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The Role of Grit in Predicting Student Performance in Introductory Programming Courses: An Exploratory Study

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ABSTRACT

This research examines the association between student grit and academic achievement in introductory computer programming courses. While several studies have established a link between grit and student success in classes with lower failure rates, this exploratory work is the first to investigate the relationship in courses with high failure rates. Our survey data show that grittier students earn higher grades in introductory programming courses than less gritty students, thus providing support for extending the student grit-performance relationship to high failure courses.

Keywords

Grit, programming, academic success, student performance.

INTRODUCTION

Grit, defined as trait-level perseverance and passion for long-term goals (Duckworth, Peterson, Matthews, & Kelly, 2007), has been found to be an important contributor of academic achievement (Duckworth et al., 2007; McCord, 2013; Powell, 2013). However, much of that stream of work was conducted in courses with low failure rates (Strayhorn, 2013). It is not clear whether these findings apply in high failure rate courses, such as introductory computer programming.

An empirical test of this relationship will be meaningful for IT education. Despite hundreds of studies and decades of "remedies," the failure rate for introductory computer programming courses remains alarmingly high (Bennedsen & Caspersen, 2007; Porter, Guzdial, McDowell, & Simon, 2013; Robins, Rountree, & Rountree, 2003) at 30% - 50% (Jenkins, 2002). Thus, an extension of the grit-student performance relationship to high failure-rate classes will provide IT educators with another tool to enhance student learning.

LITERATURE REVIEW

Grit

Duckworth et al. (2007) defines grit as a trait-level perseverance and passion for long-term goals. Several studies suggest that grit is an important contributor to academic success (Duckworth et al., 2007; McCord, 2013; Powell, 2013). For example, grit has been linked to success among Ivy League undergraduates, United States Military Academy, West Point, cadets (Duckworth et al., 2007), African American males attending predominantly white institutions (Strayhorn, 2013), as well as contestant rankings in the National Spelling Bee (Duckworth et al., 2011). While the link between intelligence and academic achievement has been firmly established (e.g., Laven, 1965), Duckworth et al. (2007) suggests that grit may be a better predictor of student success than talent or intelligence.

While previous student achievement studies are encouraging, there are limits to the existing research on grit. To date, most grit studies reviewed above have focused on high achievers (e.g., Military Academy cadets, Ivy League undergraduates and spelling bee champions). Even the few studies focused on public elementary students have examined students at high achieving magnet schools. With a few notable exceptions (e.g., Duckworth et al., 2011 and Strayhorn, 2013) grit studies have examined subjects in settings with low failure rates. It remains unclear whether the effects of grit apply in technical, high-failure rate situations.

Programming Courses

Programming is cognitively taxing and difficult to learn and teach. For example, Heaney and Daly (2004) suggest that computer science has the highest failure rate of all college majors. Programming courses are the entry point for computer-related careers. The high failure rate acts as a barrier to entry, causing discouraged students to switch majors (Benford & Gess-Newsome, 2006). As Heaney and Daly (2004) observe, these individual decisions affect the future of computing.

The problem is exacerbated by the intractable lack of diversity in the "computing pipeline" (Whitney, Gammal, Gee, Mahoney, & Simard, 2013). While America and its college campuses are increasingly diverse, computing has largely remained a white and male pursuit. Over the past two decades, the number of women and minority students pursuing computer-related majors has declined (Alvarado & Judson, 2014) as female and minority students account for an increasing percentage of college enrollment.

Programming Student Success Factors

The high failure rate in programming classes has been widely studied (Bennedsen & Caspersen, 2007; Porter et al., 2013; Robins et al., 2003). This line of research has uncovered several factors which influence novices' success in computing courses. Among the factors most commonly cited are standardized college entrance exam scores (McGill, Volet & Hobbs, 1997), previous computing experience (Volet & Styles, 1992), participation in high school programming courses (Taylor & Luegina, 1991) and science and mathematics background (Evans & Simkin, 1989).

Unfortunately, many of these factors are either nonmalleable (that is, fixed) or occur long before the student ever enters the college programming classroom (for example, prior experience with computers and participation in high school programming courses) (Bennedsen & Caspersen, 2007). Two factors which are associated with student success in computing courses that are also malleable (that is, changeable) are computer playfulness and computer self-efficacy.

Computer Playfulness

Webster and Martocchio (1992) defined computer playfulness as a user's tendency to interact spontaneously and creatively with computers. Computer playfulness is a system-specific trait that correlates with a user's familiarity with a particular system (Hackbarth, Grover & Yi, 2003) Hackbarth et al. (2003) notes that an individual's general level of playfulness may differ from their playfulness with computer technology. Computer playfulness is correlated with computer experience (Webster & Martocchio, 1992) and negatively correlated with computer anxiety (Hackbarth et al., 2003). Previous work has found that computer playfulness is positively correlated with academic success in computer programming courses (Potosky, 2002).

Computer Self-Efficacy

Computer self-efficacy (CSE) is a judgment of one's capabilities to use a computer in diverse situations (Compeau & Higgins, 1995). Venkatesh and Davis (1996) found that those with high CSE have greater comfort with, and are more likely to have positive perceptions of, computers. Additionally, extant research has found that CSE is affected by gender (i.e., males have higher CSE compared to females) (e.g., Compeau & Higgins, 1995) and age (i.e., younger subjects have higher CSE) (e.g., Burkhardt & Brass, 1990). Previous research has found a positive correlation between computer self-efficacy beliefs and student success in computer programming courses (Kanaparan, Cullen, & Mason, 2013).

In sum, existing research has not investigated grit as a predictor of student programming performance. This study aimed to fill the gap in the literature and examine these two research questions:

1. Does grit predict student performance in high-failure rate courses as it does in low-failure rate ones?
2. If so, is grit a more powerful predictor of student performance than talent or intelligence as Duckworth et al. (2007) argued?

METHOD

Participants

To examine the association between grit and academic achievement, we conducted a survey of undergraduate students at a large public university in the Midwest. Participants were 64 students who had recently completed one of the two college-level introductory programming courses at the same university. The average age of respondents was 27.24 years (SD = 9.19). Forty-seven students provided gender information. Of these, 34 (72.4%) were male, and 13 (27.6%) were female. Forty-seven students provided ethnicity information. Of these, 2 (4%) self-identified as Black or African American, 2 (4%) as Hispanic or Latino, 5 (10.6%) as Asian and 37 (78.7%) as white. One respondent self-identified as "mixed ethnicity."

Procedures

Participants were solicited via email and asked to complete an online questionnaire. Participants were not compensated. Prior to administering the questionnaire, we obtained the required institutional review board (IRB) approval.

Measures

Grit was captured using the Grit-S scale (Duckworth & Quinn, 2009). In addition to grit, the questionnaire also captured demographic information, self-reported academic achievement (e.g., grade from the programming course, ACT score as a measure of intelligence, high-school GPA), and several other factors (e.g., computer self-efficacy and computer playfulness) associated with success in introductory programming courses. All measurement scales were extracted from the existing literature.

Construct	Items	Cronbach's Alpha
Grit	12	0.7760
Computer Playfulness (Play)	4	0.7384
Computer Self-Efficacy (CompSE)	6	0.8899

Table 1. Reliability Analysis for the Measured Constructs

The grit scale consisted of 12 items (α = *.78*), the computer self-efficacy scale of 6 items (α = *.89*), and the computer playfulness scale consisted of 4 items (α = *.74*). A Cronbach's alpha exceeding .70 suggests that the internal reliability is sufficient (Nunnally, 1967).

Variable	N	Mean	p50	Min	Max	Sd
HSgpa	40	3.528	3.550	2.000	4.700	0.545
ACT	39	25.744	26.000	13.000	32.000	4.290
Grit	64	3.456	3.542	2.000	4.500	0.514
Grade	39	3.256	4.000	0.000	4.000	1.044
Play	47	4.048	4.000	2.750	5.000	0.642
CompSE	47	4.525	4.500	2.333	5.000	0.646

Table 2. Summary Data

RESULTS

Variables	Grit	HSgpa	ACT	Play	CompSE	Grade
Grit	1.000					
HSgpa	0.032	1.000				
	(0.858)					
ACT	-0.266	0.349	1.000			
	(0.135)	(0.047)				
Play	-0.414	0.116	0.042	1.000		
	(0.017)	(0.521)	(0.816)			
CompSE	-0.339	-0.036	0.371	0.601	1.000	
	(0.054)	(0.843)	(0.034)	(0.000)		
Grade	0.423	0.352	0.255	-0.048	0.008	1.000
	(0.014)	(0.045)	(0.153)	(0.789)	(0.963)	

Table 3. Cross-Correlation Table

Ordinal Logistic Regression Analysis

Following Duckworth et al. (2007), we used ordinal logistic regression models to test the effect of predictors on student achievement.

$$(1)\quad Pr(Grade = m \mid x_i) = F(\tau_m - x\beta) - F(\tau_{m-1} - x\beta)$$

where

$$x\beta = \beta_{grit}\, Grit + \beta_{hsgpa}\, HSgpa + \beta_{act}\, ACT$$

	(1) Grade	(2) Grade	(3) Grade	(4) Grade
Grit	1.405*	1.706*	1.727*	2.332**
	(2.34)	(2.48)	(2.55)	(3.04)
cut1	0.866	7.128	5.610	11.23*
	(0.41)	(1.85)	(1.66)	(2.54)
cut2	2.047	8.385*	6.903*	12.53**
	(1.04)	(2.19)	(2.04)	(2.85)
cut3	3.282	9.766*	8.125*	13.87**
	(1.66)	(2.49)	(2.34)	(3.06)
cut4	4.532*	11.10**	9.532**	15.52**
	(2.21)	(2.74)	(2.65)	(3.28)
ACT		0.213*		0.256*
		(2.21)		(2.20)
HSgpa			1.122	0.370
			(1.56)	(0.45)
Observations	39	34	34	33

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Ordinal Logistical Regression Table

As Table 4 (Model 4) shows, both grit (*OR = 10.300, β = 2.332, p = .002) and ACT (OR = 1.291, β = 0.256, p = .028*) have a positive and significant relationship with course grade. However, grit explains considerably more variance in course grade than the ACT score. Data also shows that high-school GPA (HSgpa) did not significantly predict grade (*OR = 1.448, β = 0.370, p = .650*).

DISCUSSION

Grit and Student Achievement

Our data suggest that there is a positive association between grit and student success in introductory programming courses (*β = 2.332, p = .002*). That is, grittier students earn higher grades. This result provides an affirmative answer to the first research question -- grit does predict student performance in high failure-rate courses as it does in low-failure rate ones.

The results on the influence of ACT were mixed. Though the correlation matrix shows an insignificant link between ACT and grades in introductory programming courses, the relationship is statistically significant in the regression analysis (*β = 0.256, p = .028)*. However, ACT score, as a proxy of student intelligence, has much less influence on course grade than grit. Thus, the answer to our second research question is also affirmative – grit is a more powerful predictor of course grade than student intelligence.

There are a few other observations of the regression results. The impact of high school GPA on course grade was mixed – a significant relationship in the correlation matrix, but a nonsignificant one in the regression.

In addition, the results suggest that computer playfulness (Play) has a significant positive relationship with computer self-efficacy (CompSE), but a negative one with grit. However, different from Potosky (2002), neither playfulness nor self-efficacy was related to student grades in introductory programming courses.

Finally, consistent with Duckworth et al. (2007), there is a negative but insignificant correlation between ACT and grit. However, the ordered logistical regression analysis suggests that both of them are positively and significantly associated with student success in introductory programming courses. These results suggest that more work is needed to learn of the nature of the association between grit and other factors known to contribute to student success in introductory programming courses.

Implications for Pedagogy

This work is inspired by Goodwin and Califf (2007) and Cutts et al. (2010) and part of a larger research effort whose aim is to uncover tangible actions that programming instructors can implement to improve student success. Goodwin and Califf (2007) found that time management training improved student performance in introductory computer programming courses. Cutts et al. (2010) found that outside interventions could change students' learning mindsets in computer programming courses.

While this work suggests that grittier students earn higher grades in introductory programming courses, important questions remain. For example, can grit be taught? If so, what is the best way to help students improve their grit? Moreover, should grit instruction take place in introductory programming courses, or via outside interventions?

While over-all grit has been defined as a trait, extant literature suggests that context-specific grit may be teachable (Hoerr, 2013; Packer, 2007; Yeager & Dweck, 2012). So, if instructors cannot make their students grittier in all situations, they may be able to strengthen students' context-specific grit through classroom interventions. Equipped with the finding that higher grit leads to improved performance in not only low-failure rate, but also high-failure rate courses, we may wish to implement grit training for all IT students, if not all students campus-wide.

CONCLUSION

While previous work has already established a link between grit and student success in classes with low failure rates (Duckworth et al., 2007; McCord, 2013; Powell, 2013), this exploratory work is the first to investigate the association in courses with high failure rates.

Our findings suggest that grit has a significant influence on student achievement in diverse settings, and that its impacts are stronger than intelligence. However, more work is needed to determine the association between grit and other factors known to contribute to student success in introductory programming courses.

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