 admission cohort perform significantly better than previous cohorts.

One limitation of this study is that it mainly relies on self-reported data from a convenience sample of students. Future studies may require using random stratified sampling for survey application, along with triangulating other sources of evidence. Concerning findings, this may be influenced by the fact that both engineering and bachelor students have courses on math and basic science, in conjunction with this course, so there may be hidden effects related to other curricular and extracurricular activities experienced by students.

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Appendices

Appendix A: Cornerstone Course Context and Summary

In this highly selective school in Chile, the Engineering program during the first years of studies, students follow a common civil engineering curriculum. However, they then graduate from one of the following Engineering Departments: Construction Engineering and Management, Structural and Geotechnical Engineering, Hydraulic and Environmental Engineering, Transport and Logistics Engineering, Mechanical Engineering, Chemical Engineering and Bioprocesses, Electrical Engineering, Computer Science, and Mining Engineering [16].

In this cornerstone course, students study a real life topic chosen by the course professors. This topic varies from Urban Cyclists (2014), Adapted Sports (2023), Reduce, Reuse, Recycled (2016), Firefighters *(2015), Inclusion of Older (2023), Animal-Human Relationship (2024), within others. Students work in teams studying the semester topic and interviewing users, stakeholders, and key informants. Each team finds a unique opportunity for innovation, design, prototype, and test a solution. These solutions are presented in a technological fair where stakeholders evaluate each project. The following Table presents the course summary.

Table A.1: Course Summary [17]

Teaching Methods	Project-based Learning within Flipped Classroom
Course content	Engineering Design Process.
Learning Outcomes	1. Solve a real-world problem. Apply a user-centered design methodology to an engineering problem. Produce a device that responds to a specific group's social, economic, or environmental vulnerability inequalities. 2. Articulate individual contributions to teamwork to develop a joint project.
Assessment Methods	Individual assessment, team assessment, and peer assessment regarding contribution to teamwork.

Evaluation Criteria	The professor assesses the design process during the semester, and stakeholders assess the final deliverable at a technology fair.
Course Sections and Teams	During the first semester, the course is taught in ten sections, each one with a different professor. In the second semester, there are three sections. As the course is taught using flipped classroom methodology, all sections use the same teaching material uploaded in Canvas, and students perform the same activities in class. Each section has 12 teams, and each team runs from seven to nine students. In the first semester, there are 120 teams, and in the second semester, there are 36 teams.

Appendix B: Response rate by questionnaire administration

Year	Semester	Program	Student enrollment	Pre	Post
2019	1	Civil Engineering	787	n=418 (53.11%)	n=350 (44.47%)
2020	1	Civil Engineering	837	n=556 (66.43%)	n=313 (37.4%)
2020	2	Science bachelor	287	n=211 (73.52%)	n=91 (31.71%)
2021	1	Civil Engineering	854	n=429 (50.23%)	n=244 (28.57%)
2021	2	Science bachelor	230	n=44 (19.13%)	n=42 (18.26%)
2022	1	Civil Engineering	851	n=135 (15.86%)	n=135 (15.86%)
2022	2	Science bachelor	212	n=96 (45.28%)	n=59 (27.83%)
2023	1	Civil Engineering	820	n=570 (69.51%)	n=50 (6.1%)
2023	2	Science bachelor	215	n=85 (39.53%)	n=104 (48.37%)
2024	1	Civil Engineering	831	n=377 (45.37%)	-

Note: Due to the 'social outbreak' in Chile, the questionnaire was not administered in the second semester of 2019. The analyses were conducted during the first half of 2024; therefore, data from the post-administration of the questionnaire during this period, as well as from the second half of the year, were not included.

Appendix C: Tukey Honest Significant Differences post-hoc tests.

1. Dimension: Collaborative problem-solving.

term	group1	group2	Null. value	estimate	conf.low	conf.hig	p.adj	p.adj.signi
Program	Engineering	Sc.B.	0	-0.10	-0.16	-0.04	0.00	***
Pre-post	Post	Pre	0	-0.28	-0.33	-0.23	0.00	****
Year	2019	2020	0	-0.05	-0.15	0.04	0.64	ns
Year Year	2019	2021	0	0.12	0.01	0.22	0.02	*
Year	2019	2022	0	0.04	-0.08	0.17	0.92	ns
Year	2019	2023	0	0.08	-0.03	0.18	0.29	ns
Year	2019	2024	0	-1.60	-1.73	-1.47	0.00	****
Year	2020	2021	0	0.17	0.07	0.26	0.00	****
Year	2020	2022	0	0.10	-0.02	0.21	0.19	ns
Year	2020	2023	0	0.13	0.03	0.22	0.00	**
Year	2020	2024	0	-1.55	-1.68	-1.43	0.00	****
Year	2021	2022	0	-0.07	-0.20	0.05	0.58	ns
Year	2021	2023	0	-0.04	-0.14	0.07	0.90	ns
Year	2021	2024	0	-1.72	-1.85	-1.59	0.00	****
Year	2022	2023	0	0.03	-0.09	0.16	0.97	ns
Year	2022	2024	0	-1.65	-1.79	-1.50	0.00	****
Year	2023	2024	0	-1.68	-1.81	-1.55	0.00	****

2. Dimension: Solution development.

term	group1	group2	Null. value	estimate	conf.lo	conf.hig	p.adj	p.adj.signi
Program	Engineering	Sc.B.	0	0.22	0.14	0.29	0.00	****
Pre-post	Post	Pre	0	-0.11	-0.17	-0.05	0.00	***

3. Dimension: Autonomous learning and critical thinking.

term	group1	group2	Null. value	estimate	conf.lo	conf.hig	p.adj	p.adj.signi
Program	Engineering	Sc.B.	0	0.03	-0.04	0.09	0.45	ns
Pre-post	Post	Pre	0	0.02	-0.03	0.08	0.42	ns
Year	2019	2020	0	0.08	-0.04	0.19	0.38	ns
Year	2019	2021	0	0.13	0.00	0.25	0.05	ns
Year	2019	2022	0	0.11	-0.04	0.26	0.28	ns
Year	2019	2023	0	0.08	-0.05	0.20	0.50	ns
Year	2019	2024	0	0.25	0.10	0.41	0.00	****
Year	2020	2021	0	0.05	-0.07	0.16	0.84	ns

Year	2020	2022	0	0.03	-0.11	0.17	0.98	ns
Year	2020	2023	0	0.00	-0.11	0.11	1.00	ns
Year	2020	2024	0	0.18	0.03	0.32	0.01	**
Year	2021	2022	0	-0.01	-0.16	0.13	1.00	ns
Year	2021	2023	0	-0.05	-0.17	0.07	0.87	ns
Year	2021	2024	0	0.13	-0.03	0.29	0.17	ns
Year	2022	2023	0	-0.03	-0.18	0.11	0.98	ns
Year	2022	2024	0	0.14	-0.03	0.32	0.17	ns
Year	2023	2024	0	0.18	0.02	0.33	0.01	*