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Early Warning System to Identify Poor Time Management Habits*

LEONHARD E. BERNOLD
Department of Civil, Construction and Environmental Engineering, North Carolina State University, Raleigh, NC 27695, USA. Email: Bernold@ncsu.edu

Student-centred as well as lifelong learning, require vastly different study skills than those needed to succeed in today's mainly lecture-based engineering classes. This paper presents the result of a survey that assessed the study skills of engineering freshmen. Because surveys do not capture how students actually use their study skills, this study was carried out to discover some facts related to time management. Data collected from 295 students taking Chemistry 101 focused on 30 online homework sets. It was used to search for patterns in the routine that students develop while entering answers as many times as they desired. The aim of the effort was to assess if it could be possible to monitor student habits whilst supporting them, to recognize and overcome detrimental time-management skills early in their college career. The result of the data analysis did point to the fact that procrastinators who achieved poor final grades in chemistry can be identified based on their homework submission patterns. Furthermore, it confirmed the common belief that A students tend to finish their homework earlier and, in this case, also use fewer entries to complete when compared to C and D students.

Keywords: Student-centred; lifelong learning; lecture-based; freshmen; survey; time management; chemistry; submission patterns

INTRODUCTION

INFORMATION-BASED TO KNOWLEDGE-BASED—as we move from one type of society to another, engineering colleges are challenged to reassess their goals in educating the engineering professional of the future. In particular, it is questionable if the most important outcome of studying engineering is to be able to apply properly a lectured formula to come up with the correct answer. It is believed that the most important skill of graduating students will be the ability to find facts and communicate relevant information and knowledge in a self-directed manner. Not only are dispensing facts via lecturing and having students actively seek information drastically different pedagogical constructs, they require very different learning methods from the students.

Learning skills at college entrance

Skills sufficient to survive in the hometown high school are very often insufficient for a demanding freshman engineering curriculum. Unfortunately, the effect of being unprepared for college study may be 'droned' out by all the other pressures and noises associated with being a freshman. Having achieved an important step in their lives, new students enter an environment ' . . . that has many unknown expectations and leaving the new students not only unaware of their deficiencies but in their exuberance they overestimate their learning skills' [1]. Because of their ignorance and the demands that are put on them, many students '. . . reach erroneous conclusions and make unfortunate choices' [2]. Not surprisingly, poor study skills have been linked to poor academic performance with an increased likelihood that it will lead to a withdrawal from the university [3]. Some universities started offering help on a voluntary basis with the unfortunate result that those who needed it most did not take part [4].

ABET's call for lifelong learning competency

The American Accreditation Board for Engineering and Technology (ABET) required in Criteria 3 (i) that students acquire 'a recognition of the need for, and an ability to engage in life-long learning' [5]. This is arguably one of the most important, but also the most difficult, of all criteria. While the issue of lifelong learning is nothing new, the emergence of the knowledge society has drastically changed its meaning. While it might have been sufficient to take a Continuing Education workshop every now and then, lifelong learning has become a daily task. Not surprisingly, Felder and Brent proposed teaching objectives to address ABET Criteria 3 (i) that focus on making the students independent learners in that they are able to 'a) find relevant sources of information about a specified topic in the library and on the World Wide Web (or perform a full literature search), b) identify his or her learning style and describe its strengths and weaknesses. Develop strategies for overcoming the weaknesses . . .' [6]. Item a) addresses a necessity to become information literate, while b) pushes for a

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competency in self-directed learning. The Association of College and Research Libraries (ACRL) reasoned that information literacy and lifelong learning are closely intertwined in that both rely on intellectual reasoning, critical thinking and self-directed learning. Their competency standard for an information literate student includes six outcome groups [7]:

1. Identifies a variety of types and formats of potential sources for information;
2. Considers the costs and benefits of acquiring the needed information;
3. Selects the most appropriate investigative methods or information retrieval systems for accessing the needed information;
4. Articulates and applies initial criteria for evaluating both the information and its sources;
5. Synthesizes main ideas to construct new concepts;
6. Applies new and prior information to the planning and creation of a particular product or performance.

Information literate people ' . . . know how knowledge is organized, how to find information, and how to use information in such a way that others can learn from them. They are people prepared for lifelong learning, because they can always find the information needed for any task or decision at hand' [8].

Growing challenge

ABET's requirement to prepare engineering students for lifelong learning has been welcomed by many in both academia and industry. However, it is less clear how this should be accomplished. The answer to this question is of fundamental importance particularly since the US Department of Education [9] reported that, in 2001, 87% of engineering professors in the US spent the entire class time lecturing to a passive group of students. Self-directed and lifelong learning needs students to understand how knowledge is acquired, how to develop personal learning strategies and how to find new bodies of knowledge. Asking almost 90% of the engineering faculty to change from the note-taking/homework/test approach to actively inquisitive learning, demands that students and teachers acquire skill sets that are totally new to both of them. The following two comments by a student and a distinguished faculty member of NC State University who had peer-reviewed my teaching are used to underline the challenge that the academic community is facing. A senior complained on the course evaluation form: 'How can you expect me to read a book chapter when I don't understand it?' The peer-review report faulted me: 'Dr Bernold expects his students to read the chapter before coming to class. This is much too hard for the average student and needs to be changed'. It is apparent that these statements reflect the belief that 'sage-on-the-stage' lectures are the way to teach engineering. At the same time, they raise the question of preparedness for lifelong learning when reading a chapter is considered too difficult by both students and faculty.

Lifelong learning, information literacy, inquiry-based and self-directed learning all require some basic skills in reading, self-monitoring, writing and time management to accomplish those higher level thinking tasks.

ASSESSING THE LEARNING SKILLS OF ENGINEERING FRESHMEN

With the aim of establishing a basic understanding of how prepared engineering students begin their college career, 920 freshmen starting in the fall of 2002 filled out the online version of the Learning and Study Strategies Inventory (LASSI) questionnaire. The tool, designed at the University of Texas at Austin [10], evaluates the methods that students employ to study and learn in ten separate areas, or scales. On each scale the student receives a score between 0 and 100 accompanied by suggested remedial activities. A score of less then 50 indicates a serious deficiency requiring immediate help. Table 1 lists the ten scales, their meanings and the summary results from the fall 2002 survey.

Since the individual scores vary widely, the means, standard deviations and the percentage of students receiving less then 50 points are used to describe the cohort. Most surprisingly, the Attitude (ATT) scale, measuring the student's motivation to succeed in college, turned out to be the scale where the students received the lowest score (30.9). Perhaps a bit less surprising are the next two lowest scores for Time Management (TMT) and Self Testing (SFT). Questions related to TMT probe the students about their habits with statements like: 'I set aside more time to study the subjects that are difficult for me'. LASSI recommends that poor scoring students need to learn how to create a schedule and how to deal with distractions, competing goals and procrastination. The fifth column reveals how widespread the deficiencies are. For example, 78% of the freshmen scored below 50 on ATT, 68% on TMT and 67% on SFT.

While most of the LASSI scales are independent of each other, an analysis of the LASSI data reveals strong correlations between some of the scales as depicted in Fig. 1.

The three trendlines shown in Fig. 1 a) relate MOT, ATT and CON to the TMT scores. As can be expected, the lowest curve in the graph represents the relationship between TMT and ATT. A student with 50 points for Time Management (indicated by the double dashed line) is most likely to have a 35 in ATT (Attitude), a 55 in MOT (Motivation) and 58 in CON (Concentration). It is interesting to note that the trendlines for CON and MOT are almost identical. The association between TMT-MOT supports the notion that a person using more effective time-management strategies is also more motivated to work hard.

Table 1. Learning and study strategies, inventory survey of engineering freshmen

LASSI scales	Capability assessed	Mean	Standard deviation	% deficient
1. Attitude (ATT)	Student's interest and motivation to succeed in college; and willingness to perform the tasks necessary for academic success	30.9	25.8	78
2. Motivation (MOT)	Degree to which the student accepts the responsibility for performing those tasks by utilizing self-discipline and hard work	49.8	27.1	56
3. Time Management (TMT)	Extent to which the student creates and uses schedules to manage effectively his or her responsibilities).	37.4	25.5	68
4. Anxiety	Degree of anxiety the student feels approaching academic tasks	62.1	26.5	34
5. Concentration (CON)	Ability of the student to focus his or her attention, and avoid distractions, while working on school-related tasks like studying	48.8	25.2	56
6. Information Processing	Ability to process ideas by mentally elaborating on them and organizing them in meaningful ways	51.8	25.1	49
7. Selecting Main Ideas	Magnitude of the student's ability to ferret out the important information in a learning situation	52.9	24.2	41
8. Study Aids (STA)	Student's ability to use study aids that help the learning process	40.2	26.6	62
9. Self Testing (SFT)	Student's awareness of the importance of self-testing and reviewing when learning material; and use of those practices	37.4	27.1	67
10. Test Strategies	Student's ability to prepare effectively for an exam and to reason through a question when answering it	53.0	24.7	41

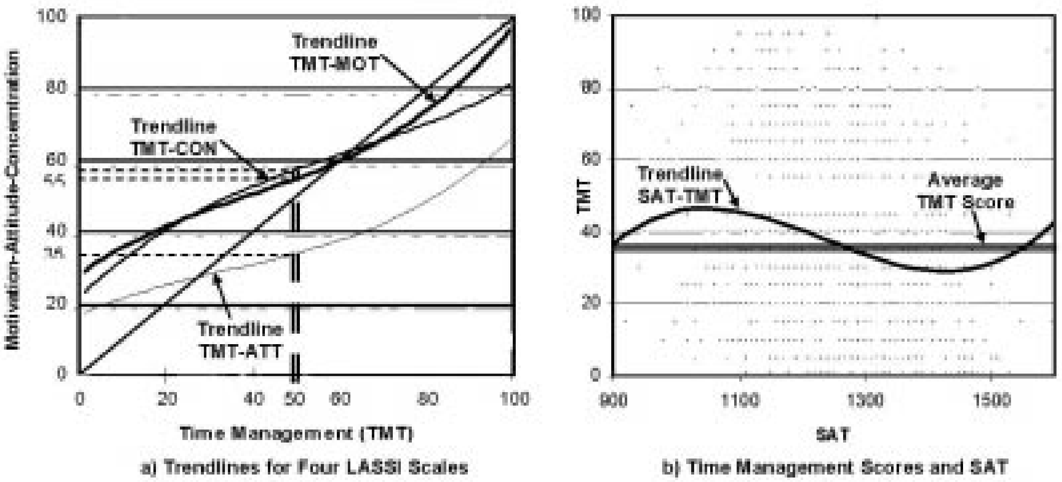

Fig. 1. Correlations and trends between LASSI scales

Fig. 1b) illustrates the fact that the TMT scores have no functional relationships with the SAT scores. This last graph indicates that, overall, remedial actions in time management should not be targeted according to SAT.

In summary, the LASSI survey revealed that the average engineering freshmen in the autumn of 2002 began their college career with significant deficiencies in several study skill areas. This finding is significant in that it is believed that poor time management is indicative of procrastination and task avoidance. However, research with students has shown that passive procrastination is an indicator of psychological problems while active procrastination is a sign of dislike for a particular subject [11,12,13]. Because of the potential for identifying health problems of students early, the study on learning skills focused on time management.

It is apparent that the result of the LASSI survey only mirrors the students' responses to queries about their potential behaviour and not what they actually do. For this reason answers to two related questions were sought:

1. How do students manage homework?
2. Do time related actions correlate with the final grade in a course?

The main data collection tool for this part of the investigation was an online homework management system.

HOMEWORK HABITS AS GRADE PREDICTORS

Traditional homework provides students with the opportunity to test and deepen their understanding of the material. Most commonly, homework is assigned throughout the semester, each with a fixed due date for submission and grading. On the other hand, online homework systems permit students to enter their answers anytime before they are due and even permits multiple entries. Since students face similar deadlines for papers, reports, quizzes and tests, distributing the workload does require basic time-management skills. It was hypothesized that the timing of homework entries on an online system would provide quantifiable data useful to find answers for the two questions concerning the time-management habits of students.

After the freshman class from autumn 2002 provided the initial information about the serious deficiencies on LASSI's time-management subscale, Chemistry 101, a freshman course, was selected to gather data about actual student behaviour. Unfortunately, it was impossible to focus on the 2002 freshman cohort since by 2004 they had already matriculated into the various engineering programmes.

Chemistry homework managed by WebAssign

Many teachers in the maths and sciences departments at NC State University use WebAssign [14], a home-grown web-based system that manages homework, quizzes, and tests taken from remote computers. Assignments can be created by either selecting individual questions from a list of pre-coded problems or by creating new ones. For each homework the instructor is able to define:

a) due date/hour/minute;
b) the maximum number of allowable submissions;
c) the amount of feedback a student will get after a submission.

Additionally, numeric variables for quantitative problems can be randomized for each student. Fig. 2 presents a typical view of a chemistry homework after the first submission.

As the screen download indicates, the assignment was due Wednesday, 16 February 2005 at 11:15 AM EST. So far, the student in the example made one submission, receiving a score of 3 out of 6, and is allowed four more entries if the student wants to try to improve the score.

Design of data collection procedure

A new cohort of students from three parallel sections of Chemistry 101, taught by the same professor, was solicited to volunteer for an experiment to monitor how they managed their assignments. Of the 600 students, 295 signed the necessary agreement. Each of the 30 homework

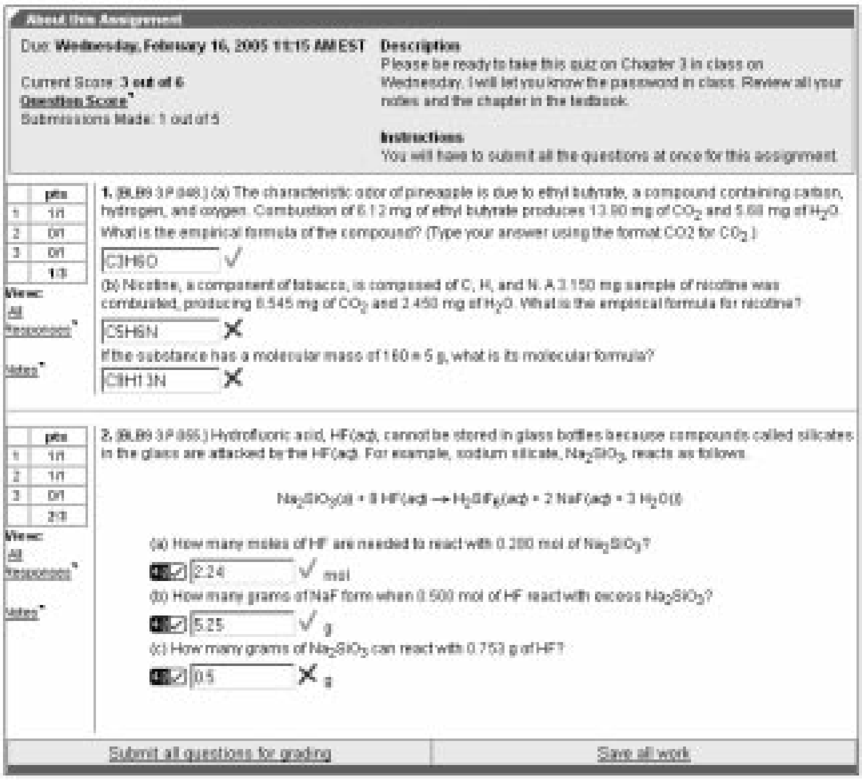

Fig. 2. Example feedback from WebAssign after submitting answers to problems 1 and 2

sets was due at midnight at a pre-specified date that paralleled the progress of the class. Each set included multiple questions ranging from simple Yes/No to those needing calculations. Students could download the questions anytime after the start of the semester, begin submitting their answers whenever they were ready and try as many times as they wished.

The data collected for each assignment included:

a) hours before due time when the first solution was entered;
b) hours before due time when the last attempt was made;
c) number of attempts;
d) total score;
e) number of homework problems attempted.

At the end of the semester a final grade for the course was calculated as weighted average comprising scores from several tests, a final exam and WebAssign homework.

Analysis of start and end-times as grade predictors

Pursuant to the two questions that led to this investigation, the timings of the first and the last submissions measured in hours before due time were used for the analysis. The data sets of the 295 participating students were combined to create the diagram shown in Fig. 3 where each data point represents an average after 30 homework entries. As the labelled axes indicate, the graph relates hours with the course grade in per cent and as a letter.

In a surprisingly distinctive manner, the visible patterns created by the shape of the two trendlines show how students who begin and end their homework early ultimately earn higher grades. Viewing the quadratic function between start time and final grade one recognizes that the time difference between students earning a low C and a low B in loading down a homework is $\Delta T_1 = 42$ hours which narrows to $\Delta T_2 = 27$ hours between low As and low Bs. Similar trendlines surface when the submission time are plotted. For example, low A students submit on average $\Delta T_3 = 16$ hours earlier than the low B students. At the bottom left of the graph one recognizes a significant number of students who consistently make the last entry close to midnight ending up with Ds. On the other hand, there are plenty of students that also submit late but still end up with letter grades of A and B. This group comprises those students who are active or managing procrastinators finishing the homework under self-imposed pressure just-in-time to meet the deadline.

Using the simple quadratic function shown in Fig. 3 to model the relationships between the variables, final grade and start time result in a poor fitness level $R^2 = 0.13$. A slightly better curve is achieved by subtracting the mean of the start values and then adding the squares of the variable. In the following polynomial function the variable called Start-Mean represents the start time of a particular student minus the overall mean of the class.

$$\text{Final Grade} = 85.0 + (0.3739 * \text{Start-Mean}) - (0.0045 * \text{Start-Mean})^2 \quad R^2 = 0.20 \tag{1}$$

Nevertheless, the $R^2 = 0.20$ indicates a better but still low level of the predictability it was hoped

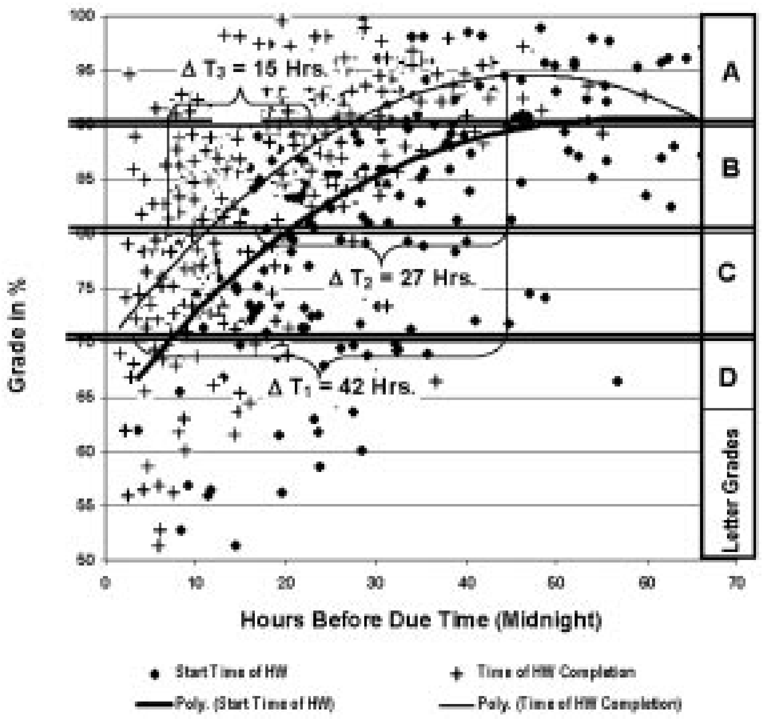

Fig. 3. Correlations of homework submission habits and end of course grades

would provide better results. Equation (2) shows the result of the regression analysis that also uses the time of the student and the Mean called Last-Mean (last submission minus the mean time).

$$\text{Final Grade} = 80.8 + (0.79 * \text{Last-Mean}) - (0.0113 * \text{Last-Mean})^2 \quad R^2 = 0.27 \qquad (2)$$

However, the $R^2 = 0.27$ is still at a level that indicates a weak albeit improved fit. It is desirable to show a minimum of 0.35 in instances where the population is so varied as in a chemistry class where freshmen and sophomores in a diverse programme take the same class.

Since combining the two variables did not improve the fit, a third measure, the number of submissions, was introduced as well.

Number of attempts to solve homework

As mentioned earlier, online homework systems offer the students an opportunity not only of immediate feedback about what they have missed or done correctly but also, as in this case, opportunities to redo the homework as many times as they want. It might be possible to identify students who manage their homework in a timely fashion and therefore will use fewer attempts because they take their time to find the correct solution and avoid 'guessing' the answers. In order to study if such a correlation exists, the number of attempts was plotted against the final grade.

As Fig. 4 indicates, the number of attempts is distributed between all grade levels. Only the area between 5 and 8 is more populated by higher grades. Interestingly, the one student who shows an average of 5.4 attempts received a 99.4% for homework and a 65.5 for the combined test grade and thus ended up with 66.2 or a D^+. It is hard to understand why s/he was able to do the homework extremely efficiently and end up with such a low score. The large difference between the two grades and the fact that it only took five attempts to score high in the homework seems to indicate that the student received help doing the homework that was not available during tests. The best effort in finding a fitting curve resulted in a line shown in Fig. 4 represented by the following equation:

$$\text{Final Grade} = 102.73 - (1.64 * \text{Attempts}) \quad R^2 = 0.16 \qquad (3)$$

Considering the result of the visual inspection of the data presented in Fig. 4 one cannot be surprised about the low $R^2 = 0.16$. In the final attempt to achieve an acceptable level of fitness for the grade prediction curve all three variables were included resulting in Equation (4).

$$\text{Final Grade} = 82.58 + (0.149 * \text{Start-Mean}) - (0.00168 * \text{Start-Mean})^2 + (0.483 * \text{Last-Mean}) - (0.0081 * \text{Last-Mean})^2 - (1.37 * \text{Attempts}) \quad R^2 = 0.37 \qquad (4)$$

As the R^2 of 0.37 reveals, this complex function consisting of three variables provides an acceptable prediction of final grades based on start time, last submission and the number of submissions. Although it might be possible to improve the R^2 with the reminder that the purpose of this paper is to investigate if it possible to use the two sets of data to identify students whose poor time-management skills hurt their grades.

SUBMISSION PATTERNS OF STUDENTS NEEDING SUPPORT

As mentioned earlier, one issue that makes it difficult to use the lateness of submission as a strong predictor of poor grades is the fact that students who manage their procrastinations will finish their homework late and still end up with high course grades. In fact, such examples are easily recognizable, in Fig. 3 as crosses in the top left section of the graph. A significant number of students complete in average less than five hours

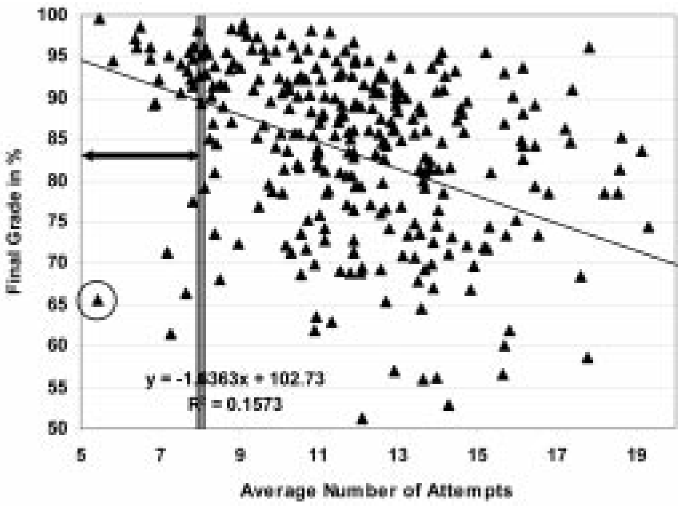

Fig. 4. Relationships between number of attempts and final grades

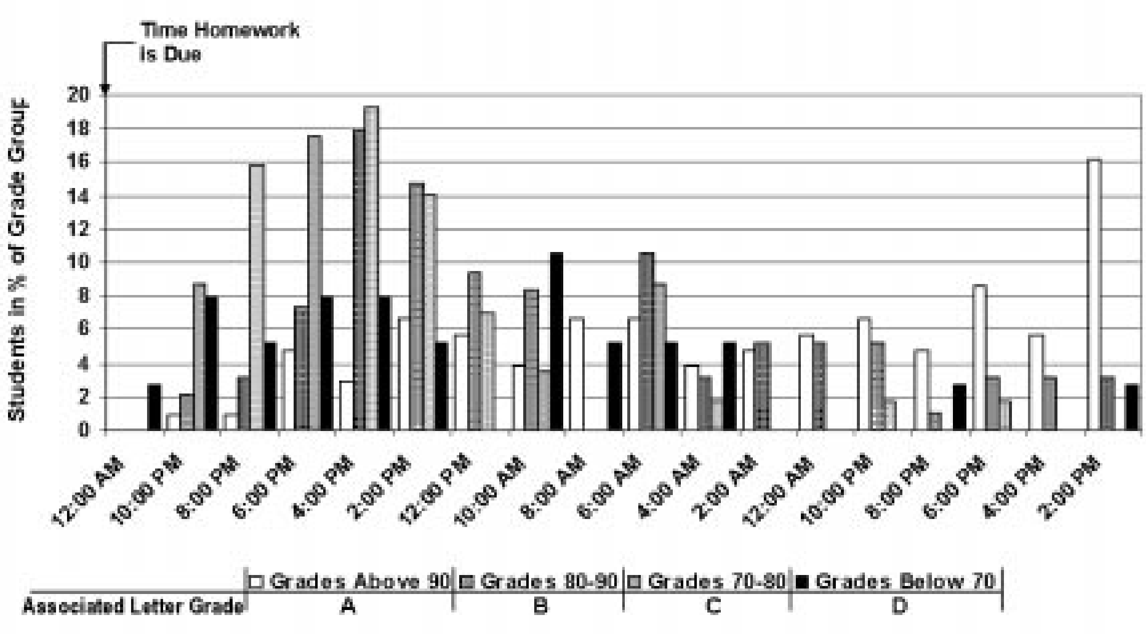

Fig. 5. Time-spaced submission habits of students grouped by final grades

before midnight but end up with As and Bs but an even larger number received Cs, Ds or Fs. Because the goal of a predictive function is to identify only those who are in danger of getting low grades, while not disturbing those who developed excellent methods, an approach is sought that allows the two groups of procrastinators to be distinguished.

Submission habits during final hours

Two different data sets were analysed:

(a) average time of last homework entry grouped according to final grades;
(b) average number of solution attempts also organized according to final grades.

Figure 5 depicts how the four grade groups A, B, C, D, measured in percentage of the students in that group, submitted during the 36-hour time span before midnight when the homework was due. As the white bars in the graph show, 16% of the high achievers submitted their 30 homework between mid-day and 2:00 PM the previous day. After that, 4–6% of the A group submits steadily within the two hours time spans until 6:00 PM when it suddenly drops to 1%. The group that differs from this the most is C, which exhibits a reverse trend. The first significant number, namely 14%, of submitting students enters their final solutions between mid-day and 2:00 PM the day it is due. After that, the percentages rise and fall like a wave with 8% working until two hours before midnight. Interestingly, the percentages for group B follow a similar pattern to that of group C; however, they complete four hours earlier resulting in a sharp drop of the bar towards the end. On the other hand, group D, represented by black bars, does not exhibit a clear pattern other than that their percentages are generally lower than those of group A a gap that is getting larger towards the due time.

The only 'clean' but not very useful time-related predictor for low final grades is the last two hours, since 3% or one single D student clearly fell into this time bracket. The next best predictor is the time block that starts at 6:00 PM. As evidenced by the small bars for the grade groups A and B as compared to the bars of groups A and B, only a few of the high achievers are still submitting. Table 2 summarizes the distribution of the students who fall within this time-span.

The sharp rise in the bars between the percentages of C and D students is a less dramatic number of individuals since group sizes are getting smaller. Overall, 2% or two of the A students, 5% or five of the B students, 24% or 14 of the C students and 16% or six of the D students submitted. Thus, the data in Table 2 tell us that, in the case of the observed chemistry class, 20

Table 2. Distribution of students who completed 30 hrs homework within last 6 hrs

Group	Grade (%)	Total Group (Students)	Students (%)	Students (Individ.)	
A	90 - 100	105	2	2	Total = 27 Students
B	80 - 90	95	5	5	
C	70 - 80	57	24	14	
D	0 - 70	38	16	6	

students (14 + 6) who predictably will end up with lower grades could be reached by contacting the total 27 students who finish and submit within the last six hours at the beginning of the semester. Even the seven students who are not really in danger might benefit from extra coaching since they do not know what their grade is going to be. Considering the fact that receiving help in study skills would not diminish somebody's success, one could argue for extending the threshold time from six to eight hours adding three students from group D, 10 from group C, six from group B and five from the A group or a significant 41% of all C students.

While it is evident that using time spans could be a tool to identify individuals who could benefit from an early intervention, the submission count could provide additional clues to pinpoint students in need.

Homework submission counts and final grades

It was earlier explained that the professor teaching chemistry allowed the students to try solving each multi-question assignment as many times as they wanted. After each submission, the online system, WebAssign, gave immediate feedback about which questions were still incorrectly answered. The following analysis uses a special set of data stored by WebAssign for each student:

(a) time of latest/last submission;
(b) cumulative number of submissions at that time.

This information was again averaged and grouped according to the final grade in the course. Figure 6 graphs the averages of this computation for the final 36 hours of all 30 assignments.

One is immediately able to recognize that D students have the tendency to try more often especially when compared to the A students. In general, D students who submit late show a cumulative count that is between 2–3 attempts higher than the others. With the exceptions of the six A students that submitted between 3–6 PM and the single A student who submitted between 6– 9 PM, A students averaged 10 tries while the B students consistently made 12.5 submissions overall. Finally, the C students, with the exception of the two who finished during the last three hours, averaged approximately 13 submissions. These observations do indicate that submission count in combination with submission time might provide a reliable tool.

FINDING THRESHOLD LEVELS TO TRIGGER COACHING EFFORTS

The previous sections demonstrated that two values, the time and the number of submissions, show some linkages to the final grade that a student received in the investigated chemistry class. In this last section of the paper the effect of combining the two values will be studied.

The two related graphs in Fig. 7 resulted from computing the total number as well as the percentages of students who showed similar averages in the cumulative number of submissions for two time periods: a) 6:00 PM—12 midnight (< 6 Hrs), and b) 12 AM the previous day—6:00 AM (18 >< 36 Hrs).

While Fig. 6 presented averages for each time segment, Fig. 7 highlights the differences between the high (A-B) and the low (C-D) achievers by plotting the cumulative changes of each as a function of submission counts. The double-line marker for <10 homework submissions, previously picked more or less arbitrarily, clearly differentiates D and C students. By moving the threshold to <11 submissions for the same time slot, three more C and D students would be added to the group of students who are predicted to become low performers, one of which would, according to the historical data, end up with a B. Comparing these observations to the graphs from the student groups submitted during the second time bracket,

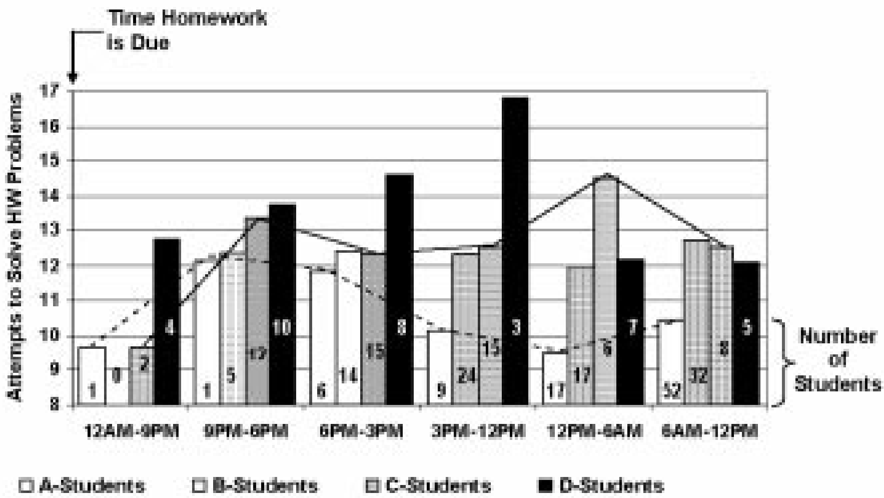

Fig. 6. Average quantity of homework submissions during final hours by different grade groups

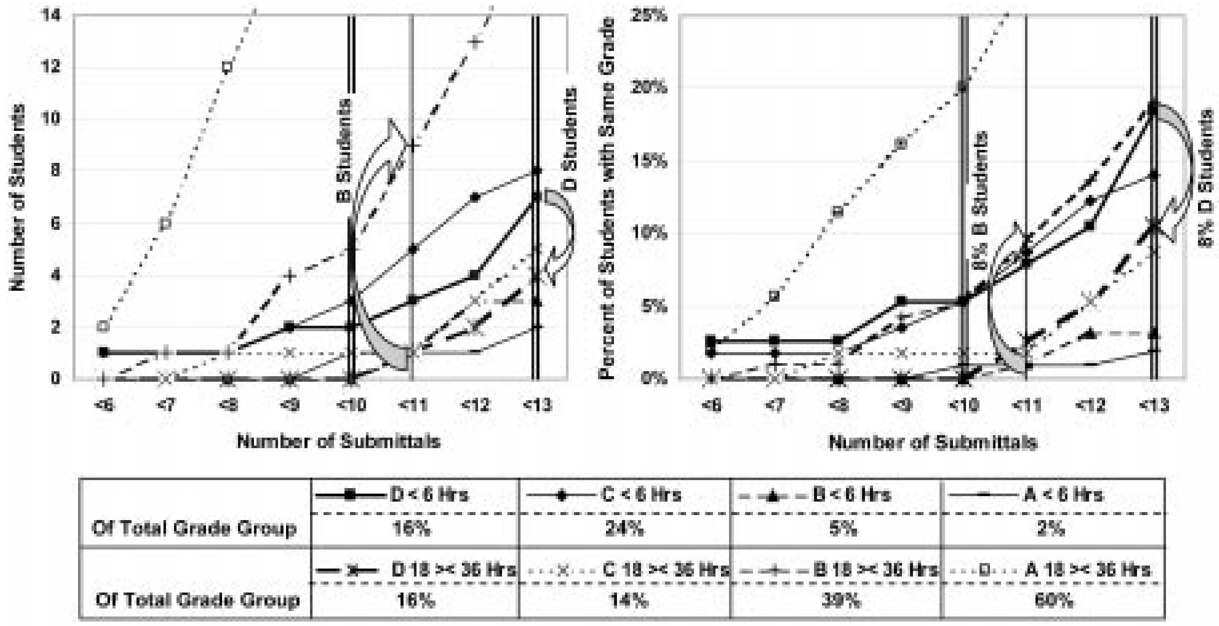

Fig. 7. The combined effect of time and number of attempts on final grades

18–36 hours, one recognizes some unique differences. As the four arrows indicate fewer of the C and D students, both in absolute and percentage terms, solved the homework sets <13 times, while the opposite is true for A and B students. One also realizes that within the 18–36 hours time bracket, the percentage of students who submitted <11 times is significantly higher for A and B than for C and D students.

In summary, the data reveal that by setting a threshold level of <10 or <11 for submissions during the final six hours before due time, it is possible to identify students who will predictably end up with low final grades because not only are they mostly the ones who have not finished yet but they also make more attempts. This simple rule does not work for those students that submit between 18–36 hours. While the data point on the <10 submission marker confirms that the largest contingent with a lower submission count is the A group (20%) followed by the B group with 5% and the C group with 2%. None of the D students had submitted in less time. On the other hand, the relative percentages of A and D students who submit in excess of 13 times is 32%, the same, while it is even more for the C and especially for the B students. This fact seems to indicate that the submission counts as a means of identifying students in danger will only work when used in combination with time brackets closer to the due time or, in other words, when poor time-management skills add to their peril.

SUMMARY AND CONCLUSIONS

Similar to master craftsmen, college students need skills that allow them to work effectively. This paper presents the results of a project that assessed the learning abilities of engineering freshman, revealing that more than 50% of a 920 students cohort were seriously deficient in several study-skill areas. The survey scores were particularly low when students were queried about how they manage study time, monitor their comprehension and what study aids they use. The widespread deficiencies in learning skills is of special concern considering ABET's requirement to prepare the pupils to recognize the need for, and have the ability to engage in, lifelong learning. Since surveys only capture what the students think they do, not how they actually operate, a second study involving 295 chemistry students was conducted. For this effort, the habit displayed by each while completing 30 online homework sets was captured. One of the subsequent analyses focused on correlating the average time of submission, measured in hours before due, with the final grade. The search for a fitting predictive function led to a quadratic equation that combined three variables and resulted in an R square value of 0.37. The three variables consisted of the time the student started the homework, the time the last submission was entered and the number of attempts used to solve it. Responsibility for the moderate R square value is in the differences in the students' background, such as the years of college or the programme they were in, as well as the fact that some procrastinators are managing this habit well. From that perspective, the attained level of fitness must be considered acceptable.

The third section of the paper examined the potential for identifying early on in the semester students who are at risk of achieving low final grades due to 'unhealthy' time-management skills. Here again, the online homework system served as the data pool. By clustering the students into four groups according to the letter grades A, B, C and

D, their traits during the 36 hours before the homework sets were due could be compared. It was found that during the last 6-9 hours, fewer of A and B students but more of the C and D students submitted. At the same time, the A and B groups had accumulated a smaller submission count. The differences in the number of submissions become more pronounced for those students finishing the homework sets 18-36 hours before due. Not only are 60% of the A students completing in this time bracket, compared to only 16% of the D students, they also needed significantly fewer attempts to complete. For example, on average, one-third of the 60% or 20% of all A students used fewer than 10 uploads to finish while none of the D students did.

It is felt that the presented study could lay the foundation to not only help skill-deficient students to acknowledge their deficiencies but, even more importantly, coach them to adopt time-management habits so effectively used by A students.

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Leonhard E. Bernold is an Associate Professor in Civil Engineering at the North Carolina State University. As the director of the Construction Automation and Robotics Laboratory he experienced firsthand the importance of cross-disciplinary approaches in addressing engineering problems including engineering education. As investigator on several educational research projects he has been active in observing and documenting the effectiveness of inquiry-based teaching and learning in civil engineering. Over the years he has received several best paper awards for his contributions to engineering education.