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Professional Skills Development for Digital Transformation in Engineering Students: A Comparative Study

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Abstract

The growing demand for engineering professionals trained to lead Digital Transformation (DT) in the industry demands that academic training transcends theoretical knowledge and comprehensively fosters applied professional skills. This study focuses on analyzing the impact of a pedagogical strategy based on a Community Engagement (CE) Project, associated with the transversal subject of the Engineering School of a Chilean university, specifically Management of Digital Transformation, where these skills are developed. The research problem arises from the observation that, in the subject of Digital Transformation Management, one group of students developed solution proposals for authentic Small and Medium-sized Enterprises (SMEs) that participated in the CE project. In contrast, another group that did not participate developed proposals for fictitious companies. The research question guiding this work is: How does the development of professional skills in this subject compare between students who participated in the CE project and those who did not, as perceived by engineering students?

The research adopts a quantitative methodology with a quasi-experimental design, using pre-existing and non-randomized groups. The sample comprises students in the first semester of 2025, enrolled in 8 sections of careers in industrial engineering and computer science, across day and afternoon sessions. The experimental group consisted of 147 students who participated in the CE project, applying the Project-Based Learning (PBL) and agile Scrum-kanban methodologies to address real-world problems. The control group, with 138 students, developed their proposals in a simulated context with fictitious companies. Both groups were given a self-perception survey called "Professional Skills of Digital Transformation in Engineering", designed to measure the self-perception of the development of a series of competencies. Preliminary results show that the control group (simulated context) obtained higher self-perception scores in 8 out of 10 dimensions, with significant differences in four. However, these results may reflect overconfidence derived from controlled environments rather than superior competence. The experimental group (real SMEs) showed lower but potentially more realistic self-perceptions, suggesting greater metacognitive calibration.

Keywords: Digital Transformation, Community Engagement, Professional Skills, Project-based learning, Agile Methodologies

Introduction

Digital Transformation (DT) has redefined the competencies required of contemporary engineers, demanding not only technical knowledge but also applied professional skills to lead change processes in the industry. The growing demand for professionals trained to implement digital strategies in organizations, especially in Small and Medium-sized Enterprises (SMEs), has highlighted the need for academic training that transcends a theoretical focus and comprehensively develops practical and soft skills. This study analyzes the impact of a pedagogical strategy based on a Community Engagement (CE) Project, associated with the subject "Digital Transformation Management" at a Chilean engineering faculty, where students developed solution proposals for real SMEs. In contrast, another group of students worked in simulated contexts with shell companies. The research question that guides this work is: How does the development of professional skills in this subject differ between students who participated in the CE project and those who did not, as perceived by engineering students?

DT requires skills beyond the technical, including complex problem-solving, agile project management, effective client communication, and multidisciplinary teamwork. Previous studies, such as those by [1] [2], highlight the importance of integrating experiential approaches, such as Service-Learning (SL) and Project-Based Learning (PBL), to develop these competencies. This article presents a comparative quantitative analysis of two groups of students, using a quasi-experimental design, to evaluate the development of 10 dimensions of professional skills related to DT. The findings reveal an unexpected pattern that challenges conventional assumptions about the superiority of real-context learning in self-perception measures, which we interpret through the lens of metacognitive calibration and feedback literacy [8].

The context of DT in industry demands that engineers not only understand emerging technologies but also manage change, develop solutions, and align digital strategies with business objectives. Traditional training, focused on fictitious cases, can limit the development of these applied skills. Therefore, this study seeks to demonstrate the value of CE as a pedagogical strategy that connects students to real problems, using agile methodologies such as Scrum and Kanban. However, as will be shown, the benefits of CE may not be immediately visible through conventional self-report instruments, a finding that has important implications for educational assessment**.** The findings of this work can guide educational institutions in designing more effective curricula for the digital age.

Theoretical Framework

The theoretical framework of this study is based on recent research that validates the importance of professional skills in the training of engineers for DT, which requires a multifaceted professional profile, with skills in strategic management, organizational change, innovation, and risk management, among others [3]. CE and PBL have proven to be effective in developing applied and soft competencies [1], [4], although their specific impact on DT skills in engineering has been less explored.

Engineering education faces the challenge of moving from an approach focused on theoretical knowledge to one oriented towards the development of applied competencies and "soft skills" demanded by the labor market [1]. This transition responds to the growing need to train professionals capable of leading Digital Transformation processes in real organizational contexts. Service-Learning (SL), conceptualized in our study as Community Engagement (CE), emerges as an effective pedagogical strategy for simultaneously developing professional and social competencies in university students.

A high-level taxonomy that structurally validates the specific dimensions of professional skills for DT investigated in our study is provided by [3]. Its framework establishes direct connections between our operationalized dimensions and the macro-competencies recognized as critical for the modern engineer:

- Digital Strategy Management is linked to Systems and Strategic Thinking.
- Change Management is directly related to Leadership and Resilience.
- Innovation in Solution Design corresponds to Creative and Innovative Thinking.
- The Integration of Information Systems is aligned with Digital Competencies.

This correspondence validates that our measurement instrument assesses practical components of fundamental competencies for the digital age.

Their identification of key competencies, such as problem solving, critical thinking, teamwork, creativity, and communication, as essential for engineering students finds resonance in our operationalization of DT dimensions [2]. In particular, its six soft skills development strategies (especially the combination of competency-based and action-oriented approaches, and the integration of formal and non-formal learning) pedagogically underpin our CE and PBL-based intervention.

The study by [5] demonstrates the successful application of quasi-experimental designs with pre-existing groups in innovative learning environments. Their identification of constraints, such as the need for prolonged interventions and contextual relevance to achieve meaningful impact, informs our design of CE projects with adequate duration and an explicit connection to students' work environment.

In addition, [4] offer solid empirical evidence on the effectiveness of active and technologically mediated pedagogical strategies. Their approach reinforces our conceptual framework, in which CE and PBL, combined with agile methodologies, serve as catalysts for the development of applied professional skills.

A crucial theoretical addition to our framework is the concept of "feedback literacy" developed by [8], which argues that participation in real projects fosters a more sophisticated ability to process and use constructive criticism, modulating self-perception toward greater accuracy and often lower scores on simple self-perception scales. Similarly, the Dunning-Kruger effect provides a relevant lens: students in controlled, simpler problem environments may overestimate their competence, whereas students exposed to complexity and corrective feedback may underestimate theirs due to heightened awareness of their knowledge limits [6].

The integration of these theoretical references allows us to build a comprehensive framework that supports the central hypothesis of our research: Community Engagement, implemented through Project-Based Learning in real contexts, significantly develops the professional competencies required for Digital Transformation in engineering students, although this development may not be adequately captured by conventional self-perception instruments and may manifest as lower but more realistic self-assessment scores.

Methodology

A quasi-experimental design was adopted, with pre-existing, non-randomized groups. The sample consisted of students in the first semester of 2025, enrolled in 8 sections of engineering careers in the industrial area and computer science. The experimental group (n=147) participated in a CE project in which PBL and the agile Scrum-Kanban methodology were applied to solve real problems in SMEs. The control group (n=138) developed proposals in a simulated context with fictitious companies.

A self-perception survey titled "Professional Skills of Digital Transformation in Engineering" was used, comprising 33 items grouped into 10 dimensions, rated on a Likert scale from 1 (Very Low) to 5 (Very High). The dimensions and their associated skills are defined in Table 1.

Table 1. Instrument Dimensions and Associated Skills

Dimension	**Associated Skills**
Digital Strategy Management	Strategic Business Analysis. Systems Thinking. Strategic Planning.

Dimension	Associated Skills
	Strategic Management. Strategy Integration.
Change Management	Change Management. Term Leadership. Conflict Resolution. Effective Communication.
Innovation in Solution Design	User-Centered Design. Innovation. Technological Innovation.
Risk Management	Risk Analysis. Risk Assessment. Risk Management.
Digital Business Models	Business Model Development. Impact Assessment.
Project management	Transformation Project Management. Technological Resource Management. Informed Decision Making.
Information Systems Integration	Information Systems Planning.
Digital Evolution	Digital Maturity Assessment. Digital Maturity Analysis. Organizational Maturity Assessment. Digital Evolution Planning.

Dimension	Associated Skills
Application of Frameworks	Understanding of DT Frameworks. Practical Application Ability.
Digital Organizational Design	Organizational Design. Collaborative Work.

Instrument Reliability and Validity

Reliability was assessed using Cronbach's α for each dimension, ranging from 0.78 to 0.92, indicating acceptable to excellent internal consistency. Confirmatory Factor Analysis (CFA) was conducted to verify the 10-dimension structure, yielding acceptable fit indices (CFI = 0.91, RMSEA = 0.06, SRMR = 0.05). These results support the instrument's reliability and construct validity.

Statistical Analysis

For each dimension, the arithmetic mean and standard deviation were calculated for both groups. A t-test for independent samples was used to compare the means, and the effect size was calculated as Cohen's d. Given the 10 dimensions compared, a Benjamini–Hochberg False Discovery Rate (FDR) correction was applied ($q = 0.05$) to control for Type I error due to multiple comparisons. Additionally, 95% confidence intervals were calculated for each mean difference and for Cohen's d.

To account for potential section-level clustering (8 sections, day/afternoon schedules), we estimated cluster-robust standard errors at the section level. Baseline covariates (prior GPA, program, year, schedule) were compared between groups; no significant differences were found ($p > 0.05$ for all).

A retrospective pre-test design was embedded in the survey, asking students to rate their initial competence before the course. A repeated-measures ANCOVA using retrospective pre-test scores as covariate was conducted to isolate the treatment effect.

Robustness checks included Mann–Whitney U tests for non-normal distributions and sensitivity analysis excluding extreme outliers (±3 SD). Normality was assessed using Shapiro–Wilk tests; homogeneity of variances was verified using Levene's test.

The analysis was performed with a significance level α = 0.05. The data was processed using Python with the *pandas* and *scipy* libraries. For each student, the average number of responses for each dimension was calculated based on the answer established in each column. Then, the mean and standard deviation of these averages were calculated for each group.

Results

The data were obtained from the survey responses of the 285 students. For each dimension, the average score for each student was calculated from the corresponding items. For example, the "Management of Digital Strategies" dimension included 6 items, and responses were averaged to obtain a score per student. This process was repeated for all dimensions.

Table 2 presents the means (M) and standard deviations (SD) for each dimension in both groups. Tables 3-6 show the corresponding data analysis.

Table 2. Comparison of Dimensions by Skill and Group.

		Experimental group		Control group	
Dimension	**Skill**	**M**	**SD**	**M**	**SD**
Digital Strategy Management	Business Strategic Analysis	4.41	0.75	4.35	0.73
	Systems Thinking	4.35	0.76	4.41	0.76
	Strategic Planning	4.40	0.84	4.43	0.76
	Strategic Management	4.40	0.84	4.47	0.66
	Strategic Management	4.32	0.86	4.31	0.83
	Strategy Integration	4.35	0.90	4.31	0.85
Change Management	Change Agent	4.27	0.87	4.32	0.76
	Leadership in Digital Transformation	4.23	0.87	4.38	0.85
	Conflict Resolution	4.27	0.86	4.35	0.86
	Effective Communication	4.34	0.87	4.38	0.91
Innovation in solution design	User-Centered Design	4.19	0.85	4.37	0.79
	Innovation	4.26	0.87	4.37	0.77
Risk Management	Technological Innovation	4.31	0.80	4.51	0.72
	Risk Analysis	4.32	0.75	4.35	0.77
	Risk Assessment	4.36	0.78	4.38	0.75
	Risk Management	4.34	0.84	4.29	0.88
Digital business models	Business Model Development	4.27	0.81	4.37	0.81
	Impact Assessment	4.30	0.85	4.47	0.74
	IT Project Management	4.21	0.81	4.50	0.72

Project Management	Management of Technological Resources	4.20	0.73	4.37	0.84
	Informed Decision Making	4.43	0.78	4.49	0.76
Information Systems Integration	Information Systems Planning	4.31	0.76	4.50	0.63
Digital Evolution	Digital Maturity Diagnosis	4.46	0.81	4.38	0.73
	Digital Maturity Analysis	4.44	0.77	4.35	0.79
	Digital Maturity Assessment	4.38	0.77	4.29	0.73
	Digital Evolution Planning	4.38	0.85	4.38	0.73
Application of Frameworks	Understanding of DT Frameworks	4.09	0.91	4.29	0.90
	Practical Application Ability	4.05	0.86	4.26	0.92
Digital Organizational Design	Organizational Design	4.21	0.89	4.37	0.79
	Collaborative Work	4.21	0.82	4.57	0.68

Table 3. Comparison of averages by dimension and group.

Dimension	**Experimental Group (n=147)**		**Control group (n=138)**		**Difference of Average**
	M	**SD**	**M**	**SD**	**M**
Digital Strategy Management	4.37	0.82	4.38	0.52	-0.01
Change Management	4.28	0.87	4.36	0.55	-0.08
Innovation in Solution Design	4.25	0.84	4.42	0.50	-0.17
Risk Management	4.34	0.79	4.34	0.53	0
Digital Business Models	4.29	0.83	4.42	0.51	-0.13
Project Management	4.38	0.77	4.45	0.52	-0.07

Information Systems Integration	4.31	0.76	4.50	0.54	-0.19
Digital Evolution	4.42	0.80	4.35	0.53	0.07
Application of Frameworks	4.07	0.89	4.28	0.55	-0.21
Digital Organizational Design	4.21	0.85	4.47	0.52	-0.26

Table 4. Statistical Test Results by Dimension (with 95% CI and FDR correction)

Dimension	**t Value**	**P Value**	**95% CI for Mean Difference**	**Cohen's d (95% CI)**	**FDR q-value**	**Significance**
Digital Strategy Management	-0.12	0.905	[-0.15, 0.13]	-0.02[-0.25, 0.21]	0.905	Not significant
Change Management	-0.95	0.341	[-0.24, 0.008]	-0.11[-0.34, 0.12]	0.426	Not significant
Innovation in Solutions	-2.08	0.038	[-0.33, -0.01]	-0.25[-0.48, -0.02]	**0.076**	**Significant**
Risk Management	0.00	1.000	[-0.13, 0.13]	0.00 [-0.23, 0.23]	1.000	Not significant
Digital Business Models	-1.63	0.104	[-0.29, 0.03]	-0.19 [-0.42, 0.04]	0.173	Not significant

Dimension	t Value	P Value	95% CI for Mean Difference	Cohen's d (95% CI)	FDR q-value	Significance
Project Management	-0.92	0.359	[-0.22, 0.08]	-0.11 [-0.34, 0.12]	0.448	Not significant
Systems Integration	-2.42	0.016	[-0.34, -0.04]	-0.29 [-0.52, -0.06]	**0.040**	**Significant**
Digital Evolution	0.88	0.381	[-0.09, 0.23]	0.10| [-0.13, 0.33]	0.476	Not significant
Application of Frameworks	-2.45	0.015	[-0.37, -0.05]	-0.29 [-0.52, -0.06]	**0.038**	**Significant**
Digital Organizational Design	-3.08	0.002	[-0.42, -0.10]	-0.37 [-0.60, -0.14]	**0.010**	**Significant**

Note: FDR correction applied with q = 0.05. After correction, three dimensions remained significant: Information Systems Integration, Application of Frameworks, and Digital Organizational Design.

Table 5. Top 5 Dimensions with the Greatest Average Differences (Exp – Con).

Dimension	Difference of Averages
Digital Organizational Design	-0.26
Application of Frameworks	-0.21
Information Systems Integration	-0.19
Innovation in Solution Design	-0.17

Digital Business Models	-0.13

Table 6. Top 5 Skills with the Largest Average Differences (Exp-Con).

Skill	Dimension	Difference (M)
Collaborative Work	Digital Organizational Design	-0.36
Transformation Project Management	Project Management	-0.29
Information Systems Planning	Information Systems Integration	-0.19
Impact Assessment	Digital business models	-0.17
Technological Innovation	Risk Management	-0.20

Overall, the Control Group performs better than the Experimental Group across most of the evaluations. Specifically, the Control Group scores higher in 8 of the 10 dimensions assessed. The largest gaps in favor of the Control Group appear in Digital Organizational Design, Application of Frameworks, and Integration of Information Systems, indicating a clearer advantage in structural and methodological aspects as well as in connecting and aligning systems.

The Experimental Group shows better results only in Digital Evolution, where it achieves a slight advantage of +0.07 (4.42 vs 4.35), although this difference is not statistically significant ($p=0.381$; after FDR, $q=0.476$). In Risk Management, both groups obtain the same average score (4.34).

Robustness Checks

Mann–Whitney U tests confirmed the same pattern of significant differences ($p < 0.05$ for the same three dimensions). Sensitivity analysis excluding outliers (±3 SD) did not alter the conclusions. Shapiro–Wilk tests indicated slight deviations from normality in some dimensions, justifying the non-parametric robustness checks. Levene's test showed homogeneity of variances across most dimensions ($p > 0.05$), except for Digital Organizational Design ($p = 0.04$), where variances were unequal.

Cluster-robust standard errors (clustered by section) yielded wider confidence intervals but did not change the significance pattern. The ANCOVA using retrospective pre-test scores as covariate confirmed the post-test differences between groups ($F(1,282) = 5.89$, $p = 0.016$), indicating that the observed differences are unlikely due to pre-existing disparities.

Finally, the variability analysis shows that the Experimental Group has higher variability across all dimensions, with standard deviations roughly 0.76–0.89, compared with approximately 0.50–0.55 in the Control Group. This pattern suggests that the Experimental Group's responses are more heterogeneous, potentially reflecting a wider range of experiences or varying levels of exposure to real-world projects.

Discussion

The results reveal an unexpected pattern: the control group outperformed the experimental group in 8 of the 10 dimensions assessed, with statistically significant differences in three dimensions after FDR correction (Information Systems Integration, Application of Frameworks, and Digital Organizational Design). This outcome contrasts with the initial hypothesis, which anticipated advantages for the Community Outreach experimental group. Rather than indicating a straightforward failure of the intervention, these findings should be interpreted in light of the fundamentally different pedagogical conditions experienced by each group, and in particular the distinctive demands introduced by engagement with real SME contexts.

Higher self-perception scores in simulated contexts may reflect confidence derived from controlled scenarios rather than transferable professional competence. Students in the control group faced predictable, well-structured problems with clear success criteria, which may have inflated their self-assessment through a Dunning-Kruger effect—the tendency for individuals with limited exposure to complexity to overestimate their abilities. In contrast, the experimental group experienced ambiguity, iterative feedback, and real-world constraints, leading to more conservative and calibrated self-perceptions.

A central explanatory factor is the iterative, feedback-intensive nature of the experimental condition. Students working with SMEs received continuous feedback not only from instructors but also from entrepreneurs and organizational stakeholders, whose criteria were grounded in operational constraints and immediate feasibility rather than purely academic expectations. In this environment, initial proposals could be rejected outright or require substantial revision to align with the realities of the SME, generating heightened uncertainty and a persistent need for adaptation. Such iteration also entailed significant reprocessing, revisiting assumptions, redesigning deliverables, and negotiating scope, while exposing students to direct criticism from real stakeholders. Although these elements are pedagogically valuable for professional formation, they can simultaneously depress self-assessed competence when students evaluate themselves against shifting requirements and authentic scrutiny.

Moreover, the experimental setting embedded competitive dynamics that likely amplified performance pressure. Teams within the same section competed not only for academic outcomes but also for real-world acceptance of their proposals, which introduced an external, highly salient benchmark. The public visibility of results, coupled with ongoing comparison between teams, may have fostered a performative climate in which students became more aware of relative standing and perceived shortcomings. This social comparison process can adversely affect self-perception of competence, particularly when teams observe peers achieving stakeholder approval or progressing more quickly under similar constraints.

Our interpretation is strongly supported by the concept of "feedback literacy" [8], which argues that participation in real projects fosters a more sophisticated ability to process and use constructive criticism, modulating self-perception toward greater accuracy and often lower scores on simple self-perception scales. Similarly, [6] meta-analysis on student self-assessment found that learning contexts presenting authentic problems and frequent external feedback tend to generate more conservative and critical self-perceptions, whereas simulated environments tend to lead students to overestimate their abilities.

The contrast in task structure between groups further contextualizes the observed differences. While the control group engaged with standardized, predictable theoretical cases, the experimental group confronted poorly structured problems characterized by multiple uncontrolled variables and limited information. Each SME introduced idiosyncratic organizational constraints, diverse cultures, and context-specific needs, requiring students to tailor solutions rather than apply general templates. In addition, the potential real impact of recommendations, affecting actual organizational decisions, likely increased perceived responsibility and cognitive load. Practical limitations common in SMEs, such as constrained or non-existent budgets for proposed initiatives, further restricted solution spaces, and required students to balance innovation with feasibility, a tension that the instrument’s dimensions may not fully capture.

These contextual differences also raise the possibility that well-documented cognitive biases influenced the self-perception measure. One plausible explanation is a Dunning-Kruger effect: students in the control group, operating in a more controlled, simpler problem environment, may have overestimated their competence, whereas students in the experimental group may have underestimated theirs due to repeated exposure to complexity, ambiguity, and corrective feedback. Relatedly, a humility bias may be operating, whereby students immersed in authentic professional challenges become more aware of the limits of their knowledge and skills, thereby reporting lower self-perceived performance despite meaningful learning gains. In this view, lower scores in the experimental group may reflect increased calibration and metacognitive awareness rather than weaker capability.

From a pedagogical standpoint, these results suggest that lower self-perception scores in the experimental group may reflect a more realistic appraisal of professional competence rather than diminished learning. The iterative cycles of negotiation, revision, and stakeholder feedback characteristic of SME collaborations may foster adaptive expertise, resilience, and tolerance for ambiguity, competencies that are critical in professional practice but not necessarily foregrounded in conventional self-report instruments. Furthermore, the combination of authentic feedback and competitive pressure may more closely approximate contemporary workplace conditions, where external stakeholders evaluate deliverables, success criteria evolve, and teams must continuously adapt under resource constraints. Consequently, the observed pattern may indicate that Community Outreach experiences shift students from confidence rooted in controlled academic tasks toward a more professionally grounded self-assessment shaped by real-world complexity.

Conclusions

The results of this study, which show significantly lower self-perception among students in the Community Engagement (CE) group compared to the control group, are not an indicator of pedagogical ineffectiveness but rather a phenomenon documented in the literature on experiential learning in complex environments. As [6] point out in their meta-analysis on self-assessment in higher education, learning contexts that present authentic problems and frequent external feedback tend to generate more conservative and critical self-perceptions. In contrast, simulated and standardized environments tend to lead students to overestimate their abilities. This finding aligns directly with our observation, where exposure to the real organizational complexity of SMEs, budget constraints, and the need for iterations based on feedback from external stakeholders [7] acted as catalysts for a more realistic and less accommodating self-assessment.

The discussion of our results finds strong support in the concept of "feedback literacy" developed by [8]. They argue that participation in real projects fosters a more sophisticated ability to process and use constructive criticism, which, in turn, modulates self-perception, making it more accurate and often lower on simple self-perception scales. This dynamic explains why our experimental group, subjected to an iterative process with entrepreneurs, reported lower scores. In addition, [9] highlight that inductive teaching methods, such as project-based learning in real contexts, although superior for developing applied competencies, expose students to uncertainty and the multidimensionality of problems, which can inhibit inflated self-evaluation. This corroborates our interpretation that lower scores reflect a mature awareness of the complexity inherent in digital transformation, rather than a learning deficit.

Limitations

A key limitation is that certain dimensions of the measurement instrument may privilege structured environments, potentially underrepresenting competencies developed through ambiguity and negotiation. Skills such as resilience, adaptability, tolerance for uncertainty, and the ability to manage complex feedback—central to real-world digital transformation—are not fully captured by conventional Likert-type self-perception scales. Future instruments should incorporate authentic assessment methods (e.g., portfolios, external stakeholder evaluations, performance-based assessments).

Additionally, the absence of a true pre-test (only a retrospective pre-test) limits causal inference. Although we attempted to control for baseline differences using ANCOVA, a true longitudinal design with pre-post measurements would provide stronger evidence. The quasi-experimental design with non-randomized groups also introduces potential selection bias, despite covariate balance checks. Future research should employ randomized controlled trials or natural experiments where feasible.

Finally, the study was conducted in a single university with specific SME contexts, which may limit generalizability to other institutional or cultural settings. Replication studies in diverse contexts are needed.

The pedagogical implications derived from these findings are profound and require a reconceptualization of the assessment instruments. As [10] warns, there is a frequent dissociation between self-assessment and objective performance in innovative educational scenarios. Therefore, it is imperative to complement the self-perception scales with formative and authentic assessment tools that capture dimensions such as resilience, adaptability, and the ability to manage complex feedback, competencies intensively developed in CE but not adequately quantified in the instrument used for this study. It is proposed that evaluation in these contexts should be multidimensional, incorporating portfolios of evidence, guided reflections, and the perspectives of external actors (SMEs) to triangulate a fairer picture of the development of competencies and/or skills.

In summary, this research contributes to evidence, such as that presented by [1] and [4] that the value of active and environment-related pedagogical strategies lies in their potential to generate deep learning and realistic professional self-awareness, even if this translates into lower self-perception scores in the short term. The results do not refute the hypothesis of the superiority of the experiential approach, but rather qualify it, revealing that its optimal impact may not be immediately evident in traditional self-reporting instruments. Future research, following the limitations identified by [5]should adopt longitudinal designs to track the evolution of this self-perception and correlate it with subsequent professional performance, and should also incorporate mixed methodologies that capture the qualitative richness of students' experiences in these challenging and authentic environments.

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