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Riding the bumps in mathematics learning: Relations between academic buoyancy, engagement, and achievement

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A R T I C L E I N F O

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A B S T R A C T

Academic buoyancy is conceptualised as the capacity to successfully navigate the typical adversities experienced during the course of schooling. Studies have shown positive relations between academic buoyancy and beneficial achievement-related beliefs, emotions, and behaviours. Relations with achievement are often small and studies of reciprocal relations are lacking. In a sample of 1,242 primary school students, we examined reciprocal relations between academic buoyancy, engagement, and achievement. Baseline levels of academic buoyancy and engagement positively predicted subsequent achievement. Achievement predicted gain in academic buoyancy but not engagement. Engagement, but not academic buoyancy, predicted gain in achievement. However, academic buoyancy predicted achievement gain indirectly, mediated through concurrent engagement. Building engagement, academic buoyancy, and foundational mathematics skills, could work synergistically to show downstream benefits for students' achievement.

1. Introduction

Low-level educational adversities and setbacks will be experienced by many students. Understanding those psychological attributes that assist students in successfully overcoming adversities raises the prospect of nurturing such attributes through routine instruction, or intervention, to allow students to flourish. Academic buoyancy is one such attribute that relates positively to achievement-related beliefs, emotions, and behaviours (e.g., Bostwick et al., 2022). Relations with achievement are often small, however, and no studies, thus far, have investigated whether relations are reciprocal over time. Accordingly, the present study examined reciprocal relations between academic buoyancy and achievement by incorporating a feature that may strengthen the relationship from academic buoyancy to subsequent achievement, namely a short time-lag of one week. We also included a measure of behavioural engagement in order to assess the potential of value of academic buoyancy beyond that accounted for by the prima facia predictor of achievement.

1.1. Academic buoyancy

Academic buoyancy is considered to be an asset-driven psychological attribute defined as the ability of students to successfully manage minor adversities typically encountered during everyday schooling (Martin, 2013a; Martin & Marsh, 2008). Such adversities include receiving negative feedback or a lower than anticipated grade on a piece of work, temporary declines motivation and engagement, difficulties in relationships with peers and teachers, and pressures associated with tests and exams. Academic buoyancy is differentiated from academic resilience which is seen as the response needed to deal with major adversities such as bullying, school refusal, chronic underachievement, and so on (Martin, 2013b; Martin & Marsh, 2009). Accordingly, buoyancy can be positioned as a proactive response to adversity that is relevant to the majority of school students, and resilience as a retroactive response that is, thankfully, relevant to the minority (Martin, 2013b). Academic buoyancy is typically conceptualised as a domain-general construct (see Malmberg et al., 2013); when discussing relations between academic buoyancy and achievement-related beliefs, emotions, and behaviours, and achievement itself, in the following sections, academic buoyancy was measured as subject-general unless we specifically highlight otherwise.

1.2. The benefits of academic buoyancy

In keeping with the conceptualisation of academic buoyancy as an asset-driven psychological attribute, studies have shown how higher

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academic buoyancy is positively related to beliefs, emotions, and behaviours, that are beneficial for learning and achievement, and negatively related to those that hinder learning. For example, studies using cross-sectional and prospective designs in samples of primary and secondary school students have shown greater behavioural (e.g., effort, persistence), affective (e.g., higher enjoyment, lower anxiety), and cognitive (e.g., academic self-efficacy, uncertain control), facets of engagement (e.g., Hirvonen et al., 2020; Martin, Ginns, et al., 2013; Martin et al., 2010; Putwain et al., 2012; Ursin et al., 2021). These, and other studies, demonstrate the potential educational benefits of academic buoyancy. However, the status of academic buoyancy as driving positive outcomes will always be ambiguous in studies using cross-sectional or prospective designs.

Studies controlling for, autoregressive and concurrent relations in two-wave designs have shown higher academic buoyancy to predict lower academic anxiety, uncertain control, emotional instability, and neuroticism, in secondary school students after a twelve-month interval (Martin et al., 2013). Also using samples of secondary school students, and two waves of measurement, higher academic buoyancy predicted greater academic self-concept, valuing of school, and more positive perceptions of the school climate after an interval twelve-months (Bostwick et al., 2022) and lower test anxiety after an interval of three months (Putwain et al., 2015). After controlling for autoregressive, but not concurrent, relations, Hirvonen et al. (2019) showed academic buoyancy predicted lower school-related stress (work overload and high school demands) in primary school students. The aforementioned studies using two-wave designs demonstrate that educational gains *follow* from higher academic buoyancy.

1.3. Academic buoyancy and achievement

Students high in academic buoyancy would be expected to possess and employ a range of cognitive, emotional, and behavioural, self-regulation strategies that would enable them to either proactively maintain achievement in the face of adversity or successfully overcome adversity to return levels of achievement to prior levels (or higher). It is somewhat surprising, therefore, given evidence linking academic buoyancy to those beliefs (e.g., academic self-concept), emotions (e.g., enjoyment), behaviours (e.g., effort), that are known to assist achievement, that relations from academic buoyancy to achievement are often small and not statistically significant.

For instance, in secondary school students, small positive relations (rs = 0.07 to 0.19) have been shown between academic buoyancy and achievement (Collie et al., 2015; Datu & Yang, 2021; Lei et al., 2022; Martin, 2014; Putwain & Aveyard, 2018; Putwain et al., 2015, 2016). Fong and Kim (2019) showed comparable a comparably small relation between academic buoyancy and GPA (r = 0.11) in a sample of undergraduate students. Using a domain-specific measure of academic buoyancy (second language acquisition), however, a larger relation (β = 0.31)[1] was shown by Yun et al. (2018) in undergraduate students. Small positive relations, however, were shown between domain-specific academic buoyancy (mathematics and reading) and standardised test performance (rs = 0.10 and 0.09 for mathematics and reading respectively) in primary school students (Colmar et al., 2019).

This body of work does not show academic buoyancy to be a substantial direct predictor of academic achievement. There may be numerous reasons for this including the time lag between measurements of academic buoyancy and subsequent achievement, that students endorsing high academic buoyancy may yet to have overcome their adversity in ways that are facilitative for achievement, and that relations are indirect and mediated through achievement related through achievement-related beliefs (e.g., Collie et al., 2015; Colmar et al., 2019). Furthermore, academic buoyancy could buffer achievement against adversity even if not directly related (e.g., Martin & Marsh, 2020; Putwain, Gallard, & Beaumont, 2020). The optimal time-lag between variables can be difficult to establish and depend, in part, on the nature and stability of the constructs in question, one's research questions, and methodological reasons (Cole & Maxwell, 2003; Dormann & van de Ven, 2014). The risk of a non-optimal time lag is to underestimate relations although, all things being equal, relations will gradually weaken over time (Cohen et al., 2003). Where time lags in the aforementioned studies were reported, they have varied between three (e.g., Putwain et al., 2015) and twelve months (e.g., Collie et al., 2015) showing academic buoyancy to be relatively stable (stability estimates were βs = 0.56 and 0.55 in Putwain et al. and Collie et al., respectively).

The aforementioned stability estimates also imply a degree of malleability in academic buoyancy (also see Martin, 2013a). Since academic buoyancy may change, measurements taken in closer proximity to achievement may reflect greater accuracy in a student's capacity to employ achievement-facilitative regulation strategies. Adopting a shorter time lag between academic buoyancy measurement and achievement, therefore, would be a useful method of evidencing whether stronger academic buoyancy-achievement relations are found. In addition, the beneficial achievement-related belief, emotion, and behaviour (e.g., lower test anxiety and higher control), associated with academic buoyancy, would likely enable students proactively deal with the pressures of testing. Other adversities (e.g., a dip in engagement, poor feedback on work) may take longer for students to recover. Given the potential advantages of demonstrating stronger relations with shorter time-lag in "shortitudinal" studies (see Dormann & Griffin, 2015) we opted for a one-week lag in the present study (see Fig. 1; T_1 academic buoyancy to T_2 mathematics test performance, and T_3 academic buoyancy to T_4 mathematics test performance).

1.4. Engagement in learning

Many of the studies we have reviewed included behavioural (i.e., planning and persistence), cognitive (i.e., academic self-efficacy and uncertain control), and emotional (i.e., enjoyment and value of learning), facets of engagement as predictors or outcomes of academic buoyancy. Although engagement is often defined in hazy terms, and there is inconsistency over its conceptualisation and measurement (Fredricks et al., 2004, 2011), it is typically thought of as the behavioural manifestation of motivation in action (Skinner & Pitzer, 2012). Of the three forms of engagement, behavioural engagement is most strongly related with achievement. For instance, in a meta-analysis of 69 studies comprising 196,473 participants, Lei et al. (2018) showed relations between behavioural engagement and achievement were r = 0.35 in comparison to cognitive (r = 0.25) and emotional (r = 0.22) facets. Accordingly, we included behavioural engagement in the present study to establish whether academic buoyancy (behavioural engagement and academic buoyancy were measured concurrently at T_1 and T_3 in Fig. 1) shows relations with achievement over and above that of the prima facia proximal predictor (for expediency we refer to behavioural engagement henceforth as simply engagement).

1.5. Reciprocal relations between academic buoyancy, engagement, and achievement

It is plausible that if academic buoyancy were to predict achievement, achievement would, in turn, predict academic buoyancy in a reciprocal fashion. This reasoning is partly on the basis that higher achievement would encourage and reinforce beliefs in one's capacity to overcome school-based adversity. Furthermore, the empirical links between academic buoyancy and achievement-related beliefs, behaviours, and emotions (Martin et al., 2010; Martin, Ginns, et al., 2013; Martin & Marsh, 2008; Putwain et al., 2016), make it likely that, ceteris paribus,

[1] The r was not reported. A β < 0.25 is considered as 'large' (Keith, 2014) in contrast to the rs 0.07 to 0.19 that would be considered as negligible to small (Muijs, 2011).

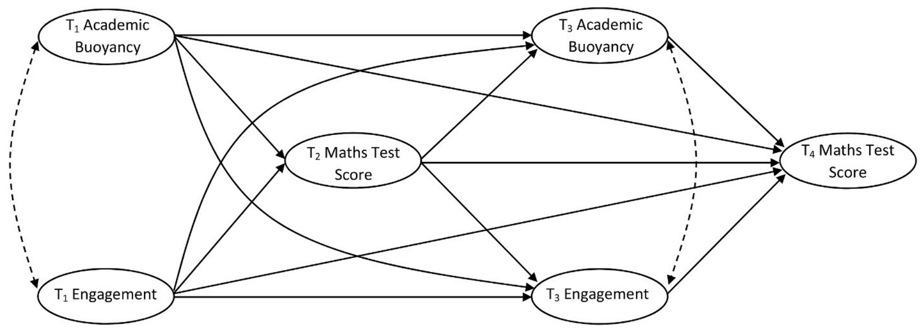

Fig. 1. The Hypothesised Fully Forward Model
Note. Dotted lines represent correlations and solid lines structural paths. Gender was included as a covariate on all variables and, in order to avoid over cluttering, omitted from Fig. 1.

achievement would also predict academic buoyancy. The time-lag from achievement to subsequent academic buoyancy/engagement was seven months at the request of participating schools (see Fig. 1; T_2 mathematics test performance to T_3 academic buoyancy/engagement) and more typical of those found in the educational psychology literature. While the reinforcing effect of achievement on academic buoyancy may decrease over time, we anticipate relations would remain over seven months. Given that tests are relatively infrequent in the sample used for the present study (primary school students aged 9–10 years) it is reasonable to anticipate that students' experience of the test would leave a powerful impression. Although, few studies have examined the time lags from achievement to subsequent psychoeducational variables, Marsh et al. (2005) showed relations from mathematics test performance to subsequent mathematics academic self-concept remained within, but not beyond, a school year.

As we noted above, engagement positively predicts achievement; a reflection of greater effort, persistence, and immersion, in learning. Higher achievement may also reinforce subsequent engagement and low achieving students may experience a range of obstacles that hinder subsequent engagement (e.g., undermined motivation and externalising problems to name but two; Seaton et al., 2014; Zimmermann et al., 2013). Few studies have investigated reciprocal relations in cross-lagged panel models, thus far, showing mixed results. Wang et al. (2019) found reciprocal relations in primary school students whereas Guo et al. (2015) found, in elementary school students, achievement to predict subsequent engagement but not vice versa. Despite these equivocal findings, we believe the reasoning for expecting reciprocal relations is sound.

As already mentioned, positive relations have been found between academic buoyancy and engagement (e.g., Datu & Yang, 2018; Martin et al., 2010). After controlling for autoregressive relations, however, Martin and Marsh (2008) found engagement to predict academic buoyancy but not vice versa. Thus, high levels of engagement can reinforce beliefs that one can overcome adversity in a similar way to that of engagement reinforcing achievement described above. Although Martin and Marsh's (2008) study did not empirically support the relation from buoyancy to subsequent engagement, the theoretical proposition that high academically buoyant students would be more engaged is in keeping with conceptualisation of buoyancy as a proactive asset.

1.6. Aims of the present study

In the present study, the principle aim was to examine reciprocal relations between academic buoyancy and achievement in the context of mathematics, over and above the relations shown with engagement (see Fig. 1). Secondary aims were to examine reciprocal relations between engagement and achievement, and between academic buoyancy and engagement. Data were measured over four waves in a single school year in a sample of students in their penultimate year of primary school. Although younger students have shown higher *mean* levels of academic buoyancy (e.g., Martin et al., 2010; Martin & Marsh, 2008), we would not expect differences in *relations* between academic buoyancy, engagement, and achievement, for students in the latter stages of primary education compared to those in secondary education. However, as few studies of academic buoyancy have been conducted on primary school students thus far (e.g., Colmar et al., 2019; Hirvonen et al., 2020; Ursin et al., 2021) our study contributes to a broadening of evidence base for academic buoyancy in a younger sample of students.

Self-reported academic buoyancy and engagement were measured at the first and third waves (T_1 and T_3). Mathematics achievement was measured at the second and forth waves (T_2 and T_4) through a 40-min test scheduled one week after the measurement of academic buoyancy and engagement. As noted in Section 1.5, the lag from T_2 to T_3 was longer at seven months, at the request of participating schools, so not to involve further disruption to lessons within a relatively short space of time. Gender and age were considered as possible covariates; male and younger students have reported higher academic buoyancy in previous studies (e.g., Martin et al., 2010; Martin & Marsh, 2008). The following hypotheses were tested:

Hypothesis 1. Positive reciprocal relations will be shown between academic buoyancy and achievement.

Hypothesis 2. Positive reciprocal relations will be shown between engagement and achievement.

Hypothesis 3. Positive reciprocal relations will be shown between academic buoyancy and engagement.

2. Method

2.1. Participants, procedure, and missing data

There were 1,242 participants students in the initial wave of data collection from twenty-four primary schools with a mean age of 9.3 years (SD = 0.49); 633 participants were male and 609 were female. Participants were in Year 5 (In England this is the penultimate year of primary education). Most students came from a white Caucasian heritage (n = 876; 70.5%), followed by Asian (n = 246; 9.8%), black (n = 58; 4.7%), Chinese (n = 11; 0.9%), other (n = 22; 1.8%), and mixed heritage (n = 29; 2.3%), backgrounds. This is broadly representative of other English schools. In the school year that data were collected (2018–19), 73.6% of participants were from a white ethnic background (Department for Education, 2019).

Schools were recruited from the two 'opportunity areas' situated in the North West of England (see Department for Education, 2017). These were areas following a local plan to reduce social and economic deprivation through education; hence schools in these areas were receptive to research examining factors that may hinder or help achievement. Head Teachers from the primary schools located in the two 'opportunity areas' were invited to a face-to-face meeting with the research team where the aims of the research were shared and feedback on the methodology was invited. Although we did not collect data on the socio-economic status of individual participants, the location the schools indicate a greater degree of socio-economic deprivation than is typical.

Data were collected within a school year, over four waves, and drawn from a wider study. At T_1 and T_3 participants completed measures of academic buoyancy, engagement, classroom-related emotions, and control-value appraisals. Mathematics achievement was measured at T_2 and T_4 through a 40-min test scheduled one week after the measurement of academic buoyancy and engagement. Relations between control-value appraisals, emotions, and mathematics achievement, and whether relations between emotions and mathematics achievement were moderated by academic buoyancy have been reported elsewhere (Putwain, Schmitz, Wood, & Pekrun, 2022; Putwain, Wood, & Pekrun, 2022). Research questions and analyses concerning the relations between academic buoyancy, engagement, and mathematics achievement, have not been reported elsewhere.

All data (self-reports and tests) were collected in school by the students' usual mathematics teacher who followed a standardised script, and linked across the four waves using a self-generated anonymous code. Self-report questionnaires and mathematics tests were accessed online and, in order to minimise missing data, alerted to participants if an item or response was missing. An institutional research ethics panel (19/EHC/01) approved the project. The Head at participating school and a parent/carer of the participants provided written consent. Verbal assent was sought from participants prior to each wave of data collection and those who chose not to participate were given an alternative activity for the duration of the data collection. As commonly found in other longitudinal studies, participant attrition was found in subsequent waves of data collection (11% at T_2, and an additional 15% at T_3, and again at T_4). In total, 19.9% of data were missing.

Since missing data can introduce bias into a dataset, an omnibus test for missing completely at random (MCAR) was conducted using Little's test (Little, 1988). As Little's test was statistically significant ($p < .001$), MCAR could not be assumed and sources of missingness probed (see Supplementary Materials). Participants with lower T_1 academic buoyancy and engagement, and lower T_2 mathematics test scores, were more likely to show missing data on later waves. Accordingly, data was treated as missing at random (MAR; i.e., the causes of missingness can be identified) and handled in subsequent analyses using full-information-maximum-likelihood (FIML) estimation. When the causes of missingness are included in analytic models, FIML has been shown under MAR assumptions to result in unbiased parameter estimates (Nicholson et al., 2017).

2.2. Measures

Academic buoyancy and engagement were measured on a five-point scale (1 = strongly disagree, 3 = neither, 5 = strongly agree). Mathematics achievement was measured through two 40-min class tests worth twenty marks in total. All measures showed good internal consistency (McDonald's ωs $\geq$ 0.75 estimated from the measurement model described in Section 3.1; see Table 1).

2.2.1. Academic buoyancy

The Academic Buoyancy Scale (ABS: Martin & Marsh, 2008) comprised four items designed to measure adaptive responses to everyday academic adversities. In the present study items were adapted to be mathematics specific (e.g., "I don't let a bad mark in maths affect my confidence" [2]). Previous studies have shown strong support for the unidimensional factor structure, and internal consistency, of domain-general (e.g., Martin & Marsh, 2008) and domain-specific (e.g., Malmberg et al., 2013) versions of the Academic Buoyancy Scale.

2.2.2. Engagement

The five-item behavioural engagement subscale of the Engagement vs. Dissatisfaction with Learning Questionnaire (Skinner et al., 2009) in which items (e.g., "When I'm in my maths lessons, I listen very carefully") were made specific to mathematics. In previous studies, the internal consistency of this subscale, and unidimensional factor structure (when used in isolation or within the context of other subscales from the Engagement vs. Dissatisfaction with Learning Questionnaire), have been shown in domain-general (e.g., Skinner et al., 2009) and domain-specific versions (e.g., Nicholson & Putwain, 2020).

2.2.3. Mathematics achievement

Test were created from a pool of items drawn from six National Curriculum Test reasoning papers (2016–2018).[3] Items covered the different elements of the Key Stage 2 (Years 3–6; age 7–11 years) English National Curriculum for Numeracy (Department for Education, 2013) including ratio and proportion, simple algebra, and geometry, fractions and statistics, and measurement. Only items corresponding to Years 3–5 of the National Curriculum were selected and were independently checked and confirmed by two primary school teachers who were unconnected with the study. Participants were not informed of their test scores.

2.2.4. Demographic variables

Participants were asked to self-report gender (0 = male, 1 = female), age, and ethnic heritage.

2.3. Analytic strategy

Data were analysed in three steps. First, the descriptive characteristics of data of data were checked, and a measurement model tested using confirmatory factor analysis (CFA). Second, the measurement invariance of academic buoyancy and engagement across T_1 and T_3, a necessary condition for modelling longitudinal relations over time (Widaman et al., 2010), was established using CFA. Third, the hypothesised model, to examine relations between academic buoyancy, engagement, and mathematics achievement, was tested using structural equation modelling (SEM). All analyses were performed using the Mplus v.8 software (Muthén & Muthén, 2017). The fit of data in CFA and SEM was assessed using the Root mean error of approximation (RMSEA), standardized root mean residual (SRMR), confirmatory fit index (CFI), and Tucker-Lewis index (TLI). RMSEA ≈0.06, SRMR ≈0.08, and CFI/TLI ≈0.95, indicate a relatively good fit (Hu & Bentler, 1999). Many authors have cautioned against an overly strict interpretation of these values, generated using simulated data, when using naturalistic data (e.g., Heene et al., 2011; Lance et al., 2006).

3. Results

3.1. Descriptive statistics, bivariate correlations, and measurement invariance

Descriptive statistics are shown in Table 1. All variables showed skewness and kurtosis within ±1, with the exception of engagement that showed a negative, leptokurtic, distribution. The proportion of variance between schools was relatively small for academic buoyancy and engagement (ρ_Is $\leq$0.04) and larger for mathematics test score (ρ_Is = 0.12 and 0.15). The maximum likelihood estimator with robust standard errors, and the "Type = complex" command, was used to deal with the

[2] In the United Kingdom, mathematics in referred to in everyday parlance as maths.

[3] See: https://www.gov.uk/government/collections/national-curriculum-assessments-practice-materials for papers and mark schemes.

Table 1
Descriptive statistics and factor loadings for study variables.

Variable	Mean	SD	ω	ρ_I	Skewness	Kurtosis	Factor Loadings
T_1 Academic Buoyancy	15.10	3.76	.75	.04	−0.72	0.15	.58–.70
T_1 Engagement	22.27	3.39	.75	.01	−1.75	3.72	.58–.74
T_2 Mathematics Test Score	4.46	3.39	.81	.12	0.85	0.25	–
T_3 Academic Buoyancy	22.06	3.46	.85	.04	−0.51	−0.26	.67–.74
T_3 Engagement	15.58	3.85	.79	.03	−1.71	3.56	.67–.74
T_4 Mathematics Test Score	9.55	4.72	.85	.15	0.12	−0.74	–

Note. ω = McDonalds omega. ρ_I = intraclass correlation coefficient (ICC1).

non-normal distribution of engagement and the clustering of mathematics test score within schools in subsequent latent variable modelling.

A measurement model comprising of academic buoyancy (four items each at T_1 and T_2), engagement (five items each at T_1 and T_2), mathematics achievement (modelled as a single-item latent variable), and socio-demographic covariates as manifest variables (age and gender; 0 = male, 1 = female), was tested in a CFA. Corresponding indicators for academic buoyancy and engagement at T_1 and T_2 were allowed to correlate. For mathematics test score the factor loading was set to $\lambda = 1$ and residual variance (σ_ε) calculated by multiplying the variance in mathematics test score by 1-ρ (where ρ is the internal consistency; Brown, 2006; Little, 2013).

Initial checks of engagement showed correlated residual variances for two pairs of items with similarly wording ("I try hard to do well in my maths lesson" with "In my maths lessons, I try as hard as I can" and "I pay attention in my maths lessons" with "When I'm in my maths lessons, I listen very carefully"). While acknowledging that post-hoc addition of residual variances is a controversial procedure it can be justifiable when the likely cause is method effects resulting from item wording (Cole et al., 2007) and was preferable than dropping items.

The CFA showed a good fit to the data, χ^2 (174) = 280.93, $p < .001$, RMSEA = 0.022, SRMR = 0.031, CFI = 0.982, and TLI = 0.977, and factor loadings (see Table 1) were all substantive (λs ≥ 0.58). Latent bivariate correlations are shown in Table 2; academic buoyancy, engagement, and mathematics test score, were all positively correlated. Temporal measurement invariance of item-factor loadings and item intercepts (i.e., that they are equivalent at T_1 and T_3; strong invariance) is a necessary precondition to modelling structural relations in reciprocal effects models (Widaman et al., 2010). For completeness, we also tested for the equivalence of item residual variances at T_1 and T_3 (strict measurement invariance). Academic buoyancy and engagement demonstrated strict temporal measurement invariance no substantive loss of fit (see Supplementary Materials for the models).

3.2. Structural equation modelling

The hypothesised, fully forward, model was tested in a SEM. Gender was added as a covariate as negatively correlations were shown with T_1 academic buoyancy and T_2 mathematics test score. Age did not correlate with any substantive variables hence was not included as a covariate. The SEM showed a good fit to the data, χ^2 (160) = 270.41, $p < .001$, RMSEA = 0.021, SRMR = 0.032, CFI = 0.983, and TLI = 0.978, and results are reported in Table 3 (also see Fig. 2). T_1 Academic buoyancy (β = 0.13, $p = .03$) and T_1 engagement (β = 0.24, $p < .001$) predicted T_2 mathematics test score. T_2 mathematics test score, in turn, predicted T_3 academic buoyancy (β = 0.10, $p = .03$), after accounting for the autoregressive relation with T_1 academic buoyancy (β = 0.53, $p = .03$). T_2 mathematics test score did not, however, predict T_3 engagement (β = 0.05, $p = .28$), after accounting for the autoregressive relation with T_1 engagement (β = 0.53, $p < .001$). T_3 academic buoyancy (β = −0.14, $p = .02$) and T_3 engagement (β = 0.21, $p = .002$) predicted T_4 mathematics test score after accounting for the autoregressive relation with T_2 mathematics test score (β = 0.84, $p < .001$). T_1 academic buoyancy (β = 0.14, $p = .07$) and T_1 engagement (β = −0.11, $p = .09$) did not predict T_4 mathematics test score. Male students reported higher T_1 academic buoyancy (β = −0.10, $p = .001$) and T_2 mathematics test score (β = −0.09, $p = .004$).

The direction of the coefficient from T_3 academic buoyancy to T_4 mathematics (β = −0.14) was reverse of the bivariate correlation (r = 0.26) indicating an instance of statistical suppression (Maassen & Bakker, 2001). To allow for a substantive interpretation of this coefficient we followed Kessler and Greenberg's (1981) solution (see p.80). If it is assumed downstream relations from T_1 academic buoyancy to T_4 mathematics test score are indirect, the path from T_3 academic buoyancy to T_4 mathematics test score represents the combined influence of change in academic buoyancy on change in mathematics test score as well as the level of T_3 academic buoyancy on T_4 mathematics test score. To disaggregate the two sources of influence, the reversed path of T_1 academic buoyancy to T_4 mathematics test score (which represents change; β = −0.14) can be deducted from the path from T_3 academic buoyancy to T_4 mathematics tests score estimated in the SEM (β = −0.14). The true estimate of the level of T_3 academic buoyancy on T_4 mathematics test score (−0.14 minus −0.14) is, therefore, zero.

In a supplemental analysis, we tested the possibility that T_3 engagement was mediating the link between concurrent T_3 academic buoyancy and T_4 mathematics test score. The fully forward model (Fig. 1) was re-specified such that a directional path from T_3 academic buoyancy to T_3 engagement replaced the previous correlation. This model showed a good fit to the data, χ^2 (161) = 274.85, $p < .001$, RMSEA = 0.022, SRMR = 0.032, CFI = 0.983, and TLI = 0.977; standardised path coefficients for are reported in Table 4. The indirect path from T_3 academic buoyancy to T_4 mathematics test score, mediated by T_3 engagement, was assessed by creating 95% confidence intervals (CIs) around the standardised regression coefficient; CIs that do not

Table 2
Latent bivariate correlations for study variables and demographics (gender and age).

	1	2	3	4	5	6	7	8
1. T_1 Academic Buoyancy	–	.68***	.30***	.61***	.46***	.32***	−.10**	−.01
2. T_1 Engagement		–	.33***	.47***	.60***	.33***	.06	−.01
3. T_2 Mathematics Test Score			–	.30***	.27***	.85***	−.11**	.07
4. T_3 Academic Buoyancy				–	.62***	.26***	−.07	−.01
5. T_3 Engagement					–	.35***	.05	−.01
6. T_4 Mathematics Test Score						–	−.07	.10
7. Gender							–	–
8. Age								–

*$p < .05$. **$p < .01$. ***$p <. 001$.

Table 3
Standardized path coefficients for the fully-forward reciprocal relations model.

Variable	T1 Academic Buoyancy	T_1 Engagement	T_2 Mathematics Test Score	T_3 Academic Buoyancy	T_3 Engagement	T_4 Mathematics Test Score
T_1 Academic Buoyancy			.13*	.53***	.08	.14
T_1 Engagement			.24***	.08	.53***	−.11
T_2 Mathematics Test Score				.10*	.05	.84***
T_3 Academic Buoyancy						−.14*
T_3 Engagement						.21**
Gender	−.10**	.06	−.09**	−.03	.03	.02

*$p < .05$. **$p < .01$. ***$p < .001$.

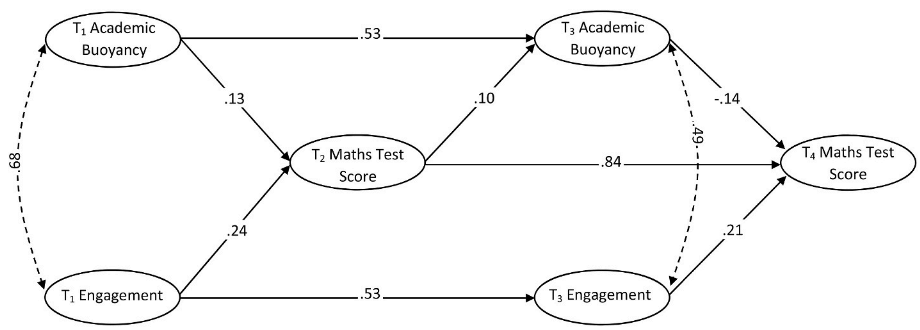

Fig. 2. Statistically Significant Standardised Correlation and Path Coefficients from the Structural Equation Model
Note. Dotted lines represent correlations and solid lines structural paths. Gender was included as a covariate on all variables and, in order to avoid over cluttering, omitted from Fig. 1.

Table 4
Standardized Path Coefficients for the Fully-Forward Reciprocal Relations Model to Examine Indirect Relations Between T_3 Academic Buoyancy and T_4 mathematics test score.

Variable	T1 Academic Buoyancy	T_1 Engagement	T_2 Mathematics Test Score	T_3 Academic Buoyancy	T_3 Engagement	T_4 Mathematics Test Score
T_1 Academic Buoyancy			.13*	.53***	−.18	.14
T_1 Engagement			.24***	.08	.45***	−.11
T_2 Mathematics Test Score				.11*	−.01	.84***
T_3 Academic Buoyancy					.49***	−.14*
T_3 Engagement						.21**
Gender	−.10**	.06	−.09**	−.03	.05	.02

*$p < .05$. **$p < .01$. ***$p < .001$.

cross zero indicate a statistically significant ($p < .05$) indirect relation. T_3 academic buoyancy was positively and indirectly related to T_4 mathematics test score via T_3 engagement: $\beta = 0.10$, $SE = 0.03$, 95% CIs [0.06, 0.16]. There were no substantive differences in interpretation of other paths to those reported for the fully-forward model above.

4. Discussion

The principal aim of the study was primarily to examine reciprocal relations between academic buoyancy and achievement, beyond relations with engagement. Critically, we used a shortitudinal time lag of one week from the measurement of academic buoyancy and engagement to the class test used to assess achievement. In addition, reciprocal relations between engagement and achievement, and academic buoyancy and achievement, were examined. Baseline (i.e., T_1) academic buoyancy positively predicted T_2 academic achievement. After accounting for autoregressive relations, T_2 academic achievement positively predicted subsequent academic buoyancy (i.e., the gain in academic buoyancy having accounted for baseline levels) but not vice versa. Hypothesis 1 was, therefore, partially supported as relations were unidirectional rather than bidirectional. Engagement positively predicted academic achievement at baseline (i.e., T_1 engagement to T_2 academic achievement). Engagement also predicted gains in academic achievement (i.e., T_3 engagement to T_4 academic achievement, having accounted for autoregressive relations) but not vice versa. Hypothesis 2 was partially supported as relations were unidirectional. Hypothesis 3 was not supported as no cross-lagged relations between academic buoyancy and engagement were shown. In summary, after accounting for autoregressive relations, engagement, but not academic buoyancy directly predicted achievement gain; academic buoyancy did, however, indirectly predict achievement gain mediated through concurrent engagement. Achievement predicted academic buoyancy, but not engagement, gain.

4.1. Relations between academic buoyancy and achievement

With one exception (Yun et al., 2018) previous studies have shown relatively small direct relations between academic buoyancy and achievement (Collie et al., 2015; Datu & Yang, 2021; Fong & Kim, 2019; Lei et al., 2022; Martin, 2014; Putwain & Aveyard, 2018; Putwain et al., 2015, 2016). We reasoned relations between academic buoyancy and achievement may be strengthened if using a short time lag. There was little difference in the magnitude of the bivariate correlations when separated by a one week ($rs = 0.30$ and 0.26) or seven months ($rs = 0.30$ and 0.32). Thus, a short time lag can be discounted as a possible influence on the magnitude of academic buoyancy and achievement relations.

Achievement was positively related to subsequent academic buoyancy over and above the variance accounted for by previous academic buoyancy (i.e., the gain in academic buoyancy). Thus, as anticipated, higher achievement reinforced academic buoyancy over a seven-month interval. All things being equal, performing well at a test enhances one's belief that one can withstand testing pressures. Collie et al. (2015) found no direct paths from achievement to academic buoyancy with a twelve-month interval in a sample of secondary school students; they were indirect and mediated by concurrent control beliefs. Notwithstanding the absence of control beliefs in the present study, it is plausible that the reinforcing effects of achievement on academic buoyancy decay over time (see Marsh et al., 2005, for a cognate example with academic self-concept). Furthermore, there was an absence of further tests in the seven-month interval to undo the reinforcing impact of achievement.

T_1 academic buoyancy (i.e., the baseline measure of academic buoyancy) predicted T_2 achievement independently of T_1 engagement. After a transformation to account for statistical suppression, T_3 academic buoyancy however, did not predict T_2 achievement gain independently of T_3 engagement. Just as Collie et al. (2015) found that academic buoyancy was not directly related to subsequent achievement, but was mediated by concurrent control beliefs, we showed an indirect relation from buoyancy to achievement mediated by concurrent engagement. Thus, even when stronger bivariate correlations are found (as in the present study) academic buoyancy does still not directly relate to subsequent achievement. Downstream influences of academic buoyancy on achievement are achieved through intervening beliefs (e.g., control as shown by Collie et al., 2015) and behaviours (engagement as shown in the present study); a similar finding would be expected for emotions (e.g., higher enjoyment and lower anxiety) although this proposition has yet to be tested.

In contrast to the aforementioned achievement-beliefs, emotions, and behaviours, academic buoyancy is not directly concerned with achievement but overcoming adversity. This may explain, in part, why the influence of downstream academic buoyancy is indirect. Academic buoyancy is the driver of effective cognitive, emotional, and behavioural, self-regulation strategies, that are employed in the face of adversity and reflected in the evidenced relations between academic buoyancy and achievement-related beliefs, emotions, and behaviours. It is the achievement-related beliefs, emotions, and behaviours, however, that are the primary drivers of achievement. Hence, when academic buoyancy in modelled alongside variables such as control (see Collie et al., 2015) and engagement (the present study) insufficient variance remains in academic buoyancy to predict achievement.

4.2. Relations between engagement and achievement, and academic buoyancy and engagement

In keep with many findings from the extant literature (e.g., Lei et al., 2018; Reyes et al., 2012; Wang & Holcombe, 2010), engagement predicted achievement (both baseline and gain). This is a likely result of more effective learning resulting from greater attention to, and participation in, class learning activities. We did not find, however, achievement to predict subsequent engagement gain. This finding is in contrast to existing studies of elementary school students showing reciprocal relations between engagement and achievement (Wang et al., 2019) and that achievement predicts subsequent engagement (Guo et al., 2015). It is possible that the longer (seven-month) lag from achievement to subsequent engagement weakened the relation in contrast to the one-week lag from engagement to subsequent achievement. The reinforcing effects of achievement on engagement could be time sensitive and undermined if students experienced lower than expected feedback, or work perceived to be difficult to master, in the intervening period.

Although academic buoyancy and engagement were correlated at each wave of measurement (rs = .68 and .49), we did not find cross-lagged relations. Previous studies have shown, after controlling for autoregressive relations, that engagement predicted academic buoyancy (Martin et al., 2010; Martin & Marsh, 2008), but buoyancy did not predict subsequent engagement (Martin & Marsh, 2008). In a two-wave study, academic buoyancy was concurrently related to, but showed no cross-lagged relations over time with, persistence (Bostwick et al., 2022). Our findings are not, therefore, inconsistent with the extant literature. Notwithstanding the aforementioned seven-month lag, it is possible that direct cross-lagged relations from engagement to subsequent academic buoyancy were weakened after the indirect positive relations from engagement to mathematics achievement, and from mathematics achievement to buoyancy were accounted for. Furthermore, cross-lagged relations from academic buoyancy to subsequent engagement weakened by participants finding the T_2 mathematics test difficult (as indicated by the relatively low mean score).

4.3. Limitations and suggestions for future research

Although our study utilised a multi-wave panel design, and a robust analytic approach, there are five limitations to highlight. First, with only two measurement points each for academic buoyancy/engagement, and achievement, the opportunity to estimate forward paths, after controlling for autoregressive relations, is limited. A study involving additional measurement points would provide additional opportunities to assess reciprocal relations. In doing so, researchers may wish to adapt a 'classic' cross-lagged approach whereby achievement is measured at the same point as academic buoyancy and engagement. Second, unequal time lags were used from academic buoyancy/engagement to achievement, and from achievement to academic buoyancy/engagement. The strength of the paths with different time lags were not, therefore, directly comparable and must be balanced accordingly. Studies using equally short time-lags between all measurement points would be beneficial.

Third, the study used between-person variances to test processes that are hypothesised to be intra-individual. Indeed, this has been the basis for critique of cross-lagged panel analyses that do not disentangle between-person from within-person relations (e.g., Hamaker et al., 2015). Building on the aforementioned desirability of additional waves of measurement, future studies could aim, specifically, to collect data from all measures over three or more time points. This would enable the use of random intercepts in cross-lagged panel analyses to model between-person variance leaving the remaining autoregressive and cross-lagged paths to reflect within-person variance. Studies adopting experience-sampling methods would be one such way to collect multiple waves of data (see Malmberg, 2020).

Forth, we only included a behavioural facet of engagement in the present study and did not include cognitive or emotional facets. A more thorough examination of the indirect links from academic buoyancy to subsequent achievement should also include achievement-related beliefs (see Collie et al., 2015) and emotions (see Putwain et al., 2015). Fifth, the analyses used in the present study followed a variable-centred approach. Variable-centred analyses cannot identify possible sub-groups for whom links between academic buoyancy and achievement may be stronger. Future analyses, could consider the benefits of using latent profile and latent transition analyses to identify such subgroups.

4.4. Educational implications

Findings of the present study imply that enhanced engagement would have downstream benefits for achievement. Relational, instructional, and behavioural/organisational supports in the classroom, have all been shown to improve engagement (e.g., Pianta et al., 2012; Strati et al., 2016); these principles can be incorporated into routine classroom instructional as well as intervention. Although academic buoyancy was not directly related to achievement gain in the present study, there may still be benefits in helping students to maintain or enhance engagement in the face of adversity which, in turn, is assistive for achievement. Although academic buoyancy interventions have not been widely studied, programmes designed to enhance emotional and cognitive regulation through principles of cognitive-behavioural intervention, and commitment and acceptance therapy (Puolakanaho et al., 2019;

Putwain et al., 2019) have shown promising findings. Finally, enhanced achievement could strengthen subsequent academic buoyancy. Numerous interventions have been shown to raise mathematics learning and achievement in primary classrooms including more detailed and structured teacher feedback, building foundational mathematics skills (e.g., conceptual understanding, strategy use for solving mathematics problems, and basic number skills) and the use of computerised learning tools (Simms et al., 2019). Such strategies could also build students capacity to overcome future adversities in learning mathematics. Building engagement, academic buoyancy, and foundational mathematics skills, could work synergistically to positively enhance the others, and ultimately achievement.

5. Conclusion

The findings of the present study add to the body of work showing the educational benefits of academic buoyancy. Notably, previous studies have not, in the main (Yun et al., 2018, excepted), shown substantive relations between academic buoyancy and achievement. The present study showed that baseline measurement of academic buoyancy predicted achievement independent of engagement, and subsequent measurement of buoyancy predicted achievement gain indirectly, mediated by engagement. Achievement, also, predicted gain in academic buoyancy. Building academic buoyancy skills would likely show downstream benefits for students and could be achieved through intervention or incorporating skills designed to manage adversity into routine classroom instruction and feedback.

Author statement

David W Putwain: Project administration, funding acquisition, conceptualisation of study, methodology, formal analysis, data curation, data collection, and writing (original draft).

Peter Wood: Project administration, funding acquisition, conceptualisation of study, methodology, data collection, and writing (review and editing).

Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2022.101691.

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