

Assessing Learning Gains Attributable to Curricular Innovations

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Abstract

This Evidence-Based Practice paper is motivated by industry's identification of the lack of hands-on experience as one of the major competency gaps in engineering education. This need has led to the development of new engineering and technology curricula balancing theoretical knowledge with integrated hands-on experiences. While such curricula are a welcome development, less has been done to formally assess the learning gains specifically attributable to these new approaches. This paper describes a long-term project which has developed an innovative curricular model that provides students with hands-on skills highly sought by industry; as well as an accompanying standardized test to measure student achievement on the competencies spanned by the curricular innovation. It gives a formal summative evaluation of the curricular model; and describes a comparative study being undertaken to compare the learning gains achieved under the new curricular model with those attained by comparison groups studying the same content but without participating in the particular curricular innovation.

Introduction

Lack of practical, hands-on experience in manufacturing is one of the major competency gaps in manufacturing engineering education¹. This paper reports on work that was undertaken to respond to this need through the development of the Manufacturing Integrated Learning Laboratory (MILL) concept. The MILL concept is predicated on the use of integrated projects spanning multiple courses to give students relevant and realistic hands-on experiences. It entails coordination of the hands-on activities in the multiple targeted courses around the unifying theme of designing and making a functional product^{2,3}. This was collaborative work between four institutions namely: Wayne State University, Prairie View A&M University, New Mexico State University, and Macomb College. Four knowledge areas were identified for study namely: (1) drafting/design, (2) manufacturing processes, (3) process engineering, and (4) CAD/CAM. A collaborative curriculum writing process was undertaken, in which a core set of common course-level learning outcomes was developed, and an analysis was carried out to determine which outcomes contributed most to meeting institutional educational objectives. This resulted in a common core of learning outcomes serving the needs of all participating institutions. This forms the ***MILL Manufacturing Competency Model*** (MILL Model for short). The MILL Model was implemented at all four institutions⁴. The student outcomes and competencies addressed under the MILL curricular model are shown in Table 1.

Table 1: Curricular Competencies of the MILL Model.

Manufacturing Processes		Process Engineering	
M1	Given a part design, select appropriate machining processes and tools to make the part	P1	Plan and analyze part design for productivity
M2	Determine the important operating parameters for each of these machines	P2	Analyze and improve manufacturing processes
M3	Describe selected manufacturing processes, including their capabilities and limitations	P3	Analyze tolerance charting in part design
M4	Identify and operate conventional lathe, drilling, and milling machines	P4	Apply logical design of a manufacturing process plan
M5	Communicate effectively using written and graphical modes	P5	Perform manufacturing process planning of a given part
M6	Work successfully as a member of a team	P6	Communicate effectively in oral and written formats
M7	Specify fit and tolerance of standardized and/or interchangeable mating parts	P7	Select the optimal manufacturing equipment
Drafting/ Design		CAD/CAM	
D1	Use a state-of-the-art CAD program to develop parametric solid model representations of parts and assemblies	C1	Describe and identify geometric modeling in CAD domain
D2	Visualize objects 3-dimensionally	C2	Perform computer-aided numerical control programming
D3	Create orthographic views of objects		
D4	Create 3D models using wireframe and solid modeling		
D5	Sketch objects freehand to communicate concepts		
D6	Create constraint-based modeling using a state-of-the-art CAD program		

Implementing the MILL Model entails modifying existing courses by incorporating appropriate hands-on activities, but not developing new courses. Because it is implemented into existing courses, this approach makes the MILL Model both readily transferable and highly sustainable. Coordination of the hands-on activities in those courses around the unifying theme of making a functional product is the key to the innovation. The same physical product is encountered by students from different perspectives in different courses as they progress through the curriculum. Thus, students get to address a wide range of issues involved in the design, planning, fabrication, assembly and testing of an actual product. The MILL Model was implemented in five different educational programs at the four partner schools. Figure 1 shows some of the products made by students during this work at the various participating institutions. This shows that students were successful in acquiring hands-on manufacturing skills under the MILL Model based curricula at the various schools.



Figure 1: Sample ‘Unifying Products’ Made by Students.

There is evidence that despite the development of hands-on experiences for students such as the MILL Model, engineering schools continue to maintain a predominant emphasis on theory over practice⁵. The SME Education and Research Community’s *Curricula 2015* report examined the state of manufacturing education and industry, emerging issues, and opportunities for improvement^{6,7}. It says that as manufacturing becomes more established as a discipline, it is necessary to work towards a strong yet flexible core curriculum. There is a need for a consistent model that can be used to design and assess programs. It states that new methods impact how manufacturing can be taught. In particular it is essential to apply hands-on and distance education along with effective use of the Internet, and other computer aided engineering and manufacturing software^{8,9}.

Even where there has been an increase in the use of experiential learning in engineering, not a lot has been done to formally assess the learning gains directly attributable to these new approaches. Our work to date has established that the MILL Model is an innovative curricular reform that provides students with hands-on skills highly sought by industry. In addition, we have developed a psychometrically reliable and valid standardized assessment instrument to measure student achievement on the competencies spanned by the MILL Model as described below.

The Proprietary Standardized MILL Assessment Instrument

The MILL Model was structured to help address the industry-identified gaps in hands-on manufacturing experience, meet ABET student learning outcomes, and satisfy the respective participating institutions’ specific program objectives. Current ABET criteria show a major shift away from reporting on process “inputs” (e.g., number of credit hours, volumes in the library). The focus has instead turned to institutions demonstrating through assessment and evaluation that they are reaching their desired outcomes¹⁰. This need to document program level outcomes implies that curricular innovations including the MILL Model also need to demonstrate their effectiveness in meeting the stated outcomes. To demonstrate the efficacy of the MILL Model,

we developed a standardized assessment instrument to gage student attainment relative to the model’s curricular outcomes.

There are two primary assessment methodologies used in the field of engineering education, namely: (1) descriptive (or qualitative) designs that describe the current state of a phenomenon, and (2) experimental (or quantitative) designs that examine how a phenomenon changes as a result of an intervention¹¹. A third less established methodological approach, called ‘mixed methods’ involves the collection or analysis of both quantitative and/or qualitative data in a single study¹². To assess student outcomes under the MILL Model, an experimental design was used to develop a proprietary parallel forms standardized test incorporating a hands-on manipulative to provide direct assessment of student learning. The four knowledge areas identified above formed the subscales of the test. Each subscale contains multiple competencies, which formed the test blueprint. See Table 1 for the individual competencies. The test questions developed frequently refer students to an accompanying physical artifact to tie in with relevant hands-on experiences. This approach, using a standardized test incorporating a physical manipulative to evaluate attainment of hands-on engineering competencies, is unique in the field.

Research Design for MILL vs. Comparison Student Performance

The MILL standardized test will be administered to students at the four MILL sites and three comparison sites in the form of a pre-test and a post-test to assess actual learning gains. Initial demographics indicate a wide spread of school-based criteria, the similarity of which will be confirmed via a series of chi-squared tests. The design is shown in Table 2.

Table 2: Research Design

M →	MILL	O _{1C,D,M,P}	X	O _{2C,D,M,P}
M →	Comparison	O _{3C,D,M,P}	–	O _{4C,D,M,P}

where, M → = school-based matching criteria,
 C = CAD/CAM MILL subscale,
 D = Design/Drafting MILL subscale,
 M = Manufacturing Processes MILL subscale, and
 P = Process Engineering MILL subscale.

In terms of data analysis, this research layout dictates a MANCOVA analysis on the O₂ and O₄ posttest scores with O₁ and O₃ pretest scores used as the covariates. The data analyses will be three-fold:

- (i) The omnibus hypothesis will determine the impact of the MILL intervention on the multiple outcome subscale measures.
- (ii) There is no prior data among our MILL faculties, all of whom throughout the course of our previous project were trained in the MILL intervention and hence are homoscedastic with regard to their instructional delivery, to suggest they present random effects¹³. Despite the current popularity of testing for nesting effects in school based research, there is ample evidence in the literature that the automatic serial testing for “teacher” effects prior to “school (i.e., treatment vs. comparison)” effects is guaranteed to

inflate the experiment-wise Type I error rate¹⁴. The inflation will reach almost twice nominal alpha in this context. Hence, the outcome variables will first be analyzed with a Bonferroni-adjusted ANOVA model to determine if a nesting effect exists prior to conducting a multivariate hierarchical linear model (MGLM) of a class within school by location analysis.

(iii) A meta-analysis will be computed on separate MANCOVAs with Stouffer's Z.

All statistical tests will be conducted at nominal $\alpha = 0.05$ level. Preliminary tests of underlying assumptions (e.g., multicollinearity, normality), will be computed, with appropriate adjustments to prevent the inflation of experiment-wise Type I errors due to serial testing. Robust, non-parametric, or exact (e.g., approximate permutation) methods will be substituted as necessary. This is an innovative use of standardized testing for programmatic evaluation as opposed to standard comparison curricula. It can document attainment of specific targeted learning outcomes for accreditation and other assessment purposes. By comparing performance on the test instrument between intervention groups and comparison non-intervention groups, this work will document the learning gains directly attributable the MILL Model intervention.

Psychometric Analysis of the Standardized MILL Assessment Instrument

Preliminary testing at the participating schools in the 2014-15 academic year has provided data for analyzing the psychometric characteristics of the MILL standardized test instrument. Content validity of the test was assessed by the blueprint approach to test construction. The psychometric structure of the test was pursued through an item deletion approach. The entire item pool was administered to a total of $N = 125$ students; 89 at the MILL schools and 39 at the comparison schools. Below, we discuss the results of the preliminary testing.

Psychometrics

A variety of psychometric analyses were conducted on the test results. Item 2 of the 32 items was discovered to be problematic, and was deleted prior to psychometric analyses, leaving $N = 31$ items in the pool for examination.

Reliability

Internal Consistency is a measure of the internal homogeneity of subject matter. For example, the test is randomly split into two parts and the correlation, is computed on the scores for the two parts. This form of internal consistency is called split-halves, r_{SH} , which is dependent on the fashion in which the test is split. Cronbach's α is an improvement on this. Conceptually, Cronbach's α is the long-run average correlation obtained from all possible permutations of splitting the test into two parts. For the MILL test instrument, Chronbach's α I was 0.783, and based on standardized items it was 0.783. Item statistics are presented in Table 3, item-total statistics in Table 4, summary item statistics in Table 5, and total scale statistics in Table 6. Based on reliability information; items 7, 25, and 31 are candidates for deletion, any of which would increase the total scale reliability above 0.80.

Table 3: MILL Item Statistics.

	Mean	Std. Deviation
Q1	0.29	0.455
Q3	0.66	0.474
Q4	0.70	0.462
Q5	0.75	0.434
Q6	0.76	0.429
Q7	0.64	0.482
Q8	0.88	0.326
Q9	0.58	0.495
Q10	0.72	0.451
Q11	0.72	0.451
Q12	0.55	0.499
Q13	0.55	0.499
Q14	0.22	0.419
Q15	0.50	0.502
Q16	0.58	0.496
Q17	0.36	0.482
Q18	0.65	0.480
Q19	0.56	0.498
Q20	0.20	0.402
Q21	0.56	0.498
Q22	0.41	0.493
Q23	0.70	0.458
Q24	0.22	0.413
Q25	0.47	0.501
Q27	0.36	0.482
Q28	0.69	0.465
Q29	0.30	0.458
Q30	0.23	0.424
Q31	0.25	0.434
Q32	0.47	0.501
Q33	0.53	0.501

Table 4: Item-Total Statistics.

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q1	15.78	25.691	0.504	0.773
Q3	15.40	26.274	0.354	0.779
Q4	15.37	26.993	0.212	0.786
Q5	15.31	26.749	0.287	0.783
Q6	15.30	26.891	0.258	0.784
Q7	15.42	28.569	-0.112	0.800
Q8	15.18	26.684	0.425	0.779
Q9	15.48	25.284	0.541	0.770
Q10	15.34	26.340	0.363	0.779
Q11	15.34	26.615	0.302	0.782
Q12	15.51	27.784	0.036	0.794
Q13	15.51	25.687	0.451	0.775
Q14	15.84	27.506	0.123	0.789
Q15	15.56	25.797	0.426	0.776
Q16	15.49	25.671	0.458	0.774
Q17	15.70	25.597	0.491	0.773
Q18	15.42	25.680	0.476	0.774
Q19	15.50	24.994	0.598	0.767
Q20	15.86	27.457	0.143	0.788
Q21	15.50	25.204	0.553	0.770
Q22	15.66	26.018	0.389	0.778
Q23	15.36	26.039	0.422	0.777
Q24	15.85	28.517	-0.106	0.798
Q25	15.59	28.566	-0.111	0.801
Q27	15.70	26.920	0.214	0.786
Q28	15.38	25.769	0.474	0.774
Q29	15.77	26.647	0.288	0.782
Q30	15.83	28.093	-0.011	0.794
Q31	15.82	29.280	-0.266	0.804
Q32	15.59	25.985	0.388	0.778
Q33	15.54	25.831	0.420	0.776

Table 5: Summary Item Statistics.

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance
Item Means	0.518	0.200	0.880	0.680	4.400	0.036
Item Variances	0.216	0.106	0.252	0.146	2.367	0.001

Table 6: Total Scale Statistics.

Mean	Variance	Std. Deviation	N of Items
16.06	28.222	5.312	31

Internal Validity Structure

An examination of the psychometric structure was initially undertaken by exploratory factor analysis (EFA) methods. Principal components extraction with varimax rotation with Kaiser normalization was used, followed by two traditional methods of factor identification (i.e., scree plot, eigenvalue ≥ 1.0). In the first iteration of 32 items, a 10 factor solution was obtained, accounting for 63.3% of total variance explained. Results suggested the deletion of Q1, Q6, Q16, Q23, Q28, and Q33 due to loading on multiple factors. The second iteration suggested further elimination of Q9, Q10, Q12, Q15, Q27, and Q30; the third iteration the elimination of Q20, Q22, and Q32; and the fourth solution the elimination of Q25 and 31. The fifth and final iteration produced the final factor analysis solution.

The final exploratory factor scree plot is presented in Figure 2 below. The rotated component matrix (final 5 factor solution) is presented in Table 7, Total Variance Explained in Table 8, and Component Transformation Matrix in Table 9. The final 5 factor model accounted for 60.8% of total explained variance.

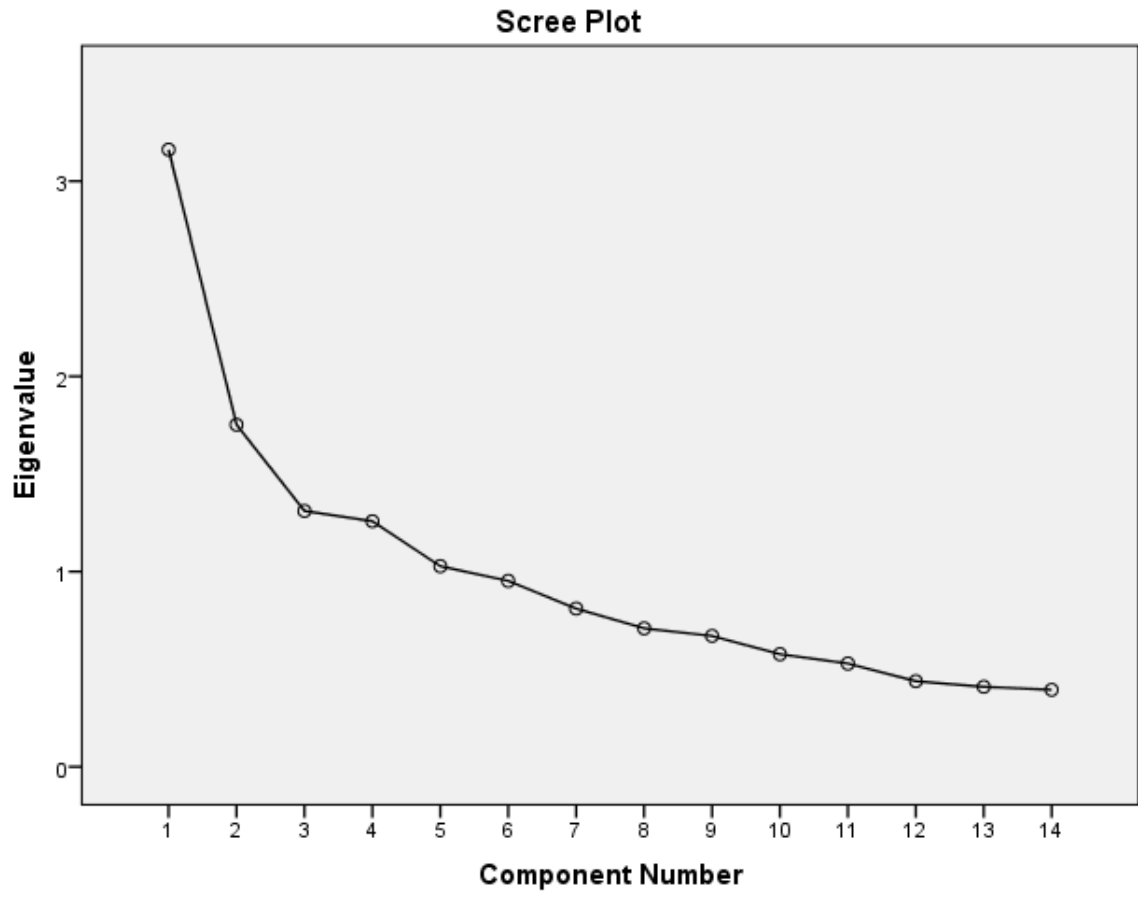


Figure 2: Final MILL Scree Plot

Table 7: Rotated Component Matrix.

	Component				
	1	2	3	4	5
Q17	0.729				
Q13	0.696				
Q18	0.669				
Q19	0.665				
Q21	0.651				
Q7		-0.792			
Q29		0.699			
Q14		0.688			
Q4			0.865		
Q3			0.741		
Q5				0.898	
Q8				0.645	
Q24					-0.827
Q11					0.498

Table 8: Total Variance Explained.

Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	2.505	17.890	17.890
2	1.769	12.635	30.525
3	1.577	11.261	41.786
4	1.436	10.260	52.046
5	1.224	8.740	60.786

Table 9: Component Transformation Matrix.

Component	1	2	3	4	5
1	0.804	0.286	0.337	0.309	0.249
2	-0.025	-0.839	0.457	0.286	0.071
3	-0.566	0.380	0.228	0.624	0.307
4	-0.151	0.263	0.780	-0.396	-0.379
5	0.098	0.035	-0.130	0.527	-0.834

Item Statistics and Ability Grouping

Item statistics are compiled in Table 10. The column titled P is also known as the item's difficulty index. P values close to 1 indicate the items are easy, whereas P values close 0 indicate the items are hard. For example, item 8 would be considered easy because 88% ($P = 0.88$) of the students obtained the correct answer, whereas item 20 would be considered hard because only 20% ($P = 0.20$) answered the item correctly. Ideally, in a standardized test, the average P value should be close to the middle, or $P = 0.5$. In this case, the mean P value is $= 0.518$, which is very close to the desired middle point.

The column titled D refers to item discrimination, which is an index of higher performing students' performance on that item as compared with lower performing students' performance. Values that are negative are candidates for exclusion. Hence, item 7 should be reviewed for that purpose. Generally, values of D closer to 0 indicate less discrimination ability, whereas values closer to 1 indicate more discrimination ability. However, this rule of thumb only pertains to items with a P value of 0.5. Items that are easier or more difficulty than average produce a truncated D scale, and must be interpreted accordingly, meaning values as low as $D = 0.6$ may represent maximal discrimination ability. The point-biserial (PB) correlation, also compiled in Table 10, is another method of assessing discrimination ability, and generally follows the same rules of thumb in interpretation as in D. Ability grouping is also presented in Table 10. It is an indication of the percent correct obtained by those students scoring below the median (Low) vs those scoring above the median (High).

Table 10: Item Statistics and Ability Grouping.

Item Number	Item Statistics			Ability Grouping	
	P	D	PB	Low	High
1	0.29	0.64	0.57	0.05	0.69
2					
3	0.66	0.49	0.43	0.40	0.89
4	0.70	0.37	0.29	0.40	0.77
5	0.75	0.37	0.36	0.58	0.94
6	0.76	0.34	0.33	0.55	0.89
7	0.64	-0.07	-0.02	0.54	0.46
8	0.88	0.35	0.47	0.65	1.00
9	0.58	0.73	0.61	0.28	1.00
10	0.72	0.50	0.44	0.48	0.97
11	0.72	0.42	0.38	0.53	0.94
12	0.55	0.09	0.13	0.4	0.49
13	0.55	0.66	0.52	0.25	0.91
14	0.22	0.19	0.20	0.22	0.15
15	0.50	0.63	0.50	0.50	0.23
16	0.58	0.64	0.53	0.28	0.91
17	0.36	0.65	0.56	0.13	0.77
18	0.65	0.57	0.54	0.38	0.94
19	0.56	0.83	0.66	0.18	1.00
20	0.20	0.21	0.22	0.08	0.29
21	0.56	0.74	0.62	0.18	0.91
22	0.41	0.57	0.47	0.20	0.77
23	0.70	0.47	0.49	0.48	0.94
24	0.22	-0.05	-0.03	0.28	0.23
25	0.47	-0.03	-0.02	0.38	0.34
26	0.36	0.38	0.30	0.28	0.66
27	0.69	0.6	0.54	0.40	1.00
28	0.30	0.48	0.37	0.18	0.66
29	0.23	0.05	0.07	0.18	0.23
30	0.25	-0.21	-0.19	0.30	0.09
31	0.47	0.59	0.47	0.30	0.89
32	0.53	0.61	0.50	0.25	0.86

Conclusion

The data showed strong discriminatory ability for all test items. With an average difficulty index P of 0.518, the test instrument is very close to ideal for a standardized test. Together, these results indicate that this test is as a valid, high-quality instrument for assessing

student achievement of MILL Model outcomes. To continue with the assessment process, the test was administered in Fall 2015 to the MILL implementations sites as well as the comparison sites as the Pretest. The test will be administered again in Spring 2016 as the Posttest. Learning gains between the two test groups will be compared to ascertain the relative gains (if any) that are directly attributable to the MILL model intervention, which is the objective of this work.

Acknowledgement

The work described in this paper was supported by the National Science Foundation IUSE Program under grant number *DUE-1432284*. Any opinions, recommendations, and/or findings are those of the authors and do not necessarily reflect the views of the sponsors.

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