

Bipartite Network Analysis Utilizing Survey Data to Determine Student and Tool Interactions in a Makerspace

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Abstract

Engineering makerspaces are a powerful new tool in the educators' toolboxes. Although a growing body of empirical data demonstrates their benefits to student learning, more needs to be done to ensure they meet their full potentials. Analyzing the design of these spaces to maximize student-tool interactions and identifying barriers to entry are parts of the goals for these spaces to be inclusive environments where all students are comfortable. The representation of student interactions with tools in a graph form enables analysis of the tools by mapping combinations between tools and shared student. The bipartite model of the network allows for students to be the "actors" while the tools are the "events" that students interact with. Using the one-way interaction allows for a matrix, simplifying the complex interactions in the space. The matrix can then be manipulated to yield important information about makerspaces. The results of this ongoing research will result in recommendations regarding what tools and tool types are the most accessible to students, primarily high interaction tools such as basic 3D printers and handheld tools. Utilizing the tool analysis can also reveal how tools depend on higher interaction tools such as the advanced forms of 3D printing, as well as what student groups have may need extra support or outreach to increase their inclusion within the makerspace.

Keywords

Makerspaces; network design; engineering education; Network analysis

Introduction

The benefits of makerspaces for educating the modern engineer require careful analysis as the prevalence of these hands-on spaces increase. Research on makerspaces has focused on student impact, with three elements suggested as essential for success by Martin [1]: 1) rapid prototyping, digital tools, and low-cost microcontroller; 2) events and interactions within the community; and 3) a failure-positive mindset that encourages collaboration. Research on the barriers to makerspaces is limited, focusing primarily on inclusive environments and training/mentoring [2]. Other barriers found that impede student interaction include student lack self-confidence, fear of failure, and a lack of visibly alike peers [3-5]. A deeper understanding of makerspaces, which provide a uniquely creative and accessible hands-on experience to students, is vital to further enhance engineering curriculums [6, 7]. The analysis done here seeks to quantitatively establish the social demographics of the space to further understanding barriers and mitigate their effects, as well as further understanding the tools that can aid in introducing students to the space.

Results of a survey on student makerspace participation suggest that students who were self-motivated and participated in the space outside of the required class times showed higher confidence in their work for design tasks [6, 8-10]. The work highlights the importance of involving students in the space early, allowing for growth and experimentation with different

tools. Interactions with friends, classes, projects, and other staff and instructors have also been shown to aid in student involvement within the space [6]. Reoccurring tools such as the 3D printer and computer stations were also often identified as "gateway" tools that could aid in the early introduction of the students into the space [11]. Knowing the importance of tools and their interactions can help create a pathway for students to enter the space and become more comfortable with tools in the future [11, 12]. The approach taken here, which looks for ways to better engage students within the makerspace by understanding their interactions with tools in the space, can further improve their ability to apply their engineering education. Through seeing which tools are more often used than not and the order that they are learned in allows for visualization of the complex network.

This paper introduces a method to improve our understanding of the network of tools and students that forms as these spaces are used as well as the influence of specific tools on a student's interactions and comfort within the space. A quantitative ability to analyze student usage to determine both the tools commonly used by students and the combinations of tools capability to increase/decrease the accessibility of the rest of the space. This will aid instructors' use of the space as an education tool and associated investing and maintenance. The analysis here 1) models the makerspace in a bipartite network, 2) identifies key tools that are being used and bring students into the space, and 3) identifies initial dependencies of tools.

The bipartite network analysis used here is a network analysis technique primarily used in the social sciences [13] to determine and interpret underlying structures in complex social networks made up of "actors" and "events" [14]. Bipartite networks refer to a network that can be broken into two separate subsets A and B, with links connecting subset A to B [15]. The bipartite analysis was used by NASA to determine innovation networks for the space app challenge, enabling them to identify barriers to innovation and a "catalyst" that aid in completing the challenges [16]. Bipartite graphs are also used in ecology to analyze mutualistic (ex. plant-pollinator) networks and to conduct modularity analysis to further understand the networks [17]. The student and tool interactions that make up a makerspace network are analogous to both types of studies, with students being the "actors" and the tools the "events" of interest [18]. The network approach, which has yet to be applied to makerspaces, enables the complex interactions to be quantitatively mapped and studied. The work seeks to identify tool and interaction importance, demographic information that would allow involvement of a variety of students, and tool groupings that support student involvement.

Methods

Data Gathering and Surveys

The dataset for the analysis was obtained by conducting end-of-semester surveys distributed to Senior Design students in one university. The makerspace there is primarily student run. Surveys included question exploring several different aspects of students' relationships and usage of the makerspace. The main area of focus the survey is determining the tools students are using in the makerspace. The survey also evaluates the sequence of learning the tools, the reason students were using the space, and the impact of pre-university experiences on interactions within the

makerspace. Student attitudes and perceptions of the makerspace were recorded as well, with scales recording indices of design anxiety, confidence in communication, and other similar perspectives in this vein. Student motivations for using the space was also documented as an interest point. There are a variety of classes, extracurricular groups, and individual enthusiasts that use this makerspace. Accordingly, students were prompted to detail what, if any, classes, they were using the space for. The survey additionally included an open-ended text entry opportunity to detail the reasons for using the space. Lastly, general demographic information was collected to capture data that may inform as to how gender, ethnicity, major, and other factors play into students’ tool usage.

The analysis in the results section focuses on the responses of two questions in this survey pertaining to tool usage and the order of tools learned (questions 63 and 64). 148 students participated in the survey, most of whom were senior mechanical engineering students. As a result, the dataset is sufficiently large enough to conduct a preliminary analysis on the space that can later be compared to different makerspaces and future seniors in the space. The survey also included 22 tools and an open-ended "Other" option for tooling included in the main campus makerspace. The specific tools included can be seen in Figure 1. “Tools” in this case were resources available in the makerspace that the student was able to use. The survey thus provides a unique opportunity to capture engineering education from start to finish by capturing information of graduating students that have used the space in the past.

Question 63: Please indicate which equipment you have used in the [Name of Main university makerspace] or other makerspaces (select all that apply):

Tool #	Tool Name	Tool # Continued	Tool Name Continued
1	Basic 3D Printer (Ultimaker 2/3)	13	CNC Metal Mill
2	SLS Professional Printer (Formiga)	14	CNC Wood Router
3	Formlabs Form2 3D Printer	15	Manual Mill/Lathe
4	Stratasys 3D Printers	16	Handheld Tools
5	Resin 3D Printers	17	Electronics Area
6	Lasercutter	18	Metal Room
7	3D Scanner-Faro Arm	19	Wood Room
8	Vinyl/paper cutter	20	Studied at Tables
9	Sewing Machine	21	Just hung out
10	Embroidery Machine	22	Mentored by older students
11	Waterjet		Other (text entry)

Figure 1: Survey Question 63: Usage of tools in makerspace. All possible answers are included in the table.

Question 63, shown in Figure 1, prompts students to detail the tools, areas, and activities with which they were involved. Data from this question served as the basis of the network analysis presented herein. Demographic and other identifying information was anonymized, and identifiers were generated and paired to their respective tool usage results. A score of one indicates student-tool interactions while a score of zero is indicative of a lack of interaction. In this format, all results could be converted into the symmetric matrix necessary to execute a network analysis. The symmetric matrix will be more extensively explained in the following network creation section.

While question 63 elicits information about tool usage across students' entire makerspace careers, question 64 is concerned with the order tools were learned. Question 64, as it appears to participants, reads: "Think about when you first learned to use various tools in the makerspace. Can you list 5-10 tools in the approximate order of which you learned to use them?" Unlike question 63, this question was answered through 10 text entry boxes, representing the first 10 tools they learned. In question 63, students are given 22 fixed answers and only one open-ended option in an effort to ensure the data from this question is suitable for the network analysis. Questions were left open-ended in question 64 as to not restrict potential unanticipated responses, such as a student indicating "screwdriver" as the first tool they learned as opposed to our prescribed equivalent answer of "hand tools." In retrospect, this posed certain problems with ambiguous answers. More specifically, students would report that the first tool they learned was "3D printer," without specifying which model or type, forcing certain results to be left out of analysis and other answers lumped together. Results of question 64 were not involved in any way in the network analysis. Instead, entries across all students were simply summed and compared to observe trends and potential patterns in the order students are learning tools in makerspaces. By knowing which tools are learned first and the general patterns tools are used in, taken from question 63 of this survey, the research team will have a comprehensive snapshot of how students are using the space.

Given that identification and demographic information was recorded during this survey, the results of questions 63 and 64 could be analyzed with respect to various factors. Demographic information collected with the high sample sizes yielded for an analysis of participation and learning habits between genders and ethnicities. Throughout engineering education, marginalized groups seldom experience the full benefits of the various instructional modes, activities and resources an engineering program has to offer [3]. How gender, race, and ethnicity impact makerspace usage of students at the institution is a major focus of the analysis presented in the results section.

The current analysis provides a preliminary view of the interactions within a makerspace and can begin to show groupings between different networks.

Network Creation

The data is represented as a bipartite network: a network with two different groups of actors whose interactions can only go between the two groups (no interactions within a group are modeled) [13]. The survey data was used to create the bipartite network matrix: when student j interacts with tool i a value of one is assigned in the a_{ij} entry of the adjacency matrix - if there is

no interaction a zero is entered [13, 15]. A hypothetical small-scale scenario is shown in Figure 2, where seven students interact with three different tools (Figure 2a). Figure 2b and c show the makerspace represented as a bipartite directional graph and an adjacency matrix, respectively.

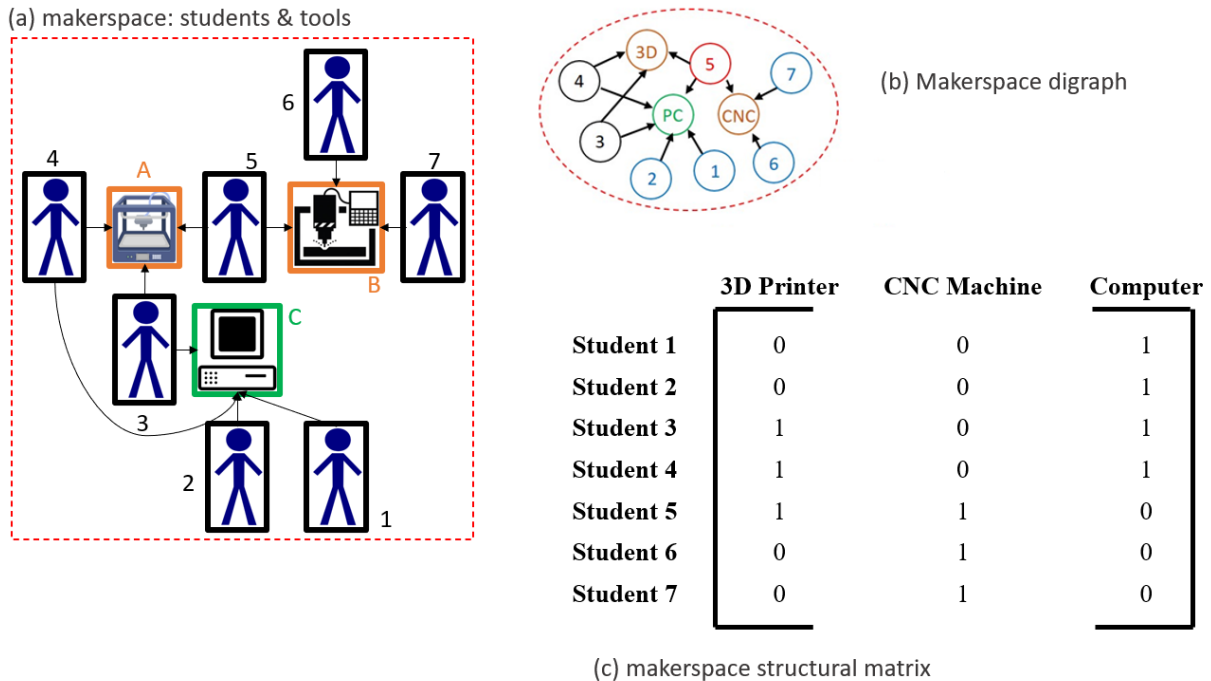


Figure 2: Hypothetical representation of the makerspace outlining the matrix quantification of interactions: a) A small-scale hypothetical makerspace with interactions, b) a digraph representation of those makerspace interactions, and c) the resultant makerspace adjacency matrix. Figure is based on [18].

The adjacency matrix in Figure 2c provides a big picture view of the many complex interactions that occur in a makerspace. Representing the space in matrix form allows for network analysis techniques to be applied, providing valuable information of the student and tool interactions making up the space. The adjacency matrix has students as the rows and tools as the columns.

Survey questions 64 and 65 from the survey section were used to create the adjacency matrix. A value of one is entered in the matrix if a student signifies that they interacted with the tool and a zero is entered if no response was provided for that tool. The analysis here used an encrypted number for the students to enable tracking with future semesters.

A major limitation to the bipartite network representation is that the model is binary, which causes the frequency of interaction information to be lost [19]. The results only describe the frequency that a tool has been used by a students *at least once*. This limitation can result in both inflated or under-represented tool usage results – for example, some tools may be used by a student once and get a value of one, while a student may use a tool hundreds of times and still

only receive a one. Reducing the impact of this binary limitation will be done in future work with entry/exit surveys at the makerspace to capture tool frequency usage information.

Data Analysis

Data analysis is done through a series of matrix manipulations that stem from social network analysis (SNA) used to analyze interactions between actors and events [13]. The node mappings from Figure 2b are redrawn in Figure 3 to highlight the two groups of network actors, students (S1-7) and tools (3D, CNC, PC).

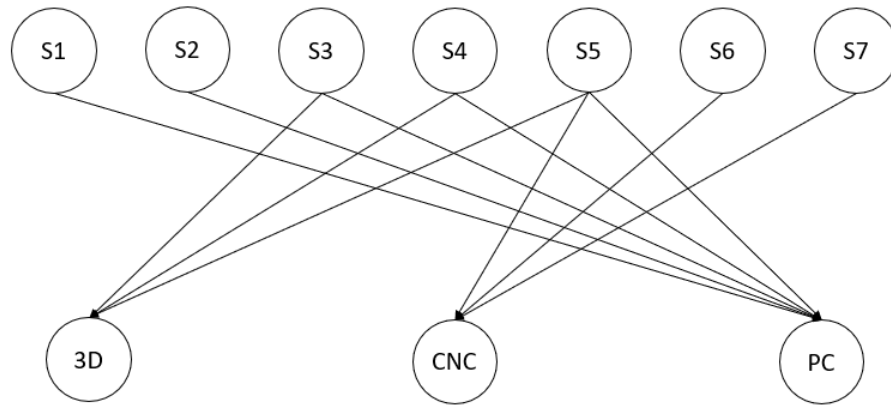


Figure 3: Node mapping from the network in Figure 2. The nodes on the top represent the students in the diagram, while the nodes on the bottom represent the tool used in the makerspace. The arrow signifies a one-way interaction with the students interacting with the different tools.

The system structure of the paper mirrors that of the structure in Figure 3. Students are represented as the upper nodes interacting with the tools in a one-way interaction [13]. Representing the makerspace in this form allows for a clear view of the interactions between the students and the tools and captures the one-way information transfer with students utilizing tools but tools not utilizing the students [6]. The adjacency matrix can be created by utilizing the interactions as stated in previous sections and converted for analysis.

The adjacency matrix from Figure 2 is recreated as matrix \mathbf{A} in Figure 4. Students in the matrix are in the rows with the tools in the columns with a one signifying an interaction and a zero signifying no interaction. Matrix \mathbf{A} is then multiplied by its inverse to create a modified view of the system [13]. The multiplication of matrix \mathbf{A} by its inverse generates a matrix that gives information on the tools. The diagonal entries signify the total students who used a particular tool, while the off-diagonal entries show the number of students that used both tools in combination. An illustration showing a sample matrix \mathbf{A} along with its multiplication is shown in Figure 4.

Matrix A

	3D	CNC	PC
S1	0	0	1
S2	0	0	1
S3	1	0	1
S4	1	0	1
S5	1	1	1
S6	0	1	0
S7	0	1	0

Matrix A'*A

	3D Printer	CNC Mill	Computer (PC)
3D Printer	3	1	3
CNC Mill	1	3	1
Computer (PC)	3	1	5

Figure 4: Adjacency matrix for the network in Figure 3. The matrix shows ones where there is a shared interaction. On the right, Matrix A'*A shows the manipulation as well as the result from this analysis, with the diagonals signifying the total students who used the tool and the off-diagonal shared interactions.

An “event” view of the network is done by taking **A** times its inverse (**A'A**) [13, 14], creating a “unipartite” network where both rows and columns are of the same category. This matrix format allows for a clear comparison *between* tools, highlighting how each tool correlates to one another in terms of their connections to the students.

The survey data interactions were converted into a bipartite interaction matrix, where the columns are tools and the rows are students that participated in the survey, creating a 148 x 23 matrix for analyzing between-tool interactions. The matrix **B'B** outlines interactions between tools. This is similar to the process shown in Figure 4 and the results are shown in Table 1, which are discussed in the Results and Discussion section.

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Table 1: Converted matrix showing the student-tool interaction for the 148 students. The diagonal entries highlighted signify the total number of students who utilized tools while the off-diagonal entries demonstrate the shared number of students that used both tools in combination.

	Basic 3D Printer	SLS Professional Printer	Formlabs form 2 3D printer	Stratasys 3D Printers	Resin 3D Printers	Lasercutter	3D Scanner- Faro Arm	Vinyl/Paper Cutter	Sewing Machine	Embroidery Machine	Waterjet	CNC Metal Mill	CNC Wood Router	Manual Mill/Lathe	Handheld Tools	Electronics Area	Metal Room	Wood Room	Studied at Tables	Just Hung Out in the Space	Mentored by Older Students	Other Equipment or Activities
Basic 3D Printer	113	13	12	21	15	74	4	24	12	6	55	28	20	61	77	39	36	71	41	28	10	4
SLS Professional Printer	13	15	3	7	2	12	1	5	2	0	8	4	1	6	9	6	3	10	6	6	1	0
Formlabs form 2 3D Printer	12	3	12	8	6	9	2	5	4	2	9	6	6	8	9	6	6	9	7	5	4	0
Stratasys 3D Printers	21	7	8	27	4	19	3	7	4	1	13	9	8	17	21	10	4	16	8	9	4	0
Resin 3D Printers	15	2	6	4	17	11	3	6	7	3	12	7	8	11	10	8	6	11	9	6	4	0
Lasercutter	74	12	9	19	11	92	2	19	13	6	52	27	22	51	67	35	30	56	37	27	11	4
3D Scanner- Faro Arm	4	1	2	3	3	2	5	1	1	1	3	3	3	3	3	2	2	2	1	1	1	0
Vinyl/Paper Cutter	24	5	5	7	6	19	1	24	7	4	15	6	7	15	21	14	9	17	12	15	6	0
Sewing Machine	12	2	4	4	7	13	1	7	14	5	8	4	7	8	10	9	6	9	9	8	4	0
Embroidery Machine	6	0	2	1	3	6	1	4	5	6	4	2	3	4	5	5	4	5	4	4	2	0
Waterjet	55	8	9	13	12	52	3	15	8	4	66	22	18	42	50	21	28	46	30	19	9	1
CNC Metal Mill	28	4	6	9	7	27	3	6	4	2	22	37	17	28	28	14	10	24	17	9	4	1
CNC Wood Router	20	1	6	8	8	22	3	7	7	3	18	17	27	19	23	10	10	20	15	12	6	0
Manual Mill/Lathe	61	6	8	17	11	51	3	15	8	4	42	28	19	71	64	26	25	54	31	22	10	3
Handheld Tools	77	9	9	21	10	67	3	21	10	5	50	28	23	64	96	43	35	67	39	28	12	4
Electronics Area	39	6	6	10	8	35	2	14	9	5	21	14	10	26	43	52	20	33	19	17	6	3
Metal Room	36	3	6	4	6	30	2	9	6	4	28	10	10	25	35	20	42	39	24	13	6	2
Wood Room	71	10	9	16	11	56	2	17	9	5	46	24	20	54	67	33	39	84	39	26	8	4
Studied at Tables	41	6	7	8	9	37	1	12	9	4	30	17	15	31	39	19	24	39	50	25	10	1
Just Hung Out in the Space	28	6	5	9	6	27	1	15	8	4	19	9	12	22	28	17	13	26	25	36	11	1
Mentored by Older Students	10	1	4	4	4	11	1	6	4	2	9	4	6	10	12	6	6	8	10	11	12	0
Other Equipment or Activities	4	0	0	0	0	4	0	0	0	0	1	1	0	3	4	3	2	4	1	1	0	6

Results and Discussion

Table 1 shows that certain tools have a higher impact on the tool interaction matrix. Tools that had a high interaction rate can be seen highlighted in gray, with the diagonals showing the total number of students who used the tool. Groupings of tools can start to be seen with the Basic 3D printer and the SLS Professional printer. Thirteen out of the fifteen students that reported using the SLS Professional printer *also* used the Basis 3D printer, suggesting a strong connection *between* the two. The tool connections seem to hold for all the 3D printers in the space (Formlabs, SLS Professional printers, Stratasys, Resin 3D printers) that have usage overlap with the basic 3D printer. Thus, the Basic 3D printer can be seen as a "gateway tool" that potentially introduces students in the space to utilize more complex, less frequently interacted tools. "Introductory" makerspace tools, things such as the Basic 3D printer and handheld tools that have low training requirements, are often used by a large percentage of students and make up a large portion of students who use other tools in the space. The connections between the Basic 3D printer and other more advanced 3D printers in the space are also seen for other "introductory tools." Handheld tools, the laser cutter, and the wood room make up a significant portion of usage rates by students.

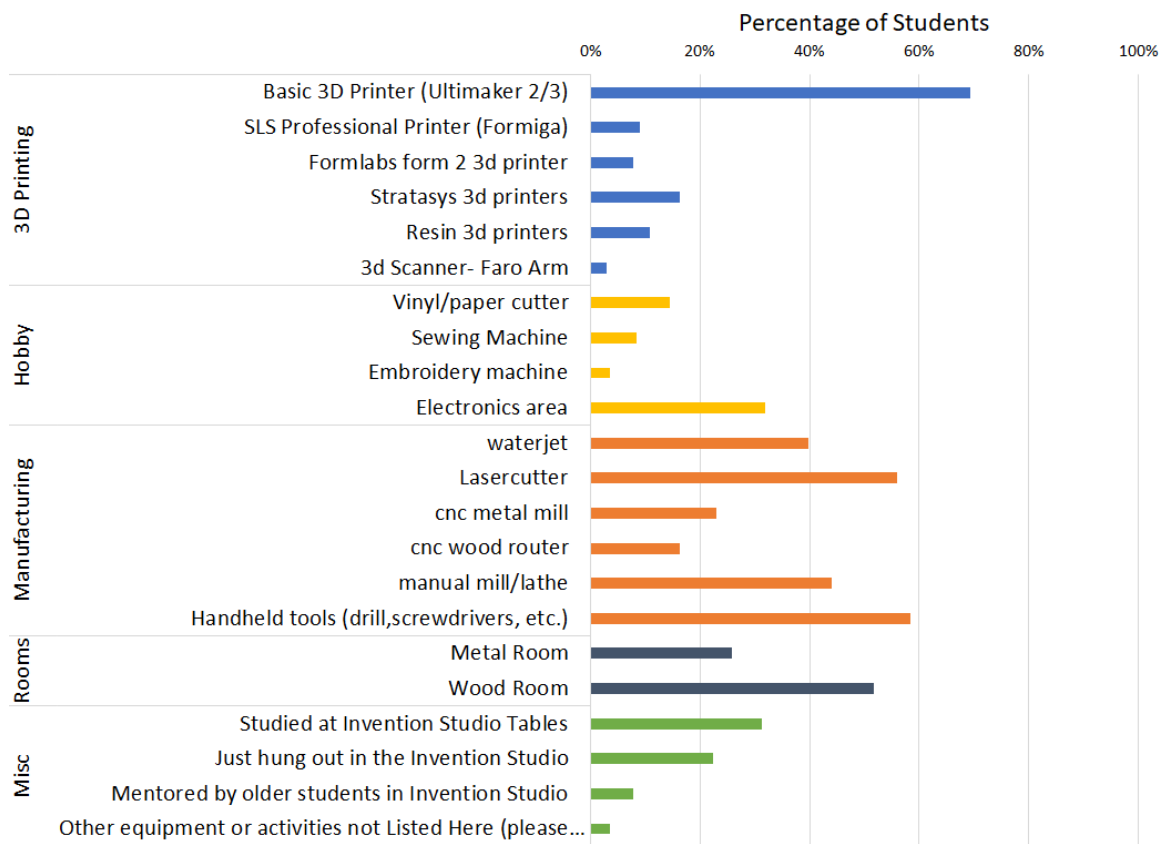


Figure 5: Proportion of students who have used tools in the makerspace, throughout their entire makerspace experience, 148 students (100% on the y-axis would be all 148 students).

Grouping tools into "use" categories highlights information about the type of tools and overlap in their uses (confidence that if one tool is used by a student, another tool will also be used). Tools can be analyzed within each grouping to study usage overlap. Figure 5 shows the total percentage of the population (100% = the total sample population of 148 students) who used a tool at least once in the semester surveyed. Tool interactions are categorized into four groups based on the tool usage results. Table 2 categorizes the tools according to these groupings. Tools for the grouping were selected at grouped intervals and primarily allowed for generalization of the tools and to aid in further analysis.

Table 2: Tools categorized by percentage use of the 148 students surveyed. Group 1 tools were used by 50% of students at least once, Group 2 tools were used by 25-50% of students at least once, Group 3 tools were used by 10-25% of the students at least once, Group 4 tools were used by less than 10% of students at least once.

Tool	Student Tool Usage	Tool Grouping
Basic 3D Printer	Majority of Students Used At Least Once	Group 1
Lasercutter		
Handheld Tools		
Wood Room	Most Students Used At Least Once	Group 2
Waterjet		
CNC Metal Mill		
Manual Mill/Lathe		
Electronics Area		
Metal Room		
Studied at Invention Studio		
Just hung out in the Invention Studio		
Vinyl/Paper Cutter	Few Students Used At Least Once	Group 3
CNC Wood Router		
Stratasys 3D Printers		
Resin 3D Printer		
SLS Professional Printer	Minimal Students Used At Least Once	Group 4
Formlabs Form2 3D Printer		
3D Scanner – Faro Arm		
Sewing Machine		
Embroidery Machine		
Mentored by Older Students		
Other Equipment or Activities		

Tools with high interactions in Group 1 were reported as having been used at least once by more students in the space. However, this does not mean that minimal student interaction tools are not as important to the makerspace because this analysis does not capture a single student's usage frequency (for example, a tool may have been used by few students, but those students used it continuously throughout the semester). The groupings thus allow quick categorization of tools and enable inferences about usage overlap between individual tools.

- **Group 1 Tools:** The tools in this category are likely very important to makerspaces. They consist of tools that are either used in classes, learned early on, or easy to learn, (such as the handheld tools). These tools are well connected with all other tools and students in the network.
- **Group 2 Tools:** Tools in this category are still critical in the space but start to be more specialized. Interactions are not as widespread to tools on lower categories but are well connected to high used tools.
- **Group 3 Tools:** Tools in this category often are more specialized tools. Typically, tools in this category are usually introduced from tools higher up in interaction, such as the different forms of 3D printing.
- **Group 4 Tools:** Tools in this category are highly specialized tools that have specific uses and will not be commonly used.

The tools in Table 2 are paired with like tools with similar interactions. Groupings were created using percentages where clear division of tools could be visualized. Tool group interactions could be compared with one another to further analyze the shared interactions found in Table 1. Further analyzing the individual groupings, tools in the higher interaction categories tended to have higher interactions with each other and shared a large number of students. Tools in lower categories shared fewer interactions with one another, which shows that increased specialization will result in decreased usage frequency. Results from Figure 6 highlight the difference in shared interactions between tools.

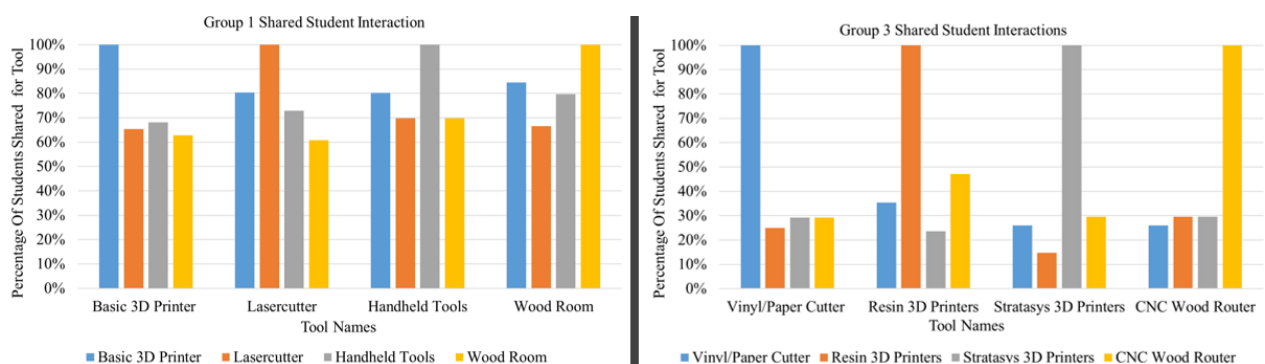


Figure 6: Within-Tool Grouping Interactions. Interactions show the percentage of tool makeup by tools of that category. Group 1 represents tools with a high student interaction and Group 3 represents tools with few student interactions.

Figure 6 analyzes the tool groupings for connections within groups. The smaller the total interaction between groups, the smaller the usage overlap between tools. The high interaction tools from Group 1 share over 50% of their student interactions with other tools within their own category. Usage overlap dropped lower for the fewer interactions between tools in Group 3, with tools sharing less than 30% on average. This shows that tools in this category are more specialized. One important note for the minimal use tools from Group 4 was the interaction between the embroidery machine and the sewing machine. Over 80% of the students surveyed who used the embroidery machine also used the sewing machine, but less than 40% of students surveyed who used the sewing machine used the embroidery machine as seen in Figure 7, showing the potential for "one-way" interactions of tools, particularly when one tool's use might stem from the use of another tool. The one-way interactions would suggest that while one tool may share almost all of its users with another one, the shared tool may only be a small percentage of users for the other. This idea is further expanded upon when comparing the basic 3D printer to other tools in the space. Students who used the 3D printer make up a large percentage of other tools, such as the wood room, but this percentage is a smaller percentage when looking at the 3D printer.

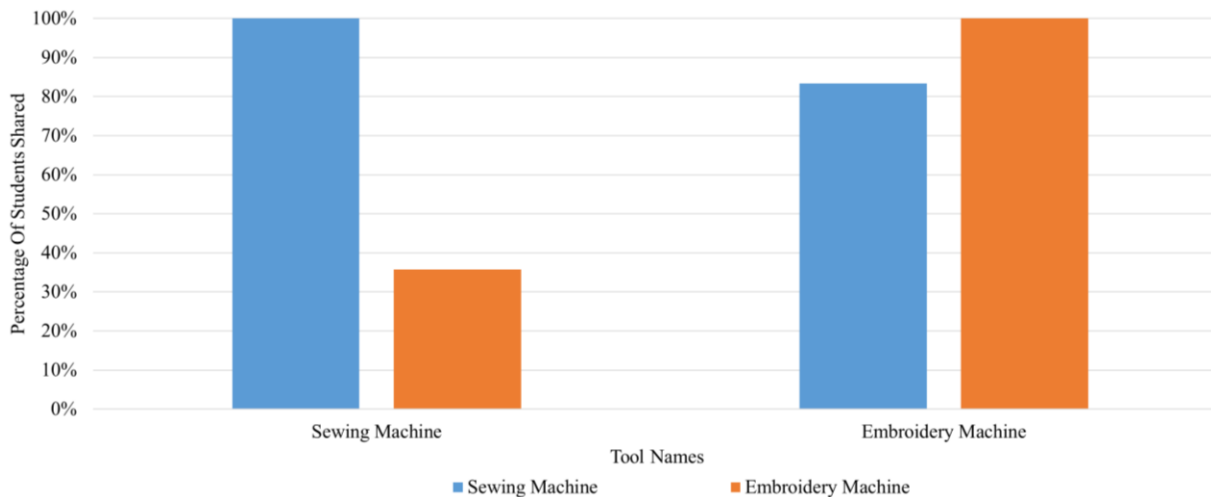


Figure 7: Shared Student interactions between the embroidery machine and the sewing machine.

Observations from the one-way interactions and the higher used tools act as a gateway and makes up a large percentages of other lower use tools, suggest that there may be tool dependencies within the space. Tool combinations, such as the sewing and embroidery machines and the different styles of 3D printing being largely connected to the more specialized 3D printing, suggest that basic tools are being learned first and easing students into interacting with other, often more complex, tools in the space.

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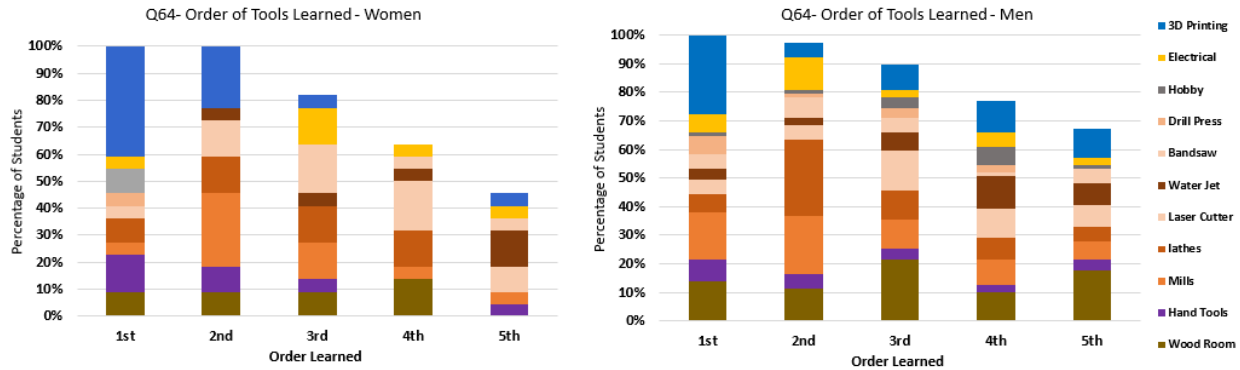


Figure 8: Order of tools learned by gender. The respective populations are 24 and 87. Results are from student answers of survey question 64, in which students recall the order which they learned tools in the makerspace.

Combining both the matrix analysis as well as survey information, potential answers as to why certain tools are used more than others, as well as patterns, can be deciphered. Graphs indicate that the tools that are learned first are often the tools that fall in the high use interaction group with the 3D printer and the handheld tools. Medium interaction tools such as the lathes and mills are learned after a higher use interaction tool, showing that students first learn a more commonly used tool before fully delving into the space.

Figure 8 provides a valuable insight into how men and women are using the space differently. Generally speaking, across the first five tools learned, men are learning a greater diversity of tools, particularly with respect to tools and machinery in the metal room of the makerspace. Furthermore, response rates for women dropped off drastically past the "2nd tool learned" portion of the question, with only 48% of women have reported learning a 5th tool, while 68% of men reported learning a 5th tool. This, in conjunction with the lower diversity of tools learned, may suggest that women may be using only tools like 3D printers wood room tools. These are the tools most commonly used in capstone and other course-related work, with some classes explicitly incorporating training in these tools as a portion of the class. Conversely, men using this space may be using the space not only for class-related activities, but also for personal projects and other extracurricular endeavors. Although sample sizes for African American and Hispanic students did not form a large enough population to draw definitive conclusions from (n=16 and n=7, respectively), although trends for these two groups were similar to those of women. Accordingly, there is a need to promote the diversity of tools learned and general participation for essentially all marginalized groups in makerspaces, as these attributes are conducive to better engagement, space usage, and ultimately superior learning experiences [20]. How the space is used, whether it is used exclusively for class or for extracurricular activities, has major ramifications on students' overall participation, as is evident in Figure 9.

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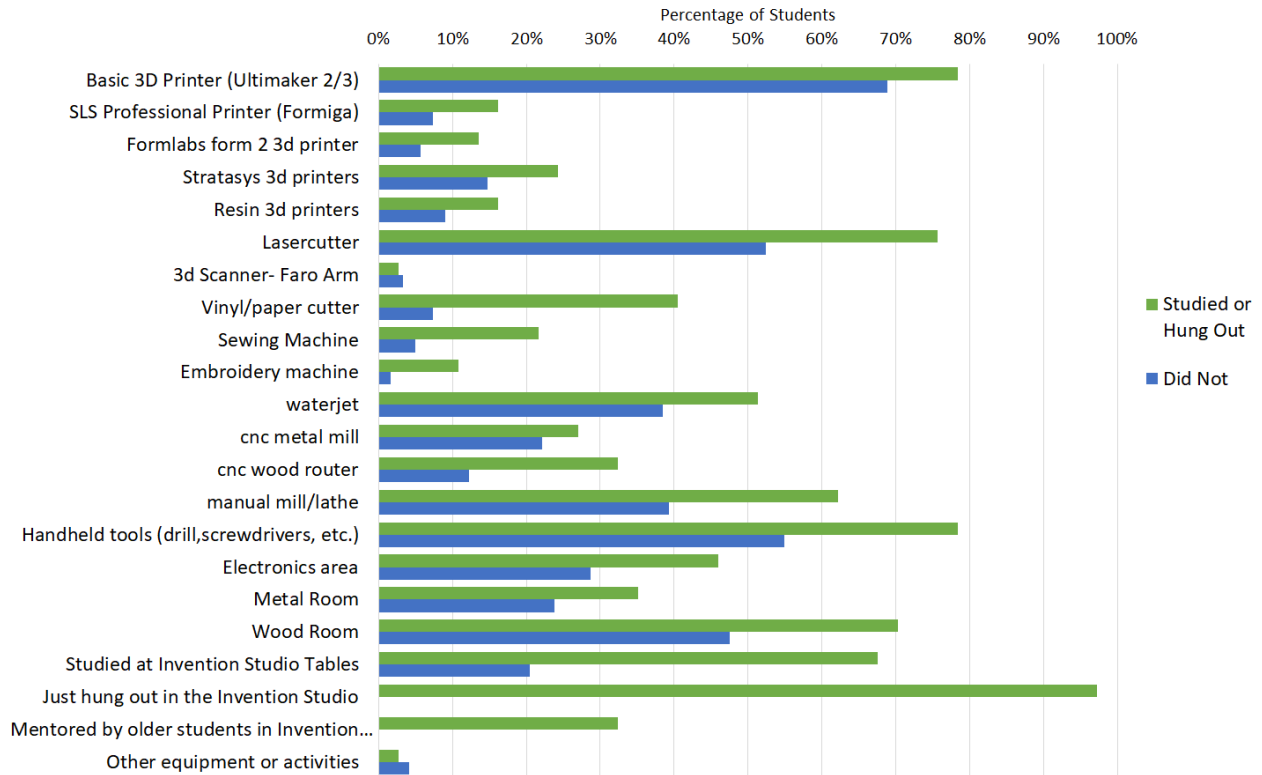


Figure 9: Comparison of tool usage for those using the makerspace as a hang out or study location, versus those who used the space exclusively for making. The percentage of students along the top horizontal axis signifies the percentage of those students surveyed.

Students who used the space as a common area for activities like meeting with groups, studying, or simply hanging out with friends demonstrated higher participation across all tools in the makerspace. Given a major barrier for students in makerspaces is a sense of intimidation from more complicated tools and machines, simply being in the space and observing or collaborating with other students may be conducive to reducing the conventional stresses students experience in these spaces. In addition, the disparity in tool usage between those using the spaces for studying or hanging out and those who did not was particularly high for more niche tools, such as the vinyl cutter and embroidery/sewing machines. There may be a relationship between general participation in the makerspace and for what reason students are using the space, whether that be strictly academic, personal use, or one who views the makerspace as a multi-purpose common area.

While this work has casted a light onto a handful of related factors that are conducive to better makerspace outcomes, moving forward it will be pertinent to better understand this relationship. More specifically, better understanding how general participation is influenced by the different reasons' students may use the makerspace. A stronger understanding of the types of making activities and space usage motivations that are conducive to higher participation and a greater diversity of tools used, can help improve the design and use of makerspaces.

Moving forward, COVID-19 and makerspaces reformed protocols and regulations will provide a novel insight into makerspace usage. Namely, using the space as a social area or study space is prohibited. Moreover, students may generally be deterred from using the space for hobbies and extracurricular activities, potentially creating a temporary makerspace culture where the overwhelming majority of making is done for class purposes only. With similar data to the results presented herein from this era, the relationships between the students' various motives, the impact it has on their learning outcome, and general participation may be better understood.

Analysis on the importance of tools in the makerspace should aid in the future design of design space and allow for setup to combine tools with similar usage rates. While this analysis gives insight into the interactions between the tools and the students, and each tool's role has in engineering education, further analysis will be needed to expand and optimize the analysis. Potential future analysis includes modularity analysis to see the groupings of students and tools.

There are certain limitations to this study concerning the sample population that may indicate the results presented herein are not entirely indicative of the general makerspace users. Namely, students are recruited from a mechanical engineering-based capstone course. While it is possible for students from outside mechanical engineering to take this course, the bulk of students enrolled in this class are predominantly mechanical engineers, resulting in 80% of participants of this study being Mechanical Engineering majors. Furthermore, women, people who identify as non-binary, and people of color constituted relatively small proportions of the sample population. Accordingly, statistical analysis for said populations was not possible. Even with relatively well-represented minorities, sample sizes were relatively small, with women, for instance, having a sample size of $n = 35$.

Certain survey questions also ask students to recall information that may not be easily recalled. There were questions asking students about what point they first learned certain tools, or which tools they had used prior to this semester and their college entry. Given the time between when tools were used and when students completed the surveys in question, their answers may not have perfectly reflected their experiences. This difficulty in recalling the timeline of tool usage and when tools were learned is compounded particularly with simple tools and features of the makerspace, such as hand tools, whiteboards, or even a desk. Given that such tools and features have particularly interesting ramifications for makerspaces efficacy and their outcomes, the information lost from this could be considerable.

While the information gathered does not perfectly capture how makerspaces are being used and the motivations behind this usage, it has nonetheless provided a valuable insight into makerspace usage in the invention studio. Most importantly, this data provides a critical benchmark that results from subsequent surveys at more than one university, allowing for a comparison of a student run versus a staff run makerspace. The surveys and their distributions will need to be enhanced to ensure that the results from such a comparison are more indicative of populations at different schools and their respective makerspaces.

Conclusions

The network analysis suggests potential key tools in the makerspace that can aid in engineering education. Tools like hand tools and simpler 3D printers, for instance, serve as a critical starting to get students into the space and start making. The results suggest that laser cutters and woodworking tools serve as a steppingstone for students to get involved with more intimidating machining tools, which historically are difficult to promote. The analysis sections tools into different usage tiers and uses student demographic and tendencies to understand the space. Results from this analysis can aid future makerspaces in prioritizing makerspaces tools as well as organizing tools based on their interactions and shared usage between students. The analysis found tools ranged from frequently used tools to low usage tools and with higher-level tools introducing students to the makerspace and to different tools. The orders that students learned tools provides a view to the process students follow as they enter the space. Tracking this progress with class schedules in the future, as well as demographic data, could greatly improve understanding of the makerspace. Future work for this research includes expanding the survey pool to different years as well as using data from the makerspace in other universities to get a wider view of two different makerspaces, one being the current student-led makerspace and the other a faculty-led makerspace. Additionally, utilizing modularity analysis to determine “roles” for each of the tools in the space could greatly aid the research breakdown.

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References

- [1] L. Martin, "The Promise of the Maker Movement for Education," *Journal of Pre-College Engineering Education Research*, vol. 5, no. 1, pp. 30-39, 2015, doi: 10.7771/2157-9288.1099.
- [2] Make/Intel, "Maker market study and media report: An in-depth profile of makers at the forefront of hardware innovation," 2012. Accessed: 5/2019. [Online]. Available: Makezine.com: <https://cdn.makezine.com/make/sales/Maker-Market-Study.pdf>
- [3] M. Tomko, R. Nagel, M. Alemán, and J. Linsey, "Learning in Academic Makerspaces: How Inclusivity Affords Learning for Female Students in Various University Makerspaces," presented at the ASEE Annual Conference, Salt Lake City, UT, 2018.
- [4] V. Bean, N. M. Farmer, and B. A. Kerr, "An exploration of women's engagement in Makerspaces," *Gifted and Talented International*, vol. 30, no. 1-2, pp. 61-67, 2015, doi: 10.1080/15332276.2015.1137456.
- [5] J. L. Saorín, D. Melian-Díaz, A. Bonnet, C. C. Carrera, C. Meier, and J. De La Torre-Cantero, "Makerspace teaching-learning environment to enhance creative competence in engineering students," *Thinking Skills and Creativity*, vol. 23, pp. 188-198, 2017.
- [6] R. Morocz *et al.*, "Relating Student Participation in University Maker Spaces to their Engineering Design Self-Efficacy," in *American Society for Engineering Education Annual Conference*, New Orleans, LA, 2016.
- [7] R. P. Smith and A. Leong, "An observational study of design team process: A comparison of student and professional engineers," 1998.

2021 ASEE Conference

- [8] E. Hilton, M. Tomko, A. Murphy, R. Nagel, and J. Linsey, "Impacts on Design Self-Efficacy for Students Choosing to Participate in a University Makerspace," presented at the International Conference on Design Creativity, Bath, UK., 2018.
- [9] E. Hilton, M. Tomko, W. Newstetter, and R. Nagel, "Investigating why students choose to become involved in a university makerspace through a mixed-methods study," presented at the ASEE Annual Conference, Salt Lake City, UT, 2018.
- [10] T. Barrett *et al.*, "A Review of University Maker Spaces," presented at the American Society for Engineering Education Annual Conference, Seattle, WA., 2015.
- [11] M. Tomko, "Developing One's "Toolbox of Design" through the Lived Experiences of Women Students: Academic Makerspaces as Sites for Learning " PhD Dissertation, Georgia Institute of Technology, Atlanta, GA, 2019.
- [12] J. Lewis, "Barriers to women's involvement in hackspaces and makerspaces," *Access as spaces. Available at: <http://access-space.org/wp-content/uploads/2015/10/Barriers-to-womens-involvement-in-hackspaces-and-makerspaces.pdf> (accessed 10 May 2016)*, 2015.
- [13] F. B. K. Song Yang, Lu Zheng, *Social Network Analysis*. United States of America: SAGE Publications, 2017.
- [14] M. Latapy, C. Magnien, and N. Del Vecchio, "Basic Notions for the Analysis of Large Affiliation Networks / Bipartite Graphs," pp. cond-mat/0611631. [Online]. Available: <https://ui.adsabs.harvard.edu/abs/2006cond.mat.11631L>
- [15] M. O. Jackson, *Social and Economic Networks*. New Jersey: Princeton University Press, 2008.
- [16] E. C.-N. Fatima Senghore, Pavel Fomin, James S. Wasek,, "Using Social Network Analysis to Investigate the Potential of Innovation Networks;," *Procedia Computer Science*, vol. Procedia Computer Science, pp. 380-388, 2014.
- [17] J. B. Jens M. Olesen, Yoko L. Dupont, Pedro Jordano, "The modularity of pollination networks," *Proceedings of the National Acedemy of Sciences*, 2007.
- [18] C. Brehm, J. Linsey, and A. Layton, "Using a Modularity Analysis to Determine Tool and Student Roles within Makerspaces," presented at the 2020 ASEE Virtual Annual Conference, Virtual Online, June 22-26, 2020, 29636.
- [19] P. R. John Moore, Kevin McCann, Volkmar Wolters, *Adaptive Food Webs*. Cambridge University Press, 2018.
- [20] A. C. Barton, E. Tan, and D. Greenberg, "The makerspace movement: Sites of possibilities for equitable opportunities to engage underrepresented youth in STEM," *Teachers College Record*, vol. 119, no. 6, pp. 11-44, 2016.