Exploring the Entrepreneurial Learning Goals of Academic Entrepreneurs through Machine Learning and Natural Language Processing

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Abstract

This study explores the entrepreneurial learning goals of graduate students and faculty engaged in academic entrepreneurship, focusing on how their roles and career stages influence their priorities. Using advanced natural language processing (NLP) and machine learning techniques, we analyzed qualitative survey responses to uncover key themes in entrepreneurial training. The analysis identified three primary desired learning goals of entrepreneurial teams: enhancing teamwork and collaboration, understanding market segmentation, and developing customer discovery and commercialization strategies. Graduate students emphasized teamwork and collaboration, reflecting their early career focus on skill-building and professional development, while faculty prioritized commercialization, aligning with their strategic and leadership roles. These findings reveal how career stages shape the learning needs of academic entrepreneurs and how NLP can be used to analyze and synthesize qualitative survey data.

Introduction

Translating scientific discoveries into marketable products has become a core function of modern universities in the innovation economy. As hubs of knowledge creation, universities are able to address societal challenges such as public health and sustainability through the commercialization of academic research (Wright et al., 2017). Universities also play a vital role in regional and national economic growth by supporting startups and enhancing innovation ecosystems (Etzkowitz, 2003; Siegel & Wright, 2015). However, to fully harness the potential of academic entrepreneurship, institutions must effectively leverage human capital.

Graduate students and faculty researchers represent two distinct but complementary groups of entrepreneurial talent in universities. Faculty contribute deep subject-matter expertise, well-established networks, and extensive research experience, making them valuable catalysts of innovation and commercialization (Rothaermel et al., 2007). In contrast, graduate students contribute fresh perspectives, enthusiasm, and a willingness to engage in entrepreneurial risks (Bercovitz & Feldman, 2008). These attributes make students adept at navigating uncertainties and challenges inherent in the launch of new ventures. Many believe that together, these two groups form a synergistic relationship that leads to creativity, problem-solving, and a strong foundation for translating university research into impactful innovations.

There are many motivations for pursuing academic entrepreneurship. These include personal aspirations, career goals, and institutional support (Abreu & Grinevich, 2013; Hayter et al., 2018). For faculty, motivations often include the potential for societal impact, financial rewards, and professional recognition (Lam, 2011). Graduate students, on the other hand, are more likely to be motivated by the opportunity to gain entrepreneurial skills, advance their careers, or explore alternative career paths outside academia (Mosey et al., 2012). Designing training that effectively serves these two groups requires a deep understanding of their distinct motivations and expectations (D'Este & Perkmann, 2011).

In this study, we employ natural language processing (NLP) and machine learning techniques to analyze open-ended survey responses from participants in the National Science Foundation (NSF) I-Corps program. I-Corps is a multi-week entrepreneurship training program designed to catalyze academic researcher involvement in commercialization activities at universities across the U.S. Using MDCOR machine learning software, we examined pre-program survey data to uncover key themes in participant learning expectations for their entrepreneurial teams. This novel methodological approach highlights the importance of examining qualitative data to understand better how universities can support academic entrepreneurs.

Literature Review

This literature review explores the domain of academic entrepreneurship, focusing on differences between faculty and graduate students. We focus on three key areas: 1) academic entrepreneurship in bridging research and commercialization, 2) challenges encountered by faculty and graduate students, and 3) the potential of advanced methodological approaches to analyze qualitative data in entrepreneurial research. By addressing these themes, we provide a foundation for understanding the role of career stages and methodological advancements in entrepreneurship research.

Roles and Contributions of Academic Entrepreneurs

Academic entrepreneurs are individuals within universities who engage in entrepreneurial activities, such as patenting, technology commercialization, startups, and technology licensing (Perkmann et al., 2013). Early research focused primarily on faculty members as academic entrepreneurs based on their expertise and access to research and commercialization resources (Bercovitz & Feldman, 2008). Studies have found that high publication counts and other measures of faculty excellence correlate with increased involvement in patenting and industry collaboration (Perkmann et al., 2011). This suggests that faculty members are more likely to engage in technology transfer activities when they are recognized for their research capabilities, thereby bridging the gap between academia and industry.

Over the past decade, studies have begun to recognize graduate students as a critical group of academic entrepreneurs. Hayter et al. (2016) highlighted that graduate students serve as operational leaders in entrepreneurial projects, managing day-to-day activities necessary for launching startups. This is particularly true in fields such as biotechnology and engineering, where their technical expertise and innovative ideas are essential for transforming academic research into marketable products (Bagheri, 2011). Students bring fresh perspectives and enhance the diversity of entrepreneurial activities within universities (Guerrero et al., 2020).

Motivations driving graduate students to engage in academic entrepreneurship are multifaceted. They are drawn by the opportunity to apply their research in real-world contexts, enhance their professional development, and explore alternative career pathways in an increasingly competitive job market (Bell, 2015; Turin et al., 2021). Financial incentives and the potential for societal impact further motivate their entrepreneurial pursuits (Hayter et al., 2016).

Barriers to Academic Entrepreneurship

Both faculty and graduate students face several common challenges when they become involved in academic entrepreneurship. Financial constraints are a significant issue for launching technology startups and their subsequent development. A lack of capital can delay or halt entrepreneurial activities, placing immense pressure on academic entrepreneurs to secure adequate funding (Sahu et al., 2023; Sapir & Oliver, 2016).

Another challenge is navigating complex bureaucracies within universities. Slow and complicated institutional policies and practices can impede commercialization. Miller et al. (2018) emphasized that bureaucratic hurdles create delays and additional work, making it difficult for academic entrepreneurs to participate efficiently. External factors also present challenges; Koladkiewicz et al. (2023) observed that a lack of experience navigating market dynamics can hinder commercialization because academics often have difficulty identifying market opportunities and meeting industry standards.

Faculty face additional challenges when seeking tenure and promotion. Entrepreneurial activities do not always align with traditional measures of academic success, such as securing external funding and publishing impactful research. Miller et al. (2018) point out that this tension can discourage faculty from fully engaging in entrepreneurial activity. Faculty also face challenges when reallocating resources from research projects to entrepreneurial initiatives.

Hayter et al. (2016) highlighted this difficulty, noting that resource reconfiguration within university spinoffs is persistent. Hall et al. (2023) explain that navigating issues such as patenting, licensing, and ownership rights can deter faculty from pursuing entrepreneurial ventures.

Graduate students also face challenges related to their career stage. Among the most pronounced is a lack of experience in business. Graduate students often struggle to develop business models, secure funding, and understand the entrepreneurial landscape when navigating it for the first time (Boldureanu et al., 2020; Hannon et al., 2005). Furthermore, graduate students have limited professional networks compared to faculty, which restricts their ability to connect with potential investors, mentors, and industry partners. Hayter et al. (2016) noted that these restricted social networks are a significant barrier, given that mentorship and networking are crucial for entrepreneurial success.

Entrepreneurship Education and Resources

Delivering entrepreneurship education and training to academic researchers is considered a way to address some of the barriers academic entrepreneurs face. Universities and government agencies with significant investments in basic research are offering faculty and graduate students training to catalyze involvement in academic entrepreneurship. Most prominent is the National Science Foundation's Innovation Corps (NSF I-Corps), which was launched in 2011 (Huang-Saad et al., 2017). I-Corps is a multi-week entrepreneurship training program designed to equip researchers with the skills necessary to transform their discoveries into business ventures. This involves conducting primary market research through a process known as customer discovery, and developing viable business models (Huang-Saad et al., 2017; Radu Lefebvre & Redien-Collot, 2013). I-Corps conducts systematic program evaluation through pre-, post-, and longitudinal surveys to assess motivations for participating in the training, and its effectiveness in terms of market validation and commercialization outcomes.

<u>Advanced Computational Tools for Analyzing Qualitative Data</u>

Qualitative data is key to gaining unique insights into participant experiences and learning priorities (Fayemi & Madueke, 2023). Unlike predefined survey options, open-ended questions allow respondents to articulate their goals, challenges, and expectations in their own words, providing flexibility that enables emergent themes to surface (Fleck et al., 2020; Nazri et al., 2014). Traditional tools for qualitative analysis, such as NVivo and ATLAS.ti, require substantial manual effort and are prone to researcher bias, particularly during the coding and interpretation stages (Woods et al., 2016). While effective for smaller datasets, they can become cumbersome and inefficient when applied to large-scale qualitative data.

In contrast, advanced natural language processing (NLP) and machine learning can efficiently process substantial volumes of text data, enabling the analysis of responses from larger cohorts without compromising analytical rigor (González Canché, 2023). NLP's machine-learning algorithms minimize researcher bias in coding and theme identification by applying uniform criteria across the dataset, thereby enhancing reliability and reproducibility (Woods et al., 2016). Furthermore, NLP and machine learning use unsupervised learning techniques to uncover emergent patterns and themes without relying on predefined codes, a feature that is especially valuable for exploratory research. NLP and machine learning techniques also preserve the context and nuance of participant responses, moving beyond frequency counts to synthesize richer and more complex qualitative data (González Canché, 2023).

<u>Statement of the Problem</u>

The NSF I-Corps program collects program evaluation data through surveys comprised primarily of quantitative survey items and a few open-ended items. To gain insight into the learning priorities of entrepreneurial teams, we examined responses to the open-ended question: "What aspects of your team would you like to strengthen as a result of the I-Corps course?" Given the large number of I-Corps participants across the U.S., it would be very challenging and time-consuming to analyze responses to this one specific question using traditional qualitative research methods. Therefore, we used and NLP approach and innovative software tool referred to as MDCOR (Machine-Driven Classification of Open-Ended Responses, González Canché, 2023), to analyze responses to this question.

Data Analysis and Findings

<u>Population</u>

Our dataset included responses from 3,453 participants in the I-Corps program, comprising both Entrepreneurial Leads (ELs or graduate students) and Principal Investigators (PIs or faculty).

Among them, 2,803 participants answered the qualitative question, “What aspects of your team would you like to strengthen as a result of the I-Corps course?”. Of these, 1,480 responses were from ELs and 1,323 from PIs. It should be noted that I-Corps also includes business mentors on teams; however, our analyses focused specifically on the motivations of faculty and graduate student academic researchers.

Methodology

We used MDCOR software (González Canché, 2023) to process and analyze the qualitative responses to the open-ended survey question. MDCOR is an unsupervised machine-learning tool designed to analyze large-scale qualitative data without manual coding. Using probabilistic modeling, it identifies latent themes within text while preserving participants' original voices, making it particularly valuable for extracting insights from complex responses. MDCOR performed text cleaning and preprocessing, removing redundant words, stemming words to their root forms, and filtering out non-informative terms. It then applied a classification algorithm to determine the optimal number of themes. Based on the model’s convergence metrics, we identified three distinct themes that best captured participants' priorities. The software then assigned each response to one of these themes. To validate the results, we analyzed word frequency distributions, reviewed representative responses for each theme, and ensured coherence across classifications.

Results

Our analysis of responses resulted in three themes representing the knowledge and skills that ELs and PIs were interested in obtaining through I-Corps to strengthen their teams:

1. Team dynamics and team building: Understand how to form effective teams and collaborate successfully.
2. Market segmentation: Learn strategies for defining and targeting appropriate market segments for entrepreneurial ventures.
3. Customer discovery and commercialization: Gain insights into customer needs and identify a viable path to commercialization.

Representative quotes for each theme are presented below.

Theme 1: “The PI and I (the EL) have had a relationship for four years, and have always worked very well together. During the I-Corps program, I would like to transition from an advisor-student relationship, to a business partner relationship. I expect this transition to be welcome and to occur naturally. The [business] mentor and I have limited experience working with one another. I would like to strengthen our working relationship in all aspects. By the end of the program, if a ‘go’ decision is made, I would like to understand and affirm the roles and responsibilities of each individual.”

Theme 2: “Understanding needs within different market segments — understanding of current products' shortcomings from doctor's perspective- identifying best target market for initial product launch/application- how to best differentiate our product.”

Theme 3: "Develop a strategy to commercialize our technology. Create a solid portfolio to pique interests of clients and also attract investors. Develop a vision to build our company."

Qualitative Theme Analysis

Descriptive Statistics and Subgroup Comparison

The descriptive statistics (Table 1) offer a quantitative summary of theme counts and text contributions for each thematic code, disaggregated by group membership of ELs and PIs. Text contribution measures how representative a participant response is within its assigned theme. It is calculated as the probability of the response belonging to the theme relative to the highest probability observed within the theme. Text contribution scores ranged from 0 to 1, with higher values indicating responses that are more strongly aligned with the theme's defining characteristics. These metrics offer insights into how ELs and PIs articulate their learning priorities and the extent to which their responses fit within the broader thematic structure.

Table 1. Descriptive Statistics for Theme Frequency and Text Contributions by Subgroup

Theme	Group	Count	Mean	SD	Median	Min	Max	Skewness	Kurtosis	95% CI
1	EL	571	0.67	0.06	0.66	0.59	1.00	1.34	5.55	0.66 –0.67
1	PI	373	0.66	0.06	0.64	0.59	0.92	1.5	5.49	0.65 –0.66
2	EL	512	0.79	0.05	0.78	0.73	1.00	1.05	4.24	0.79 –0.80
2	PI	502	0.79	0.05	0.78	0.72	0.98	0.94	3.87	0.78 –0.79
3	EL	397	0.79	0.04	0.78	0.72	0.97	1.04	4.41	0.78 –0.79
3	PI	448	0.79	0.05	0.77	0.73	1.00	1.22	4.59	0.78 –0.79

Across all themes, text contribution scores are relatively high (0.657–0.793), suggesting strong alignment between participant responses and the themes identified by MDCOR. ELs and PIs exhibited similar mean scores within each theme, although EL responses tend to be slightly more consistent (lower standard deviations), while PI responses show greater variation.

Distribution of Qualitative Themes by Subgroup

Comparing ELs and PIs revealed notable differences in thematic focus. ELs reported significantly higher interest in teamwork (theme 1), whereas PIs exhibited relatively greater engagement with commercialization (theme 3). Both groups demonstrated similar levels of interest in market segmentation (theme 2). These findings reflect the unique learning priorities of each subgroup, shaped by their roles and experiences within the entrepreneurial ecosystem.

Relative Text Contribution Across Themes and Subgroups

Relative text contribution (ranging from 0 to 1) was analyzed across the three thematic codes to explore participant engagement. ELs generally contributed slightly more text across all themes, with higher median contributions compared to PIs. However, the variability within subgroups was more pronounced for teamwork compared to market segmentation or commercialization themes—a larger proportion of EL responses clustered around higher text contributions for teamwork. In contrast, PIs' contributions were more concentrated around the median values across all three themes.

Statistical Comparison of Thematic Engagement by Subgroup

To further investigate the magnitude of differences in thematic engagement between Entrepreneurial Leads (ELs) and Principal Investigators (PIs), both chi-square tests of independence and Poisson regression analyses were conducted. These methods provide complementary insights into the frequency and distribution of contributions to the three themes. The results offer a nuanced understanding of how role-specific factors shape engagement within these thematic areas.

Chi-Square Test

The chi-square test results ($\chi^2 = 36.026$, df = 2, $p < 0.001$) indicated a highly significant difference in the distribution of thematic contributions between ELs and PIs. This finding reveals the influence of role-specific responsibilities on engagement with the themes. ELs were more likely to emphasize teamwork and collaboration, while PIs contributed proportionally more to commercialization. These differences suggest that role shapes the focus of entrepreneurial activities and the learning priorities within the I-Corps program.

Poisson Regression Analysis

Poisson regression was employed to further quantify the relationship between role (EL or PI), thematic focus, and their interaction. The model evaluated the frequency of thematic contributions (Count ~ Theme * Subgroup) and revealed several key patterns:

- Theme: Contributions to market segmentation (Code 2) and commercialization (Code 3) were generally lower than teamwork (Code 1) across both subgroups (Estimate = -0.1773, $p < 0.001$), highlighting that at the pre-training stage, participants prioritized collaboration, which aligns with foundational entrepreneurial activities.
- Subgroup: PIs consistently contributed less than ELs across all themes (Estimate = -0.629, $p < 0.001$), particularly in teamwork and collaboration. This disparity reflects the strategic, oversight-oriented responsibilities of PIs compared to the operational focus of ELs.
- Interaction Effect: The interaction between role and thematic focus (Estimate = 0.2624, $p < 0.001$) suggests that the difference between ELs and PIs is smaller for market segmentation and reverses for commercialization. PIs already focus on market readiness at this stage, suggesting they emphasize commercialization even before formal training.

The statistical analyses revealed distinct role-based engagement patterns across themes: (a) Role-Specific Priorities: ELs exhibit greater engagement with teamwork and market segmentation, emphasizing collaborative and exploratory aspects of entrepreneurship. Conversely, PIs demonstrate a stronger focus on commercialization, reflecting their strategic leadership roles from the outset. (b) Theme-Dependent Dynamics: While ELs dominated teamwork contributions, their expressed engagement decreased in market segmentation and commercialization, where PIs were comparatively more active. This pattern suggests that PIs play a more prominent role in commercialization-related discussions before beginning training.

Discussion

The purpose of this study was to use a new approach to analyze qualitative survey data collected from academic entrepreneurs at the start of entrepreneurship training. This allowed us to offer a more nuanced understanding of participants' learning goals and expectations for training. The findings contribute to the field of entrepreneurship education research by offering empirical insights that can inform the design of tailored educational interventions for different participant groups, while demonstrating the use of novel data analysis methods.

The analyses revealed distinct differences in participant responses, shaped by their roles, career stages, and professional objectives. ELs strongly emphasized teamwork and collaboration, likely due to their early-career positioning and need for network expansion. At the same time, PIs prioritized commercialization outcomes, aligning with their strategic leadership responsibilities and focus on technology transfer.

These differential priorities can be understood through the lens of Career Development Theory (Sampson et al., 2014, 2019; Super, 1980), which posits that individuals' professional priorities evolve with career progression. As early-career professionals, ELs naturally prioritize interpersonal skill development and collaborative experiences that facilitate their transition into entrepreneurial roles. In contrast, PIs, as established professionals, leverage their expertise to focus on strategic objectives, such as market readiness and commercialization. These findings reinforce how career stage influences academic entrepreneurs' goals and engagement with entrepreneurial activities. They also reinforce prior research findings indicating that graduate students face barriers, including limited professional experience and smaller networks, making teamwork and collaboration essential for their success (Hayter et al., 2016). On the other hand, faculty navigate dual responsibilities as researchers and entrepreneurs, struggling to balance time and resources between academic responsibilities and commercialization activities (Miller et al., 2018).

Beyond advancing entrepreneurial education research, this study demonstrates the value of NLP and machine learning in qualitative analysis. As stated, traditional qualitative methods are often time-consuming, labor-intensive, and costly, making it difficult to analyze large-scale textual data effectively. This study enhances research efficiency and productivity by employing machine-assisted classification techniques, allowing for the rapid processing of large-scale textual data while maintaining analytical rigor. This approach offers several key advantages over traditional methods, including reducing the time and cost required for large-scale qualitative analysis and uncovering insights that may be difficult to detect through manual qualitative analysis.

As for the implications for entrepreneurial education, the research suggests that program administrators should align curricula and resources with the distinct needs of graduate student and faculty researchers. For graduate students, training programs should emphasize collaborative skill-building and exposure to entrepreneurial networks (Hayter et al., 2016; Cai et al., 2021).

For faculty, training should focus on managing academic and entrepreneurial responsibilities, including strategic planning, resource allocation, and navigating complex commercialization pathways (Miller et al., 2018).

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