Exploring Non-Cognitive Reasons behind Success after Failure

Elle Yuan Wang, James Cunningham, Philip Arcuria, Tom Fikes, and Lou Pugliese

Action Lab, Edplus at Arizona State University
{elle.wang; jim.cunningham; parcuria; thomas.fikes; lou.pugliese}@asu.edu

ABSTRACT: The availability of large-scale online courses enabled assessment of academic performances at scale. Equally important is the opportunity to investigate the state of non-cognitive or soft skills of online learners to inform design of interventions to improve learning outcomes. The present analysis looked learners who successfully passed the course, either passed at their first attempts or passed after failed attempts, and compared how their soft skills differ from the rest of learners. The findings suggested that 1) Learners who successfully passed the course tend to have strong skill sets related to time and project management; 2) Learners who successfully passed the course after failed attempts tend to have higher skill sets related to decision making and leadership. Discussions and interpretations are also included.

Keywords: Online learning, non-cognitive skills, learning analytics

1 INTRODUCTION

Pathways to success vary. In the context of academic settings, some students may experience more failures than others, before achieving success. Some failures may be productive and necessary (Kapur, 2008; Kapur, 2010). Learners with varied prior knowledge may require a diverse range of "desirable difficulties" (Schmidt & Bjork, 1992). Nevertheless, learners may treat failure differently. Some learners may be more discouraged than others when facing failure, which may be due to cognitive and non-cognitive differences among learners. While educators and researchers are developing various cognitive interventions to help learners succeed, more studies have looked into decoding the non-cognitive differences among learners (McAbee, Oswald, & Connelly, 2014; Farkas, 2003).

Researchers have demonstrated that, on average, every dollar invested in development of non-cognitive skillsets such as those on social emotional learning programs yields over 10 times that amount in long-term benefits (Belfield et al., 2015).

Social and emotional learning constitutes a critical part of non-cognitive skillsets. Non-cognitive skills (Heckman & Rubinstein, 2001) refer to social and emotional learning capabilities beyond academic knowledge. These skills comprise a diverse range of aspects including conscientiousness (Camara et al., 2015), growth mindset (Dweck, 2006), time management, and self-regulation (Gutman & Schoon, 2013), to name a few.

It has been shown that the predictive power of non-cognitive skills on academic achievement across wide range of educational settings is at least equal to or better than the predictive power of cognitive skills. Non-cognitive skills have been associated with various academic outcomes (e.g., Lleras, 2008) including persistence in postsecondary settings with attendance and retention (e.g., Credé, Roch, & Kieszezynka, 2010) and engagement (McClenney, Marti, & Adkins, 2006). Moreover, non-cognitive skills have also been linked to career advancement (Heckman et al., 2006), well-being (Strickhouser, Zell, & Krizan, 2017) and key 21st century competencies, such as critical thinking and problem solving (Buckingham Shum & Crick, 2016).

Therefore, it is imperative to understand why some learners are more likely to continue their learning processes after failure than others. To respond to this research question, the present study included analyses to investigate how learners who succeeded in passing an online mathematics course after failed attempts differ regarding to their non-cognitive skillsets.

2 METHOD

2.1 Data Source/Participants

This study used the passing rates of online college algebra students at a large public university in the southwestern United States to examine the relationship between soft skills and academic performance. The online course was offered during the fall and spring of the 2016-2017 academic school year and used the adaptive learning system ALEKS (e.g., Hagerty & Smith, 2005) which guides students through practice and assessment of 383 mathematics topics related to college algebra. A passing grade in this course is considered to be a letter grade of “C” or better. Students in this course had an opportunity to retake college algebra at no additional cost if they were unsuccessful in passing on the first try. Although, an instructor is assigned to each section of the online course, the students’ primary interaction is with the adaptive online learning system as they read about each math concept, work through problems, request examples, and take assessments.

2.2 25 soft skill competency assessments

A total of 255 learners of the math course voluntarily participated in a non-cognitive skillsets assessment developed by Indigo Project (Indigo, 2017), designed as part of an online orientation course. 25 types of non-academic skillsets (Table 1), developed based on the 21st century competencies (TTI, 2012), were collected on the student level. The 25 types of skillsets were developed based on the 21st century competencies. This type of assessment has been used in the field of engineering entrepreneurship education (Pistrui et al., 2011), surgical training (Bell et al., 2012), as well as secondary science education (Bonnstetter, 2003).

2.3 2 Types of outcomes

Two types of binary outcome measures were included in the present analyses: “Passing the course” and “Passing the course after failure”. “Passing the course” was computed as 1 for passing; the rest were coded as 0. Similarly, “Passing the course after failure” was computed as 1 for learners who passed the course after experiencing at least one failed attempt; the rest were coded as 0.

2.4 Analyses

A principal component analysis based on the 25 competency assessments was conducted. The extracted principal components were then used in two logistic regression models to predict the two types of outcome measures: passing the course, and passing the course after failed attempts.

3 RESULTS

3.1 Principal Component Analyses

A principle component analysis of the 25 skillsets was conducted. Five components explaining 63.76% of the variance were extracted. An oblimin rotation provided the best-defined component structure. Loadings higher than .45 are in bold in Table 1 to highlight the stronger contributions from the skillsets for each of the 5 components.

Component 1: High on Empathy and Teamwork Skills
The first principal component is strongly correlated with five of the original variables. The first principal component grows with increasing “Appreciating Others”, “Customer Focus”, “Diplomacy”, Interpersonal Skills:”, “Teamwork”, and “Understanding Others” scores.

Component 2: High on Decision Making and Organizational Skills
The second principal component is strongly correlated with three of the original variables. This component grows with increasing “Decision Making”, “Planning Organizing”, and “Project Management”.

Component 3: High on Creativity
The third principal component is strongly correlated with five of the original variables. This component grows with increasing “Conceptual Thinking”, “Continuous Learning”, “Creativity Innovation”, “Flexibility”, and “Futuristic Thinking” scores.

Component 4: Low on Leadership Skills
The fourth principal component is strongly correlated with four of the original variables. This component grows with decreasing “Conflict Management”, “Influencing Others”, “Leadership”, and “Negotiation” scores.

Component 5: Low on Time management Skills
The fifth principal component is strongly correlated with five of the original variables. This component grows with decreasing “Goal Orientation”, “Project Management”, “Resiliency”, “Self-Starting”, and “Time Management” scores.

Table 1: Factor loadings based on a principle component analysis with oblimin rotation for 25 skillsets from the Indigo assessment.

	Components				
	1	2	3	4	5
Appreciating Others	**.854**	-.084	.134	.143	.111
Conceptual Thinking	.074	.038	**.864**	.041	.142
Conflict Management	.421	.205	-.016	**-.575**	.054
Continuous Learning	-.061	.232	**.588**	-.079	-.215
Creativity Innovation	.011	-.160	**.803**	-.086	-.049
Customer Focus	**.556**	.268	.011	.046	-.107
Decision Making	-.007	**.874**	.050	-.022	.090
Diplomacy	**.597**	.258	-.001	-.137	.058
Development Coaching	.444	.123	-.092	-.260	-.303
Flexibility	.130	-.007	**.595**	.102	-.360
Futuristic Thinking	-.052	.112	**.745**	-.163	.064
Goal Orientation	.006	.047	.135	-.244	**-.653**
Influencing Others	-.074	-.088	.179	**-.835**	-.096
Interpersonal Skills	**.594**	-.015	.104	-.327	-.077
Leadership	.054	-.111	.186	**-.480**	-.434
Negotiation	.214	.241	.087	**-.623**	.045
Personal Accountability	.345	.151	.240	.290	-.415
Planning Organizing	.107	**.682**	-.088	.008	-.228
Problem Solving	-.056	**.717**	.126	-.031	-.059
Project Management	.008	.331	.042	-.254	-.473
Resiliency	.208	.037	.148	.057	**-.502**
Self-Starting	.165	-.242	.163	-.082	**-.585**
Teamwork	**.674**	-.155	-.153	-.121	-.164
Time Management	-.066	.251	-.157	.006	**-.788**
Understanding Others	**.621**	-.085	.228	-.142	-.109

3.2 Logistic Regression

Logistic regression analyses were conducted to test whether the five components derived from the 25 skillsets can predict learners' performance. Two types of indicators for performances were used: passing the course and passing the course after failure.

3.2.1 Passing the course

A logistic regression using the backward selection method was conducted to predict whether a learner passes the course based on the 5 component scores derived from the 25 skillsets. The final model included Component 1 and Component 5. The Wald test results showed that Component 1, *High* on Empath and Teamwork Skills, χ^2 (1) = 4.951, p = .026, and Component 5, *Low* on Time Management Skills, χ^2 (1) = 5.793, p = .016 were individually each statistically significant within the combined model.

Increasing Component 1 was associated with a reduction in the likelihood of passing the course; increasing Component 5 was also associated with a reduction in the likelihood of passing the course. In other words, increasing scores on empath and team work skills were associated with a lower likelihood of passing the course; whereas increasing scores on time management scores were associated with a higher likelihood of passing the course.

Table 2: Logistic Regression Analysis on Passing the Course

	B	S.E.	Wald	df	Sig.	Exp(B)
Component 1	-.344	.155	4.951	1	**.026**	.709
Component 5	-.372	.154	5.793	1	**.016**	.690
Constant	.083	.136	.369	1	.543	1.086

3.2.2 Passing after failure

A logistic regression using the backward selection method was conducted to predict whether a learner passes the course after prior failures based on the 5 component scores derived from the 25 skillsets. The final model included Component 2, Component 3, and Component 4. The Wald test results showed that Component 2, *High* on Decision Making and Organizational Skills, χ^2 (1) = 5.109, p = .024, and Component 4, *Low* on Leadership Skills, χ^2 (1) = 9.800, p = .002 were individually each statistically significant within the combined model.

Increasing Component 2 was associated with an increase of likelihood of passing the course after failure; increasing Component 4 was associated with a reduction in the likelihood of passing the course after failure. In other words, increasing scores on decision making and organizational skills as well as leadership skills were associated with higher likelihood of passing the course after failure.

Table 3: Logistic Regression Analysis on Passing after Failure

	B	S.E.	Wald	df	Sig.	Exp(B)
Component 2	.847	.375	5.109	1	**.024**	2.332
Component 3	-.634	.346	3.353	1	.067	.531
Component 4	-1.410	.450	9.800	1	**.002**	.244
Constant	-3.822	.540	50.165	1	.000	.022

4 DISCUSSION

4.1 What predicts passing?

Based on the results above, higher scores on empathy and teamwork were negatively associated with the probability of passing the course. This result is somewhat counter-intuitive. One possible interpretation is that data for the present analysis was collected from a math course where the final grade was not dependent upon interaction with fellow learners. For this specific course, it is possible that learners may benefit more from focused independent learning sessions.

By contrast, the time management skillsets are positively associated with passing the course. This finding is expected since time management skills were found to be an important factor that influenced the learners' online learning experiences (e.g., Song, et al., 2004). This finding suggests that improvement on online learners' time management skills may lead to better learning outcomes.

4.2 What predicts passing after failure?

Planning, organizational, and leadership skills were found to positively associate with the likelihood of passing the course after failure. It is possible that learners who are more skilled in planning and organization are more likely to objectively treat their failure as a useful learning process and decided to keep trying after that. It is worth investigating as to why this group of learners failed the course before they achieved success afterwards.

5. CONCLUSION

The present paper investigated non-cognitive differences behind learners who took different pathways toward success in an online mathematics course. Results from this paper suggested that it is meaningful to investigate differences in terms of learners' soft skill competencies to help understand why learners exhibit differed learning outcomes. Future studies, by employing follow-up interviews with learners, can look into specific reasons behind those identified soft skills. For example, one follow-up research question could be: Do learners whose assessment showed a lack of time management skillsets actually share the same concern when interviewed? If so, what are the reasons behind the lack of the time management skills? This way, targeted and effective interventions can be designed to help learners to achieve better learning outcomes.

REFERENCES

Bell, R. M., Fann, S. A., Morrison, J. E., & Lisk, J. R. (2012). Determining personal talents and behavioral styles of applicants to surgical training: a new look at an old problem, part II. *Journal of surgical education*, *69*(1), 23-29.

Belfield, C., Bowden, A. B., Klapp, A., Levin, H., Shand, R., & Zander, S. (2015). The economic value of social and emotional learning. *Journal of Benefit-Cost Analysis*, *6*(3), 508-544.

Bonnstetter, R. J. (2003). A triad of disposition instruments used in secondary science education to help teachers better understand self and others. *Science Education International*.

Buckingham Shum, S., & Crick, R. D. (2016). Learning Analytics for 21st Century Competencies. *Journal of Learning Analytics*, *3*(2), 6-21.

Camara, W., O'Connor, R, Mattern, K, Hanson, M. A. (2015). Beyond Academics: A Holistic Framework for Enhancing Education and Workplace Success. (ACT Research Report 2015-4). Retrieved from http://www.act.org/content/dam/act/unsecured/documents/ACT_RR2015-4.pdf

Credé, M., Roch, S. G., & Kieszczynka, U. (2010). Class attendance in college: A meta-analytic review of the relationship of class attendance with grades and student characteristics. *Review of Educational Research*, *80*, 272–295.
Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House Incorporated.
Hagerty, G., & Smith, S. (2005). Using the web-based interactive software ALEKS to enhance college algebra. *Mathematics and Computer Education*, *39*(3), 183.
Heckman, J. J., & Rubinstein, Y. (2001). The importance of noncognitive skills: Lessons from the GED testing program. *The American Economic Review*, *91*(2), 145-149.
Lleras, C. (2008). Do skills and behaviors in high school matter? The contribution of noncognitive factors in explaining differences in educational attainment and earnings. Social Science Research, 37(3), 888-902.
McClenney, K., Marti, C. N., & Adkins, C. (2006). *Student engagement and student outcomes: Key findings from CCSSE validation research.* Austin, TX: Center for Community College Student Engagement.
Indigo. (2017). Assessment validity, reliability, measurement variables, competitor landscape, customers & partners. Retrieved from: https://static1.squarespace.com/static/56c15de859827ef22c082045/t/5977c46220099e603532e532/1501021287959/Indigo+Validity+Datapoints+Competitors+Schools.pdf
Gutman, L. M., & Schoon, I. (2013). The impact of non-cognitive skills on outcomes for young people. *Education Empowerment Foundations, London*. Retrieved from: http://hdl.voced.edu.au/10707/287500
Kapur, M. (2008). Productive failure. *Cognition and instruction*, *26*(3), 379-424.
Kapur, M. (2010). Productive failure in mathematical problem solving. *Instructional Science*, *38*(6), 523-550.
Schmidt, R. A., & Bjork, R. A. (1992). New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training. *Psychological Science, 3*(4), 207–217.
Silva, E. (2009). Measuring skills for 21st-century learning. *Phi Delta Kappan*, *90*(9), 630-634.
Song, L., Singleton, E. S., Hill, J. R., & Koh, M. H. (2004). Improving online learning: Student perceptions of useful and challenging characteristics. *The internet and higher education*, *7*(1), 59-70.
Strickhouser, J.E., Zell,E., & Krizan, Z. (2017). Does personality predict health and well-being? A metasynthesis. *Health Psychology,* 36(8), 797-810.
Pistrui, D., Bonnstetter, R., Bonnstetter, B. J., & Fry, C. C. (2011). Creating, Educating and Assessing a New Class of Entrepreneurial Minded Engineers. *The Journal of Engineering Entrepreneurship*, *2*(2), 1-14.

TTI Success Insights. (2012). *TTI Technical Reports Compendium*. Retrieved from: https://static1.squarespace.com/static/56c15de859827ef22c082045/t/59789c569f74560e1d74da91/1501076569619/TTI+Technical+Report.pdf