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Abstract

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Keywords

chemistry, perception, examinations, Kruger-Dunning

Cover Page Footnote

The authors thank Ericka Barnes, Adiel Coca, James Kearns, Gregory Kowalczyk, Edward Krainer, JiongDong Pang, and Camille Solbrig for allowing us to collect data from their courses. We would also like to thank all of the students for their willingness to participate in this study.

The Role of Student Major in Grade Perception in Chemistry Courses

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The Kruger-Dunning effect was studied as it related to performance in chemistry courses based on student differences in academic background. Student major was chosen as the classification to look at the effect of students with different interests/specializations. Chemistry majors tended to predict lower performance than biology majors, while unexpectedly many non-natural science majors predicted higher examination scores than those majoring in the physical sciences.

INTRODUCTION

As part of our ongoing analysis of grade perceptions and the Kruger-Dunning effect in a chemistry program, we wanted to explore the role students' academic background has on their ability to perceive their own performance in the setting of a science course – more specifically, a chemistry course. For the purposes of this study the academic backgrounds are classified based on the major of the student. More information as to this breakdown is included in the experimental section. Kruger and Dunning showed that those who are poorly prepared for a task are unable to realize that their preparation is lacking. These poorer performing individuals often lack the self-awareness and ability to accurately assess their own abilities (Kruger & Dunning, 1999)

While it is anecdotal the common perception among students is that chemistry is one of the most difficult academic subjects. In fact, studies that have explored this concept have found consistent results: science classes, especially chemistry and physics, are perceived to be the most difficult courses at every level of education (Coe et al., 2008 and included references; Fitz-Gibbon & Vincent, 1994; Sparkes, 2000). In one study, Coe demonstrated that the perception of "difficult" in STEM courses is not just an issue of perception of the courses, but also that the level of difficulty in most STEM courses, based on examination difficulty, is the highest of any general area (Coe et al. 2008). This is not a new phenomenon since these studies have been ongoing for more than forty years. In 1974 the first significant study in this area by Nuttall et al. (1974) looked at five different methods of comparing student perception of difficulty and also found that chemistry and physics were the hardest subjects for the students involved. Newbould (1982) examined gender and difficulty in a variety of subjects, similar to many of the other works also found that chemistry, physics, and foreign languages were rated as the most difficult subjects. Newbould's study also indicated that male students found the physical science subjects to be more difficult than did the female students. However, our recently published results showed that female students generally perceive their abilities in chemistry as lower than their male classmates (although their level of performance is equal) (Karatjas & Webb, 2015).

Additional studies have continued to show the same effects (Coe et al., 2008 and included references; Fitz-Gibbon & Vincent, 1994; Sparkes, 2000). Coe and coworkers' extensive review (Coe 2008) on the subject shows that regardless of the method used to assess difficulty, the results are largely the same: physics, chemistry, and foreign languages were found to be consistently ranked as the most difficult subject areas. Additional studies show that, for many students, courses in the sciences raise their level of anxiety (Mallow 2006). Mallow attributes some of these anxiety issues to items such as a perception that only the elite can excel in the sciences, a lack of training in analytical thinking, stereotypes, and a lack of proper role models. While the roots of science perception and anxiety are interesting questions, the current study does not seek to explore these areas, but to explore the differences in perception based on student background.

Work by Kruger and Dunning on student perception suggests that people who are the weakest at a skill or task often overestimate their own ability (Kruger & Dunning, 1999), a phenomenon known as the Kruger-Dunning effect. Their work found that the weaker one was at a task, the more egregious the overestimation of his or her own ability was. Top performers tend to be more accurate in their predictions; however, the highest performers generally tend to under-predict their performance. This type of self-assessment has most often been explored in psychology (Kruger & Dunning, 1999). Limited studies also have been done in statistics (Jordan, 2007), geology (Wirth & Perkins, 2005), biology (Bowers, et al., 2005), economics (Grimes, 2002), and pharmacy (Austin & Gregory, 2007).

Previous studies of the Kruger-Dunning effect in chemistry have been limited until very recently (Bell & Volckmann, 2011; Potgieter, et al., 2010; Karatjas, 2013; Pazicni & Bauer, 2014; Karatjas & Webb, 2015). Bell and Volckmann (2011) used knowledge surveys to assess perceived knowledge on the final exam in two general chemistry classes. While their study indicated clear evidence of the Kruger–Dunning effect, it did not explore the role that student background may play in self-perception. Karatjas has completed the only study which looks at organic chemistry courses and also found a clear indication of the Kruger-Dunning effect (Karatjas, 2013). Karatjas and Webb (2015) recently published a study exploring the relationship between the Kruger-Dunning effect in 100-level chemistry courses as it related to gender. However, none of these studies sought to explore the role that students' background plays in their ability to perceive their preparation for and performance on chemistry examinations.

This study seeks to use student major as the primary descriptor of background. It was postulated that students who are chemistry majors might have a more accurate self-assessment of their potential performance due to increased knowledge about the subject and its difficulty. It was also postulated that while students majoring in other sciences might view chemistry as a challenging course, their science interest/background might allow them to have a more accurate self-assessment of their abilities. Furthermore, it was thought that non-science majors, some of whom fear their science courses due to the reputed difficulty, would have decreased expectations leading to a lessening of the Kruger-Dunning effect.

METHODOLOGY

Students were asked to complete a brief pre-examination survey which was stapled to the front of their examination. This was done to ensure completion of the survey before the start of each examination. The data reported here are from 100-level up to 500-level chemistry courses. The data were collected from courses that were taught in the Spring 2013, Summer 2013, Fall 2013, and Spring 2014 semesters. The courses involved in this study were: CHE 101 (Chemistry in Contemporary Issues), 103 (Crime Scene Chemistry), 120 (General Chemistry I), 121 (General Chemistry II), 125 (General, Organic, & Biochemistry), 240 (Quantitative Analysis), 260 (Organic Chemistry I), 261 (Organic Chemistry II), 340 (Environmental Chemistry), 370 (Physical Chemistry I), 371 (Physical Chemistry II), 445 (Chemical Hazards/Laboratory Safety), 450 (Biochemistry I), 451 (Biochemistry II), 456 (Medicinal Chemistry), 500 (Advanced Organic Chemistry), and 540 (Advanced Analytical Chemistry). Each course included in this study gives three or four examinations throughout the semester plus a cumulative final examination. The results from all semester examinations (but not cumulative final examinations) were included in this study. (*Note: Final examinations were excluded because some courses involved used an American Chemical Society (ACS) final examination that could artificially alter student perceptions based on the standardized nature of the examination*.)

The study was approved by the IRB at Southern Connecticut State University. Students were informed of the study at the start of the semester and asked to sign a consent form to indicate willingness to participate. Demographic information was collected on the survey including: gender, major, course, and section number.

For the students' backgrounds, they were divided into the following categories: Business (Accounting, Business Management, Business Administration, Marketing, and Finance), Biology, Chemistry, Earth Science, Physics, Science (Biology, Chemistry, Earth Science, Physics, and Engineering), Non-Science (All majors not listed under science), Nursing, Liberal Studies (or None – these encompass students who have not yet declared a major, as well as part time students who are not currently pursuing a degree), Education (are not listed below since the N in each category < 5), Social Sciences (Anthropology, Communications, Geography, History, Journalism, Sociology, Psychology, and Political Science), Humanities (Art, English, Philosophy, and Music), and Health and Human Services (Athletic Training, Communication Disorders, Exercise Science, Social Work, and Public Health).

An example of the survey used is found in Figure 1. The survey for exams 2 & 4 is identical to the one found in Figure 1 (Appendix A) while the survey for exam 1 omits question #4.

Overall, 3070 surveys, which contained predicted examination grades, were collected in the 100 – 500 level courses. The results below discuss differences in prediction by student major for these completed surveys.

RESULTS AND DISCUSSION

Table 1 shows the overall results from all students in all courses included in the survey. As expected, strong evidence of the Kruger-Dunning effect is seen as the top students (score > 90%) underestimate by almost one full letter grade (9.82 points). On average, students in the 80-89% range are the most accurate (under-predicting their examination score by 2.87 points). Students in the 70-79% range are the first to show an over-prediction. As scores decrease, the level of over-prediction increases. Students that score below 50% on these exams overestimate on average by more than 30%.

Table 1. Comparison of student predictions to actual performance in all-level courses.

Group of Students (examination score)	Number of students	Predicted Examination Grade (Mean) (%)	Actual Examination Grade (Mean) (%)	Difference of Means (%)
> 90%	505	85.53	95.35	-9.82
80 – 89%	500	81.48	84.36	-2.87
70 – 79%	712	78.83	74.40	4.43
60 – 69%	506	76.17	64.58	11.60
50 – 59%	345	72.31	54.76	17.55
< 50%	502	67.81	36.57	31.24

Students majoring in the natural sciences accounted for 1291 out of the 3070 completed examination surveys (42%). When we look at these students, majoring in the natural sciences at the time of the surveys across all course levels, almost no change is seen from the overall data (Table 2). Students at the highest level (> 90%) show almost no difference from the overall group. The remaining groups all show similar results to the overall group of students with the largest change being for students scoring between 80 – 89% where the science majors on average under-predict by one more point than the overall group. However, in all cases, the difference between science majors and the overall group is no more than one percentage point.

Table 3 explores the differences between different natural science majors. While there are some differences seen for earth science and physics majors, the sample sizes here are fairly small and may not be of significance. However, of particular interest is the comparison between biology majors and chemistry majors. For the top two groups of students, both of whom generally under-predict their examination grades, the chemistry majors have a significantly larger under-prediction (3 points for the >

90% students and 4 points for the 80 – 89% students). This does show a clear difference in perception based on student background. It may be that chemistry majors are more familiar with courses and their reputation and predict lower scores than their counterparts in the biology department. For students in the 70 – 79% range, virtually no difference is seen between chemistry and biology majors. However, for the remaining groups, biology students tend to over-predict by larger margins than the chemistry students. This again indicates that chemistry students may have a slightly higher level of awareness of the difficulty of their subject. However, the expected Kruger-Dunning effect is still clearly seen through the examination results of all students.

Table 2. Comparison of student predictions to actual performance for science majors.

Group of Students (examination score)	Number of students	Predicted Examination Grade (Mean) (%)	Actual Examination Grade (Mean) (%)	Difference of Means (%)
> 90%	211	84.88	94.80	-9.92
80 – 89%	270	80.18	84.20	-3.99
70 – 79%	267	77.91	74.48	3.42
60 – 69%	196	75.94	64.50	11.48
50 – 59%	153	72.30	54.80	17.50
< 50%	194	68.73	36.59	32.14

The results in Table 4 show the results for non-natural science majors. The results here were somewhat unexpected. It was postulated that students majoring in subjects outside the natural sciences due to the reputation and difficulty of science courses would expect to do worse within the courses. For the lowest performing students, this was the case. Non-science students that scored below 50% were slightly more accurate in their predictions than were the analogous science major students. For the students in the range of 50 – 69%, prediction accuracy was virtually identical to students who were science majors. However, the top three score groups all showed that non-science majors generally predicted higher examination scores than their science major counterparts. This was to a large extent the opposite of what was initially predicted. The reasons for this result could have to do with the fact that many of the non-science majors are used to grades coming from less quantifiable non-majors' courses. Additionally, it could be non-science majors' general lack-of-knowledge about what a science course is. It is also speculated that given the reputation of science courses that the chemistry courses may attract a higher performing non-science major student than other courses. It would be of interest to compare across identical courses: unfortunately, not enough non-science majors take the traditional General Chemistry sequence, and virtually no science majors take the non-major chemistry courses.

Table 5 shows the results of T-tests comparing natural science majors and non-natural science majors. As previously stated, the groups scoring between 50-69% showed virtually identical results and this is displayed clearly by the T-tests with both groups showing p values of close to one for these groups. Only the groups scoring between 70-79% and 80-89% showed p values below 0.05 indicating that there were significant differences between physical science majors and non-physical science majors. For other groups which saw similar but not identical results, this is well reflected by the higher p values found from the T-tests comparing the groups by examination grade.

Table 3. Comparison of student predictions to actual performance for science majors divided by area.

Group of Students (examination score)	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Biology majors	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Chemistry Majors	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Earth Science Majors	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Physics Majors
> 90%	-9.31 (76)	-12.15 (81)	-11.60 (15)	-10.39 (23)
80 – 89%	-2.01 (78)	-5.98 (126)	-2.10 (8)	-3.88 (16)
70 – 79%	2.80 (119)	2.78 (124)	6.90 (7)	4.95 (11)
60 – 69%	12.02 (94)	10.86 (80)	N < 5	14.10 (10)
50 – 59%	17.35 (77)	15.85 (58)	22.00 (6)	20.80 (5)
< 50%	32.56 (106)	30.70 (65)	38.50 (9)	31.90 (10)

Table 4. Comparison of student predictions to actual performance for non-natural science majors.

Group of Students (examination score)	Number of students	Predicted Examination Grade (Mean) (%)	Actual Examination Grade (Mean) (%)	Difference of Means (%)
> 90%	333	86.56	95.49	-8.93
80 – 89%	395	82.12	84.28	-2.16
70 – 79%	384	79.39	74.29	5.11
60 – 69%	331	75.94	64.52	11.42
50 – 59%	202	72.05	54.65	17.40
< 50%	297	67.06	36.71	30.35

Table 5. Results of T-tests for two samples containing unequal variances. Comparison of Physical Science Majors to non-physical sciences majors.

Data Groups Compared	$P(T \leq t)$ two-tailed
All students	0.38715
> 90%	0.204289
80 – 89%	0.017583
70 – 79%	0.02452
60 – 69%	0.954914
50 – 59%	0.944411
< 50%	0.233778

Tables 6 and 7 breakdown the non-science majors into additional sub-categories. Students without a de-

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clared major or liberal studies majors do show significant differences from the overall group, most specifically in the area of students scoring < 50%, showing the smallest under-prediction of any group studied. However, this group has students with a large variety of backgrounds so the importance of this result is unclear. What is clear is as we explore areas outside of the natural sciences, is that we see a noticeable lessening of the over-prediction for the lowest performing students with the exception of the nursing students (and a small number of business students). Business majors as a whole (though a small sample size) show higher predictions at almost every level. Social science students tend to predict lower (and more accurate) scores for most groups of students. Nursing majors were of particular interest because their program requires a minimum GPA in a number of their courses (including chemistry) so we wondered if there would be a higher level of self-awareness. However, there was not a significant difference in accuracy of perception among them except for the lowest performing students.

Table 6. Comparison of student predictions to actual performance for non-natural science majors divided by area.

Group of Students (examination score)	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Business majors	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Liberal Studies	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Social Science Majors	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Humanities Majors
> 90%	-8.31 (16)	-9.90 (26)	-9.22 (34)	-14.50 (9)
80 – 89%	1.79 (17)	-1.50 (38)	-2.50 (32)	N < 5
70 – 79%	3.70 (20)	7.20 (26)	8.03 (62)	1.91 (11)
60 – 69%	11.47 (17)	11.70 (29)	11.64 (52)	N < 5
50 – 59%	22.13 (15)	17.30 (17)	15.63 (36)	N < 5
< 50%	37.85 (13)	18.40 (29)	27.95 (43)	29.36 (22)

Table 7. Comparison of student predictions to actual performance for non-natural science majors divided by area.

Group of Students (examination score)	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Nursing majors	Difference of Means of Predicted Examination Grade and Actual Examination Grade (N) – Health and Human Services Majors
> 90%	-8.50 (168)	-9.80 (67)
80 – 89%	-2.32 (211)	-3.74 (89)
70 – 79%	5.07 (188)	2.87 (69)
60 – 69%	10.35 (139)	12.57 (83)
50 – 59%	17.86 (70)	17.47 (55)
< 50%	34.80 (105)	27.75 (80)

Table 8 (Appendix B) gives the results of all 45 T-tests between all of the different groups of students. Each combination of $P(T \leq t)$ two-tailed values can be found. For some of the groups with smaller N values, the p values found for the T-tests are, not surprisingly, less meaningful. However, for larger groups such as the chemistry majors, the p values verify the averages seen in the above tables. For example, the p value for biology versus chemistry is extremely significant (3.4×10^{-5}). This shows that the very different averages found in Table 3 are reflective of two very different groups of students. This can also be seen by comparing chemistry to humanities, health and human services, business, biology, and social sciences. A comparison of chemistry majors to nursing majors shows a larger p value and a more similar sample. Comparison of earth science and humanities gives somewhat unexpected p values compared to the comparison of averages, but this is most likely a result of the small sample size for these groups. Although one might expect students who are not natural science majors to have very different perceptions than those that are natural science majors, for the most part, the data indicates that there is limited difference in these populations. Table 8 reveals that overall, many of the p values (with the exceptions discussed above) are somewhat large showing that there is limited difference in the students between academic backgrounds.

CONCLUSIONS

Some distinctions within the accuracy of predictions clearly exist based on students' academic background. For example, chemistry majors in this study tend to predict lower scores on examinations than biology majors ($p = 3.4 \times 10^{-5}$). Nursing majors, where they have a minimum grade requirement for their chemistry courses at the university involved in this study, exhibited results similar to other majors with the notable exception of the lower-performing students who had a significantly smaller over-prediction. Surprisingly it was also found that for most non-science majors, exam predictions were higher than those of science majors. This continues to strengthen the implications of the Kruger-Dunning effect. Even in a field such as chemistry, perceived by difficult by most students, there is no lessening of the Kruger-Dunning effect. Further study will be required to help to explain this result.

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The authors thank Ericka Barnes, Adiel Coca, James Kearns, Gregory Kowalczyk, Edward Krainer, JiongDong Pang, and Camille Solbrig for allowing us to collect data from their courses. We would also like to thank all of the students for their willingness to participate in this study.

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APPENDIX A

Figure 1. Pre-Examination Survey

Chemistry Grade Perception Survey 2013

Addendum to Exam 3:

Name: ____________________________

Course / Sec.: ______________________

Major:____________________________

1. When did you start preparing for this exam? (Circle ONE option)

Greater than 7 days   Less than 7 days   Less than 1 day   Other ______

2. Which of the following "tools" assisted your studying the most? (Please Circle **ONE** option)

- Textbook
- Homework / Problem Sets
- Class Notes
- Old Exams
- Any Tutoring Service
- Quiz's

3. What score (out of 100) do you anticipate on this exam? ________________

4. What score (out of 100) did you earn on your previous exam? ________________

5. What grade range do you anticipate you will achieve at the end of the semester in this course? (Circle ONE option)

A   B   C   D   F

Return of this survey indicates my consent to have my data used in this research.

APPENDIX B

Table 8. Results of T-tests for two samples containing unequal variances by student major.

	Chemistry	**Biology**	**Earth Science**	**Physics**	**Business**	**Liberal Studies**	**Social Sciences**	**Humanities**	**Nursing**	**Health and Human Services**
Chemistry	**N/A**									
Biology	$3.36*10^{-5}$	**N/A**								
Earth Science	0.281044	0.693019	**N/A**							
Physics	0.873131	0.080816	0.348786	**N/A**						
Business	0.00806	0.59409	0.511719	0.070025	**N/A**					
Liberal Studies	0.167871	0.092085	0.691034	0.406697	0.121846	**N/A**				
Social Sciences	0.000117	0.676623	0.577588	0.060646	0.795559	0.065433	**N/A**			
Humanities	0.01692	0.281703	0.274102	0.043795	0.513932	0.082323	0.371692	**N/A**		
Nursing	0.120101	0.001511	0.54534	0.485556	0.043159	0.691344	0.002983	0.046873	**N/A**	
Health and Human Services	0.005948	0.250522	0.968601	0.203323	0.253065	0.448706	0.170268	0.144215	0.100105	**N/A**