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Science motivation, academic achievement, career aspirations in early adolescents

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ABSTRACT

Studies have shown how expectancy and subjective task values (STVs) support, and perceived cost can undermine, science achievement and aspirations. Studies that combine multiple facets of STVs and cost with expectancy to explore impacts of science achievement and aspiration, in early adolescence, are lacking. The sample comprised 1240 students (498 males, mean age of 12.4 years) who self-reported expectancy, STVs, and cost. Between one and two weeks later students self-reported science aspirations and took a 30-min science test. A latent profile analysis indicated a four-profile solution was optimal. A profile comprised of high expectancy and STV, with low cost, showed the highest achievement and aspirations. In profiles where expectancy and STV were lower, or cost higher, achievement and aspirations were lower. Our findings imply classroom strategies, or interventions, to raise expectation and STV, and reduce cost, would benefit students at a critical age.

Educational implications statement: In students aged 11–14 years the highest science achievement and aspirations were found in a motivational profile where success was expected in combination with a perception of science being interesting/enjoyable, important, and useful, along with a perception that the cost of studying science (e.g., the effort involved) was low. Science achievement and aspirations were lower in motivational profiles where expectations and interest/enjoyment in science was lower, and cost was higher. Instructional strategies, interventions, and outreach activities, that raise accurate expectations of success and interest/enjoyment in science, and which reduce costs, would be possible ways to boost science aspirations and achievement.

1. Introduction

The present study concerns the science motivation, achievement, and aspirations, of students in the initial phase of secondary education. Maintaining the flow of scientifically trained individuals into the workforce is essential for continued national economic competitiveness and investment. Numerous studies, however, have highlighted a shortage of graduates with the requisite STEM (science, technology, engineering, and mathematics) skills to work in many sectors (Smith & White, 2018). It is therefore imperative to understand what factors might lead students to choose to study higher-level science courses or a career in science. As intrinsic value in general (e.g., Scherrer & Preckel, 2019) and interest in science, specifically, typically declines throughout adolescence (e.g., Steidtmann et al., 2023), an opportune period to study the influences on science achievement and career aspirations are the early years of secondary education. This is especially the case in England, where the present study was located, where many schools do not teach discrete science subjects until the later years of secondary education.[1]

Studies have shown secondary school students with profiles comprising high expectancy of success and subjective task value to show higher achievement and aspirations in science (e.g., Andersen & Chen, 2016). In contrast to expectancy and value, fewer studies have considered another important element of motivation, namely perceived cost (Watt et al., 2019), or students in early adolescence. Moreover, multiple distinct facets of STV and cost are not always considered, thereby missing potential nuances in how they combine to influence educational choice and achievement. In the present study we address these limitations to consider how expectancy combine with multiple facets of STVs, and cost, to motivate science achievement and career aspirations for students in the first three years of secondary education.

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[1] This decision is at the discretion of individual schools. Some may choose to continue with a combined science course.

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1.1. The situated expectancy value theory

Situated Expectancy Value Theory (SEVT) is a comprehensive theory of student motivation that combines proximal socio-cognitive determinants of educational choices and achievement, with distal sociocultural determinants (Eccles & Wigfield, 2020; Wigfield & Eccles, 2020). Situatedness was implicit in earlier versions of this model, simply referred to as Expectancy Value Theory (EVT: Eccles (Parsons et al., 1983). However, to emphasise the dynamic, situational sensitivity, and recursive, nature of the constructs, EVT was renamed SEVT. The proximal socio-cognitive determinants of educational choices and achievement are expectancy of success (henceforth referred to as expectancy for brevity), subjective task value (STV), and perceived cost.

Expectancy refers to time- and task-specific, beliefs about the probability of success on a forthcoming task (Eccles & Wigfield, 2020). STV is determined by three components, namely, intrinsic value, attainment value, and utility value. Intrinsic value is the anticipated or actual enjoyment resulting from engaging in a task, attainment value represents the importance a task holds for a person's identity or sense of self, and utility value refers to the usefulness of a task for allowing a person to realize their current or future goals (Eccles, 2005).

Perceived costs are the drawbacks associated with a particular activity (Eccles Eccles (Parsons et al., 1983). These include effort cost (whether the effort required by a task is worthwhile), opportunity cost (a reduction in time or capacity for alternate valued tasks), and psychological cost (the personal and social consequences of failure). In the present study we differentiated between the personal (emotion cost: negative emotions) and social (ego cost: negative judgements from others) facets of psychological cost (Jiang et al., 2020).

1.2. Evidence for the situated expectancy value theory

Inspired by EVT/SEVT, numerous studies have shown how expectancy and STVs positively relate to choices and achievement in mathematics and science courses (e.g., Meece et al., 1990; Simpkins et al., 2006). Although cost was not widely considered until the last decade (Barron & Hulleman, 2015), studies have shown higher cost to predict lower engagement, future study intentions, and grades, in mathematics and science (e.g., Jiang et al., 2018, 2020; Kosovich et al., 2015). A fundamental proposition of EVT/SEVT (Eccles & Wigfield, 2020; Eccles (Parsons et al., 1983) is that both expectancy and STV/low cost are required to motivate achievement and educational choice. Higher levels of expectancy cannot offset corresponding lower levels of STV/higher cost and vice versa (which would be implied if expectancy and STV/cost combined additively).

In support of this proposition, variable-centred studies have shown STV to strengthen positive relations between expectancy and achievement and educational choices (e.g., Lauermann et al., 2017; Nagengast et al., 2011) in mathematics and science in samples of secondary school participants. Studies examining interactions with cost are scarce. In two notable exceptions, Meyer et al. (2019), and Trautwein et al. (2012), showed higher cost weakened positive relations between expectancy and mathematics achievement in secondary school students.

The aforementioned studies have provided a substantial evidence base for the impact of expectancy, STV, and cost, on educational choice and achievement in secondary school students. There are, however, three notable limitations to highlight. First, it is common for studies to include just one or two facets of STV (e.g., Guo et al., 2015) or aggregate them (e.g., Jiang et al., 2020). Second, cost has not been widely explored and existing studies have only included one or two facets of cost or aggregated them (e.g. Meyer et al., 2019). Third, although science interest and motivation has been broadly studied in early adolescence (e.g., Bernacki et al., 2014; Renninger et al., 2019), studies based on variables proposed in SEVT/EVT are scarce. Consequently, evidence for how theoretically salient facets of STV and cost may combine with expectancy to drive science achievement and aspirations at this critical age is lacking.

Combining expectancy with multiple facets of STV and cost in variable-centred interactions may not be the most appropriate analytic choice. Testing interactions for expectancy, three STVs, and four costs, would result in nineteen two-way interactions subsumed into twelve three-way interactions. This number of interactions would make sample size demands beyond the scope of many studies (e.g., Shieh, 2008) and place limits on interpretability (Morin, 2016). A plausible alternative to combining expectancy with numerous facets of STV and cost within a single analysis is to use a person-centred latent profile analysis (LPA). LPAs could identify sub-groups of participants that differ from each other in the ways conceptualized by EVT/SEVT and which mirror theoretical predictions from variable-centred interactions.

1.3. Profiles of expectancy, STV, and cost

Numerous profiles are possible based on varying combinations of expectancy, STV, and cost. Studies of secondary school students typically identify between three and five profiles as optimal in the mains of mathematics and science (e.g., Dietrich & Lazarides, 2019; Jiang & Zhang, 2023; Watt et al., 2019). The exact number and makeup of optinal profiles is likely to vary from one study to another as a function of constructs included (all or some STVs and costs), differences between instruments, and sample characteristics. Our position, therefore, is that a priori theorizing is more effective when focusing on how profiles predict salient educational outcomes rather than the exact number and composition of profiles. Conceptually, we would expect to find the highest achievement and aspirations in a profile of high expectancy and STV combined with low cost. In profiles where either expectancy or STV where lower, and cost was higher, achievement and aspirations would be lower. Achievement and aspirations would be lowest in a profile where expectancy and STV were low combined with high cost.

Many studies have shown a profile comprising higher expectancy and STV (e.g., Andersen & Chen, 2016; Lazarides et al., 2016, 2019) and additional lower cost (e.g., Dietrich & Lazarides, 2019; Jiang & Zhang, 2023; Watt et al., 2019). This profile was the most adaptive compared to other profiles in that, following assumptions of EVT/SEVT, it was associated with the highest achievement and effort, aspirations, or career plans. Another common profile comprises lower expectancy and STV (e.g., Andersen & Chen, 2016; Lazarides et al., 2016) and additional higher cost (e.g., Dietrich & Lazarides, 2019; Jiang & Zhang, 2023). This profile was typically considered as the least adaptive and, supporting EVT/SEVT, associated with the lowest achievement and effort, aspirations, or career plans. In addition, Jiang and Zhang (2023) found a profile with lower expectancy, STV, and cost (i.e., unmotivated or disengaged), and Watt et al. (2019) with higher expectancy, STV, and cost (i.e., struggling). These two profiles are notable for showing that STV and cost do not always covary in tandem.

Studies including multiple facets of STV showed more nuanced profiles comprising lower expectancy and instrinsic value, but higher utility or attainment value (e.g., Lazarides et al., 2016, 2019) and additional higher cost (e.g., Mayerhofer et al., 2024; Watt et al., 2019). These profiles highlight the importance of attending to multiple facets of STV. Students may still value the importance of achievement and usefulness of science, even if one does not expect to succeed, and interest and enjoyment are low. Many studies either include generic cost (e.g., Dietrich & Lazarides, 2019) or just one or two facets. Studies combining multiple facets of cost are rare in early adolescence in the context of science and mathematics (e.g., Jiang & Zhang, 2023; Watt et al., 2019). Nonetheless, including different facets of cost may offer insights that are lost if considering only one or two facets or when combined into an aggregated cost.

Intrinsic value may typically be negatively related to negative appraisals of effort and missed opportunies, but largely unrelated to threats of task failure (e.g., Gaspard et al., 2020). Moreover, those students with lower expectancy and intrincic value, but higher attainment and utility value (e.g., Lazarides et al., 2019), could show higher ego and emotion cost than effort and opportunity cost due to the potential benefits for achievement. When expectancy was higher in students with attainment and utility value, ego and emotion cost would likely be lower. In short, different facets of STV and cost could combine in numerous and complex ways. However, no studies to our knowledge have studied effort, opportunity, and psychological costs in samples of early adolescents in relation to science achievement and aspirations. In keeping with our proposition that a priori theorizing is best focused on the more or less adaptive nature of profiles, rather than their precise make-up, we do not hypothesize specific profile combinations of STV and cost facets, but leave this as an exploratory question.

1.4. The present study

SEVT/EVT studies examining how expectancy combines with multiple facets of STV and cost to predict science achievement and aspirations in early adolescence are lacking. In the present study we address this gap in the literature. The sample comprised students aged 11–14 years. These are critical ages, in which interest in science has been shown to decline for many, although not all, students (e.g., Steidtmann et al., 2023). Gender, age, and whether students were eligible for free school meals (FSM) as a proxy for a low-income background, were included as demographic covariates. Age was included due to the expectation of that more adaptive profiles would be found in younger students. Gender and FSM were included as students have been shown to differ across profiles in LPA studies for mathematics and science; girls and those from economically disadvantaged backgrounds are often found in less motivationally adaptive profiles (e.g., Andersen & Chen, 2016; Watt et al., 2019). Our research question concerned how facets of expectancy, STV, and cost, combined to predict science aspirations and achievement. We tested three hypotheses:

Hypothesis 1. A motivationally adaptive profile comprising higher expectancy and STV, with lower cost, will show the highest achievement and aspirations.

Hypothesis 2. Motivationally struggling profiles comprising lower expectancy, lower STV, or higher cost, will show lower achievement and aspirations.

Hypothesis 3. A motivationally disadvantaged profile comprising lower expectancy and STV, with higher cost, will show the lowest achievement and aspirations.

2. Method

2.1. Participants, procedure, and missing data

The sample comprised 1240 participants drawn from six secondary schools in the northwest of England. There were 489 males and 700 females (29 participants declined to report their gender and 22 indicated a non-binary gender). The slight over-representation of female participants resulted from one school being a single-sex girls' school. Participants were in Years 7 to 9 (the first three years of secondary education in England) with a mean age of 12.4 years ($SD = 0.90$). Economic disadvantage was judged using free school meals (FSM) as a proxy; four hundred and seventeen participants (33.6 %) indicated their eligibility. The ethnic heritage of participants was: South Asian ($n = 68$; 5.5 %), Black ($n = 130$; 10.5 %), White Caucasian ($n = 814$; 65.6 %), Chinese ($n = 42$; 3.4 %), and other ($n = 118$; 9.5 %). A mixed heritage background was reported by 67 participants (5.5 %). Participants were clustered into 64 classes for their science lessons with an average of 19.4 students per class ($SD = 0.6.98$, range = 6 to 31).

The study was approved by an institutional research ethics committee (reference: 19/EHC/001). Schools who work in partnership with the authors' institution were invited to participate in the study. Written permission was provided by the Head Teacher of the six participating schools, and consent sought from parents/carers (opt-out) and participants (opt-in). Data were collected in school during a science lesson over two waves. In Years 7 to 9, following the National Curriculum,[2] science is taught in English schools as a combined subject. In the first wave participants completed an online questionnaire covering expectancy, value, and cost, in school science, along with demographics. This questionnaire took approximately fifteen minutes to complete. To minimise within-person missing data, participants were prompted if they had not answered a question. Between one and two weeks later, participants completed a thirty-minute online science test and survey questions for science aspirations.

Of the 1240 participants who completed the Wave 1 survey, 822 completed the Wave 2 science test and aspirations questions (33.7 % attrition). Large attrition, such as this, is not uncommon in longitudinal studies (e.g., Gustavson et al., 2012). When there is no systematic identifiable cause of missing data, it is described as Missing Completely Random (MCAR) and is, essentially, random (Graham, 2012). Little's omnibus test, $\chi^2(64) = 124.84$, $p < .001$, indicated that MCAR could not be assumed for missing science test and aspirations responses. When the cause of missing data can be identified from one, or more, observed variables it is described as Missing Random (MAR) and, somewhat paradoxically, is not truly random (Graham, 2012).

To establish if MAR could be assumed, we probed the potential cause(s) of missingness. Wave 2 science test scores and responses to aspiration questions were coded as absent or not. A series of logistic regressions (for gender, FSM, and ethnicity) and *t*-tests (for all other variables) were conducted to establish whether missing responses on the Wave 2 science test and aspirations questions could be predicted from Wave 1 expectancy, value, and cost, and socio-demographic variables. Participants were more likely to be missing at Wave 2 if they had lower intrinsic ($d = -0.13$), attainment ($d = -0.12$), and utility value ($d = -0.10$), and were younger ($d = -0.32$), male ($B = -0.41$), and eligible for FSM ($B = -0.32$), at Wave 1 ($ps < 0.05$).

Accordingly, Wave 2 missing data were assumed to be Missing at Random (MAR), as the causes for missingness in science achievement and aspirations could be accounted for by Wave 1 data and included within analytic models to predict achievement and aspirations. Missing data were handled using Full Information Maximum Likelihood (FIML). FIML has been shown to provide accurate estimates under MAR assumptions when the variable(s) responsible for missingness were included in analytic models (Jeličić et al., 2009; Nicholson et al., 2017), even when attrition is substantial (Dong & Peng, 2013).

2.2. Measures

Expectancy, STV, and cost, were measured on a five-point scale (1 = “Strongly Disagree”, 3 = “Neither”, 5 = “Strongly Agree”). Science aspirations were measured on a four-point scale (1 = *Strongly Disagree* to 4 = *Strongly Agree*). The internal consistency of measures ranged from $\omega = 0.69$ to $\omega = 0.91$ (see Table 1).

2.2.1. Expectancy of success

Expectancy was measured using the four items (e.g., “I learn things quickly in science”) from the Grade 8 version of the 2019 Trends in International Mathematics and Science Study (TIMSS) *Students Confidence in Science* scale (International Association for the Evaluation of Educational Achievement, 2018). Across the countries participating in TIMSS, the longer 7-item scale showed a unidimensional factor, good internal consistency, and predictive validity for achievement (Yin & Fishbein, 2020).

[2] https://www.gov.uk/government/publications/national-curriculum-in-england-science-programmes-of-study/national-curriculum-in-england-science-programmes-of-study#key-stage-3

Table 1
Descriptive statistics for study variables.

	Scale	Mean	SD	ω	ρ_I	Skewness	Kurtosis	Factor Loadings
Expectancy	1–5	3.08	0.76	0.82	0.08	−0.11	−0.37	0.70–0.76
Intrinsic Value	1–5	3.66	0.94	0.91	0.07	−0.52	−0.41	0.79–0.89
Attainment Value	1–5	4.05	0.74	0.85	0.07	−1.06	0.78	0.56–0.86
Utility Value	1–5	3.74	0.78	0.84	0.07	−0.61	−0.05	0.73–0.76
Effort Cost	1–5	2.87	0.66	0.69	0.09	0.21	−0.26	0.43–0.76
Opportunity Cost	1–5	2.26	0.78	0.78	0.03	0.77	−0.01	0.53–0.85
Emotion Cost	1–5	2.47	0.79	0.73	0.05	0.32	−0.49	0.56–0.77
Ego Cost	1–5	2.53	0.89	0.81	0.02	0.45	−0.53	0.68–0.88
Aspirations	1–4	2.31	0.64	0.89	0.06	0.14	−0.29	0.77–0.85
Achievement	0–30	22.45	7.44	0.76	0.31	−0.68	0.64	0.43–0.87

Note. ω = McDonald's omega and ρ_I = Intraclass correlation coefficient (ICC1).

2.2.2. Subject task value

STVs were measured using a modified version of the *Michigan Study of Adolescent Life Transitions* scales (Eccles et al., 2005). Uniform scale anchors (to "Strongly Disagree" to "Strongly Agree") were used for all items which were also changed to refer specifically to science. Scales for intrinsic value (e.g., "I am interested in learning science"), attainment value (e.g., "Getting a good mark in science is important to me"), and utility value (e.g., "Learning science can help with things in everyday life") comprised of 4 items each. The factorial and predictive validity, and internal consistency, of the adapted 12-item version of this subjective task value measure has been shown in previous studies (e.g., Putwain et al., 2018, 2021).

2.2.3. Perceived cost

Perceived cost was measured using Jiang et al.'s (2020) 12-item *Cost* scale adapted to be science specific. This measure comprised of 3-item subscales for effort cost (e.g., "Doing well in science requires more effort than I want to put into it"), opportunity cost (e.g., "To do well in science requires that I give up other activities I enjoy"), ego cost (e.g., "Others would be disappointed in me if I performed poorly in science"), and emotion cost (e.g., "Studying science scares me"). Jiang et al. (2020) demonstrated factorial and predictive validity, measurement invariance for gender and grade, and internal consistency for the Cost scale.

2.2.4. Science aspirations

Science career aspirations were measured using the four-items (e.g., "I would like to work in a career involving science") from the 2006 Programme for International Student Assessment (PISA) survey *Future-Oriented Science Motivation* scale (OECD, 2009). This scale showed a good fit to the data, and good internal consistency, for the participating countries (OECD, 2009).

2.2.5. Science achievement

Science achievement was measured using items from Key Stage 3 (KS3) National Curriculum Tests (NCTs[3]) designed for students in Years 7 to 9 (the focal sample in the present study). The questions chosen for the achievement test included the three science domains included within the English National Curriculum (biology, chemistry, and physics) and focused upon thinking scientifically. This enabled participants to access the questions as their disciplinary knowledge and understanding (i.e., knowledge of how scientific knowledge is generated and grows) rather than their substantiative knowledge and understanding (i.e., curriculum-based knowledge of concepts, models, laws, and theories). The tests comprised seven questions created from a random pool of items from previous KS3 NCTs. Each question was worth a maximum of five to eight marks depending on question complexity resulting in a score from ranging from 0 to 41. Previous studies have shown NCTs to show excellent internal consistency (Newton, 2009).

2.2.6. Socio-demographic covariates

Participants self-reported gender (male, female, other, or prefer not to say), age (in years), and FSM (0 = not eligible, 1 = eligible). For the purposes of analysis, gender was coded as (male = 0, female = 1); other and prefer not to say were recoded as missing data as there were insufficient responses to warrant inclusion.

2.3. Analytic strategy

Preliminary analyses were conducted in two phases. First, to approve the factor structure of the scales used to measure expectancy, value, cost, and aspiration, using confirmatory factor analysis. Second, a series of competing measurement models for STV and cost were estimated to establish whether they should be modelled as discrete variables or combined, and whether the specific facets of value (intrinsic, attainment, and utility) and cost (effort, opportunity, ego, and emotion) should be modelled as higher- or lower-order constructs. The main analyses were also conducted in two phases. First, a measurement model comprising all variables was tested to estimate bivariate correlations. Second, a series of LPAs were estimated based on expectancy, STV, and cost. LPA model selection was based on considerations regarding the profiles obtained (separation and meaningfulness of the profiles), while taking statistical parameters into account. The "type = complex" command was used to adjust standard errors for class clustering effects.

In the LPAs, factor scores were estimated using the effects coding method (Little et al., 2006). In this approach, the factor scores reflect the observed metric of the indicators, optimally weighted by the degree to which each represents the underlying latent construct, which is recommended over standardisation (Moeller, 2015). The use of factor scores is frequently applied in recent LPA research and recommended over scale scores (Morin et al., 2016). The statistical parameters considered in the LPA model selection included the Bayesian information criterion (BIC), sample-size-adjusted Bayesian information criterion (aBIC), Entropy, adjusted Lo, Mendell, and Rubin adjusted likelihood ratio test (LMR), and the number of individuals per profile into account (Sinha et al., 2021; Weller et al., 2020). Smaller values in BIC and aBIC, and significant LMR indicate a better fit of the k-profile model compared to the k-1 profile model (Nylund-Gibson & Choi, 2018).

Finally, the Bolck et al. (2004) BCH method was used to estimate differences in aspirations and science achievement in an auxiliary model (Asparouhov & Muthén, 2021). The BCH method mitigates the risk of latent profile shifts by employing a weighted multiple group analysis, where the groups correspond to the latent profiles. Weights in the BCH method is designed to account for measurement error in the latent profile variable. During the estimation of the auxiliary model, each observation is assigned a weight according to its respective profile, and

[3] KS3 refers to the English National Curriculum Years 7 to 9. KS3 NCTs were statutory tests taken by students at the end of Year 9 for school accountability purposes. KS3 NCTs were withdrawn in 2008 following concerns, about over-testing of students in secondary education. Despite their withdrawal. KS3 NCT questions remain widely used by English schools in a non-statutory fashion to measure student progress.

the model is then estimated as a multiple group model using these weights (Asparouhov & Muthén, 2021; Bakk & Vermunt, 2016). The differences in means across profiles were subsequently examined using Wald chi-square tests (Bakk & Vermunt, 2016). The auxiliary model included the covariates gender, age and FSM to evaluate the effect of the profile variable on aspirations and science achievement controlled by the covariates (i.e., effect of covariates on latent profile variable, science aspiration and achievement). In a supplemental analysis we showed profiles were similar for the single sex girls' school and the mixed sex schools (see Supplementary Materials). All models were conducted in Mplus v8.8 (Muthén & Muthén, 1998–2018). All data, materials, and analytic code, have been made publicly available at the Open Science Framework and can be accessed at https://osf.io/s4tbd/. The study was not preregistered.

3. Results

3.1. Descriptive statistics and latent bivariate correlations

Descriptive statistics are reported in Table 1. Apart from effort cost the internal consistency of all variables was good (ωs ≥ 0.73). There was a moderate degree of between class variance for expectancy, subjective task value, effort cost, and aspiration. Between class variance was higher for achievement and lower for the remaining facets of cost. Factor loadings were all good (λs > 0.40). Having established in preliminary analyses that subjective task value and perceived costs were best represented as distinct lower-order scales, we estimated latent bivariate correlations using a set Exploratory Structural Equation Model that showed a good fit to the data and are reported in Table 2 (see Supplementary Materials for details of the preliminary analyses and the measurement model). Expectancy and STVs were positively correlated with science aspirations and achievement. Effort, opportunity, and emotion cost were negatively correlated with achievement. Effort and emotion cost were negatively correlated with aspiration, while ego cost was positively correlated with aspiration.

3.2. Motivation profiles

Latent profile models with 2 to 6 profiles are reported in Table 3. BIC and aBIC, values decreased as the number of profiles increased without reaching a minimum. Entropy values showed a similar separation between latent profiles across two to six profiles. The LMR test suggested a three-profile solution was optimal. The six-profile model contained one profile with a small number of students ($n = 79$) which is below the recommended 10 % of the sample (Sinha et al., 2021) hence was not considered. Based on statistical parameters, the three- to five-profile models were investigated in detail (see Table S4 and Fig. S1 in Supplementary Materials for overview of the 3 to 5-profile models). In contrast to the three-profile model, the four-profile model showed an additional profile with high cost and medium to high expectancy and STV, whereby most indicators showed significant different levels between profile indicators (see Table S5 in Supplementary Materials). The fifth profile, however, did not uncover any further combination of expectancy, STV, and cost, that would provide extra theoretical or explanatory use (i.e., it produced two very similar profiles of moderate to high task values with moderate to low costs). Based on the meaningfulness of the profiles, theoretical considerations, and statistical parameters, the four-profile model was retained for the subsequent analyses.

The four-profile model is depicted in Fig. 1. Participants most likely to be in the first profile ($n = 208$) showed low expectancy, intrinsic value, opportunity and ego cost combined with medium attainment/utility value, and effort/emotion cost.[4] This motivationally disadvantaged profile was labelled *low to medium value and cost* profile. Participants most likely to be in the second profile ($n = 520$) showed high STVs combined with medium expectancy, effort and ego cost, and lower values in opportunity and emotion cost. This motivationally struggling profile was labelled *high value/low to medium cost*. Participants most likely to be in the third profile ($n = 162$) showed high values in attainment and utility value, effort, ego, and emotion cost combined with medium intrinsic value and opportunity cost, and low medium to expectancy. This motivationally struggling profile was labelled *high value and cost*. Participants most likely to be in the fourth profile ($n = 350$) showed very high intrinsic and attainment value, high expectancy and utility value combined with low effort, opportunity, ego and very low emotion cost. This motivationally adaptive profile was labelled *high value/low cost*.

Most variables differed significantly between the profiles (see Table S5 in Supplementary Materials). For example, the low to medium value and cost profile differed significantly from the high value/low to medium cost profile for the indicator variables expectancy, intrinsic, attainment, and utility value, as well as ego and emotion cost ($ps < 0.05$), while effort cost ($p = .054$) and opportunity cost ($p = .547$) showed similar values. The low to medium value and cost profile and the high value and cost showed the most similarities, with similar values in expectancy ($p = .559$), intrinsic value ($p = .051$), and emotion cost ($p = .262$), while all profile indicators differed significantly between the high value and cost and the high value/low cost profile ($ps < 0.05$).

3.3. Effect of motivation profiles on science aspiration and achievement

Mean differences in science achievement and aspiration between profiles controlling for gender, age and FSM, are shown in Table 4. The *low to medium value and cost* profile showed the most disadvantageous outcomes regarding achievement and aspiration across the four profiles. Participants most likely to be in this profile showed significantly lower achievement and aspiration than students in the other profiles. The *high value/low to medium cost* profile and the *high value and cost* profiles did not differ significantly from each other regarding science achievement and aspiration. The most advantageous outcomes were reported for the *high value/low cost* profile. Participants in this profile had significantly higher achievement and aspiration than the other profiles.

In addition, the covariates reveal that girls were less likely to be in the *low to medium value and cost* profile ($OR = 0.52$, 95 % CI [0.34, 0.81]), *high value/low to medium cost* profile ($OR = 0.59$, 95 % CI [0.38, 0.91]) and *high value/low cost* profile ($OR = 0.43$, 95 % CI [0.27, 0.67]) than in the *high value and cost profile*. Participants who received FSM are significant less likely to be in the *high value/low cost* profile ($OR = 0.52$, 95 % CI [0.31, 0.86]) than in the *high value and cost* profile. There were no statistically effects of age on profile membership. Within profiles, participants who receive FSM had lower test scores in the *low to medium value and cost* profile ($B = -3.28$, $p = .015$), and in the *high value and cost* profile ($B = -3.84$, $p = .003$), but higher science career aspirations in the *high value/low cost* profile ($B = 0.15$, $p = .026$) than participants without FSM. In addition, in the *high value/low cost* profile older students perform better than younger participants ($B = 1.34$, $p = .029$).

4. Discussion

The aim of this study was to examine how expectancy, STVs, and cost, combined to predict science achievement and aspirations in a sample of students in early adolescence. Expectancy and STVs were positively related to science achievement and aspirations. Achievement was negatively related to effort and emotion cost and positively related to ego cost. A four-profile solution was selected as optimal. The most motivationally adaptive profile comprised high expectancy/STV, combined with low cost and showed the highest achievement and aspirations. A motivationally disadvantaged profile comprised low expectancy, intrinsic value, opportunity/ego cost, combined with

[4] Values between 1.0 and 1.6 ≈ very low, 1.7 to 2.5 ≈ low, 2.6 to 3.4 ≈ moderate, 3.5 to 4.3 ≈ high, and 4.4 to 5.0 ≈ very high.

Table 2
Bivariate correlations between study variables.

	2	3	4	5	6	7	8	9	10	11	12	13
1. Expectancy	0.71***	0.44***	0.55***	−0.57***	−0.25***	−0.07*	−0.70***	0.57***	0.29***	−0.13***	0.01	−0.06
2. Intrinsic Value	–	0.61***	0.70***	−0.42***	−0.19***	−0.01	−0.70***	0.64***	0.28***	−0.01	0.07	−0.03
3. Attainment Value		–	0.73***	−0.12*	−0.01	0.27***	−0.27***	0.45***	0.19**	0.08*	−0.04	−0.04
4. Utility Value			–	−0.22	−0.06	0.15***	−0.43***	0.65***	0.25***	0.04	0.01	−0.04
5. Effort Cost				–	0.62***	0.40***	0.69***	−0.22***	−0.27***	0.03	0.07	0.14***
6. Opportunity Cost					–	0.45***	0.47***	−0.02	−0.10*	0.01	0.05	0.07*
7. Ego Cost						–	0.34***	0.10**	0.05	0.13***	0.06	0.06*
8. Emotion Cost							–	−0.46***	−0.23***	0.15**	−0.01	0.02
9. Aspiration								–	0.22***	0.02	0.04	−0.03
10. Achievement									–	0.04	0.10	−0.18***
11. Gender										–	−0.05	−0.02
12. Age											–	0.10
13. FSM												–

Note. * $p < .05$. ** $p < .01$. *** $p < .001$. Expectancy, STV, cost, and aspiration, were treated as latent variables. Achievement and socio-demographic covariates as manifest variables.

Table 3
Model parameters of the two to six profiles.

N profiles	LL	df	BIC	aBIC	LMR	Entropy	*N* Per Profile
2	−10,148.87	25	20,475.81	20,396.40	≤0.001	0.87	710, 530
3	−9574.84	34	19,391.85	19,283.86	0.01	0.86	285, 533, 422
4	−9194.31	43	18,694.90	18,558.31	0.33	0.86	208, 520, 162, 350
5	−8855.46	52	18,081.30	17,916.13	0.13	0.86	141, 334, 173, 339, 253
6	−8634.08	61	17,702.66	17,508.90	0.21	0.87	79, 171, 273, 338, 183, 196

Note. LL = Log-likelihood, df = degrees of freedom, BIC = Bayesian information criterion, aBIC = sample-size-adjusted Bayesian information criterion, and LMR = Lo, Mendell, and Rubin adjusted likelihood ratio test.

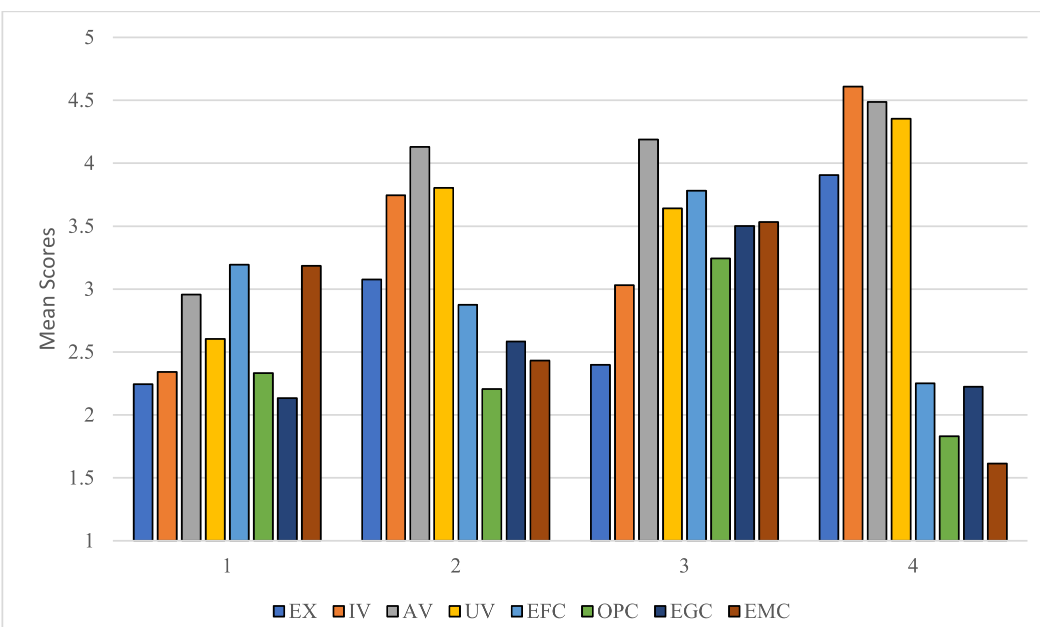

Fig. 1. Expectancy, STV, and Cost, Scores for the Four-Profile Solution. Note. EX = expectancy, IV = intrinsic value, AV = attainment value, UV = utility value, EFC = effort cost, OPC = opportunity cost, EGC = ego cost, EMC = emotion cost.

moderate to low attainment/utility value, and effort/emotion cost. This profile showed the lowest achievement and aspirations. There were two motivationally struggling profiles. One comprised lower expectancy, moderate intrinsic value and opportunity cost, combined with higher attainment/utility value, and effort/ego/emotion cost. The other comprised moderate expectancy and lower opportunity/emotion cost, combined with higher STV and effort/ego cost. Science achievement and aspirations did not differ between these profiles, but were significantly lower than the motivationally adaptive profile, and higher than the motivationally disadvantaged profile.

4.1. *Profiles of science expectancy, STV, and cost*

Previous studies of secondary school students have shown three to five profiles, estimated in LPA are optimal for mathematics and science (e.g., Andersen & Chen, 2016; Watt et al., 2019). While the exact makeup of profiles differs from one study to another, as a likely artefact of unique sample characteristics, measures chosen, and the exact

Table 4
Science aspiration and achievement across latent profiles controlling for covariates (gender, age, and free school meal).

		Achievement *M* (*SE*)	Aspiration *M* (*SE*)
1	Low-medium value and cost profile	17.82 (1.25)	1.59 (0.08)
2	High value/low-medium cost profile	21.08 (1.02)	2.16 (0.06)
3	High value and cost profile	20.99 (1.46)	2.08 (0.16)
4	High value/low cost profile	25.89 (0.86)	2.86 (0.06)
		Δμ	Δμ
	1 vs. 2	−3.26**	−0.57***
	1 vs. 3	−3.17*	−0.48*
	1 vs. 4	−8.07***	−1.27***
	2 vs. 3	0.09	0.09
	2 vs. 4	−4.81***	−0.70***
	3 vs. 4	−4.90**	−0.79***

combination of constructs included, there are typically motivationally adaptive, disadvantaged, and struggling profiles identified. Our four-profile solution was consistent with this body of work. Indeed, three of our four profiles corresponded with the three identified by Watt et al. (2019) for mathematics and science, and three of the five Jiang and Zhang (2023) identified for English and mathematics. Notably, like ours, the aforementioned studies, are rare examples of studies to include multiple facets of STV and cost for LPAs of secondary school students.

These were our profiles for: (1) *high value/low cost* which corresponded to “Positively engaged” in Watt et al. (2019) and “adaptive” in Jiang and Zhang (2023), (2) *high value and cost profile* which corresponded to “Struggling Ambitious” in Watt et al. (2019) and “high cost” in Jiang and Zhang (2023), and (3), *high value/low to medium cost* which corresponded to “Disengaged” in Watt et al. (2019) and “less motivated” in Jiang and Zhang (2023). Our fourth profile, *low-medium value and cost*, did not correspond to profiles shown in the studies by Watt et al. (2019) or Jiang and Zhang (2023). It did, however, correspond to the “low motivation (cost oriented)” profile found by Dietrich and Lazarides (2019) who used a generic measure of cost in a study of mathematics motivation in secondary school students. Our four profiles also fit broadly with others, based on secondary school mathematics and science, that may not have included multiple STV and cost facets but nonetheless, show adaptive, unmotivated, and struggling profiles (e.g., Fong et al., 2021; Lazarides et al., 2019).

4.2. Science achievement and aspirations across profiles

Our results showed science achievement and aspirations were highest in the motivationally adaptive profile, followed by the two struggling profiles, and the disadvantaged profile, supporting all three hypotheses. These findings are consistent with studies showing motivational profiles comprising high expectancy and STV together, or in combination with low cost, predict greater science aspirations and career plans (Andersen & Chen, 2016; Watt et al., 2019), and grades (Fong et al., 2021), in secondary school students, than struggling or disadvantaged profiles. Other studies have shown similar findings for mathematics (Dietrich & Lazarides, 2019; Jiang & Zhang, 2023; Lazarides et al., 2019). Support was provided for EVT/SEVT in two related ways. First, as predicted by EVT/SEVT, achievement and aspirations were highest in the profile when higher expectancy was combined with higher STV and lower cost (i.e., *high value/low cost*). In a complimentary way to that shown in variable-centred interactions (e.g., Lauermann et al., 2017; Meyer et al., 2019), when expectancy or STVs were lower, or cost was higher, as shown in three other profiles, achievement and aspirations suffered.

Second, despite expectancy and STV being positively related, and expectancy/STV being negatively related with cost, there may be sample sub-groups within which these relations may be stronger or weaker. In the present study, this was shown for the two motivationally struggling profiles. The attainment and utility values were statistically similar for both struggling profiles but differed in other respects (see Table S5). Significantly higher expectancy and intrinsic values and lower costs were shown for the *high value and cost* compared to the *high value/low-medium cost* profile (i.e., lower expectancy and intrinsic values and higher costs). It is plausible that all costs would be deemed as higher if expectancy of success and interest/enjoyment were lower. That is, the level of effort required, reduced opportunities for alternates, negative emotions, and fear of failure, are all inversely related to expectancy of success (e.g., Levi et al., 2014; Wang & Degol, 2013).

There are, however, nuances in other profiles that suggest this may not always be the case. Specifically, expectancy and intrinsic value were similar in the low-medium value and cost (i.e., motivationally disengaged) and the high value and cost profiles (see Table S5); effort, opportunity, and ego cost, were significantly higher in the high value and cost profile but there was no difference in emotion cost with the low-medium value and cost profile. The implication is that cost becomes higher in tandem with higher attainment and utility value. Furthermore, effort and emotion cost were *relatively* higher than opportunity and ego cost in the *low-medium value and cost* profile suggesting that it is specifically opportunity and ego cost that are sensitive to utility and attainment value. No differences in achievement and aspiration were shown for the two motivationally struggling profiles which is suggestive that higher attainment and utility value plays a role in supporting achievement and aspirations when expectancy and intrinsic value are lower (i.e., in the *high value/low-medium cost* profile).

Although no differences were shown between the two motivationally struggling profiles for achievement and aspiration, important differences could emerge on other important salient outcomes (i.e., cognitive, affective, and behavioural, forms of engagement) and over time the higher costs in the *high value and cost* profile could exert a greater negative impact on achievement and aspiration. The aforementioned nuances, highlight the benefit of (a) including multiple STVs and costs, and (b), using LPA; as we noted earlier modelling combinations of these variables using variable-centred interactions would result in numerous and potentially complex and underpowered effects to unpick.

4.3. Socio-demographic covariates

Girls were more strongly represented in *high value and cost* (i.e., motivationally struggling) than in the other three profiles. Unlike some studies, girls were not more strongly represented in motivationally disadvantaged profile (e.g., Fong et al., 2021; Jiang & Zhang, 2023). Niether, were girls repesented in the motivationally adaptive profile as shown in some others (e.g., Watt et al., 2019). Although unique sample characteristics may account for some differences between studies, it is also possible that social and educational perceptions of gender participation in science can play a role (e.g., Master, 2021). Some studies have suggested that girls place greater pressure in themselves to succeed at school than boys (Herrmann et al., 2019; Högberg et al., 2020) which may partially account for why they were more likely to show higher STV *and* cost. While this may offer a boost in achievement and aspirations (scores were higher than in the *low-medium value and cost* profile) there may be a cost to one's emotional and physical health.

Participants with FSM were more strongly represented in *high value and cost* than in the *high value/low cost* profile. These findings are broadly consistent with prior studies showing participants from lower socio-economic backgrounds are less strongly represented in more motivationally adaptive profiles (e.g., Andersen & Chen, 2016; Jiang & Zhang, 2023). It was notable, however, that participants in receipt of FSM did not show lower achievement in two of the four profiles, and also showed higher aspirations in the motivationally adaptive *high value/low cost* profile. Persons from economically deprived backgrounds typically perform worse than more affluent counterparts (e.g., Strand, 2014). These findings provide encouragement to the view that motivational variables are one way that education can undo, or at least, minimise the damage to achievement and aspiration arising from economic disadvantage. Previous studies have shown a decline in science interest throughout secondary education (e.g., Steidtmann et al., 2023). It is also encouraging, therefore, that age was unrelated to profile membership.

4.4. Limitations and directions for future research

The present study contributes to the literature by examining unique combinations of expectancy, STV, and cost, in LPA. Despite this contribution, there are four limitations that we would like to highlight. First, the gap between the measurement of expectancy, STV, and perceived cost, and the subsequent measurement of achievement and aspirations was short (between one and two weeks). A short gap allows for directionality to be established between motivational antecedents on the one hand and educational achievement and aspirations, on the other. Such a 'shortitudinal' gap may even be virtuous for studying motivational antecedents of career aspirations and antecedents that are conceptualized as proximal (see Dormann & Griffin, 2015). They do not, however, provide a longer-term prediction of how combinations of expectancy, STV, and cost, predict achievement and educational choices in the latter stages of secondary or upper-secondary education when students have the opportunity to exercise choice over which subjects to study for school-exit examinations.

Second, like many EVT/SEVT studies our findings do not address important personal and situational socio-cultural determinants with STVs and cost, and the subsequent link to achievement and educational choice. There is a rich seam of research drawing on 'science capital' frameworks to explore how the subjective identity offered by intersections of gender, ethnic heritage, and economic deprivation, influence achievement and educational choice (e.g., Archer et al., 2012). There are useful insights to be drawn from the science capital research for SEVT, as indeed there are for SEVT insights to be utilised by science capital researchers. It would be exciting for future studies to explore the possible synergies, inconsistencies, and contradictions of these different approaches to understanding student achievement and choice in science.

Third, attrition was relatively large across the two waves of data collection (33.7 %) attributable to lower STVs and age and belonging to a low-income family background. On the one hand these appear plausible reasons why students may choose not to participate in a round of data collection that included a test and enabled us to assume MAR. On the other hand, high rates of attrition are less than desirable. While FIML has been shown estimate accurate parameter estimates under MAR assumptions when attrition is substantial (Dong & Peng, 2013; Jeličić et al., 2009) it would be preferable if attrition was lower. To a degree rates of participation are outside of a researcher's sphere of influence. Nonetheless, there are some strategies that may assist with participant retention including the use of incentives, personalized participant reports, emphasizing benefits of participation, and reducing barriers to non-participation. Moreover, the short gap between the two waves of data collection may have inadvertently contributed to attrition whereby wave one survey questions about STV may prompted participants to reflect on reasons why they may not have wished to continue participation. Such reflections could fade with a longer lag between waves of data collection.

Fourth, our sample was somewhat imbalanced in that it contained a greater proportion of female students resulting from the inclusion of a single sex girls' school. There was no substantive difference in the composition of profiles from participants in the single sex and mixed sex schools, hence school type can be ruled out as a possible explanation of findings. Nonetheless, the generalizability of findings to single sex boys' schools is limited. Future studies could include a balanced number of mixed sex, as well as single sex girls' and boys' schools, in order to facilitate comparison of school types and broaden the generalizability of findings.

4.5. Implications for intervention and classroom practice

Broadly speaking, our study, as have others, suggest there may also be benefits for interventions to promote STV value, as well as reducing cost. While utility value interventions have been shown to boost science engagement (e.g., Hulleman & Harackiewicz, 2009) there are fewer studies of intrinsic and attainment value. Studies of science capital may prove useful in designing intrinsic value interventions through identifying those persons who do not identify with science ("a career in science is not for people like me"; see Archer et al., 2012) along with the reasons why. Attainment value interventions could develop or enhance the link between student's goals, identities, and job aspirations (Eccles & Wigfield, 2020). There are also few examples of cost reduction interventions. However, a recent study showed in undergraduate students that a cost intervention was as effective as a utility intervention for achievement (Rosenzweig et al., 2020). Similar cost interventions could be used with secondary school students. The effective components of interventions to promote STVs and reduce cost could be easily incorporated in regular classroom instruction. We believe there is an important role for educational psychologists to play in disseminating the principles behind motivational interventions to policy makers and colleagues responsible for the initial education, and continuing professional development, of teachers.

4.6. Conclusion

Our findings offer further support for the role of motivational variables included within EVT/SEVT in predicting science achievement and aspirations. Expectancy, STV, and cost, combined in different ways to enhance or constrain science achievement and aspiration. Specially, a profile comprised of high expectancy and STV, with low cost, was the most motivationally adaptive; participants showed the highest achievement and aspirations. If expectancy or STV were lower, or not higher, achievement and aspirations were lower. Our findings imply, that classroom strategies and interventions designed to boost STV or reduce cost, may benefit the achievement and aspirations for persons in early secondary education where science interest typically begins to decline.

CRediT authorship contribution statement

David W. Putwain: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Andrea Mallaburn:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Tanja Held:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

Declaration of competing interest

We have no known conflict of interest to disclose. All data, materials, and analytic code, have been made publicly available at the Open Science Framework and can be accessed at: https://osf.io/s4tbd/. The study was not preregistered. This project was funded by an award made to the first two authors by the British Academy (SRG22\220016).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2024.102577.

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