

How "Multidisciplinary" Is It? Measuring the Multidisciplinarity of Classes and Student Teams

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Abstract

The National Academies of Science, Engineering, and Medicine recommend that interdisciplinary education be evaluated against relevant criteria such as the number of students from the general population (i.e., from outside the instructor’s department) and the mix of students. How is a department, program, or institution to quantify the multidisciplinary of a class or student team? The number of majors is a simple metric, but it does not capture cognitive distance between majors. Beyond the number of majors and cognitive distance, a measure should also account for the proportion of students in each discipline. To describe the multidisciplinary of educational programs, we propose the use of the Rao-Stirling diversity index, which has been used to quantify the multidisciplinary of research papers, authors, research centers, departments, and institutions. The index requires a measure of distances between categories, in this case students’ majors. In studies on university research, bibliometric measures are used to determine distances between Web of Science categories, but the categories do not map well to undergraduate student majors. In this paper, we develop a measure of distance between majors at a research institution based on overlap in courses required in each major, and on cross-listings of courses between departments. The distance measures were then used to calculate Rao-Stirling Diversity indexes for 3 multidisciplinary student teams ($N = 85$; each team included 12-55 students, 5-7 majors, and majors from 2-5 colleges). Results are interpreted and discussed, along with limitations and future directions.

Introduction

The world faces intersecting technological and societal challenges that continue to grow in complexity, and solutions to these increasingly complex problems require collaboration between multiple disciplines [1], [2]. On a grand scale, problems include climate change, epidemics, poverty, social unrest, and energy production/storage/transmission/use. On smaller scales, progress in a wide range of contexts also requires expertise from multiple fields. In medicine, multidisciplinary teams can more effectively relieve the pain, symptoms, and stress experienced by patients with serious illnesses [3]. To build transportation systems that equitably serve communities, transportation planners and engineers are being called to collaborate with social workers and the communities they serve [4]. To develop artificial intelligence systems with effective human-AI interaction, collaboration is needed between computer scientists, systems engineers, human factors engineers, and socio-technical researchers [5].

Multidisciplinary collaborations leverage perspectives from different backgrounds, which leads to new interpretations, deeper and broader understandings, and prevents “lock-ins” of business as usual [2, p. 72]. Beyond solving specific problems, members of multidisciplinary teams also learn from each other, increasing team members’ agility in problem-solving [2]. If college graduates are to work effectively in multidisciplinary teams, cross-disciplinary collaboration must be incorporated into higher education. The National Academies in the United States have called on institutions to support interdisciplinary education and training for students, postdoctoral scholars, faculty, and researchers, and they encourage students to seek out interdisciplinary experiences [6], [7]. In the 47-country European Higher Education Area, ministers of education maintain that to contribute to the wider needs of society, college graduates need transversal, multidisciplinary skills [8]. As a result, the Higher Education Area is working to adopt multidisciplinary approaches that enable students to contextualize technological problems in

cultural, socio-economic, political, and environmental terms [9]. Calls for multidisciplinary education are not heard only from above: “Students, especially undergraduates, are strongly attracted to interdisciplinary courses, especially those of societal relevance” [6, p. 2].

Systems have been developed to assess interdisciplinarity in research to inform policy makers [2]. **If multidisciplinary education is also of value, how can it be measured?** The National Academies recommend that interdisciplinary education be evaluated against relevant criteria, such as the number of students from the general population (i.e. from outside the instructor’s department) and the mix of students [6], but measures are open to interpretation. If a student team includes electrical engineering students and computer engineering students, is it multidisciplinary? What if both majors were (or were not) housed in the same department? In this paper, we propose applying the Rao-Stirling diversity index to measure the multidisciplinary of student teams. The index is already used to quantify the interdisciplinarity of institutions, research centers, departments, and individuals. The index accounts for team composition by category, and for cognitive distances between categories. In our implementation, the units of analysis are student teams, categories are student majors, and the relative difference between majors is based on curricular overlap and course cross-listings between departments, a novel application of the index.

Background

Defining Multidisciplinarity

Searches of EBSCO Academic Search Complete show nearly linear increases in use of the terms multidisciplinary, interdisciplinary, and transdisciplinary from 1960 onward (Fig. 1). The increase occurs across the full database as well as in the higher education domain, with a steeper increase in higher education. The terms are often used interchangeably. The National Academies of Sciences, Engineering and Medicine define interdisciplinary research as a mode of research that incorporates knowledge/tools/concepts/etc. from multiple disciplines [6]. Klein places the terms multidisciplinary, interdisciplinary, and transdisciplinary on a continuum, with multidisciplinary associated with juxtaposing or coordinating; interdisciplinarity involving blending and linking; and transdisciplinarity transcending boundaries [11]

This study focuses on the **composition of student teams**, with no assumptions on the degree to which ideas are integrated. To this end, the term multidisciplinary will be used to refer to the **balance of and cognitive distances between majors of students within a student team**. The study builds on methods used in measures of interdisciplinary research, so references to those methods will use the term interdisciplinary, consistent with writings in that area. With that clarification given, Rousseau et al. place minimal emphasis on terminology, “Although some researchers make a distinction between the terms interdisciplinary, multidisciplinary, transdisciplinary and cross-disciplinary research, in empirical studies one finds a continuum which makes it difficult to distinguish among these modes” [2, p. 70].

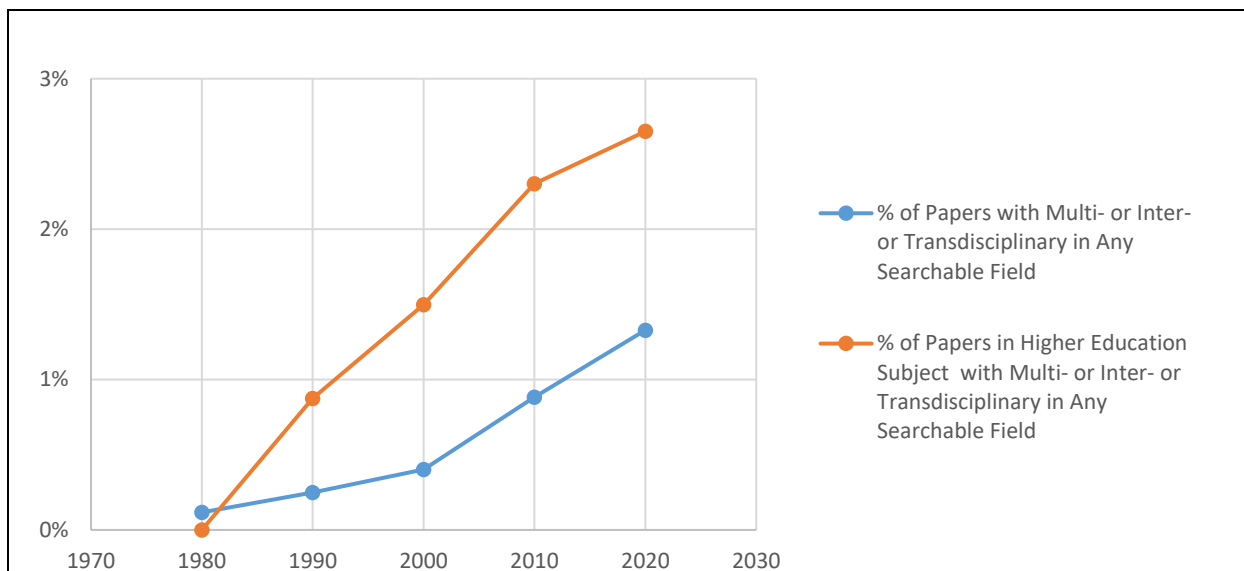


Fig. 1. Percent of Peer-Reviewed Papers in Ebsco Academic Search Complete with Multidisciplinary, Interdisciplinary, or Transdisciplinary in any Searchable Field

Framework for Measuring Multidisciplinarity

Measurement and evaluation of interdisciplinary research are distinctly different activities [2]. The two can be loosely compared to measurement of an athlete and performance evaluations of the athlete. Physical measures might include height, weight, or muscle to body mass ratio. Performance evaluations might involve speed, accuracy, or points scored. Evaluation of interdisciplinary collaboration is more complex than a measure. Evaluation requires consideration and assessment of goals, processes, and outcomes [12]. (For a detailed framework on evaluation of interdisciplinary research, see [12]). This paper focuses only on the measurement of multidisciplinary.

Substantial research has been done on the relationships between different fields of research and the intersections between distinct areas. In the field of scientometrics, researchers study the disciplinary structures of scientific literature through the analysis of publications (bibliometrics) [13], [14]. Connections between disciplines (interdisciplinarity) is studied through the lens of diversity, employing metrics from ecology: species richness (number of species in an ecosystem) and species evenness (balance in quantities of species). An ecosystem with two species (measure of richness) might have one kind of frog and one kind of fly. Two such systems could have very different balances, with 100 flies for every frog (a good day for the frogs), or 100 frogs for every fly (a bad day for the flies). In literature on interdisciplinary measures, these metrics are referred to as variety (instead of richness) and balance (instead of evenness). Porter & Rafols maintain that beyond these, a measure of interdisciplinarity should also account for the relative distance between each discipline [15]. For example, our two-species ecosystem with flies and frogs would be very different from a two-species ecosystem with red frogs and green frogs but no flies. As Rafols [16] observed, “There is more diversity in a project including cell biology and sociology than in one including cell biology and biochemistry” (p. 173). A relative distance must be incorporated into measures of interdisciplinarity to capture the difference.

Measurement approaches can be top-down, relying on existing categorizations (disciplines instead of species); or bottom-up, using data on each individual in the system (keywords in each paper, analogous to the length of each frog's legs, although that method is not used in ecology) [2]. A top-down approach to measuring the multidisciplinary of student teams would be to categorize students by major, and to treat students from a given major the same. A bottom-up approach would be to compare all courses taken by each student in a given team. The top-down approach would involve analysis of degree requirements, whereas the bottom-up approach would involve analysis of every student's transcript. While the bottom-up approach would be more accurate, it would be labor-intensive, and resulting measures would be specific to the given students. With a top-down approach, relative distances can be measured once, and then the newly developed metric can be applied to any number of teams. In this study, we chose to use a top-down approach, with the long-term goal of developing metrics that can be applied in many contexts.

Top-down bibliometric measures typically rely on the Web of Science (WoS) categories maintained by Clarivate Analytics, which assigns research fields to journals and books [2], [17], [18]. A paper on a biomedical device might cite articles from journals categorized under biomedical engineering, mechanical engineering, and physiology. This represents the knowledge integration process, because the citations document the knowledge that informed the production of new ideas [2]. Another categorization that can be used in a top-down approach is the researchers' field of study [2]. A challenge with this method is that organizational groupings may not align with research fields. For example, a biology department could include faculty in multiple WoS research fields – Cell biology, Evolutionary Biology, Microbiology, etc. Additionally, a researcher may work in more than one field of study. (An exception to this obstacle is Italy, where the Ministry of Education, University, and Research requires academic scientists to classify themselves under one of 370 fields in 14 disciplinary areas [19].)

Measures of interdisciplinarity can be based on inputs, such as researchers' fields of study; processes, which can include fields that informed the research; or outputs, such as publications and patents [2], [18]. We propose using the Rao-Stirling diversity index to measure multidisciplinary in educational contexts. When applied to a lecture-style class (a context in which students would not collaborate), the index would describe the diversity of students attracted to the course, which would be an output of course development and course listings/recruiting. When applied to a student team or project, as in this paper, the index would represent **output of course development and recruiting** as well as **inputs for the team's work**. The Rao-Stirling diversity index is based on the proportion of cases from each category and the relative distance between categories. The index can be expressed as Equation 1, where d_{ij} represents the distance between categories i and j , p_i and p_j represent the proportion of units from categories i and j , and the summation is done over half of the matrix ($i > j$) [20]. The expression is also known in ecology as the distance-weighted Simpson diversity, and in economics as the Herfindahl-Hirschman index [16]. The index can be used to describe the interdisciplinarity of individual papers [21], journals [22], institutions [23], and entire fields [15]. Because the index is based on proportions and distances, a small team and a large team could have the same index if their proportions and disciplinary distances were the same.

$$D = \sum_{i,j(i>j)} d_{ij} p_i p_j \quad (1)$$

Student major is an obvious category, but defining the distances between categories can be challenging [2]. While there are global maps of science and relative distances for WoS categories, the categories do not map well to undergraduate degree programs. A biology department may offer a single undergraduate degree in biology, but the WoS has 10 biology categories. Conversely, a university may offer multiple programs of study in modern languages, but the WoS has only one category for language and linguistics.

The distance measure is supposed to represent cognitive distance between majors. If similarity between majors can be quantified, the similarities can be used to compute relative distances. We propose using two measures of similarity: overlap in degree requirements, and cross-listings between departments. Similarity by curricular overlap is intuitive. If two majors require the same course, the curricular overlap represents similarity. For example, if two majors require a 9-credit hour physics sequence, the degree programs would have 9 credit hours of similarity.

Beyond specific degree requirements, cognitive distance can also be seen in cross-listings between departments. For example, at the Georgia Institute of Technology, three physics courses are cross-listed with courses in other departments (Table I). In physics, the courses can be used as technical electives under the “any PHYS or Technical Electives” requirement [24]. In the degree requirements for the other majors, the courses are listed under the subject code of the listing majors’ departments. If the degree requirements were compared, the cross-listed courses would not be counted as curricular overlap. Additionally, because cross-listed courses can be taught by faculty in either department, they represent a high level of cognitive similarity.

Along the same lines as cross-listings, when majors in a single department use the same subject code, they draw on the same pool of in-major electives. For example, the Georgia Tech Department of Civil and Environmental Engineering uses a single subject code, CEE, but the department offers two majors, Civil Engineering and Environmental Engineering. Students from both majors choose in-major electives from the same pool of courses, but the similarity would not be reflected in degree requirements. The clustering of majors in departments can be extended to programs jointly offered by multiple departments. A degree jointly offered by two departments would be similar to other majors offered by the two sponsoring departments, even if the majors from the sponsoring departments differed from each other. For example, Georgia Tech’s degree in Computational Media is jointly offered by the College of Computing and the School of Literature, Media, and Communication. Computational Media is similar to both Computer Science and to Literature, Media, and Communications, but Computer Science is not necessarily similar to Literature, Media, and Communications. Similarity by organizational structures was incorporated into the similarity by cross-listings scale, as described in the methods section.

TABLE I. Cross-listed Physics Courses

Physics Course	Cross-listed with	Used in Physics as	Used in Other Major as
Physics of the Weather	Earth and Atmospheric Sciences	Elective	Elective
Laser Theory and Applications	Electrical Engineering	Elective	Elective
Quantum Information and Quantum Computing	Mathematics	Elective	Elective

Methods

To apply the Rao-Stirling diversity index, Rafols recommends a four-step process: choosing the unit of analysis; classifying elements into categories; capturing relationships between categories; and generating visualizations [16]. In the following write-up, the development of a distance measure is treated as a method, and the diversity index calculations are treated as results.

Units of Analysis

The units of analysis in the study were multidisciplinary student teams in the Vertically Integrated Projects (VIP) Program at Georgia Tech in Spring 2020. In VIP, student teams are embedded in faculty research projects. Students earn academic credit and can participate for multiple semesters, supporting leadership development; faculty benefit from their teams' work, which supports long-term faculty engagement; and the model is in place at 40+ institutions around the world [25], [26]. In Spring 2020, the Georgia Tech VIP Program enrolled 1,231 students in 80 teams. Because the focus of the study was on development of a multidisciplinary measure and not an evaluation of the VIP Program, diversity indexes were computed and visualizations generated for three teams, to examine the composition of teams with low, medium, and high diversity indexes. The three teams ranged in size from 12 to 55 students.

Categories

Categories in the analysis were student majors. To limit the scope of the study, disciplinary distances were only computed for majors represented in the program-wide sample. In Spring 2020, the VIP Program enrolled students from 33 of the institution's 36 majors, with 48% from the College of Engineering, 37% from Computing, 8% from Science, 3% from Liberal Arts, 2% in joint programs, 1% from Design, and 1% from Business. The imbalance across colleges is due in part to the composition of the institution, which is technological, and to how VIP credits count toward requirements in different degree programs [27]. Although three majors were excluded (Applied Physics; Discrete Mathematics; and Global Economics and Modern Languages), they were similar to majors in the program-wide sample (Physics; Mathematics; and Economics).

Distance Measure

With student majors as the categories, credit hours were the basis of the distance measure. If the proposed method for measuring multidisciplinaryity is to be used at other institutions, differing academic calendars (quarters, trimesters, etc.) and variation in units representing courses (credit hours, credit points, etc.) would make comparisons of raw totals difficult. An intuitive similarity metric would be 0 for students in completely unrelated majors, and 1 for students in the same major. Subtracting a 0-1 similarity measure from 1 would yield disciplinary distances of $d = 0$ for students in the same major, and $d = 1$ for students in entirely unrelated majors.

Relationships between student degree programs can be observed in two general areas: **curricular overlap** and **cross-listings**. The two measures of similarity were calculated for each pair of majors, scaled to a range of 0-1 (not similar to very similar), and averaged for each major

pairing. The single scaled similarity measure for each pair of majors was then subtracted from 1 to yield a scaled distance of 0-1 (no difference to very different) for each pair.

Social network diagrams were generated to illustrate closeness between academic majors. UciNet was used to convert the data to NetDraw-readable files, and NetDraw was used to generate diagrams. Three diagrams were generated: closeness by curricular overlap; closeness by cross-listings; and closeness by the combined scale.

Similarity by Curricular Overlap

Curricular overlap refers to overlap in required and elective course credits in two majors. Required courses are the simplest to tally. If all engineering students are required to take Physics 101, all of the majors would have those 3 credits in common. To account for requirements that can be met by a variety of courses, weighting was used. If a degree program required three courses from a list of five options, if students chose their courses randomly (which we hope they do not), each course in the list would have a 3 in 5 chance of being chosen. A required course would have a weight of 1, and each course in the “choose 3 from 5” list would have a weight of 0.6. If options for a requirement were open-ended, such as any 3000-level course from the department, no courses were included in the overlap analysis. If options for a requirement included a list of courses along with an open-ended option, only courses that were listed were included. Courses that were required of all majors were not included. This included health (2 credits), English composition (6 credits), social sciences (12 credits), various versions of calculus (4 credits), and various versions of introduction to computing (3 credits).

To calculate curricular similarity, a table of degree requirements was generated with three columns for each major: subject code and course number, course name (used for reference, not used in analysis), and weighted credit hours. When multiple versions of the major were offered, the general version was used if one was offered. If a general version of the major was not offered, courses across the multiple versions were weighted. When courses were listed as equivalences in degree requirements, instead of splitting the weight of the course, the primary course was included in the main list of requirements, and the equivalent course was included in a corresponding list of alternatives/equivalents for the major.

A matrix of major-to-major curricular overlap tallies was generated in excel. In comparing major A and major B, the main list of requirements for major A was compared with the main and alternatives/equivalents list for major B. The comparison was then reversed. If the tallies disagreed, which occurred when one major accepted an alternative for a course and the other did not, the highest tally was used.

Totals for curricular overlap ranged from 0 to 61 credits, with a mean of 10 and a median of 5. The majors with the fewest credits in common with others were Applied Languages and Intercultural Studies; and Literature, Media, and Communication (4 credits in common with many majors, but none in common with engineering or computer science). Engineering and physics majors had the largest overlap with other majors (15-18 credits on average). The largest overlaps were between Environmental Engineering and Civil Engineering (61 credits), which are

housed in the same department; and Electrical Engineering and Computer Engineering (54 credits), also housed in the same department.

Self-to-self curricular overlaps were also tallied. Self-to-self overlap was high in prescriptive programs (131 credits in Industrial Engineering, and 101 in Materials Science Engineering), and low in programs with high curricular flexibility (7 credits in Applied Languages, and 19 in Economics). The mean was 67, and the median was 71. Because we defined distance as 0 for students from the same major, all self-to-self overlap values were set to the median self-to-self value of 71 (ensuring the scaled similarity measure would be 1 for self-to-self pairings). This kept highly prescriptive majors from skewing the scale, and it ensured that students from the same major would be handled in the same way (perfect similarity, zero distance), regardless of the prescriptiveness of their program.

Social network diagrams were generated to interpret results of the curricular overlap tallies. NetDraw offers a variety of graphing methods and settings. For the curricular overlap diagram, the most readable output was obtained by drawing an initial diagram with scaling ordination, and then using the non-metric multidimensional scaling of geometric distance layout (Fig. 2). This produced expected clusters, with majors offered by the same departments appearing in pairs (International Affairs major near the Modern Languages and International Affairs major; Civil Engineering near Environmental Engineering; etc.). When produced multiple times, the diagrams were slightly different, but general patterns were consistent. In the diagram, thicker lines represent greater curricular overlap. For example, the line between Applied Languages and Intercultural Studies (red, lower left) and Business (purple, center) is thin and represents 4 credits. Most of the lines emanating from Music Technology (orange, top) and going to engineering majors (blue) are thick and represent 12-19 credits.

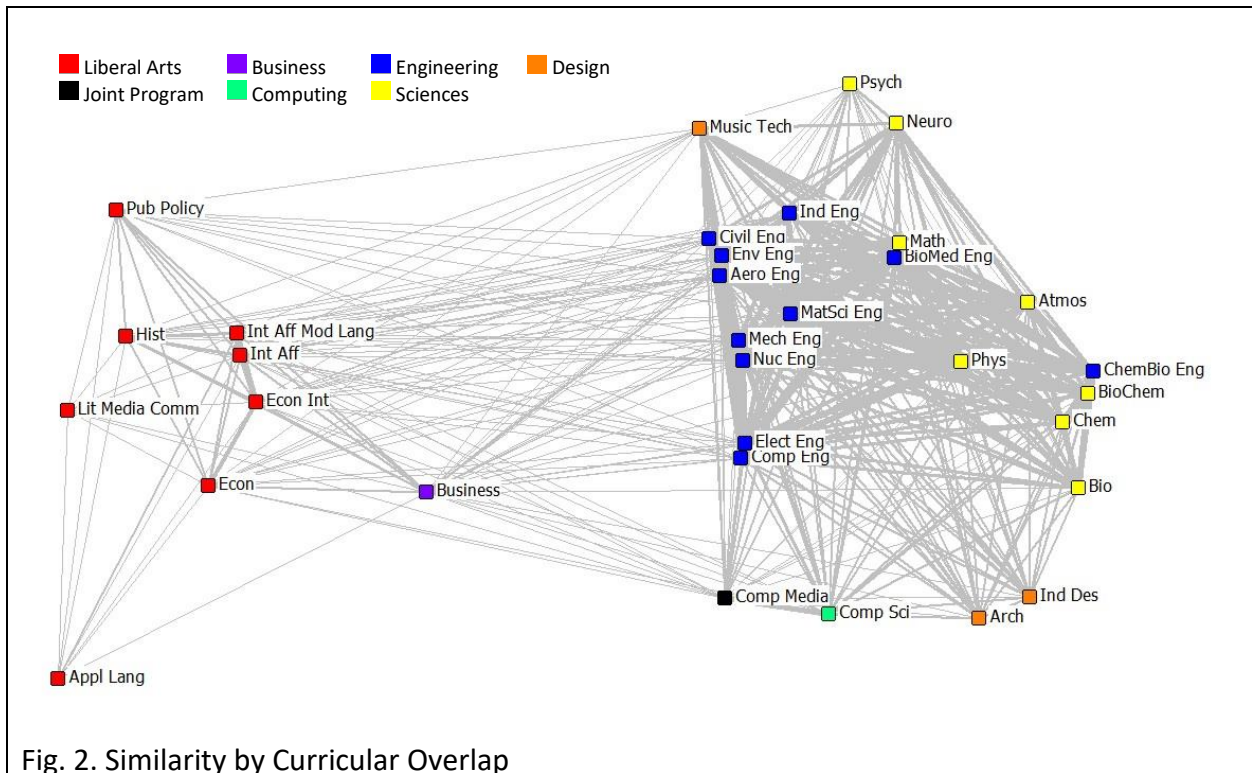
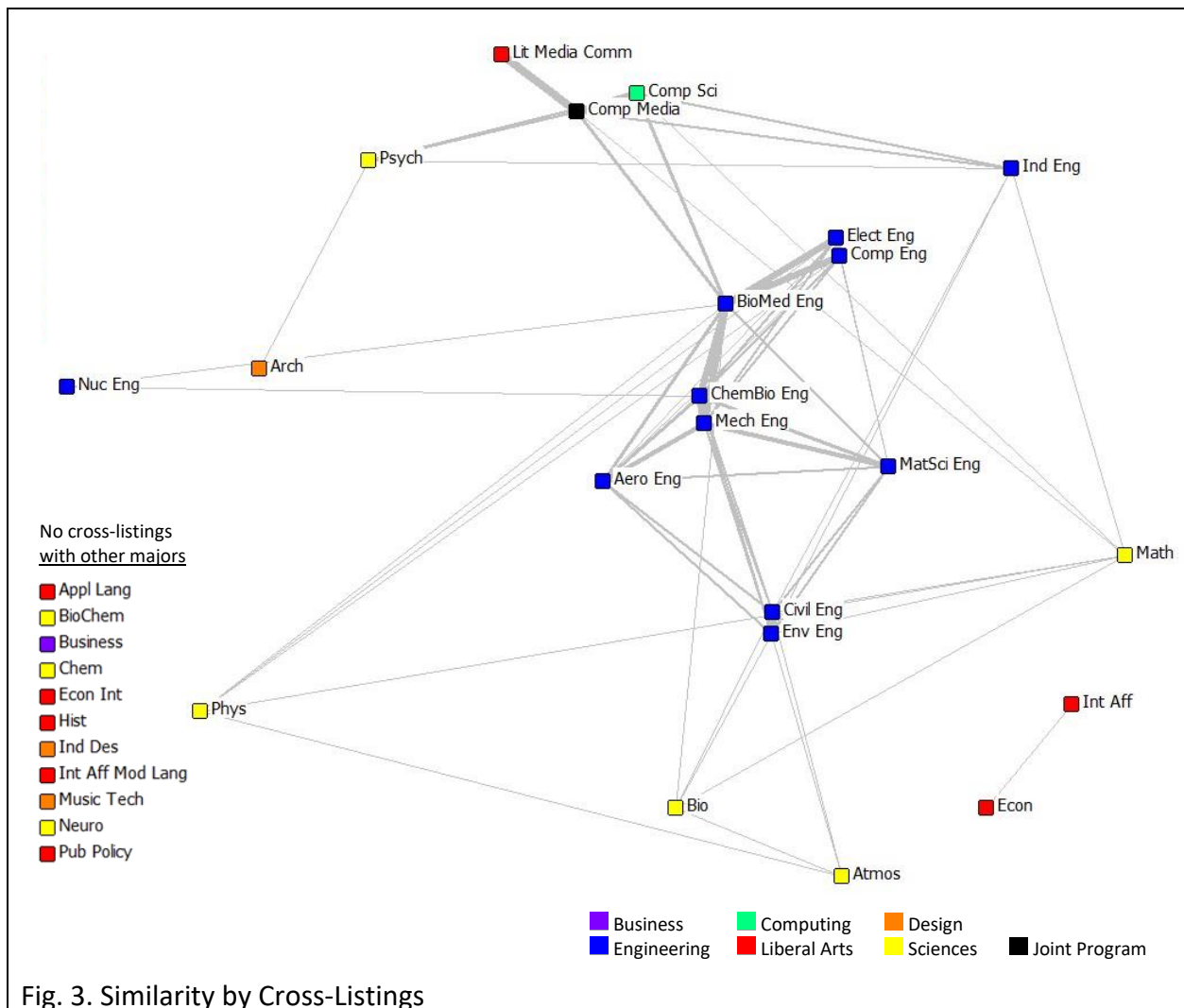


Fig. 2. Similarity by Curricular Overlap

Similarity by Cross-listings

Beyond curricular overlap, closeness between majors can be seen in course cross-listings. Courses are listed in the course catalog by subject code, and listings include cross-listings. To build the cross-listing matrix, majors included in the study were recorded by the subject code used for their major courses. A table was generated for each subject code with four columns: listing department subject code, course number, cross-listed department subject code, and credit hours. This created complimentary entries when the catalog consistently cross-listed courses to and from each subject code. To determine the number of credits cross-listed between two subject codes, cross-listed credits were summed for each cross-listing direction (major A to major B, and then major B to major A), and the maximum sum was used.

Of the 33 majors, 12 majors had no cross-listings with other majors. Of those with cross-listings, totals ranged from 3 to 46 credits, with a mean of 12 and a median of 10. To account for majors that draw their in-major electives from the same subject-code pool, values for majors offered by the same department were set to the maximum observed cross-listing value, which was 46 credits. The same was done for majors offered jointly by two departments, numerically linking

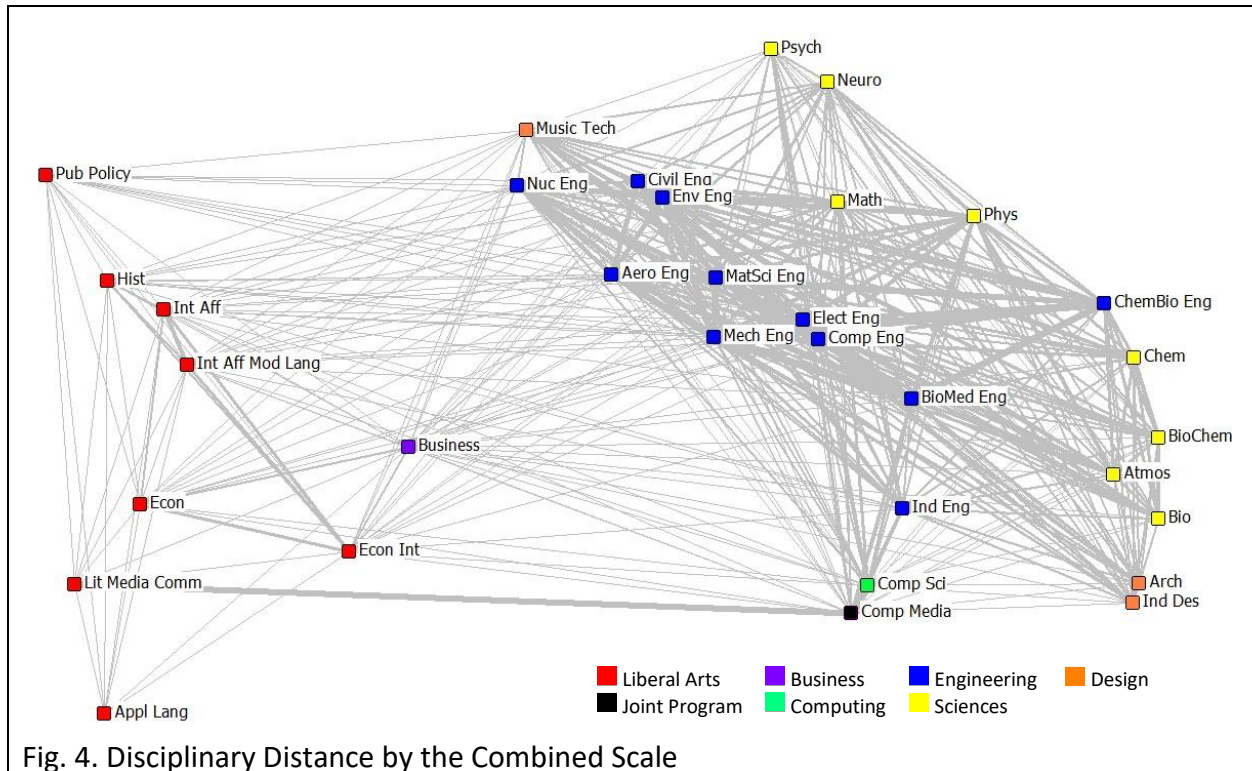


the joint major with the majors in the sponsoring departments. A self-to-self value needed to be set, because a major would have more similarity with itself than with others. A variety of values were selected and tested to determine the impact of different self-to-self values on the final combined scale. A final self-to-self value of 50 was selected (approximately 10% higher than the maximum observed cross-listing value), because it yielded a combined-scale diagram with expected clusters. For example, in the curricular overlap visualization, aerospace engineering was consistently clustered with civil and environmental engineering. Civil and Environmental were expected to be closer to each other than to Aerospace. With a self-to-self cross-listing value of 50 credits, the Civil and Environmental were consistently clustered, with Aerospace nearby. To scale the similarity by cross-listings measure to 0-1, as with the curricular overlap scale, values were divided by the maximum value (the self-to-self value) in the matrix.

The NetDraw settings used to generate the curricular overlap diagram did not work well in the cross-listing diagram, because clusters were too tight and obscured labels. To get a readable diagram (Fig. 3), only scaling ordination was used. Line thickness represents tie strength.

Combined Distance Measure

To obtain an overall similarity measure, the scaled curricular and cross-listing similarities were averaged, which yielded similarity values ranging from 0 to 1 (not similar to very similar). Scaled similarities were then subtracted from 1 to yield distance measures ranging from 0 to 1 (not different to very different). NetDraw settings used in the curricular overlap diagram worked well for the overall distance measure (Fig. 4). Again, thickness represents stronger ties.



Diversity Indexes

Using the scaled measure for disciplinary distances, Excel was used to calculate Rao-Stirling diversity indexes for three teams. Enrollment by major was used to select the three teams, with the intention of obtaining one low, one medium, and one high diversity index. The last step recommended by Rafols is to generate visualizations [16]. Science overlay maps are often used in assessment of interdisciplinary research, to show the relative distance between the fields of members of a team, in a center, etc. [28]. An overlay map was generated for each team, with node positions reflecting relative distances between majors in the global system, and node sizes representing occurrences of each major in the given team. The same scaling was used in each overlay map, so node sizes would be comparable across the diagrams.

Results

The three selected teams varied in size, number of majors, and number of colleges represented (Table II). Team size ranged from 12 to 55; number of majors ranged from 5 to 8; number of colleges ranged from 2 to 5; and diversity indexes ranged from 0.18 to 0.40 (Fig. 5).

TABLE II. Team Compositions and Diversity Indexes for Selected Multidisciplinary Teams

Team Name	Students	Majors	Colleges	Diversity Index
Robotic Human Augmentation	55	5	2	0.18
Health Informatics on FHIR	18	7	5	0.30
Global Social Entrepreneurship	12	8	5	0.40

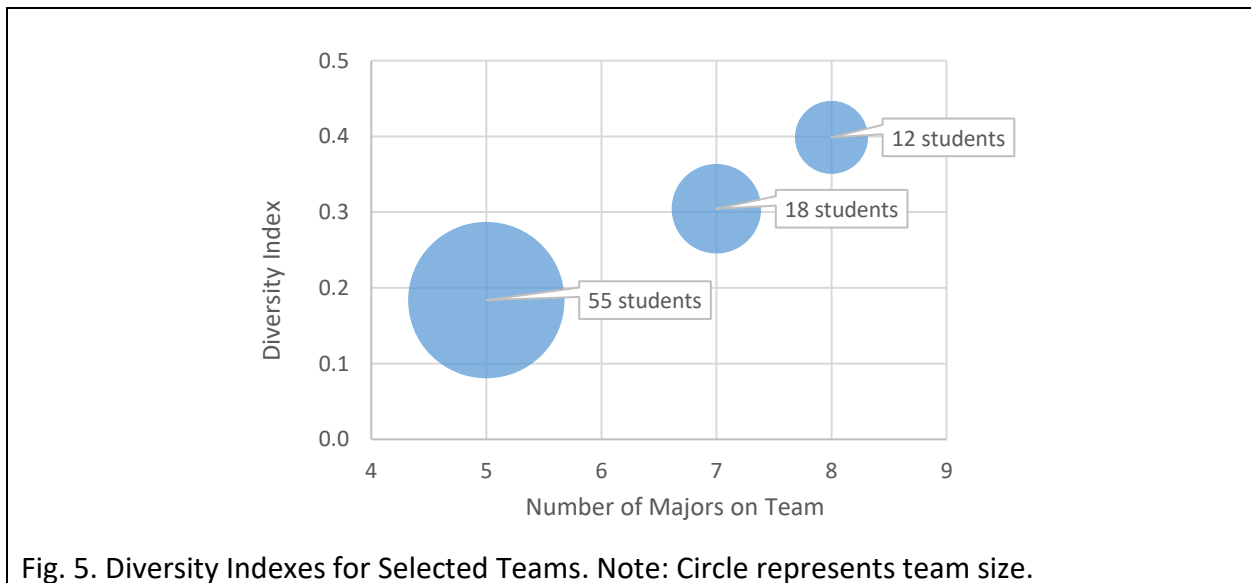


Fig. 5. Diversity Indexes for Selected Teams. Note: Circle represents team size.

Mid-level Index: Health Informatics on FHIR VIP Team

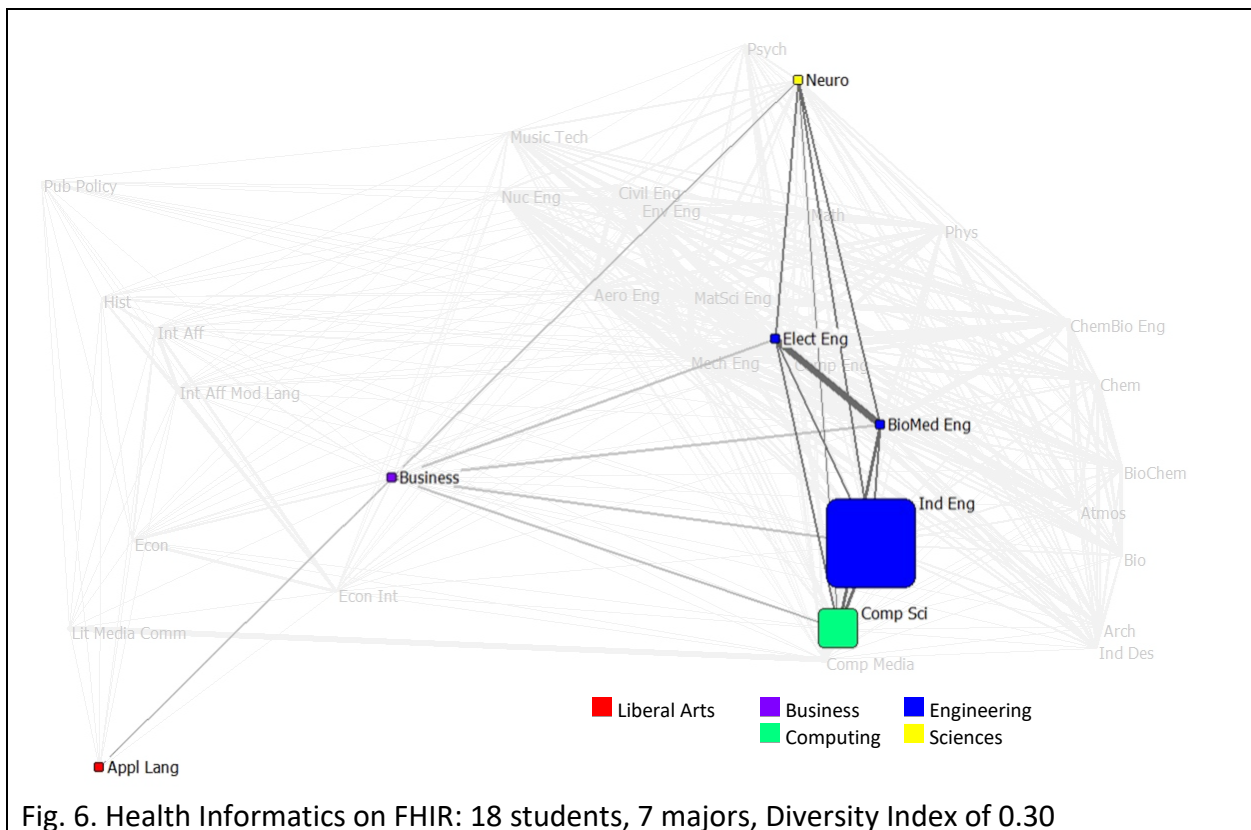
The Health Informatics on FHIR team is led by Mark Braunstein from the **School of Interactive Computing** and Myung Choi from the **Georgia Tech Research Institute**, with co-instructors Laura Kollar and Paula Braun from the Centers for Disease Control and Prevention. The FHIR

(Fast Healthcare Interoperability Resources) standard sets specifications and rules for the exchange of electronic healthcare data. The Health Informatics on FHIR team develops apps for use by medical staff and patients to address problems posed by instructors, project partners, students, and sponsors. Partners and sponsors include the Children’s Health of Atlanta, the Centers for Disease Control and Prevention, and Emory University.

The Health Informatics on FHIR team drew 18 students from 5 colleges, with:

- College of Engineering: 9 from Industrial Engineering, 1 from Biomedical Engineering, and 1 from Electrical Engineering;
- College of Computing: 4 from Computer Science;
- College of Liberal Arts: 1 from Applied Languages and Intercultural Studies;
- College of Business: 1 from Business Administration; and
- College of Sciences: 1 from Neuroscience.

This team had a diversity index of 0.30 (Fig. 6).



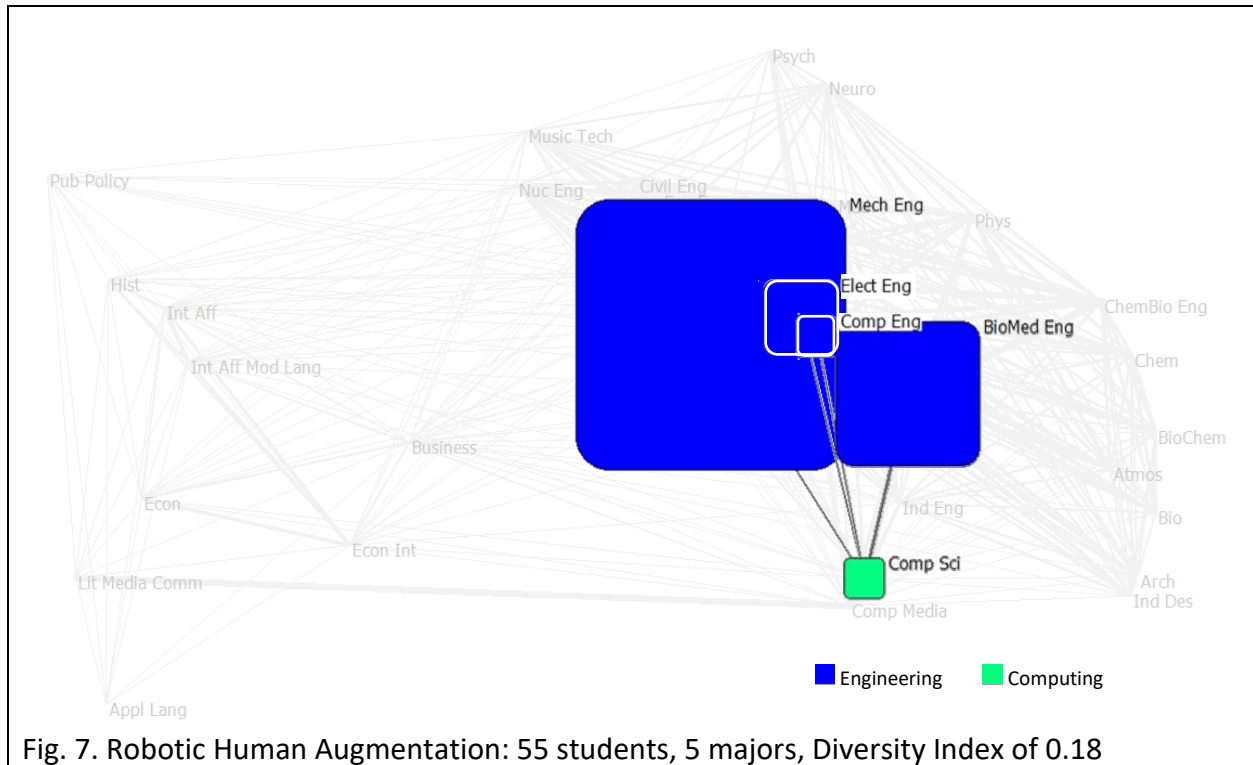
Lower Index: Robotic Human Augmentation VIP Team

The Robotic Human Augmentation team is led by Aaron Young in the School of **Mechanical Engineering**. It is one of the largest teams in the program, which is made possible by a sizeable group of graduate students who help coordinate subteams. The team develops powered prostheses and exoskeletons, with projects ranging from wearables that assist children with walking disabilities, to a hip exoskeleton that can help the wearer evade threats.

The Robotic Human Augmentation team drew 55 students from 2 colleges:

- College of Engineering: 26 from Mechanical Engineering, 14 from Biomedical Engineering, 7 from Electrical Engineering, and 4 from Computer Engineering;
- College of Computing: 4 from Computer Science.

The team had a diversity Index of 0.18 (Fig. 7).



Higher Index: Global Social Entrepreneurship VIP Team

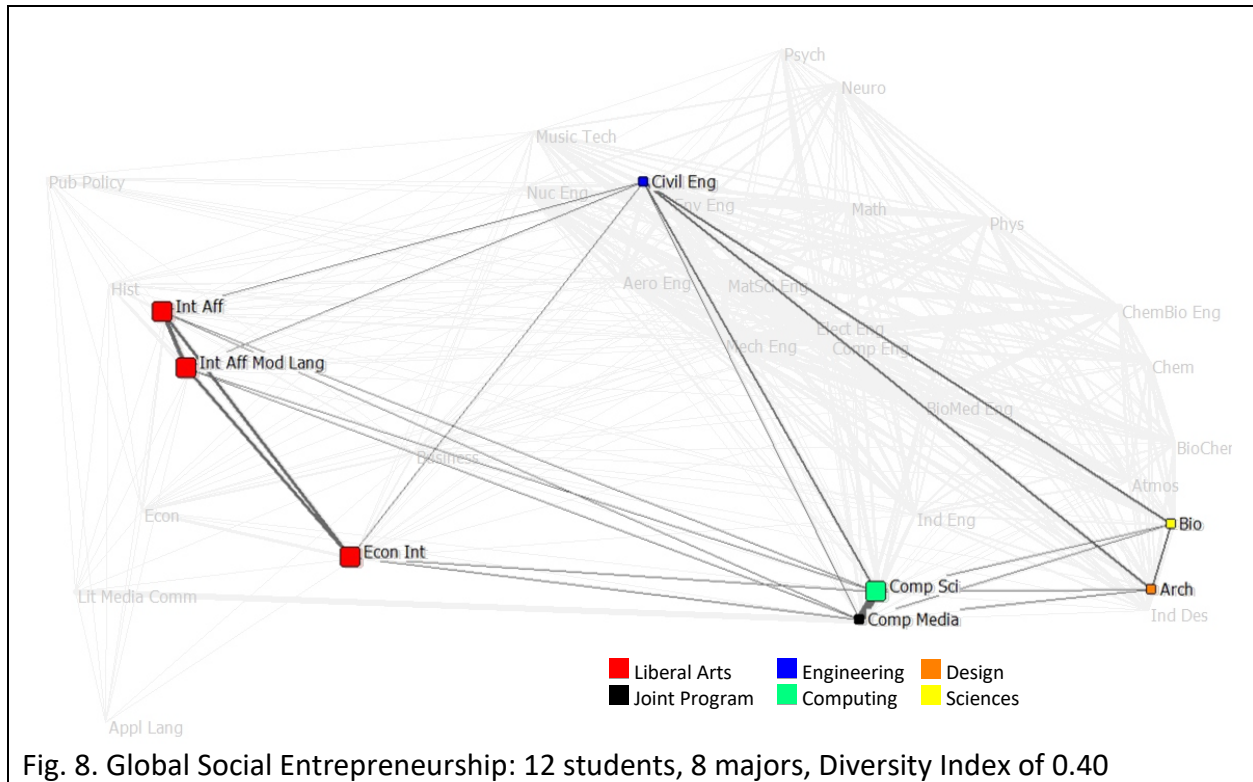
The Global Social Entrepreneurship team was led by Kirk Bowman in the School of **International Affairs** in the College of Liberal Arts. The goal of the project was to identify social innovators in the global south; increase awareness of the innovators and their ongoing work to transform their communities; and generate resources to support/continue/expand their work. The team employed the sidekick model of global philanthropy and the Rise Up social entrepreneurship method. Products included high quality film, children's books, and other media. The team is still in operation but changed its name in 2023 to Soccer, Community, Innovation, Politics.

The Global Social Entrepreneurship team drew 12 students from 5 colleges, with:

- College of Liberal Arts: 2 from International Affairs; 2 from Economics & International Affairs, and 2 from International Affairs and Modern Languages;
- College of Computing: 2 from Computer Science; 1 from Computational Media (jointly administered by the College of Computing and the School of Literature Media and Communication);
- College of Design: 1 from Architecture;

- College of Sciences: 1 from Biology;
- College of Engineering: 1 from Civil Engineering.

This team had a diversity index of 0.40 (Fig. 8).



Discussion

This study involved two distinct components, development of a new measure for disciplinary distance between college majors, and use of the developed measure to calculate Rao-Stirling diversity indexes for three multidisciplinary student teams.

Disciplinary Distance

While measures of interdisciplinary research typically rely on bibliometrics and web of science categories, our disciplinary distances are based on undergraduate degree requirements, cross-listings, and organizational structures that represent similarities between majors. A strength of the distance measure is that it is based primarily on measurable aspects of the curriculum. The two subjective aspects were how to handle self-to-self values in both similarity measures (curricular and cross-listings/organizational), and how to weight the two similarity measures in the combined measure. In the curricular overlap measure, we set all self-to-self values to the median observed self-to-self value. A strength of this approach is that it kept highly prescriptive degree programs from skewing the scaled measure. A weakness is that information was lost – students from very flexible programs were treated the same as students from highly prescriptive programs. In the similarity by cross-listings measure, the self-to-self value was chosen through trial and error, to yield combined measures that made sense to the investigators. This enabled the

investigators to tune the final measure, which is both a strength (the measure needs to make sense) and a weakness (no longer an objective measure). In weighting, we chose to equally weight the curricular and cross-listing measures. The trial-and-error selection of the self-to-self value in the cross-listing measure was based on the final map for the combined measure with curricular and cross-listing similarity equally weighted. This may have corrected or obscured shortcomings in one measure or the other.

The visualization of the curricular overlap scale (Fig. 2) showed clustering by college, with majors from the College of Liberal Arts (red) to the left; STEM majors to the right; and Business (purple) in the middle. One of the three majors in the College of Design (orange) is above the cluster of majors from the College of Engineering (blue), while the other three College of Design majors are below the Engineering cluster. Majors from the College of Sciences (yellow) are to the right of the Engineering cluster, with one Engineering major in the Sciences area. The single major from the College of Computing (green) is near the major jointly offered (black) by the College of Computing and the School of Literature, Media and Communication in the College of Liberal Arts (red). Averaging the curricular overlap and organizational structures scales resulted in looser clustering (Fig. 4). Sciences majors became further removed from the Engineering cluster, but Chemical and Biomolecular Engineering stayed to the right, near Chemistry.

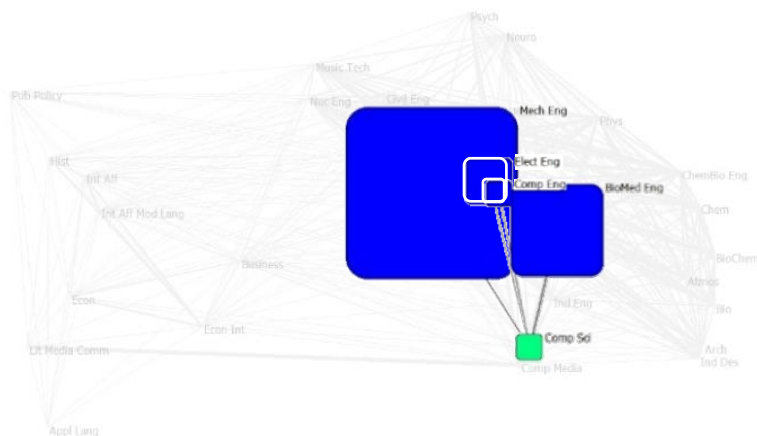
A weakness of visualizations is that the numeric distance measures cannot be accurately represented in a 2 (or even 3) dimensional space. For example, in Fig. 4, Aerospace Engineering is closer to Material Sciences Engineering than it is to Mechanical Engineering, but in the numeric scale Aerospace is most similar to Mechanical Engineering ($D = 0.57$). Similarly, the thick line between Literature, Media and Communications and Computational Media represents a strong tie ($D = 0.49$), but similarities/differences with other majors leaves the two quite far apart in the visualization.

A limitation of the disciplinary distance measure is that it is based on the curriculum and practices of a single institution. It is shaped by the groupings of majors within academic units; campus and department subject-code conventions; and collaboration between departments. For example, a technical writing course might be offered by an English/ Communications department, showing connections between all technical majors that make use of the class. If a technical department required their own version of the course under their own subject code, the apparent connection with other majors would disappear. The measure is especially sensitive to campus and department subject code conventions. If two majors are offered by the same department under the same subject code, they would have high similarity in the cross-listing component of the measure. However, if one of the two majors was highly prescriptive with no in-major electives, the assumed similarity would be unfounded.

Diversity indexes

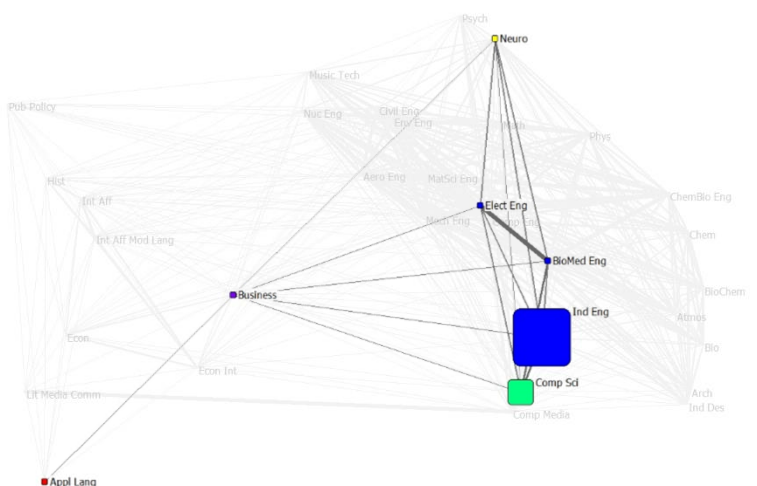
Diversity indexes were calculated for three teams, and overlay maps generated for each. The progression from a high concentration of students in similar majors (Fig. 10a), to a wider range of majors with uneven concentrations (Fig. 10b), to a more even concentration of students across dissimilar majors (Fig. 10c) corresponds with increasing diversity indexes.

Lower
Diversity
Index



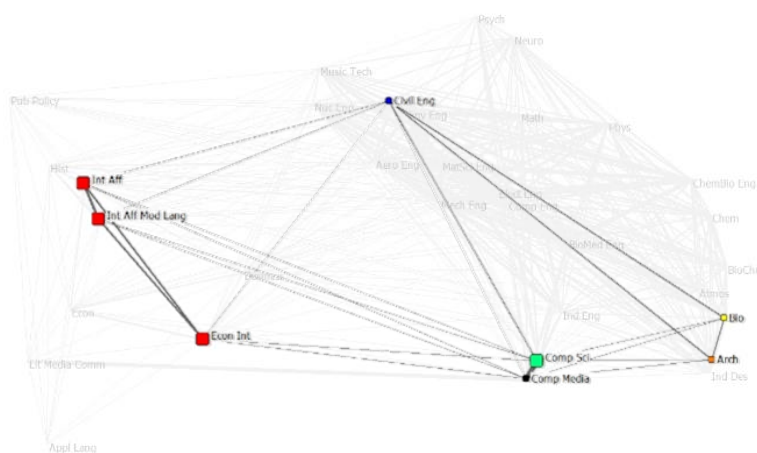
a) Robotic Human Augmentation, $D = 0.18$

Mid-level
Diversity
Index



b) Health Informatics on FHIR, $D = 0.30$

Higher
Diversity
Index



c) Global Social Entrepreneurship, $D = 0.40$

Fig. 10. Overlay Maps for Three Teams, from Lowest Diversity Index to Highest

The loose correlation between diversity index and number of majors was expected, but there may also be an operational relationship between team size and diversity index. It may be easier for an instructor to scale-up a team when students are from similar fields of study. On the 55-student Robotic Human Augmentation team ($D = 0.18$), Mechanical Engineering graduate students help lead subteams, and all subteam students are from majors closely related to the project: Mechanical Engineering, Electrical Engineering, Computer Engineering, Biomedical Engineering, and Computer Science. Adding students from unrelated majors would add complexity to the project, which might make the large team size untenable.

Conversely, teams composed of students from very different fields of study may have an upper limit on size. The 12-student Global Social Entrepreneurship team ($D = 0.40$) included students from five colleges as well as a jointly administered program. This requires the instructor to oversee work further outside of his/her expertise, which would involve additional effort.

The team with the mid-level diversity index is an interesting case, because it has students from unrelated majors, but a high concentration of students from Industrial Engineering. This high concentration may bring core competencies to the team, while other disciplines extend the team's range of expertise.

Conclusion

In this paper, we proposed a method for measuring the multidisciplinary of student teams. We developed a measure for disciplinary distances between 33 degree programs at a research university. We then used the measure to calculate Rao-Stirling diversity indexes for three multidisciplinary student teams, along with visualizations of the distances between team members. Results for the three teams were presented alongside the contexts in which the teams formed/worked.

The profiled projects emphasize the difference between the measurement and evaluation of multidisciplinary. Three key elements of project-based learning are that projects focus on problems that are meaningful and important to the students; that students engage in “authentic, situated inquiry” in which they learn and apply knowledge from their disciplines; and that the collaboration between students, faculty, and partners emulates “the complex social situation of expert problem solving” [29, p. 318]. While they have very different Rao-Stirling diversity indexes, the work of all three profiled teams is worthwhile, and all three projects engage students in meaningful knowledge creation. The diversity indexes quantify the compositions of the teams, and they confirm the potential for complex social situations that can arise from working with people from different disciplinary backgrounds. To assess the degree to which teams achieve multidisciplinary interaction/collaboration, diversity indexes could be combined with social network analysis. Social network analysis has been used to describe the degree to which students cross disciplinary lines within multidisciplinary teams [30]–[32], and diversity indexes would add depth to these studies.

The Rao-Stirling diversity index can be used to examine and showcase the multidisciplinary of student teams, courses, and programs. The results would be of particular interest to administrators, sponsors, and prospective program participants. Development of the disciplinary

distance measure was time consuming. To obtain a generalizable measure, measures could be calculated across a large number of institutions, and distributions, ranges, and outliers could be considered for each major-to-major distance. There would likely be substantial differences by country and region of the world, particularly between nations/regions with highly prescriptive and very liberal educational systems. The measure could feasibly be used to contextualize similarities and differences between educational systems.

In the short-term, further analysis will be done on enrollments from Spring 2020, the semester for which disciplinary distances were developed. After doing a program-wide analysis on all 80 teams, the measure will be updated to reflect curricular revisions. The subjective aspects of the measure will be reevaluated, as will the impact of curricular changes on the final scaled measure.

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