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Evaluation of Students' Interest, Experience, and Commitment to Participate in Construction Competitions

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Construction education at universities, community colleges, and trade schools plays a vital role in preparing students with the technical knowledge and professional marketable skills needed to successfully join the construction workforce. High-quality programs integrate classroom learning, hands-on experiences, and other activities to ensure graduates are workforce-ready. One of those other activities includes construction competitions that provide opportunities to students to apply classroom concepts in practical and competitive environments. Unfortunately, some construction programs are challenged to effectively identify and recruit students continuously who have the right mix of interest, availability, and experience. Thus, the problem addressed by this paper is the lack of data-driven understanding of the impact of students' interest, experience, and commitment to participate in construction competitions. The overall goal of this study is to serve as an attempt to fill this gap by achieving two distinct objectives: (1) deconstructing the students' selection criteria represented by "Total Score" and (2) predicting the probability of a candidate's final status outcome (i.e., accept an invitation to be part of a team). This research followed a quantitative research methodology. Data was collected through a detailed questionnaire distributed to construction students. The responses were analyzed to identify patterns in students' readiness and engagement, as well as gaps in experience or scheduling availability. The findings aim to inform faculty advisors and team coordinators in the selection and development of competition team members, ensuring that teams are composed of students with the appropriate balance of interest, experience, and availability.

Keywords: Construction Competitions, Construction Education, Evaluation, Learning, Students

Introduction and Background

Construction education programs are tasked with preparing students by providing them with the necessary technical knowledge and professional marketable skills to succeed in the workforce (Sulbaran, 2023). Furthermore, the construction industry requires a continually better-skilled and educated workforce (Stephen & Festus, 2022). To prepare the educated workforce, high-quality curricula integrate traditional classroom learning with practical and hands-on experiences, including participation in construction competitions.

Educational literature suggests that competitions promote learning and introduce students to innovative thinking and to effective teamwork (Gadola & Chindamo, 2019). These competitions are invaluable activities that allow students to apply theoretical concepts in realistic and competitive environments, where learning is achieved through the process of preparing for the competition, independent of the student's score in such a competition (Burguillo, 2010). This emphasizes the role of competitions to prepare students for collaborative, real-world challenges, underscoring the role of competition in fostering both technical and soft skills.(McGuire, 2025)

Team formation is challenging (Vasiljević & Lavbič, 2023) and data-driven studies on students' competition teams are limited. However, team formation in professional settings has been studied more. These studies could be organized into three main categories of evaluations: (1) Personality Traits, (2) Professional Marketable Skills, and (3) Hard Skills.

The personality traits studies have focused on the interplay between individual personality traits and team performance, particularly in collaborative and skill-intensive environments (Vasiljević & Lavbič, 2023). Broadly speaking, these studies attempt to define the relationship between "Big Five" personality traits (emotional stability, extraversion, openness to experience, agreeableness, and conscientiousness) and team performance (Driskell et al., 2006).

The professional marketable skills studies have looked into the core competencies that are transferable to multiple scenarios. These professional marketable skills include: career & self development, oral and written communication, critical thinking, professionalism, leadership, teamwork, technology, critical thinking, creativity, communication, collaboration, curiosity/lifelong learning, initiative, persistence, adaptability, leadership, and social & cultural awareness (Ganguli, 2023).

The hard skills studies have focused on multi-criteria approaches for team formation using multiple dimensions, including: performance, quality, workload, and expertise (Arias et al., 2017). Unfortunately, the existing studies do not appropriately address the aspects and procedures to be adopted in the development of tools to meet most scenarios, besides not providing a concrete solution useful from a practical perspective (Cunha et al., 2022) to form students' competition teams. The formation of teams should include several criteria and characteristics, such as effort, professional role, performance, as well as hard and soft skills (Cunha et al., 2022).

Unfortunately, many construction programs face the primary challenge of recruiting students willing to participate in the competitions (Ahmed, 2024). Furthermore, there is limited data available that provides insights into how to identify and recruit those students who possess the optimal mix of interest, availability, and relevant experience. Thus, the problem addressed by this paper is the lack of a data-driven understanding regarding the impact of students' interest, experience, and commitment on their participation in construction competitions.

The overall goal of this study is to serve as an attempt to fill this gap by achieving two distinct objectives: (1) deconstructing the composite student "Total Score" and (2) predicting the probability of a candidate's final status outcome (i.e., acceptance of a team invitation).

Research Methodology

To identify trends and patterns that could inform strategies for recruitment and team formation, a quantitative research methodology was utilized to collect and analyze measurable data related to students' interest, experience, and commitment toward participating in construction competitions. A Quantitative methodology was used because the literature justified its use from the mathematical points of view and applicability to real cases. (Moraga et al., 2020). The data was collected through an online survey administered through Qualtrics, capturing responses at a single point in time to assess the current state of the students.

Structured Survey Components

The structured questionnaire, developed as the primary instrument for data collection, ensured uniformity and comparability across respondents. The survey instrument consisted of five main sections, each targeting a different dimension of the research objective:

1- *Consent:* The participants were provided a brief overview of the study and given the opportunity to consent or not before proceeding with the questions.

2- *Identifier Information:* The participants were asked names and e-mail addresses to be able to contact them to provide the results of the team selection process.

3- *Interest and Availability:* The participants were asked about their interest in participating in the ABC and TEXO/ASC Competition using a Likert-scale with 4 items (from “High Interest” to “No interest”). A 4-item Likert Scale was selected to avoid central tendency responses. Additionally, the participants were asked about the number of hours that they could dedicate to preparing per day during the Fall Semester, Winter Break, and Spring Semester. Again, a Likert-scale was used with 5 options from “~4 to 3 hours per day” to “~1 to 0.5 hours per day”

4-*Competition, Industry, and Student Organization experience:* The Participants were asked whether or not they had previously participated in construction or STEM-related competitions, and the number of overall, field, and office construction experiences they had. A Likert scale ranging from “More than 6001” hours to “No Experience” was provided to answer this question. Lastly, the students were asked if they actively participate in some of the construction organizations such as ABC, AGC, NAHB, ACI, or others

5- *Academics:* The participants were asked when they were expecting to graduate, their overall University GPA, and whether or not they had completed a selected number of construction courses in the program

Target Population and Sampling

The target population for this study consisted of undergraduate students enrolled in the Construction Science and Management (CSM) program at the University of Texas at San Antonio (UTSA). This population was selected because it represents the group from which one of the members of the research team recruited students to participate in construction competitions.

A census sampling approach was used, in which 100% of the enrolled CSM students in the Fall 2025 semester were invited to express interest in participating in the construction competitions. This approach ensured the representativeness of the findings in the context of the CSM program at UTSA.

Survey Distribution for Data Collection

The survey was distributed electronically via email to all CSM students using the college’s mailing list. The data collection was conducted over a three-week period from August 11th, 2025 (Before classes started) until September 2nd (2nd Week of the Fall Semester). As previously indicated, a consent statement was included at the beginning of the survey, and students had to affirm their agreement before proceeding. In addition to the initial invitation, three reminder emails were sent.

Data Analysis

The data analysis was divided into two main stages, corresponding to the two distinct objectives of the study: (1) deconstructing the composite student "Total Score" and (2) predicting the probability of a candidate's final status outcome (i.e., acceptance of a team invitation).

- *The Total Score Deconstruction:* The student's Total Score was treated as a ratio or continuous variable. Therefore, an Ordinary Least Squares Regression (OLS) analysis was conducted to deconstruct and represent the underlying scoring process. OLS was used because it allowed to examine the specific effects variables have on one another (Burton, 2021). In this research isolated the closest weights (coefficients) assigned to each predictor variable (survey question) in the calculation of the Total Score.
- *Prediction of Student Status:* Focus on predicting the Student Status as an ordinal outcome variable (0, 1, & 2). The student status 0 corresponded to “Not to invite to the team”, the student status 1correponded to “Invite to the team, but likely to not accept”, and the student status 3 corresponded to “Invite to the team and likely to accept”. A two-step approach was employed due to the sample size (n=31) and the number of predictor variables (11 survey questions).
  The first step was applying the Principal Component Analysis (PCA) to the 11 original predictor variables. This technique linearly transforms the data into a smaller set of uncorrelated Principal Components (PCs), reducing model complexity and helping to stabilize subsequent parameter estimation. The resulting three PCs (PC1, PC2, and PC3) were calculated using the standardized Z-scores of the raw survey data, along with the derived component original predictor means (μ_i) and standard deviations (σ_i), and the component Loading_i.
  The second step involved applying an Ordinal Logistic Regression (OLR) model, using the extracted principal components (PCs) as predictors. OLR was appropriate because the dependent variable had ordered categories (Status 0, 1, and 2). This model estimates the cumulative log-odds of a candidate student being at or below a given status level. The probability associated with each specific status category (0, 1, and 2) was then obtained by differencing the cumulative probabilities. In other words, subtracts the cumulative probability of the preceding status from that of the one of interest.

Results and Findings

Demographic Profile of Respondents

The initial dataset had 68 responses, which were filtered for uniqueness (no duplication), completeness, and timely submission, resulting in a final analysis cohort of 31 unduplicated, completed, and timely submitted responses.

This dataset is composed of the responses to eleven questions categorized into six factors: (1) Interest, (2) Time Commitment, (3) Competition Experience, (4) Work Experience, (5) Graduation Year, and (6) GPA. Regarding Interest in the ABC and TEXO Competitions, the data was collected on a 4-point Likert scale (4 = High Interest, 1 = No Interest). The average interest level was 3.5, indicating that candidates, on average, fell right in the middle between "High Interest" and "Medium Interest." For Time Commitment was measured on a 5-point Likert scale (5 = 28 hrs. to 21 hrs. per week, ~4 to 3 hours per day, 1= 7 hrs. to 3.5 hrs. per week, ~1 to 0.5 hrs. per day), the average commitment was 2.8. This suggests a commitment level somewhere between 14 hrs. to 10.5 hrs. per week (~2 to 1.5 hours per day), 10.5 hours to 7 hours per week (~1.5 to 1 hour per day). In terms of Competition Experience, it was measured with positive/negative questions (1=No and 2=Yes), the average was 1.2, confirming that most students have not participated in competition experience. Conversely, Work Experience was measured on a 9-option scale (9 = more than 6001 hours, ~more than 3 years full-time equivalent to 1 = no experience, ~0 months of full-time equivalent). The average score was 4, suggesting that candidates had accumulated 1001 to 2000 hours of work experience (0.5 to 1 year full-time equivalent), and they are just at the beginning of their construction careers. The expected Graduation Year was measured on a 12-option Likert scale (1 = Spring/May 2026 to 12 for Fall/Dec 12= 2029), the average was 4, suggesting an expected graduation date around Spring 2027 (May).

Finally, the GPA was collected in 10 ranges (10 = 4.0–3.8, 1 = 2.19 and below), and the average range score was 7.3. This score suggests the candidates had a good GPA, placing them between the 3.20–3.39 range and the 3.40–3.59 range.

Scoring Interest, Experience, and Commitment

The Total Score for each student, based on their survey responses, was a ratio or continuous variable. Therefore, an Ordinary Least Squares Regression (OLS) analysis was conducted to deconstruct and represent the underlying scoring process (Burton, 2021). This approach is critical because it isolates the closest weights applied to each predictor, allowing different institutions and decision-makers to understand the precise criteria used to determine a student's total score.

The OLS analysis, using all survey questions as predictors, yielded an R-squared value of 1. This perfect fit indicates that the Total Score was not an estimated outcome, but was calculated as a direct linear combination of the predictor variables (survey responses). Consequently, the resulting OLS equation serves as the explicit scoring formula used in the original data generation. The resulting equation is presented below, and the specific coefficients (weights) are shown in Table 1.

$$Total\ Score = I + \sum_{n=1}^{N} X_n * \beta_n$$

Table 1. OLS Coefficients for Each Predictor/Question

ID (X)	Predictor Description	Coefficient (β)	P-Value
X_1	Q3_1 Interest in ABC Competition	β_1: 0.0098	0.0010
X_2	Q3_2 Interest in TEXO Competition	β_2: 0.0105	0.0000
X_3	Q3_3 Time Commitment Fall	β_3: 0.0159	0.0000
X_4	Q3_4 Time Commitment Winter Break	β_4: 0.0099	0.0000
X_5	Q3_5 Time Commitment Spring	β_5: 0.0196	0.0000
X_6	Q4_1 Experience in Competitions	β_6: 0.0100	0.0002
X_7	Q4_2 Experience Work Overall	β_7: 0.0162	0.0000
X_8	Q4_3 Experience Work Field Only	β_8: 0.0171	0.0000
X_9	Q4_4_Experience Office Only	β_9: 0.0168	0.0000
X_{10}	Q5_1 Graduation Year	β_{10}: -0.0002	0.4472
X_{11}	Q5_2 GPA	β_{11}: 0.0302	0.0000
I	Intercept	I: 0.0002	0.9775

As shown in Table 1, the Ordinary Least Squares (OLS) regression analysis resulted in a very clear formulation to determine "Total Score". The most influential factor in the calculation is X_{11} (Q5_2 GPA), which holds the largest positive coefficient β_{11} = 0.0302, indicating it contributes the most significantly to achieving a higher Total Score. The vast majority of the predictors (ten out of eleven) are highly statistically significant with P-values below 0.05, a finding that, coupled with the model's excellent fit (R^2 = 1), confirms that these factors are systematically incorporated into the score's calculation formula. In contrast, X_{10} (Q5_1 Graduation Year) has a negligible negative coefficient (β_{10}: = -0.0002) and a high, non-significant P-value (0.4472), demonstrating that the variable has either no impact or almost no impact on the Total Score and strongly suggests it was effectively excluded or assigned a zero weight in the score's original calculation formula

Selection of the Most Appropriate Students to Compete - Status

Using a scoring system based on interest, experience, commitment, and perhaps other factors is probably a good first step in selecting members for a competition team. However, it is equally important to predict which of those qualified students will accept the invitation and subsequently be available and committed to producing the best outcome during the competition.

To model this selection challenge, the students' results were organized into three ordinal Status groups: Status 0 corresponding to “Not to invite to the team”, Status 1correponding to “Invite to the team, but likely to not accept”, and Status 2 corresponding to “Invite to the team and likely to accept”.

Given the sample size (n=31) and the number of survey questions (11 predictors), the model complexity was first reduced using Principal Component Analysis (PCA). The PCA was used because it is a versatile statistical method for reducing a cases-by-variables data into its essential features - Principal Components (Greenacre et al., 2022). This facilitated the subsequent Ordinal Logistic Regression (OLR), which was used to predict the student's Status group.

The PCA grouped the eleven original predictors (See Table 1) into three Principal Components (PC1, PC2, and PC3 (See Table 2), which collectively captured 63.3% of the total variance in the original data. The primary composition and interpretation of these components were as follows:

- *PC1 - Overall Time Commitment & Interest*: This component is defined almost entirely by the scores on the Commitment and Interest questions. As all major loadings are negative, a high score on PC1 signifies a low overall degree of reported commitment and interest from the candidate.

- *PC2 - Overall Work and Competition Experience*: This component is clearly defined by the four Experience questions (work and competition). Since all major loadings are positive, a higher PC2 score directly translates to a higher overall experience in work and competitions.

- *PC3 - Interest, Commitment, and Graduation:* This component represents an independent dimension defined by a mix of variables, primarily contrasting strong Interest and Graduation Year with Commitment on one specific question. This component is more complex and captures a more comprehensive, orthogonal trade-off in the survey responses.

The resulting equation used to calculate the value of any Principal Component for any candidate is shown below. This calculation requires the candidate's standardized scores (Z_{score}), which are derived using the original predictor means (μ_i) and standard deviations (σ_i), and the component $Loading_i$ shown in Table 2.

$$PCi = \sum_{n=1}^{N} Loading_{PC_i} * Z_{Score_i}$$

Where the Z_{Score} for any Predictor X_i is calculated as follows:

$$Z_{score} = \frac{Xraw_i - \mu_i}{\sigma_i}$$

Table 2. Results from Principal Component Analysis (PCA)

PC	ID (X)	Predictor	Mean (μ_i)	Std. Dev (σ_i)	Loading$_i$
PC1 - Overall Time Commitment & Interest					
	X_1	Q3_1 Interest in ABC Competition	4.45	0.57	-0.4707
	X_3	Q3_3 Time Commitment Fall	3.03	1.16	-0.4572
	X_4	Q3_4 Time Commitment Winter Break	3.58	1.41	-0.4556
	X_5	Q3_5 Time Commitment Spring	3.10	1.33	-0.4049
PC2 - Overall Work and Competition Experience					
	X_7	Q4_2 Experience Work Overall	4.52	0.57	0.5704
	X_8	Q4_3 Experience Work Field Only	3.48	2.31	0.5281
	X_9	Q4_4_Experience Office Only	4.45	0.57	0.3799
	X_6	Q4_1 Experience in Competitions	3.10	1.33	0.3786
PC3 - Interest, Commitment, and Graduation					
	X_2	Q3_2 Interest in TEXO Competition	4.52	0.57	0.5870
	X_{10}	Q5_1 Graduation Year	3.48	2.31	0.5715
	X_1	Q3_1 Interest in ABC Competition	4.45	0.57	0.3165
	X_4	Q3_4 Time Commitment Winter Break	3.10	1.33	-0.3526

After the Principal Component Analysis (PCA) was concluded, the Ordinal Logistic Regression (OLR) was performed, and the analysis determined that only Principal Component 3 (PC3) was included in the final converged model.

The OLR model predicts the cumulative log-odds/probability of a candidate being at or below a certain status (0, 1, or 2). Therefore, to determine the individual probability of a candidate being in a specific status category (0, 1, or 2), the cumulative probabilities must be differentiated. This is achieved by subtracting the cumulative probability of the preceding status from the current one. This results in a set of individual prediction equations to determine the precise probability of a candidate belonging to each of the three status categories, as follows:

- Status 0 - Probability that the student will "Not to invite to the team" equations are as follows:

$$Probability_0 = \frac{e^{L_0}}{1 + e^{L_0}}$$

  Where the L_0 for $Probability_{0i}$ is calculated as follows

$$L_0 = LogOdds_{\ 0} = -0.1376 - 0.2381\ PC_3$$

- Status 1 - Probability that the student will "Invite to the team, but likely not to accept" equations are as follows:

$$Probability_1 = \frac{e^{L_1}}{1 + e^{L_1}} - Probability_0$$

  Where the L_0 for $Probability_{0i}$ is calculated as follows

$$L_1 = LogOdds_1 = 0.5169 - 0.2381\, PC_3$$

- Status 2 - Probability that the student will “Invite to the team and likely to accept” equations are as follows:

$$Probability_2 = 1 - \frac{e^{L_1}}{1 + e^{L_1}}$$

It is worth noting that the OLR analysis concluded that only using Principal Component 3 (PC3). Because it was the best approach to determine the final converged model of status probability (shown in the previous equations). Additionally, the result shows the relationship is statistically lacking strength, because the PC3 itself yields a P-value of 0.5313 with a Standard Error of 0.3803. Additionally, the model's baseline cut-off points corresponding to status 0, which define the cumulative log-odd, has a P-Value of 0.7725 and a Standard Error of 0.4758, and the cut-off for Status 1 has a P-Value of 0.1356 and a Standard Error of 0.3463. These values suggest that either a large dataset (with more students) or additional refinement of the parameter will be beneficial to increase the likelihood of predicting the probability of a candidate's final status outcome (0, 1, or 2).

Summary

This study serves as a step toward data-driven team formation for construction competitions by evaluating the interest, experience, and commitment of students within a construction program. The research successfully quantified student readiness through a two-stage analysis. The analysis yielded two key findings: one concerning the student scoring process and one concerning the predictability of a student's final status (acceptance of an invitation to be part of a competition team).

The scoring process was deconstructed using the Ordinary Least Squares (OLS) regression, confirming that regression is able to identify a linear combination of survey responses. The GPA was identified as the most influential factor, possessing the largest positive coefficient, while Graduation Year was effectively excluded from the scoring formula.

The prediction of student status (0, 1, or 2) was accomplished in two steps. The first step used was the Principal Component Analysis (PCA) to reduce the data into three principal components. The second step consisted of implementing an Ordinal Logistic Regression (OLR) model, which retained the Principal Component 3 that reflected Interest, Commitment, and Graduation as predictors. However, the result shows the model lacks statistical strength in the coefficient.

The results indicated that while the selection process based on the Total Score is systematic, the final predictor of a student's commitment status (acceptance/rejection) is not statistically reliable within this sample size.

The study results are valuable in their current form. However, it is also important to acknowledge key limitations, primarily stemming from the sample size and students' variability among others, which challenge the generalizability of the findings beyond particular Construction programs. Future research could focus on addressing these limitations and expanding the understanding of student engagement. Increasing the dataset size (more students) or refining the OLR parameters could be an interesting research direction to improve the statistical strength and predictive likelihood of the model. Conducting broader surveys across multiple construction education institutions could be another direction to compare results and enhance generalizability. Utilizing a qualitative follow-up to explore Barriers and Motivators for competition, including open-ended items detailing reasons for nonparticipation, will provide a deeper understanding of the commitment challenges identified by the OLR model.

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