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EXAMINING GOAL CONGRUENCE ON ENGINEERING DESIGN AND INNOVATION STUDENT TEAMS

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ABSTRACT

Goal congruence, defined as agreement by all members of a team on a common set of objectives, has been positively associated with team cohesion, team performance and team outcomes, including grades earned. Yet there is little in-depth study at scale and across types of engineering design and innovation classes in higher education that examines the goals students set for their work together. This research explores goal congruence in 857 teams involving 1470 students across 18 classes over four years. To examine goal congruence, we use student assessments of their level of agreement on their goals as well as evaluations of their written goal statements. Machine learning techniques are used to automatically identify goal types and congruence between goals. We find that goal congruence on student teams is relatively low, even when they assess it as high, partly due to variety in the types of goals they identify. We categorize the goals students articulate for their teams into grade-, completion-, teaming-, learning-, problem-, output- and outcome-oriented goals and report variance in the types of goals identified in different pedagogical settings. Our findings have implications for how faculty design their classes, link learning outcomes to team projects and facilitate goal setting on student teams.

Keywords: goal congruence, teams, learning objectives, problem-based learning, cooperative learning

1. INTRODUCTION

The ABET criteria for accrediting engineering programs includes as one of seven desired student outcomes "an ability to function effectively on a team whose members together provide leadership, create a collaborative and inclusive environment, establish goals, plan tasks and meet objectives" [1]. Learning to function in teams might be accomplished in problem-based learning situations in which students must write their own problem definition statements or in cooperative learning settings in which students are asked to accomplish a common goal, set either by faculty or by students themselves [2].

It is well established that successful teaming starts with a shared purpose or goal [3]. Multiple studies have shown that goal setting is a powerful predictor of academic accomplishment including grades and test scores, aspects of motivation such as effort, persistence and interest, and positive classroom behaviors [4]. Bradley et al., for example, studied business student teams to show that team goal congruence scores were highly correlated with both team cohesion and team project grades, and that teams with higher goal congruence performed better than teams with lower goal congruence [5]. Other research shows that successful design teams work through consensus to build robust shared understanding of the design problem they are tackling [6]–[8]. Goals affect performance by directing attention and effort towards goal-relevant activities, regulating effort expenditure, encouraging persistence and promoting strategy-searching [9].

Goal congruence is needed not only to guide a team to develop shared processes for their work together, but more broadly to create shared language to communicate the team's problem domain and build shared mental models [10]. Team members in turn use mental models to organize or encode information such as the dynamics of the environment in which they are embedded and the response patterns needed to manage these dynamics, the purpose of the team, and the interdependencies among team members' roles [11]. Team-related mental models address team functioning and expected behaviors. Task-related mental models contain information regarding the materials needed for the task or the way the equipment is used [12]. Goal congruence is instrumental in getting to these mental models. Successful problem solving in real-world, complex domains, such as engineering design, requires teams to effectively detect and resolve uncertainty. Designers can be uncertain not only about how to solve a problem, but also about what the underlying problems are [13]. Iteratively developing shared goals or mental models for their work together is integral to dealing with this uncertainty.

Goal congruence, defined as "agreement by all members of a group on a common set of objectives" is often paired with behavioral congruence or "alignment of individual behavior with the best interests of the [team] regardless of the individual's own goals" (Kennedy and Widener 2019, p. 1). Indeed, congruence between individual and team performance goals has been shown to create greater team member contributions to the team's task and greater satisfaction with the team [15]. Thus, development of shared goals on a team necessarily entails understanding the individual goals of the team members as well, a concept grounded in the theory of intersubjectivity [16]. Team performance in higher education in particular is enhanced when goals are participatively set rather than assigned and when they are specific and hard rather than "do-your-best" goals [5].

Three characteristics that make a shared goal effective are that it is clear, challenging, and consequential [17]. Clear goals describe where a team is going, and how it will know when it gets there, thus orienting and aligning the team. Challenge goals energize and motivate the team. Consequential goals describe why it is important that the team achieve its desired outcomes, are engaging and leverage team members' knowledge and skills.

Goals can be oriented along three dimensions: learning, performance-prove and performance-avoid [18]. Teams with high learning goal orientation show effortful processing of task-relevant information and creation of task-relevant knowledge as well as high level information synthesis and codification of knowledge. A performance-prove orientation leads to goal setting with external referents, evaluating oneself or one's team relative to peers or peer teams, and creates a sense of competition among individuals and teams. A performance-avoid orientation focuses on avoiding failure in front of others and is consistently shown to have deleterious effects on performance [19].

Teaming – and the associated challenges around goal congruence – are core to teaching design and innovation. A 2017 engineering education benchmarking study found that the top-rated engineering schools involved the application of user-centered design throughout the curriculum along with multiple opportunities for hands-on, experiential learning often focusing on problem identification as well as problem solution, and supported by state-of-the-art maker and team working spaces [20]. Furthermore, the "wicked problems" [21] tackled by engineering graduates, whether in start-ups or when taking on a social responsibility agenda, require diversity in perception and heuristics [22]. That diversity comes from working in teams.

Cooperative learning in which students work closely with others to maximize their own and each other's learning also employs teams to promote effective learning in and outside of the classroom [23]. Both problem-based and cooperative learning settings reduce college dropouts due to the failure to establish a social network of friends and classmates or to become academically involved in the classroom [24].

Despite the clear importance of goal setting and goal congruence to successful team outcomes, including on design and engineering teams, there is a dearth of literature that empirically explores goal setting by student teams in higher education. In this paper, we examine 3639 responses from 1470 students in 18 classes to the question "what is your team's shared goal for its work together?". All the classes involved design or innovation in some way. The classes ranged from lab-based classes that were prescriptive about what students had to complete and the focus of that work (e.g., windmills, turbines, etc.) to classes in which outputs (e.g., performance, presentation) and/or learning outcomes (e.g., learn human centered design) were prescribed, but students were given freedom to identify the focus of their project (e.g., reduce bullying on Instagram).

We describe our attempts to measure goal congruence and subsequent findings not only of the lack of goal congruence, but of significant differences in the types of goals articulated by the students. Our findings have important implications for how team-based learning experiences might best be constructed for students, in some cases linking team goals to course learning objectives, and in other cases better facilitating student teams in their own goal development.

2. MATERIALS AND METHODS

2.1 Data

Our research data is drawn from 18 engineering, design and innovation courses that employed versions of a Teaming by Design (teamingxdesign.com) curriculum from 2015-2020. Teaming assessments were given to students in these classes at intervals selected by faculty to best match their pedagogical needs. Some teams were assessed more than once during a given project; others were assessed only at the end of a project.

Teaming assessments were given to a total of 1470 students, 92.5% of whom completed the assessments in 18 different classes, some repeated over multiple years. We altered the questions in the assessments slightly over the years (and will make clear in the findings below which data were drawn from which surveys). In version 1, students were asked "Did your team have a shared goal for your work together? If so, what was it?". Students answered this compound question with short phrases describing the shared goal for their team. In version 2, we split the prompt into two questions so that students provided a binary response to the question "Does your team have a shared goal for your work together?" and then answered, "In 1-2 sentences, please state the team's shared goal". Students responded with yes or no to the first question and then with 1-2 sentences describing the shared goal for their team in the second question. In version 3, students were provided a 7-point Likert scale to express their agreement with the statement "Our team was clear about the shared goal for our work together" and then asked to state what their shared goal was. Students responded with an assessment of how strongly they agreed with the statement and then 1-2 sentences describing their shared goal.

Figure 1 shows the distribution of lengths of the student goal statements. The average statement length was 16-17 words with a standard deviation of 14. 79.4% of the statements were under 25 words.

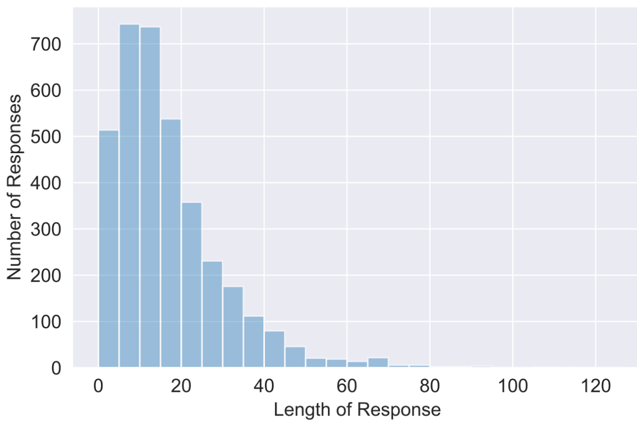

FIGURE 1: Length of Student Goal Statements in Number of Words (outlier response with length of 209 words omitted)

For the purposes of this study, we used three different subsets of the surveys to address the questions at hand. To cluster class types around our labelled goal types, we utilized the entire dataset after removing students that did not respond. To address congruence around goal type, we considered teams for which more than three students responded. To investigate a possible gap between perceived and actual levels of congruence around goals, we used classes and assessments in which we explicitly asked for a binary response to the question "Did your team have a shared goal for your work together?" (version 2) or captured agreement on a 7-point Likert scale with the statement "Our team was clear about the shared goal for our work together" (version 3). To combine our data from versions 2 and 3, we normalized responses to the 7-point Likert scale to a binary response. enabled us to evaluate the correlation between a team's perceived congruence and our measured goal-type congruence. This resulted in the datasets with participation as shown in Table 1. (Note: Student and class values do not add up as the same students may have taken different versions of the survey or classes offered different versions of the survey across different semesters).

TABLE 1: Number of Responses per Dataset

Dataset	Classes	Teams	Students	Responses
Version 1	11	548	880	2346
Version 2	3	232	307	970
Version 3	7	77	313	323
Entire	18	857	1470	3639

2.2 Methodology

We started our examination by seeking to measure the degree of congruence between individual goal statements within teams with the intent of providing students feedback about when they needed to improve goal congruence on their teams. While this work is often done by a panel of experts marking the data by hand, we chose instead to employ Natural Language Processing (NLP) and Machine Learning (ML) techniques for several reasons. First, given the sheer scale of the data used in this study, it would be impractical to engage a panel of experts to tag the data. Secondly, in the interest in giving students useful feedback over many projects and classes, we wanted to create tagging methodology that could be efficiently applied to any set of student responses. Lastly, we were particularly interested in finding underlying patterns and trends in the data that might go unnoticed due to the scale and complexity of the data. Based on our objectives and constraints, applying NLP and ML based approaches was the best choice for this study.

Our approach to assessing the congruence between students' goals relied on the following logic: goal congruence between two given team members can be derived by quantifying the similarity between their goal statements. To create a similarity metric, we relied on a well-documented method in the ML literature, transforming goal statements using sentence-to-vector encodings and comparing the resulting vectors using cosine similarity. However, despite encoding statements using state-of-the-art transfer-learned language models like ULMFiT [25], this approach failed to accurately rate the similarity of pairs of goals. We determined that this low accuracy could be attributed to extreme differences in goal types identified by individual students on a single team and variance in the specificity with which goals were stated (e.g., the difference between "To create a device that could positively help others." vs. "Build a barbell attachment that could track reps for users." vs. "To prototype and test a fitness tracking device for gym enthusiasts that makes their phone usage to a bare minimum while exercising in the gym.").

To improve the model's performance, we first sorted student statements into goal types. Next, we trained a classifier for each of the three goal types initially identified with manual tagging: grade-, completion- and problem-oriented. To generate models with reasonable accuracy, each logistic regression classifier was trained using 5-fold cross-validation on a subset of the data vectorized using a pre-trained Word2Vec language model chosen for good pre-trained performance and accuracy in shorter documents. Based on these results, the models' hyperparameters were tuned to optimize accuracy, precision, and recall, before being tested on another subset of the dataset to see whether it could generalize properly [26]. These models were then used to tag each of the three identified goal types.

While the model was able to tag grade-oriented and completion-oriented goals in the training and test subsets at 96.8% and 93.0% accuracy respectively, the problem-oriented goals were not accurately identified by our model, failing to reach a rate of accuracy higher than 90%. This was due to the multiple problem domains included in the dataset; with classes focusing on domains from turbine blade redesign to grappling with mental health challenges on college campuses, problem-based goal statements had too much variability for the machine learning models to properly identify them. Creating domain agnostic machine learning models is viewed generally as a difficult challenge [27], which made it difficult to generalize machine-tagging of the problem- oriented goals.

After applying our classifier to the dataset and filtering grade-oriented and completion-oriented goals, it became clear that there were other major goal types that existed within the problem-based goal data. We thus proceeded to iterate between manual and ML-assisted tagging to distinguish types of goals within the problem-based goal type segment. Based on this work and existing research in the types of goals surfaced by teams, we defined three new goal types: learning-oriented, teaming-oriented, and content-oriented. Three sub-categories of content-oriented goals focused on: the problems the students aimed to solve, the outputs they intended to create or the outcomes they aimed to achieve. We then returned to the data, manually tagging each problem-based goal with the additional goal types we found by comparing them to the agreed upon definitions and resolving disagreements with discussion. The analysis here represents the combination of machine and manual-tagging, although we expect to be able to train the machine to recognize many of the learning-, teaming- and outcome-oriented goals in future work.

With goal statements categorized, we returned to assessing goal similarity. This time, instead of assessing congruence around the content of the statements using pairwise cosine similarity, we computed similarity around goal-type using a metric based on the maximum variance of projections. This allowed us to quantify similarity (or lack-thereof) between extremely different statements without directly considering a goal's semantic meaning. While parsing the subtle connections between connotation, semantics, and context is key to grasping similarities between two closely related statements, these connections are less helpful when comparing highly dissimilar statements. So, we removed semantic context from the picture. Further, the change of metric addresses a major drawback with cosine similarity: despite being a well-documented approach, it was only capable of capturing similarity in a pairwise fashion. We needed a metric that generalized cosine similarity to multiple statement vectors and thus could measure goal similarity across a 4–6-person team.

To do this, we treated each *i*th student's response's goal type as a vector $\overrightarrow{v_i}$ of indicators with elements v_{ij} such that:

$$\vec{v}_i := [\, v_{grade} \quad v_{completion} \quad \cdots \quad v_{outcome}] \tag{1}$$

$$v_{ij} := \begin{cases} 1: & i\text{th response has goal type } j \\ 0: & \text{otherwise} \end{cases} \tag{2}$$

These derived vectors were then grouped into matrices, V, representing a team of student responses and centered for which:

$$V := [\, \vec{v}_1 \quad \vec{v}_2 \quad \dots \quad \vec{v}_n] \tag{3}$$

$$\hat{v} := \tfrac{1}{n}\textstyle\sum_{i=1}^{n} \vec{v}_i \tag{4}$$

$$\hat{V} := [\, \vec{v}_1 - \hat{v} \quad \vec{v}_2 - \hat{v} \quad \dots \quad \vec{v}_n - \hat{v}] \tag{5}$$

To find the maximum variance of the projections of the data, we determined the direction along which the variance of the projections is maximized. Given that the variance along any direction specified by unit vector $\vec{u}$ has the value

$$\sigma^2_{(u)} := \tfrac{1}{n}\textstyle\sum_{i=1}^{n}((\vec{v}_i - \hat{v})^T\vec{u})^2 \tag{6}$$

or equivalently

$$\sigma^2_{(u)} = \vec{u}^T\left(\tfrac{1}{n}\hat{V}\hat{V}^T\right)\vec{u} \tag{7}$$

we framed our search for this direction as the optimization problem:

$$\max_{\vec{u}} \vec{u}^T\left(\tfrac{1}{n}\hat{V}\hat{V}^T\right)\vec{u} \tag{8}$$

Since the optimal direction $\vec{u}^*$ that maximizes the variance is the solution to the optimization problem, we can substitute this value back into the objective function (8) to obtain a maximum variance metric $\sigma^2_{(u^*)}$

$$\sigma^2_{(u^*)} = \vec{u}^{*T}\left(\tfrac{1}{n}\hat{V}\hat{V}^T\right)\vec{u}^* \tag{9}$$

To simplify our calculations, we utilize the fact that the optimal direction $\vec{u}^*$ that maximizes the variance of the projections of our data is given by the first principal component. Based on the relationship between singular value decomposition (SVD) and principal component analysis (PCA), we can then determine $\sigma^2_{(u^*)}$ by finding the first eigenvalue of $\hat{V}$.

This metric of maximum variance of the data projected along any given direction (shortened to "maximum variance metric" for convenience) is uniquely suited to our purposes because of the metric's inherent directionality. Relative to a metric such as a set's total variance, the variance along the first principal component is less sensitive to small disagreements in goal type. Since extreme differences in goal type account for the greatest increases in variance, our "maximum variance" resists the effects of noise by only considering the most extreme differences present within teams through the orienting of the first principal component. We thus used the maximum variance metric to assess goal type congruence within teams.

3. RESULTS AND DISCUSSION

3.1 Types of Goals

Based upon the iterative machine-human tagging of the students' goal statements, we identified five primary categories of goals cited by students as being the shared goals for their teams' work together:

1. **Grade Oriented**: These goals focused on getting some sort of academic mark, whether a specific grade (e.g., "get an A") or an expression of doing well in the class (e.g., "be successful in this class").

2. **Completion Oriented:** These goals focus specifically on completing an assignment or task, achieving a milestone in the class or an element of a design process. These often emphasize wanting to "complete our assignments" or "finish the lab" as a primary driver of their work. Grade-oriented and completion-oriented goals are widely recognized in the literature as performance-focused goals [18], [19].
3. **Learning Oriented:** These goals explicitly identify an interest to learn, sometimes specific content in the class (e.g., manufacturing tolerancing), other times about problem-related knowledge (e.g., serving homeless) and other times learning from one another. General "do your best" learning goals, as opposed to the more specific learning goals that an individual might set, can improve team performance [28].
4. **Teaming Oriented:** Some students expressly identify team-oriented goals such as "fairly allocating work", "communicating well" or cultivating "a creative and harmonious spirit" on the team. Goals associated with learning teaming skills have been recognized in the literature for some time [29].
5. **Content Oriented:** Goals in this category primarily address the problem the team is tackling, what the team aims to create or design or the outcomes they are seeking from their work. These are the goals that domain agnostic machine learning models struggle to categorize. Often goals in this category are of the challenging or consequential nature identified as critical to successful team outcomes. There were three subcategories of content-oriented goals:
    a. *Problem-focused:* These goals describe a problem space that the team is addressing (e.g., enhance the public transportation experience, improve chronic disease prevention in Brazilian slums)
    b. *Output-focused:* These goals identify either specific (e.g., turbine, phone accessory) or more general (e.g., MVP, story, prototype, presentation, performance) outputs associated with their projects.
    c. *Outcome-focused:* These goals identify a bigger agenda the team has for its work together (e.g., creating something unique, sustainable, portfolio-worthy).

Very few student statements (2%) said that their team did not have a shared goal or did not identify a shared goal for their teams. Most students (78%) listed just one type of shared goal for their team's work together while the remaining 20% provided a compound goal statement with 2-3 types of goals represented (Table 2).

Table 3 shows the distribution of types of goals identified in the dataset. (Because each student's statement could contain up to three goal types, the percentages here add up to more than 100%.) 72% of student statements included a reference to the content of their projects, whether to the problem to be solved, the output to be generated or the desired outcome. 37% of student statements focused on desired performance in the class, whether to get a good grade (8%) or to simply complete the work as assigned (29%). 20% of the goal statements referred to learning or teaming outcomes that students aimed to achieve. We further unpack this result in class comparisons below.

TABLE 2: Number of compound goal statements

Number of Goal Types Per Statement	Percent
None: stated that the team did not have a shared goal or did not identify such goal	2%
One: e.g., "allocate work more evenly" [teaming oriented], "learn about the technology" [learning oriented], "finish the project" [completion oriented], "ace the class" [grade oriented], "generate awareness about mental health on the campus" [content problem oriented].	78%
Two: e.g., "Effectively learn the material of the course together and grow as engineers [learning oriented]. We would like to be able to build off of each other's differing knowledge and to work cohesively through our various tasks [teaming oriented]".	18%
Three: e.g., "Complete the lab tasks [completion oriented] with equal contributions from everyone [teaming oriented]. Ensure that everyone is learning [learning oriented]."	2%

TABLE 3: Distribution of types of goals

Goal Type	Number of Statements Including Goal Type	Percentage of Statements Including Goal Type
Grade-oriented	266	7.9%
Completion-oriented	988	29.4%
Learning-Oriented	297	8.8%
Teaming-Oriented	391	11.6%
Content-Problem	1063	31.6%
Content-Output	862	25.6%
Content-Outcome	504	15.0%

A correlation analysis (Table 4) of the types of goals with one another shows relatively low correlation suggesting that the goal categorization yielded largely unrelated categories of goals. The highest correlation is a negative correlation between problem-oriented goals and completion-oriented ones which we will show is associated with classes in which students define their own problem spaces and that thus have increased emphasis on students getting to shared problem-oriented goals for their work together. Students on these teams place less emphasis in their stated goals on achieving milestones than on working towards some resolution to the problem they are tackling.

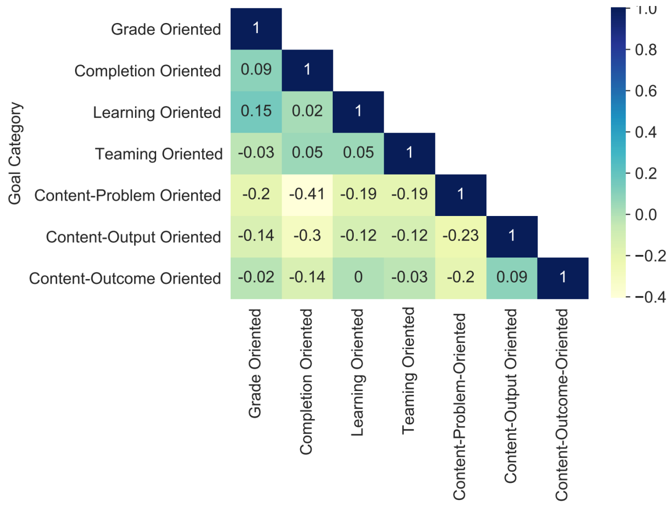

FIGURE 2: Correlation Among Goal Types Identified in Individual Student Statements

3.2 Categorization of Classes by Types of Goals

A cluster analysis on the numbers of types of goals identified by students across 18 different classes resulted in three clusters of classes (Figure 2). Thirteen of the classes, Cluster 1, were clustered around shared dominance of problem-focused goals. This category includes such classes as reimagining slums, redesigning food systems, board game design, needfinding around staying sane as a university student, and tackling challenges in the local community. All the classes in Cluster 1 either provided students with a (wicked) challenge or allowed students to select a challenge on which to work.

Four of the classes, Cluster 2, were clustered around shared dominance of completion-oriented goal statements. These classes were more lab- or problem-set-based, teaching around topics such as manufacturing tolerancing, designing for sustainability, and materials processing. Students in these classes tended to focus their goals more around submitting lab reports in a timely and high-quality fashion. The third cluster, Cluster 3, includes just one class which stood out from the others due to its intense focus throughout the semester on wind turbine design. Student goal statements often specifically cited wind turbines as the focus of their work together in output-focused goals.

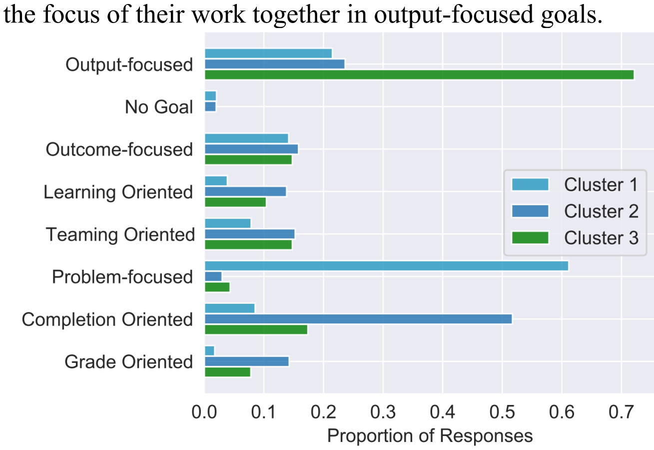

FIGURE 3: Goal Type Character by Cluster

TABLE 5: Goal-type Clusters Characterization

Cluster	Type of Classes	Dominant Goal Types Identified
1	Problem-based Learning	Problem and output focused
2	Cooperative Learning	Completion and output focused
3	Cooperative Learning	Output focused

These clusters (Table 5) are congruent with literature that distinguishes types of situations in which students might learn to work in teams [30]: Cluster 1 is characterized by problem-based learning while Clusters 2 and 3 are characterized by cooperative learning. Students in the problem-based learning classes articulate grade-based and completion-based goals less often than do students in cooperative learning environments. Students in the cooperative learning environments articulate shared team goals that are more focused on accomplishing what they have been asked to do in their assignments and lab work. Although more analysis is required to fully parse out the extent to which these goals are clear, challenging, and consequential, some early hypotheses might associate these goal characteristics with the goal types: Grade- and completion-oriented goals are generally clear in nature, specifying the grades desired and the milestones to be accomplished in each assignment. The outcome-based goals tend to fall in the challenge category as they offer an opportunity to go above and beyond (e.g., to create a unique solution, develop something worthy of widespread adoption). Problem-based goals are more of the consequential nature, describing an important problem to be tackled by the team (e.g., improving disaster response for large-scale fires).

3.3 Goal Congruence

As stated above, goal congruence is associated with higher team cohesion and ultimately with higher team performance. We thus turn here to an evaluation of goal congruence among the goal statement types on student teams, the relationship of assessed goal congruence to measured goal congruence and differences in goal congruence across classes.

Of the 1470 students in 18 classes, 313 students in 7 classes were asked to assess the degree to which they believed their team had a shared goal for its work together on a seven-point Likert scale (7=strongly agree, 1=strongly disagree). Average degree of agreement with the statement that "Our team was clear about the shared goal for our work together" was 6.3 with a standard deviation of 0.91. Figure 4 shows the distribution of scores for the 313 responses.

Based on the student response data (Figure 4), students in general feel that they have clarity around the shared goal for their work together. However, when we calculate maximum variance metrics for each of these teams, we find no correlation between student assessments of their team's goal congruence and the degree of goal type congruence on the team ($r = -0.17$). While it is quite possible that students do agree on their shared goals but are each stating a different element of the shared goal, this data suggests that there is some work to be done to help students ensure that they are on the same page for their work together.

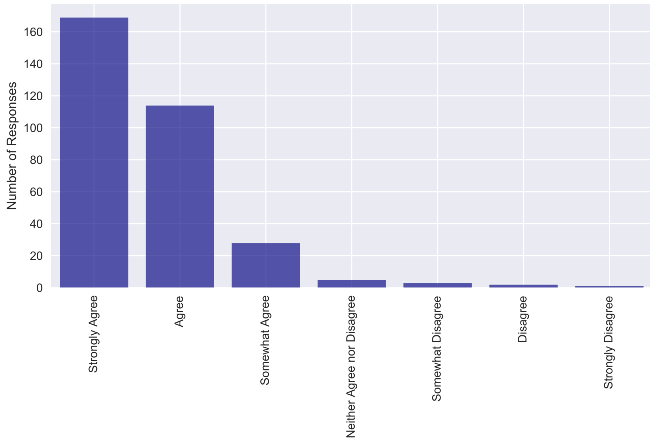

FIGURE 4: Distribution of Responses to "our team was clear about the shared goal for our work together"

Figure 5 captures the max variance metric distribution for all 18 classes and 599 teams. The average max variance metric across all teams is 0.56 with a standard deviation of 0.30. 87 teams had no variance as all members of the team stated a form of the same type of goal. Note that just because students all stated a version of the same type of goal, they did not necessarily all state the exact same goal. The goals might vary in degree of specificity, such as these two problem-focused goals from the same team: "address mental health environment on campus" and "devise prototypes and products that would help others engage in a conversation about mental health". Others might differ in the descriptors they use, such as these outcome-focused responses from another team: "create a project that is challenging but also practical", "create something useful", "design and manufacture something we are excited to create". Further assessment of congruence of goals *within* goal type will help us unpack this further. In short, our max variance metric captures the best possible level of goal congruence on these teams as it measures the extent to which the team members at least shared the same goal types.

Given that goal congruence is important to achieving team cohesion, which subsequently enhances team performance, the lack of goal congruence on teams in these classes suggests an opportunity to enhance student learning by facilitating higher goal congruence on teams. Examination of the max variance distributions in our two clusters of classes sheds additional light on this possibility.

Figure 6 shows the max variance distribution for Cluster 1: Problem-based learning classes. The average max variance metric for these classes is 0.47 with a standard deviation of 0.27. Nearly 80% of the zero maximum variance teams (69 of 87) are in the problem-based learning classes.

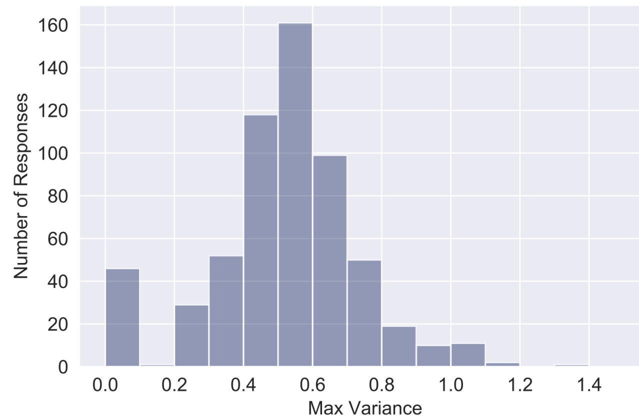

FIGURE 5: Max Variance Distribution Across All Teams (Number of teams)

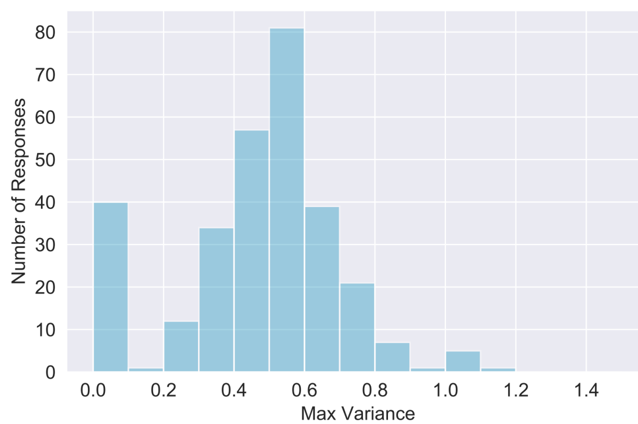

FIGURE 6: Max Variance Distribution for Cluster 1 – Problem-based Learning Classes (Number of Teams)

Problem-based learning classes engage students in iteratively resolving the uncertainty associated with a problem space either of the students' choosing or assigned by the faculty [13]. These classes follow a design process, often human- or user-centered design, and as part of that process, explicitly focus on framing the problem to be solved [31]–[33]. Thus, when asked what the shared goal for their team's work together is, students often focus on the problem they are tackling (e.g., "educate others about the corporate privatization of water"). These students also often identify the output they are designing as a response to their problem (e.g., "build a campaign to raise awareness of the corporate privatization of water").

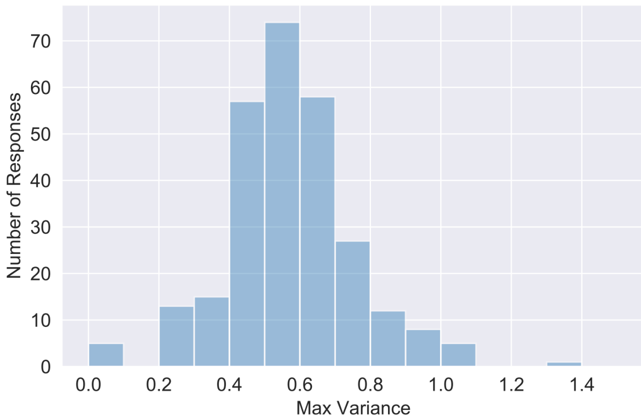

FIGURE 7: Max Variance Distribution for Cluster 2 – Cooperative Learning Classes (Number of Teams)

Figure 7 shows the max variance distribution for Cluster 2: cooperative learning classes. The average max variance metric for cooperative learning teams was 0.57 with a standard deviation of 0.19. A t-test comparing the max variance distributions for problem-based and cooperative learning-based classes shows that they are significantly different from one another (Table 6).

TABLE 6: t-Test Comparing Max Variance for Problem-based and Cooperative learning-based clusters

	Cooperative	**Problem Based**
Mean	0.57	0.47
Variance	0.04	0.06
Observations	275	299
Hypothesized Mean Difference	0.00	
df	561	
t Stat	-5.82	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.00	
t Critical two-tail	1.96	

Cooperative learning classes engage students in peer-to-peer learning through assignment of problem sets, labs and sometimes short design projects [23]. Students in these classes focus more on completion goals, e.g., "complete our labs and project in a timely manner" than do students in the problem-based classes. They often mix completion-oriented statements with statements of other goal types, e.g., "do well on assignments and learn as much as possible" (learning), "complete lab tasks with equal contributions from everyone" (teaming). Others on the same team, however, might focus their statements more on the output the team will produce, e.g., "make a device to make roads safer". While the problem-based learning classes guide students towards a focus on one goal type that is associated directly with understanding and designing for a problem space, students in cooperative learning environments are often less guided in their selection of goals for their work together. Cluster 3 with the single class focused on wind turbine design is a standout exception to our finding about goal type variance in problem-based versus cooperative learning environments. In this class, teams of students repeatedly called out, for example, "make an efficient and viable windmill", "design wind turbine", "create a working design for a windmill" and "make a working turbine" as the shared goals for their work together. Examination of the syllabus for this course shows the dominance of "wind turbine" in all the assignments throughout the course, a characteristic not apparent in the other course syllabi.

3.4 Recommendations for Engineering and Design Educators to Improve Team Outcomes

Successful teaming is a multi-dimensional challenge [13], [34] with goal-setting as one of the most critical dimensions [28]. This research suggests that there are data-driven means that might be employed to evaluate the goals students set for themselves and for their teams, to determine the extent to which those goals are shared, and ultimately to make recommendations for improving goal congruence. The research also suggests ways in which faculty might facilitate higher goal congruence, particularly in cooperative learning environments where higher variance in goal statement types occurs.

Students need more guidance in identifying and articulating shared goals. The type of help they need varies by the type of teams that are being used in the class. In problem-based learning classes where students are learning some version of a design process and actively iterating their understanding of a problem space, creating regular check-ins for student teams to revisit and coalesce around a revised goal is valuable in facilitating the development of shared language around their work together [6]. Creating time, whether in class or with assignments calling for explicit statement of team goals, shows students that the course faculty understand the importance of goal congruence and provides faculty with a quick way to check in on how teams are doing. As we continue to develop models for assessing team goal congruence, we hope to provide support to faculty for such evaluations.

In cooperative learning environments where the problem to be solved is not necessarily the primary focus of the class, faculty can help students by first identifying the different types of goals they might identify for the class: grade, completion, learning, teaming, problem, output, and outcome. The distinction between individual and team goals can be particularly important in these team settings as students may not agree on their goals, particularly within certain goal types. The student who is taking the class pass/fail, for example, will have a different grade-oriented outcome than the student who wishes to get an A. Some students may have specific learning goals (e.g., master a particular software tool), but more general shared team-level learning goals (e.g., understanding design tolerancing) improve team performance [28].

In cooperative learning environments, team-level learning goals are generally associated with explicitly stated learning outcomes for the course. Faculty can facilitate goal congruence on teams by being clear about what the learning objectives are and can test understanding of those learning objectives by evaluating student goal statement content and congruence. Increased focus on learning goals (e.g., learn manufacturing processes) to shift focus away from strictly completion-oriented work (e.g., complete the lab on time) creates more challenging goals. Increased focus on outcome-oriented goals (e.g., create something we are proud of that has impact) creates more consequential goals. While grade- and completion-oriented goals provide clarity, having challenging and consequential goals increases team engagement.

Regardless of the type of course, faculty have an opportunity to increase student engagement and learning in their courses by designing the course such that students can find challenging and consequential goals for their work together. One of the courses in our sample, for example, added a short project to the end of the course for which students were given a choice as to what they designed rather than have them design changes to a given product. Students in this section articulated more problem- and outcome-oriented goals than did students in prior versions of the class. They can also increase student understanding of goal setting by describing the different types of goals they might have for their work together, both individually and as a team, and giving the team time to share their individual goals with one another and come to agreement as to what their team goals are. Asking students to articulate their initial goals and submit them as a homework assignment and then checking in with them periodically on the accomplishment or revision of their stated goals will increase goal congruence not only at the start of the class, but throughout the class as goals change and evolve.

3.5 Limitations and Future Research

The methodologies we experimented with in this paper form a powerful set of tools for unpacking and better understanding goal congruence and goal setting around teams. While we were able to uncover interesting relationships between pedagogy and goal setting by using these methods, there is still more work to be done around the quantification of goal congruence. These classification methods, while effective, fall short of capturing a complete picture of goal congruence, particularly among team members who presented goals of the same type.

Since our initial attempts to capture goal congruence through transfer-learned language models failed to consistently grade high degrees of dissimilarity, we can use classification steps in combination with the max variance statistic to handle highly dissimilar data with more precision. We will experiment further with a two-stage process for assessing goal congruence: first we will categorize goal statements by goal type and then we will assess goal congruence within statements of a given goal types.

In addition to developing models for fully assessing goal congruence on teams, we aim to address differences in goal specificity as well. While "make an awesome project" is a nice goal to have, "make a structurally sound and light structure" provides more guidance for a team to evaluate its performance. Ideally, we will be able employ machine learning to distinguish specific from non-specific goals and ultimately use the results to engage students in more meaningful goal development.

Other future work will explore alternative pedagogical approaches to supporting students in goal setting to facilitate clearer articulation of shared goals for their work together. This will include looking at different approaches to helping students articulate their initial goals for their work together and using different methods to help students check in on how they are doing in achieving their goals and whether their goals have changed at various points during their work together. It will also consider different types of course structures, such as problem-based and cooperative learning based.

This initial research has provided insight into how students think about the goals for their work together and some initial guidance as to how we might improve goal congruence on student teams to ultimately improve their team performance and overall learning. Future work will further develop understanding of what kinds of approaches work best in which class settings, whether goal congruence differs on assigned versus self-selected teams, and whether goal congruence can be improved as students progress through their projects. Ultimately, we aim to create a set of tools that might be used to assess goal congruence and provide feedback to students and faculty for its improvement in real time.

CONCLUSION

Agreement about the goals for a student team's work together improves team performance and student learning. This research finds, however, that goal congruence on student teams is low. Student goal statements are often of a completely different type from those of their teammates. Goal congruence on student teams can be improved by helping them identify different types of goals for their work together – grade, completion, learning, teaming, problem, output, and outcome focused goals – and by clearly articulating faculty-set goals for the teams. Machine learning can help in assessing goal congruence on student teams and providing feedback to students and faculty as to where and how goal congruence might be improved.

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