Research Article

Hammill Institute on Disabilities

Journal of Disability Policy Studies
1–11

DOI: 10.1177/1044207319863635
jdps.sagepub.com
SAGE

Measuring Grit in Adolescents With and Without Disabilities

Allison R. Lombardi, PhD[1], Graham G. Rifenbark, PhD[1,2], Jennifer Freeman, PhD[1], and Michael W. Harvey, PhD[3]

Abstract

In recent policy initiatives focused on college and career readiness, Grit is often lumped with other noncognitive skills deemed as important. Yet, very little is known about the relationship between Grit and disability among adolescents. In this study, we examine measurement invariance of the Grit scale in a sample of adolescents with and without disabilities (n = 5,039). Findings show the scale functions similarly for students with and without disabilities, and the Perseverance factor of Grit significantly predicted grade point average for both groups. Implications for practice suggest use of the scale in school-wide data collection efforts that might be driven by college and career readiness policy initiatives that emphasize measuring noncognitive skills in *all* students, and an age-appropriate transition assessment in secondary special education.

Keywords

invariance, Grit, college and career readiness, multitiered systems of support, high school, age-appropriate transition assessment

Defined as the combination of Perseverance and passion for long-term goals (Duckworth, Peterson, Matthews, & Kelly, 2007), the construct of "Grit" has garnered much attention over the past decade. By "long-term," Duckworth and colleagues (2007) clarified that Grit entails perhaps years of sustained efforts toward particular goals regardless of setbacks or failures. Grit has gained substantial traction over more recent years not only in the social and positive psychology literature base but also in mainstream literature (e.g., Tough, 2012) and in evolving conceptual models of college and career readiness for adolescents (e.g., Farrington et al., 2012). Tough (2012) suggested Grit might be the character trait that makes all the difference in academic achievement and lifelong success in school children and adolescents, and the United States Department of Education endorses instruments and interventions that promote Grit, tenacity, and Perseverance and recommend educators adopt and integrate them into practice (Shechtman, DeBarger, Dornsife, Rosier, & Yarnall, 2013). Potentially, there will be policy implications that involve measuring Grit as a noncognitive trait in adolescents.

To learn more about teaching Grit to adolescents, including integrating the construct into various curricula and instruction, it is critical to measure the trait in schools. Fortunately, validated measures exist that are free, easy-to-access, quick to administer (online or paper-based), and could be integrated in K–12 environments. However, to date, much of the psychometric work on measures of Grit is based on adult samples (Duckworth et al., 2007; Duckworth & Quinn, 2009). As such, there is a critical need to better understand the Grit trait in adolescents specifically. The purpose of this study was to examine the structural validity of the Grit scale and compare the psychological trait in adolescents with and without disabilities to inform policy and practice specific to college and career readiness and noncognitive skills, as specified in the Every Student Succeeds Act (ESSA) of 2015, as well as age-appropriate transition assessment as specified in the Individuals With Disabilities Education Improvement Act (2004).

The Urgency of Noncognitive Skills

Researchers often lump Grit with self-control, growth mind-set, and conscientiousness, all of which are referred to as "noncognitive skills" (West et al., 2015). Noncognitive skills are not as established as their counterpart, "cognitive skills," which include intelligence and achievement; rather, typical traits that are measured in educational contexts.

[1]University of Connecticut, Storrs, USA
[2]University of Kansas, Lawrence, USA
[3]The Pennsylvania State University, University Park, USA

Corresponding Author:
Allison R. Lombardi, Associate Professor, Department of Educational Psychology, University of Connecticut, 249 Glenbrook Rd., unit 3064, Storrs, CT 06269, USA.
Email: allison.lombardi@uconn.edu

Noncognitive, therefore, is an umbrella term for skills that are independent of intelligence and achievement and not typically or systematically measured but somehow agreeably important for student outcomes. Grit entails two of these noncognitive skills: Perseverance and Consistency of Interests toward long-term goals (Duckworth el al., 2007).

Policy initiatives over the past two decades have resulted in the advent of conceptual school-wide models of college and career readiness (CCR) that include multiple noncognitive skills (e.g., Farrington et al., 2012), some of which are specific to students with disabilities (Morningstar, Lombardi, Fowler, & Test, 2017). These policy initiatives created a sense of urgency around teaching and embedding these skills in content-area courses. For example, ESSA emphasizes CCR by mandating that states develop challenging academic standards as well as identify indicators of students' success that support a well-rounded education. Through ESSA, states are provided with provisions to support CCR and have broad flexibility in development of their educational systems (Tomasello & Brand, 2018), and as such, states may decide to measure noncognitive skills, including Grit, as an indicator of student success within an ESSA state plan.

Furthermore, Grit is an important character trait identified in education, business, and industry (Duckworth & Gross, 2014; Duckworth, Quinn, & Seligman, 2009; Polirstok, 2017; Shih & Margoongroge, 2017). Specifically, prior research findings show a positive relationship between Grit and job performance (Ion, Mindu, & Gorbanescu, 2017) and innovation (Mooradian, Matzler, Uzelac, & Bauer, 2016). These findings support the inclusion of Grit within school-wide CCR efforts and secondary special education and transition, and related policy initiatives that affect youth with disabilities and workforce development.

With regard to disability, very little is known about the functionality of noncognitive measures. Because noncognitive skills are not systematically measured in school contexts, these measures are mostly in the preliminary stages of development (West et al., 2015). There is a need for psychometrically rigorous measures of these skills, so that generated scores can be used to make support decisions about students. As such, it is increasingly critical to examine invariance in noncognitive skill measures, as more recently educators have prioritized the need to emphasize these skills alongside academic achievement (West et al., 2015), and prior evidence shows that noncognitive skills can account for variance beyond achievement measures (Chang, 2014; Duckworth et al., 2007; Strayhorn, 2014).

More recently, Lombardi, Freeman, and Rifenbark (2018) tested a CCR measurement model that included noncognitive skills. In this study, the Grit scale was used alongside several other measures of noncognitive skills, such as academic engagement, learning processes, critical thinking, interpersonal engagement, and transition knowledge. The results of this particular study showed that items from the Perseverance factor of the Grit scale loaded onto one general factor of CCR, empirically demonstrating an overlap between Perseverance and the other noncognitive skills that were measured. Notably, the authors of this study proposed a two-factor measurement model, which entailed general CCR and transition knowledge, and determined it functioned similarly for adolescents with and without disabilities. These findings support the notion that CCR can and should be defined in the same way for both groups and that many of the noncognitive skills associated with CCR are not distinct enough to be separate constructs.

In sum, Grit is one example of a noncognitive skill that has been proposed by various researchers as important to measure in schools (Shechtman et al., 2013) to promote CCR (Farrington et al., 2012; Lombardi et al., 2018; Morningstar et al., 2017) and inform relevant policy and practice. Yet, despite its rise in more mainstream contexts (e.g., Tough, 2012), very little is known about Grit in adolescents, particularly between those with and without disabilities. It is critical we further examine how to measure Grit in school contexts, so that we better inform policy initiatives around CCR and age-appropriate transition assessment in secondary special education.

Measuring Grit

There are two options of the Grit scale available: a 12-item and 8-item version, both of which have reported psychometric properties and evidence of construct validity (Duckworth et al., 2007; Duckworth & Quinn, 2009). Both are widely used in the literature, despite some mixed findings on psychometric rigor. For example, mixed results show some concern for using the total scale score, or "grittiness," as opposed to disentangling the two lower-order factors, Perseverance and Consistency of Interests (Credé, Tynan, & Harms, 2017). Overall, across multiple studies in which the Grit scale was used, evidence shows strong predictive validity for Perseverance (Anestis & Shelby, 2015; Chang, 2014; Meriac, Slifka, & LaBat, 2015), yet more questionable evidence for Consistency of Interests, including lack of predictive validity, inadequate reliability (Arslan, Akin, & Çîtemel, 2013; Meriac et al., 2015), and weak correlations between the two constructs (Datu, Valdez, & King, 2016; Meriac et al., 2015). Thus, although both versions of the scale are widely used across children, adolescents, and adults, there are some persisting issues with psychometric properties: (a) the appropriateness of using an overall Grit score, as opposed to using Perseverance and Consistency of Interests as separate scores, and (b) the ongoing psychometric issues with Consistency of Interests, namely, lack of predictive validity and inadequate reliability estimates. Importantly, these salient issues are not specific to the functionality of the scale on the basis of disability.

Importantly, not only has construct validity of Grit been established, but the construct has been found to predict college student achievement as measured by grade point average (GPA; Chang, 2014; Duckworth et al., 2007; Strayhorn, 2014). Yet, less is known about the predictive validity of the scale on high school student achievement. These findings suggest that Grit is a distinct, potentially malleable, construct that could be explicitly taught to enhance achievement. However, in a meta-analytic study, Credé and colleagues (2017) found Perseverance factor to be a stronger predictor of performance than Consistency of Interests and recommended Perseverance only be used rather than a combined Grit score in future research. As such, it is important to clarify the use of an overall Grit score, as there are mixed findings with regard to predictive validity; some studies show overall Grit is predictive of achievement, and others show only the Perseverance score should be used.

Ultimately, the potential for identifying a supplemental area beyond achievement on which to focus is intriguing in the context of special education and policy. In other words, if teaching noncognitive skills such as Grit can help promote CCR among students with and without disabilities, then prioritization of Grit within secondary special education curriculum and instruction should occur. First and foremost, these efforts begin with a close examination of available measures. In the current study, measurement invariance of the Grit scale was examined using a sample of adolescents with and without disabilities in Grades 9–12. A secondary objective was to examine whether the relationship between Grit and GPA differed across these groups, as GPA is a typical academic indicator of CCR (American Institutes for Research, 2014; Welch, Abulhab, & Therriault, 2017).

Method

Participants

Participants were adolescents in Grades 9–12 at 13 high schools in a Midwestern state. Students with (n = 784) and without (n = 4,253) disabilities were included in the sample. "Disability" was defined as those students who have an Individualized Education Program (IEP) and receive special education services. Of the students with disabilities, the majority of them fell into either the learning disability (44%) and other health impairment (36%) categories. Compared with the national average (National Center for Education Statistics, 2014), this sample included a high percentage of African American students overall (41% in sample, 15.7% nationally) and within special education (49% in sample, 15.3% nationally). Table 1 shows detailed sample characteristics.

Table 1. Sample Characteristics.

Group	SPED	Non-SPED	Overall
n	784	4,253	5,039
Gender			
Male	67%	49%	51%
Female	33%	51%	49%
Ethnicity			
Caucasian	25%	28%	27%
African American	49%	40%	41%
Hispanic/Latino	22%	25%	24%
Asian	2%	6%	5%
Other	1%	2%	2%
Grade			
9th	40%	35%	35%
10th	26%	27%	27%
11th	23%	23%	23%
12th	10%	15%	15%
Free/reduced-price lunch			
Yes	69%	60%	61%
No	31%	40%	39%
Disability			
Learning disability	44%	—	—
Other health impairment	36%	—	—
Emotional disturbance	6%	—	—
Autism spectrum disorder	5%	—	—
Intellectual disability	5%	—	—
Other	4%	—	—

Note. Overall *n* contains two more observations due to omission of SPED status. SPED = special education.

Procedures

Participating schools were recruited as a part of a larger study examining CCR in high schools that were implementing Positive Behavioral Interventions and Supports (PBIS). Specifically, to recruit schools, the researchers distributed fliers via email and in-person at PBIS-related conferences (e.g., Northeast PBIS leadership forum, National PBIS leadership forum) and through existing technical assistance relationships to high school administrators and PBIS coaches. Interested administrators followed up with the researchers to volunteer for the study and signed a data access agreement to release specified school data. Participating schools were provided with a parental notification letter and were asked to send it home at least 1 week prior to the planned administration. The notification letter provided parents with a web link to view the surveys online and the offer to view paper-based versions of the survey, which were made available in the front office of participating schools. Parents were given the opportunity to opt their student out of participation by signing and returning the notification letter. In addition, students were given the opportunity to opt out during the assent process on the day of administration. Students who chose not to participate or whose parents opted them out were allowed to work on other classroom activities during the time of administration. All study protocols were approved by the institutional review board for the protection of human subjects.

Students took a compilation of surveys including the Grit scale using the online survey program Qualtrics and on school-based computers. An administration window for data collection was determined between the researchers and school partners that spanned over a 3-week period. Schools determined time of day and class period(s) in which to administer the survey, and they were asked to administer school wide (e.g., all students take the survey). Schools were provided with a web link that was unique to their school to distribute on school computers on the administration dates. A script was provided to teachers to introduce the study and inform students of their right to choose not to participate. Students gave assent to participate by answering *yes* to Question 1: "I would like to take these surveys." During administration, students were instructed to ask for help if they had any questions or wished to have one or more items read aloud by an adult. Upon this request, we instructed staff members to read aloud the specified item, then step away from the computer and allow the student to respond independently. School personnel were told to provide accommodations (e.g., extra time, translated materials) for any students and/or families for which these accommodations are routinely provided. All items were optional and students were able to discontinue the survey at any point without penalty. During the survey administration window, research team members monitored the number of responses and coordinated follow-up survey administrations with school contacts if needed (e.g., the numbers of respondents was considerably low after the first 2 weeks). Students were asked to enter their school-issued identification numbers at the beginning of the survey. After survey administration, student responses were matched with extant school data using the identification numbers. The mean response rate across the 13 schools was 50% (SD = 18%), with a minimum rate of 9% and a maximum of 75%.

Measures

Grit scale, 12-item version. Responses on the original 12-item Grit scale (Duckworth et al., 2007) were collected from all participants. Item responses range from 1 (*Not at all like me*) to 5 (*Very much like me*) representing a 5-point Likert-type scale. Item stems for Perseverance were commensurate with its construct (e.g., *Setbacks don't discourage me*), whereas, item stems for Consistency of Interests were negatively worded (e.g., *My interests change from year to year*). As such, all negatively worded items were reverse scored (Duckworth et al., 2007) to calculate a composite score, where higher scores indicate "more Grit." Duckworth and colleagues (2007) reported internal consistency estimates for the composite across six studies, these estimates ranged from 0.77 (Study 4: 2008 West Point Cadets) to 0.85 (Study 1 and 2: Adults aged 25 years or more). In the current sample, internal consistency was estimated to be 0.824 for Consistency of Interests and 0.829 for Perseverance.

Demographic characteristics. School extant data records were used to gather student grade level, gender, race, free and reduced lunch status, and disability status.

Cumulative GPA. Cumulative GPA was gathered from student records and was recorded on a scale ranging from 0.0 = "F" to 4.0 = "A." For the current sample, the distribution of GPA scores was found to be anchored at just above a "C" average and was slightly platykurtic with a small negative skew (M = 2.21, SD = 0.92); therefore, the distribution of cumulative GPA scores flatten as scores approach 4.0.

Data Analysis

Like all noncognitive measures (e.g., personality traits), it is assumed that the Grit scale items are measured with error; therefore, it is necessary to model these data using confirmatory factor analysis (CFA; Brown, 2015). To identify the CFA models, the marker variable method of identification was utilized to aid in the assessment of invariance across the latent parameters (Brown, 2015) to set the scale and ensure the resulting parameter estimates are unique solutions. In this approach, the loading of the first indicator per construct is fixed to 1.0, and in the event, the mean structure is included, its respective intercept is fixed to 0.0.

Model fit. The adequacy of a CFA model is determined by the hypothesized factor structure's ability to replicate the observed covariance matrix via tracing rules, adhering to an expected versus observed test of model fit that is χ^2 distributed. Therefore, fit will be determined using fit indices from two separate perspectives: (a) incremental, interpreted as the increase in model fit conditioning on the worst fitting model and (b) absolute, which views model fit as a departure from the best model possible or saturated model. Specifically, the Tucker–Lewis index (TLI; Tucker & Lewis, 1973) and Comparative Fit Index (CFI; Bentler, 1990) were used to assess model fit from the incremental perspective. Both of these values should be 0.90 or higher to represent acceptable fit (Hu & Bentler, 1999). Regarding fit from the absolute perspective, the root mean square error of approximation (RMSEA; Steiger & Lind, 1980) and the standardized root mean square residual (SRMR) were examined. Values should be 0.08 or less to indicate acceptable fit (Hu & Bentler, 1999).

Invariance. A lack of measurement invariance is characterized as an instance where an instrument is found to function differently across groups of people. Using a *multiple group confirmatory factor analysis* (MG-CFA; Jöreskog, 1971; Sörbom, 1974) approach, unique parameter estimates for each group result; therefore, it is possible to constrain sets of parameters in a sequential manner to be the same across groups, while assessing the effect such constraints have on global model fit. In succession, form—no constraints,

metric—loadings are constrained, and scalar—intercepts are constrained—will be investigated. These constraints will be deemed tenable if the decrease in CFI (ΔCFI) is no more than 0.01 (Cheung & Rensvold, 2002).

If metric invariance passes (e.g., the variance structure holds across groups), then latent variances and covariances can be compared. If scalar invariance is met (e.g., the mean structure holds across groups), then latent means can be compared (Millsap, 2012). With regard to examining invariance in latent parameters, we relied on χ^2 difference tests, in which the significance of the change in χ^2 is tested relative to the change in degrees of freedom. When the null hypothesis is rejected ($p < .05$), the parameter under investigation cannot be constrained to be the same across groups and therefore is not invariant.

Missing data. Modern treatments available to remedy missingness are *multiple imputation* and *full information maximum likelihood* (FIML). FIML is a model-based approach, in which the relationship between manifest and latent variables are used to inform the estimation of model parameters and their standard errors in a single step. Both approaches produce unbiased results when missingness results from either a *missing completely at random* (MCAR) or *missing at random* (MAR) process (Enders, 2010); therefore, FIML was utilized as it was assumed that missingness did not stem from an unmeasured phenomenon (e.g., *missing not at random)*.

All analyses were executed within the R environment (R Core Team, 2016) using the *cfa* function from the *lavaan* package (Rosseel, 2012). For all model estimation, the *missing* argument was set to "fiml" and the *meanstucture* argument was set to "TRUE," allowing FIML estimation to be employed. Prior to data analysis, histograms were consulted to determine whether or not responses were symmetrical or asymmetrical. As Likert-type scales are ordinal in nature (Rhemtulla, Brosseau-Liard, & Savalei, 2012), this step allowed us to make an informed decision with respect to estimation method.

GPA on Grit. To determine the relationship of Grit and achievement, GPA was entered into the model as a manifest variable and was regressed onto the exogenous latent variable representing Grit. To establish whether this predictive relationship was the same for students with and without disabilities, we constrained this parameter to be the same across groups and tested whether this was tenable via a χ^2 difference test.

Results

Upon consulting histograms and estimating the skew and kurtosis of the items, it was evident that there were no severe departures from normality. Specifically, skew estimates ranged from −0.52 to 0.14, and kurtosis estimates ranged from −0.99 to −0.53; therefore, all CFA models were estimated using *robust maximum likelihood* (MLR) to account for the slight asymmetry found in the items. With respect to missing data, approximately 22% of the sample responses were missing, however, by utilizing FIML estimation, these responses were estimated along with the estimation of model parameters. Due to the various samples utilized in this study, the correlations, standard deviations, and means for the overall sample and by disability status are available upon request from the first author.

Confirmatory Factor Analysis

Overall. The measurement model conditioning on the total sample ($n = 4{,}063$) was found to have acceptable fit to the data. With regard to incremental fit indices, CFI and TLI were 0.922 and 0.902, respectively, whereas the absolute fit indices approached close model fit, specifically, RMSEA was 0.064 (90% confidence interval [CI] = [0.061, 0.067]) and the SRMR was estimated as 0.056. All structural parameter estimates were statistically significant and different from 0. With respect to Consistency of Interests, Item 7 (*I often set a goal but later choose to pursue a different one*) was the most discriminating between those who have high and low levels of Consistency of Interests (estimate = 1.527, $SE = 0.053$, $Z = 28.932$). In terms of Perseverance, Item 10 (*I have achieved a goal that took years of work*) was most indicative of the trait (estimate = 1.243, $SE = 0.037$, $Z = 33.809$). Variability within each construct was significantly different from 0, where the Consistency of Interests estimate was 0.353 ($SE = 0.022$, $Z = 15.831$) and Perseverance was 0.461 ($SE = 0.023$, $Z = 19.895$). The latent covariance was negative (estimate = −0.123, $SE = 0.012$, $Z = -10.455$), which translates to a latent correlation of −0.304.

CFA by group. Prior to assessing measurement invariance, models were estimated separately for each group to determine model fit for students with and without disabilities because global fit indices are not available for each population when an MG-CFA is estimated. A total of 582 and 3,480 responses were available from the disability and nondisability groups, respectively, for these preliminary CFA models. No problematic fit indices resulted and a sufficient number of responses were available for a series of MG-CFA analyses.

Invariance. The first model tests whether or not form invariance is tenable. If tenable, this becomes the baseline model for the following models. This model had acceptable fit to the data, specifically the CFI and TLI were 0.921 and 0.901, respectively, whereas the RMSEA was 0.064 (90% CI = [0.060, 0.067]) and the SRMR was 0.057. Thus, we established form invariance (i.e., the factor structure is the same across groups). Through the progression of models,

simultaneous constraints on the loadings and intercepts were tenable, and therefore established metric and scalar invariance. Table 2 shows all structural parameter estimates from the scalar invariant model. The next step was to assess how the latent means and variances/covariance differed across groups using the scalar invariant model as the comparison model. Table 3 shows all relevant information regarding invariance of both measurement and latent parameters.

Test of Latent Parameters

We tested the latent parameters in order to examine group differences between students with and without disabilities on Perseverance and Consistency of Interests. Because the MLR estimator was used, it was necessary to carry out appropriate χ^2 difference tests. A user defined R function was written and utilized to automatically carry out the appropriate test (Satorra & Bentler, 2001). This required the input of the scaling factor resulting from both the baseline and comparison models.

Latent variances. The first set of parameters to be constrained across groups were the variances and the covariance. This omnibus test for variances was not found to be tenable ($\Delta\chi^2_{df=3} = 50.128, p < .001$). Due to this, the constraint on the latent covariance between Perseverance and Consistency of Interests was lifted, allowing this parameter to freely vary across groups; this constraint was found to be tenable ($\Delta\chi^2_{df=2} = 0.729$, $p = .694$). Therefore, groups differed on the covariance between Perseverance and Consistency of Interests. These freely estimated covariances translate to latent correlations of ($r = -0.640$) for those with disabilities and ($r = -0.257$) for those without disabilities.

Latent means. The final set of latent parameters were constrained to be the same across groups; therefore, two latent means were estimated, rather than four. This constraint was not tenable ($\Delta\chi^2_{df=2} = 54.371, p < .001$). The latent means were further decomposed, where the equality constraint was placed only on Consistency of Interests and was not tenable ($\Delta\chi^2_{df=1} = 35.165, p < .001$). Next, a similar model was estimated that relaxed the constraint on the latent means for Consistency of Interests and was placed on the Perseverance construct instead. In doing so, it was found that this constraint was not tenable ($\Delta\chi^2_{df=1} = 6.378, p = .012$). Therefore, groups differed on the latent mean for Perseverance and Consistency of Interests.

Final model. The most parsimonious model without degrading model fit constrained the latent variance for Consistency of Interest ($\Psi = 0.349$) and Perseverance ($\Psi = 0.465$) to be the same across groups, while allowing their covariance to be freely estimated across nondisability (–0.104) and disability (–0.258) groups. In terms of the latent means, it was found that neither the Consistency of Interests ($\alpha_{nondisability} = 2.971$, $\alpha_{disability} = 2.813$) nor Perseverance ($\alpha_{nondisability} = 3.445$, $\alpha_{disability} = 3.358$) estimates could be constrained across groups. Importantly, this final model shows group differences on the covariance between Perseverance and Consistency of Interests, and the latent means of these constructs. To better understand the magnitude of these group differences, we calculated latent effect sizes (*d*; Hancock, 2001) using the following formula:

$$Latent\ d = \frac{\alpha_{disability} - \alpha_{nondisability}}{\left(\frac{n_{disability}\Psi_{disability} + n_{nondisability}\Psi_{nondisability}}{n_{disability} + n_{nondisability}} \right)}$$

Where, α represents group latent means; Ψ represents the respective latent variance; and n refers to the group sample size. Hancock (2001) suggested that a latent *d* falling between 0.1 and 0.4, refers to a small effect; between 0.3 and 0.5 refers to a medium effect; and latent *d* greater than 0.5 representative of a large effect. Small effects were found for the difference in latent means between those with and without disabilities for Perseverance ($d = -0.128$, $SE_{pooled} = 0.682$) and Consistency of Interests ($d = -0.267$, $SE_{pooled} = 0.591$).

Regression of GPA on Perseverance

A secondary study objective was to examine the relationship of Grit and cumulative GPA for students with and without disabilities. In this analysis, cumulative GPA was regressed on Perseverance. Due to our findings on Consistency of Interests, we determined it was not advisable to utilize the composite Grit score (e.g., combined Perseverance and Consistency of Interests scores). As such, we used the Perseverance score only and clarified whether or not the strength of this relationship differed by disability status. Therefore, we used the multiple group approach to determine whether this pathway could be constrained across groups. Prior to entering cumulative GPA into the model, we assessed structural invariance conditioning on Perseverance. The overall change in CFI from the form to scalar invariant model was 0.009; this latter model had exceptional fit to the data. The CFI and TLI were 0.971 and 0.969, respectively. The resulting RMSEA was 0.05 (90% CI = [0.044, 0.057]) and the SRMR was 0.025. Using this scalar invariant model, we included a structural pathway from Perseverance to cumulative GPA and allowed it to be freely estimated across groups to serve as the baseline model. Afterwards, the structural path was constrained to be the same across groups, resulting in a Δdf of 1. This constraint was tenable ($\Delta\chi^2_{df=1} = 3.622$, $p = .057$), and thus sufficed for both groups ($\beta = 0.195$, $SE = 0.026$, $Z = 7.636$).

Table 2. Scalar Invariant Model Parameter Estimates.

Construct/Item Stem	λ	*SE*	ν	*SE*
Consistency of Interests[a]				
New ideas and projects sometimes distract me from previous ones.	1.000	—	0.000	—
My interests change from year to year.	1.363	0.047	–0.875	0.139
I have been obsessed with a certain idea or project for a short time but later lost interest.	1.349	0.043	–0.848	0.13
I often set a goal but later choose to pursue a different one.	1.529	0.053	–1.335	0.157
I have difficulty maintaining my focus on projects that take more than a few months to complete.	1.344	0.042	–0.902	0.123
I become interested in new pursuits every few months.	1.227	0.047	–0.527	0.138
Perseverance				
I have overcome setbacks to conquer an important challenge.	1.000	—	0.000	—
Setbacks don't discourage me.	0.995	0.031	–0.358	0.105
I am a hard worker.	1.110	0.032	0.052	0.114
I finish whatever I begin.	1.218	0.037	–0.826	0.127
I have achieved a goal that took years of work.	1.234	0.036	–0.995	0.126
I am diligent.	1.064	0.031	–0.333	0.106

Note. λ = factor loading; ν = indicator intercept.
[a]Items reverse scored.

Table 3. Invariance Testing Across Group.

Step	Model	χ^2	*df*	$\Delta\chi^2$	Δ*df*	*p*	RMSEA	CFI	TLI	Tenable?
	Measurement invariance									
0.0	Independence (null)	11,066.61	132	—	—	—				
1.0	Form invariance	974.42	106	—	—	—	0.064	0.921	0.901	Yes
2.0	Metric invariance	1,009.40	116	—	—	—	0.062	0.918	0.907	Yes
3.0	Scalar invariance	1,079.72	126	—	—	—	0.061	0.913	0.909	Yes
	Invariance of latent parameters									
	Variances									
4.0	Omnibus	1,132.24	129	50.13	3	<0.01	0.062	0.908	0.906	No
4.1	Covariance freed[a]	1,085.30	128	0.73	2	0.694	0.061	0.912	0.910	Yes
	Means									
5.0	Omnibus	1,130.33	128	54.37	2	<0.01	0.062	0.908	0.905	No
5.1.1	Consistency of interests	1,105.75	127	35.17	1	<0.01	0.062	0.910	0.907	No
5.1.2	Perseverance	1,086.53	127	6.38	1	0.012	0.061	0.912	0.909	No

Note. $\Delta\chi^2$ reflects the change in χ^2 conditioning on the resulting scaling factor from baseline and alternative models. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker–Lewis Index.
[a]Final model.

Discussion

In this study, Grit was examined on the basis of disability status (yes/no) using a sample of adolescents from 13 high schools in suburban and urban settings. Latent parameters could be appropriately compared across groups due to passing metric and scalar invariance; in other words, the scale functions similarly for adolescents with and without disabilities (see Table 3). This finding is promising and important for educational researchers and practitioners who have already identified Grit as one of several important noncognitive skills related to CCR (e.g., Farrington et al., 2012; Lombardi et al., 2018; Morningstar et al., 2017) as well as recent policy that promotes the use of a wide range of measures to capture a full picture of student readiness for college and careers (ESSA, 2015). The broad implications of this finding support use of the scale in school-wide data collection efforts that might be driven by CCR and/or other policy initiatives that emphasize measuring noncognitive skills, as well as secondary special educators use of the scale as an age-appropriate transition assessment (Individuals With Disabilities Education Act [IDEA], 2004).

Beyond evidence of measurement invariance, the current study findings add several important clarifications to the literature base on Grit, some of which are contrary to previous research. The findings directly address the two salient points identified in the literature review, which are (a) the use of an overall Grit score, as opposed to using two separate scores for Perseverance and Consistency of Interests and (b) lack of psychometric rigor in Consistency of Interests, including a lack of predictive validity. In addition, the findings extend the literature base on the Grit scale with regard to the relationship between the two second order constructs, Perseverance and Consistency of Interests, and how this relationship differs for adolescents with and without disabilities.

In previous studies, an overall Grit score is used (Duckworth et al., 2007; Strayhorn, 2014; West et al., 2015). Duckworth and colleagues (2007) posited Grit is a higher order construct comprised of two second order factors, Perseverance and Consistency of Interests. This factor structure has been questioned previously, resulting in suggestions to utilize the two factors as separate scores or use only Perseverance due to stronger and more consistent construct validity evidence (Credé et al., 2017). Our study findings support the suggestion to utilize Perseverance and Consistency of Interests scores separately. In particular, an inverse relationship between Perseverance and Consistency of Interests has not been previously reported in the literature; in fact, previous studies showed either mixed results (Credé et al., 2017) or a weak relationship (Datu et al, 2016; Meriac et al., 2015).

Furthermore, the strength of the inverse relationship significantly differs on the basis of disability. The relationship between Perseverance and Consistency of Interests was stronger for the disability group (estimate = −0.258, SE = 0.024, Z = −10.580; r = −0.640) than the nondisability group (estimate = −0.104, SE = 0.012, Z = −8.730; r = −0.257). Overall, this finding suggests that Perseverance is moderately and negatively related to Consistency of Interests regardless of disability status. For students with disabilities, this relationship is intensified. In fact, adolescents with stronger endorsements of Perseverance were more inconsistent with their interests. In the interpretation of the inverse relationship, the item text should be revisited and considered. Perseverance items speak to accomplishing goals over a long period of time (e.g., "years of work"), working hard, diligence, and overcoming setbacks. Consistency of Interests items address this notion of changing one's mind, such as setting a goal and then pursuing another, and becoming interested in new ideas, projects, and goals every month or year, losing interest over time, and difficulty maintaining focus. Because our findings show an inverse relationship between these two factors for the whole sample, potentially this can be interpreted to mean that changing one's mind does not necessarily interfere with goal accomplishment and overall achievement. Adolescence is a time of change, whether it be biological, cognitive, or social (Wigfield, Byrnes, & Eccles, 2006). Changing interests and goals, as well as starting and stopping to refocus, might be a natural part of adolescent development. Ultimately, changing one's mind might help adolescents persevere even more.

The inverse relationship was found to be more pronounced for students with disabilities. Potentially, this finding speaks to the special education transition process itself; a time of ongoing data collection driven by student interests, which is then incorporated into special education in the form of IEP goals (Kohler, 1996). In other words, within secondary special education transition services, students are encouraged to explore careers, discover strengths and weaknesses, and vocalize their interests to adults (Mazzotti, Rowe, Cameto, Test, & Morningstar, 2013). In some ways, it is not surprising they might frequently change their minds. In fact, they might be encouraged to do so as a function of the transition process.

In the current study, we decided to retain only the Perseverance factor in our examination of the impact on GPA, rather than utilize an overall Grit score, as the inverse relationship between Perseverance and Consistency of Interests would not warrant such an approach. Our study results supported this decision conditioning on the whole sample as well as by disability status and further builds on previous findings that Perseverance is the more rigorous and straightforward of the two factors of Grit (Credé et al., 2017). Due to this finding, we intentionally used the Perseverance score as the sole predictor of GPA, and results show this estimate is significant and holds across students with and without disabilities (β = 0.195, SE = 0.026, Z = 7.636). As such, Perseverance is an important trait to measure in adolescents and should be considered in school-wide data collection efforts.

Limitations

In this study, there are several important limitations to consider in the interpretation of the findings. First, data collection was left up to the schools to carry out. As such, school personnel coordinated the dates and class periods in which the survey was administered, and ultimately controlled which students had access to the survey. As such, the response rate was not 100% per school; in fact, on average across the 13 schools the mean response rate was 50%. School-wide is suggestive of universal, or Tier 1, data collection efforts, which implies *all* students in the school. Despite our request to include all students, school personnel ultimately controlled this aspect of the data collection.

As shown in Table 1, our sample was not entirely reflective of national trends in race and disability category. There was higher proportional representation of African Americans, most notably, both within and outside of special

education, who were represented at 41% and 49% in the study sample in the general education and special education groups, respectively (as compared with the national average of 15.7% and 15.3%, respectively). Regarding disability categories, some were well represented and reflected national trends (e.g., learning disability). Yet, for other categories, representation in the sample was far below national trends (e.g., emotional disturbance, autism spectrum disorder). As such, the findings may not be generalizable on a national scale.

In the interpretation of the current study findings, it is important to consider the sample characteristics (see Table 1). As previously reported, the sample was diverse, large, and consisted of 9–12 graders. Much of the previous studies in the literature include samples of college-aged students and adult populations (Anestis & Shelby, 2015; Chang, 2014; Duckworth et al., 2007; Meriac et al., 2015; Strayhorn, 2013). There are few previous studies of the Grit scale that focus on adolescents and minority populations; specifically, two published studies include samples of 8th graders (West et al., 2015) and Filipino high school students (Datu et al., 2016). Our sample was comprised of high school students with an overrepresentation of African American students as compared with the national average both in general and special education; a sample distinctly different from the Grit literature. Importantly, more diverse study samples should be prioritized in future research on the Grit scale, and potentially more exploration of the impact of respondent bias given the self-report items. Equally important is continued investigation and validation of Grit as a construct that has implications for academic outcomes (Tang, Wang, Guo, & Salmela-Aro, 2019).

Implications

Findings from the current study further support that students with disabilities should be included in college and career readiness school-wide data collection efforts. At best, these efforts should emulate a multitiered system of support (MTSS). A key feature of MTSS is a three-tiered continuum of academic and behavior support (Sugai & Horner, 1994; Walker et al., 1996). Potentially, findings from the current study can help to inform future research and policy initiatives on embedding noncognitive skills into a high school MTSS. If educators are to truly emphasize noncognitive skills related to college and career readiness (e.g., Farrington et al., 2012; Morningstar et al., 2017) in a multitiered fashion, then ensuring these skills are measured at Tier 1 (universal or school-wide) is critical. Adequate measurement tools are necessary given the emphasis on data-based decision making as a central tenet to MTSS (e.g., Simonsen et al., 2010). If the Grit scale were to be used at Tier 1, then it is critical for it to function similarly across a diverse range of adolescents with and without disabilities. Potentially, the scale could be packaged with other noncognitive measures that map onto college and career readiness skills and used as a universal screening tool to identify students who need more targeted, intensive supports. Secondary special educators may also find the Grit scale useful as an age-appropriate transition assessment. Importantly, educators should consider using only the Perseverance factor score as opposed to using one combined Grit score.

Conclusion

Ultimately, if Grit continues to gain traction in both the popular and scholarly realms of education and be prioritized in policy initiatives, as well as be linked to long-term success in the workplace, it is increasingly important to consider the measurement of the construct. Furthermore, it is critical to use the data gathered with rigorous measures to drive instructional and programmatic decisions concerning college and career readiness for all students. The findings from this study support this process and will help general and special educators to determine the utility of measuring and teaching Grit to adolescents in preparation for adult life.

Author's Note

During the course of this research, author Graham Rifenbark's affiliation changed from the University of Connecticut to the University of Kansas.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

References

American Institutes for Research. (2014). *Measurement Practice Guide* (College and Career Readiness and Success Center). Washington, DC: American Institutes for Research. Retrieved from http://www.ccrscenter.org/products-resources/measurement-practice-guide

Anestis, M. D., & Shelby, E. A. (2015). Grit and perseverance in suicidal behavior and non-suicidal self-injury. *Death Studies*, *39*, 211–218. doi:10.1080/07481187.2014.946629

Arslan, S., Akin, A., & Çîtemel, N. (2013). The predictive role of grit on metacognition in Turkish university students. *Studia Psychologia*, *55*, 311–320.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*, 238–246. doi:10.1037/0033-2909.107.2.238

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. New York, NY: Guilford Press.

Chang, W. (2014). *Grit and academic performance: Is being grittier better?* (Unpublished doctoral dissertation). University of Miami, FL.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*, 233–255.

Credé, M., Tynan, M. C., & Harms, P. D. (2017). Much ado about grit: A meta-analytic synthesis of the grit literature. *Journal of Personality and Social Psychology*, *113*, 492–511. doi:10.1037/pspp0000102

Datu, J. A. D., Valdez, J. P. M., & King, R. B. (2016). Perseverance counts but consistency does not! Validating the short grit scale in a collectivist setting. *Current Psychology*, *35*, 121–130. doi:10.1007/s12144-015-9374-2

Duckworth, A., & Gross, J. J. (2014). Self-control and Grit: Related but separate determinants of success. *Current Directions in Psychological Science*, *23*, 319–325. doi:10.1177/0963721414541463

Duckworth, A., Quinn, P. D., & Seligman, M. E. P. (2009). Positive predictors of teacher effectiveness. *The Journal of Positive Psychology*, *4*, 540–547. doi:10.1080/17439760903157232

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, *92*, 1087–1101. doi:10.1037/0022-3514.92.6.1087

Duckworth, A. L., & Quinn, P. D. (2009). Development and validation of the Short Grit Scale (GRIT–S). *Journal of Personality Assessment*, *91*, 166–174. doi:10.1080/00223890802634290

Enders, C. K. (2010). *Applied missing data analysis*. New York, NY: Guilford Press.

Every Student Succeeds Act, Pub. L 114-95, 20 U.S.C. § 6301 et. seq. (2015).

Farrington, C. A., Roderick, M., Allensworth, E., Nagaoka, J., Keyes, T. S., Johnson, D. W., & Beechum, N. O. (2012). *Teaching adolescents to become learners. The role of noncognitive factors in shaping school performance: A critical literature review*. Chicago, IL: University of Chicago Consortium on Chicago School Research.

Hancock, G. R. (2001). Effect size, power, and sample size determination for structured means modeling and MIMIC approaches to between-groups hypothesis testing of means on a single latent construct. *Psychometrika*, *66*, 373–388. doi:10.1007/BF02294440

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1–55. doi:10.1080/10705519909540118

Individuals With Disabilities Education Improvement Act, 20 U.S.C. § 1400 et seq. (2004).

Ion, A., Mindu, A., & Gorbanescu, A. (2017). Grit in the workplace: Hype or ripe? *Personality and Individual Differences*, *111*, 163–168. doi:10.1016/j.paid.2017.02.012

Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika*, *36*, 409–426. doi:10.1007/bf02291366

Kohler, P. D. (1996). *A taxonomy for transition programming: Linking research and practice*. Champaign: University of Illinois, Transition Research Institute.

Lombardi, A. R., Freeman, J., & Rifenbark, G. G. (2018). Modeling college and career readiness for adolescents with and without disabilities: A bifactor approach. *Exceptional Children*, *84*, 159–176. doi:10.1177/0014402917731557

Mazzotti, V. L., Rowe, D. A., Cameto, R., Test, D. W., & Morningstar, M. E. (2013). Identifying and promoting transition evidence-based practices and predictors of success: A position paper of the division on career development and transition. *Career Development and Transition for Exceptional Individuals*, *36*, 140–151. doi:10.1177/2165143413503365

Meriac, J. P., Slifka, J. S., & LaBat, L. R. (2015). Work ethic and grit: An examination of empirical redundancy. *Personality and Individual Differences*, *86*, 401–405. doi:10.1016/j.paid.2015.07.009

Millsap, R. E. (2012). *Statistical approaches to measurement invariance*. New York, NY: Routledge.

Mooradian, T., Matzler, K., Uzelac, B., & Bauer, F. (2016). Perspiration and inspiration: Grit and innovativeness as antecedents of entrepreneurial success. *Journal of Economic Psychology*, *56*, 232–243. doi:10.1016/j.paid.2016.08.001

Morningstar, M. E., Lombardi, A., Fowler, C. H., & Test, D. W. (2017). A college and career readiness framework for secondary students with disabilities. *Career Development and Transition for Exceptional Individuals*, *40*, 79–91. doi:10.1177/2165143415589926

National Center for Education Statistics. (2014). *Digest of education statistics: 2014*. Washington, DC: Author. Retrieved from http://nces.ed.gov/programs/digest/2015menu_tables.asp

Polirstok, S. (2017). Strategies to improve academic achievement in secondary school students: Perspectives on grit and mindset. *SAGE Open*, *7*(4). doi:10.1177/215844017745111

R Core Team. (2016). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Available from https://www.R-project.org/

Rhemtulla, M., Brosseau-Liard, P. E., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods*, *17*, 354–373. doi:10.1037/a0029315

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36.

Satorra, A., & Bentler, P. M. (2001). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrical*, *66*, 507–514. doi:10.1007/BF02296192

Shechtman, N., DeBarger, A. H., Dornsife, C., Rosier, S., & Yarnall, L. (2013). *Promoting grit, tenacity, and perseverance: Critical factors for success in the 21st century*. U.S. Department of Education, Office of Education Technology. Retrieved from http://pgbovine.net/OET-Draft-Grit-Report-2-17-13.pdf

Shih, A. F., & Margoongroge, S. (2017). The importance of grit in medical training. *Journal of Graduate Medical Education*, *9*, Article 339. doi:10.4300/JGME-D-16-00852.1

Simonsen, B., Shaw, S. F., Faggella-Luby, M., Sugai, G., Coyne, M. D., Rhein, B., . . . Alfano, M. (2010). A schoolwide model for service delivery: Redefining special educators as interventionists. *Remedial and Special Education*, *31*, 17–23. doi:10.1177/0741932508324396

Sörbom, D. (1974). A general method for studying differences in factor means and factor structure between groups. *British Journal of Mathematical and Statistical Psychology*, *27*, 229–239. doi:10.1111/j.2044-8317.1974.tb00543.x

Steiger, J. H., & Lind, J. C. (1980, May). *Statistically based tests for the number of common factors*. Paper presented at the Annual Spring Meeting of the Psychometric Society, Iowa City, IA.

Strayhorn, T. L. (2014). What role does grit play in the academic success of black male collegians at predominantly White institutions? *Journal of African American Studies*, *18*(1), 1–10. doi:10.1007/s12111-012-9243-0

Sugai, G., & Horner, R. (1994). Including students with severe behavior problems in general education settings: Assumptions, challenges, and solutions. In J. Marr, G. Sugai, & G. Tindal (Eds.), *The Oregon conference monograph* (Vol. 6, pp. 102–120). Eugene: University of Oregon.

Tang, X., Wang, M. T., Guo, J., & Salmela-Aro, K. (2019). Building grit: The longitudinal pathways between mindset, commitment, grit, and academic outcomes. *Journal of Youth and Adolescence*, *48*, 850–863.

Tomasello, J., & Brand, B. (2018, January). *How ESSA and IDEA can support college and career readiness for students with disabilities: Considerations for states*. Washington, DC: American Institutes for Research. Retrieved from https://ccrscenter.org/sites/default/files/ESSA-IDEA_CollegeCareerReadiness.pdf

Tough, P. (2012). *How children succeed: Grit, curiosity, and the hidden power of character*. New York, NY: First Mariner.

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, *38*, 1–10. doi:10.1007/BF02291170

Walker, H. M., Horner, R. H., Sugai, G., Bullis, M., Sprague, J. R., Bricker, D., & Kaufman, M. J. (1996). Integrated approaches to preventing antisocial behavior patterns among school-age children and youth. *Journal of Emotional and Behavioral Disorders*, *4*, 193–256. doi:10.1177/106342669600400401

Welch, M. J., Abulhab, A., & Therriault, S. B. (2017). *College and career readiness in Boston: Understanding and tracking competencies and indicators*. Washington, DC: American Institutes for Research, College and Career Readiness and Success Center.

West, M. R., Kraft, M. A., Finn, A. S., Martin, R. E., Duckworth, A. L., Gabrieli, C. F., & Gabrieli, J. D. (2015). Promise and paradox: Measuring students' non-cognitive skills and the impact of schooling. *Educational Evaluation and Policy Analysis*, *38*, 148–170. doi:0162373715597298

Wigfield, A., Byrnes, J. P., & Eccles, J. S. (2006). Development during early and middle adolescence. *Handbook of Educational Psychology*, *2*, 87–113.