American Journal of Pharmaceutical Education 2015; 79 (2) Article 20.

RESEARCH

An Exploratory Analysis of Personality, Attitudes, and Study Skills on the Learning Curve within a Team-based Learning Environment

Adam M. Persky, PhD,[a] Teague Henry,[b] Ashley Campbell, PharmD[a]

[a] University of North Carolina at Chapel Hill, Eshelman School of Pharmacy
[b] University of North Carolina at Chapel Hill

Submitted May 04, 2014; accepted November 19, 2014; published March 25, 2015.

Objective. To examine factors that determine the interindividual variability of learning within a team-based learning environment.
Methods. Students in a pharmacokinetics course were given 4 interim, low-stakes cumulative assessments throughout the semester and a cumulative final examination. Students' Myers-Briggs personality type was assessed, as well as their study skills, motivations, and attitudes towards team-learning. A latent curve model (LCM) was applied and various covariates were assessed to improve the regression model.
Results. A quadratic LCM was applied for the first 4 assessments to predict final examination performance. None of the covariates examined significantly impacted the regression model fit except metacognitive self-regulation, which explained some of the variability in the rate of learning. There were some correlations between personality type and attitudes towards team learning, with introverts having a lower opinion of team-learning than extroverts.
Conclusion. The LCM could readily describe the learning curve. Extroverted and introverted personality types had the same learning performance even though preference for team-learning was lower in introverts. Other personality traits, study skills, or practice did not significantly contribute to the learning variability in this course.

Keywords: team-based learning, latent curve model, cooperative learning, motivation, personality, study skills

INTRODUCTION

Student learning is dependent on situational factors, including course structure (eg, class size, instructional strategies),[1,2] content (eg, mathematics),[3,4] and the learners' characteristics (eg, personality traits, reaction to team environments, study habits, motivation).[5-7] The instructor's goal is to help students achieve the course objectives while taking these interacting factors into consideration. To achieve this, it may be beneficial for instructors to understand what factors may differentiate higher performing students from lower performing students. Knowing these factors helps to better address the learning needs of all students and improve course design or supplemental material and instruction.

In a previous study, we described the use of team-based learning (TBL) in pharmacokinetics—a mathematically-based discipline required in the training of pharmacists.[8] Team-based learning incorporates an amalgamation of reading, writing, discussing, analyzing, and synthesizing information, which moves the emphasis of learning from memorizing facts to developing skills and engaging in activities.[9] This approach promotes engagement, motivation, and shared responsibility.[1,9] However, Chamarro-Premuzic and colleagues suggested that student learning in a cooperative environment, such as team-based learning, can be influenced by personality traits.[10] One personality trait implicated is the introversion/extroversion continuum.[11,12] Within a team, there are members who are dominators (high participators), while others surface as the "quiet ones." The dominators are not necessarily the most knowledgeable members of the team, but they are likely the extroverts of the group and may potentially influence or dominate group discussion.[13]

Aside from personality, learner characteristics can vary tremendously, encompassing self-views of intelligence, study habits, and motivation.[2] People's self-views of intelligence have resulted in a theoretical construct based on the continuum in which individuals believe that intelligence is either entity-based and effort-independent (eg, "I was born good at math"), or incremental-based and

Corresponding Author: Adam M. Persky, PhD, 2312 Kerr Hall, CB#7569, Division of Pharmacotherapy and Experimental Therapeutics, UNC Eshelman School of Pharmacy, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599. Tel: 919-966-9104. Fax: 919-962-0644. E-mail: apersky@unc.edu

effort-dependent (eg, "With effort, I can get better at math"). These self-views can be used to predict achievement at various grade levels. For example, Dweck showed that younger students with entity-based views were less likely to challenge themselves when presented with a difficult situation compared to their counterparts with incremental-based views.[14] Among college students, Teunissen and Bok suggested that while females had similar average grades as males in math, they had higher levels of anxiety than males because of females' perceived beliefs about having lower competence levels, which may indicate an entity theory of learning regarding mathematics.[3] Recently, self-theories have been discussed in the development of medical students and how those theories may impact professional development and acceptance of feedback.[15]

Other components affecting student learning are study strategies and motivation. There is a large body of research on the impact of study strategies and motivation on academic success. The Motivated Strategies for Learning Questionnaire (MSLQ) is used to help characterize learning strategies (eg, study habits) and motivation, which can be further quantified by amount of practice.[16] Aspects of the MSLQ have been found to correlate with academic performance in the health professions.[17-19]

The primary purpose of this study was to determine if learning pharmacokinetics in a team-based environment would be impacted by various student characteristics, including personality, attitude regarding intelligence, attitude regarding team-learning, motivation, study skills, or amount of practice. The secondary purpose was to determine whether personality, attitudinal, or motivational factors would impact student views of team or cooperative learning. These questions were to be explored using the latent curve modeling (LCM) approach.

METHODS

Pharmacokinetics is a 3-credit hour course that meets once a week for 3 hours. Enrollment in 2012 was 159 students spread across 3 campuses and synchronically videoconferenced. The course format was previously described.[8] In prior years, the course consisted of 5 team-based learning modules spread across the first 14 weeks, with more integrated cases reserved for the last 2 weeks. During 2012, these modules were spread across the first 9 weeks of the course. This compression allowed additional time for more integrated pharmacokinetic cases during the last 7 weeks of the course and a comprehensive course review. During the final weeks of the class, integrated cases that combined various topics within the course (eg, multiple dosing with renal clearance concepts) were used to scaffold learning (ie, repeat topics with progressively less support). These cases were often open-ended for calculations or multiple-choice or fill-in-the-blank for concepts. Within the TBL modules, cases were predominately focused on conceptual aspects of pharmacokinetics and minimally focused on actual calculations; calculations were introduced after the readiness assessment process, when appropriate but were the focus of the homework assignments. Cases involved a brief introduction to a patient or scenario, often including snippets from secondary databases with pharmacokinetic information, and 3-5 multiple-choice questions. Within a given class period, 3-4 cases were completed.

A learning curve was generated through the completion of 4 interim cumulative assessments and a fifth cumulative final examination. These assessments were completed prior to the start of TBL (baseline, week 1), mid-way through the content (week 4/5), after the completion of material and TBL section (week 8/9), half way through the more complex, integrative cases (week 12), and at the end of the semester (week 15/16, final examination). Each assessment consisted of 9 pools of information: pharmacodynamics, single dose bolus, extravascular, infusion, multiple dose, nonlinear kinetics, multicompartment behavior, hepatic clearance, and renal clearance. The first 4 assessments were completed online through a learning management system (Sakai, Sakai Foundation, Creative Common Attribution, Ann Arbor, MI). These assessments consisted of 4 questions from each pool for a total of 36 questions. Each pool contained 12-20 questions from previous course examinations over the past 7 years. More than 90% of the questions were at Bloom's Taxonomy level of application or higher. Like the online assessments, the final examination consisted of 4 newly created questions per pool.

Latent curve modeling is a statistical technique used to assess interindividual variability in intraindividual change,[20] and is employed extensively in developmental and educational science, where it is used to examine trajectories of change.[21,22] The LCM technique was used in this study to explore potential factors contributing to the variability associated with learning rates. These factors included 3 main areas: prior academic experience (ie, grades, standardized examination scores), study skills (ie, number of practice problems, study strategies, motivation), and personality traits and attitudes (ie, introversion/extroversion, self-views of intelligence, attitudes towards team learning environments). The development and approach to the LCM can be found in Appendix 1. All models were analyzed with MPlus Version 7 for Windows 64-bit (Muthén & Muthén, Los Angeles, CA).

To account for baseline variation in academic ability, variables from the admissions process were incorporated into baseline LCM models. These variables included Pharmacy College Admissions Test (PCAT) composite scores, PCAT subsections (reading comprehension, qualitative, biology, chemistry, verbal), grade point average (GPA) upon admission, and presence of a prior 4-year degree. There was no formal hypothesis testing conducted with these measures.

The first factor examined was the role of practice. Practice quizzes, problem sets and inclass cases were used to monitor amount of practice. All practice-related activities, with the exception of inclass cases, were available either on Sakai or an online learning module (Foundations in Pharmacokineics, University of North Carolina at Chapel Hill, NC), and both formats allowed the instructor to track completed practice activities. For the practice problems, approximately 75% were individual effort problems (eg, self-assessments, homework, online assessments), and 25% were team effort problems (eg, inclass cases). In addition, to gauge students' study habits and motivations within this particular course, the MSLQ was administered at week 8 of the semester.[23] The MSLQ assesses different components of motivation (intrinsic goal orientation, extrinsic goal orientation, task value, control beliefs, self-efficacy for learning, and performance and test anxiety) and learning strategies (rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment, effort regulation, peer learning, and help seeking). We hypothesized that practice, motivation, and learning strategies would partially explain interindividual variability in learning. Specifically, we hypothesized that students who performed more practice problems would have higher performance.

Personality and attitudes were assessed several ways. The Myers-Briggs Type Indicator (MBTI) was completed on the first day of class (MBTI Self-Scorable - Form M, CPP, Inc, Sunnyvale, CA). Team assignments were based on balancing personality types using a previously used algorithm.[24] At the beginning of the semester, students' self-views of intelligence were assessed generally[14] and specifically related to comfort with mathematics.[25] Student attitudes toward team learning were assessed using a previously validated tool on team-based learning at the beginning of the semester.[26] Overall, we hypothesized that students' personality and attitudes towards team learning would partially explain interindividual variability in learning. Specifically, we hypothesized that the variability in learning would be associated with the introversion/extroversion scale or with the student's view of intelligence as related to comfort with mathematics. This study was deemed exempt from review by the University of North Carolina at Chapel Hill Institutional Review Board.

RESULTS

The 4 online assessments were constructed from a random pool of previous examination questions, which precluded them from reliability analysis. However, the previous assessments from which the questions were pulled had acceptable levels of internal reliability ($n=15$ examinations, $\alpha=0.74 \pm 0.14$). The final examination also had acceptable levels of reliability ($\alpha=0.73$). Individual scores for all the assessments can be found in Figure 1.

To control for the effect of academic ability, various measures (GPA, PCAT, etc) were incorporated into the model. The path diagram for this model can be found in Figure 1 of Appendix 1 and summary of all the model fits can be found in Table 1 of Appendix 1. The only significant factor associated with the overall rate of learning ($b=.22 \pm 0.11, p<0.05$) was GPA, suggesting that higher GPAs were associated with a faster rate of acquiring and understanding the information. No other measure of prior academic success was a significant factor.

Summary statistics for measures of practice problems, study skills, and motivation can be found in Table 2 of Appendix 1. There was no significant effect of practice on learning, suggesting that practice did not explain interindividual variability. There was a weak correlation between final examination score and the total amount of practice ($\rho=0.17, p<0.05$).

In some instances the final examination score was inconsistent with the trajectory established by students' prior assessments. It could be that greater effort was made in preparing for the high stakes final examination than for the lower stakes interim assessments (ie, more time or more practice before the final). To answer this question,

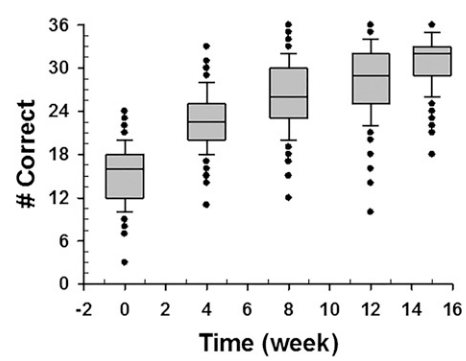

Figure 1. Assessment scores over time (maximum scores is 36). The boundary of the box closest to zero indicates the 25th percentile, a line within the box marks the median, and the boundary of the box farthest from zero indicates the 75th percentile. "Whiskers" (ie, error bars) above and below the box indicate the 90th and 10th percentiles. Points represent outliers.

we conducted a correlation analysis of the change in assessment scores between assessment 4 and the final examination and the respective change in practice. There was no significant correlation between the change in assessments scores and amount of practice.

When examining other factors associated with learning strategies and motivation, metacognitive self-regulation (ie, planning, monitoring, and regulating of cognition and learning) did explain some of the variability in the rate of learning (b=-0.126 ± 0.059; $p<0.05$). When this factor was added to the model, the final examination score became unrelated to baseline performance (eg, where the learner started), and the relation between the rate of learning and final examination score increased (b=6.8 to b=12.5). This suggested 2 things: (1) that a higher level of metacognitive self-regulation is associated with a slower rate of learning, and (2) that a substantial amount of the variability in the rate of learning is accounted for by metacognitive self-regulation; that is, controlling for metacognitive self-regulation makes the relationship more apparent between rate of learning and the final examination performance. The latter part may be explained by a significant correlation between metacognitive self-regulation and measures within the MSLQ of critical thinking (ie, degree to which students report applying previous knowledge to new situations to solve problems; ρ=0.58), elaboration (ie, putting material in one's own words and relating old material to new material; ρ=0.68), and intrinsic goal orientation (ie, students' perception that they are participating in a task for reasons of challenge, curiosity, and mastery; ρ=0.53). In terms of the motivation components of the MSLQ, none of the factors explained interindividual variability.

Summary statistics for measures of personality and attitude measures can be found in Table 2 of Appendix 1. All 16 MBTI categories were present in the class. No factor within the MBTI explained interindividual variability in learning; however, the addition of personality factors did impact the effect of GPA on the rate of learning, which resulted in GPA becoming nonsignificant in explaining interindividual variability. This suggests that adding personality traits to the model influenced some of the effect of GPA (ie, GPA x personality interaction). There was a significant correlation between entrance GPA and both introversion (ρ=0.17, $p<0.05$) and judging (ρ=0.19, $p<0.05$), which may partially explain the finding.

We used 2 assessments of students' self-views of intelligence: a general assessment and 1 related to mathematics; the latter had 5 subscales: membership, acceptance, affect, trust, and fade. Two facets of mathematical intelligence theory significantly explained the interindividual variability related to the baseline performance, affect (ie, being at ease, comfortable, calm, and not anxious, tense, or nervous with respect to math; b=0.57 ± 0.29, $p<0.05$) and desire to fade (ie, desire to say little, not actively participate, fade into the background when doing math, b=0.56 ± 0.23, $p<0.05$). "Affect" and "desire to fade" were negatively correlated with each other (ρ=-0.50, $p<0.05$), but both had a positive impact on baseline performance, which may indicate each variable affects a different part of interindividual variability. This finding may be partially explained in that "affect" and "desire to fade" were significantly correlated with intrinsic goal orientation (affect, ρ=0.21; fade, ρ=-0.17) and self-efficacy (affect, ρ=0.42; fade, ρ=-0.31). Finally, no factor within team attitudes explained the interindividual variability in learning.

A full correlation analysis was performed on all potential predictors of success used in this investigation, but factors related to team attitudes were specifically reviewed. Significant correlations are presented in Table 1. Students with a higher sense of belonging to the math community, or those with incremental (or growth) self-views of intelligence, tended to have a more favorable, although still weak, view of team learning. Students who were more comfortable learning on their own, or those with stronger tendencies towards introversion, tended to have a lower view of team learning.

DISCUSSION

One of the primary goals of the study was to determine the impact of personality traits on learning, particularly if introverted students were adversely impacted by a team-learning (ie, cooperative learning) environment. To date, extroversion has not been shown to be a strong influence on academic performance,[27] but there is little data specific to cooperative learning environments. This study did not find a notable difference between introverts and extroverts in course performance. While introverts tended to rate the team experience lower, this association was weak. One reason introverts may not be impacted negatively is that, in a true cooperative learning environment, there is time for individual focus and reflection prior to engaging in conversation, a situation that favors introverted personalities. Other studies examined the relationship between personality factors and academic performance. Gore and colleagues found that conscientiousness measurements within the 5-factor inventory was associated with being a good academic citizen, which could relate to being a good team member in a cooperative environment.[28] Using the 5-factor inventory and a learning styles inventory, Komarraju and colleagues found that personality and learning styles explained a small fraction of the variance in GPA,

Table 1. Correlation Matrix (Spearman Rank) of Various Metrics and View of Team Learning; Only Significant Correlations are Shown

		Overall Satisfaction with Team Experience	Team Impact on Quality of Learning	Satisfaction with Peer Evaluation	Team Impact on Clinical Reasoning Ability	Professional Development
Sense of Belonging Scale	Trust	0.18	0.23	0.24	0.17	0.25
Overall Self-View of Intelligence	Incremental	0.17	0.20	0.28	ns	0.23
Other	Comfort learning on their own	-0.26	-0.37	-0.20	-0.23	ns
Motivated Strategies Learning Questionnaire	Intrinsic Goal Orientation	ns	ns	ns	ns	0.32
	Task Value	ns	ns	ns	ns	0.26
	Self-Efficacy for Learning Performance	ns	ns	ns	0.19	0.25
	Elaboration	ns	ns	ns	ns	0.25
	Organization	ns	ns	ns	ns	0.20
	Metacognitive Self-Regulation	ns	ns	ns	ns	0.21
	Time and Study Environment	ns	ns	ns	ns	0.20
	Peer Learning	ns	0.32	ns	0.22	ns
	Help Seeking	ns	0.25	ns	ns	0.19
Myers-Brigg Type Indicator	Introversion	-0.27	-0.32	ns	-0.21	-0.16

15% and 3%, respectively.[29] Furnham found that learning style, personality traits, and intelligence accounted for around 10% of the variance in college examination success.[30] Of the studies that looked at personality traits, the introversion/extroversion scale did not seem to be predictive or associated with learning performance but may have been potentially related to learning strategies (ie, deep vs surface vs strategic)[31] or instructional techniques (ie, lecture vs interactive).[10]

One finding of particular note was the lack of effect the number of practice problems completed before each assessment had on performance. This null finding may indicate that practice problems have minimal effect on explaining interindividual variability, but practice may form an integral part of the class for individuals and assist in creating the learning curve trajectory. Within the course, there are sufficient opportunities to practice, including self-assessment quizzes (80 questions total), problem sets (102 questions total), quizzes to assess preparation (59 questions total), inclass cases (135 questions), and interim cumulative assessments (225 questions total). Other studies examining the learning curve associated number of practice problems with efficiency or overall performance.[32-35]

Study skills and motivation were explored as potential causes of interindividual differences. The only factor that significantly impacted the model was metacognitive self-regulation. Within the MSLQ, this measure assesses the planning, monitoring, and regulating of cognition and learning. In our study, we found a negative relationship between self-regulation and the rate of learning. If self-regulation is associated with deep processing of information, that might explain the slower growth curve and reinforce the concept that learning needs to be a slow process.[36] Metacognitive self-regulation was highly correlated ($\rho > 0.5$) with intrinsic goal orientation, elaboration, and critical thinking, which may support the notion of "deep" processing. Typically self-regulation is associated with higher overall performance,[37] and higher levels of metacognitive ability have been associated with learning ability.[38]

Finally, we examined individual views on the malleability of intelligence in general and specifically related to mathematics. There were 2 significant effects: affect and desire to fade. These factors may have coincided, as female students reported lower perceived confidence than males in mathematics, despite equal performance,[3] a potentially important finding to a population that is roughly 65% female. Affect and desire to fade were significantly correlated with intrinsic goal orientation. Thus, high values for affect (comfort with math) and low values of fade (being less inclined to hide) were both associated with high levels of motivation and self-efficacy.

There were several limitations to this study. The first limitation is the small variability of assessment scores. The insufficient variability can be attributed to the relatively small range of values and the selectivity of students. While a larger sample size may assist, assessments that have a greater degree of differentiability may be better. This phenomenon of insufficient variability is common when studying individuals with high academic achievement, for example, children with advanced intellectual and academic abilities in the gifted research arena. Another reason for the lack of variability was the focus of the course on competency. Although the course learning objectives were aimed at the upper levels of Bloom's Taxonomy, the learning goal was for students to achieve competency of these objectives. As such, assessments were aimed at 85-90% core skills (ie, competencies students should be able to do) and less than 15% for ranking or stratifying purposes (ie, competencies that only the top achieving students should be able to accomplish). Courses that focus on stratifying students may have larger variability in assessment performance.

The second limitation was accurately counting the practice problems. Within the course, practice activities ranged from voluntary (self-assessment quizzes, homework) to required (inclass cases, quiz questions, interim assessments). Voluntary practice activities were tracked through the learning management system to indicate number of times each student went through the available questions. Additionally, counting practice activities did not include assessing their quality.

A third limitation was the validity and reliability of measures like the MBTI and the self-views of intelligence. The MBTI was used to assess personality traits in lieu of more valid measures like the 5-factor inventory. The reasons for using the MBTI were the availability of previous research using the MBTI to form groups, accessibility of the assessment through campus resources, and availability of resources to provide to students about using MBTI as a reflective tool. We attempted to compensate for some inherent weaknesses in the MBTI by using continuous scales for each attribute. However, most research on personality and academic performance is conducted with the 5-factor model. Finally, some of the assessments of self-views may have lacked rigor in reliability and validity. Again, by using a continuous scale, we may have at least been able to differentiate variability within self-theories.

The course was modified from the previous year to optimize learning. The first optimization was to improve scaffolding (ie, increase application difficulty with time) by using the TBL format to facilitate a supportive application of concepts. The remainder of the course was used to review material through the use of integrated cases completed individually instead of by teams. The second optimization was to increase opportunities for retrieval practice using multiple cumulative assessments. Thirdly, we increased feedback on learning progress through multiple cumulative examinations—both retrieval and feedback demonstrate strong abilities to increase learning.[39] Other changes implemented included removing the midterm examination (due to the implementation of the interim assessments) and 3 of the 4 reflective writings to lower overall work burden.

CONCLUSION

Of the various personality and study traits investigated, none appear to have impacted the overall rate of learning. Most noteworthy is that introversion/extroversion did not impact performance in a TBL environment, though it may have impacted student attitudes about the course environment. This finding is important because the use of cooperative learning techniques is becoming a larger part of higher education. Further work is needed to identify potential factors that may contribute to interindividual differences in such learning environments.

ACKNOWLEDGMENTS

Ashley Campbell, PharmD, is currently a PGY1 resident at the University of Pittsburgh Medical Center – St. Margaret. The authors would like to particularly thank Abigail Panter, PhD, Jennifer Smith, PharmD, Wendy Cox, PharmD, and Rebecca Deranian for their help in preparing this manuscript.

REFERENCES

1. Moore KD. *Effective Instructional Strategies: From Theory to Practice*. 2nd ed. Thousand Oaks, Calif.: Sage Publications; 2009.
2. Fink LD. *Creating Significant Learning Experience: An Integrated Approach to Designing College Courses*. 1st ed. San Francisco, Calif.: Jossey-Bass; 2003.
3. Goetz T, Bieg M, Ludtke O, Pekrun R, Hall NC. Do girls really experience more anxiety in mathematics? *Psychol Sci.* 2013; 24(10): 2079-2087.
4. Rabia Z, Irum N. Personality traits and learning styles among students of mathematics, architecture, and fine arts. *J Behav Sci.* 2011; 21(1): 92.
5. Ackerman PL, Heggestad ED. Intelligence, personality, and interests: evidence for overlapping traits. *Psycholl Bull.* 1997; 121(2): 219-245.
6. Breckler J, Joun D, Ngo H. Learning styles of physiology students interested in the health professions. *Adv Physiol Educ.* 2009; 33 (1):30-36.
7. Schunk DH, Zimmerman BJ. *Motivation and Self-regulated Learning: Theory, Research, and Applications*. New York: Lawrence Erlbaum Associates; 2008.
8. Persky AM. The impact of team-based learning on a foundational pharmacokinetics course. *Am J Pharm Educ.* 2012; 76(2):Article 31.
9. Michaelsen LK, Knight AB, Fink LD. *Team-based Learning: A Transformative Use of Small Groups*. Westport, Conn.: Praeger; 2002.
10. Chamorro-Premuzic T, Furnham A, Lewis M. Personality and approaches to learning predict preference for different teaching methods. *Learn Individ Differ.* 2007; 17(3): 241-250.
11. Hutchinson M, Gul FA. The interactive effects of extroversion/introversion traits and collectivism/individualism cultural beliefs on student group learning preferences. *J Account Educ.* 1997; 15(1):95-107.
12. Ramsay A, Hanlon D, Smith D. The association between cognitive style and accounting students' preference for cooperative learning: an empirical investigation. *J Account Educ.* 2000;18 (3):215-228.
13. Menges RJ, Svinicki MD. *College Teaching, from Theory to Practice*. San Francisco: Jossey-Bass; 1991.
14. Dweck CS. *Self-theories: Their Role in Motivation, Personality, and Development*. Philadelphia, PA: Psychology Press; 1999.
15. Teunissen PW, Bok HG. Believing is seeing: how people's beliefs influence goals, emotions and behaviour. *Med Educ.* 2013; 47 (11):1064-1072.
16. Pintrich PR, Schunk DH. *Motivation in Education : Theory, Research, and Applications*. 2nd ed. Upper Saddle River, N.J.: Merrill; 2002.
17. Carroll CA, Garavalia LS. Factors contributing to the academic achievement of pharmacy students: use of the goal-efficacy framework. *Am J Pharm Educ.* 2004;68(4):Article 88.
18. Pizzimenti MA, Axelson RD. Assessing student engagement and self-regulated learning in a medical gross anatomy course. *Anat Sci Educ.* 2014.
19. Turan S, Konan A. Self-regulated learning strategies used in surgical clerkship and the relationship with clinical achievement. *J Surg Educ.* 2012;69(2):218-225.
20. Meredith W, Tisak J. Latent curve analysis. *Psychometrika.* 1990;55(1):107-122.
21. Windle M. A latent growth curve model of delinquent activity among adolescents. *Appl Dev Sci.* 2000;4(4):193-207.
22. Reynolds CA, Finkel D, McArdle JJ, Gatz M, Berg S, Pedersen NL. Quantitative genetic analysis of latent growth curve models of cognitive abilities in adulthood. *Dev Psychol.* 2005;41(1):3-16.
23. Pintrich PR, Smith DAF, Garcia T, McKeachie WJ.. Reliability and Predictive Validity of the Motivated Strategies for Learning Questionnaire (Mslq). *Educ Psychol Meas.* 1993;53(3):801-813.
24. Jensen D, Feland J, Bowe M, Self B. *A 6-Hats Based Team Formation Strategy: Development and Comparison with an MBTI Based Approach*; 2000.
25. Good C, Rattan A, Dweck CS. Why do women opt out? Sense of belonging and women's representation in mathematics. *J Pers Soc Psychol.* 2012;102(4):700-717.
26. Parmelee DX, DeStephen D, Borges NJ. Medical students' attitudes about team-based learning in a pre-clinical curriculum. *Med Educ Online.* 2009; 14: 1.
27. Poropat AE. A meta-analysis of the five-factor model of personality and academic performance. *Psychol Bull.* 2009;135(2):322-338.
28. Gore JS, Kiefner AE, Combs KM. Personality traits that predict academic citizenship behavior. *J Appl Soc Psychol.* 2012;42 (10):2433-2456.
29. Komarraju M, Karau SJ, Schmeck RR, Avdic A. The Big Five personality traits, learning styles, and academic achievement. *Pers Indiv Differ.* 2011;51(4):472-477.
30. Furnham A. Learning Style, Personality Traits and Intelligence as Predictors of College Academic Performance. *Individ Diff Res.* 2012;10(3):117-128.

31. Duff A, Boyle E, Dunleavy K, Ferguson J. The relationship between personality, approach to learning and academic performance. *Pers Indiv Differ.* 2004;36(8):1907-1920.
32. Anzanello MJ, Fogliatto FS. Learning curve models and applications: Literature review and research directions. *Int J Indust Erg.* 2011;41(5):573-583.
33. Hope WW, Hooks Iii WB, Kilbourne SN, Adams A, Kotwall CA, Clancy TV. Assessing resident performance and training of colonoscopy in a general surgery training program. *Surg Endoscop.* 2013;27(5):1706-1710.
34. Roediger III HL, Smith MA. The "pure-study" learning curve: the learning curve without cumulative testing. *Mem Cognition.* 2012; 40(7): 989-1002.
35. Wiersma E. Conditions that shape the learning curve: factors that increase the ability and opportunity to learn. *Manage Sci.* 2007;53 (12):1903-1915.
36. Marsh E, Butler AC. Memory in educational settings. In: Reisberg D, ed. *The Oxford Handbook of Cognitive Psychology*. Oxford; New York: Oxford University Press; 2013:299-317.
37. Pintrich PR, De Groot EV. Motivational and self-regulated learning components of classroom academic performance. *J Educ Psychol.* 1990;82(1):33-40.
38. Kornell N, Metcalfe J. Study efficacy and the region of proximal learning framework. *J Exp Psychol Learn.* 2006; 32(3): 609-622.
39. Butler AC, Karpicke JD, Roediger rHL. The effect of type and timing of feedback on learning from multiple-choice tests. *J Exp Psychol Appl.* 2007;13(4):273-281.

Appendix 1. Model Development

Latent curve models can be expressed in several different ways. For the purposes of this study, the LCM is expressed as a structural equation model:[1]

$$y_i = \Lambda \eta_i + \varepsilon_i$$

Where y_i is the i-th individual's vector of repeated measures, Λ is a matrix of set factor loadings that determine the functional form of the growth curve, η_i is a vector of the i-th individual's growth factor scores, and $\epsilon_i$is the vector of the i-th individual's error, or the discrepancy of the individual's true scores from their predicted scores.

In the structural equation framework, model fit, (ie, the ability of the model to reproduce the observed data), is assessed with a variety of fit indices. In this study, 3 common indices of model fit were used, including the χ^2 test of model fit, the comparative fit index (CFI), [2] and the root mean squared error of approximation (RMSEA).[3] The χ^2 test is the most common metric of model fit and assesses the discrepancy between the model implied covariance matrix and the sample covariance matrix. One of the issues with χ^2 test of model fit is its sensitivity to large sample sizes, which leads to rejecting a model on the basis that it does not exactly reproduce the covariance matrix of a large sample.[4]

To provide more measures of fit without the issues as the χ^2 test, comparative fix index (CFI) and root mean squared error of approximation (RMSEA) were used. CFI is a normed fit measure that ranges from 0 to 1, with 1 being the best fit. It compares the model with a baseline independence model, where there is no relationship between any of the variables, and provides an index of whether the model in question provides a better fit to the data than the baseline model.[2] The standard cutoff for good fit is a CFI of 0.95.[4]

Root mean squared error of approximation is a parsimony normed badness-of-fit measure that ranges from 0 on, with 0 indicating best fit.[3] The RMSEA fit is one of the few indices where the distribution is known, and therefore, confidence intervals and hypothesis tests are available. The most common hypothesis test is a close-fit test that assesses whether the population value that RMSEA estimates is below 0.05, which would indicate close fit of the model to the observed data.[5] The RMSEA values within the interval of .05-.08 are considered marginally acceptable models, and RMSEA values of above 0.1 indicate unacceptable fit.[4]

We approached this analysis in 2 steps. The first step was to determine an unconditional model with no covariates that best described the change over time in the assessment scores. Following establishment of a best fitting unconditional model, we proceeded to include time varying covariates (TVCs), specifically looking at the amount of practice completed before each assessment. Following that analysis, we examined the effects of the time invariant covariates (TICs) on the growth factors. Due to both a small sample size and the number of TICs, a simultaneous analysis of all sets of TVCs was unsound. Rather than include all sets of TVCs simultaneously, we examined each set of TVC's independently. The advantage of this method is that independent analysis avoids over-fitting the model to the data, while the disadvantage is that this method does not control for the other sets of TVCs. The independent analysis of sets also fit with the exploratory focus of this study.

We began to establish an unconditional linear model by first fitting the 5 assessment scores to a linear growth curve model. The first model attempted was a linear growth curve that specified that each individual's assessment scores improve over time at a constant rate. This model exhibited extremely poor fit ($\chi^2(10)=161.2$, $p<.05$, RMSEA=.32 [.278, .36], CFI=.19), suggesting that the rate of increase in assessment scores did not follow a linear trend.

A visual inspection of a plot of the assessment scores suggested that the change in score followed a quadratic trend, with scores increasing rapidly at the beginning of the course, and the change in scores slowing as the course continued. While the quadratic model showed an improvement in fit from the linear model, it did not fit the data well ($\chi^2(9)=100.7$, $p<.05$, RMSEA=.26 [.216, 3],

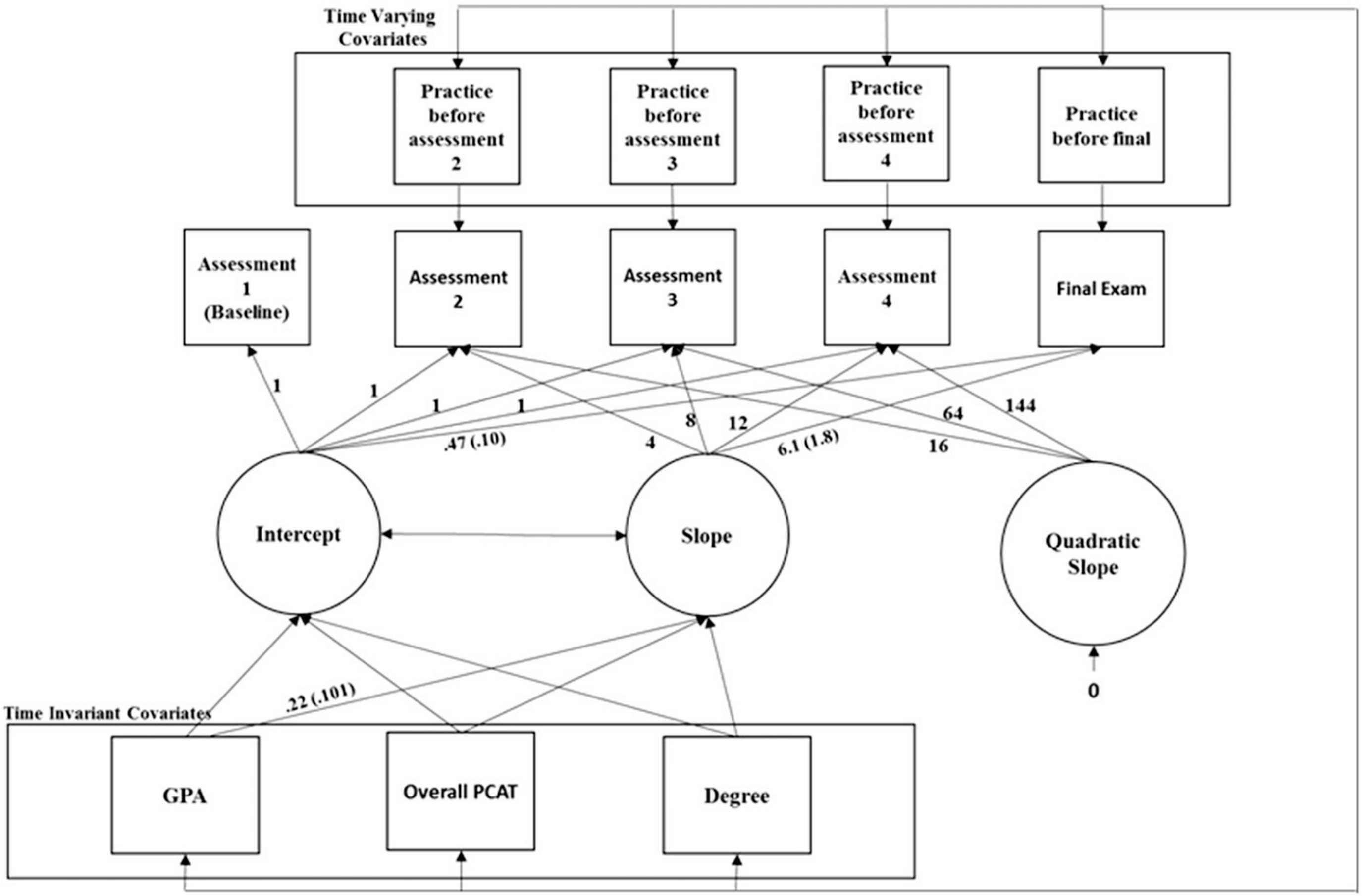

Figure 1 of Appendix 1. Baseline Covariate Model: For parsimony, only significant paths and preconstrained paths are shown. Significant paths are of the form: Estimate (Standard Error). Single headed arrows are regressions. Double or multiheaded arrows are covariances.

CFI=.50). While a visual inspection of the data suggested that on average, a quadratic trend would fit the assessment scores, the results from this model indicated that the assessment scores did not follow a strictly quadratic trend. To more finely assess model fit in this case, predicted scores were calculated and compared to actual scores.

An inspection of the residual plot for the quadratic model suggested that the proposed growth curve was best at predicting the first and last assessments (the latter being the final examination), and less proficient at predicting the score of the middle 3 assessments. Based on these observations and that the first 4 assessments were more similar (ie, random questions from a pool where the final examination was not), a quadratic model was fit to the first 4 assessments only. Fit was excellent ($\chi^2(4)=5.51$, $p=.24$, RMSEA=.050, CFI=.99), which suggested that it was indeed the final assessment that was driving the bad fit of the full quadratic model.

Due to the behavior of the residuals of the quadratic model and the excellent fit of the quadratic model with only 4 assessments, the next model fit was a quadratic-regressive, where the first 4 time points were fit to a quadratic model, and then the final assessment

Table 1 of Appendix 1. Summary of Latent Curve Model

Covariate	Model Fit	*p* value	RMSEA	CFI
Prior Academic Success	$\chi^2(31)= 39.2$	0.15	0.041 [.00, .076]	0.96
Practice	$\chi^2(22)= 27.4$	0.19	0.039	0.97
MBTI	$\chi^2(43)= 50.2$	0.21	0.03 [0.00, .065]	0.96
Theory of Intelligence / View of Mathematics	$\chi^2(46)= 54.6$	0.18	0.034 [.00, .65]	0.96
Motivation / Study Strategies	$\chi^2(43)= 72.5$	0.096	0.040 [.00, .66]	0.93
Team Attitudes	$\chi^2(49)= 55.4$	0.25	0.029 [.00, .61]	0.97

Comparative fit index (CFI); root mean squared error of approximation (RMSEA).[3]

Table 2 of Appendix 1. Summary of Assessments of Student Characteristics

	Sub-categories	Average	Median	Max	Min
Study Skills and Motivation					
Number of Practice Problems	Total	613	597	1226	339
	0-4 wk	184	168	459	78
	4-8 wk	196	190	330	128
	8-12 wk	88	77	269	41
	12-15 wk	145	148	543	36
MSLQ (motivation)	Intrinsic Goal Orientation	4.7	4.8	7.0	2.0
	Extrinsic Goal Orientation	4.7	4.8	6.8	2.3
	Task Value	5.1	5.0	7.0	1.8
	Control Beliefs	5.1	5.3	7.0	2.3
	Self-efficacy for Learning and Performance	4.8	4.9	7.0	1.6
	Test Anxiety	4.3	4.2	7.0	1.4
MSLQ (study strategies)	Rehearsal	4.0	4.0	6.3	1.3
	Elaboration	4.6	4.5	6.7	1.0
	Organization	4.3	4.3	7.0	1.5
	Critical Thinking	3.4	3.4	6.8	1.2
	Metacognitive Self-Regulation	4.9	4.8	6.7	2.9
	Time and Study Environment	4.9	4.9	7.0	2.3
	Effort Regulation	5.2	5.3	7.0	2.0
	Peer Learning	3.1	3.0	7.0	1.0
	Help Seeking	3.7	3.8	7.0	1.0
Personality and Attitudes					
MBTI	Introversion/Extroversion	0.43	1.0	21	-23
	Intuition/Sensing	-4.2	-6.0	26	-26
	Feeling/Thinking	-0.14	0	24	-24
	Perceiving/Judging	-5.1	-6.0	22	-23
General Theory of Intelligence/	Incremental/Entity	3.8	5.0	24	-24
View of Mathematics	Membership	4.9	5.0	8.0	0.0
	Acceptance	5.4	5.8	8.0	0.0
	Affect	5.0	5.1	8.0	0.0
	Trust	5.8	6.0	8.0	1.8
	Fade	3.4	3.0	7.8	0.0
Team Attitudes	Overall Satisfaction with Team Experience	3.9	4.0	5.0	2.0
	Team Impact on Quality of Learning	3.4	3.3	5.0	1.0
	Satisfaction with Peer Evaluation	3.6	3.8	5.0	1.8
	Team Impact on Clinical Reasoning Ability	3.7	3.7	5.0	1.7
	Professional Development	3.9	4.0	5.0	2

MSLQ: Motivated Strategies for Learning Questionnaire; MBTI: Myers- Briggs Type Indicator

score was predicted both from the slope and the intercept factor (the quadratic factor had variance set to 0). This was implemented for 2 reasons. First, by not using the final examination score to define the quadratic growth curve, the quadratic trend estimated better fit the first 4 time points than a model including the final assessment score in the growth curve. Secondly, by predicting the final assessment score from both growth factors, we included the final assessment's information in the model, without restricting it to a quadratic trend.

The path diagram for the quadratic factor-regressive model is presented in Figure 1 of Appendix 1. Model fit was improved from the full quadratic model ($\chi^2(5)=13.1$, $p=.041$, RMSEA=.086, CFI=.96), however fit was not ideal. Both the slope and intercept factor significantly predicted final examination score (b=.47, 6.8, $p<.001$, .05), suggesting, not surprisingly, that the slope factor had a greater association with final examination score than the intercept factor. Due to both the pattern of residuals that the full quadratic model exhibited, as well as the excellent fit for the quadratic model on the first 4 assessments, this quadratic factor-regressive model was retained as the unconditional model.

To control for practice and prior ability, we included time varying and time invariant covariates. To model the effect of practice on assessment scores, difference scores were calculated to determine how many practice problems a student did between each assessment. Four different scores were calculated (0-4 week, 4-8, 8-12, 12-15). Using the unconditional model, assessment scores at

4, 8, 12, and 15 weeks were regressed on the difference score for the time period preceding that assessment. Due to the exogenous nature of the difference scores, they were freely correlated with each other. This model fit the data well ($\chi^2(31)=27.5$, $p=.19$, RMSEA=.039, CFI=.97). This model was retained for the following analysis of time invariant predictors to investigate if a relation was clarified with the addition of covariates.

To control for the effect of ability, as measured by the PCAT, subsections of the PCAT (reading comprehension, qualitative, biology, chemistry, verbal), GPA upon admission, and presence of a prior degree were added to the practice time varying covariate model as time invariant covariates, with the slope and intercept latent growth factor being regressed on cumulative GPA, overall PCAT percentile, and presence of a degree. Additionally, the residual covariance between the slope and intercept factor was estimated, so that any covariance between growth factors not explained by the TIC was allowed into the model.

The path diagram for this model is presented in Figure 1 of Appendix 1. This model fit well, ($\chi^2(31)=39.2$, $p=.15$, RMSEA=.041 [.00, .076], CFI=.96), and was retained as the baseline model to which covariates of interest would be added as time invariant predictors of the growth factors. To test various hypotheses of interest, covariates were added to the above model as additional time invariant covariates. Full results can be found in Tables 1 and 2 of Appendix 1.

REFERENCES FOR APPENDIX 1

1. Bollen KA, Curran PJ. *Latent curve models : a structural equation perspective*. Hoboken, N.J.: Wiley-Interscience; 2006.
2. Bentler PM. Comparative Fit Indexes in Structural Models. *Psychol Bull.* 1990;107(2):238-246.
3. Steiger JH. Structural model evaluation and modification - an interval estimation approach. *Mult Behav Res.* 1990;25(2):173-180.
4. Hu LT, Bentler PM. Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives. *Struct Eq Model* 1999;6(1):1-55.
5. Kline RB. *Principles and practice of structural equation modeling*. 2nd ed. New York: Guilford Press; 2005.