

# Taking Stock: Analysis of IJEE Publications from 1996–2020 to Examine Impact and Coverage of Topics\*

CORY BROZINA

Youngstown State University, Youngstown, OH, USA. E-mail: scbrozina@ysu.edu

ANDREW KATZ

Virginia Tech, Blacksburg, VA, USA. E-mail: aktaz4@vt.edu

ADITYA JOHRI

George Mason University, Fairfax, VA, USA. E-mail: johri@gmu.edu

In this paper, we present findings from analyses of papers published over the past 25 years (1996–2020) in the International Journal of Engineering Education (IJEE). Our goal was two-fold: (1) to understand the *impact* of papers published in the journal as measured by citations, and (2) to understand the *coverage of topics* over time. To understand impact, we qualitatively analyzed abstracts of articles with at least 30 citations each ( $N = 218$ ) and to understand coverage of topics we used the Scopus database to download abstracts of all available articles ( $N = 3,173$ ) published in the journal between 1996–2020. After data cleaning 2,960 articles were analyzed using text network mapping. In terms of impact, the topics that have been cited the most include ways of teaching, learning styles, new technology applications, PBL, and engineering design. The overall topical coverage reflects these findings and shows these same themes were consistently popular over the past 25 years. Major changes over the years have been an increase in attention to learning processes, first-year students, and teamwork.

**Keywords:** citation analysis; bibliometric analysis; impact analysis; topical coverage

## 1. Introduction

The field of engineering education research has seen a significant growth in terms of researchers, institutions, publications outlets, and conferences in the past couple of decades [1–4]. This increase and interest and participation in the field has occurred not just in the United States, where the expansion has been substantial, but in countries and institutions across the world [5]. As the field has developed, different journals and conferences have captured different aspects of the changes in the field. This diversity is not only evident in the regional associations and their meetings, but also in the coverage of different journals. But what has been the impact in terms of knowledge areas across journals and in specific journals? As [6] have shown, publication venues in engineering education reflect different geographical perspectives and interests. In this paper we analyze articles published in the International Journal of Engineering Education (IJEE) over the past 25 years (1996–2020).

In 2009, as the field of engineering education was on the verge of almost a decade of robust expansion, [7], discussing the findings of a small study consisting of a subsample of scholars engaged in engineering education research, argued that there is a “lack of clarity and continued sense of ambiguity about the identity and status of engineering education research (p. 39)” among participants. Is there

more clarity within the field now in 2020? The field is on a firmer footing in terms of metrics such as number of publications, doctoral programs, funding, and institutions and organizations engaged with engineering education [8–9]. Yet, in terms of the nature of work there seems to be increased diffusion given the interdisciplinary nature of the field and the social, economic, and cultural variations in engineering education practices across the world; diversity within the field is not only reasonable but expected. Therefore, we believe there is value in assessing the scholarship within engineering education because, as [10] has argued, “Researchers can benefit by understanding this process and its outcomes because it reveals the vitality and the evolution of thought in a discipline and because it gives a sense of its future [10, p. 156].” And in a field that is still seeing substantial growth this understanding is more beneficial as it serves as a foundation for the field and helps in its maturity.

There are many ways to better understand any field or discipline but our strategy of looking at a specific journal comes from the nature of publication venues within engineering education where each of the major journals with “engineering education” in the title has carved a niche for itself across certain parameters. The IJEE, as the title indicates, has an international appeal and attracts submissions from across the globe as could be seen from

the listed affiliations of the authors of the published papers. It also has more inclusivity in terms of authorship as one could observe from the biographies of the authors. Based on the topics covered in all issues, inclusivity extends to the nature of the work that is published (research or application with a slight lean towards practice). It is also a well-established journal with decades of publications and has a strong lineage within the field.

The strategy of looking at specific journals is not new within engineering education [5]. [11] compared engineering education research in the European Journal of Engineering Education (EJEE) and the Journal of Engineering Education (JEE) through citation and reference analysis and found that over time both journals have transitioned to become engineering education research journals and JEE made that transition first. As the field became more institutionalized, it attracted more researchers and this shift towards research increased the number of citations within the journals in the field of papers that were education and psychology related. This shift was also accompanied by an increase in the number of papers per issue and the number of single author papers but a decrease in citations of science and engineering sources. Overall, the authors found that EJEE has a broader geographic spread of authors compared to JEE which is largely U.S. based. They also cautioned that overall a ‘silo’ mentality is evident from the journals where scholars who are primarily in the field of engineering education research do not seem to engage with disciplinary engineering researchers who also undertake engineering education research. Although many of the nuances of the collaborations within a field are hard to gauge from publications in a specific journal, analyzing what gets published in itself tells us what is valued in the field. For instance, [12], analyzed articles from Journal of Engineering Education (JEE) and European Journal of Engineering Education (EJEE) as the two journals represent the field but from the American and European perspectives. They analyzed volumes published during the years 1998, 1999, and 2000 to determine their subject coverage and authorship characteristics. In both journals the main subjects covered are “courses,” “programs” and “assessment.” The topics “freshman” and “women and minorities” have a good representation of articles in JEE. Papers on other societal issues (“society”) are present at a higher proportion in the EJEE. JEE published more papers on “administrative” matters than the European journal and both publications are concerned with some of the central issues related to engineering education such as “teaching” and “technology.”

## 2. Approach

In this section we discuss our approach for data collection and analysis. Overall, we had two goals. One, to look at impact by using citation information and second, to look at coverage of topics over a long time period. Our approach differs from prior studies as we focused impact and also because we use a much larger dataset than previous studies for quantitative analysis. Other papers that have used citations previously have looked at the networks (e.g., [1]) but not at the content of the publications.

Although impact can be studied in different ways [13], we use citations as a measure of how much a paper influenced the field. Analysis of citations is a simple yet effective method for understanding impact – is a paper being read, is it being referenced and thus shaping other work. Citations are not a perfect measure of impact, papers can be read and discussed without being cited, but in the absence of other forms of data it is the best metric available. The problems with citations are well documented and relevant for this work. The primary concern with citation analysis is that there is a wide variation in citations across fields. Therefore, an overall lower citation count within a field or journal is not necessarily indicative of more or less impact. In relation to engineering education, which is an interdisciplinary field but with publications that resemble social sciences more than engineering, it is important to understand that citations will necessarily be lower than what one sees in engineering disciplines [14–15]. This is even true for other fields such as medicine where interdisciplinary fields that are more practice oriented have overall lower citations [16].

The other concern with using citations is the source of the citations. Reporting of citations varies across sources such as Web of Science, Google Scholar, Scopus, and others. We decided to use the count of citations from Google Scholar as opposed to a more traditional bibliometric service like Web of Science. We wanted to be comprehensive in our understanding and therefore used Google Scholar as a metric of citations. Google Scholar is the most inclusive among the different reporting options. According to [17], Google Scholar has a broader range of data sources including those not (well) covered in International Scientific Indexing (ISI). Furthermore, they argue, Google Scholar provides an additional advantage over other platforms in that it is freely available and democratizes citation analysis [18].

The overall data corpus consisted of 3,127 papers before data cleaning since it included editorials and guest editorials. Filtering out these editorials, since

they do not include abstracts, reduced the corpus to 2,960 articles. The information about each article in our data included title, year, number of citations, authors, and abstract.

### 3. Impact Analysis (1996–2016)

To understand impact, we undertook a qualitative analysis of the abstracts of papers. We identified and collated papers with at least 30+ citations published in IJEE. We chose 30+ citations as we

were looking for the top 200 or so papers in the journal. We are aware that citations take time and therefore the sample we have is skewed towards papers that were published earlier in the life of the journal. We try to capture the recent work reported in the journal through the qualitative analysis we present later in this paper. After collecting a list of the papers with at least 30 citations we then took the next step of collecting the abstracts of the paper to undertake the qualitative analysis. Although we used other data mining methods (as we discuss

**Table 1.** Qualitative Analysis

| Code                                  | Description  | Example Papers With Highest Citation Counts (citations)   |
|---------------------------------------|--|---|
| Ways of Teaching                      | Paper describes or reports on implementation of different approaches for teaching.   | Coyle, E., et al. EPICS: Engineering projects in community service, 2005. (372)<br>Drake, P. Using the analytic hierarchy process in engineering education, 1998. (187)   |
| New Technology Applications           | The paper focuses on the application of a new technological tool or technique for engineering teaching or learning.                    | Dormido, S. et al. The role of interactivity in control learning, 2005. (160)<br>Coller, B. & Shernoff, D. Video game-based education in mechanical engineering: A look at student engagement, 2009. (144)  |
| Assessment/ ABET/EC2000               | Paper focuses primarily on assessment of teaching or program.  | Volkwein, J., et al. Engineering change: A study of the impact of EC2000, 2004. (94)<br>Williams, J. The engineering portfolio: Communication, reflection, and student learning outcomes assessment, 2002. (88)   |
| Engineering Design                    | The paper focuses primarily on engineering design education.   | Gregory, J. Scandinavian approaches to participatory design, 2003. (227)<br>Hey, J., Linsey, J., Agogino, A., & Wood, K. Analogies and metaphors in creative design, 2008. (196)  |
| Program Design or Development         | The paper describes the design and/or development of a comprehensive program for teaching and learning (broader than a single course). | Carlson, L. & Sullivan, J. Hands-on engineering: Learning by doing in the integrated teaching and learning program, 1999. (276)<br>Sheppard, S., et al. Examples of freshman design education, 1997. (188)  |
| Remote/ Virtual Labs                  | The paper primarily describes, discusses, or studies some aspect of virtual or remote labs.  | Ertugrul, N. Towards virtual laboratories: A survey of LabVIEW-based teaching/learning tools and future trends, 2000. (200)<br>Gilet, D. et al. The cockpit: An effective metaphor for web-based experimentation in engineering education, 2003. (96)   |
| Topical                               | The paper focuses primarily on a specific topic or domain (e.g., creativity, entrepreneurship, innovation, sustainability, etc.).      | Huntziner, D. et al. Enabling sustainable thinking in undergraduate engineering education, 2007. (131)<br>Duval-Couetil, et al. Engineering students and entrepreneurship education: Involvement, attitudes and outcomes, 2012. (103)   |
| Miscellaneous                         | Others   | Geisinger, B., & Raman, D. Why they leave: Understanding student attrition from engineering majors, 2013. (135)<br>Jesiek, B. et al. Mapping global trends in engineering education research, 2005-2008, 2011. (59)   |
| Project/ Problem-Based Learning (PBL) | Paper focuses primarily on an aspect of project/problem-based learning including implementation.                                       | Graaf, E., & Kolmos, A. Characteristics of problem-based learning, 2003. (929)<br>Kitcher, A. Effective teaching and learning in higher education, with particular reference to the undergraduate education of professional engineers, 2001. (132)  |
| Workforce/ Transition                 | Paper focuses on workplace practices or transition to the workforce after a formal engineering degree.                                 | Sheppard, S., et al. What is engineering practice?, 2007. (158)<br>McMasters, J. Influencing engineering education: One (acrospace) industry perspective, 2004. (76)  |
| Learning Styles                       | The paper describes, discusses or studies learning styles (including MBTI, etc.)   | Felder, R., & Spurlin, J. Applications, reliability and validity of the index of learning styles, 2005. (1788)<br>O'Brien, T., Bernold, L., & Akroyd, D. Myers-Briggs type indicator and academic achievement in engineering education, 1998. (86)  |
| K12                                   | Paper focuses primarily on an aspect of K through 12 education related engineering.  | Cejka, E., Rogers, C., & Portsmore, M. Kindergarten robotics: Using robotics to motivate math, science, and engineering literacy in elementary school, 2006. (126)<br>Riskowski, J., et al. Exploring the effectiveness of an interdisciplinary water resources engineering module in an eighth grade science course, 2009. (119) |
| Women in engineering                  | Paper focuses on women in engineering (academia or workforce).   | Stonyer, H. Making engineering students-making women: The discursive context of engineering education, 2002. (96)<br>Phipps, A. Engineering women: The gendering of professional identities, 2002. (76)   |

**Table 2.** Number of papers in each category, total citations per category, cites per paper in a category

| Code Description               | N          | % of Total    | Total Citation Count | Ratio        |
|--------------------------------|------------|---------------|----------------------|--------------|
| Ways of teaching               | 38         | 17.4%         | 2498                 | 65.74        |
| New technology applications    | 34         | 15.6%         | 2060                 | 60.59        |
| Assessment/ABET/EC2000         | 26         | 11.9%         | 1246                 | 47.92        |
| Engineering Design             | 20         | 9.2%          | 1530                 | 76.50        |
| Program design or development  | 16         | 7.3%          | 1116                 | 69.75        |
| Remote/Virtual Labs            | 15         | 6.9%          | 923                  | 61.53        |
| Topical                        | 16         | 7.3%          | 979                  | 61.19        |
| Miscellaneous                  | 16         | 7.3%          | 770                  | 48.13        |
| Project/Problem Based Learning | 15         | 6.9%          | 1731                 | 115.40       |
| Workforce/transition           | 7          | 3.2%          | 535                  | 76.43        |
| Learning Styles                | 5          | 2.3%          | 2068                 | 413.60       |
| K12                            | 5          | 2.3%          | 372                  | 74.40        |
| Women in engineering           | 5          | 2.3%          | 326                  | 65.20        |
| <b>Totals</b>                  | <b>218</b> | <b>100.0%</b> | <b>16154</b>         | <b>74.10</b> |

later) we realized that performing a qualitative analysis using experts in the field is probably the best way to make sense of the publications.

**Analysis steps:** As is common in content analysis, we first did a free coding of all the abstracts using multiple codes (up to four codes for each paper). The codes in this step included words and terms such as: “design education, freshmen engineering, course design, control engineering education, interactive tools, project-based pedagogy, studio courses, engineering practice, effective teaching and learning, PBL, MATLAB, among others.” The goal was to be diverse enough to capture the content of each abstract but also ensure that the words or terms were related to the field of engineering education. As a next step, the codes were coalesced or grouped into a smaller number of codes (18) and the abstracts were re-coded. The codes were revisited and grouped further to reduce the final list to 13 codes. Two coders independently coded the abstracts using the 13 codes and in the final round assigned only one code to each abstract. Any variations were recorded and then the abstracts were coded again until consensus was achieved on all abstracts. The final list with details is in Table 1.

The categories included a minimum of five papers and a maximum of 38 papers, as shown in Table 2. The top category, “Ways of teaching”, included 38 papers which made up a total of 17.9% of all papers and also had the largest total citation count of 2,498. “Ways of teaching” covers a wide range of issues. However, the second largest total citation count came from the category “Learning styles”, which only had five papers. Incidentally, this category included the paper with the greatest number of citations (1788) which is over 800 more than the second largest cited paper (929). “New technology applications” and “Problem/project-based learning (PBL)” were two other highly cited areas of work. In terms of impact, certain papers have had more

impact than others. Average citation per paper (Ratio show in Table 2) for most topics is in the 60s. Ratio is a way to normalize the citation count column to understand and see impact across categories.

#### 4. Analysis of Coverage of Topics Over 1996–2020

In addition to analyzing the impact of IJEE articles by looking at the most cited papers, we further analyzed the larger corpus of articles dating back to 1996. We used a text network approach for natural language processing, as described next, and used visualizations for better understanding the results [19].

##### 4.1 Text Networks – General Methods

To analyze changes in IJEE articles over time, we used a network analysis approach, as outlined by [20] and [21]. This approach models texts as collections of phrases and connections between those phrases as co-occurrences in the same segment of text. When phrases consistently appear together, they can begin to form topics. An overview of the sequence is illustrated in Fig. 1. To begin this analysis, we first created a corpus of IJEE articles available from the Scopus database. As mentioned above, this produced 3,173 articles. After data cleaning to remove articles that were missing abstracts, 2,960 articles remained in the corpus.

Next, we extracted the abstract and title for each article and tokenized terms so that similar phrases would be represented consistently throughout the analysis. For example, “engineering students”, “engineering student”, and “students in engineering” mapped to the same phrase in our analysis rather than three distinct phrases. We followed this process for the top 2,000 terms (determined by frequency) in the corpus of article abstracts and titles, excluding common stop words (e.g., “a”, “an”, “the”, etc.) and monograms, which tended to be less informative than multi-word phrases. This way, the phrase “engineering student” would not be split into “engineering” and “student”. Consequently, we considered phrases from two to six words in length. After identifying these phrases, less informative phrases were also removed. These included phrases such as “engineering education, year engineering, year students, aim of this study, paper reviews, year engineering students, methods study, main purpose, main conclusions, study show, other things.” On the other hand, we maintained phrases like “new approach”, “various approaches”, and “year engineering”, which we suggest are actually informative because they tell us where they may have been novelty (new

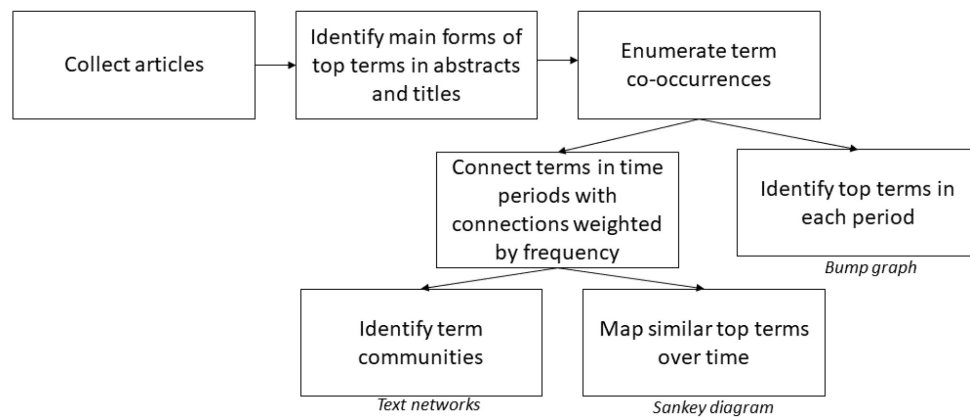


Fig. 1. Steps for text processing method.

approach), an array of options pursued (various approaches), and when researchers were focusing on a specific class standing of students (first-year, second-year, etc.) in engineering education.

To capture the temporal dynamics of conversations within the journal, we divided the corpus into five evenly spaced periods: 1996–2000, 2001–2005, 2006–2010, 2011–2015, and 2016–2020. Within each period, we looked at the top 100 most frequently occurring terms. For this subset of terms, we calculated the co-occurrences of phrases in the text – how often each phrase occurred with each of the other top 100 phrases in that same time period. If terms appeared together in the same sentence, that connection was weighted more heavily than if terms appeared within a stretch of two sentences. The weights decayed exponentially as a function of the sentence distance between terms.

With these edge weights, we created a graph of the term co-occurrence networks. The vertices (nodes) in the graphs represent phrases from the text. The edges (links) between the vertices represent the weighted sum of the times the terms appeared together. For example, if the phrases “problem-based learning” and “engineering design” appeared together in the span of three sentences then we noted that in an adjacency matrix with an appropriately diminished weight. If they appeared together multiple times in the corpus, then the edge weight grew proportionally. From this adjacency matrix of co-occurring phrases, we then generated an undirected graphical network. The resulting graphs display how the top 100 terms appear in the text and are given in Supplementary Material Figs. 1–5. We trimmed edge weights below a certain threshold to maintain only the strongest co-occurrence relationships.

Finally, to detect frequently occurring term communities (i.e., groups of terms that appear together and therefore represent a topic or theme), we used the Louvain community detection algorithm. These

communities appear as colored bubbles in the figures. One can interpret these communities/clusters of co-occurring phrases as representing latent topics. We followed this text network and community detection process for each of the five sequential time periods listed above. These five period text networks are shown in the Supplementary Material.

#### 4.2 Sankey Diagrams – Methods

The text networks provide static pictures of each period. To capture the dynamics between periods, we created a Sankey diagram. This diagram shows how terms in one text community in one period transition to another text community in an adjacent period. For example, if the terms “capstone design”, “design team”, and “design process” all appeared together in the same cluster in two consecutive periods, the diagram would contain a gray stream connecting the blocks in each period. Darker streams signified more shared terms between clusters. Larger blocks indicated more terms within that particular cluster. For example, a narrow block might represent four co-occurring phrases while a larger block represents 12 co-occurring phrases in that phrase cluster. The labels adjacent to each block are intended to summarize the terms in that cluster. Each block was tagged with a summarizing label such that terms about design process, capstone course, and Harvey Mudd design workshop might be labeled as Harvey Mudd design. Finally, the shades of grey in the diagram have no inherent meaning – they are simply intended for distinguishing one block from another. Using these diagrams, one can see how the collection of topics shifts from one period to the next. Multiple connections

#### 4.3 Sankey Diagrams – Results

The Sankey diagram in Fig. 2 shows topics in five evenly spaced intervals from 1996–2020. These

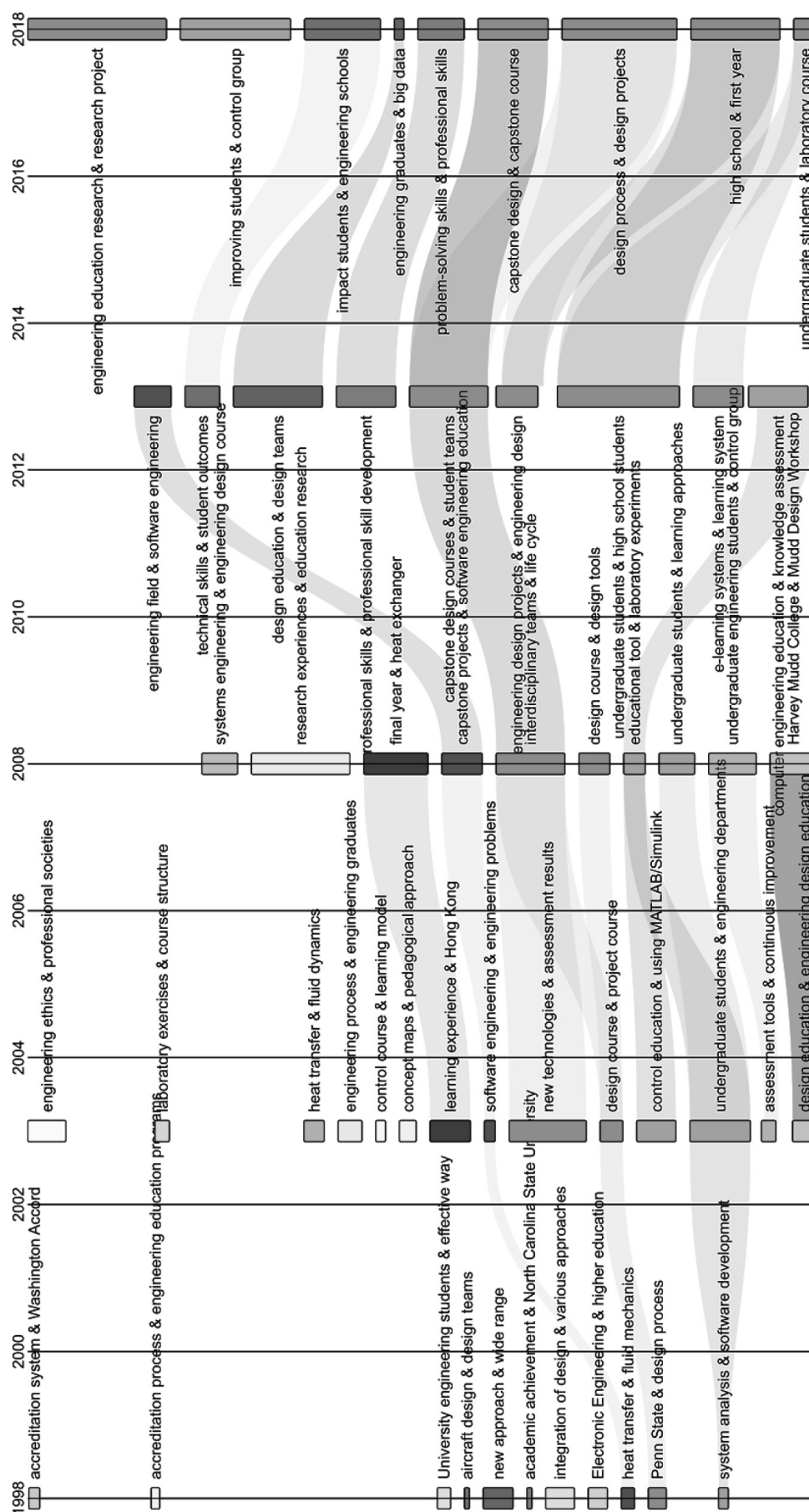


Fig. 2. Sankey Diagram of topics from 1996–2020.

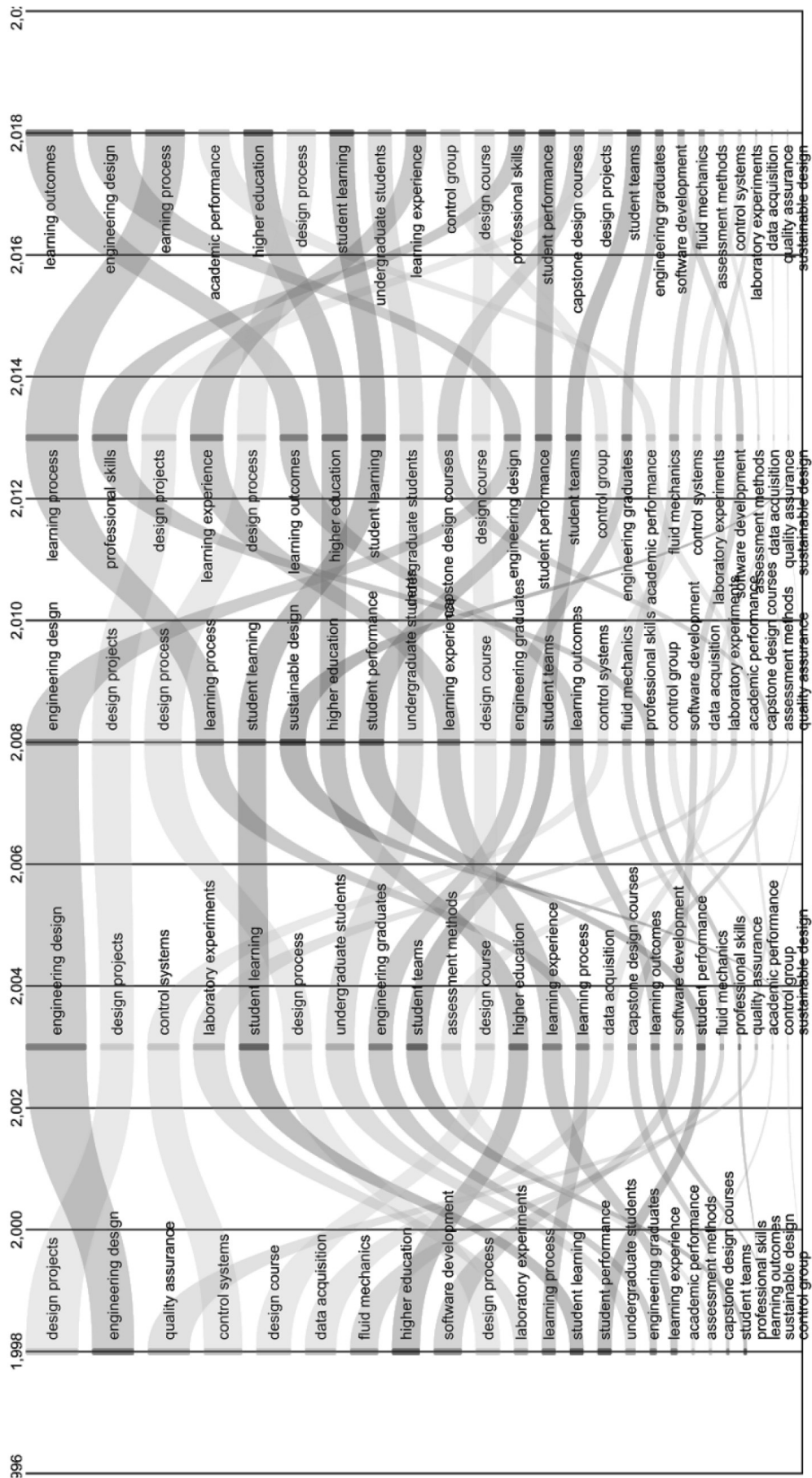


Fig. 3. Top ten terms per period in IJEE abstracts from 1996–2020.

topics comprise groups of terms in the titles and abstracts from each period and correspond to summaries of the text networks in the Supplemental Material. One major theme from this analysis was the continuity of design and design education throughout the journal's lifetime. This umbrella topic ranged from applications of the design process to design education to capstone design courses. A second consistent theme was laboratory experiments and laboratory courses. These included discussions around not only lab courses but also specific ways to implement virtual labs, which appeared to be the predominant aspect of labs featured in the journal. A third consistent theme was assessment. Initially these articles appeared to involve program assessment related to ABET outcomes, but over time these shifted to student assessment tools more generally.

Along with these consistent themes, there were also ones that emerged and/or faded over time. Some of the more recent themes included articles on professional skills and first-year engineering programs. A particularly popular subtopic within professional skills was teamwork and design teams. Among the themes that faded were accreditation and a cluster of concepts often associated with chemical engineering such as process control, heat transfer, and fluid mechanics. It is not surprising that the topic of accreditation might be fading over time given the attention that the topic garnered from ABET's EC2000 criteria and relatively few changes over the interim period since then up until 2018.

#### 4.4 Top Ten Terms Over Time – Methods

To simplify the network graphs and Sankey diagrams, we also looked at the top ten terms in each period and tracked their popularity over time. To do this, we first divided the timeline into the same five evenly spaced periods as before. We then identified the top ten terms in each period. If the top ten terms in each period were different then this list would have contained 50 terms. In practice, however, several periods shared some of the same popular terms, such as the term “engineering education”, which was consistently a top term. With this list of popular terms, we then tracked each term's popularity (defined by its use frequency) in each time period. For example, the term “engineering design” started as the fourth most popular term in the initial time period from 1996–2000 and then climbed to the second most popular term in the next two time periods (2001–2005 and 2006–2010). As with the Sankey diagrams, the width of each stream indicates the relative popularity of that term in that particular period – wider streams correspond to higher usage. Also, the colors once again have no

intrinsic meaning and are only used for identification purposes.

#### 4.5 Top Ten Terms Over Time – Results

While the text networks provide a deeper view into themes in the corpus, we can also glean a higher-level view of the journal by looking at the top phrases over the same five periods, as shown in Fig. 3. As with the text networks above, observations can be organized around terms that (a) remained consistently popular, (b) became increasingly popular, and (c) conversely decreased in popularity. Among the consistent terms were “engineering education” and “design education” (and associated terms such as “design process” and “design projects”). Notably, “sustainable design” experienced a fleeting moment of popularity, but that appears distinct from the general trends of design education. Although the term “engineering education” could have been removed from the list of terms given its inevitable popularity, we sought to avoid ad hoc term removal.

More recently there have been increases in terms related to learning (e.g., “learning process”, “learning outcomes”, and “student learning”), “professional skills” (which, upon further inspection, seemed to coincide most directly with teamwork), and “undergraduate students”. The latter seemed especially connected with first-year students when looking at the text networks in period five (2016–2020). On the other hand, “laboratory experiments”, terms related to chemical engineering core concepts (e.g., “control systems” and “fluid mechanics”), “differential equations”, and “quality assurance” have all faded. We caution that this observation about laboratory experiments appeared to be associated with a shift in language (i.e., focusing more on virtual labs) than an absolute drop in the topic of labs per se.

### 5. Discussion

In this paper we present an analysis of papers published in IJEE between 1996–2020. From our analyses there are some clear topics and trends that can be identified. Engineering design, virtual labs, and PBL are all topics that have been published more and had an impact in terms of being cited by others. Through our qualitative analyses we also ascertained that most papers in IJEE are application oriented with comparatively fewer papers that are research intensive. Many of the applications are assessed but fully formed research studies are rare. It is also possible they are not that heavily cited and therefore did not appear in the qualitative analyses.

Using a text network approach for natural language processing with the full corpus, we also



observed similar trends as those reflected in the qualitative analysis of heavily cited articles. Engineering design and virtual labs were consistently among the top themes over time, which underscores their (a) centrality to engineering education and (b) interest in how to improve their manifestation in the curriculum. In contrast, other themes appeared to be more ephemeral. Topics like accreditation and quality assurance received attention around the time of ABET's accreditation changes but faded soon after. This shift might suggest a relative lack of innovation in meeting accreditation standards or simply a decrease in its relative importance compared to other topics. Topics like student learning and teamwork appeared to exhibit the opposite trend, becoming more popular over time. This might suggest a stronger focus on students' classroom experiences and how those prepare students from both a conceptual understanding perspective as well as professionalization perspective (i.e., cognitively and behaviorally).

We used different methods to analyze the data and it is important to discuss this as well. We undertook the qualitative analysis as a way to look closely at what was being published and because our experience with this and previous analyses had raised doubts about machine learning techniques, especially Latent Dirichlet Allocation (LDA) analysis for topic modeling which has commonly been used for such analysis [22]. With the relatively small corpus of abstract data, LDA analysis did not give any meaningful results, thus we did not include those results here.

Finally, through our analysis we are not in a position to explain why the trends occur although one explanation we found from our closer reading of the volumes is that IJEE publishes several special issues each year and these correspond to a rise in the number of papers on a topic in that year. For instance, every other year, IJEE publishes papers from the MUDD Design Conference organized at Harvey Mudd College and this has definitely con-

tributed to the prevalence of engineering design education related scholarship in the journal.

There are several limitations to this work. Since we have focused on citations, our analysis is not comprehensive in terms of all that is published in the data. The data that we have captured is limited based on our access to sources. We have limited our analysis to the abstracts of the papers and therefore the papers could have included more or different information in the full text that we did not analyze. This work does not speak to research methods or to epistemologies as most abstract did not refer to it. Finally, our interpretation is derived from our knowledge of the field and our experience with the journal and is not necessarily inclusive of the editor or editorial board or others associated with the journal.

## 6. Conclusion

We present findings from analyses of papers published over the past 25 years (1996–2020) in the International Journal of Engineering Education (IJEE). We qualitatively analyzed abstracts of articles with at least 30 citations each ( $N = 218$ ) and to understand coverage of topics we used abstracts of all available articles ( $N = 3,173$ ) published in the journal between 1996–2020. In terms of impact, the topics that have been cited the most include ways of teaching, learning styles, new technology applications, PBL, and engineering design. The overall topical coverage reflects these findings and shows these same themes were consistently popular over the past 25 years. Major changes over the years have been an increase in attention to learning processes, first-year students, and teamwork.

*Acknowledgements* – This work is partly supported by U.S. National Science Foundation Awards#1941186, 1939105, 1938744, 2027486. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding agencies.

## References

1. K. Breznik and V. Skrbinjek, Citation network analysis of documents on engineering and technology education, *Global Journal of Engineering Education*, **19**(3), 2017.
2. B. Jesiek, M. Borrego and K. Beddoes, Expanding global engineering education research collaboration, in *Proceedings of the 2008 SEFI Annual Conferences*, 2008.
3. A. Johri and B. Olds (Eds.), *Cambridge Handbook of Engineering Education Research*, Cambridge University Press, NY, 2014.
4. P. Wankat, Analysis of the first ten years of the Journal of Engineering Education, *Journal of Engineering Education*, **93**(1), pp. 13–22, 2014.
5. P. Chou and W. Chen, Global Resources in Engineering Education: A Content Analysis of Worldwide Engineering Education Journals, *International Journal of Engineering Education*, **30**(3), pp. 701–710, 2014.
6. B. Williams, P. Wankat and P. Neto, Not so global: a bibliometric look at engineering education research, *European Journal of Engineering Education*, **43**(2), pp. 190–200, 2018.
7. B. Jesiek, L. Newswander and M. Borrego, Engineering education research: Discipline, community, or field? *Journal of Engineering Education*, **98**(1), pp. 39–52, 2009.

8. K. Madhavan, A. Johri, H. Xian, G. Wang and X. Liu, Tools for Large-scale Data Analytic Examination of Relational and Epistemic Networks in Engineering Education, *Advances in Engineering Education*, **4**(2), n2, 2014.
9. K. Madhavan, H. Xian, A. Johri, M. Vorvoreanu, B. Jesiek and P. Wankat, Understanding the Engineering Education Research Problem Space Using Interactive Knowledge Networks, *Proceedings of Annual Conference and Exposition of the American Society of Engineering Education*, 2011.
10. M. Culnan, The Intellectual Development of Management Information Systems, 1972–1982: A Co-Citation Analysis, *Management Science*, **32**(2), pp. 156–172, 1986.
11. P. Wankat, N. Williams and P. Neto, Engineering education research in European Journal of Engineering Education and Journal of Engineering Education: citation and reference discipline analysis, *European Journal of Engineering Education*, **39**(1), pp. 7–17, 2014.
12. L. Osorio and M. Osorio, Engineering Education in Europe and the USA, *Science & Technology Libraries*, **23**(1), pp. 49–70, 2002.
13. K. Madhavan, M. Vorvoreanu, N. Elmqvist, A. Johri, N. Ramakrishnan, G. Wang and A. McKenna, Portfolio Mining, *IEEE Computer*, **45**(10), pp. 95–99, 2012.
14. A. Harzing, *The publish or perish book*, Tarma Software Research Pty Limited, 2010.
15. A. Harzing and S. Alakangas, Microsoft Academic is one year old: the Phoenix is ready to leave the nest, *Scientometrics*, **112**(3), pp. 1887–1894, 2017.
16. N. van Eck, L. Waltman, A. van Raan, R. Klautz and W. Peul, Citation Analysis May Severely Underestimate the Impact of Clinical Research as Compared to Basic Research, *PLOS ONE*, **8**(4): e62395, 2013.
17. A. Harzing and R. van der Wal, Google Scholar as a new source for citation analysis?, *Ethics in Science and Environmental Politics*, **8**(1), pp. 61–73, 2008.
18. L. Meho and K. Yang, Impact of data sources on citation counts and rankings of LIS faculty: Web of Science versus Scopus and Google Scholar, *Journal of the American Society for Information Science and Technology*, **58**(13), pp. 2105–2125, 2007.
19. K. Madhavan, A. Johri, H. Xian, G. Wang and X. Liu, iKNEER: Interactive System to Assess and Visualize Relational and Epistemic Networks, *Proceedings of Learning and Knowledge Analytics*, Leuven, Belgium, 2013.
20. A. Rule, J. Cointet and P. Bearman, Lexical shifts, substantive changes, and continuity in State of the Union discourse, 1790–2014, *Proceedings of the National Academy of Sciences*, **112**(35), pp. 10837–10844, 2015.
21. B. Raimbault, J. Cointet and P. Joly, Mapping the emergence of synthetic biology, *PLOS ONE*, **11**(9), e0161522, 2016.
22. A. Johri, G. Wang, X. Liu and K. Madhavan, Utilizing Topic Modeling Techniques to Identify Emergence and Growth of Research Topics in Engineering Education, *Proceedings of IEEE FIE*, 2011.

**Cory Brozina** is an Assistant Professor, Director of the First-Year Engineering Program, and Associate Director of the Rayen School of Engineering at Youngstown State University. He studies student support and success of understudied groups in engineering such as nontraditional students and commuter students. He is the recent recipient of the Distinguished Professor Award for Scholarship from YSU.

**Andrew Katz** is an Assistant Professor of Engineering Education in the College of Engineering at Virginia Polytechnic Institute and State University. He studies ways to characterize, understand, and improve decision-making processes throughout engineering education systems.

**Aditya Johri** is Professor of Information Sciences & Technology in the College of Engineering and Computing at George Mason University, Fairfax, VA USA. He studies how the use of technology shapes learning in both formal and informal spaces, including the workplace, online communities, and extracurricular activities. More information at: <http://mason.gmu.edu/~johri>

**Supplementary Material (see below)**

## Supplementary Material

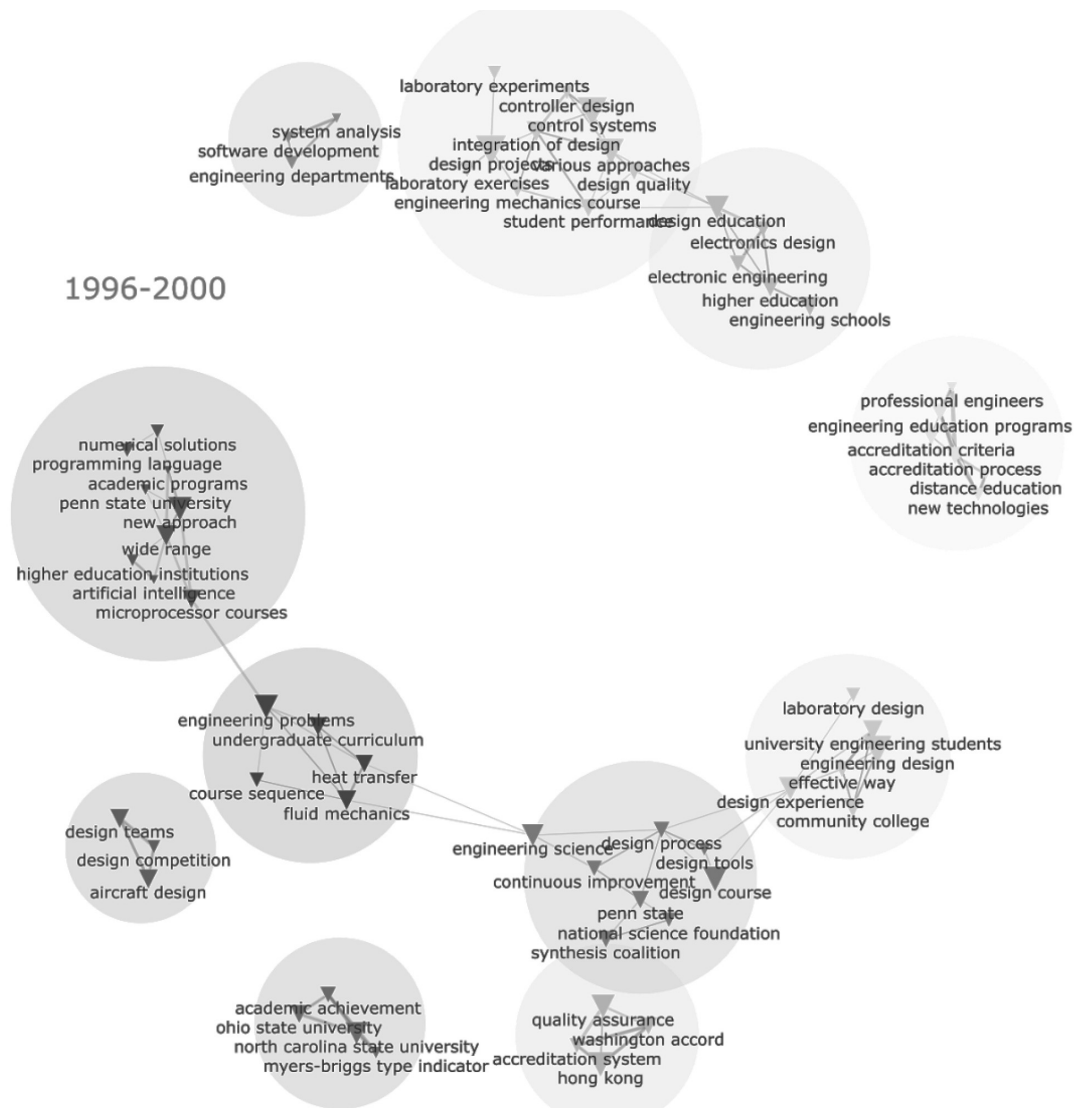


Fig. S1. Text Networks of top 100 terms in 1996–2000.

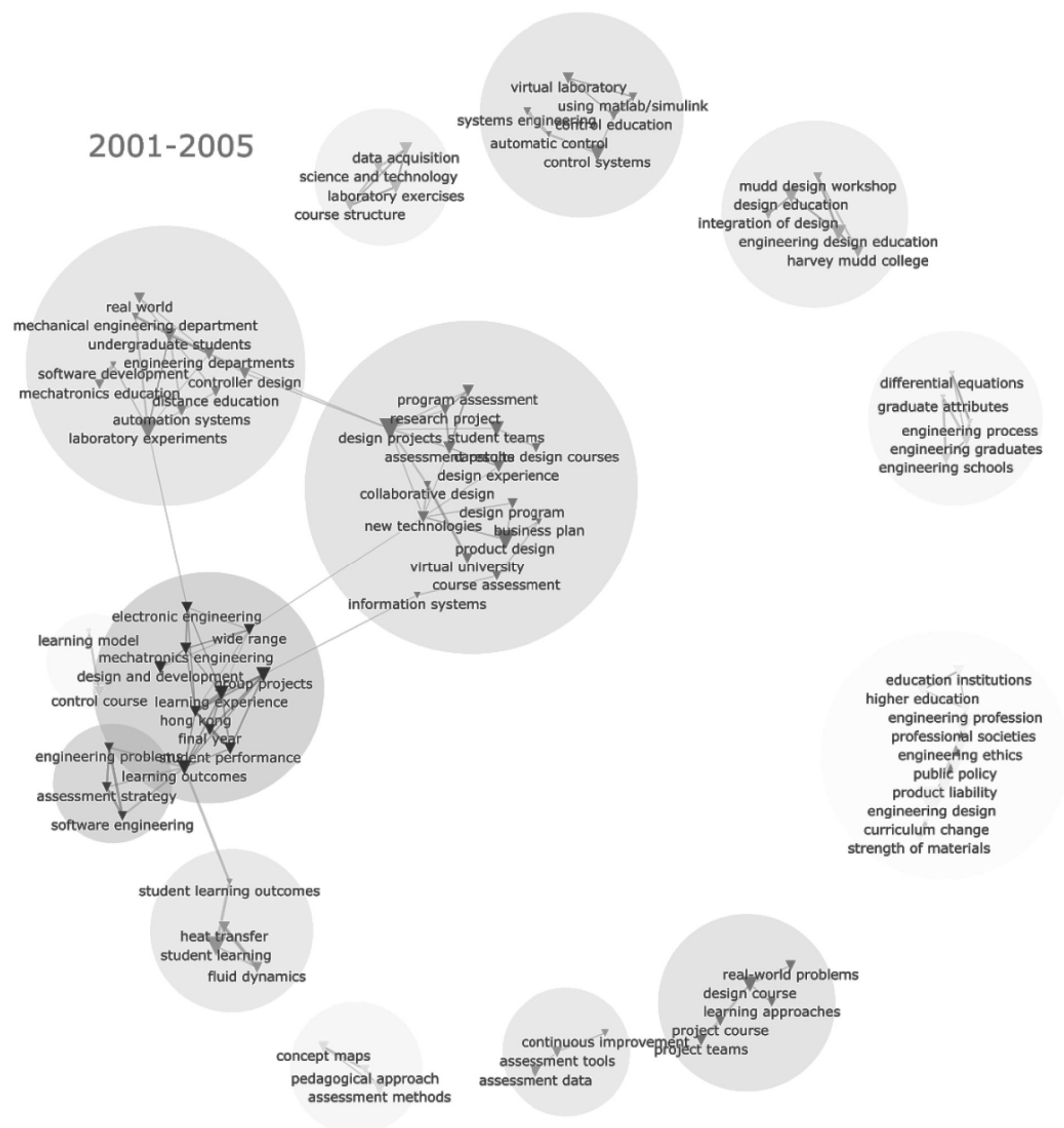


Fig. S2. Text Networks of top 100 terms in 2001–2005.

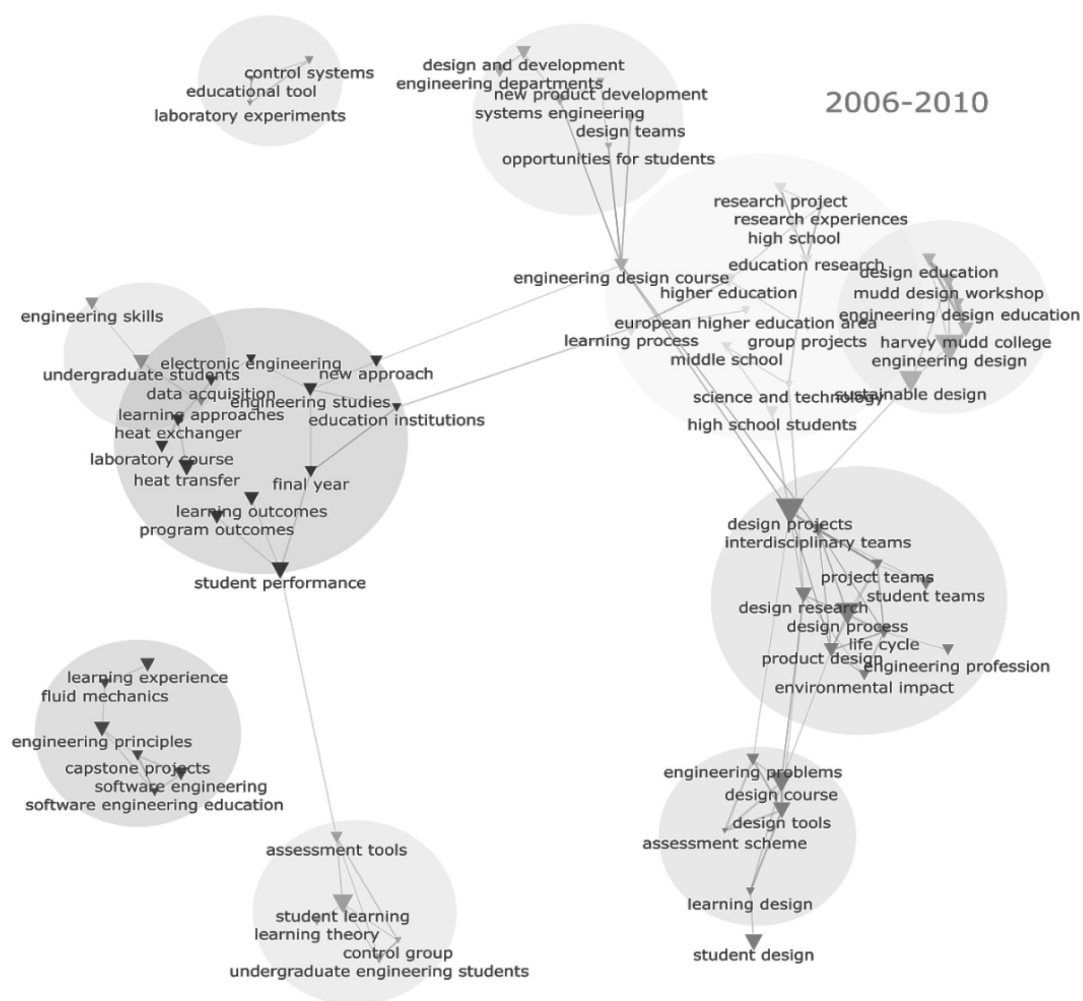
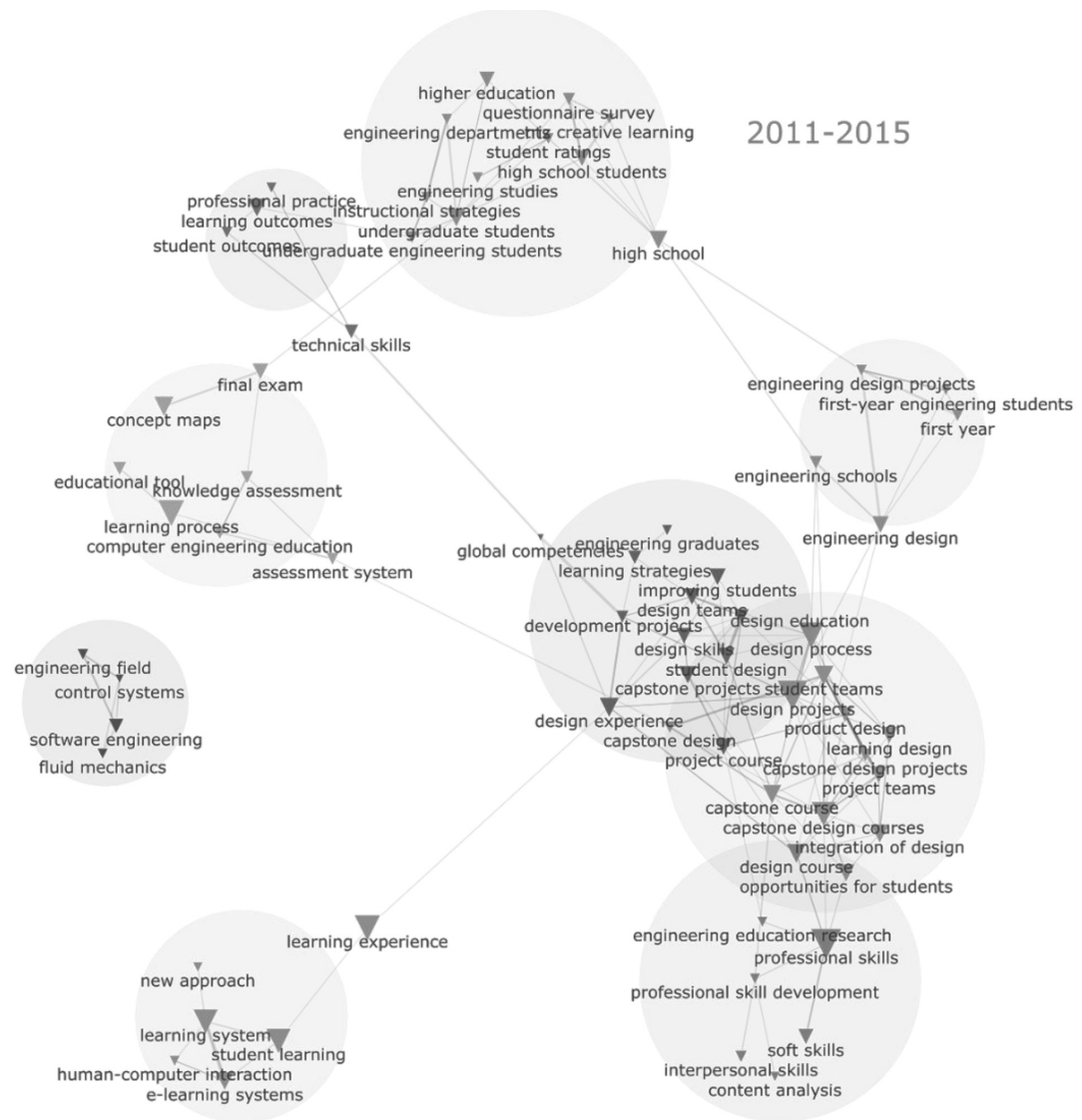


Fig. S3. Text Networks of top 100 terms in 2006–2010.



**Fig. S4.** Text Networks of top 100 terms in 2011–2015.

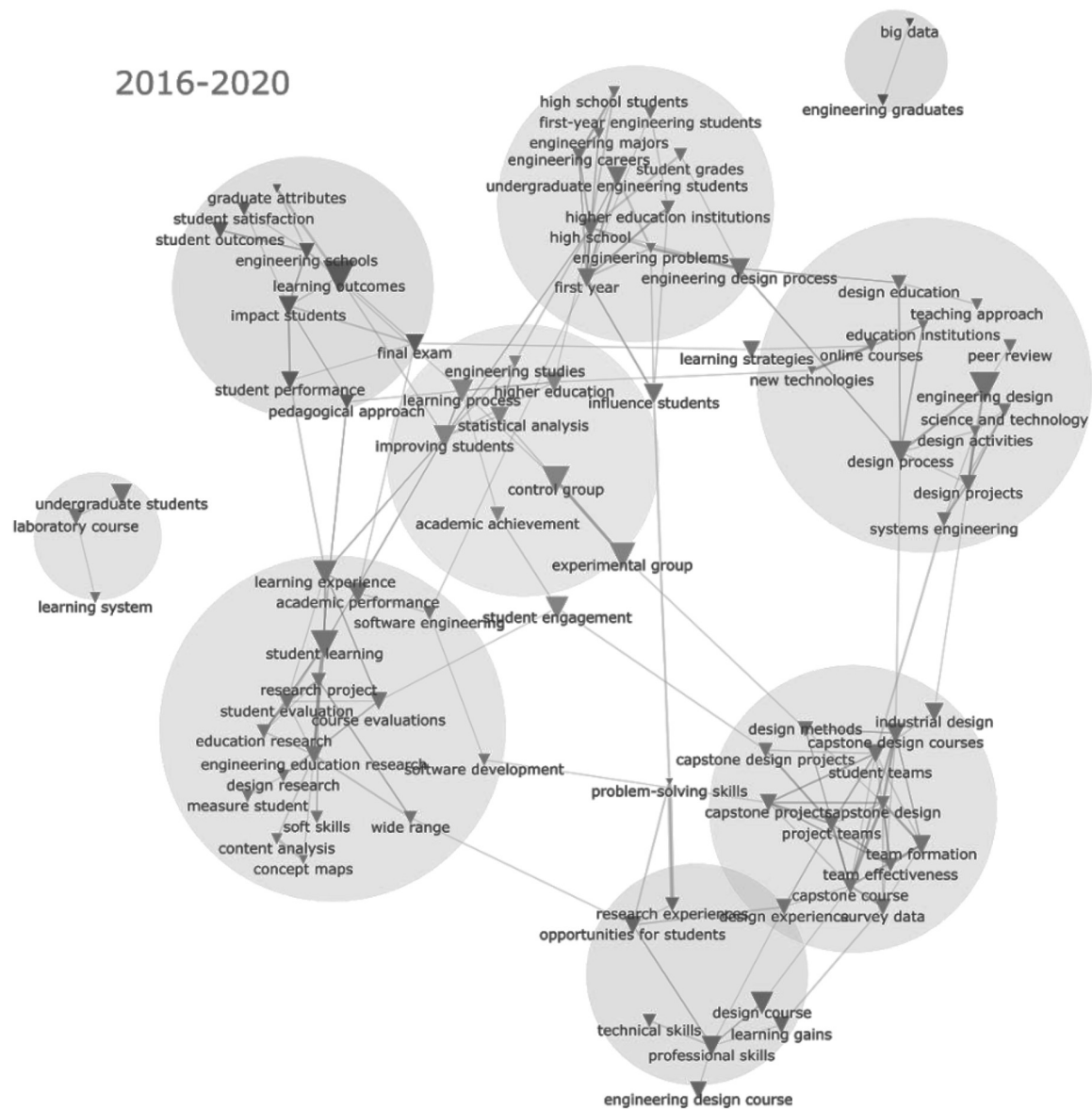


Fig. S5. Text Networks of top 100 terms in 2016–2020.