A study of the influence of technical attributes of beginner CAD users on their performance

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Abstract

In this work, we aim to answer the question: what does it take to create a competent CAD user? Certainly, the answer involves technical factors that provide the ability to learn as well as personal attributes and attitude. This paper starts with a description of the progress of a group of trainees as they undergo a training program in solid CAD (Pro/Engineer). Initially, the technical attributes of 44 CAD trainees (all mechanical engineering seniors), in a university setting, are uncovered. This is accomplished via a written questionnaire that queries the trainees about their background in CAD-related topics such as math foundation, computer science, and mechanical engineering background. A methodology is established that addresses the framework that may be described using the following process:

(1) Construct a questionnaire by using focused, CAD specific written questions to reveal the trainees’ technical attributes.
(2) Assess the development of CAD skills as training progresses.
(3) Establish a correlation between the answers of the questionnaire and the performance measures of CAD skill development in order to determine the relevance of individual questions.
(4) Analyze the correlation results to determine the degree by which the trainees’ technical attributes influence CAD competence development.

This work is envisaged to pave the way for complementary work that investigates the effects of the trainees’ personality attributes (e.g., motivation/attitude and perception/imagination) and learning styles on CAD competence building.

Keywords: CAD user; Questionnaire; Training; Technical attributes

1. Introduction

Ye et al. [6] examined the various roles of CAD personnel including the basic CAD user. They defined a set of technical topics necessary for 3D CAD users: namely, mathematics, computer science, design, and CAD-related skills. Also, Field [1] discussed the attributes that he considered necessary for the success of the majority of CAD users in the auto industry. In this work, we look for these attributes in a pool of 44 novice trainees (spread over two consecutive years: 23 in the first year and 21 in the second year) all being mechanical engineering seniors on their way to becoming users of 3D mechanical CAD. We developed a written questionnaire in which specific questions queried trainees about their technical background. In order to determine the significance of these attributes on trainees’ performance, we correlated them to trainees’ performance using the methodology originally presented in [2] and further verified in [3]. This methodology tracks the efficiency (speed) as well as the effectiveness (as evidenced by the constructed models’ sophistication) of the CAD knowledge as it gets acquired by trainees. It should be noted that we expanded the survey used in [4] into a more expansive and more specific one so that it may be conducted at several stages during training for the purpose of continuously monitoring the trainees’ attributes. The objective was to have more specific responses (especially on technical attributes) that were found to be critical in the improvement and progress of training. The aforementioned technical attributes include mathematical skills (e.g., solid geometries and their representation) and mechanical design plus engineering skills, which are especially helpful towards the making of a competent
CAD user. Also parts of the technical attributes are computer science-related knowledge and graphics plus graphical visualization skills. The former is critical in the proper utilization of CAD databases, user interfaces, and file management, while the latter may prove valuable where spatial imagination is required.

This research attempts to link the technical background of trainees to their performance so as to draw generalized conclusions about the contributions of certain educational backgrounds to successful CAD training. This information may be used by educators to design educational programs that would better prepare students to CAD training and, moreover, help them get the most out of it. This is especially applicable in systems where students are able to choose early on the specific field of study (e.g., mechanical CAD design and modeling), thus requiring academic institutions to design focused programs that correspond to those fields. Therefore, the findings of our research can greatly assist institutions in designing programs that maximize the learning process of students in courses of design and modeling utilizing solid CAD.

2. Training and performance assessment

In [2], the authors developed an assessment methodology of CAD performance during formal training. The CAD tool utilized was Pro/Engineer (Parametric Technology Corporation), version Wildfire. This is high-end CAD software that utilizes parametric and associative characteristics. A solid, three-dimensional (3D) model is constructed of features-of-size which are 3D geometric shapes such as protrusions, cuts, holes, etc. The trainees had fairly homogenous technical backgrounds and were senior mechanical engineering students. The training program was conducted twice a week for two hours per session for a total of four hours per week. The training lasted over 15 weeks. Trainees were assigned one homework exercise after each lecture consistent with the taught material. In addition, the trainees also practiced in their own time.

For assessment purposes, four test models, Fig. 1(a)–(d), that are comparable in complexity, were constructed by the trainees at prescribed intervals. Performance was measured based on (1) the time needed to construct the test CAD models and (2) the total number of features-of-size employed to build these models. These two performance measures evaluated both the initial performance and learning rate of trainees, and represented the efficiency and effectiveness, respectively, by which trainees acquire CAD skills. The rest of this section provides a brief overview of these measures for the sake of completeness and due to their pivotal role in this research.

2.1. Performance efficiency

The times taken by the average trainee to construct the four models and the corresponding standard deviations shrunk continuously but by increasingly smaller values. As Fig. 2(a) shows, the class performance time (speed, or time needed to build the test parts) was found to decrease with cumulative experience (shown with spread bars) and to conform to a power expression that follows the Wright’s learning curve [5]

\[ T(t) = T(1)e^{-bt}. \] (1)
Table 1
Quantified class responses: Basic math foundation

<table>
<thead>
<tr>
<th>Question</th>
<th>BM0</th>
<th>BM1</th>
<th>BM2</th>
<th>BM3</th>
<th>BM4</th>
<th>BM5</th>
<th>BM6</th>
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<tbody>
<tr>
<td>Class average</td>
<td>2.9</td>
<td>3.7</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
<td>4.0</td>
<td>3.9</td>
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<tr>
<td>Max</td>
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<tr>
<td>Min</td>
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<td>2.0</td>
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<td>2.0</td>
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<tr>
<td>Std</td>
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<td>0.5</td>
<td>0.7</td>
<td>0.8</td>
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2.2. Performance effectiveness

As training progressed and trainees accumulated more procedural knowledge, they were able to dream up increasingly more sophisticated construction scenarios. To a certain degree, it was found [2,3] that this trend of using fewer, yet more complex, features results in reduced overall construction time. An effective CAD task is one that is done smartly by using fewer number of features, \( F(t) \). This learning curve (see Fig. 2(b)) was fitted to the power form in (1) but using the recorded number of features data

\[
F(t) = F(1) e^{-bt_f}
\]

where \( F(t) \) is the number of features that trainees employed in modeling at time \( t \), \( F(1) \) is the number of features utilized in construction at first repetition, and \( b_f \) comprises the number-of-feature progression (decrease) rate. The class learning curve that describes the evolution of model sophistication suggests values of 10.79 features and 0.474 for \( F(1) \) and \( b_f \), respectively. Note that the asymptote shown as the horizontal line in the figure, and which the experimental learning curve seems to approach, represents two features being the ultimate minimum number of features required for the given test part construction. This indicates that an effective CAD task is one that is done smartly by using fewer number of features, \( F(t) \).

The widely varying individual student performance (see spread bars in Fig. 2(a) and (b)) indicate drastically differing capabilities in CAD competence development even within a fairly homogenous class of CAD trainees.

3. The questionnaire and the resulting trainees’ technical profile

We consider all the attributes addressed by Ye et al. [6] and present them in the form of a questionnaire, which is included in Appendix A. All the answers were quantified based on a scale from 1 (lowest) to 5 (highest), and then basic statistics were computed as reported in Tables 1–7. By inspecting the statistical data in these tables, one could observe that a good level of the mathematical foundation is acquired by students, during their studies. Some questions relating to more advanced topics than those expected on an undergraduate engineering level, such as surface geometry (CM2 and CM4), scored relatively low.

Moreover, certain computer science skills (Table 4) that are potentially helpful to trainees’ performance in CAD
modeling were not prevalent in the results. On the other hand, backgrounds in data structures (CSE5) and databases (CSE6), which were also found to be uncommon among the surveyed students, may be thought of as non-essential to CAD model construction, although one could argue that they can help trainees to a certain extent in associating feature complexity with computer storage and processing costs, and in gaining insights into the internal data representation and storage of mechanical shapes. In contrast, and as a sign of the times, trainees seem to be well versed in internet-related technology (CSE7). Incidentally, this attribute will be shown below to contribute significantly to CAD skills development.

As to skills that are more directly related to CAD modeling (i.e., methodologies related to CAD and mechanical design, in Tables 5 and 7, respectively), students seem to have an average or slightly better than average background. This may be expected since students normally acquire such background through various mechanical engineering courses during the four years they have been taking courses. On the other hand, the survey results revealed that students have noticeably weaker education in graphic interfaces and 3D visualizations (Table 6). This, coupled with the not-so-excellent skills in computer tools and programming, suggests that mechanical engineering students should be introduced to more Information Technology (IT) material given the increasingly growing role of this area in all aspects of engineering and related disciplines.

4. Correlation of performance with technical attributes

In this section, we present correlation results that relate to the trainees’ class average. The results of correlating the class technical attributes with the average efficiency and effectiveness performance data are presented thereafter. Quantifying efficiency via speed metrics is fairly common practice for performance assessment purposes. More specifically, a training manager may be interested in finding out which technical attributes correlate the most with fast learners (good performers in the $b_t$ criterion), or which ones better prepare students to being efficient CAD modelers (good performers in the $T(1)$ criterion). Measuring effectiveness represents a novel approach which we believe to shed more light on the relationship between technical attributes and qualitative performance.

We begin by performing a basic statistical correlation of the above attributes to CAD performance through correlating the responses to individual questions in each category. Being engineering seniors, one may expect relative uniformity in

### Table 2
Quantified class responses: Advanced math foundation

<table>
<thead>
<tr>
<th>Question</th>
<th>AM1</th>
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<th>AM3</th>
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<tr>
<td>Std</td>
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### Table 3
Quantified class responses: CAD-related math foundation

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<th>Question</th>
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<th>CM3</th>
<th>CM4</th>
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<tbody>
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<td>Class average</td>
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<td>4</td>
<td>5</td>
<td>5</td>
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<td>1</td>
<td>1</td>
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<td>Std</td>
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### Table 4
Quantified class responses: Computer science foundation

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<th>Question</th>
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<th>CSE4</th>
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<tr>
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<td>Std</td>
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### Table 5
Quantified class responses: CAD methodology foundation

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<th>Question</th>
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<td>2.7</td>
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</tr>
<tr>
<td>Std</td>
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<td>1.1</td>
<td>1.2</td>
<td>1.0</td>
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### Table 6
Quantified class responses: Graphics foundation

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<th>Question</th>
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<th>G3</th>
</tr>
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<td>1.7</td>
</tr>
<tr>
<td>Max</td>
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<td>5</td>
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<tr>
<td>Min</td>
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<td>1</td>
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<tr>
<td>Std</td>
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<td>1.0</td>
<td>0.9</td>
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</tbody>
</table>

### Table 7
Quantified class responses: Mechanical design foundation

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<tr>
<th>Question</th>
<th>MD1</th>
<th>MD2</th>
<th>MD3</th>
<th>MD4</th>
<th>MD5</th>
<th>MD6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class average</td>
<td>3.1</td>
<td>3.9</td>
<td>3.9</td>
<td>3.5</td>
<td>0.6</td>
<td>2.0</td>
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</tr>
<tr>
<td>Min</td>
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</tr>
<tr>
<td>Std</td>
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<td>0.8</td>
<td>1.0</td>
<td>1.4</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Table 10 shows that all four questions are applicable in that they query students about background and skills that help them being efficient trainees at the start of the training (fast times). This seems plausible given that these questions (see Appendix A for CM1–CM4) relate to the geometry and visualization of elementary CAD shapes. Moreover, the responses to CM1 prove to being related to the learning effectiveness of trainees in modeling CAD parts with smaller numbers of features.

### 4.1. Correlation with individual question responses

#### 4.1.1. Mathematical foundation

**Basic math (BM).** Table 8 shows that most of the basic math topics significantly correlate to initial construction speed as indicated by the *p* values of less or better than 0.05. (Table cells shown with blank *p* values are found to be statistically insignificant. Most of the contributing responses were found to range from statistically significant to extremely statistically significant as evidenced by the *p* values cited). Note that the correlation coefficient values (numerically bound between −1 and +1) shown in the table are almost all negative, which indicates that stronger attributes (larger values) result in smaller performance times as well as fewer number of employed features. For the novice level of CAD exercises presented here, the ‘vague’ topic of mathematical modeling as well as the topics of vector algebra, transforms, and differential equations were all found to have weak statistical correlation. (These topics may be of more significance, though, if more advanced users were to be evaluated.) Despite the weak correlation of some individual questions, all questions were retained for the purpose of calculating the ‘lump sum’ correlation coefficients for the entire “Basic Math” category yielding a coefficient of −0.46 in Table 15. Had weak questions been excluded, values reported in Table 15 would have been even more significant, of course.

**Advanced math (AM).** For the advanced math category, the correlation results in Table 9 demonstrate that only the answers to AM1 correlate appreciably with the performance data. More specifically, this question asks about spatial geometry, which is justifiably much more related to CAD modeling than differential geometry (AM2) and optimization techniques (AM3).

**Mathematical foundation for CAD (CM).** In this category of questions, which deals with the mathematical foundation for CAD, Table 10 shows that all four questions are applicable in that they query students about background and skills that help them being efficient trainees at the start of the training (fast times). This seems plausible given that these questions (see Appendix A for CM1–CM4) relate to the geometry and visualization of elementary CAD shapes. Moreover, the responses to CM1 prove to being related to the learning effectiveness of trainees in modeling CAD parts with smaller numbers of features.
4.1.2. Computer science and engineering foundation

The computer science and engineering (CSE) foundation questions are applicable mostly to the efficiency of building CAD models, as evidenced by the correlation results in Table 11. This is expected since CSE skills are supposed to enhance the knowledge and skills of students in using computer tools and technologies. As seen in Table 11, these factors have correlated well with the speed of CAD model construction, and this is due to the trainees’ familiarity with computer hardware and software concepts and interfaces. Questions relating to competence in programming (CSE4) and internet technology (CSE7) were found to particularly score well not only in the $T(1)$ measure but also in relation to the increased probability of efficient learning ($b_f$).

4.1.3. Methodologies related to CAD

As Table 12 shows, the questions in this category correlate well with the efficiency performance of students. The questions MR1, MR2, MR3, and MR4 probe students about their backgrounds in modeling methodologies, and these seem to have made them efficient performers at the onset of the training. The questions MR6 and MR7, which are similar to the above four questions, also correlate well with efficiency. Finally, it is not surprising to discover that questions MR8 and MR9, which try to gauge the students’ understanding of manufacturing-related familiarity (but not necessarily their solid modeling related skills), did not score high.
4.1.4. Graphics foundation

It was not surprising to find out that, in Table 13, all three questions in this category showed significant correlations with both efficiency and effectiveness of building CAD parts. This is because they involve computer graphical user interfaces (GUIs), drawing skills, and 3D Max, all of which are directly concerned with building CAD parts using a GUI-based computer tool, like Pro/E.

4.1.5. Mechanical design foundation

The questions in this group generally yield the same impressive results (Table 14) as the ones in the previous category, again because they are concerned with CAD-specific skills and knowledge.

4.2. Correlation of performance by category

Next, having done individual question correlations, we correlate the results for each category. After having established the significance for each question, we group the responses for the questions within each category and determine the correlation for the average of the entire set of data that correspond to the category. Shown in Table 15 are the resulting correlations for all seven technical categories (columns) and for all four performance measures (rows).

In Table 15, sorting the findings across columns reveals that the basic math (BM) category plays one of the most basic roles in preparing students to undertake CAD training, as reflected in the relatively high correlation results of $T(1)$, and also for being able to develop their CAD skills during the training (i.e., reflected in the high values of $b_f$). Furthermore, BM is found to be significant when it comes to building the effectiveness of students over the duration of the training ($b_f$) to devise more effective strategies (a fewer number of features) in building CAD models. This can be linked to the fact that BM promotes general problem solving skills in trainees, and these in turn improve their abilities in dreaming up more complex features when constructing CAD models. On the other hand, advanced math does not seem to correlate well. Two other significant categories are the graphics foundation, GF, and mechanical design, MD, categories. Both of these categories appear to have strong influence across the board. As to the remaining attributes, the discussion presented in the above subsection (i.e., concerning the individual questions) also applies here in the general sense, meaning in accordance with the majority of the questions in each category.

Exploring the results based on the rows in Table 15 confirms that practically all technical attributes (AM excepted) strongly contribute to CAD competence in the initial performance time category. The same conclusion is almost equally applicable to the closely related measure “rate of efficiency (speed) improvement”. This is in stark contrast to the measures having to do with the solid model build “strategy”, namely $F(1)$ and $b_f$. In the former, the only two technical categories found to have significant correlation are the graphics foundation, GF, and mechanical design, MD, foundations. For the measure of the rate of effectiveness (number of features) $b_f$, the only meaningful correlation was found to exist with the basic math (BM) technical attribute.

In all, the entries in Table 15 strongly indicate that the successful novice CAD user is one who possesses the right mix of CAD-relevant technical attributes that allows him/her to achieve his/her impressive initial speeds. Having done initially well, the CAD user honed the recently learned skills in order to improve his or her speed utilizing roughly the entire gamut of skills. The above findings bear practical implications which may prove beneficial to training or hiring managers where they, for example, may be interested in finding out which technical attributes better prepare current or future employees to being efficient CAD modelers (good $T(1)$ performance measure) or which ones correlate the most with fast learners (good performers in the $b_f$ performance measure). Similarly, some CAD-based design/analysis jobs may require exceptional insight/perception, thus favoring CAD users who are effective in handling the complexity. Users with good $F(1)$ and $b_f$ values would best fit this last variety.

5. Discussion

Having proved the statistical contribution of the above technical attributes to CAD performance, we now establish the quantitative contribution of these attributes to this performance. For illustration, the mechanical design foundation (MD) category is used. In Fig. 3, we plot one of the performance measures, the initial performance time (minutes), versus the trainees’ quantified MD strength. Based on the data plotted in
the figure, the correlation coefficient of $-0.66$ in Table 15 was addressed in the correlation study above. What is dealt with here is the linear fit of the initial performance time (IPT) versus the attribute value. It is made up of an intercept and a slope according to

$$\text{IPT} = \text{Slope}_{\text{IPT,MD}} \times \text{MD} + \text{IPT}(0)$$  \hspace{1cm} (3)

Fig. 3 shows the values of $-12.1$ and $60$ for the slope and the intercept, respectively. The MD scale is plotted versus initial performance with highest category score recorded of just above 4. Similar equations may similarly be derived for each of the other three performance parameters versus all technical attributes corresponding to Table 15.

The significance of the slope in the performance equations, such as the one in Eq. (3), cannot be understated. The slope reflects to what degree the technical attribute influences performance, i.e. the larger the value of the intercept, the larger the effect, and vice versa. The slope values for the performance equations which relate the technical attributes to the initial performance time for the class average are shown graphically in the form of a web plot in Fig. 4. Having eliminated the non-contributing AM, the figure reflects the important role that these technical attributes play in preparing prospective CAD users to be efficient at the start of CAD training. In terms of the individual attributes, the plot stresses the extreme significance of basic math (BM) and mechanical design (MD) as foundations for the average CAD user. As important, but to a lesser degree, are all the other technical topics.

In a following work, other and more “natural means”, such as those that deal with personal skills and facets (e.g., motivation and dedication), will be studied to understand their role in CAD training performance. It will be revealed that non-technical attributes (personality attributes such as perception and imagination) also contribute towards building models with less time and fewer, more complex, features of size.

6. Conclusions

The focus of the paper was on linking the technical attributes of beginner CAD users to their efficiency (speed) and effectiveness (critical thinking) performance. The technical attributes were measured at the start of the training through a detailed survey with a standard form and clear questions. The performance data was obtained throughout the training and hence, this study was a discovery endeavor whose outcomes are meant to be generalized and learned from. Armed with such knowledge, a student can better choose from a pool of elective courses that would maximize his or her performance in applied mechanical CAD courses. Moreover, undergraduate program designers can employ this information to develop a curriculum that would best serve students who want to pursue a mechanical CAD career. In all, this study established a strong link between basic math foundation and all performance measures. The other studied attributes also correlated strongly with performance, but either to a lesser degree or to certain measures and not others.

Acknowledgement

The authors wish to acknowledge the financial support of the University Research Board (URB) of the American University of Beirut.

Appendix A

A.1. Mathematical foundation

Basic math (BM)

BM0. My background/knowledge in Mathematical modeling is (low → high)

A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM1. My background/knowledge in Math can be described as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM2. My general problem solving skills can be described as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM3. My background/knowledge in trigonometry can be described as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM4. My background/knowledge in calculus can be described as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM5. My background/knowledge in linear algebra is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM6. My background/knowledge in vector algebra is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM7. My background/knowledge in transforms is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM8. My background/knowledge in basic analytical geometry is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

BM9. My background/knowledge in ordinary and partial differential equations is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

Advanced math (AM)

AM1. My background/knowledge in spatial geometries and their mathematical representations can be described as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

AM2. My background/knowledge in differential geometry is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

AM3. My background/knowledge in optimization techniques is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

Mathematical foundation for CAD (CM)

CM1. My background/knowledge in analytical curves and surfaces is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

CM2. My background/knowledge in non-uniform rational B-spline (NURBS) curves and surfaces is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced
CM3. My background/knowledge in *intersections and Boolean operations* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

CM4. My background/knowledge in *boundary representations (B-reps) and constructive solid geometry (CSG)* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

### A2. Computer science and engineering foundation (CSE)

CSE1. My knowledge/skills in *computer hardware* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

CSE2. My knowledge/skills in *application programming interface (API), e.g. AutoLisp, etc., programming* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

CSE3. My knowledge/skills in *VBA programming* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

CSE4. My knowledge/skills in *C/C++ programming* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

CSE5. My knowledge/skills in *data structure* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

CSE6. My knowledge/skills in *data base technology* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

CSE7. My knowledge/skills in *internet technology* is (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

### A3. Methodologies related to CAD (MR)

MR1. I rate my familiarity with topics of solid geometry construction such as *primitive geometry modeling and constraint-based modeling* as (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

MR2. I rate my familiarity with design philosophies such as *top-down/bottom-up design methodology* as (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

MR3. I rate my familiarity with *parametric modeling methodology* as (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

MR4. I rate my familiarity with *feature-based modeling methodology* as (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced

MR5. I rate my familiarity with *concurrent engineering methodology* as (low → high)
- A. Non existent
- B. Basic
- C. Average
- D. Strong
- E. Advanced
MR6. I rate my familiarity with reverse engineering as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

MR7. I rate my familiarity with part family design as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

MR8. I rate my familiarity with product data management (PDM)/product life cycle management (PLM) as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

MR9. I rate my familiarity with enterprise resource planning (ERP) as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

A.4. Graphics foundation (GF)

G1. My experience in using computer software packages with graphic user interfaces (GUIs) is (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

G2. I rate my familiarity with graphics/drawing skills as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

G3. I rate my familiarity with 3D Max as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

A.5. Mechanical design foundation (MD)

MD1. I rate my mechanical design skills as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

MD2. I can easily hand sketch the following: (you can select more than one answer)
A. Cube
B. Cylinder
C. Pyramid
D. Cone
E. Torus

MD3. On a scale of 0–4, I rate myself as being ‘mechanically inclined’ (low → high)
A. 0
B. 1
C. 2
D. 3
E. 4

MD4. I rate my skills in 2D AutoCAD as (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

MD5. Besides 2D AutoCAD, I am also familiar with 3D solid CAD packages OTHER than Pro/E. Name (SolidWorks, CATIA, etc.) if any: (you can indicate more than one answer)
A. ...........
B. ...........

MD6. Before I took this class, my skills in Pro/Engineer were: (low → high)
A. Non existent
B. Basic
C. Average
D. Strong
E. Advanced

References