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Examining Student Cognitive Engagement in Integrated STEM (Fundamental)

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Abstract
While there are many approaches to integrated STEM instruction (iSTEM), the integration of engineering design is the most widely-studied and practiced pedagogical approach to iSTEM in K-12 classrooms. Research has shown that the inclusion of engineering-design improves students' attitudes, as well as interest and engagement in pursuing STEM-related careers. Furthermore, studies have shown enhanced 21st century skills for students engaged in iSTEM learning contexts. However, more research is needed to understand how iSTEM and its critical features are operationalized to promote positive student outcomes. To address this need, this study examined the relationship between student cognitive engagement in iSTEM and its hypothesized predictors: curricular opportunities for STEM content integration, engagement in multiple solution development, agency in STEM practices, evidence-based reasoning, data practices, and collaboration. The study is guided by Roehrig et al.'s (2021) *Detailed Conceptual Framework of Integrated STEM and* Moore et al.'s (2014) *framework for Quality K-12 Engineering Education*. We utilized multinomial logistic regression (MLR) analysis due to the polytomous categorical distribution of the outcome variable. This study used classroom video data from previous work that examined the presence of critical features of K-12 iSTEM. Scores using a novel and validated iSTEM observation protocol (Dare et al., 2021) from 2,007 iSTEM lessons were used. Through preliminary analyses, we determined that the assumptions for MLR have been sufficiently met. Three categories of the outcome variable, student cognitive engagement, reported on were lessons that provide opportunities for students to (1) analyze/evaluate STEM concepts, (2) use/apply STEM concepts, and (3) know/understand STEM concepts (which was set as the baseline or reference category). All predictor variables except for curricular opportunities for collaboration and data practices were statistically significant in the model. The final MLR model has a total of 12 predictor categories. The deviance goodness-of-fit test indicated that the model was a good fit to the observed data, $\chi^2(234) = 207.605$, $p = .892$, with 137 (36.2%) cells having zero frequencies. The final model statistically significantly predicted the outcome variable over and above the intercept-only model, $p < .001$. Furthermore, it has a pseudo R-squared value of .643 (Nagelkerke R^2) and correctly classified 72.8% of cases. Among other findings, we found that the odds of multidisciplinary lessons providing opportunities for students to analyze and/or evaluate STEM concepts was 2.401 times higher than that for monodisciplinary lessons, $\chi^2(1) = 24.963$, $p < .001$. In addition, lessons with opportunities for students to redesign a solution to the engineering task are more likely to provide opportunities for students to analyze/evaluate STEM concepts ($\exp(B) = 126.038$) compared to lessons without such curricular opportunity, $\chi^2(1) = 22.033$, $p < .001$. In conclusion, engineering-centric iSTEM instruction that engage students in higher levels of cognition are marked by the presence of multidisciplinary content, engagement in designing solutions to an engineering problem, agency in STEM practices, and evidence-based reasoning.

Introduction

With the current state of global affairs and looming threats posed by misinformation, STEM education continues to be relevant and vital to developing a scientifically-literate citizenry who are both critical consumers of information and creative problem-solvers. Coupled with concerns about increasing student interest in STEM careers to meet the increasing demands of the STEM workforce, researchers and policy-makers advocated for an integrated approach to STEM education that led to curricular developments such as the Next Generation Science Standards (NGSS) in the United States [1], [2].

The resulting increased demand to improve STEM education around the world has led to new and varied models of integrated STEM instruction (iSTEM) [3]. Implementation and views of integrated STEM differ with regard to which of the STEM disciplines should be the focus, how many of the four STEM disciplines should be present and to what degree they should each be emphasized, the main purpose of learning in STEM, whether other non-STEM subjects should be incorporated, etc. While there are many approaches to iSTEM, the integration of engineering design is the most widely-studied and practiced pedagogical approach to iSTEM in K-12 classrooms [3], [4]. Research has shown the inclusion of engineering-design improves students' attitudes and learning [5], [6] and increases students' interest and engagement in pursuing STEM-related careers [7]. Furthermore, there are studies that have shown enhanced 21st century skills among students in these kinds of integrated STEM learning contexts [8], [9].

Unfortunately, there remains a gap in the literature about the operationalization of integrated STEM pedagogies, specifically the engineering-centric approach, in terms of how it promotes the improvement of student outcomes. One way to investigate this is by exploring curricular opportunities and associated pedagogical strategies that support student learning. Classroom activities that promote student cognitive engagement serve as a window to the potential of a pedagogical approach to promote student learning. In the context of iSTEM, identifying the pedagogical features associated with higher cognitive engagement among students can inform further research on improving STEM pedagogies and supporting positive student outcomes.

Thus, this study aims to examine the relationship between student cognitive engagement in iSTEM and key predictors that are identified from pertinent literature and theoretical frameworks.

Theoretical Frameworks and Related Literature

Features of Integrated STEM Instruction

In the advent of the Next Generation Science Standards (NGSS), most schools in the United States are embracing integrated STEM education, either explicitly or implicitly in their curricula. The National Research Council and National Academies of Engineering have called for educators to reconsider their current teaching styles in light of STEM instruction, emphasizing the need for explicit and intentional integration of STEM subjects [10], [11]. However, the varied definitions and conceptualizations of integrated STEM instruction pose a great challenge to accomplishing the more universal goals of STEM education [3]. Fortunately, recent research [12] laid out a detailed conceptual framework for K-12 integrated STEM education that can be used by researchers, curriculum developers, educators, and other stakeholders as a shared vision. Building upon the existing literature on integrated STEM, the framework specifies seven defining features of integrated STEM: (1) centrality of engineering design, (2) driven by authentic problems, (3) context integration, (4) content integration, (5) STEM practices, (6) 21st century skills, and (7) informing students about STEM careers.

While most of these features cater to the improvement of student affective outcomes such as motivation in learning STEM, the current study takes interest in aspects of integrated STEM that promote positive cognitive outcomes. For instance, engagement in engineering design promotes creative problem solving and divergent thinking [13], [14]. Furthermore, allowing students to engage in redesigning their solutions provides them opportunities to think analytically about their design choices to come up with better and more innovative designs [15]. Content integration using multidisciplinary approaches prompts students to consolidate and apply concepts and practices from multiple disciplines [16], [17]. Activities that allow students to engage in STEM practices and exhibit 21st century skills support students' active construction of knowledge and higher-order thinking skills [18], [19].

Engineering Focus

Moore et al.'s [15] framework for quality K-12 engineering education specifies some of the aforementioned features as vital to the implementation of engineering-centric instruction and use of engineering design. Most if not all of its 12 indicators align with the features described in the aforementioned iSTEM framework [12]. However, Moore and colleagues [20] determined that among these indicators, three are central to engineering and engineering education. These are Processes of Design (POD), Apply Science, Engineering, and Mathematics content (SEM), and Engineering Thinking (EThink). First, engineering practice is centered on design processes. Solving engineering problems is an iterative process involving knowledge building, planning, and evaluating the solution. Second, the application of science, mathematics, and engineering concepts are vital to the practice of engineering itself. As such, K-12 engineering education should emphasize this interdisciplinary nature. Finally, engineering thinking involves critical and creative problem solving and using informed judgment to make decisions. Moreover, learners in engineering education should be independent and reflective thinkers capable of seeking out new knowledge and learning from failure in problem-solving situations.

These common pedagogical features present in both frameworks are sufficiently documented in the literature to improve student cognitive outcomes. For instance, English and colleagues [21] and Li and colleagues [22] emphasize the benefits of integrative approaches to STEM education, particularly when engineering content is present in the lesson. Supporting literature indicates that engineering provides context for the application of science and mathematics concepts and thus helps students see the interconnectedness of the STEM disciplines [3], [18], [23]. In addition, several researchers argue that engineering-design pedagogy improved students' attitudes and learning [1], [5], [24]\. For example, Sharunova and colleagues [25] illustrated how the processes of engineering-design aligns with the increasing complexity of cognitive abilities in Bloom's taxonomy. The research emphasized that when students engage in the iterative process of design, students are prompted to use higher-order thinking skills.

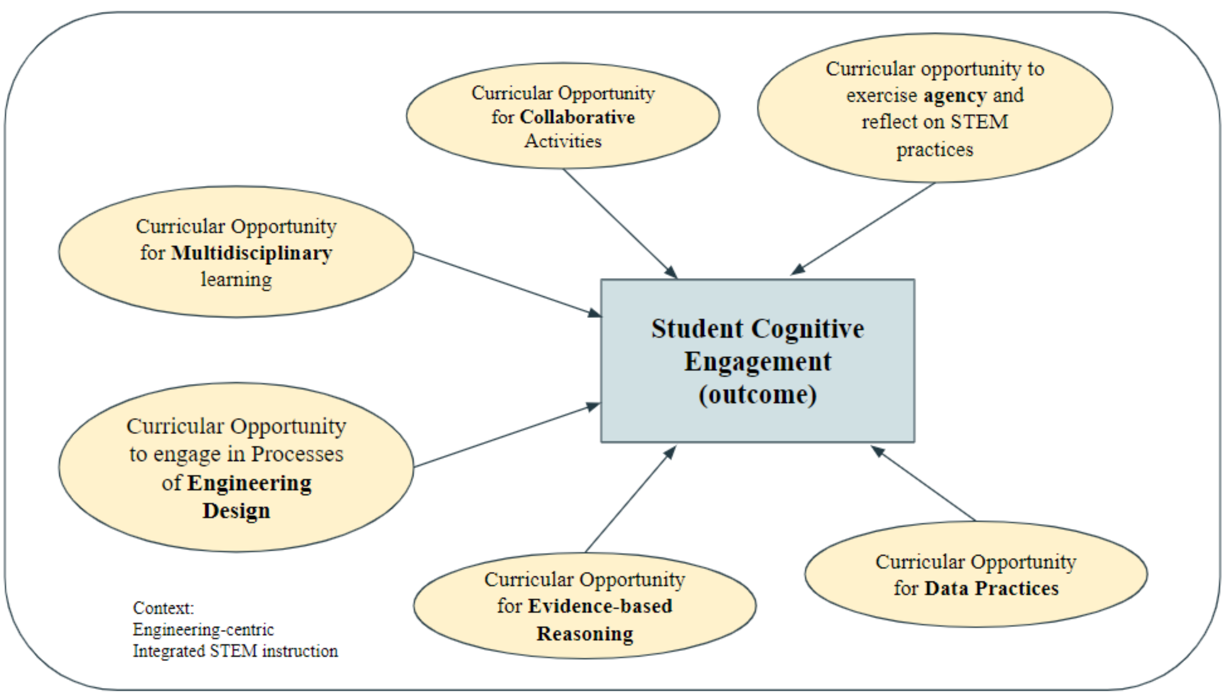
Despite these accounts of engineering-centric iSTEM's posited effect on student achievement, there remains a gap in the literature about the dynamics of the curricular features that lead to these desirable student cognitive outcomes.

Our Conceptual Model

Upon reflection on the insights from our theoretical frameworks and key literature, we determined that there are critical features of engineering-centric iSTEM that may help us predict the level of student cognitive engagement. First, students consolidate and critically apply concepts and practices from multiple disciplines when they are learning in a multidisciplinary context [26], [27]. Second, students think creatively and critically when they engage in engineering design which entails having to come up with design solutions to the problem [20], [28]. Third, students analyze and evaluate other people's ideas when they are asked to negotiate to come up with a group consensus [29]. Fourth, students develop and exercise critical thinking skills when they engage in evidence-based reasoning which requires justification of claims and design decisions with evidence [30], [31]. Fifth, students construct knowledge through collection, analysis, and evaluation when they engage in data practices [32], [33]. Lastly, learning becomes more meaningful to students when they exercise agency in and reflect on STEM practices, as they are able to construct their own knowledge [34], [35]. These studies inform our understanding that individually, these six features of iSTEM have a unidirectional relationship with student cognitive engagement. It is worth noting at this point, however, that while we hypothesize unidirectional relationships between our sets of variables, we limit our investigation to predictive relationships and not causal relationships.

Figure 1 illustrates our conceptual model about the relationship between the outcome and predictor variables.

Figure 1. Conceptual model for predictor variables and outcome



Throughout this paper, we aim to answer the following research question: *Do the presence of curricular opportunities for learning multidisciplinary lesson content, engineering-design activities, agency in STEM practices, data practices, collaboration, and evidence-based reasoning predict the level of student cognitive engagement in iSTEM lessons?*

Based on this question, we formulated the following set of hypotheses:

Null Hypothesis (H_0): There is no predictive relationship between student cognitive engagement and curricular opportunities for learning multidisciplinary lesson content, engineering-design activities, agency in STEM practices, data practices, collaboration, and evidence-based reasoning.

Alternative Hypothesis (H_a): There is a predictive relationship between student cognitive engagement and curricular opportunities for learning multidisciplinary lesson content, engineering-design activities, agency in STEM practices, data practices, collaboration, and evidence-based reasoning.

Methodology

This study utilizes a correlational research design with regression analysis that aimed to examine the relationship between student cognitive engagement in engineering-centric iSTEM (outcome) and curricular opportunities for learning multidisciplinary lesson content, engineering-design activities, agency in STEM practices, data practices, collaboration, and evidence-based reasoning. The study context and sample, instrument, data, research design and approach, and statistical analysis are discussed in the following sections.

Research design

In order to address the research questions, this study used a correlational design with multinomial logistic regression analysis. It is an ex post-facto research [36] because the lesson implementations have already occurred and the dataset used for the analysis comes from a previous work (see [4]). Such research design and approach are used to determine the presence and strength of relationships between outcome and predictor variables without implying causality. In the present study, the results of the multinomial logistic regression (MLR, hereafter) analysis would show whether a predictive relationship exists between student cognitive engagement in iSTEM and its hypothesized predictors (opportunities for learning multidisciplinary content, engagement in engineering design, evidence-based reasoning, data practices, agency in STEM practices, and collaboration). Further details about MLR will be discussed in the statistical analysis section.

Instrument, Data, and Study Context

This study used secondary data obtained from a previous work that examined the presence of critical features of integrated STEM in various K-12 lessons using a novel STEM observation protocol [4].

The instrument consists of ten items, each with four scoring levels (0-3) and were designed to measure the characteristics of integrated STEM outlined in Roehrig et al.'s [12] theoretical framework. In establishing the validity of the instrument, the authors sought external review by a panel of STEM experts and subjected the instrument draft to multiple iterations to ascertain that each item sufficiently captures the aspects of their corresponding constructs. Furthermore, they provided additional validity evidence through examining the internal structure of the instrument which they described in length in another study (see [37]). To evaluate item reliability, they assigned a team of seven coders to use the instrument to independently score a random sample of roughly 200 classroom videos drawn from the video repository (see [4]). All items achieved inter-rater reliability above the acceptability threshold of Krippendorff's $\alpha \geq 0.6$ with the slight exception of an item referring to the integration of STEM content that achieved $\alpha \geq 0.58$.

For the current study, we selected items from the instrument that measure our variables of interest. Table 1 outlines these variables and their corresponding STEMOP items.

Table 1. Alignment of study variables and STEM-OP items

Variables in this study	**STEM-OP item**
Student Cognitive Engagement	Item 4: Cognitive Engagement in STEM
Engagement in the Processes of Engineering Design	Item 3: Developing Multiple Solutions
Multidisciplinarity of Instruction	Item 5: Integrating STEM Content
Exercising Agency in and Reflection on STEM Practices	Item 6: Student Agency
Engagement in Collaborative Activities	Item 7: Student Collaboration
Engagement in Evidence-based Reasoning	Item 8: Evidence-based Reasoning
Engagement in Data Practices	Item 9: Technology Practices in STEM

Each of the 2,030 cases in the dataset represents a video-recorded observation of STEM classroom teaching. Collected in a previous research project [38], these videos are 50-minutes long on average and were recorded daily for the entirety of a curriculum unit that ranged between one to several weeks of instruction. The participant teachers were recruited from five school districts (representing urban and suburban environments in the midwestern United States) to complete a three-week PD workshop designed to promote science learning through engineering design activities and the development of integrated STEM curriculum that highlighted engineering as the integrator of STEM content [20], [39]. They taught grades 3-9 (primarily elementary teachers, elementary science teachers, and middle school science teachers) and demonstrated teaching of physical science, earth science, and life science lessons.

The original dataset for the analysis included 2,030 classroom video observations generated from the previously described project. However, because we are primarily interested in student cognitive engagement in the context of iSTEM, we excluded video observations where students were not learning any STEM content. Upon applying this exclusion criterion, we ended up with 2,007 cases. This dataset represents a wide range of teachers (99 teachers), classroom settings (996 physical science, 427 earth science, and 584 life science classrooms), curriculum units (48 in total), and grades (849 pre-K and elementary, 1100 middle school, and 58 high school observations).

While all the STEM-OP items have four descriptive levels, we decided to collapse some of these and re-coded them into new categories that reflect the kind of detail in our variables of interest. For example, because we are only interested in whether there are multiple STEM disciplines present in a given iSTEM instruction, we collapsed levels 1-3 of STEM-OP Item 5 into just one category that represents multidisciplinarity. The same principle (presence vs absence of a feature) applies to Items 7, 8, and 9. However, Item 3 was not binary-coded because we are particularly interested in the alignment between the levels of cognitive engagement and the main stages of the engineering design [25]. Meanwhile, Item 6 is a multidimensional measure (i.e. evidence of STEM practices vs none, student agency vs procedural task, reflection on STEM practices vs none).

All the predictor categories have to be re-coded in inverse order because the analysis software (SPSS v.27) automatically sets the last category of each predictor as the reference category. In order to come up with a more comprehensible interpretation of results, we decided to set the lowest level or absence of a variable measured as the referent. A summary of the re-coding done (and inverse coding with respect to the statistical analysis) is provided in Table 2.

Table 2. Coding labels for each of the study's measures

STEM-OP Item (Measures)	**Re-coding Scheme and Coding Labels**
Item 4/ Student Cognitive Engagement (outcome)	reverse coding: 0 - opportunities for students to analyze/ evaluate STEM content 1 - use/ apply 2 - know/ understand
Item 3/ Engagement in the Processes of Engineering Design	reverse coding: 0 - opportunities for students to redesign solutions 1 - evaluate design solutions 2 - design solutions 3 - no opportunities for students to design solutions
Item 5/ Multidisciplinarity of Instruction	binary coding: 0 - multidisciplinary instruction 1 - monodisciplinary instruction

Item 6/ Exercising Agency in STEM Practices	reverse coding: 0 - opportunities for students to reflect on STEM practices 1 - exercise agency in doing STEM practices 2 - perform procedural tasks 3 - no opportunities for students to engage in STEM practices
Item 7/ Engagement in Collaborative Activities	binary coding: 0 - opportunities for student collaboration 1 - no opportunities for student collaboration
Item 8/ Engagement in Evidence-based Reasoning	binary coding: 0 - opportunities for students to engage in evidence-based reasoning 1 - no opportunities for students to engage in evidence-based reasoning
Item 9/ Engagement in Data Practices	binary coding: 0 - opportunities for students to engage in data practices 1 - no opportunities for students to engage in data practices

Of special interest here is the set of categories/levels for the outcome variable, Student Cognitive Engagement. The levels progress in terms of complexity of cognitive ability. At the lowest level, students participate in tasks that require lower-order thinking skills such as remembering facts and exhibiting their understanding of concepts. Meanwhile, lessons which prompt students to apply what they have learned, analyze concepts, and evaluate ideas are given higher scores. Dare and colleagues [4] indicated that while the item levels were phrased to denote that opportunities for cognitive engagement were provided, emphasis has to be given on what students were actually doing. In other words, the observers must see evidence that students are acting on those opportunities for cognitive engagement. Additionally, multiple types of opportunities for cognitive engagement can be present in a single classroom instruction and the observations were scored based on the highest level of cognitive engagement that was evident. This is supported by our theoretical position and related literature on the hierarchy of cognitive engagement in which there is preference for engaging students in higher-order thinking skills. This is also aligned to the overarching goals of STEM education, among which is helping learners become critical consumers of information and creative problem solvers.

Power analysis

Since there is no standard way to calculate a priori power for multinomial regression, we have to resort to convention in terms of the required number of cases for the analysis. Using a standard rule of thumb, an appropriate sample size calculated for multinomial regression was the number of independent predictors times 10, which required at least 50 individual observations or cases for this study [40]. A more conservative estimation involved a factor of 30 times the number of independent predictors for a sample size of 150 cases (see [40], [41]). Given the large dataset used in this study, we ascertain that the analyses performed are sufficiently powered.

Statistical Analysis

To examine the relationship between student cognitive engagement and its hypothesized predictors, we utilized logistic regression analysis in this study. Specifically, we employed a multinomial logistic regression (MLR) analysis due to the polytomous categorical distribution of the outcome variable. MLR analysis is used to find the best model to describe the relationship between the outcome variable, student cognitive engagement, and the hypothesized predictors. The resulting value of the logistic regression equation is the chance of the event being used as a measure for classification [42]. This data analysis technique mostly involves the following steps: (a) estimating parameters, that is to estimate the logit model with a qualitative scale response variable using the maximum likelihood method, (b) testing the significance of the parameters using a partial test such as a Wald test, and (c) calculating the accuracy of the classification.

Results and Discussion

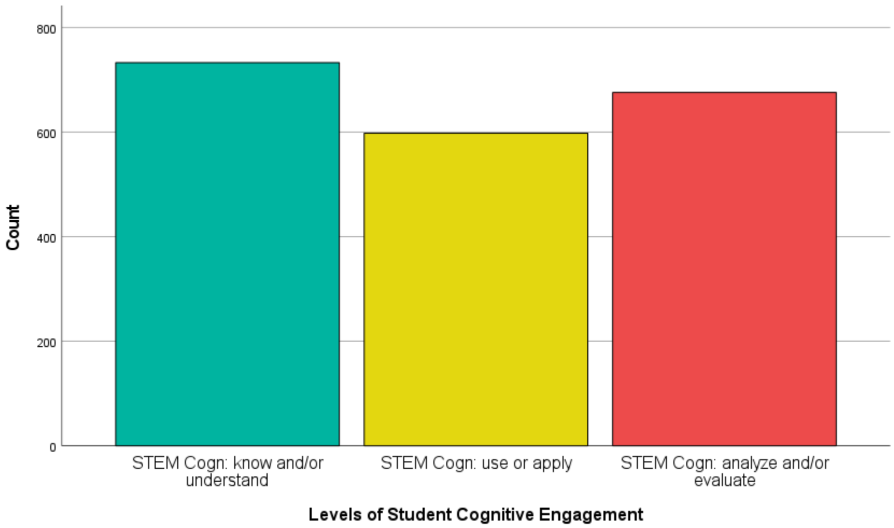
The purpose of this study is to examine whether the presence of curricular opportunities in engineering-centric iSTEM can indicate the level of student cognitive engagement in iSTEM lessons.

In the following sections, we discuss statistics pertaining to the description of the characteristics of the sample, addressing the assumptions of multinomial logistic regression, and evaluation of the results of the multinomial logistic regression analysis with regard to the research question and hypotheses.

Descriptive Statistics

Student cognitive engagement is the outcome variable for this study. Applying the exclusion criterion helped us focus on the three categories of the variable which correspond to levels 1 to 3 of the STEM-OP item 4. Of the 2,007 classroom video observations analyzed, the most frequent was level 1 (opportunities for students to know/understand STEM content). The distribution of STEM-OP item 4 scores is shown in Figure 2. While the graph shows a non-normal distribution of the said scores, normality is not a requirement of multinomial logistic regression [43].

Figure 2. Frequency distribution of Student Cognitive Engagement categories



The predictor variables in this study are multidisciplinarity of lesson content, engagement in engineering design, agency in STEM practices, data practices, evidence-based reasoning, and collaborative tasks. More than half (64.5%) of the classroom observations involved lesson content from more than one STEM discipline. Meanwhile, 48.8% of these observations feature students engaging in designing, evaluating, and redesigning engineering solutions. 46.2% (928) of 2,007 video observations involved procedural tasks for students while 32% (643) of these involved classroom activities that allowed for student agency. Meanwhile, about half (46.7%) of the classroom videos observed featured activities that provided opportunities to engage in evidence-based reasoning, 20% involved data practices, 87.2% included collaborative tasks (see Table 3).

Table 3. Descriptive Statistics for each predictor categories

Predictor Variables	**Predictor Categories**	**Frequency**	**Percent**
Multidisciplinarity of Lesson Content (STEM-OP Item 5)	multidisciplinary	1295	64.5%
	monodisciplinary	712	35.5%
Collaboration (STEM-OP Item 7)	engagement in collaborative tasks	1751	87.2%
	no opportunity for collaboration	256	12.8%
Evidence-based Reasoning (STEM-OP Item 8)	engagement in evidence-based reasoning	938	46.7%
	no opportunity for evidence-based reasoning	1069	53.3%
Data Practices (STEM-OP Item 9)	engagement in data practices	402	20.0%
	no opportunity for data practices	1605	80.0%

Engineering Design (STEM-OP Item 3)	redesigning solutions	226	11.3%
	evaluating design solutions	250	12.5%
	designing solutions	502	25.0%
	no opportunity to design solutions	1029	51.3%
Agency in STEM Practices (STEM-OP Item 6)	reflection on STEM practices	44	2.2%
	agency in STEM practices	643	32.0%
	procedural STEM practices	928	46.2%
	no opportunity for STEM practices	392	19.5%
Total		**2007**	**100%**

Assumptions of Multinomial Logistic Regression (MLR)

In order to ascertain valid and appropriate interpretation of the predictive model for student cognitive engagement using the specified predictor variables, we evaluated whether the study met the assumptions of the multinomial logistic regression model. Three key assumptions are appropriate sample size, no multicollinearity, and independence of observations.

Appropriate sample size. Based on the estimate of 10 cases per predictor variable included in the model [40], a minimum sample size of 50 cases was needed to achieve significance ($p < .05$) at a power of .80. A more conservative approach requires 30 cases per predictor variable which would indicate 150 cases [41]. The dataset used in this study has over 2,000 cases; therefore, the study met the sample size requirements and was adequately powered.

No multicollinearity. Multicollinearity occurs when there are two or more independent variables that are highly correlated with each other [44]. To determine whether it exists among the predictor variables in this study, we employed the variance inflation factor (VIF) method via SPSS v.27. VIF values greater than 10 and Tolerance values smaller than 0.1 indicate strong multicollinearity [42]. After regressing dummy-coded predictor variables and the outcome variable, we examined the resulting collinearity diagnostics, VIF and Tolerance values (see Appendix C) which demonstrated that there is no multicollinearity among the predictors.

Independence of observations. Another assumption of MLR is independence of observations and that the outcome variable should have exclusive and exhaustive categories. In the context of this study, we cannot claim that the observations are truly independent of each other because some video observations may be part of a lesson that has been divided into several days. Also, because multiple lessons are parts of a curriculum unit, some video observations are related to others. For instance, if the curriculum unit implements an engineering design challenge (EDC), we expect to see call backs to the EDC in different lessons in that same unit.

Nevertheless, we believe that such kind of dependence has a small effect on our findings because we have a significantly large number of cases, as well as several predictor variables in our model. The second part of the assumption implies that the odds of preferring one category over another do not depend on the presence or absence of “irrelevant” alternative categories. In this study, a classroom observation can only be classified into one (highest) level/category for STEM-OP Item 4 (outcome variable). Thus, this part of the assumption has been satisfied.

Main Findings

Using SPSS v.27, we performed multinomial logistic regression on the study data. The regression analysis began with the selection of significant predictor variables using an automated forward stepwise method in SPSS (see Table 5 for statistically significant predictor variables). The model fitting criteria, shown below in Table 4, shows the calculated -2 log likelihoods and the likelihood ratio (LR) test for the null versus the final model. The chi-square statistic demonstrates the difference between the null model (no predictors) and the final model (fully fitted for all significant predictor variables).

Table 4. SPSS output for model fit information

Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2200.135			
Final	502.409	1697.727	16	.000

In Table 5, we present the -2 log likelihood of the reduced model to evaluate the importance of each of the predictor variables to the full fitted model. The chi-square LR test involves subtracting the value of the reduced model from the full fitted model. The difference represents the change in the model fit when that predictor was removed. Each of the chi-square tests had significant results ($p < .05$) except for STEM-OP Item 7 (collaborative tasks) and Item 9 (data practices) indicating that each predictor variable except collaboration and data practices improved the accuracy of the fitted model. Since more than one of the predictors were significant to the fitted prediction model ($p < .05$), the null hypothesis that there is no predictive relationship between the predictors and student cognitive engagement was rejected.

Table 5. Results of Likelihood Ratio Tests

Likelihood Ratio Tests

Effect	Model Fitting Criteria: -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests: Chi-Square	df	Sig.
Intercept	502.409[a]	.000	0	.
Item5TransBinary	532.737	30.329	2	.000
Item8TransBinary	715.355	212.946	2	.000
Item3Transformed	1078.094	575.686	6	.000
Item6Transformed	705.334	202.925	6	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

The final MLR model has a total of 12 predictor categories, which correspond to the categories in Table 3 except for those of collaboration and data practices. The deviance goodness-of-fit test indicated that the model was a good fit to the observed data, $\chi^2(234)$ = 207.605, p = .892, with 137 (36.2%) cells having zero frequencies.

For the study data, the pseudo R^2 statistics were moderate (Cox-Snell = .571; McFadden = .386; Nagelkerke = .643). Being the logistic analog of R^2 in ordinary least squares regression, pseudo R^2 is considered as a goodness-of-fit statistic. Nonetheless, many researchers have practiced great caution in using the direct statement that pseudo R^2 is a direct measure of the proportion of variance accounted for in the dependent variable [42]. While the moderate pseudo R^2 results in this study may provide insight to how the predictors explain the outcome, they also inform us that there may be other factors that may influence opportunities for student cognitive engagement. These include faculty demographics such as teaching experience and alternative teaching approaches to curriculum content [45], [46], differences among gender, grade bands and science area [24], [47], and other confounding variables that have not been included in this study.

Another way to evaluate the prediction model is to examine the observed and predicted classifications which are presented in Table 6. Logistic regression is commonly used to predict whether cases can be correctly classified (i.e., predicted) from the predictor variables [42]. If the estimated probability of the event occurring is greater than or equal to 0.5 (better than even chance), SPSS classifies the event as occurring (e.g., students are using/applying STEM concepts). If the probability is less than 0.5, SPSS classifies the event as not occurring. Overall, the final model can only correctly predict 72.8% of the categorical outcomes based on the predictors. This means that the prediction model can correctly classify 1,461 observations into each of their corresponding STEM-OP item 4 categories.

Table 6. Classification Table for the Predictive Accuracy of the Final Model

	Predicted			
Observed	STEM Cogn: know and/or understand	STEM Cogn: use or apply	STEM Cogn: analyze and/or evaluate	Percent Correct
STEM Cogn: know and/or understand	657	37	39	89.6%
STEM Cogn: use or apply	230	258	110	43.1%
STEM Cogn: analyze and/or evaluate	74	56	546	80.8%
Overall Percentage	47.9%	17.5%	34.6%	72.8%

In addition, the relatively low accuracy of the predictive model in classifying "use/apply" provides insight to the relative complexity of what using or applying STEM content means in iSTEM implementation that the set of predictors in our model cannot sufficiently account for. Such variability can be due to the possible multidimensionality of that category. For instance, because the instrument did not explicitly include synthesis (see [48]) in the levels of STEM-OP item 4, there may be more variability in scoring video observations where students are creating solutions and synthesizing ideas. It could also be possible that certain classroom activities that are inherently opportunities to use/apply concepts appear as another level of cognitive engagement to observers. One example is when students have to use evidence in making a claim. It is possible that some observers would see such activity as requiring students to analyze while some would consider it as simply requiring students to use data in making a claim.

Furthermore, in the interpretation of the parameter estimates of the final model, while each of the predictors was significant to the improvement of the fitted model, each predictor category was not significant in the estimation of the odds ratios for every comparison. The odds ratio, Exp(B), is "the exponentiation of the fitted model coefficient . Since logistic regression models use a log likelihood statistic, the exponentiation of this value provides an odds ratio" [49]. We consider this statistic in particular because it allows more intuitive interpretation of the results. The statistic can be interpreted as that for every one unit change in the predictor variable, the odds ratio is the percentage of likelihood that the outcome changes [44], [50]. Odds ratios equal to 1 means that the outcome event (e.g. multidisciplinary lessons) was equally likely to occur as the reference outcome (e.g. monodisciplinary lessons). Odd ratios greater than 1 indicated that the outcome event was more likely than the reference event and odds ratios less than 1 indicated that the outcome event was less likely than the reference event.

We have summarized below the *statistically significant results* using the odds ratios from the multinomial logistic regression for opportunities for learning multidisciplinary lesson content, opportunities for engaging in processes of engineering design, opportunities for agency in and reflection on STEM practices, and opportunities for evidence-based reasoning. The complete table of parameter estimates for the final model is included in Appendix A.

- Classroom instruction with opportunities to learn **multidisciplinary** lesson content is 1.798 times more likely to engage students in using/applying STEM concepts and 2.401 times more likely to engage students in analyzing/evaluating STEM concepts, compared to monodisciplinary lessons.
- Classroom instruction with opportunities for students to come up with a **design** solution to the engineering task is 1.576 times more likely to engage students in using/applying STEM concepts compared to lessons without such curricular opportunity.
- Classroom instruction with opportunities for students to **evaluate** their design solution to the engineering task are 5.432 times more likely to engage students in using/applying STEM concepts and 82.930 times more likely to engage students in analyzing/evaluating STEM concepts, compared to lessons without such curricular opportunity.
- Classroom instruction with opportunities for students to **redesign** their solution to the engineering task are 2.844 times more likely to engage students in using/applying STEM concepts and 126.038 times more likely to engage students in analyzing/evaluating STEM concepts, compared to lessons without such curricular opportunity.
- Classroom instruction with opportunities for students to do **evidence-based reasoning** is 3.596 times more likely to engage students in using/applying STEM concepts and 13.502 times more likely to engage students in analyzing/evaluating STEM concepts, compared to those without such curricular opportunity.
- Classroom instruction with opportunities for students to **reflect on STEM practices** is 4.720 times more likely to engage students in using/applying STEM concepts and 20.922 times more likely to engage students in analyzing/evaluating STEM concepts, compared to one without opportunities for students to engage in any STEM practices at all.
- Classroom instruction with opportunities for students to **exercise agency** in doing STEM practices is 8.115 times more likely to engage students in using/applying STEM concepts and 19.949 times more likely to engage students in analyzing/evaluating STEM concepts, compared to one without opportunities for students to engage in any STEM practices at all.

- Classroom instruction with opportunities for students to engage in **procedural STEM practices** is 2.411 times more likely to engage students in analyzing/evaluating STEM concepts compared to one without opportunities for students to engage in any STEM practices at all.

We learn from these results that iSTEM classroom instruction that involves multidisciplinary content are more likely to engage students in higher-order thinking skills compared to monodisciplinary lessons. Particularly, the integration of engineering provided several opportunities for applications of science and mathematics content such as in designing and evaluating solutions to the engineering problem [12], [14], [15]. Mathematics integration in science and engineering lessons also engage students in practices that require the application of concepts and/or analysis of data from experiments and testing of design solutions [12], [27], [51].

Furthermore, opportunities related to STEM practices such as engaging in the process of engineering design process, evidence-based reasoning, and exercising agency in and reflecting on STEM practices are very likely to prompt higher student cognitive engagement. These insights from our results align with the literature findings. For instance, learning in a multidisciplinary context requires students to consolidate and critically apply concepts and practices from multiple disciplines [26], [27]. Second, engagement in engineering design entails that students have to think creatively and critically to come up with design solutions to the problem [20], [28]. Third, by allowing students to exercise agency in and reflect on STEM practices, learning becomes more meaningful to them as they are able to construct their own knowledge [34], [35]. And finally, evidence-based reasoning activities require students to develop and exercise critical thinking skills and justify their claims and design decisions with evidence [30], [31].

While potentially important in promoting cognitive engagement among students [29], [32], [33], collaboration (STEMOP item 7) and data practices (STEMOP item 9) fell out of the predictive model because they do not significantly contribute to the accuracy of the model with respect to our dataset. This may be due to the fact that collaborative tasks are not always indicative of cognitive engagement because students can also be using higher-order thinking skills when they are working individually. Similarly, students do not always employ data practices when they are doing activities that require cognitive engagement.

In addition, the seemingly large parameter estimates for the categories of the predictor variable, engagement in engineering design, is particularly intriguing at first sight. However, the standard error values for these estimates do not indicate any issues in terms of their accuracy and the variability in the data. Nonetheless, such magnitude of these estimates illustrate the possible high association between the outcome variable, cognitive engagement, and the predictor, engagement in engineering design, especially at their highest levels. It is also worth noting that in terms of predicting the outcome, analyze/evaluate, the magnitude of the estimates for engagement in engineering design increases and peaks at the highest category. This tells us that *opportunities to redesign engineering solutions are more likely to engage students' higher cognitive abilities compared to when they are just designing solutions the first time or evaluating whether their design meets the criteria or not*. This supports research claims [20], [25], [28] that it is critical that students fully engage in the iterative engineering design process and engage in at least one cycle of redesign.

In summary, we demonstrated the predictive relationship between curricular opportunities in engineering-centric iSTEM and student cognitive engagement. We determined that the final predictive model fits the data well and has a modest overall accuracy in classifying the outcome categories. Based on the results, engineering-centric iSTEM instruction that engage students in higher levels of cognition are marked by the presence of multidisciplinary content, engagement in designing solutions to an engineering problem, agency in and reflection on STEM practices, and evidence-based reasoning.

Limitations

The inferences made in this study are limited to iSTEM implementations where an engineering component is present and those that use the same iSTEM and engineering education frameworks described earlier in this paper. Other approaches to iSTEM that do not include engineering, for example, may have other variables that better determine the levels of student cognitive engagement. Furthermore, the setting in which the data was collected were science classrooms where iSTEM approaches were implemented. Most of these are from elementary and middle school classes, and the dataset has significantly fewer cases of high school classes compared to the other grade bands.

Conclusion and Implications

One practical way of ensuring that engineering-centric iSTEM delivers its promised outcomes in terms of student learning is by looking into the curricular affordances that support and prompt higher-order cognitive skills. This study addresses this by examining curricular opportunities in iSTEM that can predict whether a given classroom instruction provides opportunities for student cognitive engagement. Considering the findings in this study, we conclude that engineering-centric iSTEM implementations that prompt students to engage in higher levels of cognitive tasks are marked by the presence of curricular opportunities to learn multidisciplinary lesson content and to engage in various STEM practices such as designing solutions to an engineering problem, exercising agency, and evidence-based reasoning. The increasing magnitude of the odds ratios for the engineering design variable (STEM-OP item 3) underscores the importance of giving students opportunities to evaluate and redesign their solutions. Doing so allows students to engage in higher-order thinking skills.

This study may help inform future research on which iSTEM features must be explored further. For instance, the relatively high parameter estimates for the higher categories under STEM-OP item 3 (engagement in processes of engineering design) indicates that redesign activities can be optimized to help students develop critical thinking and creative problem solving. More detailed investigation on the content integrative approaches can also be done to determine their effect on learning each discipline’s core ideas and set of skills. A richer literature base about these features/components of iSTEM will definitely improve teaching practice and ensure the fulfillment of the more universal goals of STEM education.

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Appendix

Appendix A. Parameter Estimates for the Final Model

Parameter Estimates

Item4[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp (B)	
								Lower Bound	Upper Bound
STEM Cogn: use or apply	Intercept	-1.645	.151	119.490	1	<.001			
	[Item5TransBinary=.00]	.587	.140	17.596	1	<.001	1.798	1.367	2.365
	[Item5TransBinary=1.00]	0[b]	.	.	0	.	.	.	.
	[Item3Transformed=.00]	.972	1.071	.824	1	.364	2.644	.324	21.589
	[Item3Transformed=1.00]	1.692	.762	4.928	1	.026	5.432	1.219	24.206
	[Item3Transformed=2.00]	.455	.162	7.873	1	.005	1.576	1.147	2.166
	[Item3Transformed=3.00]	0[b]	.	.	0	.	.	.	.
	[Item8TransBinary=.00]	1.280	.173	54.819	1	<.001	3.596	2.563	5.046
	[Item8TransBinary=1.00]	0[b]	.	.	0	.	.	.	.
	[Item6Transformed=.00]	1.552	.628	6.100	1	.014	4.720	1.378	16.172
	[Item6Transformed=1.00]	2.993	.325	85.018	1	<.001	19.949	10.559	37.691
	[Item6Transformed=2.00]	.179	.156	1.315	1	.251	1.196	.881	1.626
	[Item6Transformed=3.00]	0[b]	.	.	0	.	.	.	.
STEM Cogn: analyze and/or evaluate	Intercept	-3.278	.244	180.980	1	<.001			
	[Item5TransBinary=.00]	.876	.175	24.963	1	<.001	2.401	1.703	3.385
	[Item5TransBinary=1.00]	0[b]	.	.	0	.	.	.	.
	[Item3Transformed=.00]	4.837	1.030	22.033	1	<.001	126.038	16.727	949.690
	[Item3Transformed=1.00]	4.418	.737	35.911	1	<.001	82.930	19.551	351.768
	[Item3Transformed=2.00]	-.200	.207	.933	1	.334	.819	.546	1.228
	[Item3Transformed=3.00]	0[b]	.	.	0	.	.	.	.
	[Item8TransBinary=.00]	2.603	.189	189.587	1	<.001	13.502	9.322	19.558
	[Item8TransBinary=1.00]	0[b]	.	.	0	.	.	.	.
	[Item6Transformed=.00]	3.041	.649	21.959	1	<.001	20.922	5.865	74.634
	[Item6Transformed=1.00]	2.094	.393	28.394	1	<.001	8.115	3.757	17.529
	[Item6Transformed=2.00]	.880	.233	14.326	1	<.001	2.411	1.529	3.803
	[Item6Transformed=3.00]	0[b]	.	.	0	.	.	.	.

a. The reference category is: STEM Cogn: know and/or understand.

b. This parameter is set to zero because it is redundant.

Appendix B. Parameter Estimates for Outcome Category: know/understand

Parameter Estimates

Item4[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp (B) Lower Bound	Upper Bound
STEM Cogn: know and/or understand	Intercept	3.278	.244	180.980	1	<.001			
	[Item5TransBinary=.00]	-.876	.175	24.963	1	<.001	.416	.295	.587
	[Item5TransBinary=1.00]	0[b]	.	.	0	.	.	.	.
	[Item3Transformed=.00]	-4.837	1.030	22.033	1	<.001	.008	.001	.060
	[Item3Transformed=1.00]	-4.418	.737	35.911	1	<.001	.012	.003	.051
	[Item3Transformed=2.00]	.200	.207	.933	1	.334	1.221	.814	1.831
	[Item3Transformed=3.00]	0[b]	.	.	0	.	.	.	.
	[Item8TransBinary=.00]	-2.603	.189	189.587	1	<.001	.074	.051	.107
	[Item8TransBinary=1.00]	0[b]	.	.	0	.	.	.	.
	[Item6Transformed=.00]	-3.041	.649	21.959	1	<.001	.048	.013	.171
	[Item6Transformed=1.00]	-2.094	.393	28.394	1	<.001	.123	.057	.266
	[Item6Transformed=2.00]	-.880	.233	14.326	1	<.001	.415	.263	.654
	[Item6Transformed=3.00]	0[b]	.	.	0	.	.	.	.

Appendix C. Collinearity Statistics - Tolerance and VIF values

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	Item5TransBinary	.917	1.091
	Item8TransBinary	.588	1.701
	Item7TransBinary	.875	1.143
	Item9TransBinary	.928	1.078
	Item3TrRedesign	.614	1.629
	Item3TrEvdesign	.635	1.575
	Item3TrDesign	.665	1.504
	Item6TrReflect	.845	1.183
	Item6TrAgency	.302	3.310
	Item6TrProce	.473	2.116

a. Dependent Variable: Item4