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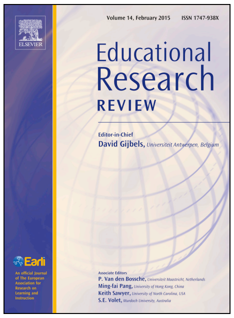

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PII: S1747-938X(21)00025-7

DOI: https://doi.org/10.1016/j.edurev.2021.100402

Reference: EDUREV 100402

To appear in: *Educational Research Review*

Received Date: 24 January 2021

Revised Date: 16 May 2021

Accepted Date: 1 July 2021

Please cite this article as: Rudd, G., Meissel, K., Meyer, F., Measuring academic resilience in quantitative research: A systematic review of the literature, *Educational Research Review*, https://doi.org/10.1016/j.edurev.2021.100402.

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Measuring academic resilience in quantitative research: A systematic review of the literature

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Declarations of interest: none

Measuring academic resilience in quantitative research: A systematic review of the literature

Abstract

Academic resilience research has the potential to improve the learning outcomes of students at risk of school failure, yet there is no standard approach to its measurement. This review aimed to provide an overview of the ways in which academic resilience has been measured and analysed within quantitative research over the last 20 years. Our findings extended upon those in existing reviews by focussing on how academic resilience has been operationalised as a specific construct. A systematic search of the literature returned 127 studies that drew conclusions about academic resilience based on quantitative data. Three distinct approaches to the measurement of academic resilience were identified using thematic analysis techniques: the definition-driven, process-driven, and latent construct approaches. Each of these approaches align with different types of analyses which, in turn, shape the inferences that researchers can make about academic resilience. The implications of these variations in measurement are discussed. At the macro-level, the utilisation of resilient characteristics and the omission of risk indicators within existing measures may undermine the validity of studies investigating the construct of academic resilience. At the micro-level, the purpose of the study, usability, and inclusivity of the measurement approach influence how researchers choose to operationalise academic resilience. This review emphasises the importance of considering the methodological decisions that researchers make and contributes to the ongoing refinement of academic resilience as a specific construct in resilience research.

Keywords: Academic resilience; Risk factors; Protective factors; Operationalisation; Measurement

1. Introduction

Resilience is a burgeoning field in psychological research. Resilience research embraces the natural variation in individual responses to personal stress and seeks to identify the determinants of positive adaptation in the face of life adversities (Rutter, 2012). An understanding of these factors and processes is valuable because the promotion of protective factors has the ability to support people to overcome threats to positive development. The transition from a deficit framework to the strength-based concept of resilience champions the promotion of healthy functioning over the prevention of maladaptive functioning (Morales & Trotman, 2010) and reflects a fundamental shift in expectations for people's minimum standards of living and in realising their potential. Accordingly, resilience research explores ways to improve people's lives across a variety of different domains and for different groups of people, including in relation to the COVID-19 pandemic (Barzilay et al., 2020), cancer patients (Min et al., 2013), and those with adverse childhood experiences (Poole et al., 2017).

Understandings of resilience have changed over time. Initially posited as a fixed trait, resilient children were described as 'invulnerable' to life's adversities (Alva, 1991; Anthony, 1974). However, these conceptualisations have evolved to understand resilience as a process of positive adaptation, involving the dynamic interaction between the individual and their environment (Luthar et al., 2000, Rutter 2012). These developments have resulted in new considerations for the study of resilience. Firstly, contemporary resilience theory is underpinned by the belief that everyone is capable of positive functioning and can 'bounce back', given the right conditions (Morales & Trotman, 2010; Rutter, 2012). Consequently, studies of resilience often seek to identify protective factors that can then be fostered in others. Secondly, the dynamism of resilience acknowledges that an individual's levels of resilience can change over time. This "ontogenetic instability" (Luthar et al., 2000, p. 11) contributes to the construct's complexity, particularly for its measurement. Thirdly, it raises questions as to whether resilience should be captured as a process or as an outcome (McGubbin, 2001).

The concept of resilience has been applied to the academic domain. Wang and colleagues (1994) defined academic resilience as “the heightened likelihood of success in school and other life accomplishments, despite environmental adversities brought about by early traits, conditions and experiences” (p. 46). Here, the concept of resilience is specifically related to the context of education. Students who demonstrate academic resilience are those who have been exposed to adverse circumstances, such as low socioeconomic status (SES), that put them at a heightened risk of school failure, yet they demonstrate continued high levels of academic performance. Academic resilience is, therefore, often referred to as ‘better than expected’ educational outcomes (e.g., Borman & Overman, 2004). Academic resilience is often conflated with academic buoyancy. However, it differs in that academic resilience relates to success among populations that experience acute or chronic adversities, while academic buoyancy reflects a resilience to lesser day-to-day setbacks (Martin & Marsh, 2008). Academic buoyancy, therefore, has a much broader application than does academic resilience, but is restricted in that it does not provide insight into factors enabling ongoing academic success despite more adverse circumstances. Consequently, studies of academic resilience, in their focus on severely disadvantaged groups, can provide important insight into such factors.

While there is consensus as to the definition and broad conceptualisation of academic resilience, there is no standard approach to its measurement. The variation in these approaches present difficulties for estimating the prevalence rates of academic resilience and comparing the effectiveness of its protective factors (Tudor & Spray, 2018). The multiple components of academic resilience (risk and competence) combined with its dynamic nature has provided researchers with challenges to creating a measure that effectively captures its essence (McGubbin, 2001). In quantitative studies, researchers must decide how to reduce the different components of academic resilience into a single variable or statistical model. While these decisions are the prerogative of the researcher, this responsibility cannot be underestimated. How academic resilience is operationalised ultimately determines who is and is not identified as resilient and thus who our conclusions about resilience are based upon. Luthar and colleagues (2000) raised similar concerns about general resilience research and encouraged researchers to be transparent about their method of measurement. Discussions about such methodological decisions and their implications for the field of academic resilience will ensure that contemporary research does justice to this important group of students.

The current review aims to contribute to this discussion by looking into the different ways in which academic resilience has been measured. Existing reviews have documented such variations, which will be outlined in the following section. However, it is important to note that there are limitations to these reviews which ultimately provide support for the current review. Cosco et al. (2016) identified three methods of operationalisation used to capture resilience in longitudinal studies of ageing. *Definition-driven* methods utilised pre-determined indicators of risk and competence to identify resilient populations. Consequently, there was a clear demarcation between those who were resilient and those who were not. In contrast, *data-driven* methods were based on patterns within the data itself. Rather than nominating *a priori* thresholds, similar individuals were grouped together, for example based on their levels of depression, and then identified as resilient based on how these groups performed relative to each other. Thirdly, *psychometrically driven* methods referred to established resilience scales. While Cosco et al.'s (2016) findings helped to describe and categorise the variation in methods used to measure general resilience, academic resilience is a related but distinct construct that requires specific attention. Accordingly, Tudor and Spray (2018) reviewed the different ways in which risk, positive adaptation, and protective factors had been assessed in the measurement of academic resilience and outlined two approaches commonly used in its analysis. *Variable-focussed* approaches investigated how protective factors functioned to ameliorate risk, typically using mediation or moderation analyses to explore the interplay between risk, protective, and achievement factors. Alternatively, studies employed *person-centred* approaches to explore group differences between those identified as resilient and non-resilient and identify protective factors.

When combined, the two reviews noted here convey a cohesive overview of the ways in which academic resilience has been previously investigated. Tudor and Spray (2018) concluded that measures of academic resilience should include indicators of risk, positive adaption, and protective factors, while Cosco and colleagues (2016) incorporated similar measures of adversity and adaptation to identify three methods of operationalising resilience. These methods described the different ways in which the measures of risk and competence were combined to capture resilience. Tudor and Spray (2018) also presented two approaches to the analysis of academic resilience which related to Cosco et al.'s (2016) methods of operationalisation. The *definition*- and *data-driven* methods were employed to identify resilient and non-resilient groups which were then analysed using *person-centred* approaches. In contrast, the continuous nature of the *psychometrically driven* method lent itself to *variable-focussed* approaches which positioned the resilience measure as the outcome of the interaction between risk and protective factors.

While the findings of these reviews seem to align, they are based on different samples and focus on different constructs. Accordingly, the value in the current work is its comprehensive review of the ways in which the academic resilience of students in educational settings has been measured and analysed within a single sample identified through a systematic search of the literature. Therefore, the primary research question directing this review is: How has academic resilience been operationalised in the quantitative literature over the last 20 years? The secondary research question for this review is: What are the common types of statistical analyses used to investigate academic resilience? This review will describe the existing approaches to the measurement of academic resilience with the aim of giving both prospective and existing researchers practical findings to contextualise existing studies and inform future research.

2. Method

To answer the research questions, a systematic search and review of the literature was conducted. Three databases were searched: PsycInfo, ERIC, and EbscoHost: Education Research Complete. The abstracts of the articles in each database were searched using the terms (“academic resilience” OR “educational resilience”). The same search terms were then used in Google Scholar to ensure that all relevant records had been captured. Given the breadth of articles included in Google Scholar, the search was limited to the title section of each record, using the advanced search function. Searches conducted on all databases were limited to results:

- In the English language,
- Distributed between January 2000 and August 2020, and
- Of both peer-reviewed and unreviewed works that were available in the databases.

The included date range was chosen to return the most recent articles exploring academic resilience to ensure that the findings would be relevant to contemporary society. Non-peer reviewed and unpublished works were included in an attempt to reduce the effect of publication bias. Given that there is no standard approach to the measurement and analysis of academic resilience in quantitative research, the inclusion of unreviewed works was also used to explore how all levels of researchers chose to investigate academic resilience and whether the approaches taken in unreviewed works differed from those in published works.

2.1. Screening process

After the removal of duplicates, the four database searches returned 607 individual records which were subject to the screening process. Consistent with the PRISMA guidelines (Moher et al., 2009) the screening process was conducted in two stages: title and abstract screening, and eligibility testing. The inclusion criteria at Stage 1 were:

1. The article presents a quantitative analysis of primary or secondary empirical data,
2. In the quantitative section of the article, an indicator of individual academic resilience of students is created and/or investigated, and
3. The article investigates academic resilience within a formal or informal educational context.

The small number of criteria reflects the intention to capture all studies that drew conclusions about academic resilience based on quantitative data and reduced the likelihood that articles of interest were prematurely rejected. This was important because many studies did not explicitly operationalise academic resilience in their methods. Any article that was qualitative in nature or analysed findings of existing studies (e.g., literature reviews) were excluded (*n* = 309). A further 105 records were excluded because they reported on other forms of resilience, such as psychological resilience or academic buoyancy, or did not investigate academic resilience of students at the individual level (e.g., school-level resilience or teacher resilience). Consequently, a total of 414 articles were rejected at Stage 1.

Full-text copies of the remaining 193 records were then downloaded. In three cases the full-text copy of the work could not be accessed because the record related exclusively to the research brief. The authors were contacted via email in an unsuccessful attempt to locate the related full-text work. In one case the corresponding full-text work had already been captured by the database searches (i.e., duplicate). Full-text copies of five theses were also not accessible via the corresponding university websites or the ProQuest Dissertations and Theses Global database. Thus, nine records were excluded in addition to those removed at Stage 1, leaving 184 independent records subject to eligibility testing. The eligibility criteria for Stage 2 were:

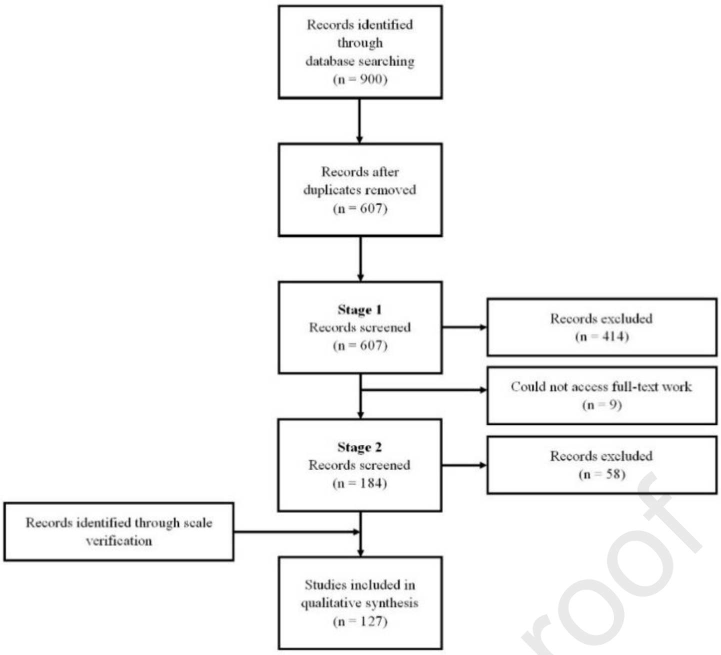
1. The conclusions drawn about academic resilience are based on a quantitative measurement or analysis of academic resilience, and
2. Articles employing academic resilience scales (or the original article describing the development of the scale) contain sufficient information about the nature and number of factors and scale-items used.

Studies that purported to measure academic resilience but used resilience scales not specific to the educational domain were excluded (*n* = 17; e.g., The Connor-Davidson Resilience Scale; Connor & Davidson, 2003). This distinction was important to distinguish between studies that explored general resilience within an educational context (e.g., its association with academic achievement) and those that studied academic resilience as a specific construct. Similarly, articles that were conceptually linked to academic resilience but did not actually measure the construct were excluded (*n* = 15). For example, Torsney and Symonds (2019) concluded that increasing school engagement would strengthen students' academic resilience, however their study did not measure academic resilience. Studies were also excluded if they used an existing academic resilience scale that could not be verified (e.g., the original work could not be sourced in English; *n* = 14) or did not contain enough information about the scale (*n* = 2). This was to ensure that the current review considered all information relevant to how academic resilience had been measured. In addition, one study was excluded because no quantitative results were reported with respect to the operationalisation outlined, while another was excluded due to conflicting information about what scale had been used. Where articles reported on the same findings, the original work was retained, while subsequent iterations were excluded (*n* = 8).

At the conclusion of the screening process 126 articles remained. Where an article used a scale developed by other researchers that had not already been identified in the screening process, the original article describing the creation of the scale was added to the final sample (*n* = 1; Carlson, 2001). This record was not captured using the current review criteria because it did not include the search terms in its title or abstract. However, it was included as two studies drew conclusions about academic resilience from its application and the measure was clearly reflective of the academic resilience construct. As a result, a total of 127 articles from the last 20 years were included for review (see Figure 1).

Figure 1

PRISMA Diagram of Search Process



2.2. Data analysis

The studies were reviewed using a thematic analysis approach as outlined by Braun and Clarke (2006). This approach is a six-phase process (familiarisation, coding, searching for, reviewing, and naming themes, and reporting) used to identify “patterns of shared meaning” (Braun & Clarke, 2020, p. 4) in qualitative data. Identifying themes across the different studies investigating academic resilience was undertaken to provide an overview of the ways in which academic resilience has been measured and analysed. Firstly, relevant information about the study characteristics, sample population, and analyses were extracted from each study (see Appendix), facilitating data familiarisation (phase 1). The operationalisations of academic resilience were then coded based on their shared characteristics (phase 2). These codes related to the two components of resilience: risk (risk factors, at-risk sample, risk threshold) and competence (discrete, continuous, achievement related, characteristics, scale), as well as the analyses conducted (predictors of resilience, interaction between risk and protective factors, resilience as independent variable). The studies were organised based on their codes to make meaning from the different approaches to the measurement of academic resilience (phase 3). Initial themes included direct and indirect, categorical and continuous operationalisations of academic resilience, which were subsequently refined to reflect the main approaches to the measurement of academic resilience in quantitative literature (phase 4). This involved defining and naming each of the themes (phase 5):

1. The definition-driven approach,
2. The process-driven approach, and
3. The latent construct approach.

These themes take inspiration from the methods outlined by Cosco et al. (2016). The definition-driven approach, akin to the *definition-driven* method, predetermines criteria by which resilient students are identified by, while the latent construct approach expands on the *psychometrically driven* method to include all measures that use characteristics to infer resilience. Lastly, the process-driven approach replaces the *data-driven* method, capturing how the interaction between risk and protective factors are manifested in students' levels of achievement. The themes also map onto the two analysis approaches outlined by Tudor and Spray (2018), with the definition-driven approach explored using *person-centred* analyses and the process-driven and latent construct approaches typically investigated using *variable-focussed* analyses. While there are similarities between the current categorisations and those outlined in previous works it was important that the themes were not predetermined, but rather grounded in the data itself (i.e., inductive). Each of the 127 studies was categorised into one of the three approaches, with four studies falling under two approaches. The results of the thematic analysis are presented in the following section (phase 6).

3. Results

Considerable variation in how academic resilience is operationalised was evident in the current sample. Three distinct approaches to the measurement of academic resilience were identified, and each of these main approaches was underpinned by two sub-approaches. Two of the main approaches sought to measure academic resilience 'directly', that is, by utilising a measure of achievement to capture educational success. Forty studies employed a definition-driven approach which explicitly identified a subsample of students who were academically resilient. This group was then compared with a non-resilient group to investigate differences in their characteristics, such as levels of self-efficacy. The second direct measure, the process-driven approach, implicitly identified academic resilience (n = 36). The process-driven approach investigates academic resilience (reflected by high levels of achievement) as the outcome of the interaction between risk and protective factors. Thirdly, the latent construct approach provided an 'indirect' (i.e., non-cognitive) measure of academic resilience. This approach, employed by 55 studies, measures characteristics associated with academic resilience which are used to calculate a resilience score. These approaches are summarised in Table 1.

Table 1

Descriptions of the Main Approaches to the Measurement of Academic Resilience

Measurement approach	Description	Proportion of included studies
Definition-driven	Identifies a resilient sub-sample based on predetermined risk and achievement criteria	31%
Process-driven	Investigates interaction of risk and protective factors on an achievement outcome; higher levels of achievement reflect higher levels of resilience	28%
Latent construct	Continuous measure which calculates a resilience score based on characteristics indicative of a student's capacity for resilience	43%

Note. Proportion of included studies adds to more than 100% because of the four studies that fall under two approaches.

3.1. The definition-driven approach

Studies that explicitly identified their resilient sub-sample before conducting statistical analyses used a definition-driven approach to the measurement of academic resilience. This approach reflects the concept of academic resilience in its most literal sense: academic achievement despite adversity. Students could fulfil the criteria required to be resilient in two ways. In the first sub-approach students needed to be a member of a high-risk group while simultaneously being a member of a high achieving group. In the second, students were deemed to be resilient if they attained a better than expected achievement outcome, given their level of risk exposure. Resilient students were then contrasted with non-resilient ones to create a categorical variable.

3.1.1. High-risk and high achieving group membership

Under the first sub-approach resilient students were identified in two steps. Firstly, researchers identified a high-risk sample. For example, Programme for International Student Assessment (PISA) defined a disadvantaged student as one who fell within the bottom quarter of their national socioeconomic measure (i.e., socioeconomic risk; Schleicher, 2019). Other studies used indicators of demographic (e.g., ethnicity) or academic risk (e.g., low achievement; see Table A1). It should be noted that simply using ethnicity as a risk factor has been extensively critiqued since the risk is generally associated with conflated factors such as SES or systemic bias (Kingdon & Cassen, 2010; Strand, 2014). Secondly, a threshold of achievement was nominated. For example, Agasisti et al. (2018) defined their resilient sample as disadvantaged students who achieved at or above PISA Level 3 in science, reading, and mathematics. This threshold represents an absolute measure of performance. That is, the score or behaviour used to indicate high achievement remains constant. Indicators of risk and achievement could also be captured using a relative threshold. For example, PISA defined high achievement as performance within the top 25% of the achievement distribution (Schleicher, 2019). Thus, students who were in the lowest 25% of the national SES distribution and the top 25% of the reading achievement distribution were identified as resilient using relative thresholds of risk and achievement. When a relative threshold is employed, a student's level of achievement, and therefore resilience status, is dependent on their position within the context's achievement distribution.

3.1.2. Resilience residuals

The second sub-approach, resilience residuals, also identifies a high achieving group from within an at-risk sample by applying a relative achievement threshold, however, it employs regression analysis to account for the impact that risk has on achievement. For example, Cheung and colleagues (2014, 2017) defined resilience as disadvantaged students who achieved in the top 25% of the achievement distribution, after accounting for SES. This sub-approach can also be interpreted as identifying students demonstrating better than expected educational outcomes. Disadvantaged students who achieve well above their predicted grade and have a 'positive residual' are here deemed to be resilient. For example, Borman and Rachuba (2000) used SES and prior achievement to predict mathematics outcomes among sixth graders in the United States of America (USA). Resilient students were those whose standardised residuals were 0.33 or above on their Grade 6 mathematics test. A much stricter threshold was used by Wills and Hofmeyr (2019), with resilient students required to perform two standard deviations above their predicted score at two time points. Just 78 students out of the whole sample (n = 2,379) met this criterion, although this is almost double what would be expected assuming a normal distribution. Unsurprisingly, the number of resilient students nearly doubled when the threshold was reduced to 1.5 standard deviations above students' predicted score.

3.1.3. Common types of analyses using the definition-driven approach

Analyses investigated the differences in characteristics between the resilient and non-resilient subsamples. These person-centred analyses were either conducted using *t*-tests and analyses of variance, or logistic regression analysis. The former treats academic resilience as a grouping variable. For example, results from Borman and Rachuba's (2000) multivariate analysis of variance suggested that resilient students had significantly greater levels of self-efficacy in mathematics, were more positive about school, and demonstrated higher levels of engagement, compared to their non-resilient counterparts. Similarly, Waxman et al. (2012) found that resilient students perceived higher levels of competition in the classroom and demonstrated higher levels of on-task behaviours than average and non-resilient students. When treated as an independent variable, resilient and non-resilient groups were typically compared based on their levels of positive learner attributes, such as academic aspirations and self-efficacy (e.g., Borman & Rachuba, 2000; Murray, 2018; Patterson, 2012), and indicators of school quality, such as school climate and teacher support (Brule, 2015; Vincent, 2007). These desirable student and school characteristics expectedly favoured the resilient sub-samples.

Logistic regression was the most popular method of analysis, likely because it positions academic resilience as the outcome, providing a logical method for the identification of protective factors. For example, foster youth with high levels of student engagement and more supportive teacher-student relationships were more likely to be resilient (Strolin-Goltzman et al., 2016). Logistic regression analyses calculated odds ratios, which offered a standardised effect size, quantifying the increase in likelihood associated with the presence of a specific protective factor. Accordingly, for every unit increase in student engagement the likelihood of academic resilience in foster youth increased over four times, while the same increase in rating of teacher-student relationships increased this likelihood over eight times. Therefore, while both these variables could be described as protective, a positive teacher-student relationship seemed to more strongly promote post-secondary education attendance.

The ability to test the predictive strength of multiple variables simultaneously within a single logistic regression model facilitated the investigation of a wide range of protective factors spanning different developmental contexts. At the student-level high levels of subject self-concept increased the likelihood of resilience (e.g., Cheung, 2017; Sandoval-Hernandez & Cortes, 2012), while parental investment in and expectations of their children's academic progress (e.g., Arnold, 2003; Pettit, 2016; Sacker & Schoon, 2007) were family-level predictors of resilience. Elements of external contexts of development also predicted resilience, such as school resourcing (e.g., Agasisti et al., 2018; Hofmeyr, 2019). When multiple protective factors are explored within a logistic regression model, the interpretation of the strength of each predictor is done so while holding each of the other predictors constant, thereby isolating the contribution of individual protective factors.

The types of analyses used here are determined by the construction of academic resilience as a categorical variable. Person-centred analyses distinguish between resilient and non-resilient groups to identify protective factors. However, academic resilience could also be constructed as a continuous variable within the definition-driven approach by omitting the achievement threshold, allowing students to span the vulnerability-resilience continuum. Just one study employed the resilience residuals sub-approach to create a continuous measure. Searle (2011) predicted students' levels of school engagement (an indirect measure of academic resilience) using a cumulative index of risk indicators. Academic resilience scores ranged from -3.31 to 2.98 (M = 0, SD = 1) and were approximately normally distributed. Path analyses were used to investigate the associations between parent-child relationships, mental health problems, self-concept, and academic resilience. Thus, the definition-driven approach can be used to facilitate both person-centred and variable-focussed analyses of academic resilience.

3.1.4. Strengths and weaknesses of the definition-driven approach

In focussing on the extremes of the risk and achievement distributions the definition-driven approach significantly reduces the sample size and statistical power used to explore protective factors. Indeed, some studies reduced their achievement thresholds simply to increase their resilient sub-sample (e.g, Murray, 2018). Yet, this flexibility also enables researchers to nominate thresholds that are sensitive to the lived realities of the chosen population. For example, in their study of homeless and highly mobile students, a highly vulnerable student group, Cutuli et al. (2013) and Obradovíc et al. (2009) operationalised high achievement as achieving one standard deviation below mean achievement, or above. This was the lowest achievement threshold used in the current sample. The resilience residuals sub-approach also facilitates the development of context-specific measures by accounting for the impact that risk has on achievement. This will make it ‘easier’ for extremely disadvantaged students to reach the achievement threshold and arguably capture a more accurate sample of resilient students on which to base inferences about resilience on.

The variation in resilience measures within the definition-driven approach has contributed to the disparate findings related to academic resilience. However, the use of international large-scale assessment datasets, such as PISA, has helped to standardise resilience measures. For example, Cheung and colleagues (2014, 2017) controlled for the international SES-achievement association, meaning that resilient students were disadvantaged within their own context, but demonstrated high achievement on the international stage. This operationalisation enabled comparisons of academic resilience and its protective factors among five East Asian education systems, with Shanghai consistently producing the highest rates of resilience (19% of all students). Therefore, while the flexibility of the definition-driven approach is beneficial to the researcher by enabling the application of context-specific measures, standardising measures of academic resilience also has benefits by facilitating comparisons across contexts.

3.2. The process-driven approach

Contemporary understandings of academic resilience as a dynamic interaction between the individual and their environment were reflected in studies that employed the process-driven approach. Here, the achievement outcome was continuous, with studies looking to identify factors that predict higher levels of achievement. This approach is underpinned by the implicit assumption that higher levels of achievement reflect higher levels of academic resilience. Consequently, students fall along the vulnerability-resilience continuum. Within the process-driven approach, the two sub-approaches identified differed in the way in which risk was captured.

3.2.1. Predicting achievement for an at-risk sample

As in the definition-driven approach, risk was commonly captured using socioeconomic, demographic, or academic variables (see Table A2). Once the sample had been narrowed to those at risk of school failure, the first sub-approach tested for the association between protective factors and achievement. This sub-approach included intervention studies which sought to investigate whether school programmes improved at-risk students' levels of achievement. For example, Kanevsky et al. (2008) investigated how the School in the Park programme increased at-risk students' levels of mathematics achievement compared to a control group. There were no significant differences in mean levels of achievement between the two groups, suggesting that the intervention did not improve students' levels of resilience.

3.2.2. The inclusion of risk factors within statistical models of resilience

A second way that academic resilience was measured involved capturing specific indicators of risk which were then entered into the statistical model as independent variables negatively associated with achievement. For example, Alfaro et al. (2009) and Abel (2013) both measured students' perceptions of discrimination as a risk factor for samples of ethnic minority youth. The relationships between risk and protective factors are explored to better understand how academic resilience is facilitated when protective factors are present. While this sub-approach is similar to the resilience residuals sub-approach there are two distinguishing features. Firstly, the process-driven approach retains the continuous nature of the achievement outcome, whereas the definition-driven approach creates a categorical variable. Secondly, the process-driven approach seeks to explore how protective factors interact with risk factors to promote positive outcomes. Thus, the investigation of the resilience process is conducted using variable-focussed analyses.

3.2.3. Common types of analyses using the process-driven approach

Exploring the function of protective factors typically involves testing the association between protective factors and achievement. Within an at-risk sample, the more positive the association between a predictor and the outcome, the stronger its protective effects. For example, using structural equation modelling Gizir and Aydin (2009) found that high home expectations and students' perceptions of their academic abilities positively predicted achievement, supporting their function as protective factors for impoverished eighth graders. In another study, Maier and colleagues (2012) investigated student- and classroom-level characteristics that predicted language and literacy achievement for four-year old Head Start students in the USA. Findings from the three multilevel regression models indicated that students' psychosocial characteristics, such as self-control, predicted baseline literacy achievement, while classroom organisation predicted literacy growth over the academic year.

In both these examples and similar to logistic regression analyses within the definition-driven approach, the protective factors studied were representative of multiple developmental contexts, reflecting the complexity of isolating the individual contribution of certain protective factors from students' social, cultural, and economic backgrounds, and their wider life experiences.

Mediation analysis seeks to explain the relationship between risk factors and the increased likelihood of school failure. Here, protective factors are identified as the mediator because it has the potential to alter the negative relationship between the risk factor and outcome. Alfaro et al. (2009) investigated the role of academic motivation in mediating the negative relationship between students' perceptions of discrimination and their grade point average (GPA). Latino boys who experienced higher levels of discrimination reported lower levels of academic motivation which, in turn, predicted lower achievement. The study highlighted how risk manifested in students' achievement, and the potential of academic motivation to interrupt this process. Whereas, Alfaro and colleagues (2009) positioned the protective factor as the mediator, two studies investigated how protective factors negatively predicted risk factors (Kang et al., 2018; Li, 2017). In their study of adolescents who had experienced a traumatic event, Kang et al. (2018) found that that developmental skills, such as social competence, and developmental supports negatively predicted mental distress which, in turn, reduced instances of bullying behaviour and substance use. In this case mental distress mediated the association between protective factors and risk factors, suggesting that protective factors may alter the impact of a risk factor by reducing how much risk students are actually exposed to, rather than providing students with assets that enable them to respond adaptively to the adversity experienced.

Lastly, a moderation analysis explores how the association between risk and achievement variables may change depending on a third variable. A moderator that reduces the negative impact of a risk factor on achievement functions as a protective factor. For example, to test the protective role of emotional intelligence, Abel (2013) conducted multiple regression analyses. Perceptions of discrimination were negatively associated with GPA, though this was not significant. When emotional intelligence was added to create an interaction term (with the risk variable) it did not ameliorate the risk associated with higher levels of perceived discrimination among Latinx and African American students. Indeed, many studies that employed moderation analyses for the study of academic resilience did not produce results that were statistically significant, implying that the protective factors of interest did not demonstrate a protective function. Despite these findings, moderation analysis arguably provides the most accurate representation of the resilience process by establishing both how risk factors negatively impact achievement, and how protective factors intervene to produce more positive outcomes.

3.2.4. Strengths and weaknesses of the process-driven approach

Studies using the process-driven approach often omitted an operational definition of academic resilience in their work. The reader, therefore, was required to infer how academic resilience had been operationalised based on the variables used, analyses employed, and conclusions drawn. Consequently, this approach had the most tenuous links to the academic resilience literature, likely contributing to it being the least used measurement approach. However, it also opens up additional opportunities for the study of resilience, with many studies using this approach without explicitly stating their focus as that of academic resilience. For example, studies that investigate the determinants of academic success among students disadvantaged by socioeconomic, demographic, or academic adversity meet the criteria for this approach. The process-driven approach offers both strengths and weaknesses in terms of its usability, but ultimately has great potential for progressing the field of academic resilience research.

3.3. The latent construct approach

The intangible nature of academic resilience has resulted in the development of psychometric measures, which take an ‘indirect’ approach to measuring resilience. That is, rather than utilising achievement data, characteristics indicative of academic resilience are collated to create a latent construct. Self-report scales were the most common approach to the measurement of academic resilience, while other studies created a latent construct without employing a scale dedicated to the measurement of academic resilience. The number and type of variables used to measure academic resilience depended upon whether the researcher proposed the construct to be unidimensional or multidimensional in nature.

3.3.1. Academic resilience as a unidimensional latent construct

As a unidimensional construct, academic resilience is measured using characteristics that directly reflect an individual’s ability to be resilient. The most popular unidimensional measure of academic resilience was the Academic Resilience Scale (ARS) created by Martin and Marsh (2003, 2006). This scale contains six attitudinal items which captured how well students reported responding to various academic adversities, such as a bad assignment mark. In the Academic Resilience in Mathematics scale (Ricketts et al., 2017), these items were specifically related to the mathematics domain (e.g., ‘I know where to get help if I’m having trouble with math’).

3.3.2. Academic resilience as a multidimensional latent construct

More commonly, studies proposed academic resilience to be a multidimensional construct. Here, multiple characteristics comprise academic resilience. Consequently, multidimensional measures include more items than unidimensional measures (see Table A3). For example, Colp (2015) constructed academic resilience as a second-order factor comprised of five first-order factors, measured using 23 items, while He (2014) used 12 items to measure three first-order factors. In both cases the exploratory and confirmatory factor analyses supported the construction of academic resilience as a multidimensional construct. Arguably, the most well-known multidimensional measure is the Academic Resilience Scale-30 (ARS-30; Cassidy 2015, 2016). The ARS-30 is comprised of 30 scale-items measuring three dimensions: Perseverance, reflecting and adaptive help-seeking, and negative affect and emotional response. This process-based measure captures students' cognitive-affective and behavioural responses to a hypothetical academic adversity.

There was both considerable overlap and marked variation in the factors used to measure academic resilience. Over 30 factors were used in the reviewed studies, with between two and ten factors used to construct each second-order factor. The first-order factors generally fell into one of two categories. Firstly, many factors captured students' attitudes and behaviours related to their learner identity. More resilient students were purported to be more confident academically, have greater levels of academic self-efficacy, and have an internal locus of control. These students were also more optimistic, both in their natural disposition and their aspirations for their academic futures. Student behaviours associated with academic resilience included academic engagement, social skills, and the ability to set goals. These factors seemed to reflect learner attributes that are beneficial to all students, regardless of their experiences of adversity.

Factors relating to experiencing and responding to setbacks more closely aligned with the essence of academic resilience. In response to adversity, a highly resilient student was likely to demonstrate high levels of emotion regulation and self-regulation, as well as low levels of anxiety. Behaviourally these students were purported to demonstrate resourcefulness, an ability to solve problems, and initiative to ask for help. Attitudinal items, such as perseverance and determination similarly reflected factors that become particularly valuable when one is facing barriers to academic success. These factors measured how greatly academic adversity would impact students' affect and their capacity to respond adaptively.

3.3.3. Common types of analyses using the latent construct approach

The latent construct approach creates a single continuous academic resilience measure. Its flexibility in analyses stems from the fact that it does not require a consideration of how risk, protective, and achievement outcome factors are ordered. Naturally, it was most common to investigate academic resilience as the outcome to identify protective factors, such as in regression analysis. For example, Cassidy (2015; 2016), Carlson (2001), and Martin and Marsh (2003; 2006) all validated their scales by testing the association between self-efficacy and academic resilience. While the association between self-efficacy and academic resilience was positive and significant in each study, the strength of the correlation coefficient varied from weak (r = .19; Martin & Marsh, 2006) to strong (r = .59; Carlson, 2001), depending on the type of correlation used and whether the dimensions of the latent construct were tested separately (e.g., Carlson, 2001) or as a combined score. Studies using regression analysis similarly found that self-efficacy positively predicted academic resilience (e.g., Martin & Marsh 2006; Rajan et al., 2017; Victor-Aigboidion et al., 2020). Other protective factors explored using the latent construct approach included grit (Calo et al., 2019; Chisolm-Burns et al., 2019), engagement (Li et al., 2019; Martin, 2012; Rajan et al., 2017), and sports participation (Harpalani, 2005; Hawkins & Mulkey, 2005).

As an independent and mediator variable itself academic resilience was often used to test the association between academic resilience and achievement. Hill (2017) used Early Childhood Longitudinal Study data to investigate the role of academic resilience in promoting the reading achievement of third graders in the USA. The latent construct of academic resilience comprised measures of student self-regulatory and academic behaviours, while the measure of social-emotional development included indicators of internalising and externalising problems. Academic resilience was found to positively predict reading achievement, as well as partially mediate the negative association between social-emotional behaviours and reading achievement. Here it could be argued that the positive association between academic resilience and achievement, and its function as a mediator, actually reflects the first-order factors of academic resilience as the protective factors of academic resilience measured using a direct measurement approach which, in this case, facilitated the reduction in risk related to internalising and externalising problem behaviours.

3.3.4. Strengths and weaknesses of the latent construct approach

Using an established scale enables findings to be compared across studies, without the need to consider measurement variation. The ARS (Martin & Marsh, 2003, 2006) has been used at the university level in Iran, the USA, Egypt, and Spain, as well as at the high school level in Australia, Romania, Turkey, Kenya, England, and India. The validation of the ARS in different contexts has provided support for the positive association between academic resilience and achievement (e.g., Khalaf, 2014; Njoki, 2018), as well as identifying a range of protective factors, including extraversion, self-esteem, and family support (e.g., Kapikiran, 2012; Tamannaeifar & Shahmirzaei, 2019). Thus, scales may contribute to the standardisation of academic resilience measures.

However, the current diversity of academic resilience scales does raise questions as to the validity of these measures. Measures derived from the latent construct approach varied in the number and combination of factors used to capture academic resilience. The number of scale-items used to measure the same first-order factors also varied. For example, Chisolm-Burns and colleagues (2019) adapted the ARS-30 (Cassidy, 2015, 2016) to measure academic resilience among pharmacy students. Despite both scales capturing perseverance as a first-order factor, it was measured using three scale-items by Chisolm-Burns et al. (2019) and 14 by Cassidy (2015, 2016). Consequently, it is important that studies employing a latent construct approach conduct appropriate factor analyses to ensure that the measure is valid within the study context.

4. Discussion

This systematic review has demonstrated the range of approaches used to measure academic resilience in the quantitative literature of the last 20 years and the myriad of decisions that researchers make regarding their chosen operationalisation. These decisions ultimately shape the findings they present. This section considers the implications of the variation in approaches to the measurement of academic resilience for the field at the macro-level. The applications of the three main approaches are then discussed at the micro-level, in relation to the study purpose, usability and inclusivity of the measures. The section concludes with consideration to the study limitations and future directions.

4.1. Considering the validity of the different approaches to the measurement of academic resilience

At the macro-level, the lack of cohesion among the three main approaches raises the question as to whether studies purporting to measure academic resilience are really doing so, or whether they are measuring related but distinct phenomena. Direct and indirect measures of academic resilience reflect fundamentally different understandings of what information can be used to infer academic resilience. Indeed, Morales and Trotman (2010), in applying the concept of resilience to the educational domain, noted that achievement was the “logical and implicit end result” (p. 4.). Thus, it is important to consider whether the utilisation of characteristics (e.g., perseverance) to measure academic resilience is an effective approach, especially as the latent construct approach was the most widely used approach.

At-risk students who score highly on characteristics related to academic resilience should also score highly on achievement tests. Arguably, the value in being resilient is the demonstrations of success despite adversity, rather than simply the acquisition of characteristics that purportedly promote academic resilience. Many studies that employed the latent construct approach did not account for achievement or test the association between academic resilience and achievement. Studies that did generally found evidence for the proposed positive association (e.g., Hill, 2017; Mendez & Bauman, 2018), however this was not always the case (e.g., Buslig, 2019; Choo & Prihadi, 2019). Furthermore, when Ricketts (2015) tested whether students' scores on the Academic Resilience in Mathematics Scale differed between resilient and non-resilient groups, measured using the definition-driven approach, they found no statistically significant differences. The findings led Ricketts (2015) to conclude that measuring academic resilience using students' own perceptions of their capacities to be resilient was not congruent with the outcome-based measure of resilience, resulting in the identification of different groups of 'resilient' students and subsequently different findings about academic resilience. Accordingly, in the included studies, the association between measures of academic resilience captured using the latent construct approach and achievement was unclear and hence less compelling as a valid measure of academic resilience.

The validity of the latent construct approach is also undermined by the general absence of risk indicators. Without screening for or simulating a context of acute or chronic adversity capturing resilient characteristics may simply reflect one's learner identity. Furthermore, many unidimensional scale-items arguably captured students' responses to lesser day-to-day setbacks, such as receiving a bad mark (e.g., Martin & Marsh, 2003, 2006). Accordingly, such measures may be capturing academic buoyancy instead. Indeed, the major distinction between the Academic Buoyancy Scale (Martin & Marsh, 2008) and the Academic Risk and Resilience Scale (ARRS; Martin, 2013), was not in the scale items themselves, but the additional adversity screening tool of the ARRS. It was common for studies to address the absence of risk indicators by employing an at-risk sample. This puts the onus on individual researchers to account for risk. Other studies made conclusions about academic resilience without acknowledging the absence of adversity, compromising the representation of academically resilient populations and the conclusions drawn about academic resilience.

4.2. Applications of the three approaches to the measurement of academic resilience

At the micro-level, the variation in measurement approaches offers researchers options when deciding how to operationalise and study academic resilience. These decisions will have a strong influence on the resulting conclusions drawn. Therefore, it is important that researchers both outline and justify their measurement approach. The following sections consider why a researcher may employ each of these approaches in three areas: study purpose, usability and, inclusivity.

4.2.1. The purpose of the study

The focus of the study will help to determine what approach should be employed to measure academic resilience. Arguably, the process-driven approach provides the most comprehensive representation of the resilience process because it captures the dynamic interaction between risk and protective factors. Rather than risk providing the context of adversity, as within the definition-driven and some latent construct approaches, risk is integral to understanding how protective factors enable resilient students to overcome adversity. The inclusion of multiple risk and protective factors within a single statistical model also helps to capture the natural complexities of everyday life. For example, Li (2017) found that in a sample of Chinese school students, low levels of school commitment and high levels of alienation and conflict were negatively associated with achievement (risk factors). However, parental supervision and school involvement and recognition negatively predicted these risk factors, suggesting that protective factors could reduce the degree to which students were vulnerable to academic adversities. Therefore, the process-driven approach, in its concomitant analysis of risk, protective and achievement factors, offers an effective representation of the academic resilience process (Tudor & Spray, 2018), as well as some flexibility in the way that that the resilience process is conceptualised (i.e., the ordering of risk and protective factors).

The definition-driven approach is often employed when there is a specific achievement outcome of interest to researchers because it allows for flexibility in how academic resilience is operationalised. This means that the measure can be developed to be meaningful within the context being explored. Indeed, studies that nominated absolute thresholds of achievement often justified their chosen threshold based on its significance for the at-risk group. For example, Agasisti et al. (2018) explained that their threshold reflected that resilient students had the minimum skills and knowledge to contribute to society. Similarly, Patterson (2012) argued that operationalising resilience as Black students who had been admitted to a prestigious university which had historically low rates of admission among ethnic minority groups offered novel insights about academic resilience. The definition-driven approach, therefore, can facilitate the exploration into the determinants of a meaningful academic outcome.

The latent construct approach captures students' capacities to be resilient in a standalone resilience score, thereby making it possible to investigate both how the collective protective factors of academic resilience can be strengthened, as well as how developing students' capacities to be resilient can subsequently improve student outcomes. However, the utilisation of characteristics as indicators of academic resilience seems to be at odds with the study of protective factors, which is arguably the primary aim of academic resilience research (Morales & Trotman, 2010). The latent construct approach raises the issue as to how researchers should delineate between protective factors and indicators of academic resilience.

Many factors used to measure academic resilience using the latent construct approach were also investigated as protective factors under the other two measurement approaches. In this way it could be argued that within the latent construct approach, measures of academic resilience without considering achievement are simply a collection of protective factors. As a result, these measures may be better employed to understand how to improve the skills and knowledge students require in order to be resilient, as demonstrated by an achievement measure.

4.2.2. The usability of academic resilience measures

The flexibility of the definition-driven approach enables its application to a range of different datasets and to different indicators of risk and competence. The researcher has autonomy as to what data is used to determine how a resilient student is identified and can, therefore, be used to construct a measure of academic resilience that is relevant to the context of interest and sympathetic to the constraints of the dataset being used. Moreover, in its most basic form, the definition-driven approach identifies two groups. Thus, group differences can be explored using *t*-tests or logistic regression analysis to understand how resilient and non-resilient groups differ. Such person-centred analyses provide an accessible introduction to the quantitative study of resilience.

Whereas the flexibility of the definition-driven approach contributes to its level of usability, the stability of existing academic resilience scales promotes accessibility within the latent construct approach. Academic resilience scales provide consistency in the measurement of academic resilience across contexts which reflects an underlying assumption that resilience can be operationalised the same way across different groups of people (Cosco et al., 2016). Utilising a scale that has been validated, especially within a context relevant to the study in question, will provide researchers with confidence that the measure is an effective one and help to produce comparable findings, supporting the consolidation of academic resilience research.

The process-driven approach is arguably the least accessible approach. The researcher must have a strong understanding of the resilience process generally, as well as how the chosen risk and protective factors function to predict the achievement outcome. In addition, the researcher must have a comprehensive knowledge of statistical methods relevant to investigating these relationships and how this will shape the inferences made about academic resilience. The sequential nature of the resilience process implied by the process-driven approach also constrains how it can be applied to resilience research. That is, the requirement to have the risk and protective factors preceding the achievement outcome, to investigate how these variables work to promote academic resilience means that this approach can only be used to identify protective factors, rather than further understandings about how resilience may influence other psychosocial processes. Therefore, the level of content and methodological knowledge required to implement this approach effectively combined with its limited ability to provide diverse insights into academic resilience reduces its level of usability.

4.2.3. The inclusivity of academic resilience measures

Inclusivity refers to who is included and excluded within the study of resilience. This is an important consideration because these decisions directly impact the conclusions drawn about academic resilience. The process-driven approach is the most inclusive approach. Rather than the researcher determining whether a student is resilient or not, the inferences about resilience are made based on the experiences of all students, regardless of whether they are at an increased risk of school failure, or not. Arguably, the inclusion of a greater number of student experiences offers more information from which to better understand the resilience process. This approach also offers a more hopeful outlook by investigating how one can improve their resilience levels. Here, instead of being categorised as resilient or non-resilient, the process-driven approach conceptually enables students to continually develop their levels of academic resilience over time.

The latent construct approach is also highly inclusive. However, the lack of adversity screening means that studies often included students who may not have experienced academic adversity, with some studies making conclusions about resilience without acknowledging the additional barriers that at-risk students must overcome to demonstrate academic resilience. As a result, this inclusivity may compromise the accurate identification of resilient populations, which should be derived from the academic competence of severely disadvantaged groups. Cassidy (2015, 2016) took a novel approach to including an element of risk by presenting students with a vignette which simulated a hypothetical academic adversity. This standardised the risk students were responding to, allowing the levels of academic resilience of students from all backgrounds to be compared, regardless of their true levels of adversity. It could be argued either way that students who have experienced significant academic adversity would score higher on these measures due to a strengthening of protective factors, or lower due to their additional vulnerabilities. However, the absence of real risk indicators within this measure does not allow for these types of insights and may understate the complexity of academic adversity and its impact on achievement.

The definition-driven approach is unique in that it distinguishes between resilient and non-resilient groups. Creating a categorical resilience variable may make this approach the least inclusive. Typically, just two groups (at the extremes of the vulnerability-resilience continuum) are used to draw conclusions about resilience. Therefore, despite the large heterogeneity in student experiences, just a sub-section of an at-risk population is used to make conclusions about academic resilience. Furthermore, while the identification of a non-resilient comparison group is based on a strengths-based framework, the use of this label may add additional barriers for children already at-risk of school failure. The use of the resilience residuals sub-approach may provide a more inclusive definition-driven approach, especially when used to construct a continuous measure. The resilience residuals sub-approach is arguably more sensitive to the heterogeneity in students' experiences, acknowledging that even within an at-risk sample, for example those below the poverty line, students will experience differing levels of financial hardship which may impact their ability to realise their academic potential. Consequently, using the resilience residuals sub-approach may result in the identification of a more accurate and, thus, inclusive sample of resilient students than measures that do not account for risk concomitantly.

Another consideration regarding the inclusivity of resilience measures is the recruitment of samples of students deemed to be at high risk of school failure. Specific samples are often employed to provide the context of adversity in which resilience can be demonstrated within. Yet, the decisions involved in this process require careful consideration. Identifying with a group that is at a heightened statistical risk of underachievement does not innately cause differences in achievement. The causes of underachievement are more complex and multifaceted. For example, disadvantaged students will likely experience additional barriers to achievement, such as stereotype threat (Steele & Aronson, 1995), low teacher expectations (Rubie-Davies et al., 2006), and deficit theorising (Smit, 2012). In particular, the risk associated with identifying with a specific ethnic group is not derived from the ethnicity itself, but rather the related experiences such groups face. Accordingly, the same risk factor may carry different meanings and implications within different contexts. For example, students' experiences of and outcomes related to the educational risks associated with a low-SES background will vary depending on how homogenous the education system is (e.g., the variation in funding and teacher quality across schools) and whether it is centralised, or not (e.g., nationalised curriculum; Broer et al., 2019). Therefore, the interpretation of at-risk samples must be sensitive to the experiences they face, rejecting the sentiment that risk factors are fatalistic, and emphasising the potential of all students to be successful.

4.3. Study limitations and future directions

It is acknowledged that not all studies related to academic resilience may have been captured by the current review as a result of the inconsistent terminology used within the field. Some studies might have followed the approaches outlined in this review without explicitly referencing academic resilience and, therefore, were not captured by the database searches. In addition, the included studies were not subject to quality assessment screenings and, thus, represent a wide spectrum quality of works that spanned the three identified measurement approaches. Finally, the search results were limited to the English language. Thus, measurement approaches may well be different in studies undertaken in other languages.

This review aimed to describe the existing approaches to the measurement and analysis of academic resilience in current quantitative research. Considering the range of datasets and studies reviewed here, future research should investigate how the approaches identified function within a single dataset to facilitate more accurate comparisons. Conducting analyses using these approaches will aid in verifying and demonstrating the inferences made by the current review, contributing to the further refinement of academic resilience as a specific construct.

4.4. Conclusion

This review has identified three distinct approaches to the measurement of academic resilience in quantitative research. These approaches were related to, but distinct from the findings of existing systematic reviews of resilience and academic resilience. The definition-driven approach creates a categorical resilience variable which facilitates the exploration of group differences using person-centred analyses. In contrast, the process-driven approach reflects conceptualisations of resilience as a dynamic process involving the interaction of risk, protective and continuous achievement outcome variables, lending itself to variable-focussed analyses. Lastly, the latent construct approach employs characteristics indicative of a student's capacity to be resilient to create a continuous resilience measure. The approach implemented will depend upon the purpose of the study, as well as the usability and inclusivity of the measure. However, while variation in the approaches to the measurement of academic resilience provide flexibility for researchers, it may also contribute to some of the disparate findings within the field, particularly when measures are derived from indirect measures of resilience or do not capture a context of adversity. Researchers must document the decisions they make regarding their chosen operationalisation and method of analysis and consider how this will shape the conclusions drawn. Such considerations will facilitate ongoing discussions about how to most effectively quantify and analyse academic resilience to further our understandings about resilient student populations and the resilience process within educational settings.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

References marked with asterisks are works that were included in the systematic review.

*Abel, N. R. (2013). *Trait emotional intelligence, perceived discrimination, and academic achievement among African American and Latina/o high school students: A study of academic resilience* [Doctoral dissertation, Minnesota State University]. Butler University Libraries. https://digitalcommons.butler.edu/coe_papers/21

*Agasisti, T., Avvisati, F., Borgonovi, F., & Lombardi, S. (2018). *Academic resilience: What schools and countries do to help disadvantaged students succeed in PISA* (OECD Education Working Papers No. 167). OECD. https://doi.org/10.1787/e22490ac-en

*Alfaro, E. C., Umana-Taylor, A. J., Gonzales-Backen, M. A., Bamaca, M. Y., & Zeiders, K. H. (2009). Latino adolescents' academic success: The role of discrimination, academic motivation and gender. *Journal of Adolescence, 32*(4), 941-962. https://doi.org/10.1016/j.adolescence.2008.08.007

Alva, S. A. (1991). Academic invulnerability among Mexican-American students: The importance of protective resources and appraisals. *Hispanic Journal of Behavioural Sciences, 13*(1), 18-34. https://doi.org/10.1177%2F07399863910131002

*Alvarez, M. J. (2003). *Hispanic pre-adolescents' academic resilience: Examining gender, Hispanicism, and school belonging, as predictors of academic achievement, and relating level of linguistic validation in the school context to school belonging* (Publication No. 3079943) [Doctoral dissertation, University of California]. ProQuest Dissertations and Theses Global.

Anagha, S., & Navyashree, G. C. (2020). Academic resilience among young adults. *Indian Journal of Health and Well-being, 11*(1-3), 79-83. https://doi.org/10.15614/IJHW.v11i01.17

*Anghel, R. A. (2015). Psychological and educational resilience in high vs. low-risk Romanian adolescents. *Procedia – Social and Behavioural Sciences, 203*, 153-157. https://doi.org/10.1016/j.sbspro.2015.08.274

Anthony, E. J. (1974). Introduction: The syndrome of the psychologically vulnerable child. In E. J. Anthony & C. Koupernik (Eds.), *The Child in his Family: Children at Psychiatric Risk* (Vol. 3, pp. 3–10). Wiley.

*Arnold, P. F. (2003). *Characteristics of families and schools that foster academic resilience: Insights gained from the National Longitudinal Study 1988-1994* (Publication No. 3098364) [Doctoral dissertation, Florida State University]. ProQuest Dissertations and Theses Global.

*Atkinson, J. (2018). *Investigating the relationships between family communication patterns, academic resilience, and students' classroom communication behaviours* (Publication No. 10790802) [Doctoral dissertation, West Virginia University]. ProQuest Dissertations and Theses Global.

*Aydin, B. G. (2017). *Examining the factors associated with the likelihood of academic resilience in science and mathematics literacies in PISA 2012* [Unpublished master's thesis]. Bilkent University.

Barzilay, R., Moore, T. T., Greenberg, D. M., DiDomenico, G. E., Brown, L. A., White, L. K., Gur, R. C., & Gur, R. E. (2020). Resilience, COVID-19-related stress, anxiety and depression during the pandemic in a large population enriched for healthcare providers. *Translational Psychiatry, 10*(291). https://doi.org/10.1038/s41398-020-00982-4

*Bell, J. (2010). *Educational resilience in primary school children in South Australia: An investigation* [Unpublished doctoral dissertation]. University of Adelaide.

Borman, G. D., & Overman, L. T. (2004). Academic resilience in mathematics among poor and minority students. *The Elementary School Journal, 104*(3), 177-195. https://doi.org/10.1086/499748

*Borman, G. D., & Rachuba, L. T. (2000, April). *The characteristics of schools and classrooms attended by successful minority students* [Paper presentation]. Annual meeting of the American Educational Research Association, New Orleans, LA.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-10. http://dx.doi.org/10.1191/1478088706qp063oa

Braun, V., & Clarke, V. (2020). One size fits all? What counts as quality practice in (reflexive) thematic analysis? *Qualitative Research in Psychology*. https://doi.org/10.1080/14780887.2020.1769238

Broer, M., Bai, Y., & Foncesca, F. (2019). *Socioeconomic inequality and educational outcomes: Evidence from twenty years of TIMSS* (Vol. 5). Springer, Cham. https://doi.org/10.1007/978-3-030-11991-1_2

*Brooks, J. E. (2010). *School Characteristics Associated with the Educational Resilience of Low-Income and Ethnic Minority Youth* [Unpublished doctoral dissertation]. The University of Texas.

*Browder, C. T. (2014). *English learners with limited or interrupted formal education: Risk and resilience in educational outcomes* (Publication No. 3637307) [Doctoral dissertation, University of Maryland]. ProQuest Dissertations and Theses Global.

*Brule, H. A. (2015). *Developmental Perspectives on Motivational Resilience: Predictors of Eighth-grade At-risk Students' Academic Engagement and Achievement* (Publication No. 2113) [Master's thesis, Portland State University]. PDXScholar. https://doi.org/10.15760/etd.2111

*Buathong, P. (2019). *The effect of a growth mindset intervention on underprivileged students' English intelligence mindset and academic resilience with perceived teacher support as a moderator* [Unpublished master's thesis]. Chilalongkorn University.

*Buslig, S. M. C. A. (2019). The academic resilience of college students in Kalinga. *International Journal of Humanities and Social Science, 9*(6), 50-63. http://dx.doi.org/10.30845/ijhss.v9n6p7

*Calo, M., Peiris, C., Chipchase, L., Blackstock, F., & Judd, B. (2019). Grit, resilience and mindset in health students. *The Clinical Teacher, 16*(4), 317-322. https://doi.org/10.1111/tct.13056

*Cappella, E., & Weinstein, R. S. (2001). Turning around reading achievement: Predictors of high school students' academic resilience. *Journal of Educational Psychology, 93*(4), 758-771. https://doi.org/10.1037/0022-0663.93.4.758

*Carlson, D. J. (2001). *Development and validation of a college resilience questionnaire* (Publication No. 3016308) [Doctoral dissertation, University of Nebraska]. ProQuest Dissertations and Theses Global.

*Cassidy, S. (2015). Resilience building in students: The role of academic self-efficacy. *Frontiers in Psychology, 6*, 1-14. https://doi.org/10.3389/fpsyg.2015.01781

*Cassidy, S. (2016). The Academic Resilience Scale (ARS-30): A new multidimensional construct measure. *Frontiers in Psychology, 7*, 1-11. https://doi.org/10.3389/fpsyg.2016.01787

*Cheung, K. (2017). The effects of resilience in learning variables on mathematical literacy performance: A study of learning characteristics of the academic resilient and advantaged low achievers in Shanghai, Singapore, Hong Kong, Taiwan and Korea. *Educational Psychology, 37*(8), 965-982. https://doi.org/10.1080/01443410.2016.1194372

*Cheung, K., Sit, P., Soh, K., Ieong, M., & Mak, S. (2014). Predicting academic resilience with reading engagement and demographic variables: Comparing Shanghai, Hong Kong, Korea, and Singapore from the PISA perspective. *The Asia-Pacific Education Researcher, 23*(4), 895-909. https://doi.org/10.1007/s40299-013-0143-4

*Chisolm-Burns, M. A., Spivey, C. A., Sherwins, E., Williams, J., & Phelps, S. (2019). Development of an instrument to measure academic resilience among pharmacy students. *American Journal of Pharmaceutical Education, 83*(6), 1373-1390. https://doi.org/10.5688/ajpe6896

*Choi, Y. (2019). *Pathways of academic resilience: Exploring the multiple developmental trajectories of low-income students during early education* (Publication No. 22621872) [Doctoral dissertation, University of Wisconsin-Madison]. ProQuest Dissertations and Theses Global.

*Choo, O. Z. H., & Prihadi, K. (2019). Academic resilience as a mediator of multidimensional perfectionism and academic performance among gen-Z undergraduate students. *International Journal of Evaluation and Research in Education, 8*(4), 637-646. http://doi.org/10.11591/ijere.v8i4.20340

*Colp, S. M. (2015). *Examining academic resilience as a mediator of post-secondary achievement and retention* [Unpublished doctoral dissertation]. University of Calgary. http://dx.doi.org/10.11575/PRISM/26012

Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). *Depression and Anxiety, 18*(2), 76-82. https://doi.org/10.1002/da.10113

Cosco, T. D., Kaushal, A., Hardy, R., Richards, M., Kuh, D., & Stafford, M. (2016). Operationalising resilience in longitudinal studies: A systematic review of methodological approaches. *Theory and Methods, 71*(1), 98-104. http://dx.doi.org/10.1136/jech-2015-206980

*Crosnoe, R., & Elder, G. H. Jr. (2004). Family dynamics, supportive relationships, and educational resilience during adolescence. *Journal of Family Issues, 25*(5), 571-602. https://doi.org/10.1177%2F0192513X03258307

*Cunningham, M., & Swanson, D. P. (2010). Educational resilience in African American adolescents. *The Journal of Negro Education, 79*(4), 473-487. https://www.jstor.org/stable/41341090

*Cutuli, J. J., DesJardins, C. D., Herbes, J. E., Long, J. D., Heistad, D., Chan, C., Hinz, E., & Masten, A. S. (2013). Academic achievement trajectories of homeless and highly mobile students: Resilience in the context of chronic and acute risk. *Child Development, 84*(3), 841-857. https://doi.org/10.1111/cdev.12013

*Das, D. (2019). Academic resilience among children from disadvantaged groups in India. *Social Indicators Research, 145*(2), 719-739. https://doi.org/10.1007/s11205-018-1899-y

*de Carvalho, E., & Skipper, Y. (2020). A two-component growth mindset intervention for young people with SEND. *Journal of Research in Special Education Needs, 20*(3), 195-205. https://doi.org/10.1111/1471-3802.12472

*de la Torre, A. (2004). *Academic resilience and perceptions of risks* (Publication No. 3155399) [Doctoral dissertation, University of Southern California]. ProQuest Dissertations and Theses Global.

*Dever, B. V. (2009). *Intersections of education and resilience: How contexts operate in the protection of at-risk adolescents* [Unpublished doctoral dissertation]. University of Michigan.

*Erberer, E., Stephens, M., Mamedovam S., Ferguson, S., & Kroeger, T. (2015). *Socioeconomically disadvantaged students who are academically successful: Examining academic resilience cross-nationally* (IEA's Policy Brief Series, No. 5). The International Association for the Evaluation of Educational Achievement. http://www.iea.nl/policy_briefs.html

*Fallon, C. M. (2010). *School factors that promote academic resilience in urban Latino high school students* (Publication No. 3419908) [Doctoral dissertation, Loyola University]. ProQuest Dissertations and Theses Global.

*Fang, G., Chan, P. W. K., & Kalogeropoulos, P. (2020). Social support and academic achievement of Chinese low-income children: A mediation effect of academic resilience. *International Journal of Psychological Research, 13*(1), 19-28. https://doi.org/10.21500/20112084.4480

*Fauziah, Wiyono, B. B., Triyono, & Lasan, B. B. (2020). The effect of authoritative parenting on the formation of student academic resilience. *International Journal of Innovation, Creativity and Change, 13*(7), 1027-1037. http://www.ijicc.net/

*Flannigan, A. E. (2017). *Thriving in a broken system: An ecological investigation of academic achievement and resilience in foster youth* [Unpublished doctoral dissertation]. University of Texas.

*Foshee, C. M. (2013). *Conditions that promote the academic performance of college students in a remedial mathematics course: Academic competence, academic resilience, and the learning environment* [Unpublished doctoral dissertation]. Arizona State University.

*Frisby, B. N., Hosek, A. M., & Beck, A. C. (2020). The role of classroom relationships as sources of academic resilience and hope. *Communication Quarterly, 68*(3), 289-305. https://doi.org/10.1080/01463373.2020.1779099

*García-Crespo, F., Galián, B., Fernández-Alonso, R., & Muñiz, J. (2019). Educational Resilience in Reading Comprehension: Determinant factors in PIRLS-Europe. *Revista de Educación, 384* (April-June), 65-89. http://dx.doi.org/10.4438/1988-592X-RE-2019-384-413

*Gizir, C. A., & Aydin, G. (2009). Protective factors contributing to the academic resilience of students living in poverty in Turkey. *Professional School Counseling, 13*(1), 38-49. https://doi.org/10.1177%2F2156759X0901300103

*Gonzalez, V. (2013). *Taking a leap to close the gap: Early academic success of low-income Latino/a children facing multiple risks* (Publication No. 3602075) [Doctoral dissertation, University of California]. ProQuest Dissertations and Theses Global.

*Harpalani, V. (2005). *Racial stereotypes and achievement-linked identity formation during adolescence: An investigation of athletic investment and academic resilience* (Publication No. 3179744) [Doctoral dissertation, University of Pennsylvania]. ProQuest Dissertations and Theses Global.

*Hawkins, R., & Mulkey, L. (2005). Athletic investment and academic resilience in a national sample of African American females and males in the middle grades. *Education and Urban Society, 38*(1), 62-88. https://doi.org/10.1177%2F0013124505280025

*He, Z. (2014). *Examining the academic resilience in mathematics performance for the underprivileged ninth graders using the national data from the High School Longitudinal Study (HSLS:09)* [Unpublished doctoral dissertation]. Texas Tech University.

*Hill, C. (2017). *The influence of home environmental factors, socio-emotional factors and academic resilience on reading achievement* [Unpublished doctoral dissertation]. Montana State University.

*Hofmeyr, H. (2019). *Performance Beyond Expectations: Academic Resilience in South Africa* (Stellenbosch Economic Working Papers: WP19/2019). University of Stellenbosch. www.ekon.sun.ac.za/wpapers/2019/wp192019

*Howell, J. A., Roberts, L. D., & Mancini, V. O. (2018). Learning analytics messages: Impact of grade, sender, comparative information and message style on student affect and academic resilience. *Computers in Human Behaviour, 89*(1), 8-15. https://doi.org/10.1016/j.chb.2018.07.021

*Irfan Arif, M., & Mirza, M. S. (2017). Effectiveness of an intervention program in fostering academic resilience of students at risk of failure at secondary school level. *Bulletin of Education and Research, 39*(1), 251-264.

*Jaramillo, J. (2020). *Youth-caseworker relationships and academic resilience of youth in foster care* [Unpublished doctoral dissertation]. Oregon State University.

*Kanevsky, L., Corke, M., & Frangkiser, L. (2008). The academic resilience and psychosocial characteristics of inner-city English learners in a museum-based school program. *Education and Urban Society, 40*(4), 452-475. https://doi.org/10.1177%2F0013124507304693

*Kang, Y., Smith, M., Ozge, E., & Rodriguez, M.C. (2018, April). *A pathway to resilience for students who experience trauma: A structural equation modeling approach* [Paper presentation]. The annual meeting of the American Educational Research Association, New York, NY.

*Kapikiran, S. (2012). Validity and reliability of the Academic Resilience Scale in Turkish high school. *Education, 132*(3), 474-483.

*Karabıyık, C. (2020). Interaction between academic resilience and academic achievement of teacher trainees. *International Online Journal of Education and Teaching, 7*(4), 1585-1601. http://iojet.org/index.php/IOJET/article/view/1032

*Kaur, S. (2017). *Academic resilience among senior secondary students: Influence of metacognition, self efficacy and learning environment* [Unpublished doctoral dissertation]. Lovely Professional University.

*Khalaf, M. A. (2014). Validity and reliability of the Academic Resilience Scale in Egyptian Context. *US-China Education Review, 4*(3), 202-210.

*Kherikhah, A. (2020). Investigating the effect of social skills training on happiness, academic resilience and self-efficacy of girl students. *Archives of Pharmacy Practice, 11*(S1), 157-164.

*Kimball, E. P. (2007). *What is the impact of a ninth grade academy transition program in building resiliency in first year freshman?* [Unpublished doctoral dissertation]. University of North Carolina.

Kingdon, G., & Cassen, R. (2010). Ethnicity and low achievement in English schools. *British Educational Research Journal, 36*(3), 403-431. https://doi.org/10.1080/01411920902989185

*Kong, K. (2020). Academic resilience of pupils from low socioeconomic backgrounds. *The Journal of Behavioural Science, 15*(2), 70-89. https://so06.tcithaijo.org/index.php/IJBS/article/view/239864

*Lanuza, M. H., Rizal, R. A. G., Aligam, N. P., & Uy, R. (2020). Contextualize program of strengthening academic resilience level of the secondary education students. *Journal of Critical Reviews, 7*(11), 286-292. http://dx.doi.org/10.31838/jcr.07.11.46

*Lawrence, S. D. (2010). *Closing the achievement gap: Factors that promote academic resilience in high school foster youth* [Unpublished doctoral dissertation]. California State University.

*Lewis, M. K. III. (2003). *Differences in emotional intelligence and related constructs among academically resilient and academically nonresilient African American undergraduate students* (Publication No. 3100454) [Doctoral dissertation, Michigan State University]. ProQuest Dissertations and Theses Global.

*Li, H. (2017). The 'secrets' of Chinese students' academic success: Academic resilience among students from highly competitive academic environments. *Educational Psychology, 37*(8), 1001-1014. https://doi.org/10.1080/01443410.2017.1322179

*Li, H., & Yeung, W. J. (2019). Academic resilience in rural Chinese children: Individual and contextual influences. *Social Indicators Research, 145*(2), 703-717. https://doi.org/10.1007/s11205-017-1757-3

*Li, C. C., Li, S. M., & Wei, C. F. (2019). The development and validation of academic resilience scale for undergraduate in Taiwan: Rasch analysis. *Advances in Social Science, Education and Humanities Research, 369*(1), 205-208. https://dx.doi.org/10.2991/ichess-19.2019.41

*Liu, B., & Platow, M. J. (2020). Chinese adolescents' belief in a just world and academic resilience: The mediating role of perceived academic competence. *School Psychology International, 41*(3), 239-256. https://doi.org/10.1177%2F0143034320908001

Luthar, S., Cicchetti, D., & Becker, B. (2000). The Construct of Resilience: A Critical Evaluation and Guidelines for Future Work. *Child Development, 71*(3), 543-562. https://doi.org/10.1111/1467-8624.00164

*Maier, M. F., Vitiello, V. E., & Greenfield, D. B. (2012). A multilevel model of child- and classroom-level psychosocial factors that support language and literacy resilience of children in Head Start. *Early Childhood Research Quarterly, 27*(1), 104-114. https://doi.org/10.1016/j.ecresq.2011.06.002

*Mamphane, R., & Huddle, C. (2017). Assessing the outcomes of school-based partnership resilience intervention. *South African Journal of Education, 37*(1), 1-13. https://doi.org/10.15700/saje.v37n1a1412

*Martin, M. (2012). *Situated academic engagement for immigrant origin males: Student centred studies of the relationship between sources of academic stress/support, academic engagement, and academic outcomes* (Publication No. 3511442) [Doctoral dissertation, New York University]. ProQuest Dissertations and Theses Global.

*Martin, A. J. (2013). Academic buoyancy and academic resilience: Exploring 'everyday' and 'classic' resilience in the face of academic adversity. *School Psychology International, 34*(5), 488-500. https://doi.org/10.1177%2F0143034312472759

*Martin, A. J., & Marsh, H. W. (2003, November). *Academic resilience and the four Cs: Confidence, control, composure, and commitment* [Paper presentation]. NZARE AARE, Auckland, New Zealand.

*Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational correlates: A construct validity approach. *Psychology in the Schools, 46*(1), 53-83. https://doi.org/10.1002/pits.20149

Martin, A. J., & Marsh, H. W. (2008). Academic buoyancy: Towards an understanding of students' everyday academic resilience. *Journal of School Psychology, 43*(3), 267-281. https://doi.org/10.1016/j.jsp.2007.01.002

*Mbindyo, M. N. (2011). *Relationship between academic resilience and college success: Cross-national experiences of low-income/first-generation students* [Unpublished doctoral dissertation]. Pennsylvania State University.

McGubbin, L. (2001). *Challenges to the definition of resilience* [Paper presentation]. The Annual Meeting of the American Psychological Association, San Francisco, CA.

*Mendez, J. J., & Bauman, S. (2018). The migrant farmworkers to first generation Latina/o students: Factors predicting college outcomes for students participating in the College Assistance Migrant Program. *The Review of Higher Education, 42*(1), 173-208. https://doi.org/10.1353/rhe.2018.0037

*Meneghal, I., Martínez, I. M., Salanova, M., & de Witte, H. (2019). Promoting academic satisfaction and performance: Building academic resilience through coping strategies. *Psychology in the Schools, 56*(6), 875-890. https://doi.org/10.1002/pits.22253

Min, J., Yoon, S., Lee, C., Char, J., Lee, C., Song, K., & Kim, T. (2013). Psychological resilience contributes to low emotional distress in cancer patients. *Supportive Care in Cancer, 21*(9), 2469-2476. https://doi.org/10.1007/s00520-013-1807-6

Moher, D., Liberati, A., Tetzlaff, J., Alteman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Med, 6*(7). https://doi.org/10.1371/journal.pmed.1000097

Morales, E. E., & Trotman, F. K. (2010). *A focus on hope: Fifty resilient students speak*. University Press of America, Inc.

*Murray, N. L. (2018). *Examining academic resilience factors among African American high school students* (Publication No. 73) [Doctoral dissertation, University of Kentucky]. UKnowledge. https://doi.org/10.13023/etd.2018.244

*Nauman, C. (2019). *Adolescent academic resilience: Teacher-child interactions as a buffer for negative mother-child relationships in early childhood* [Unpublished master's thesis]. Texas State University.

*Niemeyer, A. E. (2010). *The effects of parental involvement and Familismo on resilience in Hispanic adolescents* (Publication No. 3391712) [Doctoral dissertation, Idaho State University]. ProQuest Dissertations and Theses Global.

*Njoki, G. P. (2018). *Academic self-concept, motivation and resilience as predictor of mathematics achievement among secondary school students in Nairobi County, Kenya* [Unpublished doctoral dissertation]. Kenyatta University.

*Obradović, J., Long, J. D., Cutuli, J. J., Chan, C., Hinz, E., Heidstad, D., & Masten, A. S. (2009). Academic achievement of homeless and highly mobile children in an urbam school district: Longitudinal evidence on risk, growth and resilience. *Development and Psychopathology, 21*(2), 493-518. https://doi.org/10.1017/S0954579409000273

*Paat, Y. (2015). Children of Mexican immigrants' aspiration-attainment gap and educational resilience. *Diaspora, Indigenous, and Minority Education, 9*(1), 37-53. https://doi.org/10.1080/15595692.2014.980804

*Patterson, J. K. (2012). *The road to the top: How educationally resilient Black student defied the odds and earned admission to a selective university* (Doctoral dissertation, University of California). UCLA Electronic Theses and Dissertations. https://escholarship.org/

*Peck, S. C., Roeser, R. W., Zarrett, N., & Eccles, J. E. (2008). Exploring the roles of extracurricular quantity and quality in the educational resilience of vulnerable adolescents: Variable- and pattern-centred approaches. *Journal of Social Issues, 64*(1), 135-155. http://dx.doi.org/10.1111/j.1540-4560.2008.00552.x

*Perez, W., Espinoza, R., Ramos, K., Coronado, H. M., & Cortes, R. (2009). Academic resilience among undocumented Latino students. *Hispanic Journal of Behavioural Sciences, 31*(2), 149-181. https://doi.org/10.1177%2F0739986309333020

*Perkins, R. (2018). *A study of academic resilience among children at risk of poverty in Ireland* [Unpublished doctoral dissertation]. Dublin City University.

*Pettit, K. M. (2016). *Resilience to poverty in children's social-emotional and academic development* [Unpublished master's thesis]. The University of Texas.

*Plunkett, S. W., Henry, C. S., Houltberg, B. J., Sands, T., & Abarca-Mortensen. (2008). Academic support by significant others and educational resilience in Mexican-origin ninth grade students from intact families. *Journal of Early Adolescence, 38*(3), 333-355. https://doi.org/10.1177%2F0272431608314660

Poole, J. C., Dobson, K. S., & Pusch, D. (2017). Childhood adversity and adult depression: The protective role of psychological resilience. *Child Abuse & Neglect, 64*, 89-100. http://dx.doi.org/10.1016/j.chiabu.2016.12.012

*Powers, T. V. (2004). *The relationship among protective factors, volition, and academic resilience in chronically-ill adolescents* (Publication No. 3111121) [Doctoral dissertation, University of Washington]. ProQuest Dissertations and Theses Global.

*Rajan, S. K., Harifa, P. R., & Pienyu, R. (2017). Academic resilience, locus of control, academic engagement and self-efficacy among the school children. *Indian Journal of Positive psychology, 8*(4), 507-511.

*Ramezanpour, A., Kouroshnia, M., Mehryar, A., & Javidi, H. (2019). Psychometric evaluation of the Academic Resilience Scale (ARS-30) in Iran. *Iranian Evolutionary and Educational Psychology Journal, 1*(3), 144-150. http://ieepj.hormozgan.ac.ir/article-1-88-en.html

*Rapone, M. G. (2018). *Growing academic resilience in students of science through mimicry of forest resilience* [Unpublished master's thesis]. Montana State University.

*Reed-Hendon, C. Y. (2013). *Mentoring and academic resilience: Academic progress in a predominantly white institution as a historically marginalized student* (Publication No. 10586576) [Doctoral dissertation, Oakland University]. ProQuest Dissertations and Theses Global.

*Ricketts, S. (2015). *Academic resilience in mathematics* (Publication No. 3736854) [Doctoral dissertation, Emory University]. ProQuest Dissertations and Theses Global.

*Ricketts, S., Engelhard Jr., G., & Chang, M. (2017). Development and validation of a scale to measure academic resilience in mathematics. *European Journal of Psychological Assessment, 33*(2), 79-86. https://doi.org/10.1027/1015-5759/a000274

*Roberts, A. N. (2012). *The impact of being afforded a college education on posttraumatic growth, trauma resilience and academic resilience in individuals exposed to trauma* (Publication No. 3517881) [Doctoral dissertation, Spalding University]. ProQuest Dissertations and Theses Global.

*Rosen, J. A., Warkentien, S., & Rotermund, S. (2019). Stopping out versus dropping out: The role of educational resilience in explaining on-time completion of high school. *American Journal of Education, 125*(2), 259-287. https://doi.org/10.1086/701248

Rubie-Davies, C., Hattie, J., & Hamilton, R. (2006). Expecting the best for students: Teacher expectations and academic outcomes. *British Journal of Educational Psychology, 76*(3), 429-444. https://doi.org/10.1348/000709905X53589

Rutter, M. (2012). Resilience as a dynamic concept. *Development and Psychopathology, 24*(2), 335-344. https://doi.org/10.1017/S0954579412000028

*Sacker, A., & Schoon, I. (2007). Educational resilience in later life: Resources and assets in adolescence and return to education after leaving school and age 16. *Social Science Research, 36*(3), 873-892. https://doi.org/10.1016/j.ssresearch.2006.06.002

*Salvo-Garrido, S., Vargas, H. M., Urra, O. V., Gálvez-Nieto, J., & Miranda-Zapata, E. (2019). Students with socioeconomic disadvantages who have academic success in language: Examining academic resilience in South America. *PrePrints*. http://dx.doi.org/10.20944/preprints201912.0043.v1

*Samuels, W. E. (2004). *Development of a non-intellective measure of academic success: Towards the quantification of resilience* (Publication No. 3159861) [Doctoral dissertation, University of Texas]. ProQuest Dissertations and Theses Global.

*Sandoval-Hernández, A., & Bialowolski, P. (2016). Factors and conditions prompting academic resilience: A TIMSS-based analysis of five Asian education systems. *Asia Pacific Education Review, 17*(3), 511-520. https://doi.org/10.1007/s12564-016-9447-4

*Sandoval-Hernández, A., & Cortes, D. (2012, April). Factors and Conditions that Promote Academic Resilience: A Cross-Country Perspective [Paper presentation]. The Comparative and International Education Society, San Juan, Puerto Rico.

*Sapio, M. (2010). *Mastery goal orientation, hope, and effort among students with learning disabilities* (Publication No. 3420963) [Doctoral dissertation, Fordham University]. ProQuest Dissertations and Theses Global.

*Schelble, J. L., Franks, B. A., & Miller, M. D. (2010). Emotion dysregulation and academic resilience in maltreated children. *Child & Youth Care Forum, 39*(1), 289-303. https://doi.org/10.1007/s10566-010-9105-7

*Schleicher, A. (2019). PISA 2018: Insights and Interpretations. OECD. https://www.oecd.org/pisa/publications/pisa-2018-results.htm

*Schultz-León, J. T. (2013). *Gender and family factors as predictors of academic motivation and resilience among Latino students* (Publication No. 3550993) [Doctoral dissertation, Fordham University]. ProQuest Dissertations and Theses Global.

*Searle, A. K. (2011). *Predictors of children's classroom engagement and educational resilience across the preschool-school transition* [Unpublished doctoral dissertation]. University of Adelaide.

*Seçer, İ., & Ulaş, S. (2020). The mediating role of academic resilience in the relationship of anxiety sensitivity, social and adaptive functioning, and school refusal with school attachment in high school students. *Frontiers in Psychology, 11*, 1-12. https://doi.org/10.3389/fpsyg.2020.00557

*Skokut, M. A. (2009). *Educational resilience among English Language Learners: Examining factors associated with high school completion and post-secondary school attendance* (Publication No. 3375561) [Doctoral dissertation, University of California]. ProQuest Dissertations and Theses Global.

Smit, R. (2012). Towards a clearer understanding of student disadvantage in higher education: Problematising deficit thinking. *Higher Education Research and Development, 31*(3), 369-380. https://doi.org/10.1080/07294360.2011.634383

*Staylor, M. (2019). *Academic resilience and persistence among community college students* (Publication No. 13862298) [Doctoral dissertation, Claremont Graduate University]. ProQuest Dissertations and Theses Global.

Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology, 69*(5), 797-811. https://psycnet.apa.org/doi/10.1037/0022-3514.69.5.797

Strand, S. (2014). Ethnicity, gender, social class and achievement gaps at age 16: Intersectionality and 'getting it' for the white working class. *Research Papers in Education, 29*(2), 131-171. https://doi.org/10.1080/02671522.2013.767370

*Strolin-Goltzman, J., Woodhouse, V., Suter, J., & Werrbach, M. (2016). A mixed method study on educational well-being and resilience among youth in foster care. *Children and Youth Services Review, 70*, 30-36. http://dx.doi.org/10.1016/j.childyouth.2016.08.014

*Sturtevant, J. A. (2014). *Protective factors predicting academic resilience in adolescent at-risk students* [Unpublished master's thesis]. California State University.

*Tamannaeifar, M., & Shahmirzaei, S. (2019). Prediction of academic resilience based on coping styles and personality traits. *Journal of Practice in Clinical Psychology, 7*(1), 1-10. http://dx.doi.org/10.32598/jpcp.7.1.1

*Toprak Çelen, E. T. (2020). *A structural equation model on EFL tertiary level students' academic buoyancy, academic resilience, reconceptualized L2 motivational self system, and their academic achievement* [Unpublished master's thesis]. Bilkent University.

Torsney, B. M., & Symonds, J. E. (2019). The professional student program for educational resilience: Enhancing momentary engagement in classwork. *The Journal of Educational Research, 112*(6), 676-692. https://doi.org/10.1080/00220671.2019.1687414

*Trigueros, R., Magaz-González, García-Tascón, M., Alias, A., & Aguilar-Parra. (2020). Validation and adaption of the academic-resilience scale in the Spanish Context. *International Journal of Environmental Research and Public Health, 17*(11), 1-11. https://doi.org/10.3390/ijerph17113779

Tudor, K. E., & Spray, C. M. (2018). Approaches to measuring academic resilience: A systematic review. *International Journal of Research Studies in Education, 7*(4), 41-61. https://doi.org/10.5861/ijrse.2017.1880

*Vargas-Reighly, R. V. (2001). *The relationship between bicultural competence and academic resilience in a cross-cultural sample* (Publication No. 3019058) [Doctoral dissertation, University of California]. ProQuest Dissertations and Theses Global.

*Victor-Aigboidion, V., Onyishi, C. N., & Ngwoke, D. U. (2020). Predictive power of academic self-efficacy on academic resilience among secondary school students. *The Educational Psychologist, 12*(1), 294-306.

*Vincent, E. C. (2007). *Gender differences in protective factors associated with educational, emotional and dual domain resilience* (Publication No. 3274246) [Doctoral dissertation, Indiana University]. ProQuest Dissertations and Theses Global.

*Von Secker, C. (2004). Science achievement in social contexts: Analysis from National Assessment of Educational Process. *The Journal of Educational Research, 98*(2), 67-78. https://doi.org/10.3200/JOER.98.2.67-78

Wang, M. C., Haertel, G. D., & Walberg, H. J. (1994). Educational resilience in inner cities. In M. C. Wang & E. W. Gordon (Eds.), *Educational Resilience in Inner-City America: Challenges and Prospects* (pp. 45-72). Erlbaum.

*Waxman, H. C., Rivera, H., & Powers, R. (2012). English learners' educational resilience and classroom learning environment. *Educational Research Quarterly, 35*(4), 53-72.

*Wayman, J. C. (2000). *Educational resilience in dropouts who return to gain high school degrees* (Publication No. 9981374) [Doctoral dissertation, Colorado State University]. ProQuest Dissertations and Theses Global.

*White, S. M. (2013). *Resilience differences on Black Greek-lettered organization members and African-American students at predominantly White institutions* [Unpublished doctoral dissertation]. East Carolina University.

*Whitmore, A. C. (2017). *Finishing the race: Examining the relationships between various forms of support and the psychological and academic outcomes of African American college students* (Publication No. 10623747) [Doctoral dissertation, University of La Verne]. ProQuest Dissertations and Theses Global.

*Wills, G., & Hofmeyr, H. (2019). Academic resilience in challenging contexts: Evidence from township and rural primary schools in South Africa. *International Journal of Educational Research, 98*, 192-205. https://doi.org/10.1016/j.ijer.2019.08.001

*Yavuz, H. Ç., & Kutlu, Ö. (2016). Investigation of the factors affecting the academic resilience of economically disadvantaged high school students. *Education and Science, 41*(186), 1-19. http://dx.doi.org/10.15390/EB.2016.5497

*Zhao, G., Li, X., Fang, X., Zhao, J., Hong, Y., Lin, X., & Stanton, B. (2011). Functions and sources of perceived social support among children affected by HIV/AIDS in China. *AIDS Care*, *23*(6), 671-679. https://doi.org/10.1080/09540121.2010.525619

*Zulfikar, Z., Hidayah, N., Triyono, T., & Hitipeuw, İ. (2020). Development study of academic resilience scale for gifted young scientists education. *Journal for the Education of Gifted Young Scientists, 8*(1), 343-358. https://doi.org/10.17478/jegys.664116

Appendix

Table A1

Studies using a Definition-Driven Approach (n = 40)

Author(s) (Year)	Country	Sample	Risk indicator	Achievement indicator	Analysis
High-risk and high achieving group membership					
Agasisti et al. (2018)	International (PISA)	Approximately 2 million 15-year old students	Lowest 25% SES	Achieve at or above Level 3 in reading, mathematics, and science	DV in multilevel logistic regression analysis
Arnold (2003)	USA (NELS:88)	5,014 high school students	Lowest 25% SES	High school completion	DV in logistic regression analysis
Aydin (2017)	Turkey (PISA)	1,200 15-year old students	Lowest 25% SES	Achieve above average in mathematics and science	DV in CHAID analysis
Brooks (2010)	USA (ELS:2002)	11,360 high school students	Lowest 25% SES, African American students, Hispanic students, students from non-traditional families, students who have been retained in school, students whose first language is not English, and students with a disability	High school graduation	DV in hierarchical generalised linear regression analysis
Brule (2015)	USA	322 Gr. 6 and Gr. 8 students	Low-SES students, ethnically diverse students, and English learners	GPA above 3.60	IV in MANOVA, MANCOVA, and ANCOVA
Cappella & Weinstein (2001)	USA (NELS: 88)	1,362 high school students	Gr. 8 reading achievement at Level 0	Gr. 12 reading achievement at Level 2 or 3	DV in simultaneous multiple regression analysis
Choi (2019)	USA (ECLS-K:1998)	2,234 Gr. 3 students	Students from households below 200% of the poverty threshold	Moderately- and high-performing students in mathematics	DV in multinomial logistic regression analysis
Cutuli et al. (2013)	USA	52,975 Gr. 3 to Gr. 8 students	Homeless and highly mobile students	Scoring within or above 1 SD below the mean of the national reading or mathematics achievement norms	IV in descriptive statistics
de la Torre (2004)	USA	114 Gr. 11 students	Low-SES students, Latinx students, students whose parents speak little	Medium and high levels of academic functioning	DV in stepwise multiple regression analysis

			English, students who parents have less than a high school education, and students who live in a low resource and possibly dangerous community		
Erberer et al. (2015)	International (TIMSS)	Approximately 150,000 Gr. 8 students	Few resources category of the Home Educational Resources Index	Intermediate benchmark in mathematics	DV in logistic regression analysis
Jaramillo (2020)	USA	293 high school students	Foster youth	High school completion	DV in linear probability analysis
Kimball (2007)	USA	1,133 Gr. 10 students	Gr. 9 transition period	Promotion to Gr. 10	DV in Pearson’s chi square tests
Lewis (2003)	USA	129 undergraduate students	African American students	GPA 3.0 or above	IV in independent samples *t*-tests
Li & Yeung (2019)	China	1,212 10- to 15-year old students	Rural students	Cognitive test score 1 SD or above full sample mean	IV in ANOVA
Murray (2018)	USA (ELS:2002)	2,020 Gr. 10 students	Black, African American, and non-Hispanic students	Achieving above the 50th percentile of the combined reading and mathematics score of the full sample	DV in hierarchical linear regression analysis
Obradović et al. (2009)	USA	14,754 Gr. 2 to Gr. 5 students	Homeless and highly mobile students	Reading or mathematics achievement 1 SD below the national mean or higher	IV in descriptive statistics
Patterson (2012)	USA	16,731 Gr. 11 and undergraduate students	Black students	Admission to UCLA	IV in independent samples *t*-tests
Peck et al. (2008)	USA	1,060 high school students	Negative lifespace configuration	College attendance	DV in cluster analysis and hierarchical logistic regression analysis
Perkins (2018)	Ireland	8,568 9- and 13-year old students	Students whose families have access to a medical card	Scores on tests of literacy and numeracy are at least 0.5 SD above mean performance	DV in logistic regression analysis and structural equation modelling
Pettit (2016)	USA (ECLS-B)	2,050 kindergarten students	185% income-to-needs ratio	0.5 SD above children whose families are not in poverty in literacy or mathematics; 0.5 SD above other disadvantaged children in literacy or mathematics	DV in multinomial logistic regression analysis

Ricketts (2015)	USA	528 Gr. 7 and Gr. 8 students	Eligible for free or reduced-priced lunch	Met or exceeded the standards of a standardised mathematics assessment	IV in Many-Facet modelling and independent samples *t*-tests
Rosen et al. (2019)	USA (HSLS:09)	2,320 high school students	Experiencing a dropout episode during high school	High school completion	DV in logistic regression analysis and multinomial regression analysis
Sacker & Schoon (2007)	Britain	12,940 students 16-years old and above	Students left continuous full-time education at 16-years old	Return to full-time education	DV in logistic regression analysis
Salvo-Garrido et al. (2019)	Chile	324,525 Gr. 4 students	Low-SES students	Academic performance exceeded the cut-off score in Language test	DV in multilevel logistic regression analysis
Sandoval-Hernández & Bialowolski (2016)	Asia (TIMSS)	23,354 Gr. 8 students	Few resources on the Home Educational Resources index	At or above the mean mathematics achievement score for disadvantaged students	DV in logistic regression analysis
Schleicher (2019)	International (PISA)	Approximately 600,000 15-year old students	Lowest 25% SES	Top 25% of reading achievement	IV in descriptive statistics
Skokut (2009)	USA	115 senior high school students	Students who had not passed all portions of the high school exit exam before their senior year	Post-secondary school attendance	DV in logistic regression analysis and discriminant analysis
Strolin-Goltzman et al. (2016)	USA	102 15- to 21-year old students	Foster youth	College entry or intent to attend college	DV in logistic regression analysis
Waxman et al. (2012)	USA	189 Gr. 4 and Gr. 5 students	Teacher nominated at-risk students	Teacher nominated resilient students	IV in ANOVA
Wayman (2000)	USA	519 high school students	Experiencing a dropout episode during high school	High school completion	DV in logistic regression analysis
Yavuz (2016)	Turkey	304 senior high school students	Low-SES students	Top 27% of students' GPA	IV in MANOVA and Chi-Square Test
Resilience residuals					
Bell (2010)	Australia	164 Year 4 to Year 7 students	NA	Residual literacy and numeracy scores in the top 25%	DV in stepwise multiple regression analysis

Borman & Rachuba (2000)	USA	3,981 Gr. 6 students	At or below -0.33 standardised residuals on the standardised SES measure	Residual mathematics score at or above 0.33 SD of the full sample mean	IV in MANOVA
Cheung (2017)	Asia (PISA)	Approximately 26,000 15-year old students	Lowest 25% SES	Residual mathematics performance in the top 25% of students internationally	DV in logistic regression analysis
Cheung et al. (2014)	Asia (PISA)	Approximately 20,000 15-year old students	Lowest 25% SES	Residual reading performance in the top 25% of students internationally	DV in logistic regression analysis
García-Crespo et al. (2019)	Europe (PIRLS)	117,539 Gr. 4 students	Lowest 25% SES	Residual reading performance in the top 25% of students within the European Union	DV in binary multilevel logistic regression analysis
Hofmeyr (2019)	South Africa (TIMSS and PIRLS)	25,181 Gr. 4 and Gr. 9 students	Lowest 75% SES	Residual reading or mathematics score at or above 1.5 SD of the full sample mean	DV in logistic regression analysis
Sandoval-Hernández & Cortes (2012)	Europe (PIRLS)	Approximately 22,000 Gr. 4 students	Lowest 20% SES	Residual reading performance in the top 20%	DV in logistic regression analysis
Vincent (2007)	USA	6,504 Gr. 7 to Gr. 12 students	Low-SES students	Residual GPA score at or above 1 SD of the full sample mean	IV in MANOVA, ANOVA, and discriminant analysis
Wills & Hofmeyr (2019)	South Africa	2,383 Gr. 6 students	NA	Residual English reading performance at or above 2 SD of the full sample mean at 2 time points; Residual English reading performance at or above 1.5 SD of the full sample mean at 2 time points	DV in logistic regression analysis

Note. Significant national and international datasets presented in parentheses. ANOVA = Analysis of Variance; CHAID = Chi-squared Automatic Interaction Detector; DV = Dependent Variable; Gr. = Grade; GPA = Grade Point Average; IV = Independent Variable; MANCOVA = Multivariate Analysis of Covariance; MANOVA = Multivariate Analysis of Variance; SD = Standard Deviation; SES = Socioeconomic Status; UCLA = University of California, Los Angeles.

Table A2

Studies using a Process-Driven Approach (n = 36)

Author(s) (Year)	Country	Sample	Risk indicator	Achievement indicator	Analysis
At-risk sample					

Alvarez (2003)	USA	364 Gr. 4 to Gr. 6 students	Low-SES students, Hispanic students, and students with limited English proficiency	GPA	DV in hierarchical multiple regression analysis
Brooks (2010)	USA (ELS:2002)	11,360 high school students	Lowest 25% SES, African American students, Hispanic students, students from non-traditional families, students who have been retained in school, students whose first language is not English, and students with a disability	Mathematics achievement	DV in hierarchical generalised linear regression analysis
Cunningham & Swanson (2010)	USA	206 high school students	African American students	Self-reported grades	DV in zero order correlation analysis
Das (2019)	India	12,300 8- to 11-year old students	Socially excluded groups by religion and caste	Reading and arithmetic achievement	DV in regression analysis
Dever (2009)	USA	748 Gr. 10 students	Risk takers	Academic behaviours and outcomes	DV in hierarchical cluster analysis and ANOVA
Fallon (2010)	USA	162 Gr. 9 to Gr. 12 students	Latinx students and low-SES students	GPA, reading and mathematics achievement	DV in linear regression analysis
Flannigan (2017)	USA	343 11- to 17-year old students	Foster youth	Woodcock-Johnson III Tests of Achievement	DV in structural equation modelling
Gizir & Aydin (2009)	Turkey	872 Gr. 8 students	Low-SES students	GPA	DV in structural equation modelling
Kanevsky et al. (2008)	USA	201 Gr. 3 and Gr. 4 students	English learners	Mathematics achievement	DV in independent samples *t*-tests
Kimball (2007)	USA	1,133 Gr. 9 students	Gr. 9 school transition	Academic change score on the English 9 End-of-Course test	DV in independent samples *t*-tests and Chi-Square Test
Kong (2020)	Ireland	8,568 9- and 13-year old students	Low-SES students	Drumcondra Numerical Ability Test	DV in multiple regression analysis
Lawrence (2010)	USA	80 high school students	Foster youth	California Standardized Tests in English Language Arts and Mathematics, and GPA	DV in multiple regression analysis
Maier et al. (2012)	USA	275 preschool students	Low-SES students	Galileo System for the Electronic Management of Learning Language and Literacy scale	DV in multilevel regression analysis
Mamphane & Huddle (2017)	South Africa	53 high school students	Rural school setting	Performance in English First Additional	DV in independent samples *t*-tests

				Language, SiSwati, and Life Orientation	
Niemeyer (2010)	USA	145 Gr. 7 to Gr. 12 students	Hispanic students and students who had a parent that had not obtained a qualification beyond high school	Current grades, current GPA, and GPA for the previous semester	DV in structural equation modelling
Paat (2015)	USA	755 high school students	Mexican immigrant students	GPA and highest educational attainment	DV in multiple regression analysis
Plunkett et al. (2008)	USA	216 Gr. 9 students	Mexican-origin students	GPA	DV in dominance analysis
Powers (2004)	USA	55 13- to 19-year old students	Students diagnosed with reflex neurovascular dystrophy	GPA and attendance	DV in multiple regression analysis
Roberts (2012)	USA	146 college students and graduates	Low-SES students and experience of adversity	GPA	DV in bivariate correlation analysis and independent samples *t*-tests
Schelble et al. (2010)	USA	158 6- to 18-year old students	Students who had an open child welfare services case	School/Work performance subscale of the Child and Adolescent Functional Assessment	DV in linear regression analysis
Schultz-León (2012)	USA	165 Gr. 6 to Gr. 8 students	Latinx students and low-SES students	The Woodcock Johnson Tests of Achievement Form C/ Brief Battery	DV in hierarchical regression analysis and moderated multiple regression analysis
Sturtevant (2014)	USA	91 high school students	Low-SES students	GPA, language arts achievement, and world history achievement	DV in multiple regression analysis
Vargas-Reighly (2001)	USA	270 Gr. 9 students	Latinx and Southeast Asian students	GPA	DV in structural equation modelling
Whitmore (2017)	USA	126 undergraduate students	African American students	GPA	DV in hierarchical multiple regression analysis
Zhao et al. (2011)	China	1,299 6- to 18-year old students	Rural students affected by HIV/AIDS	In age-appropriate grade, above-average academic performance, and demonstrating school leadership	DV in multivariate regression analysis
Risk factors					

Abel (2013)	USA	79 high school students	Perceptions of discrimination among African American and Latinx students	GPA	DV in simultaneous multiple regression analysis
Alfaro et al. (2009)	USA	221 high school students	Experiences of discrimination among Latinx students	GPA	DV in multiple group structural equation modelling
Browder (2014)	USA	165 high school students	High social distance, traumatic events, lack of authoritative parental support, separation from family, exposure to negative peer influence, and hours spent working in employment experienced by English learners with limited or interrupted formal education	English proficiency attainment and gains and standardised tests of algebra, biology, and English language arts achievement	DV in bivariate and multivariate regression analysis
Crosnoe & Elder (2004)	USA	11,788 high school students	Emotional distance between parent and student	Off-track academic behaviour	DV in path analysis
Gonzalez (2013)	USA	55 kindergarten students	English language proficiency, preschool experience, special education, social emotional functioning, maternal education, paternal education, familial poverty, familial concrete support, and familial social support experienced by Latinx students	The STAR Early Literacy test	DV in hierarchical linear regression analysis
Kang et al. (2018)	USA	45,296 Gr. 8, Gr. 9, and Gr. 11 students	Bullying behaviour, substance use, and mental distress among students who have experienced one or more traumatic events	GPA	DV in structural equation modelling
Li (2017)	China	693 Gr. 11 students	Low school commitment and individual conflict attitudes	GPA	DV in structural equation modelling
Nauman (2019)	USA	1,077 Gr. 9 students	Relational adversity	GPA and language, literacy, and mathematics achievement	DV in stepwise regression analysis
Perez et al. (2009)	USA	110 high school, community	Latinx students with high levels of employment during	GPA	DV in regression analysis

		college, and university students	high school, a sense of rejection related to undocumented status, low parental educational attainment, and large family size		
Staylor (2019)	USA	789 college students	Disadvantaged background, adaptation to stressful circumstances, and adaptation and functioning despite a traumatic event	Progression through English courses	DV in multivariate linear regression analysis
Von Secker (2004)	USA	22,545 Gr. 4, Gr. 8, and Gr. 12 students	SES, racial-ethnic status, and gender	Science achievement	DV in hierarchical linear regression analysis

Note. Significant national and international datasets presented in parentheses. ANOVA = Analysis of Variance; DV = Dependent Variable; Gr. = Grade; GPA = Grade Point Average; HIV/AIDS = Human Immunodeficiency Virus/Acquired Immunodeficiency Syndrome; IV = Independent Variable; SES = Socioeconomic Status.

Table A3

Studies using a Latent Construct Approach (n = 55)

Author(s) (Year)	**Country**	**Sample**	**Scale**	**Risk indicator**	**Number of factors/Scale items**	**Analysis**
Unidimensional construct						
Samuels (2004)	USA	587 college students	ARI	NA	1/40	IV in hierarchical linear regression analysis
Kheirkhah (2020)	Iran	30 high school students	ARI (Samuels, 2004)	NA	1/40	DV in MANCOVA
Reed-Hendon (2013)	USA	769 university students	ARI (Samuels, 2004)	NA	1/40	DV in independent samples *t*-tests
Ricketts et al. (2017)	USA	528 Gr. 7 and Gr. 8 students	ARM	NA	1/9	DV in Many-Facet modelling
Liu & Platow (2020)	China	751 Gr. 9 and Gr. 10 students	ARM (Ricketts et al., 2017)	NA	1/9	DV in structural equation modelling
Ricketts (2015)	USA	1,134 Gr. 7 and Gr. 8 students	ARM (Ricketts et al., 2017)	NA	1/9	IV/DV in Many-Facet modelling, hierarchical regression analysis, and structural equation modelling
Martin (2013)	Australia	918 high school students	ARRS	10-item academic adversity screening tool	1/4	IV in structural equation modelling

Victor-Aigboidion et al. (2020)	Nigeria	1,320 secondary school students	ARRS (Martin, 2013)	10-item academic adversity screening tool	1/4	DV in regression analysis
Martin & Marsh (2003)	Australia	402 Year 11 and Year 12 students	ARS	NA	1/6	DV in factor analysis, Pearson's product moment correlation analysis, multiple regression analysis, hierarchical cluster analysis, and ANOVA
Martin & Marsh (2006)	Australia	402 Year 11 and Year 12 students	ARS	NA	1/6	IV/DV in zero order and partial correlation analysis, path analysis using multiple linear regression, and cluster analysis
Anghel (2015)	Romania	251 high school students	ARS (Martin & Marsh, 2003)	NA	1/6	DV in Mann-Whitney U Tests
Atkinson (2018)	USA	184 undergraduate students	ARS (Martin & Marsh, 2006)	NA	1/6	IV (mediator) in first-stage moderated mediation analysis
de Carvalho & Skipper (2020)	UK	18 14- to 16-year old students	ARS (Martin & Marsh, 2006)	NA	1/6	DV in Bayesian paired samples *t*-tests and Bayesian repeated measures ANCOVA
Frisby et al. (2020)	USA	213 college students	ARS (Martin & Marsh, 2006)	NA	1/6	DV in multiple linear regression analysis
Kapikiran (2012)	Turkey	378 high school students	ARS (Martin & Marsh, 2006)	NA	1/6	DV in correlation analysis
Khalaf (2014)	Egypt	190 undergraduate students	ARS (Martin & Marsh, 2006)	NA	1/6	DV in independent samples *t*-tests and correlation analysis
Mendez & Bauman (2018)	USA	245 university students	ARS (Martin & Marsh, 2006)	NA	1/6	IV/DV in hierarchical multiple regression analysis and binary logistic regression analysis
Meneghel et al. (2019)	Spain	965 university students	ARS (Martin & Marsh, 2006)	NA	1/6	IV/DV in correlation analysis and structural equation modelling
Njoki (2018)	Kenya	500 Form 3 students	Adapted ARS (Martin & Marsh, 2006)	NA	1/9	IV in multiple linear regression analysis, independent samples *t*-tests, and ANOVA
Rajan et al. (2017)	India	155 high school students	ARS (Martin & Marsh, 2006)	NA	1/6	DV in Pearson's product moment correlation analysis and independent samples *t*-tests

Tamannaeifar & Shahmirzaei (2019)	Iran	368 university students	ARS (Martin & Marsh, 2003)	NA	1/6	DV in correlation analysis and stepwise multiple regression analysis
Buslig (2019)	Philippines	100 college students	Self-created	NA	1/40	IV in Pearson’s product moment correlation analysis
Multidimensional construct						
Cassidy (2015)	UK	435 undergraduate students	ARS-30	Adversity vignette	3/30	DV in zero order correlation analysis
Cassidy (2016)	UK	532 undergraduate students	ARS-30	Adversity vignette	3/30	DV in Pearson’s product moment correlation analysis
Buathong (2019)	Thailand	216 junior high school students	Adapted ARS-30 (Cassidy, 2016)	Adversity vignette	3/16	DV in independent samples *t*-tests, ANOVA, and mediation analysis
Calo et al. (2019)	Australia	134 undergraduate and graduate-entry masters students	ARS-30 (Cassidy, 2015)	Adversity vignette	3/30	DV in point biserial correlation analysis and relative risk ratios
Chisolm-Burns et al. (2019)	USA	544 undergraduate students	Adapted ARS-30 (Cassidy, 2016)	Adversity vignette	4/16	DV in Mann-Whitney U test, Kruskal-Wallis test, and Pearson’s product moment correlation analysis
Choo & Prihadi (2019)	Malaysia	132 undergraduate students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	IV (mediator) in multiple regression analysis and mediation analysis
Howell et al. (2018)	Australia	320 undergraduate students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	DV in MANOVA
Karabıyık (2020)	Turkey	198 undergraduate students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	DV in independent samples *t*-tests, Pearson’s product moment correlation analysis, and bivariate linear regression analysis
Lanuza et al. (2020)	Philippines	363 college students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	DV in ANOVA
Ramezanpour et al. (2019)	Iran	409 high school students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	DV in correlation analysis
Seçer & Ulaş (2020)	Turkey	452 high school students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	IV (mediator) in structural equation modelling
Toprak Çelen (2020)	Turkey	436 university students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	IV in structural equation modelling

Trigueros et al. (2020)	Spain	2,967 university students	ARS-30 (Cassidy, 2016)	Adversity vignette	3/30	IV in structural equation modelling
Carlson (2001)	USA	494 college students	CRQ	NA	2/27	DV in Pearson’s product moment correlation analysis
Mbindyo (2011)	USA	106 college students	CRQ (Carlson, 2001)	NA	2/27	DV in independent samples *t*-tests
White (2013)	USA	215 university students	CRQ (Carlson, 2001)	NA	2/27	DV in ANOVA and Pearson’s product moment correlation analysis
Colp (2015)	Canada	655 undergraduate students	Self-created	NA	5/23	IV (mediator) in structural equation modelling
Cunningham & Swanson (2010)	USA	206 high school students	Self-created	NA	3/3	DV in zero order correlation analysis and hierarchical linear regression analysis
Fang et al. (2020)	China	2,328 Gr. 7 and Gr. 9 students	Self-created	NA	3/3	IV (mediator) in structural equation modelling
Fauziah et al. (2020)	Indonesia	120 high school students	Self-created	NA	4/4	DV in linear regression analysis
Foshee (2013)	USA	1,970 college students	Self-created	NA	2/4	IV/DV in hierarchical multiple regression analysis and ANOVA
Harpalani (2005)	USA	779 high school students	Self-created	NA	3/6	DV in ANOVA
Hawkins & Mulkey (2005)	USA (NELS:88)	2,217 Gr. 8 students	Self-created	NA	3/16	DV in multiple regression analysis
He (2014)	USA (HSLS:09)	2,938 Gr. 9 students	Self-created	NA	3/12	IV in structural equation modelling
Hill (2017)	USA (ECLS-K)	10,395 Gr. 3 students	Self-created	NA	8/30	IV (mediator) in structural equation modelling
Irfan Arif & Mirza (2017)	Pakistan	255 Gr. 9 and Gr. 10 students	Self-created	NA	10/40	DV in independent samples *t*-tests
Kaur (2017)	India	1,200 secondary school students	Self-created	NA	5/52	DV in independent samples *t*-tests, ANOVA, and Pearson’s product moment correlation analysis
Li et al. (2019)	Taiwan	658 undergraduate students	Self-created	NA	3/12	DV in differential item functioning analysis and Pearson’s product moment correlation analysis
Martin (2012)	USA	308 secondary school students	Self-created	NA	6/11	DV in hierarchical multiple regression analysis and Sobel's z-tests

Rapone (2018)	USA	83 Gr. 10 students	Self-created	NA	3/21	DV in independent samples *t*-tests and Spearman's rank order correlation analysis
Sapio (2010)	USA	281 Gr. 6 to Gr. 10 students	Self-created	NA	2/32	DV in MANCOVA
Searle (2011)	Australia	575 reception students	Self-created	10 risk factors	2/16	IV in path analysis, structural equation modelling, binary logistic regression analysis, MANOVA, and hierarchical multiple linear regression analysis
Zulfikar et al. (2020)	Indonesia	181 senior high school students	Self-created	NA	5/22	DV in exploratory factor analysis

Note. Significant national and international datasets presented in parentheses. ANCOVA = Analysis of Covariance; ANOVA = Analysis of Variance; ARI = Academic Resilience Inventory; ARM = Academic Resilience in Mathematics; ARRS = Academic Risk and Resilience Scale; ARS = Academic Resilience Scale; ARS-30 = Academic Resilience Scale-30; CRQ = College Resilience Questionnaire; DV = Dependent Variable; Gr. = Grade; IV = Independent Variable; MANOVA = Multivariate Analysis of Variance.

- Identifies three distinct approaches to the measurement of academic resilience
- Each identified approach strongly influences conclusions drawn about resilience
- Variation in measurement permits researchers to employ context-specific measures
- Absence of risk indicators may undermine the validity of some resilience measures
- Measurement of academic resilience not considering academic outcomes is problematic