

WIP: Modelling Engineering Career Trajectories

AraOluwa Adaramola, Tufts University

AraOluwa Adaramola is an Assistant Teaching Professor in the Chemical and Biological Engineering department at Tufts University.

Gala Sofia Campos Oaxaca, Cornell University

Gala Campos Oaxaca is a Postdoctoral Research Associate in Chemical Engineering at Cornell University. Her research is at the intersection of engineering graduate education, supervision, and communication.

Adaugo Mary-Frances Enuke, Cornell University

Adaugo Enuke is a PhD student in Chemical Engineering at Cornell University. Her research focuses on industry engagement, authentic learning, and professional skill development in engineering education.

Dr. Alexandra Coso Strong, Cornell University

As an associate professor in the School of Chemical and Biomolecular Engineering and the Systems Engineering Program at Cornell University, Dr. Alexandra Coso Strong works and teaches at the intersection of engineering education, faculty development, and complex systems design. She joined Cornell University after co-founding the School of Universal Computing, Construction and Engineering Education at Florida International University (FIU). As an assistant professor at FIU, she co-developed two degree programs, a Ph.D. in Engineering and Computing Education and a B.S. in Interdisciplinary Engineering. Prior to working at FIU, Alexandra served as an Assistant Professor of Systems Design and Engineering at Olin College. Alexandra completed her graduate degrees in Aerospace Engineering from Georgia Tech (PhD) and Systems Engineering from the University of Virginia (UVa).

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Abstract

This methods/theory work-in-progress paper overviews the methodological decision-making in an effort to model engineers' career trajectories. Available data and current studies on the engineering workforce offer a limited perspective on postgraduate engineering career trajectories. In particular, engineering careers are commonly assumed to be linear evolving from entry-level positions to managerial or technical expert roles. In reality, careers are more complex. This misalignment between career expectations and realities is concerning because assumptions about "successful" careers inform the priorities of engineering curricula, individuals' career decision-making processes and self-concepts, and occupational reward structures and evaluation systems.

This paper, framed by the Boundaryless Career Framework, presents a study that begins to address this gap by introducing a methodological approach to systematically observe and analyze the dynamics of engineering career pathways. So far, we have developed a codebook to categorize our data and ethically web-scraped 303 career profiles of alumni of one engineering department from LinkedIn. We selected cohorts from 1999, 2004, 2009, and 2014 to capture how the career trajectories of engineers were shaped by global economic events like the 2008 Recession and the COVID-19 pandemic. Additionally, we used separate pilot data from 20 LinkedIn profiles to develop a code book that standardizes career data across individuals, roles, and organizations. This codebook categorizes professional experiences by sector (determined by the organization), occupation (job task), and hierarchy (job task). In this paper, we present our current progress and introduce alternative methods for studying career data to the engineering educational research community. We raise and address key methodological issues expecting to receive feedback from the community. Looking ahead, we expect this work to support engineering faculty in career advising roles and departmental/program-level decision-making processes.

Introduction

Motivation

This paper is a work-in-progress methods/theory paper. Researchers have long sought to understand how individuals navigate increasingly nonlinear and multidirectional engineering careers from educational and training programs through transitions into the workforce [1]-[3]. One significant limitation of the current evidence on engineering careers is that it currently provides snapshots of career trajectories [4]-[5] instead of comprehensive coverage. While these cross-sectional measures are valuable for accountability, benchmarking, and program comparison, they obscure the complexity and dynamism of engineering careers over time, including cross-sector moves, changes in specialization, and shifts between technical and non-technical roles [3], [6]. In addition, the continued emphasis on first or last destinations can implicitly reinforce linear "pipeline" metaphors, even as research indicates that contemporary careers are characterized by frequent job changes, sector switching, lateral moves, and changing definitions of success [7]-[10]. Furthermore, careers unfold within broader social, economic, and policy contexts that vary across cohorts. Recent work has begun to examine how systemic shocks such as the 2008 crisis and the COVID-19 pandemic reshape the employment landscape for scientists and engineers, including patterns of unemployment, underemployment, sectoral shifts, and delayed or reconfigured labor-market entry [11]-[14]. Hence, to fully understand how engineers build, sustain, and reshape their careers, careers need to be studied as dynamic (e.g., cohort-based, longitudinal, evolving) pathways rather than as discrete endpoints. Our main motivation for this work is exploratory: we

seek to move beyond static, first-destination measures and systematically examine how engineering careers unfold as dynamic, nonlinear pathways across sectors, roles, and hierarchical levels over time. To support this aim, we introduce an innovative methodological approach that combines ethically collected LinkedIn data with a codebook that converts unstructured career histories into analyzable longitudinal sequences. This approach enables scalable, cohort-based analysis of evolving engineering career trajectories.

To address the methodological and empirical gaps in career pathway studies, we are developing a longitudinal dataset of postgraduate career pathways using ethically collected public LinkedIn data from multiple alumni cohorts from one engineering department at a private land-grant R1 institution. Our approach builds on a growing body of scholarship that uses LinkedIn and similar professional networking data to examine engineering work, discipline-specific career progression, and sectoral or gender differences in career paths [14]-[20]. We construct a detailed codebook to classify positions by sector, job task, and hierarchical level and use it to trace disciplinary, cross-disciplinary, and non-traditional trajectories across several graduating cohorts. By examining career movement across cohorts, this work aims to expand the methodological and empirical tools available to engineering education researchers for understanding the rich, multifaceted nature of engineering careers.

Theorizing Engineering Career Pathways

This study is framed by the *Boundaryless Career Framework* because its broad definition of careers captures the dynamic reality of modern careers and enables the systematic investigation of diverse engineering career pathways. A career pathway consists of unique events that can span different roles, organizations, industrial sectors, and geographic locations [7]. Historically, career boundaries (i.e., roles, industries, geographical location, etc.) served as barriers to occupational mobility. However, career mobility is increasingly enabled by organizations desiring adaptable employees who can easily transfer previous competencies and experience into new roles [7], [19] and individuals who move to prioritize their personal satisfaction, values, and goals [7]. Therefore, a successful career is determined by the individual and achieved through continuous professional development and a strong professional network. We used the boundaryless career framework to identify meaningful “boundaries” of engineering careers in this study, namely occupational sectors, tasks, and hierarchy.

Research Methods

Positionality

We are a team of Women engineers (i.e., chemical and aerospace/systems engineering) and non-engineers, our collective experiences, knowledge, and assumptions about careers and engineering informed our research interests and choices. For example, our interest in non-traditional engineering career pathways stems from our experiences as Women and knowledge that Women in engineering are more likely to have non-traditional pathways [20]-[21]. We are constantly redefining our understanding of engineering careers and research methods informed by our perspectives, career literature, and the preliminary data.

Data Collection

The practice of using LinkedIn as a data source to generate rich insights about engineering careers is well documented. Examples include, tracing destinations of South African chemical engineering graduates [22], uncovering gender differences in career progression [18], and revealing transitions

from technical to managerial roles in systems engineering graduates [16]. Outside engineering, researchers have used web scraping tools to substantially advance the collection and analysis of LinkedIn data [23]-[24]. Scraping allows automated extraction of public profiles, bypassing the scale and response rate constraints that limit survey-based or manual data collection. Overall, using LinkedIn as a data source allows access to large panel data, with frequent profile updates, and detailed employment history. However, it comes with limitations such as incomplete or inconsistently updated profiles, platform-imposed access constraints, and biases in self-reported information.

Creating a working dataset

Recognizing the role economic events play in shaping career opportunity, we selected alumni cohorts from 1999, 2004, 2009, and 2014 spanning recent events like the 2008 Recession and the COVID-19 pandemic. We obtained the graduates' names from institutional archives and organized this information into a spreadsheet listing each graduate's name, graduation year, undergraduate institution, and degree (e.g., chemical engineering). Our initial dataset contained the information of 303 graduates.

Finding Public LinkedIn Profiles

To automate the data extraction process, we developed a script that uses Google's Custom search API to find public LinkedIn profiles. The Python script combines dataset information with the keyword "LinkedIn" to find and return a LinkedIn URL, which is saved in a new spreadsheet. To facilitate manual review and verify the accuracy of the extracted URLs, we divided the original dataset into smaller batches of 30 people each. If the URL was invalid (e.g., a different individual with the same name, a nonexistent LinkedIn account) and the correct data could not be obtained through a manual search, the data was labelled as missing. We found 251 graduates LinkedIn profiles (See Table A1 (in the Appendix) for a description of the number disambiguation).

Extracting Career Data from Public LinkedIn Profiles

The extraction of career data from LinkedIn Profiles is an on-going process. We use another user-defined Python script to extract the career data from the public LinkedIn profiles. After uploading the LinkedIn URLs (in batches), the script initiates a web-browsing session and extracts the employment and educational records for each profile. Then, it extracts and cleans the data, then links it to the corresponding profile URL. Finally, the results are exported to a new CSV file. We can only access self-reported data that is publicly available on a LinkedIn profile. As a result, the degree of details varies per person. We have extracted data from the 251 profiles and are in the process of cleaning up the data as well as documenting profiles with limited information displayed.

The Codebook

In this work, we consider the following career boundaries: career sectors, tasks, and hierarchies. The codebook enables us to analyze a set of longitudinal career profiles by converting them into unique career events consisting of distinct sectors, job functions, and hierarchies (Table A2). In particular, reducing complex unstructured career data into narrow categories will enable us to analyze patterns at scale. Unexplained career gaps (e.g., due to periods of unemployment, leaves, missing information etc.) are labelled as unreported data. Figure 1 illustrates this on-going iterative process, emphasizing the different stages and resulting methodological implications. First, we manually extracted, organized, and explored the career profiles of 20 alumni (from LinkedIn) to determine the desirability of LinkedIn as a data source. Then, we individually identified and

collectively agreed on critical data features to preserve in codebook. Finally, we further refined the codebook as we applied it to the test dataset.

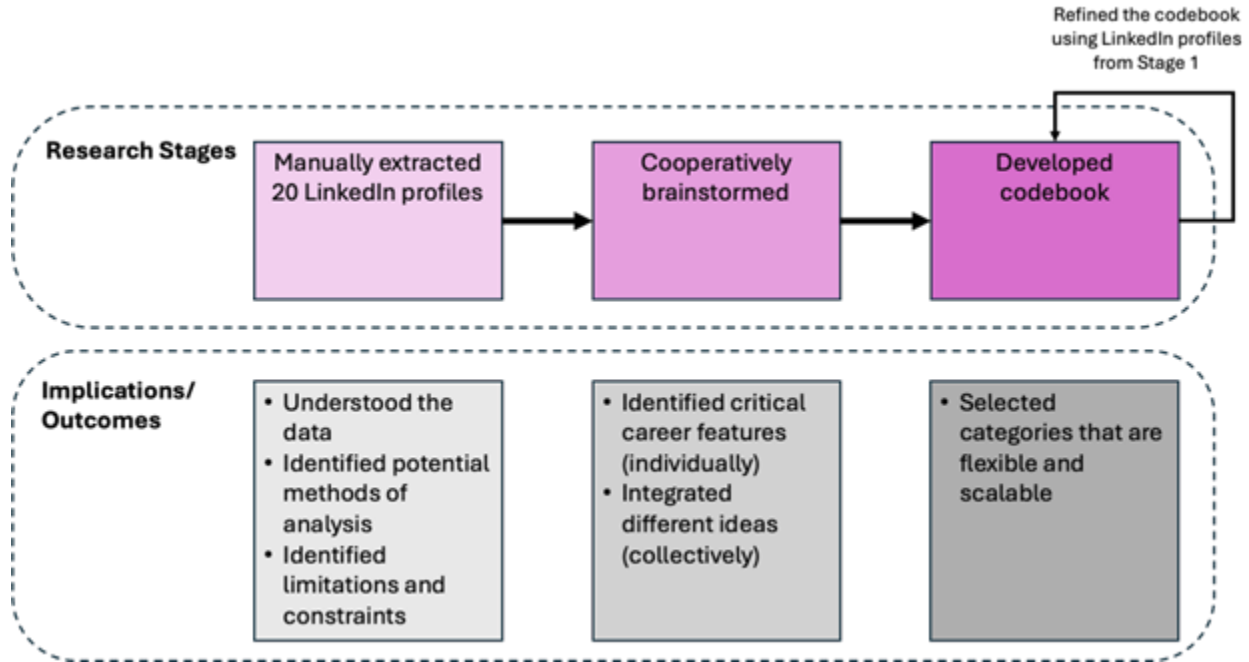


Figure A1: Overview of the Codebook Development Process

In terms of reliability, multiple researchers will independently apply the codebook to each entry. Then, we will compare the codes across researchers using interrater reliability measures.

Career Sectors

Career sectors are determined at the organizational level and refer to the economic sector primarily associated with the organization. We adopted the 2022 North American Industry Classification System (NAICS) codes [25] to classify career sectors into four broad categories: *extraction*, *production*, *provision (private)*, and *provision (public)* (Table A3). For example, *manufacturing*, *construction*, and *utilities* companies, which convert raw materials into final products, are all examples in the *production* sector. Our approach deviates from the convention of classifying chemical engineering careers descriptively, based on the output of industrial sectors (e.g., consumer products, oil and gas, education, etc.). Using the NAICS codes will enable large-scale data and comparative analysis with other studies. In addition, the labels are well-defined, extensive, and flexible enough to enable broad and granular analysis of career data.

Career Tasks

Career tasks are determined by the job function (approximated by the job title) of the role the person occupies. We were heavily inspired by two prior studies to organize career tasks based on alignment with the engineering discipline. Araújo and Selerno (2021) classified the careers of 9,041 Brazilian engineering graduates into four categories: typical engineers, related to engineering, and not related to engineering, and unavailable data [26]. While the National Academy of Engineering classified engineering roles as engineering, engineering approximate, and non-engineering [27]. Ultimately, we chose the Standard Occupational Classification (SOC)

2018 system [28] to simultaneously preserve this distinction between traditional, engineering-adjacent, and non-technical/engineering roles, and capture the finer distinctions between job functions (e.g., chemical vs. environmental engineers) (Table A4). Similar to NAICS codes, the SOC system will enable large-scale data analysis and comparisons with other career and economic studies.

Career Hierarchies

The career hierarchy category emerged from our research team discussions and a preliminary analysis of individual career trajectories. We needed a way to capture career progression to make sense of how individuals advance in their careers across sectors and job functions, from *trainee* (Level 0) to *front-line* (Level 1), *managerial* (Level 2), and *executive* (Level 3) positions (Table A5). For example, starting at Level 0 and progressing to Level 3 over the course of a career can be colloquially described as “going up the ladder”, regardless of whether tasks and sectors are also changing. It is also possible that a career move involves changes in tasks and sectors but maintain hierarchy.

Future Direction

In the next phase of this project, we will apply the refined codebook to the data extracted from the LinkedIn profiles. In this preliminary study, we will manually refine and apply the codebook to the data. However, in the future, we will explore methods that will enable automatic coding of the extensive data. In addition, we plan to explore analysis methods that will enable us to examine the dynamic nature of engineering career trajectories like sequence or network analysis.

We anticipate that our results will contribute to the field of engineering education in the following ways: (1) improving engineering student outcomes by equipping them to make more informed career decisions; and (2) supporting curricular, departmental, and program level-changes and decision making by providing engineering faculty with relevant and up-to-date career pathways data.

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Appendix

Table A1: Overview of Data Extraction Process

Extraction Stage	N
Initial names	303
Correct LinkedIn URLs automatically extracted	137
LinkedIn URLs manually extracted	114
LinkedIn URLs not found	52
Total correct LinkedIn URLs	251
Total name changes	7

Table A2: Construct-to-Measure Map

Career Boundary	Observed LinkedIn Fields	Examples	Descriptive Code(s)*
Sector	Experience > Organization	Sample University	Educational Sector
		Chemical Company 1	Chemical Manufacturing
		Consulting Company	Professional, Scientific, and Technical Services
		Chemical Company 2	Chemical Manufacturing
Task	Experience > Position + Description (if available)	Graduate Researcher	
		Senior Process Engineer	
		Associate	Business Operations Specialist
		Analytical Chemist	Physical Scientist
Hierarchy	Experience > Position + Description (if available)	Graduate Researcher	Trainee
		Senior Process Engineer	Manager
		Associate	Front line employee
		Analytical Chemist	Front line employee

* Codes are mapped to the NAICS/SOC codes.

Table A3: Career Sector Codes and Subcodes

Code	Subcode I
I. Extraction	• Agriculture, Forestry, Fishing, & Hunting • Mining, Quarrying, & Oil and Gas Extraction
II. Production (of finished goods from raw materials)	• Manufacturing I • Manufacturing II • Manufacturing III • Utilities • Construction
III. Provision (of private goods and services)	• Transportation & Warehousing I • Transportation & Warehousing II • Commerce – Wholesale Trade • Commerce – Retail Trade I

	• Commerce – Retail Trade II • Finance & Insurance • Health Care & Social Assistance • Accommodation & Food Services • Arts, Entertainment, & Recreation • Management of Companies & Enterprises • Professional, Scientific, and Technical Services • Real Estates & Rental and Leasing • Information
IV. Provision (of public goods and services)	• Educational Services • Public Administration • Other Services • Administrative and Support and Waste Management and Remediation Services

Table A4: Career Tasks Codes and Subcodes

Code	Subcode I	Subcode II
I. Architecture and Engineering	Engineers	• Aerospace Engineers • Agricultural Engineers • Bioengineers and Biomedical Engineers • Chemical Engineers • Environmental Engineers • Industrial Engineers, including Health and Safety • Industrial Engineers • Materials Engineers • Mining and Geological Engineers, including Mining Safety Engineers • Petroleum Engineers • Miscellaneous Engineers
II. Life, Physical, and Social Sciences	Agricultural and Food Scientist	• Food Scientist and Technologists
	Biological Scientists	• Biochemists and Biophysicists
	Physical Scientists	• Physicists • Chemists • Material Scientists • Environment Scientists and Specialists, Including Health • Geoscientists, except Hydrologists and Geographers • Physical Scientists, All Other

	Social Scientists and Related Workers	• Economists • Industrial-Organizational Psychologists
III. Legal Occupations		• Lawyers
IV. Educational Instruction and Library	Postsecondary Teachers	• Mathematical Science Teachers • Computer Science Teachers • Engineering Teachers • Chemistry Teachers • Physics Teachers • Education Teachers • Tutors • Instructional Coordinators • Teaching Assistants • Postsecondary Teachers, All Other

Table A5: Career Hierarchy Codes

Code	Definition
Trainee	Includes trainee positions and internships (e.g., graduate students, MBA interns).
Front-line	Individuals in entry-level positions (e.g., production engineer I, post doc, resident).
Managerial	Individuals who supervise others ranging from small teams to large departments (e.g., lead production engineer).
Executive	Individual in critical administrative and organizational decision-making roles.