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Bio-inspired human network diagnostics: Ecological modularity and nestedness as quantitative indicators of human engineered network function

Samuel Blair[1] | Garrett Hairston[1] | Henry Banks[2] | Claire Kaat[2] | Julie Linsey[2] | Astrid Layton[1]

[1]J. Mike Walker '66 Department of Mechanical Engineering, Texas A&M University, College Station, Texas, USA

[2]George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, Georgia, USA

Correspondence
Astrid Layton, J. Mike Walker '66 Department of Mechanical Engineering, Texas A&M University, College Station, TX, USA.
Email: alayton@tamu.edu

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Abstract

Analyzing interactions between actors from a systems perspective yields valuable information about the overall system's form and function. When this is coupled with ecological modeling and analysis techniques, biological inspiration can also be applied to these systems. The diagnostic value of three metrics frequently used to study mutualistic biological ecosystems (nestedness, modularity, and connectance) is shown here using academic engineering makerspaces. Engineering students get hands-on usage experience with tools for personal, class, and competition-based projects in these spaces. COVID-19 provides a unique study of university makerspaces, enabling the analysis of makerspace health through the known disturbance and resultant regulatory changes (implementation and return to normal operations). Nestedness, modularity, and connectance are shown to provide information on space functioning in a way that enables them to serve as heuristic diagnostics tools for system conditions. The makerspaces at two large R1 universities are analyzed across multiple semesters by modeling them as bipartite student-tool interaction networks. The results visualize the predictive ability of these metrics, finding that the makerspaces tended to be structurally nested in any one semester, however when compared to a "normal" semester the restrictions are reflected via a higher modularity. The makerspace network case studies provide insight into the use and value of quantitative ecosystem structure and function indicators for monitoring similar human-engineered interaction networks that are normally only tracked qualitatively.

KEYWORDS
bio-inspired design, connectance, makerspaces, modularity, nestedness, network analysis, system design

1 INTRODUCTION

Many of the world's complex networks can be simplified to directed graphs where variables and interactions are mapped between actors. Simplifying complex systems down to a graph network of interactions enables analyses that can improve our understanding of their functioning. Ecologists, for example, use graph and information theory-based approaches to study complex biological ecosystems. Plant-pollinator networks become bipartite models, and interspecies predatory networks become unipartite food web models.[1] Network graphs and their matrix depictions are used in ecological and social network analyses to map and study complex networks and their interactions.[2,3] Social science utilizes bipartite matrices where rows are actors and columns are events to understand how actors are related to each other through shared events.[2] A bipartite model can be used any time two unique groups can be identified within a chosen system boundary where interactions are only between the two groups and not within the group. NASA, for example, uses networks to study innovation in their space challenge app, finding that mapping the innovation space of different teams working on the NASA International Space Apps Challenge as a bipartite network can aid in understanding the transfer of information.[4] Other examples of bipartite networks include neuron-to-synapse interactions in neural networks, airports-flights transportation networks, and plant-pollinator models of ecosystems.[1,5,6]

Ecological Network Analysis (ENA) provides insight to ecologists about ecosystem structure and functioning that couldn't obtained otherwise.[7] This approach can identify critical actors who deserve extra conservation efforts[8] patterns in redundant feeding that supports both growth and resilience,[9] and the importance of the "brown food web" in maintaining cyclic interactions that maximize value extraction.[10,11] The graph-based approaches investigated here are nestedness and modularity.[12] These analyses are primarily used by ecologists to study plant-pollinator and other bipartite networks, where two groups of actors interact across—not within—groups.[2,3,13,14] Prior work investigated the nestedness of Eco-Industrial Parks as unipartite networks, finding that they can improve their sustainability and resilience when they have more ecologically-similar nested structures.[15,16] Nestedness has also been used to predict the stability of bipartite networks to perturbations, looking at the failure rate of global trading companies based on their role in larger industrial networks.[17,18] That work found that when companies deviated from the highly nested structure of their global training network, a few years later they had disappeared/were replaced by one that more closely followed the larger network's nested structure.[17]

This paper draws inspiration from nature's mutualistic networks (which are modeled as bipartite networks, for example, plant-pollinator and soil networks)—their resistance to disturbances and network stability has been found to relate to the levels of modularity and nestedness in their architectures,[19–21] however more recent works have found that the previously held ecological belief that "universal nestedness" existed among mutualistic networks is outdated[22,3,24] due to practices such as using only "tiny taxonomic cuts" that exclude rarely occurring species[25] or are overly dependent on network size[26] or degree.[27] Enhanced resilience is highly desirable in human networks and identifying ecological network structures associated with resilience can offer valuable bio-inspired design guidance. The ENA metrics that describe these network characteristics[28] offer a route for applying this biological system inspiration. Power grids, industrial manufacturing networks, water distribution, and supply chains have all been shown to improve their performance when they mimic the topological and functional characteristics of biological food webs.[29–34] Food webs for example, have been found to have a unique balance of redundancy and efficiency in their networks,[35,36] a characteristic that is translatable to human-engineered systems and systems of systems in such a way that their resilience is improved.[37,38]

Nestedness, modularity, and connectance of bipartite networks as a group[23,39–41] describe a network beyond just a density of connections, highlighting *where* connections are found and where they are sporadic.[42] The insights they can provide for bipartite human networks are investigated here using *university engineering makerspaces*. The goal of these spaces is to provide engineering students with a unique and hands-on educational experience where students use a wide variety of tools, and the tools serve as stepping stones through the space. The spaces however are still relatively new, with only a minimal amount of research into hidden roadblocks that can limit use by certain demographics and indirect effects that can have huge influence on usage patterns.[43–46] These characteristics are almost impossible to see with the naked eye but may be visible using network models. These spaces also provide a unique case study in contrast with more traditional unipartite networks that hopefully broaden readers' scope of when system perspectives and biological inspiration may be of value.

Prior research utilizing nestedness and modularity analysis to categorize networks and identify their underlying structures[1,12,47,48] have focused on static network depictions under normal

SIGNIFICANCE AND PRACTITIONER POINTS

Three metrics commonly used by ecologists to study mutualistic ecosystems (nestedness, modularity, and connectance) are shown here to provide valuable quantitative information about the functioning of academic engineering makerspaces, modeled as bipartite student-tool interaction networks. Although engineering makerspaces are used here as a case study, the results provide support for the use of these metrics as performance indicators for a wide variety of human-engineered networks that can be represented in a bipartite model. The findings suggest that these metrics can serve as heuristic diagnostics tools for system conditions over time resulting from both intended and unintended restrictions placed on networks.

circumstances. Understanding how a network changes over time, especially in response to a disturbance, is critical for understanding if network characteristics like nestedness and modularity can signal network health. For the makerspaces investigated here, there was interest in if the spaces had recovered from the COVID restrictions. Due to the nature of ecosystem data collection tracking modularity and nestedness changes during and after a disturbance can be difficult.[49] Modularity and nestedness have primarily been used in the ecological realm and as such this paper presents the first investigation into the ability of nestedness and modularity to measure network health over time. Modeling makerspaces through COVID-19, when significant restrictions to student usage were in place that were then gradually lifted, provides a unique opportunity to capture a system that is undergoing drastic changes.

2 | METHODS

Nestedness quantifies the structural hierarchy amongst actors in a network.[12,42,50] Multiple methods exist to calculate nestedness, but *Nestedness based on Overlap and Decreasing Fill* (NODF) is used here. NODF has supported understanding both the impact of invasive species in soil networks and resilience to external and unexpected disturbances in plant-pollinator networks.[19] Nested ecological networks have been found to avoid mass extinction events because their structure promoted interactions between specialists and generalists creating a more stable environment.[51] Nestedness alone can thus provide a strong indication about the stability of the network, with higher nestedness assuring that actors with few interactions are connected to actors with several interactions, preventing the former from failing.[50]

Ecologists have used unweighted *modularity* to identify critical species in plant-pollinator networks. The analysis of over 29 different plant-pollinator networks identified modular structures with the plants often linking the modules together.[1] Modularity also aids in understanding how a network is partitioned and can be calculated using unweighted (binary visitations) data, as is done here, or weighted (frequency) data.[52,53] Modularity identifies groupings of actors based on their interactions, as well as hub actors that highly connect the network and specialized actors that may be at risk of losing connection.[54,55] A modularity analysis of global flights was able to identify airport hubs.[6] The complex global aerial transportation network was broken up into modules which easily identified the airports that connected these modules and airports that were dangerously disconnected.[6]

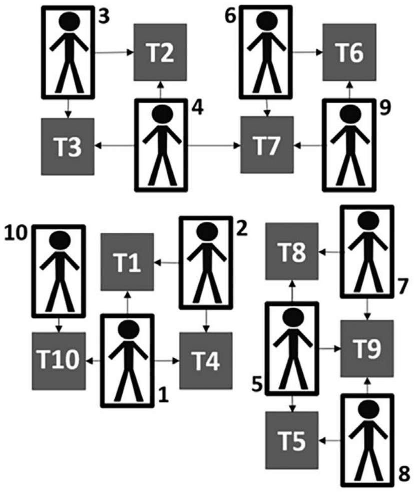
Connectance quantifies how connected a network is in reference to its total number of possible interactions.[12] Connectance is used in ecology as a measure of ecosystem complexity, with a higher connectance indicating a more diverse network.[56] While connectance alone cannot describe network stability, it provides critical information for understanding a network's nestedness and modularity as it controls their bounds.[12,56,57] Thus, by pairing the metrics together, a better understanding of a network's structure, and therefore functioning, is achieved. Connectance must be included whenever modularity and nestedness are analyzed, as will be clearly shown in the results following.

2.1 | Case study

Students use of tools across three semesters at two large university engineering makerspaces are used to illustrate the value of modularity and nestedness for understanding and designing human networks.[58] The first two semesters (Fall 2020 and Spring 2021) were semesters under increased COVID-19 restrictions limiting student use of the space. These restrictions were being removed by the third semester (Fall 2022), allowing for a look at "normal" operating conditions for the space. Students use tools such as 3D printers and laser cutters in these spaces for anything from classes to personal projects to student competition teams. When modeled as a bipartite network of students and tools, modularity and nestedness can identify hub tools and students[58] and unintentional restrictions placed on students and tools preventing use.[59] This type of information can provide valuable insight for designers, decision makers, and evaluators in a wide range of human networks with a bipartite configuration.

The makerspaces are modeled as bipartite networks of students and tools, with the goal being to understand the impact of tool use on the functioning of the spaces. The two schools have different underlying ideologies: School A is a primarily staff-run space with student volunteers where students use the space for their classes. School B is a student-run space usable for both classes and personal projects. Table S1 lists the specific tools in each space at both schools and how they were organized into 12 *general* tool types. The general makerspace model is needed for comparing the makerspace network structure across different makerspaces and schools as they will have similar general tool times but may have different specific tools in each category. The most obvious difference between using specific and general tool network representations is an increase in network size due to an increase in tools modeled. The increase in network size causes a decrease in connectance that forces a decrease in the nestedness, as outlined later in the results (Figure 5). To account for this, normalized nestedness and null models are used to compare between semesters.

The bipartite networks of students and tools were created using end-of-semester surveys. The surveys asked students to self-report the tools they used, both general and specific, over the course of that semester. For example, a student who said they used a 3D printer would then be asked which specific 3D printer was used (a drop in students' response rates was seen between the general and specific tool selections that may impact the network analysis results, see discussion). The survey did *not* ask about the frequency of a tool's use. The surveys also collected demographic information and captured experience characteristics such as class usage and social interactions. Prior work has used network analyses to look at specifics of these spaces with respect to their maintenance,[59] class versus personal usage,[60] and demographic data.[60] Survey responses were compiled into a bipartite graph and associated matrix like what is shown in Figure 1. A value of one in the matrix indicates a student interacted with a tool and zero if



	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
S1	1	0	0	1	0	0	0	0	0	1
S2	1	0	0	1	0	0	0	0	0	0
S3	0	1	1	0	0	0	0	0	0	0
S4	0	1	1	0	0	0	1	0	0	0
S5	0	0	0	0	1	0	0	1	1	0
S6	0	0	0	0	0	1	1	0	0	0
S7	0	0	0	0	0	0	0	1	1	0
S8	0	0	0	0	1	0	0	0	1	0
S9	0	0	0	0	0	1	1	0	0	0
S10	0	0	0	0	0	0	0	0	0	1

FIGURE 1 Hypothetical example makerspace network with interactions. Left—A graphic representation of the network. Right—The bipartite matrix [B] for the hypothetical network shown in Figure 1, with students (S1–10) as rows and tools as columns (T1–10). Interactions between any two are documented with a one and no interaction with a zero.

they did not. The example hypothetical bipartite makerspace network in Figure 1 is representative of those created from the surveys.

2.2 | Modularity

Once the network of interest is created and an interaction matrix constructed (Figure 1-Right), its modularity can be analyzed. A modularity analysis identifies modules present in the network by reorganizing the structure and links until its maximum modularity value is reached.[61] This optimization can be done using several different methods,[61] the Newman/Leading Eigenvector method ([61], Equation (1)) is used here for its added benefit that modules are reproducible given the same inputs to allow for a consistent modularity value to be obtained as well as providing the maximized modularity for the network.[62] The MATLAB package BiMat[62] runs the Newman method to find the modules (Q).

$$Q_b = \frac{1}{L}\sum_{ij}\left(B_{ij} - \frac{k_i d_j}{L}\right)\delta\left(g_i, h_j\right) \quad (1)$$

Equation (1) calculates the overall network modularity (Q), where E is the total number of interactions or links in the network, B_{ij} is the matrix entries (one representing an edge or zero for none), g_i and h_j are the module indices of the nodes i and j, and k_i and d_j represent the degree of the node i and j respectively. The δ term parses the module indexes for pairings between actor groups (in this case students and tools) and assigns a value of one if they are in the same module and a value of zero if they are in different modules. The process is carried out by initially splitting the network into two modules using the algorithm and calculating the Q_b. The network is further split up into more modules until the splitting no longer increases the overall network's modularity.[61] Modularity can be any value between zero and one, with a value of one indicating a perfectly modular network.

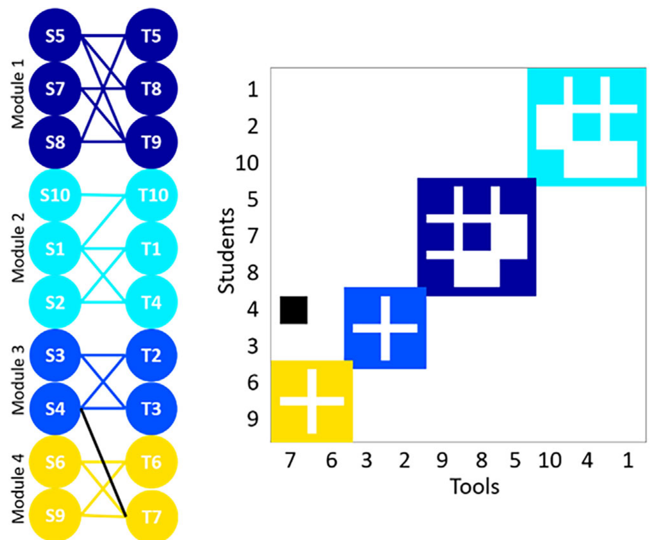
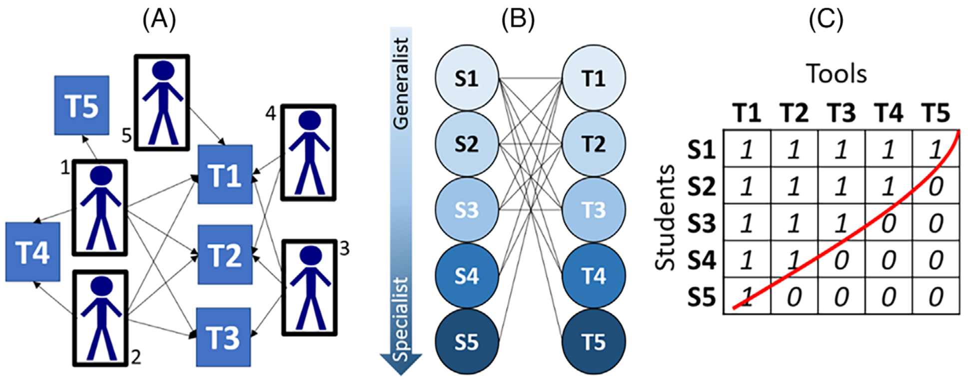


FIGURE 2 Left—Bipartite representation of the network with students (S1–S10) interacting with tools (T1–T10) and color organized by module. Right—BiMat software[62] output highlighting the network from Figure 1 with interactions (colored in squares) organized into modules, shown with four different colors (black interactions fall outside of any module).

Figure 1-Right shows the **B** matrix for the hypothetical makerspace network of Figure 1-Left with 10 tools (T1–10), tracking 10 students' (S1–10) use of the space. The matrix denotes all the network interactions found in the space with a one, and zeros indicate no interaction. As seen in Figure 2-Left, the students fall into modules based on common tool usage. For example, Students 1, 2, and 10 together form a module (teal color in Figure 2) based on Tools 1 and 2 only being used by Students 1 and 2 and Tool 10 only being used by Students 1 and 10. These types of patterns in a small and highly modular network are identified relatively easily with a simple visual scan. As a network grows in size and complexity, however, this becomes exponentially harder, if not



	T1	T2	T3	T4	T5
S1	1	1	1	1	1
S2	1	1	1	1	0
S3	1	1	1	0	0
S4	1	1	0	0	0
S5	1	0	0	0	0

FIGURE 3 A hypothetical makerspace of 5 students and 5 tools with a nested structure. (A) Diagram of the sample makerspace. (B) Bipartite graph of the makerspace. (C) BiMat nested network output visualizing the network matrix, where the curve indicates the nested interactions boundary.

impossible. MATLAB's BiMat package was used here to find modules and calculate the overall modularity following Equation (1). BiMat produces a visual depiction of a network's interactions, rearranging them to best show modules (as shown in Figure 2-Right).[62] The modularity value for the hypothetical network of Figures 1 and 2 is 0.69. The main drivers of this modularity can be seen in Figure 2-Right, where the colored boxes indicate within-module interactions and the black box indicates outside-of-module interactions. The one out-of-module interaction, student 4 using tool 7, reduces the network's modularity from a perfect value of one. A null model analysis (described in the following section) is needed to understand whether the value of 0.69 indicates that the network is *statistically significantly modular* based on a network of the same size and connectance (in this case connectance is 0.22).[12,47]

2.3 | Nestedness

Nestedness can be calculated for either a bipartite or unipartite network from the interaction matrix. Nested networks, when rearranged from most connected actor to least connected actors top to bottom rows and left to right columns, will wind up with the most general actor in the upper left of the matrix and the least general actor in the bottom-left and top-right, as seen in the sample perfect nested matrix in Figure 3.[50] Nestedness can be calculated a few different ways, with some techniques normalizing the resultant metric on a scale of zero to one and others, like the one used here, from zero to one hundred.[18,50,63] *Nestedness based on Overlap and Decreasing Fill* (NODF) is based on "overlap and decreasing fill" to evaluate a network's architecture and is considered a more appropriate metric for interaction networks.[50,63] NODF calculates nestedness values for each row and column individually before combining those values into an overall nestedness result. These column and row nestedness values can additionally be used to aid in understanding a network's architecture in more detail.

NODF first organizes the bipartite network in order of total number of interactions, with the rows organized from most to the least interactions top to bottom and the columns organized from most to least interactions from left to right. The organized matrix for the hypothetical student-tool network in Figure 3A can be seen in Figure 3C. Once organized, NODF is calculated to find the overall nestedness, ranging from 0 to 100 (or 0 to 1 if normalized) with the higher value indicating a more nested network.[12,63] Mutualistic networks in nature, like plant-pollinator and soil networks, tend to have NODF values ranging from 0.35 to 0.7 (on a scale of 0–1).[63,64]

Equations (2) and (3) are used to calculate NODF and Figure 4 walks through this process of calculating NODF for a very small 3×3 network. The two main aspects of the NODF analysis are the "decreasing fill" and "overlap." NODF pairs and compares each row with every other row and each column with every other column (as seen in Figure 4). The "decreasing fill condition" is checked first for each pair to ensure that the number of interactions in the first is more than in the second by at least one (from left to right for columns and top to bottom for rows). If this condition is not met NODF defaults to zero. When met (for example, in the C1-C2 comparison at the top of Figure 4 where C1 has more interactions than C2), the number of interactions that match from the second to the first is checked. For a column comparison, C1-C3 in Figure 4-top clarifies that only one of the two C3 interactions is also found in C1, giving this subset an N_{paired} value of 50 (i.e., 50% of interactions match between the two columns). In the case of C1-C2 both C2 interactions are found in C1 so the value is 100. Once all comparisons have been made, the N_{paired} values are averaged, producing N_{column} and N_{rows}. The final NODF value is the average of N_{column} and N_{rows}. NODF can be calculated manually for smaller networks but becomes increasingly difficult for larger networks. Matrix ordering and NODF calculations can be done within the BiMat MATLAB package.[62]

$$M_{ij} = \begin{cases} 0 & \text{if } c \leq k_j \\ \dfrac{n_{ij}}{\min(k_i, k_j)} & \text{otherwise} \end{cases} \tag{2}$$

In Equation (2), k_i is the sum of row/column i, k_j is the sum of row/column j, n_{ij} is the total number of entries that match between the

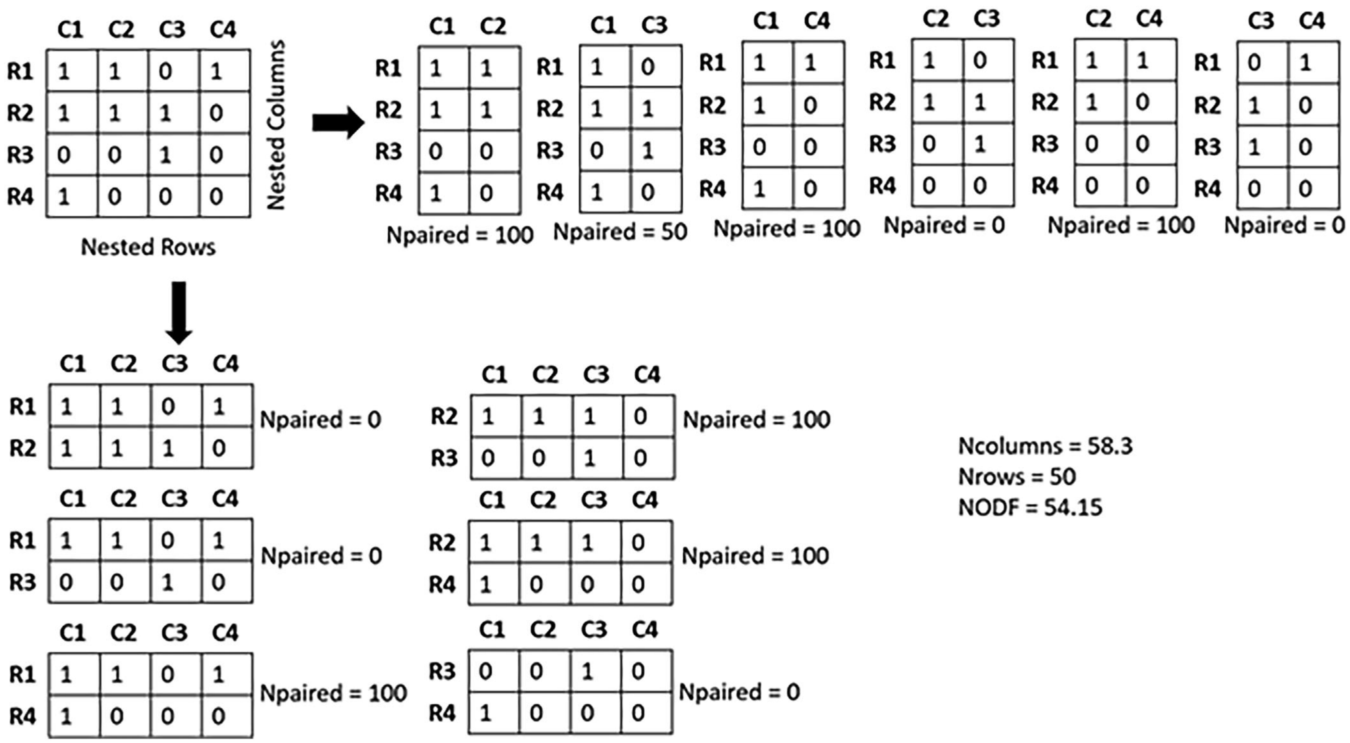


FIGURE 4 Process for calculating NODF of a hypothetical 4 × 4 network (top-left, actors R1–4 interacting with actors C1–4). The top-right process shows the column nestedness calculations and the bottom-left process shows the row nestedness calculations. The culmination of which is shown in the bottom-right with the overall NODF value.

two and c is the number of entries that have a value of 1 in k_j. Equation (3) is the NODF value normalized for the matrix size to better compare different sized matrices, producing a final NODF value from zero to one.

$$\mathrm{NODF} = \frac{\sum_{ij} M_{ij}row + \sum_{ij} M_{ij}col}{\frac{m(m-1)}{2} + \frac{n(n-1)}{2}} \tag{3}$$

The NODF calculation process also identifies generalist and specialist actors in the network.[12] Generalist actors will always be closer to the top-left of the matrix while specialist actors will be closer to the bottom and to the right. A nested makerspace network would indicate that students are using a generalist tool first, then progressing through the space to interact with more complicated and specialized tools. Figure 3B shows a perfectly nested network, with specialist students (for example S4 and S5) interacting with generalist tools (in this case T1 and T2). The nested analysis can identify generalists and specialists and how they interact in the network, the underlying causes as to why a network is nested or not may not be obvious and would require supplementary investigations.

2.4 | Connectance

While both nestedness and modularity analysis can provide valuable insight into a network, it is imperative to see both in combination to fully understand the network. Nestedness and modularity are related, with the primary connection being the network connectance (C, Equation (4) and a value from zero to one).[12] Generally, the higher a network's connectance the higher its nestedness will be, while the lower the connectance the higher the modularity.[12] There are bounds on these trends however, explored later in the results, that also depend on network size (the total number of rows, N_{rows}, and the total number of columns, $N_{columns}$).

$$C = \frac{L}{N_{rows} N_{columns}} \tag{4}$$

The numerator of Equation (4) is the total number of network connections (L, the sum of all entries in matrix **B**). The denominator is the total number of *possible* connections or the number of rows multiplied by the number of columns. A connectance of one indicates that all possible interactions are occurring meaning that everything is connected to everything. A connectance of zero indicates that no interactions exist in the network. While research has highlighted the importance of analyzing nestedness and modularity together, most work has focused on either specific connectance ranges or on the overall importance of nestedness and modularity.[12,42] The work in this paper expands on the relationship presented previously and creates a view of the full range of the relationship between the two metrics with the sample network creation to further enhance the understanding of the relationship between nestedness and modularity.

TABLE 1 Network size (rows = students × columns = tools), nestedness (NODF), modularity (*Q*), and connectance (*C*) for Schools A and B in Fall (FA) and Spring (SP) 2020, 2021, and 2022. Null models are listed for both the corresponding semester AND for SP22 only (the normal semester, for which School A's connectance is 0.34 and School B's connectance is 0.4). Results are shown for general tool groups. Null models that are significantly different from the real network at $p > .05$ are starred (*).

	Sem.	Size	*C*	*Q*	Each semester's null model *Q* (*z*-value)	SP22 null model *Q* (*z*-value)	NODF	Each semester's null model NODF (*z*-value)	SP22 null model NODF (*z*-value)
School A	FA20	54 × 10	0.25	0.34	0.36 (0.32)	0.26 (6.15)*	0.50	0.27 (6.79)*	0.36 (2.46)*
	SP21	178 × 12	0.18	0.38	0.40 (−1.25)	0.23 (17.3)*	0.33	0.20 (12.7)*	0.36 (−2.33)*
	SP22	77 × 12	0.34	0.19	0.24 (−3.93)	0.25 (−3.92)*	0.55	0.36 (9.71)*	0.36 (10.1)*
School B	FA20	57 × 13	0.39	0.18	0.21 (−2.76)*	0.21 (−2.49)*	0.64	0.40 (10.9)*	0.41 (10.1)*
	SP21	94 × 13	0.34	0.20	0.23 (−2.86)*	0.19 (0.17)	0.61	0.36 (15.0)*	0.41 (11.6)*
	SP22	95 × 13	0.40	0.18	0.2 (−1.45)	0.20 (−1.91)	0.59	0.42 (12.8)*	0.41 (10.1)*

2.5 | Null models

Determining if a network's nestedness and modularity results are statistically significant requires the generation of null models to check against the nestedness and modularity of a random network of the same size and connectance.[12,65,66] A *type-one null model*[65] is used here, with 1000 sample networks generated at each connectance value listed in Table 1. Potential errors associated with empty rows in the random network generation were accounted for by forcing all rows to have a value of one. This null model modification was previously used in host-phage interaction networks to better match the dynamics of the network, as well as maintain the null model network sizes.[47] The resultant null model networks have the same size and number of interactions as the original networks, that is, the global properties remain the same. A probability value (*p*) of .05 (z-score > 1.96 or z-score < -1.96) will be used for the network to see whether the resulting modularity and nestedness values are significantly different from those that would be randomly generated, as determined by the null models.[67] Other variations of null models exist with modifications formulated for different applications, see refs. 27, 53, 66, 68.

The procedure used here for evaluating networks undergoing disturbances is to compare a network's modularity/nestedness against a null model that uses the network's connectance from *normal* operations. Data from Spring 2022 provides connectance values for the makerspaces here during a *normal* semester, against which Fall 2020 and Spring 2021 (when COVID-19 restrictions were in place) are compared. This approach enables a network's modularity and nestedness during disruptions to be understood in comparison with how the network *should* be able to operate.

3 | RESULTS

3.1 | Modularity, nestedness, and connectance

One thousand networks at nine different network sizes, from 10 × 10 to 100 × 100, with varying connectance values were generated to highlight the relationship between nestedness, connectance, and modularity in Figure 5. The results highlight a strong negative correlation between nestedness and modularity for all but the most connected networks (in most cases a connectance of 0.85 or greater).[12,47,65] The highlighted connected networks experience a drop in nestedness due to the ideal "triangular shape" seen in Figure 3C not being achievable.[63] These results suggest that modularity and nestedness *for a specific network size* are bounded by the connectance of a network. Increasing or decreasing the modularity or nestedness of a network requires that the connectivity be changed. These findings are consistent with previous work highlighting connectance as a major limiting factor in achieving specific network properties related to degree distribution like nestedness.[57] This is the first visual depiction however of the clear relationship between these three metrics. The primarily negative relationship between modularity and nestedness also varies with a network's size, with larger networks (Figure 5-Bottom Right) more constrained to a specific modularity based on nestedness and connectance. These results are critical to guide the use of modularity and nestedness as a network design goal, and they clarify that without a specific connectance, a desired modularity and/or nestedness is not achievable.

3.2 | Makerspaces' modularity and nestedness analyses

School A was found to have a higher modularity and a lower connectance than School B during all three semesters studied. A jump in nestedness at School A during the Spring 2022 semester is seen, possibly due to COVID-19 restrictions in the space being lifted (School A had significantly more student use restrictions in the makerspace than School B due to COVID-19). The modularity and nestedness differences between the two makerspace networks can be largely attributed to differences in connectance (corresponding to student usage of tools). The makerspaces at the two schools have inherent differences in the way they are run. The space at School A is primarily staff-run and used to support course curriculums. School B's space is primarily student-run and used for both course support as well as personal projects. School B's space is also set up such that those tools with

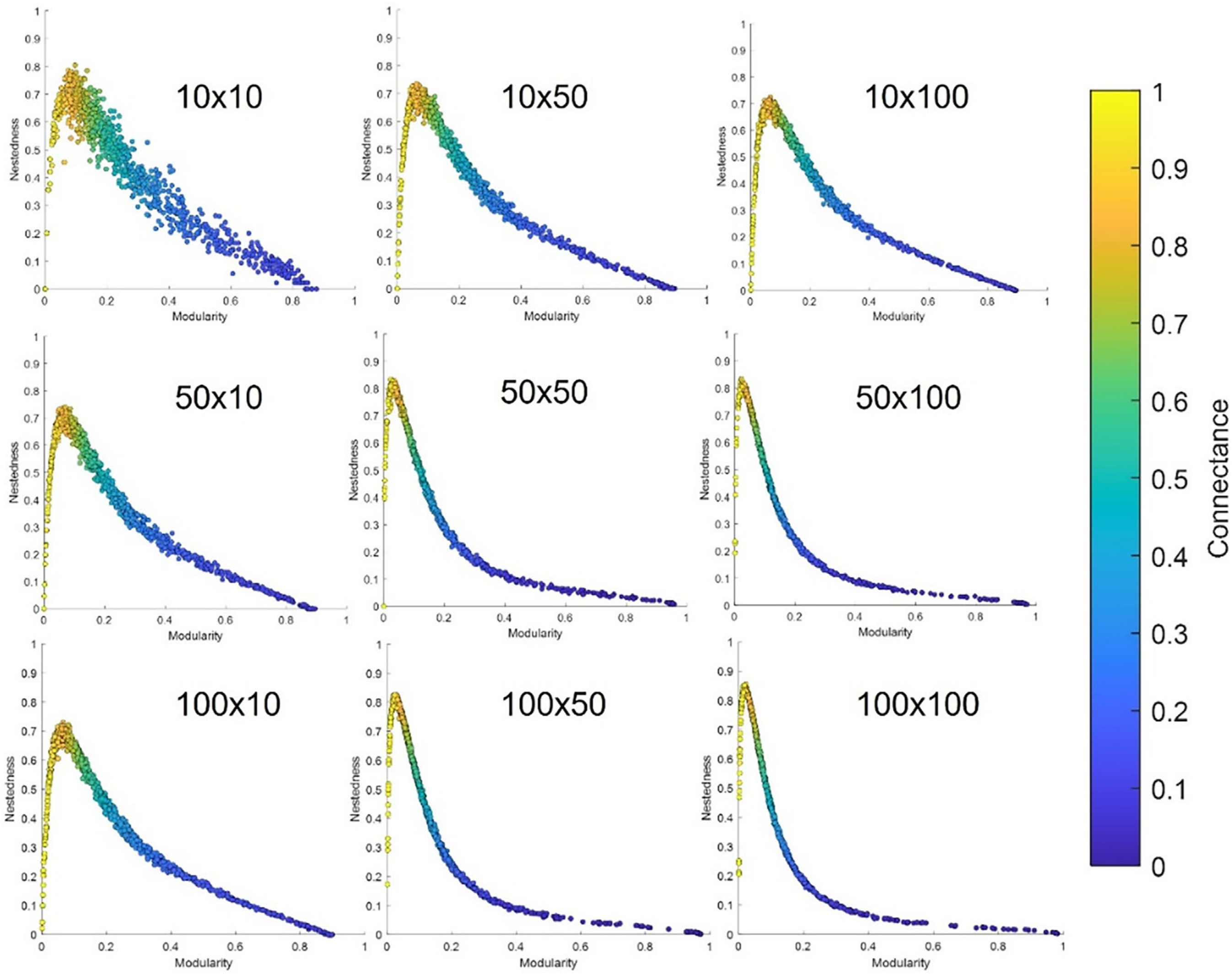


FIGURE 5 The same curve shown for a variety of network sizes, describing the impact of network size on the relationship between modularity (x-axis), nestedness (y-axis), and connectance (color scale on the right).

the most safety restrictions (for example close-toed shoes, long pants, eye protection) are placed such that students who don't meet these requirements can still enter the space. At School A, safety requirements for the most restrictive tools are used as requirements for the entire space. These operational differences, in addition to slight differences in COVID-19 restrictions, show up in the network models as differences in connectance, modularity, and nestedness.

Tables 1 and 2 highlight the properties of the networks each semester and their corresponding null models. The modularity and nestedness visualization of the networks at each school each semester can be found in the supplementary information Figures S1 and S2. Null models that are significantly different from the real network at $p > .05$ are starred. Tables 1 and 2 show a strong correlation for the networks highlighting a nested structure for the makerspace. A nested makerspace indicates many students who have minimal tool interactions in the space (this could be due to many new student(s) coming in to only use something specific) interact with tools like the 3D or other *generalist* tools.[58] The nested makerspaces also indicate that students who have more tool interactions in the space, thereby using a wider variety of tools, are more likely to use tools that are used by fewer students or *specialized* tools.[58] This trend follows intended use patterns for makerspaces. A jump in nestedness is seen Spring 2022 (Table 2 shows that nestedness increased from 0.39 to 0.51 for the specific tool model). The specific tool-based makerspace networks at School B have slightly lower nestedness values than the general tool networks. This decrease is due to the increase in network size resulting in a decrease in connectance (for example, as seen in Tables 1 and 2, Fall 2020 the network's connectance drops from 0.36 in the general network to 0.15 in the specific network). Despite the difference in connectance, the network remains nested in structure when compared to its null models.

Figure 6 visualizes the significance of the modularity and nestedness results for each school, each semester. The y-axis is the difference between the null model and the *general* or *specific* tool network models. Positive difference values indicate significantly more nested or modular than what is generated on average by a random network creation of the same size and connectance. A negative correlation indicates

TABLE 2 Network size (rows = students × columns = tools), nestedness (NODF), modularity (*Q*), and connectance (*C*) for Schools A and B in Fall (FA) and Spring (SP) 2020, 2021, and 2022. Null models are listed for both the corresponding semester AND for SP22 only (the normal semester, for which School A's connectance is 0.15 and School B's connectance is 0.22). Results are shown for specific, individual tools. Null models that are significantly different from the real network at $p > .05$ are starred (*).

	Sem.	Size	C	Q	Each semester's null model Q (z-value)	SP22 null model Q (z-value)	NODF	Each semester's null model NODF (z-value)	SP22 null model NODF (z-value)
School A	FA20	33 × 27	0.10	0.47	0.53 (−1.45)	0.40 (2.86)*	0.22	0.11 (6.95)*	0.16 (3.27)*
	SP21	122 × 76	0.06	0.44	0.42 (1.07)	0.22 (37.7)*	0.14	0.06 (23.1)*	0.16 (−4.09)*
	SP22	70 × 77	0.15	0.22	0.28 (−5.15)*	0.26 (−4.97)*	0.39	0.16 (38.8)*	0.16 (39.9)*
School B	FA20	54 × 45	0.16	0.24	0.30 (−5.09)*	0.24 (−0.19)	0.38	0.17 (20.8)*	0.23 (13.8)*
	SP21	85 × 76	0.14	0.24	0.26 (−2.50)*	0.19 (10.4)*	0.37	0.15 (40.6)*	0.23 (22.3)*
	SP22	94 × 71	0.22	0.18	0.19 (−2.00)*	0.19 (−1.89)	0.51	0.23 (44.2)*	0.23 (44.7)*

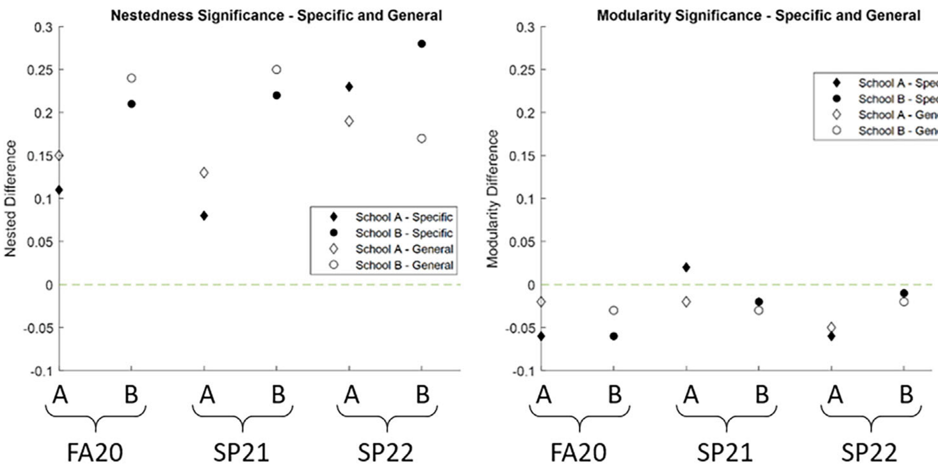


FIGURE 6 Difference between each semester's null model's nestedness (left) and modularity (right) to the modularity and nestedness of each school, each semester for both the general and specific network models.

the measured value is significantly lower than the null model. A zero, or close to zero, difference indicates that the network's nestedness or modularity is similar to what would be randomly generated and is therefore not significant. The nestedness of the spaces at both schools each semester was found to be significant. The modularity of the spaces at both schools each semester is not significant. The significance of this difference is largest for the Spring 2022 semester at both schools when the spaces were back to their normal operations.

The restrictions put in place in these makerspaces during the initial COVID-19 pandemic offer a chance to understand the value of modularity and nestedness for understanding disturbance-induced changes over time. Connectance, the number of interactions in the network versus total possible interactions (seen in Tables 1 and 2), clearly highlights the usage changes occurring due to the COVID-19 restrictions. Without COVID-19 restrictions, one would expect the connectance values of the networks to remain relatively similar from one semester to the next. Understanding how the makerspaces were impacted requires comparing the network each semester to what they would be if that semester were normal, or using a null model corresponding to the connectance of the normal semester. Spring 2022 is taken here as representative of a "normal" semester. Tables 1 and 2 list both the null model for each semester alongside the null model for the Spring 2022 (SP22) "normal" semester. Significant differences in the *z*-values at $p > .05$ of nestedness to the models are starred. The nestedness (NODF) of the "normal" null models are the same for each semester as the calculations accounted for network size when the value is normalized, causing the connectance to be the major driving factor for the null models.

Figure 7 highlights the differences in modularity (right) and nestedness (left) between the "normal" Spring 2022 semester's null model and each school's makerspace networks each semester. School A's (diamond shape) makerspace during Fall 2020 and Spring 2021 has a higher modularity than the null models, indicating that student usage of the space created a significantly modular student-tool interaction network when COVID-19 restrictions were in place. School B's makerspace during Fall 2020 and Spring 2021 compared to the "normal" Spring 2022 semester's null model are still significantly nested in both the general and specific tool formats, as well as having overall lower modularity values.

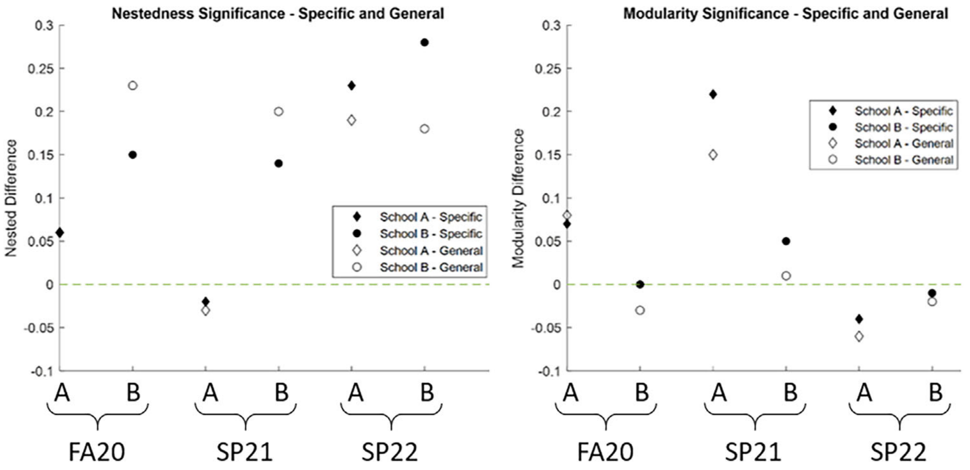


FIGURE 7 Difference between the normal (SP22) null models' nestedness (left) and modularity (right) to the modularity and nestedness of each school, each semester for both the general and specific network models.

4 | DISCUSSION

Nestedness and modularity can identify the current state of a makerspace and any hidden challenges or roadblocks that may exist. A healthy makerspace provides an environment where students can explore different ideas, interact with a variety of tools, and have ample resources to make products.[69,70] University makerspaces must also train students, providing a more hands-on approach to learning course-based material.[71] These goals should result in a nested space, which would indicate that new students are introduced first to general tools while students that have been around longer used a wider variety and more specialized tools. Metrics, such as the variation on Shannon's Index looking at interaction diversity—$H_2{}'$[53], exist that may offer an improved approach for identifying specialization amongst the network's actors using weighted interaction information. A less nested/more modular makerspace structure would indicate that students are only using tools associated with the course they are in, creating clusters or modules of student-tool interactions. An extreme version would be an almost perfectly modular network, with few if any interactions happening outside the modules indicating that students never explore the space beyond the tools used for class.

The makerspaces of the two schools appear similar in real life (both belong to large R1 schools with significant resources and are used primarily to facilitate student learning in engineering courses). The nestedness and modularity analyses used here on student-tool network models provide insight that uncovers significant differences, especially in terms of how they function during and after disruptions. The modular structure of School A's makerspace during a disruption and the nested structure of School B's makerspace staying consistent throughout the ordeal suggest that differences in makerspace operations are causing large impacts at the network level. The analysis done here and shown in Figure 5 underscores the importance of connectance in a network's modularity and nestedness. In the face of perturbations, School B remained static in all its ecological metrics. On the other hand, School A had relatively large changes to the network properties, particularly in its connectance. A static analysis of the space would have likely not yielded valuable information, as the initial null model analysis indicated a consistent trend. However, by imposing a higher expected connectance to the network, a method of analyzing how a network is performing under different conditions can be created. The potential for the shift of the network based on connectance is also highlighted in Figure 5, with connectance being the main driver of the potential nestedness and modularity of a random network. The importance of connectance thus becomes key when analyzing a perturbation, as it is likely that a network will experience potential lower connections during the duration that could drastically affect the work.

The impact of COVID-19 restrictions at each school can be quantitatively visualized using modularity and nestedness analyses and comparing against the network under normal operating conditions. The class-based use restriction at School A is hypothesized to be the primary driver of the lower connectivity and more modular makerspace use structure. The modules here for School A appear to correspond somewhat with specific courses across the different engineering majors that use the space. Variations from this could be attributed to more multidisciplinary projects, causing the non-module interactions (the black-colored interactions in the modularity plots of Figures S1 and S2). The makerspace at School B is also intended to supplement engineering courses in the same way as School A, however, it is known that School B's makerspace also has a significant number of personal projects occurring at any one time. School B also has arranged its makerspace such that personal protective equipment (PPE) restrictions vary throughout, with the entrance to the space having almost none to encourage curious students to enter. School A's PPE requirements are significant for the entire space regardless of where you are or what you are doing. The other significant difference between the two schools is that School B's space is entirely student-run, with all the "workers" in the space being paid or volunteering students. School A's space has some paid student workers but is still a primarily university staff-run space. These three major differences have resulted in a modular and less connected space at School A and a nested and more connected space at School B during and immediately after the restrictions. Students are encouraged to explore the space, likely leading to the higher interactions documented and the increase in nestedness. The overall nestedness structure of both spaces during normal operating conditions indicates that students are also primarily interacting with the "generalist" tools in the space and specializing further in more advanced tools, with students that have fewer interactions primarily working with the "generalist" tools as well.

The modularity and nestedness analyses also make the impact of COVID-19 restrictions visible in both spaces. The decreasing modularity from Fall 2020 to Spring 2022 can be attributed to decreasing COVID-19 related restrictions in both spaces. Fall 2020 and Spring 2021 semesters at School A saw restrictions within the space down to only the most basic class requirements and no student workers, resulting in an increase in modularity and a decrease in nestedness and connectance during the height of COVID-19 restrictions. Starting Summer 2021, restrictions have eased and as of Spring 2022 the school reported COVID-19 related restrictions had been completely removed. School B, while they did have some restrictions, did not remove personal projects or student workers resulting in their nested structure being lower during the height of COVID-19 restrictions but still present. The use restrictions at both spaces caused fewer interactions and thus lowered connectance values, but only at School A did that result in a significantly modular structure after the perturbation. School B, although nestedness decreased it never dropped so low that the space became modular during the perturbation. The impact of restrictions on the network structure is visible when they were lifted, in the 2022 Spring semester. Schools A and B both see large increases in how nested their students and tools are. The connectance also increases during that semester at both schools. These results offer strong support for the use of modularity and nestedness as diagnostic tools for network health. This could especially be useful for networks where equity may be of interest, energy equity for example could be investigated for a power grid network with modularity and nestedness, showing that a more nested structure has better reach to historically underserved users or neighborhoods. Translating modularity values to a water distribution network for example could help ensure that the communities have water during disturbances.

The study in Figure 5 highlights the relationship between nestedness, modularity, and connectance. Different types of networks can often be characterized by their connectance level and fill. Utilizing the sample network plot a sample operation region can be identified for what the likely modularity and nestedness results could indicate. If the network has high connectance, a positive relationship between modularity and nestedness can be expected and there is a high likelihood the network will showcase both. This can be useful when first identifying the network and obtaining overall nestedness and modularity values.

While a makerspace may seek to become more nested, other human networks may want to be more modular. For example, in electrical networks, a modular structure has been found to help mitigate the effects of network perturbations, particularly when using microgrids.[72] On the other hand, industrial water networks have been found to benefit from a more nested structure when experiencing disturbances.[15] Modularity and nestedness can also be used as diagnostics tools to see if changes in a network are affecting the network structure positively or negatively. Future work will expand the case studies investigated here to include interaction frequency data to create weighted bipartite networks, which have been found in ecology to provide enhanced pattern recognition[22] and additional insight into the network.[52,53]

5 | CONCLUSIONS

Analyzing human networks using quantitative ecosystem metrics can provide valuable information about network function across time. Changes in nestedness, modularity, and connectance are here shown to provide valuable insight into the healthy functioning of student-tool network models of academic engineering makerspaces. Network size and connectance were found to play a major role in the level of modularity/nestedness of interactions in the network. The three metrics combine yield further valuable information about the impact of usage restrictions on the network structure over time. The usage restrictions to class-based projects *only* at School A (versus personal projects allowed at School B) results in a more modular student-tool usage network at School A. The more nested usage network at School B reflects the ability of students to freely use a wide variety of tools. The impacts of COVID-19 usage restrictions, based on normal operations, were found to introduce more modularity/less nestedness at both Schools A and B. This highlights how these intentional restrictions (related to COVID-19) and the maybe unintentional usage restrictions related to personal use both limit connectance and create a more modular structure. These quantitative metrics provide measurable feedback for policymakers about how space restrictions impact system performance. Although academic engineering makerspaces are used here as case studies, the results provide support for the use of these metrics as performance indicators for a wide variety of human-engineered networks that can be represented in a bipartite model.

NOMENCLATURE

B	Bipartite network interaction matrix
C	connectance
ENA	Ecological Network Analysis
L	total number of network interactions/links
N	total number of network actors
N_{column}	number of column actors
NODF	nestedness based on overlap and decreasing fill
N_{row}	number of row actors
p	probability value
Q	modularity
z	Z-score

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Astrid Layton https://orcid.org/0000-0003-3790-2916

REFERENCES

1. Olesen JM, Bascompte J, Dupont YL, Jordano P. The modularity of pollination networks. *Proc Natl Acad Sci USA*. 2007;104(50):19891-19896.
2. Yang S, Keller FB, Zheng L. *Social Network Analysis*. SAGE Publications; 2016.
3. Latapy M, Magnien C, Vecchio ND. Basic notions for the analysis of large two-mode networks. *Soc Netw*. 2008;30(1):31-48.
4. Senghore F, Campos-Nanez E, Fomin P, Wasek JS. Using social network analysis to investigate the potential of innovation networks: lessons learned from NASA's International Space Apps Challenge. Conference on Systems Engineering Research; March 20–22. Redondo Beach, CA; 2014.
5. Barber MJ, Faria M, Streit L, Strogan O. Searching for communities in bipartite networks. AIP Conference Proceedings; 2008.
6. Guimerà R, Mossa S, Turtschi A, Amaral LA. The worldwide air transportation network: anomalous centrality, community structure, and cities' global roles. *Proc Natl Acad Sci USA*. 2005;102(22):7794-7799.
7. Fath BD, Asmus H, Asmus R, et al. Ecological network analysis metrics: the need for an entire ecosystem approach in management and policy. *Ocean Coast Manage*. 2019;174:1-14.
8. Foster A, Huang H, Narimani MR, Homiller L, Davis K. *Ecological Uniqueness for Understanding Line Importance in Power Grids*. IEEE Texas Power and Energy Conference; 2021.
9. Fath BD, Jørgensen SE, Patten BC, Straškraba M. Ecosystem growth and development. *Biosystems*. 2004;77(1-3):213-228.
10. Layton A, Bras B, Weissburg M. Ecological principles and metrics for improving material cycling structures in manufacturing networks. *J Manuf Sci Eng*. 2016;138(10):101002.
11. Steffan SA, Chikaraishi Y, Dharampal PS, Pauli JN, Guédot C, Ohkouchi N. Unpacking brown food-webs: animal trophic identity reflects rampant microbivory. *Ecol. Evol*. 2017;7(10):3532-3541.
12. Fortuna MA, Stouffer DB, Olesen JM, et al. Nestedness versus modularity in ecological networks: two sides of the same coin? *J Anim Ecol*. 2010;79(4):811-817.
13. Latapy M, Magnien C, Vecchio ND. Basic notions for the analysis of large two-mode networks. *Soc Netw*. 2008;30:31-48.
14. Delmas E, Besson M, Brice M-H, et al. Analysing ecological networks of species interactions. *Biol Rev*. 2019;94:16-36.
15. Chatterjee A, Brehm C, Layton A. Evaluating benefits of ecologically-inspired nested architectures for industrial symbiosis. *Resour Conserv Recycl*. 2021:167.
16. Brehm C, Layton A. Nestedness in eco-industrial networks: Exploring linkage distribution to promote sustainable industrial growth. *J Ind Ecol*. 2021;25:205–218.
17. Bustos S, Gomez C, Hausmann R, Hidalgo CA. The dynamics of nestedness predicts the evolution of industrial ecosystems. *PLoS One*. 2012;7(11):e49393.
18. Mariani MS, Ren Z-M, Bascompte J, Tessone CJ. Nestedness in complex networks: observation, emergence, and implications. *Phys Rep*. 2019;813:1-90.
19. Martin EA, Feit B, Requier F, Friberg H, Jonsson M. Assessing the resilience of biodiversity-driven functions in agroecosystems under environmental change. In: Bohan DA, Dumbrell AJ, eds. *Advances in Ecological Research*. Academic Press; 2019:59-123.
20. Olesen JM, Bascompte J, Dupont YL, Jordano P. The modularity of pollination networks. *Proc Natl Acad Sci USA*. 2007;104(50):19891-19896.
21. Lampo A, Palazzi MJ, Borge-Holthoefer J, Solé-Ribalta A. Hybrid structural arrangements mediate stability and feasibility in mutualistic networks. arXiv. 2021 doi:10.48550/arXiv.2105.09191
22. Lewinsohn TM, Inácio Prado P, Jordano P, Bascompte J, Olesen JM. Structure in plant–animal interaction assemblages. *Oikos*. 2006;113(1):174-184.
23. Pinheiro RBP, Felix GMF, Dormann CF, Mello MAR. A new model explaining the origin of different topologies in interaction networks. *Ecology*. 2019;100(9):e02796.
24. Staniczenko PPA, Kopp JC, Allesina S. The ghost of nestedness in ecological networks. *Nat Commun*. 2013;4(1):1391.
25. Blüthgen N. Why network analysis is often disconnected from community ecology: a critique and an ecologist's guide. *Basic Appl Ecol*. 2010;11:185-195.
26. Flores CO, Valverde S, Weitz JS. Multi-scale structure and geographic drivers of cross-infection within marine bacteria and phages. *ISME J*. 2013;7(3):520-532.
27. Payrató-Borràs C, Hernández L, Moreno Y. Breaking the spell of nestedness: the entropic origin of nestedness in mutualistic systems. *Phys Rev X*. 2019;9(3):031024.
28. O'halloran BM, Papakonstantinou N, Giammarco K, Van Bossuyt DL. A graph theory approach to predicting functional failure propagation during conceptual systems design. *Syst Eng*. 2021;24:100-121.
29. Huang H, Mao Z, Layton A, Davis KR. An ecological robustness oriented optimal power flow for power systems' survivability. *IEEE Trans Power Syst*. 2023;38(1):447-462.
30. Panyam V, Huang H, Davis K, Layton A. Bio-inspired design for robust power grid networks. *Appl Energy*. 2019:251.
31. Chatterjee A, Layton A. Bio-inspired design for sustainable and resilient supply chains. 27th CIRP Life Cycle Engineering (LCE) Conference; 2020; Grenoble, France.
32. Chatterjee A, Layton A. Mimicking nature for resilient resource and infrastructure network design. *Reliab Eng Syst Saf*. 2020;204:107142.
33. Wilson T, Chatterjee A, Layton A. Developing a supply chain modeling approach to facilitate ecology-inspired design for sustainability and resilience. ASME 2021 International Design Engineering Technical Conferences and Computers & Information in Engineering Conference; August 17–19, 2021; virtual.
34. Wilson T, Chatterjee A, Layton A. Exploring the effects of partnership and inventory for supply chain resilience using an Ecological Network Analysis. ASME 2022 International Design Engineering Technical Conferences and Computers & Information in Engineering Conference; August 14–17, 2022; St. Louis, Missouri, USA.

35. Canning AD, Death RG. Relative ascendancy predicts food web robustness. *Ecol Res*. 2018;33:873-878.
36. Ulanowicz RE, Goerner SJ, Lietaer B, Gomez R. Quantifying sustainability: resilience, efficiency and the return of information theory. *Ecol Complex*. 2009;6(1):27-36.
37. Chatterjee A, Malak R, Layton A. Ecology-inspired resilient and affordable system of systems using degree of system order. *Syst Eng*. 2022;25(1):3-18.
38. Chatterjee A, Malak R, Layton A. Exploring system of systems resilience versus affordability trade-space using a bio-inspired metric. *J Comput Inf Sci Eng*. 2021;21(5):1-13.
39. Blüthgen N, Menzel F, Hovestadt T, Fiala B, Blüthgen N. Specialization, constraints, and conflicting interests in mutualistic networks. *Curr Biol*. 2007;17(4):341-346.
40. Fortuna MA, Stouffer DB, Olesen JM, et al. Nestedness versus modularity in ecological networks: two sides of the same coin? *J Anim Ecol*. 2010;79(4):811-817.
41. Ulrich W, Kryszewski W, Sewerniak P, Puchałka R, Strona G, Gotelli NJ. A comprehensive framework for the study of species co-occurrences, nestedness and turnover. *Oikos*. 2017;126(11):1607-1616.
42. James A, Pitchford JW, Plank MJ. Disentangling nestedness from models of ecological complexity. *Nature*. 2012;487:227-230.
43. Reed, A. Feminist Makerspaces: Making Room for Women to Create. The Riverter, 2018.
44. Bean V, Farmer NM, Kerr BA. An exploration of women's engagement in Makerspaces. *Gift Talent Int*. 2015;30(1-2):61-67.
45. Hilton EC, Forest C, Linsey J. Slaying dragons: An empirical look at the impact of academic makerspaces. International Symposium on Academic Makerspaces. 2018; Palo Alto, CA.
46. Hilton EC, Smith S, Nagel R, Linsey J, Talley K. *University Makerspaces: More Than Just Toys*. ASME IDETC; 2018.
47. Flores CO, Meyer JR, Valverde S, Farr L, Weitz JS. Statistical structure of host-phage interactions. *Proc Natl Acad Sci USA*. 2011;108(28):E288-E297.
48. Donatti CI, Guimarães PR, Galetti M, Pizo MA, Marquitti FMD, Dirzo R. Analysis of a hyper-diverse seed dispersal network: modularity and underlying mechanisms. *Ecol Lett*. 2011;14(8):773-781.
49. Valverde S, Vidiella B, Montañez R, Fraile A, Sacristán S, García-Arenal F. Coexistence of nestedness and modularity in host-pathogen infection networks. *Nat Ecol Evol*. 2020;4(4):568-577.
50. Ulrich W, Almeida-Neto M, Gotelli NJ. A consumer's guide to nestedness analysis. *Oikos*. 2009;118:3-17.
51. Burgos E, Ceva H, Perazzo RPJ, et al. Why nestedness in mutualistic networks? *J Theor Biol*. 2007;249(2):307-313.
52. Beckett SJ. Improved community detection in weighted bipartite networks. *R Soc Open Sci*. 2016;3(1):140536.
53. Dormann CF, Frund J, Bluthgen N, Gruber B. Indices, graphs and null models: analyzing bipartite ecological networks. *Open J Ecol*. 2009;2:7-24.
54. Guimerà R, Amaral LAN. Cartography of complex networks: modules and universal roles. *J Stat Mech Theory Exp*. 2005;2005(02):P02001.
55. Guimerà R, Nunes Amaral LA. Functional cartography of complex metabolic networks. *Nature*. 2005;433(7028):895-900.
56. Heleno R, Devoto M, Pocock M. Connectance of species interaction networks and conservation value: is it any good to be well connected? *Ecol. Indic*. 2012;14(1):7-10.
57. Poisot T, Gravel D. When is an ecological network complex? Connectance drives degree distribution and emerging network properties. *PeerJ*. 2014;2:e251.
58. Blair S, Banks H, Linsey J, Layton A. Bipartite network analysis utilizing survey data to determine student and tool interactions in a makerspace. ASEE Annual Conference; July 19–26, 2021; virtual.
59. Blair S, Banks H, Hairtson G, Linsey J, Layton A. Modularity analysis of makerspaces to determine potential hubs and critical tools in the makerspace. ASEE Annual Conference & Exposition; June 26–29, 2022; Minneapolis, MN.
60. Blair S, Hairston G, Banks H, Linsey J, Layton A. Makerspace network analysis for identifying student demographic usage. International Symposium on Academic Makerspaces (IJAMM); Nov. 6–9, 2022; Atlanta, GA.
61. Newman MEJ. Modularity and community structure in networks. *Proc Natl Acad Sci USA*. 2006;103(23):8577-8582.
62. Flores CO, Poisot T, Valverde S, Weitz JS. BiMat: a MATLAB(R) package to facilitate the analysis of bipartite networks. *Methods Ecol Evol*. 2016;7:127-132.
63. Almeida-Neto M, Guimarães P, Guimarães PR, Loyola RD, Ulrich W. A consistent metric for nestedness analysis in ecological systems: reconciling concept and measurement. *Oikos*. 2008;117(8):1227-1239.
64. Matthews TJ, Cottee-Jones HEW, Whittaker RJ. Quantifying and interpreting nestedness in habitat islands: a synthetic analysis of multiple datasets. *Divers Distrib*. 2015;21(4):392-404.
65. Bascompte J, Jordano P, Melián CJ, Olesen JM. The nested assembly of plant-animal mutualistic networks. *Proc Natl Acad Sci USA*. 2003;100(16):9383-9387.
66. Farine DR. A guide to null models for animal social network analysis. *Methods Ecol Evol*. 2017;8(10):1309-1320.
67. Dahiru T. P—value, a true test of statistical significance? A cautionary note. *Ann Ib Postgrad Med*. 2008;6(1):21-26.
68. Gotelli NJ, Graves GR. *Null Models in Ecology*. 1st ed. Smithsonian Institution Press; 1996.
69. Tomko M, Hilton E, Forest C, et al. *Observations on Guiding Principles, or Best Practices, in University Makerspaces*. International Symposium on Academic Makerspaces; 2017.
70. Sawchuk T, Hilton E, Nagel R, Linsey J. Understanding academic makerspaces through a Longitudinal Study at Three Universities. American Society for Engineering Education Annual Conference; 2019; Tampa, FL.
71. Braga M, Guttmann G. The knowledge networks in a makerspace: the topologies of collaboration. *Int J Sci Math Educ*. 2019;17(1):13-30.
72. Mousavizadeh S, Bolandi TG, Haghifam M-R, Moghimi M, Lu J. Resiliency analysis of electric distribution networks: a new approach based on modularity concept. *Int J Electr Power Energy Syst*. 2020:117.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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