Probing for the Multiplicative Term in Modern Expectancy–Value Theory:
A Latent Interaction Modeling Study

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In modern expectancy–value theory (EVT) in educational psychology, expectancy and value beliefs additively predict performance, persistence, and task choice. In contrast to earlier formulations of EVT, the multiplicative term Expectancy × Value in regression-type models typically plays no major role in educational psychology. The present study used latent moderated structural equation modeling to explore whether there is empirical support for a multiplicative effect in a sample of 2,508 students at the end of secondary education. Expectancy and four facets of value beliefs (attainment, intrinsic, and utility value as well as cost) predicted achievement when entered separately into a regression equation. Moreover, in models with both expectancy and value beliefs as predictor variables, the expectancy component as well as the multiplicative term Expectancy × Value were consistently found to predict achievement positively.

Keywords: expectancy–value theory, achievement

Understanding why some students are more motivated than others to engage and excel in specific subjects and fields of study is one of the major concerns of educational psychology. For more than half a century, expectancy–value models of achievement motivation (Atkinson, 1957; Eccles et al., 1983; Eccles, Adler, & Meece, 1984; for reviews, see Eccles & Wigfield, 2002; Feather, 1959; Wigfield & Eccles, 2000) have been among the most influential models seeking to explain effort, choice, and achievement-related behavior. One of the core assumptions of early expectancy–value theory (EVT) models (later corroborated empirically and refined theoretically; see Feather, 1959, 1982, for reviews) was that achievement-related behavior was a multiplicative function—and not an additive outcome—of expectancy and value (and, in some models, of other factors as well). Thus, for example, the effect of expectancy on motivation was expected to be much stronger for students who placed greater value on academic study and achievement. Whether expectancy and value have an additive or synergistic interaction effect has played a lesser role in modern EVT approaches, however, and the interaction effect does not play an important role in current models. Using a large sample of upper secondary students, this study therefore explored whether the multiplicative term predicts achievement outcomes. As value beliefs are assumed to be multidimensional (see Eccles et al., 1983; Wigfield & Eccles, 2000), a further emphasis of the present study was on differentiating among four value components.

Expectancy–Value Theory

Modern EVT models in educational psychology (e.g., Eccles et al., 1983; Feather, 1988; Wigfield & Eccles, 1992, 2002) build on Atkinson’s (1957) expectancy–value theory to link performance, persistence, and task choice directly to individuals’ expectancy-related and task value beliefs. The most influential modern version of EVT in educational psychology is the Eccles et al. (1983) model of achievement-related choice, effort, and behavior and its refinements (see Eccles & Wigfield, 2002; Wigfield & Eccles, 2000, 2002). According to this model, expectancies and values directly influence performance, persistence, and task choice. Expectancies and values are in turn believed to be influenced by task-specific beliefs (e.g., individuals’ goals and self-schema) and to be affected directly or indirectly by individuals’ perceptions of other people’s attitudes and expectations, by their own interpretations of their
previous achievement outcomes, by socializers’ behavior and beliefs, by the cultural environment, and by unique historical events. Modern EVT has inspired research and applications in various areas of education for more than a quarter of a century, including effort and achievement in various school subjects (e.g., Eccles, Wigfield, Harold, & Blumenfeld, 1993; Trautwein & Lüdtke, 2007; Wigfield et al., 1997), academic choices (e.g., Nagy et al., 2008), sports (Wigfield et al., 1997), and homework (e.g., Trautwein, Lüdtke, Schnyder, & Niggli, 2006).

Modern EVT differs from Atkinson’s (1957) theory in several ways (see Wigfield, Tonks, & Klauda, 2009). First, in contrast to the laboratory environments and experimental studies used in much of Atkinson’s research, Eccles and colleagues (1983) applied their EVT model to real-world achievement situations, mostly using nonexperimental research approaches. In fact, high external validity was one of the major building blocks in the formulation of modern EVT.

Second, modern EVT uses a broader definition of expectancy and value than does Atkinson’s (1957) theory. In modern EVT, *expectancy of success* is conceptualized as a task-specific belief about success in a future academic task. Eccles et al. (1983) defined beliefs about ability as individuals’ evaluations of their competence in different areas. Theoretically, expectancy of success is closely related to other conceptions of self-beliefs (e.g., academic self-concept, Marsh, 2007; self-efficacy, Bandura, 1997; Pajares, 1996). Conceptually, the model differentiates between ability beliefs—broad beliefs about competence in a given domain—and expectancies of success on a specific upcoming task. However, in empirical studies, the two components have shown very high intercorrelations, and competence and expectancy beliefs have typically been collapsed into a single construct or used interchangeably (see Eccles & Wigfield, 2002). In fact, Eccles and Wigfield (2002) concluded that in real-world achievement situations, competence and expectancy beliefs are empirically indistinguishable (see, however, Bong & Clark, 1999). In the present study, in line with EVT, we use the term *expectancy beliefs* throughout. A self-concept instrument was used to assess these beliefs.

Another core aspect of the Eccles et al. (1983) EVT model that differs from the Atkinson (1957) conceptualization is the differentiation of four task value components: intrinsic value, attainment value, utility value, and cost (Eccles & Wigfield, 2002). *Intrinsic value* is defined as the enjoyment a person derives from performing an activity, or his or her subjective interest in a subject. The role of interest in learning has been addressed in several motivational theories and highlighted in numerous studies (see Wigfield, Eccles, & Pintrich, 1996). *Attainment value* is defined as the personal importance of succeeding in a task. *Utility value* indicates the perceived (future) individual usefulness of engagement and achievement in a certain domain. Finally, *cost* describes the perceived negative consequences of engaging in a task (e.g., performance anxiety, fear of failure, effort required, and the opportunity cost of choosing that option). Although theoretically separable, the four value components have shown relatively high intercorrelations in several empirical studies and have thus often been incorporated into a single, more general value scale (e.g., Eccles et al., 1993).

Both expectancy and value beliefs are highly domain specific (Bong, 2001; Eccles et al., 1993; Krapp, 2002). Students often have favorite school subjects and will happily volunteer reasons for preferring mathematics or sports, even if their objective performance in both subjects is the same. In fact, correlations among expectancy and value beliefs in different school subjects are typically much lower than are correlations among the corresponding grades or test scores (e.g., Denissen, Zarrett, & Eccles, 2007; Trautwein, Lüdtke, Roberts, Schnyder, & Niggli, 2009). In particular, there is a strong distinction between verbal and mathematical subjects, with students tending to report more interest in either verbal or mathematical subjects (Marsh, 1986). Empirical evidence indicates that the domain specificity of expectancy and value beliefs increases with students’ age (Denissen et al., 2007). At the same time, the associations between expectancy and value beliefs within a domain increase over time (Wigfield et al., 1997) because “children come to value what they are good at” (Wigfield et al., 2009, p. 61). On a correlational basis, both expectancy and value beliefs tend to be substantially associated with achievement-related outcome variables. When both predictors are simultaneously entered into a prediction model, however, a differential picture emerges (see Wigfield & Eccles, 2000, 2002). Whereas expectancy beliefs have been shown to be especially closely associated with performance in both cross-sectional and longitudinal studies, value beliefs are more potent predictors of choice, effort, and persistence in achievement-related activities (e.g., Eccles et al., 1984; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Meece, Wigfield, & Eccles, 1990; Nagengast et al., 2011; Trautwein & Lüdtke, 2007; Wigfield et al., 1997). In Meece et al. (1990), for instance, value beliefs did not predict achievement once expectancy beliefs were controlled, although they were positively related to achievement in a simple univariate analysis.

### The Product Term Expectancy × Value: Conceptual and Methodological Considerations

Modern EVT in educational psychology has its roots in the classical EVT model of achievement motivation (Atkinson, 1957) and in similar cognitive alternatives to classical behaviorist accounts of motivation and behavior that were developed in the 1950s (see Feather, 1959, for a review). One of the core assumptions of these approaches (see Feather, 1982, for a review) was that expectancy and task value beliefs interacted in determining achievement-related behavior. If a student did not expect to succeed on a task, even high value beliefs could not compensate for this low expectancy of success, and the student would be unlikely to choose or pursue the task. Similarly, a low task value would invariably lead to lowered motivation and engagement that could not be compensated for by a high expectancy of success. In his review of EVT models in a wide variety of domains, Feather (1982) concluded that “they usually assume that expectations and subjective values combine multiplicatively to determine force” (p. 414). Indeed, tests of the original EVT models, mostly in laboratory studies in which expectancy and values were experimentally manipulated, emphasized the multiplicative combination of expectancy and value (see Feather, 1959, 1982). In many of these studies, expectancy or value beliefs were experimentally manipulated to be “zero.”

In contrast, modern EVT in the domain of educational psychology place greater emphasis on real-world outcomes, nonexperimental designs, and interindividual differences in expectancy and
value beliefs. In these designs, interaction terms generally play a much smaller role than in experimental studies. The multiplicative combination has not been addressed—either in the initial presentation or in later presentations of the model (Eccles et al., 1983; Eccles & Wigfield, 2002). However, the founders of modern EVT have not suggested that there is no significant interaction (J. S. Eccles, personal communication, March 9, 2011). Thus, the question remains: Is there support for a multiplicative effect of expectancy and value on achievement-related behavior and, if so, how large is it?

As they do not specify an interaction term, modern EVT models in educational psychology can be called *additive effects models* (see Cohen, Cohen, West, & Aiken, 2003, for the terminology used in the present study). Additive effects models suggest that two (or more) predictors uniquely and independently predict the outcome variable. Further, the combined effect of the two predictors amounts to the combination of their separate (unique) effects. In contrast, interactive effects models with synergistic or antagonistic effects posit a statistical interaction between two (or more) predictor variables. In other words, an interactive effects model would suggest that the combined effect of expectancy beliefs and value beliefs differs from the sum of the two separate effects. On the basis of the traditional EVT models, it seems plausible to postulate a *synergistic* model (also called an *enhancing* model) according to which “both predictors affect the criterion Y in the same direction, and together they produce a stronger than additive effect on the outcome” (Cohen et al., 2003, p. 285). In other words, the achievement-related outcome will be especially high if students score high on both expectancy and value beliefs (because the interaction effect adds to the additive effect); or, equivalently, the effect of expectancy on the achievement-related outcome will be stronger for students with high value beliefs. A synergistic interaction also means that the effects of expectancy on achievement will be null or very weak if value is low, even if expectancy is high (and vice versa).

Why has the multiplicative effect of expectancy and value disappeared from modern EVT models? The explanation lies in the shift from a focus on behavioral choice in laboratory situations—which was prevalent in the historical approaches to tests of EVT—to the use of questionnaires to assess expectations and values of success in real-world contexts (see Busemeyer & Jones, 1983). In the experimental approaches, task difficulties and incentives could be manipulated directly in within-person designs. The stronger the manipulation, the larger the difference between the experimental factors. The introduction of questionnaire measures in real-world environments shifted the focus from within-person differences in achievement-related choices to between-person comparisons of engagement in the same tasks or areas. Instead of experimenter-induced differences between experimental conditions, the test of the interaction effect was based on naturally occurring differences in expectancy and value across different persons.

This shift had two consequences. First, from a conceptual point of view, it is debatable whether a statistically significant interaction should be a feature of modern EVT. In traditional EVT, the multiplicative term mainly meant that if one expected to succeed at a task but had no value for it, there was no motivation to engage in the task. In other words, if value is zero, motivation will also be zero regardless of expectancy. However, in contrast to the earlier experimental studies, it is hard to imagine there being zero value in high-achievement outcomes in typical school settings. Accordingly, a significant interaction in modern EVT using nonexperimental data from school students would have a slightly different flavor (i.e., motivation would not be zero) than that reported by Atkinson (1957) and Feather (1959), but the consequences would be similar (synergistic effect on outcome when both value and expectancy are high).

The second consequence of the shift to nonexperimental studies relates to a statistical issue. Unfortunately, it is difficult to detect interaction effects in nonexperimental research for two reasons (Aiken & West, 1991; Marsh, Hau, & Wen, 2004; McClelland & Judd, 1993). First, interaction effects in observational studies are usually small to moderate in size. In experimental studies, the distribution of the independent variables can be manipulated by the researcher to more extreme conditions, thus magnifying the effects (e.g., Fiedler, 2011); in observational studies, however, cases with pronounced profiles (i.e., individuals with high values on one dimension and very low values on the other) are rare. As demonstrated by McClelland and Judd (1993), this scarcity of cases with pronounced profiles negatively affects the power of observational studies to detect interaction effects. Second, when the two individual predictors X and Z are measured with error, the cross-product term XZ (used to assess the interaction) is even more unreliable than are the individual predictors. Unless scale scores are measured without error, product variables based on them will always be less reliable than the original variables. This unreliability invariably leads to an underestimation of the interaction effect (Busemeyer & Jones, 1983) and to a loss in statistical power to detect it. Thus, estimates of true interaction effects are complicated by the problem of unreliable predictor variables.

Large sample sizes and highly reliable predictor variables help to avoid Type 2 errors (i.e., not finding evidence for a statistically significant interaction although one exists). Moreover, structural equation modeling techniques (e.g., Bollen, 1989) that control for measurement error by modeling latent variables with multiple indicators are a potential solution for the reliability problem. However, conventional structural equation modeling cannot account for interactions and other nonlinear effects of latent variables. Models with latent interactions—although in principle available since the 1980s (e.g., Baron & Kenny, 1986)—have only fairly recently become easily accessible to applied researchers (Klein & Moosbrugger, 2000; Marsh et al., 2004).

To our knowledge, only one prior study (Nagengast et al., 2011) has documented a significant expectancy–value interaction on the basis of nonexperimental data. In the Nagengast et al. (2011) study, expectancy (science self-concept), value (enjoyment of science), and the Expectancy × Value interaction were all statistically significantly associated with engagement in science activities and intentions of pursuing scientific careers. In line with prior findings in EVT research, the value component was the stronger predictor of the two outcome variables. Unfortunately, Nagengast et al. were not able to control for prior engagement. Furthermore, achievement outcomes were not included in the study, and Nagengast et al. did not discuss the size of the interaction effect they

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1 We thank an anonymous reviewer for his or her cogent comments on the conceptual underpinnings of expectancy–value theory.
found. Hence, the empirical status of the Expectancy × Value interaction remains empirically unresolved.

The Present Investigation

In the present study, we examined the power of expectancy and value beliefs to predict achievement. A large sample of upper secondary students completed items tapping their expectancy and value beliefs about mathematics and about English as a foreign language. The task value instrument probed all four dimensions of the Eccles et al. (1983; Eccles & Wigfield, 2002) EVT model. In addition, the students were administered standardized achievement tests in mathematics and English. Sex, prior achievement, cognitive ability, and school type were also assessed and were included as control variables in the prediction models.

Our main research hypotheses were as follows. First, on the basis of the conceptual differentiation realized in the Eccles et al. (1983) EVT model, we expected to find empirical support for the differentiation of task value into several subcomponents. At the same time, in view of both conceptual considerations and previous empirical findings, we expected to find relatively high intercorrelations among the task value subcomponents as well as between task value and expectancy value. Second, we expected to find strong evidence for the domain specificity of expectancy and value beliefs. In other words, we expected to find only a small to moderate association between expectancy beliefs in mathematics and English and between value beliefs in mathematics and English.

Third, we expected that both expectancy and value beliefs would positively predict achievement and homework when entered separately into a regression equation. Fourth, we expected expectancy beliefs to be the stronger predictor of academic achievement when both expectancy and value beliefs were entered into the regression equation. Fifth, and most central to the investigation, we tested whether expectancy and value beliefs predicted achievement additively or synergistically. Specifically, we examined whether the interaction term was significant (supporting a synergistic relation) or not (supporting an additive relation). To avoid Type 2 errors, we used a multimatrix design, meaning that all students worked on a “students were in their final year of schooling (which was Grade 13 at the time the study took place); their mean age was 19.6 years (SD = 0.78). In line with the typical composition of academic track schools, girls (55.7% of the sample) were slightly overrepresented in this study. In terms of family background, 8.9% of the students were not born in Germany, and 21.3% had at least one parent who was not born in Germany.

All participating students were enrolled in a pre-university mathematics class. In the schools we studied, the level of choice with regard to mathematics is almost zero: All students have four compulsory mathematics lessons per week, and all are taught according to the same curriculum and the same achievement standards. The same holds for English as a foreign language, although students can theoretically choose to opt out of English at the upper secondary level. In practice, however, most students take English classes; in fact, 91.1% of the students in our sample were enrolled in a pre-university class in English as a foreign language.

Students participated voluntarily in the present investigation, with no financial reward. Two trained research assistants administered the materials in each school between February and May of 2006.

Instruments

Expectancy beliefs. Mathematics and English expectancy beliefs were assessed with four items (see Appendix A), each with a four-point response format (ranging from disagree to agree). The mathematics expectancy items came from the German adaptation (Schwanzer, Trautwein, Lüdtke, & Sydow, 2005) of the Self Description Questionnaire III (SDQ III; Marsh & O’Neill, 1984), a multidimensional self-concept instrument for late adolescents and young adults (sample item: “I have always been good at mathematics”). Because English as a foreign language was not included in the original SDQ III, the four items measuring English expectancy beliefs (sample item: “I’m just not good at English”) were created on the basis of the mathematics and verbal self-concept scales of the SDQ III and a prominent German self-concept inventory (see Trautwein, Lüdtke, Marsh, Köller, & Baumert, 2006). The weighted α, an estimator for composite reliability in latent variable modeling (see Bacon, Sauer, & Young, 1995), was .90 for mathematics and .92 for English.

Value beliefs. We assessed value beliefs using 12 items tailored to fit the Eccles et al. (1983) EVT model. All items are reported in Appendix B. The wording of these 12 items was strictly parallel for mathematics and English except for the subject name. The items covered all four conceptual dimensions of task value (attainment value, intrinsic value, utility value, and cost). Most were well-validated items that we adapted from previous national and international large-scale studies (see Marsh et al., 2005; Trautwein, Lüdtke, Schnyder, & Niggli, 2006; Wigfield & Eccles, 2000). All resulting scales exhibited acceptable to good internal consistency (mathematics: .86 ≤ weighted α ≤ .90; English: .75 ≤ weighted α ≤ .86).

Achievement outcomes. The standardized mathematics achievement test consisted of 68 items from the Third International Mathematics and Science Study (TIMSS; e.g., Baumert, Bos, & Lehmann, 2000). Following the procedure applied in TIMSS, we used a multimatrix design, meaning that all students worked on only a subset of the items (about 30 to 40). On the basis of the curriculum covered in the schools in our sample, we used six of the
original TIMSS clusters (A, B, I, J, K, and L) and created four assessment booklets that were randomly assigned to the students. Students were given a total of 90 min to work on the test (see Nagy, Neumann, Trautwein, & Lüdtke, 2010). Responses were analyzed using item response theory (IRT) methods and the ConQuest software (Wu, Adams, & Wilson, 1998), and the original TIMSS metric was used to generate a total mathematics achievement score. The reliability of the test scores was .88 (formula by Rost, 1996). English achievement was assessed using a shortened research version of the Test of English as a Foreign Language (TOEFL) as applied in the Institutional Testing Program. The TOEFL is the test most widely used to assess the English language skills of nonnative applicants to U.S. universities. The short version we used consisted of 70 items; students were given 60 min to work on the test. Internal consistency (KR20) was .95. In a validation study, 171 students were administered both the short research version and the full version of a (different) TOEFL (see Köller & Trautwein, 2004). The correlation between scores on the two tests was .88 (not accounting for unreliability), indicating good validity of the short research version.

Control variables. The mathematics and English grades that the students were awarded on their final Grade 10 report card were used as indicators of their prior achievement. After Grade 10, students transfer to upper secondary education. Hence, we controlled for school achievement before entry to upper secondary education. The grades were reported by the students themselves. We also assessed cognitive abilities by means of two subscales of the Cognitive Abilities Test 4-12 + R (Heller & Perleth, 2000): figural and verbal analogies. Scores on these subs tests are considered to be relatively free of environmental effects (e.g., effects of the quality of schooling). The figural analogies subtest, consisting of 25 items in multiple-choice format, was used to control for mathematics ability. The verbal analogies subtest, consisting of 20 items, was used to control for verbal ability. For both the verbal and figural analogies subs tests, item response modeling was used to create a total score. We also controlled for students’ sex. Finally, we controlled for the different school types at the upper secondary level (traditional Gymnasium vs. vocational Gymnasium). Students in both school types had comparable workloads in mathematics and foreign languages.

Statistical Analyses

Latent interaction modeling. We used structural equation modeling to predict academic achievement and tested the latent interaction effect of expectancy and value, running separate analyses for mathematics and English. Because expectancy and value beliefs were measured with at least two items per scale, we were able to correct for measurement error in the predictor variables by specifying these constructs as latent variables. We specified a set of models with increasing numbers of predictors in the structural model predicting the respective outcome variables: In the simplest models (M1 and M2), either expectancy or value was used as a single predictor for the outcome variable. In the next step, both expectancy and value were used to jointly predict the outcome (M3). Only linear effects of the predictors were considered in this conventional structural equation model. In the final model (M4), we used the latent moderated structural (LMS) equations approach (Klein & Moosbrugger, 2000, see below) to model the latent interaction between expectancy and value in predicting the outcome variables and tested the synergistic effects of the two constructs. The control variables were included in all models as additional predictor variables. The covariances between the predictor variables were freely estimated. The Mplus statistical package (Version 6.11; Muthén & Muthén, 1998–2006) was used in all modeling procedures.

The LMS equations approach was specially developed for the analysis of nonlinear structural equation models with latent interactions and quadratic effects (Klein & Moosbrugger, 2000; see also Marsh et al., 2004, for a comparison of different approaches to modeling latent interactions) and is implemented in the Mplus software. It provides unbiased estimates of interaction effects between latent variables that are corrected for measurement error. In contrast to conventional multiple moderated regression analyses, the estimation of latent interaction effects with LMS does not require the manual specification of product variables on the scale level. Instead, the LMS approach estimates latent interaction effects directly by modeling the implied nonnormal distribution of the latent outcome variable and its indicators (see Kelava et al., 2011, for a thorough but accessible description). In Mplus, the latent interaction can be specified by a single command in the model syntax (see Appendix C for an annotated example syntax). Parameter estimates for main and interaction effects in the structural model can be directly obtained from the model output. To enhance the interpretability of the results, we standardized all indicators before running the analyses. Consistent with the assumptions of the LMS approach, we treated the indicator variables as continuous (Kelava et al., 2011; Klein & Moosbrugger, 2000). All analyses used the MLR estimator in Mplus that corrects test statistics and standard errors for nonnormality of the indicator variables and for clustering of the data (see below) and that has been shown to be robust when ordered categorical variables are treated as continuous (e.g., Beauducel & Herzberg, 2006; Dolan, 1994; Lei, 2009; Lubke & Muthén, 2004; Rhetmtulla, Brosseau-Liard, & Savalei, 2010).

Model fit indices. We assessed the model fit of the linear structural equation models using the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) (Marsh, Balla, & Hau, 1996; Marsh, Balla, & McDonald, 1988; Marsh et al., 2004). In addition, we inspected the $$\chi^2$$ test statistic and carefully evaluated the parameter estimates. CFI values (on a scale from 0 to 1) greater than .90 and .95 are typically taken to reflect acceptable and excellent fits to the data, respectively. SRMR values below .09 indicate good fit. RMSEA values of less than .06 are taken to

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*Although we have no direct information on the validity of the reported Grade 10 school grades, there is some evidence that student self-reports of achievement as obtained in the present study are very accurate: The correlation between the self-reported Abiturgesamtnote (grade point average, or GPA, at the end of high school as reported 2 years later) and the actual GPA as obtained from the school files was .98 ($p < .001$). We also reran the analyses, replacing the Grade 10 grades with teacher-reported grades from the end of Grade 12 (about 9 months before the study was conducted) as a control variable. As the pattern of results was very similar to that reported here, the same overall conclusions can be drawn from this analysis. In line with expectations, most regression coefficients were somewhat smaller when we controlled for Grade 12 school grades.*
reflect a reasonable fit. RMSEA values greater than .10 are generally considered unacceptable, although there is no golden rule (Chen, Curran, Bollen, Kirby, & Paxton, 2008; Hu & Bentler, 1999; Marsh et al., 2004). The CFI contains no penalty for a lack of parsimony, so improved fit due to the introduction of additional parameters may reflect capitalization on chance, whereas the RMSEA does contain penalties for a lack of parsimony (for further discussion, see Cheung & Rensvold, 2002; Hu & Bentler, 1999; Marsh et al., 2004). We considered the fit of a model acceptable when at least two of the fit indices were in the range typically considered acceptable. However, we note that fit indices are subject to influences of seemingly arbitrary properties of the data structure (e.g., Heene, Hilbert, Draxler, Ziegler, & Bühner, 2011) that invalidate sweeping generalizations of cutoff values.

It should also be noted that conventional model test statistics and fit indices cannot be used to test latent interaction effects because they are insensitive to nonlinear misspecifications (Mooij & Satorra, 2009). In addition, the problem of assessing global model fit for structural equation models with latent interaction effects has not been resolved conclusively: Global model tests and standard fit indices do not apply because there is no saturated reference model (Jöreskog & Yang, 1996), and alternative ways of assessing the fit of nonlinear structural models are still being developed (e.g., Klein & SermellelEngel, 2010). Hence, we were unable to present tests of model fit and fit indices for the structural equation models with latent interactions estimated with LMS.

Hierarchical data structure and missing values. We used the “type = complex” option to correct for the clustering of the data. Missing data represent a potentially serious methodological problem in many empirical studies. For the variables considered here, the average percentage of missing data was 12.6% (see Appendices A and B for the exact number of missing values for each variable.) In the methodological literature on missing data (Peugh & Enders, 2004; Schafer & Graham, 2002), there is growing consensus that multiple imputation or full information maximum likelihood estimations are preferable to casewise or listwise deletion if data are missing at random. Even if data are not missing at random, there are indications that full information maximum likelihood (FIML) or multiple imputation may typically produce less biased results than listwise deletion. We therefore used the FIML approach implemented in Mplus to deal with missing values, because FIML takes all available information (i.e., also cases with missing values) into account when estimating the model parameters (see Schafer & Graham, 2002).

Results

Value Facets, Multidimensionality, and the Association With Expectancy Beliefs

Our first research question addressed the subcomponents of the task value instrument. To test the structure of the instrument empirically, we conducted separate confirmatory factor analyses for mathematics and English. Four latent factors were specified, and each item was allowed to load on only one of these factors. Residual correlations were not allowed. The analyses yielded largely parallel findings in mathematics and English and supported the four-factor structure of the instrument. Overall, the fit of the models was acceptable for mathematics, \( \chi^2(48, N = 2,508) = 544.61, p < .001, \text{CFI} = .961, \text{RMSEA} = .064, \text{SRMR} = .027 \), and for English, \( \chi^2(48, N = 2,508) = 577.43, p < .001, \text{CFI} = .945, \text{RMSEA} = .066, \text{SRMR} = .039 \).

Table 1 reports the intercorrelations among the latent factors of the task value components. In both subject domains, the lowest correlation was found for the association between cost and utility value; the highest, between intrinsic value and attainment value. In fact, the latter two scales have often been used as a single factor in prior research. However, despite the high correlations between attainment and intrinsic value, alternative models in which these two (or any other two or more) factors were combined exhibited a somewhat weaker fit in both mathematics and English, all \( \Delta \chi^2(3, N = 2,508) > 86.00, p < .001 \).

Because the statistically significant \( \chi^2 \) values in the four-factor solution indicated that model fit was not exact, we inspected the resulting modification indices. The largest modification indices were found for residual correlations within the intrinsic value factor, and—specifically in English—these residual correlations indicated a particularly high association among the three items that do not focus on school lessons (“I enjoy puzzling over mathematics/English problems”; “When I’m working on a mathematics/English problem, I sometimes don’t notice time passing”; “If I can learn something new in mathematics/English, I’m prepared to use my free time to do so”).

In sum, despite the rather high correlations among the task value subscales and the residual correlations within the intrinsic value scale, the items used in our study can be considered congruent with the idea of (at least) four separate dimensions of task value.

Table 1 also reports the correlations among the four facets of value beliefs and expectancy beliefs. The associations were rather strong, ranging from .48 (expectancy and utility beliefs in English) to .82 (expectancy and attainment beliefs in mathematics). This finding is in line with previous research and with our hypothesis that the association between expectancy and value would be quite high at the end of secondary education.

Our second research question addressed the domain specificity of expectancy and value beliefs in mathematics and English. We expected to find rather low and perhaps even negative correlations between the domains. The empirical results clearly supported this expectation, with mathematics–English correlations of -.20 (p < .001) for expectancy beliefs, -.18 (p < .001) for attainment value, -.18 (p < .001) for intrinsic value, -.09 (p < .01) for cost, and .10 (p < .001) for utility value. In sum, the results confirmed the importance of differentiating between academic domains; moreover, the distinct pattern of results for utility value provides addi-

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3 In view of the high correlation between intrinsic value and attainment value, the central regression analyses described were also run with a combined intrinsic/attainment value factor. The results of these additional analyses were almost identical to those reported here for the two separate factors.

4 We also tested the fit of a model in which a second-order value factor was specified, with loadings on all four (first-order) value components. The fit was acceptable for both mathematics, \( \chi^2(50, N = 2,508) = 569.10, p < .001, \text{CFI} = .968, \text{RMSEA} = .064, \text{SRMR} = .024 \), and English, \( \chi^2(50, N = 2,508) = 608.02, p < .001, \text{CFI} = .956, \text{RMSEA} = .067, \text{SRMR} = .033 \). However, because of the strong association between expectancy beliefs and some facets of value beliefs, we decided not to use the second-order value factor in further analyses.
Expectancy–Value or Expectancy × Value?

Predicting Mathematics Achievement

Our third, fourth, and fifth research questions addressed the association between expectancy and value beliefs, on the one hand, and achievement, on the other. We expected that both expectancy and value beliefs would predict achievement when entered separately into the regression equation (Hypothesis 3), that expectancy beliefs would be the stronger predictor of academic achievement when both expectancy and value beliefs were entered into the regression equation (Hypothesis 4), and that the product term of the two would also be positively associated with the outcome variables (Hypothesis 5). To test these hypotheses, we ran a series of structural equation modeling regression models. The results of the structural equation modeling analyses for mathematics are reported in Table 2; those for English, in Table 3.

Under the structural equation modeling framework, we first specified a baseline model in which the four control variables (sex, prior achievement, cognitive ability, and school type) were included. In this model, the residual variance amounted to .61. Thus, a total of 39% of the variance in mathematics achievement was explained by the control variables. We next regressed mathematics achievement on expectancy beliefs and the control variables, but not on value beliefs (see Model M01 in Table 2). In this model, expectancy beliefs significantly predicted mathematics achievement \( (B = .46, p < .001) \) and the residual variance decreased to .53. The statistically significant predictive effects of the control variables indicate that mathematics achievement was higher in traditional Gymnasium schools than in vocational Gymnasium schools, that male students scored higher than female students, and that higher prior achievement and higher cognitive ability were associated with higher test scores. In the next three models (M02, M03, M04), attainment value was entered as a predictor variable. In Model M02, attainment value, but not expectancy beliefs, was used as a predictor variable. In this model, attainment value statistically significantly predicted mathematics achievement \( (B = .29, p < .001) \). Hence, in line with our third hypothesis, both expectancy and value beliefs were statistically associated with mathematics achievement.

In the next model (M03), expectancy beliefs and attainment value were entered simultaneously. In line with our fourth hypothesis, expectancy beliefs proved to be the stronger predictor of mathematics achievement in this model. In fact, due to the relatively high association between expectancy and value beliefs, the coefficient of attainment value was no longer statistically significant.

Finally, in Model M04, we included both expectancy and value beliefs and their interaction. In this model, expectancy beliefs were statistically significantly positively associated with mathematics achievement, but attainment value was not. Consistent with our fifth and most central hypothesis, the Expectancy × Value product term \( (B = .14, p < .001) \) positively predicted mathematics achievement. In terms of variable explained, the residual variance was slightly smaller in M04 (.51) than in M01 (.53). Relative to the

Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Attainment</th>
<th>Intrinsic</th>
<th>Utility</th>
<th>Low cost</th>
<th>Expectancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attainment</td>
<td>.97</td>
<td>.77</td>
<td>.61</td>
<td>.82</td>
<td></td>
</tr>
<tr>
<td>Intrinsic</td>
<td>.71</td>
<td></td>
<td>.58</td>
<td>.80</td>
<td></td>
</tr>
<tr>
<td>Utility</td>
<td>.44</td>
<td></td>
<td>.18</td>
<td>.75</td>
<td></td>
</tr>
<tr>
<td>Low cost</td>
<td>.75</td>
<td>.74</td>
<td>.48</td>
<td>.75</td>
<td></td>
</tr>
</tbody>
</table>

Note. All correlations were statistically significant at \( p < .001 \).

Table 2

<table>
<thead>
<tr>
<th>Predictor variables, residual variance, and fit statistics</th>
<th>Exp. Attainment</th>
<th>Intrinsic value</th>
<th>Utility value</th>
<th>(Negative) cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model fit</td>
<td>M01</td>
<td>M02</td>
<td>M03</td>
<td>M04</td>
</tr>
<tr>
<td>( \chi^2 )</td>
<td>269.40</td>
<td>92.87</td>
<td>418.2</td>
<td>n/a</td>
</tr>
<tr>
<td>df</td>
<td>17</td>
<td>10</td>
<td>38</td>
<td>n/a</td>
</tr>
<tr>
<td>CFI</td>
<td>0.964</td>
<td>0.981</td>
<td>0.966</td>
<td>n/a</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.077</td>
<td>0.057</td>
<td>0.063</td>
<td>n/a</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.022</td>
<td>0.018</td>
<td>0.024</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Note. All multi-indicator constructs were modeled as latent variables. Traditional fit indices are not available for models with latent product terms. Exp. = expectancy beliefs; CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

* School type: 0 = vocational Gymnasium, 1 = traditional Gymnasium.

\( p < .05 \), \( ^* p < .001 \).
Table 3

Predicting English Achievement: Results From Structural Equation Modeling

<table>
<thead>
<tr>
<th>Predictor variables, residual variance, and fit statistics</th>
<th>Exp.</th>
<th>Attainment</th>
<th>Intrinsic value</th>
<th>Utility value</th>
<th>(Negative) cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expectancy beliefs</td>
<td>.54**</td>
<td>.52**</td>
<td>.57**</td>
<td>.57**</td>
<td>.51**</td>
</tr>
<tr>
<td>Value beliefs</td>
<td>.33**</td>
<td>.02</td>
<td>.00</td>
<td>.30**</td>
<td>.22</td>
</tr>
<tr>
<td>Expectancy × Value</td>
<td>.11**</td>
<td>.12</td>
<td>.05</td>
<td>.12**</td>
<td>.21</td>
</tr>
<tr>
<td>Control variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>School type*</td>
<td>.68**</td>
<td>.71**</td>
<td>.68**</td>
<td>.68**</td>
<td>.73**</td>
</tr>
<tr>
<td>Sex (1 = female)</td>
<td>.20**</td>
<td>.20</td>
<td>.15</td>
<td>.20**</td>
<td>.20**</td>
</tr>
<tr>
<td>Prior achievement</td>
<td>.12**</td>
<td>.12</td>
<td>.12</td>
<td>.12**</td>
<td>.20**</td>
</tr>
<tr>
<td>Cognitive ability</td>
<td>.30**</td>
<td>.33</td>
<td>.30</td>
<td>.29**</td>
<td>.32**</td>
</tr>
<tr>
<td>Residual variance</td>
<td>.42</td>
<td>.48</td>
<td>.42</td>
<td>.41</td>
<td>.52</td>
</tr>
<tr>
<td>Model fit</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>115.15</td>
<td>49.058</td>
<td>185.55</td>
<td>n/a</td>
<td>403.98</td>
</tr>
<tr>
<td>df</td>
<td>17</td>
<td>10</td>
<td>38</td>
<td>n/a</td>
<td>25</td>
</tr>
<tr>
<td>CFI</td>
<td>.988</td>
<td>.990</td>
<td>.987</td>
<td>n/a</td>
<td>.926</td>
</tr>
<tr>
<td>RMSEA</td>
<td>.048</td>
<td>.039</td>
<td>.039</td>
<td>n/a</td>
<td>.078</td>
</tr>
<tr>
<td>SRMR</td>
<td>.013</td>
<td>.013</td>
<td>.015</td>
<td>n/a</td>
<td>.039</td>
</tr>
</tbody>
</table>

Note. All multi-indicator constructs were modeled as latent variables. Traditional fit indices are not available (n/a) for models with latent product terms. Exp. = expectancy beliefs; CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

* School type: 0 = vocational Gymnasium, 1 = traditional Gymnasium.

*p < .05. **p < .001.

baseline model, M04 explained an additional 8% of the variance, and the interaction effect accounted for slightly above 1% of the variance. Relative to the baseline model, the product term explained 15% of the variance explained by the inclusion of expectancy, value, and their product term.

The same set of analyses was conducted with intrinsic value (see M05, M06, and M07 in Table 2), utility value (M08, M09, and M10), and (negative) cost (M11, M12, and M13) as the value components. Overall, the patterns of results for these sets of analyses were very similar. Importantly, our Hypotheses 3, 4 and 5 were confirmed in each set of analyses. The product term explained between 0.5% and 1.2% of the total variance, and 5% to 14% of the total variance was explained by expectancy, value, and their product term.

The nature of the interaction effect is illustrated for attainment value and utility value in Figure 1, which shows the model-implied regression lines for different groups of students. As depicted, mathematics achievement was particularly high when both value and expectancy beliefs were high. When interpreting the slopes in Figure 1, it is important to keep in mind that these are model-implied regression lines. Because expectancy and value beliefs are positively correlated (attainment value, $r = .82$; utility value, $r = .60$), only very few students show an extreme divergence (e.g., expectancy beliefs 2 SD below the mean and value beliefs 2 SD above the mean) in their self-beliefs.

Predicting English Achievement

We next performed the same set of analyses with English achievement as the dependent variable. We again started with a baseline model in which only the four control variables (sex, prior achievement, cognitive ability, and school type) were included. In this model, the residual variance amounted to .55. We then included the expectancy and value components. The results for these models are reported in Table 3. Overall, despite some minor differences, the pattern of results for English achievement was very similar to that reported for mathematics achievement. Most important, the Expectancy × Value product term was again statistically significant for all four value components (see Models E04, E07, E10, and E13). Furthermore, the expectancy component was the stronger predictor of English achievement when both expectancy and value beliefs were entered into the regression equation. In contrast to mathematics, there remained a statistically significant positive association between two value components (utility value, cost) and English achievement even when expectancy beliefs were included (see Models E10 and E13). As regards the total amount of variance explained, once the expectancy component was included, the amount of variance explained by either the value component or the Expectancy × Value product term did not exceed 1%. The product term accounted for up to 5% of the total variance explained by expectancy, value, and their product term. The nature of the interaction effect is illustrated in Figure 2 for attainment value and utility value.

Discussion

We examined the structure of expectancy and value beliefs and their power to predict achievement in a large sample of upper secondary students. The study had five major findings. First, we found empirical support for the conceptual differentiation of task value into several subcomponents. In line with our expectations, we also found rather high associations between expectancy and value beliefs. Somewhat unexpectedly, some of the associations among the value components were weaker than the associations between expectancy and value components. Second, we found strong evidence for the domain specificity of expectancy and value beliefs. The correlations between expectancy beliefs in
mathematics and English were small, as were those between value beliefs in mathematics and English. Third, consistent with our expectations, expectancy and value beliefs positively predicted achievement when entered separately into a regression equation. Fourth, and also in line with our expectations, expectancy beliefs were found to be the stronger predictor of academic achievement when both expectancy and value beliefs were entered into the regression equation. Fifth, and centrally, we found that expectancy and value beliefs predicted achievement synergistically. In other words, we were successful in putting the “×” back into EVT.

Putting the “×” Back into Expectancy–Value Theory

The Eccles et al. (1983) EVT model differs from the traditional model proposed by Atkinson (1957) in several respects. For ex-
ample, it differentiates subcomponents of value beliefs, elaborates a set of factors assumed to impact expectancy and value beliefs, and includes a developmental perspective (see Eccles & Wigfield, 2002, for an overview). The idea that expectancy and value beliefs predict achievement-related outcomes in a multiplicative way—

which was a central element of the Atkinson model—has found less attention in the Eccles et al. (1983) model, probably because of the nonexperimental nature of many studies on modern EVT. In nonexperimental studies in which scores on predictor variables are fairly normally distributed and in which predictor and criterion variables are measured with some error, there is typically not enough statistical power to detect interaction effects unless these effects are of unusually large size. In our study, we used a fairly large data set of upper secondary students and applied a modern approach to model latent interactions (Klein & Moosbrugger, 2000) within the framework of structural equation modeling (Muthén & Muthén, 1998–2006). This recent development in structural equation modeling promises to help to solve the pressing issue of how to detect interaction effects in observational, nonexperimental data. As yet, however, it has not been picked up by many substantive researchers in psychology and education.

Because the nature of this association has played such an important role in the history of EVT models, the finding of an interaction effect is highly important from a conceptual point of view. But what does the statistically significant regression weight of the Expectancy × Value product term indicate? Our results (see the model-implied regression lines in Figures 1 and 2) indicate that if either expectancy or value is very low, the other cannot compensate for it, and very high scores on the outcome variables emerge only when both expectancy and value beliefs are high. A student may thus excel way beyond expectations when both expectancy and value beliefs are high. Figures 1 and 2 also seem to indicate that low or very low expectancy coupled with high value beliefs is even more detrimental to achievement than is low or very low expectancy coupled with low value beliefs. In interpreting this finding, it is important to bear in mind that—because of the high correlation between expectancy and value components—there are not many students with high values on one of these components and low values on the other. Nevertheless, it can be speculated that the motivational situation is especially problematic for students with low expectancy beliefs but high value beliefs—they may be more frustrated than other students because they are well aware of the importance of the school subject in question. A somewhat similar pattern of results has repeatedly been found in studies using the mental contrasting approach developed by Oettingen (see Oettingen & Gollwitzer, 2009, 2010). In mental contrasting, a desired future—a form of valuing—is elaborated and contrasted with the (negative) reality. Through the confrontation of the (negative) present and the desired future, the importance of actively engaging in goal pursuit is highlighted. However, as a plethora of studies indicate (for a summary, see Oettingen & Gollwitzer, 2010), individuals only engage in action when expectancy beliefs are high. When expectancy beliefs are low, mental contrasting in fact leads to decreased goal-related activity.

Does the finding of a statistically significant product term imply any practical implications? In other words, how “large” is the effect we found? At first sight, one might argue that the overall effect size was quite low. In fact, the product term did not explain more than 2% of the total variance in any of our models; in most models, the amount of variance explained was below 1%. However, several factors should be borne in mind when assessing the practical implications of this effect size. First, school achievement is, of course, multiply determined. Expectancy and value beliefs are just two forces in the dynamics of school achievement. It is important to reiterate that we controlled for a set of four relatively strong predictor variables (school type, sex, prior achievement, and cognitive ability) in all of our models, which somewhat restricts the amount of variance that can be explained by motivational factors. Second, it has been shown (and replicated in our study) that expectancy beliefs are more closely related to achievement outcomes than are value beliefs when both are considered simultaneously (e.g., Wigfield et al., 2009). Value beliefs have been shown to be more potent predictors of other outcomes, such as academic effort (Nagengast et al., 2011; Trautwein, Lüdtke, Kastens, & Köller, 2006). In fact, because of the close association between expectancy and value beliefs, value beliefs lost their predictive power in our analyses when expectancy beliefs were simultaneously entered into the regression equation. Third, the effect size of the Expectancy × Value product term was not that small relative to the overall portion of the variance explained by expectancy and value components. In fact, the product term explained up to 15% of the variance explained by these constructs, and in most models the product term explained more variance than did the value component. Fourth, even small effect sizes can be considered meaningful in many situations. It should also be noted that effects of expectancy and value beliefs on achievement are potentially cumulative over time and that the total effects of expectancy beliefs, value beliefs, and their product term might therefore be stronger over longer periods of time (Neyer & Asendorpf, 2001; Prentice & Miller, 1992).

A Closer Look at Value Components

The results of the present article provide strong support for the assumed (Eccles et al., 1983; Wigfield et al., 2009) multidimensionality and domain specificity of value beliefs. However, our analyses and results also seem to open up some new avenues for research on EVT. We found some of the value facets (utility value, cost) to be more closely associated with expectancy beliefs than with other value facets. To our knowledge, this finding has not been routinely reported in prior studies. It may be important to determine whether this finding is specific to our sample of students at the end of secondary school or whether it also applies to younger students. From a conceptual point of view, our findings are not necessarily in contrast with the underlying framework of the expectancy–value model. However, they further emphasize the need to closely attend to the nature of the value facets. The value factor evidently comprises subcomponents that are quite different in nature, with attainment value and intrinsic value defining more “intrinsic” values and utility value and cost constituting more “extrinsic” factors.

Limitations and Further Research

Some limitations should be borne in mind when interpreting the results of this study. First, our findings in support of the multiplicative nature of the EVT effect need to be replicated in different samples. Moreover, the study should be replicated with other
instruments and an enriched set of outcome variables to test the generalizability of the multiplicative effect. Future studies using the Eccles et al. (1983) EVT model should therefore routinely check for potential interaction effects.

Second, our study shows that statistically significant interaction effects can be found in nonexperimental settings in which students have relatively little freedom of “choice.” Given the curriculum in the schools we studied and the relevance of mathematics and English for entrance to higher education, these subjects are important for all students. Hence, the degree of choice seems to be lower than in the experimental work by researchers such as Atkinson and Feather, and no students have “zero” value or expectancy beliefs. The findings of the present study thus seem to indicate that the multiplicative nature of the expectancy–value relationship may hold even with a somewhat more restricted range of choice. In future studies, it might be interesting to differentiate between the level of “objective” choice and the amount of “subjective” choice—despite the low level of choice available within the curriculum, students may discount the importance of some of the subjects they have to study.

Third, our study provided empirical support for the idea that task value has several subcomponents, all of which are significantly associated with the outcome variables. This may open up different avenues for enhancing individual students’ task value beliefs. For instance, utility value might be increased by highlighting the long-term gains of engaging in a specific school subject, whereas attempts to increase attainment value might place particular emphasis on the experience of competence, relatedness, and autonomy (e.g., Hidi & Harackiewicz, 2000; Krapp, 2002; Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008). Both intervention studies and nonexperimental studies should carefully check for such differential effects.

Fourth, whereas we were able to use standardized achievement tests to assess mathematics and English achievement, we measured expectancy and value beliefs solely by means of student questionnaires. However, it is common practice to use self-report measures to assess these constructs, and self-reports may in fact be the most appropriate approach for tapping expectancy and value beliefs.

Fifth, the issue of causality also needs to be considered. Establishing “causal” associations typically requires an experimental design or a design that controls for important third variables. Although we controlled for the critical pretest variables of prior achievement, cognitive ability, and school type as potential third variables, our study does not imply causality. We therefore described our results in terms of “associations” or “predictive effects.”

Sixth, as mentioned above, the extent to which the results generalize across samples and instruments is also an issue. Moreover, it is unclear to what extent cultural differences might affect the results. Although no previous studies have documented major differences between Germany and, for instance, the United States with regards to expectancy, value, and corresponding outcomes, cross-cultural studies might detect such differences.

Seventh, we constructed a short instrument to assess the four components of the Eccles et al. (1983) EVT model. Confirmatory factor analyses supported the conceptual differentiation of the task value subcomponents. However, the correlation between intrinsic value and attainment value was very high, raising the question of whether other items might have yielded a somewhat different pattern of results. Similarly, some local misfit in our confirmatory factor analyses may indicate that the value factor could be broken down into even more subcomponents. We note, however, that a larger set of (more diverse) items should be used to check for this possibility.

In terms of future studies, a combination of the “traditional” experimental approach by Atkinson (1957) with real-life school settings seems to be a promising approach to further investigation of the Expectancy × Value interaction. Although one reason for Eccles et al. (1983) using a nonexperimental approach to study expectancy and value in real-life school settings was the emphasis on ecological validity, it would of course be possible to conduct studies in which expectancy and value beliefs are experimentally manipulated in the classroom. Such experimental manipulations have well-known advantages over nonexperimental studies. At the same time, we note that such studies cannot fully replace nonexperimental approaches, because researchers and practitioners are also interested in the “typical” nature of and associations among beliefs in real-life settings. Furthermore, it is hard to effectively manipulate variables such as expectancy and value, let alone their interaction, in true experimental settings. It cannot easily be done on a student-by-student basis because of contamination/diffusion among classmates within the same classroom or potentially even the same school (particularly in secondary school settings in which students take different classes with different groups of students). Random assignment at the school level becomes very difficult (and expensive) and would probably affect the nature of the intervention.

In conclusion, by using a powerful new approach to model latent interactions, the present study produced exciting new empirical insights into the multiplicative nature of expectancy and value beliefs in predicting achievement-related outcomes—a topic that seems to have been largely overlooked in recent decades.

References


Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and
Dolan, C. V. (1994). Factor analysis of variables with 2, 3, 5 and 7
Eccles, J., Adler, T., & Meece, J. L. (1984). Sex differences in achieve-
mastery school.
achievement and achievement motives: A test of alternate theories.
available, and I know I am: Longitudinal couplings between domain-specific
achievement, self-concept and
Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, 
Fiedler, K. (2011). Voodoo correlations are everywhere—Not only in 
neuroscience.


(Appendices follow)
### Appendix A

**Descriptive Statistics for Expectancy Beliefs, Achievement Outcomes, and Control Variables**

<table>
<thead>
<tr>
<th>Variable</th>
<th>$N$</th>
<th>$M$</th>
<th>$SD$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Control variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>School type ($1 =$ traditional gymnasium)</td>
<td>2,508</td>
<td>0.58</td>
<td>0.49</td>
</tr>
<tr>
<td>Sex ($1 =$ female)</td>
<td>2,497</td>
<td>1.56</td>
<td>0.50</td>
</tr>
<tr>
<td>Prior achievement in mathematics (school grades; reverse scored)</td>
<td>2,475</td>
<td>4.46</td>
<td>0.94</td>
</tr>
<tr>
<td>Prior achievement in English (school grades; reverse scored)</td>
<td>2,465</td>
<td>4.50</td>
<td>0.83</td>
</tr>
<tr>
<td>Cognitive ability: figural analogies</td>
<td>2,505</td>
<td>0.03</td>
<td>1.01</td>
</tr>
<tr>
<td>Cognitive ability: verbal analogies</td>
<td>2,505</td>
<td>−0.04</td>
<td>0.81</td>
</tr>
<tr>
<td><strong>Achievement outcomes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Math standardized achievement test (TIMSS, national metric)</td>
<td>2,494</td>
<td>−0.05</td>
<td>0.91</td>
</tr>
<tr>
<td>English standardized achievement test (TOEFL)</td>
<td>2,505</td>
<td>508.00</td>
<td>52.81</td>
</tr>
<tr>
<td><strong>Mathematics expectancy beliefs</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am good at mathematics.</td>
<td>2,482</td>
<td>2.45</td>
<td>1.01</td>
</tr>
<tr>
<td>I have difficulty understanding everything to do with mathematics.</td>
<td>2,470</td>
<td>2.92</td>
<td>0.90</td>
</tr>
<tr>
<td>I have always been good at mathematics.</td>
<td>2,462</td>
<td>2.40</td>
<td>1.01</td>
</tr>
<tr>
<td>I am never good at tasks that require mathematical thinking.</td>
<td>2,455</td>
<td>2.92</td>
<td>0.90</td>
</tr>
<tr>
<td><strong>English expectancy beliefs</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I have difficulty understanding everything to do with English.</td>
<td>2,453</td>
<td>3.17</td>
<td>0.82</td>
</tr>
<tr>
<td>I am good at English.</td>
<td>2,462</td>
<td>2.64</td>
<td>0.94</td>
</tr>
<tr>
<td>I’m just not good at English.</td>
<td>2,461</td>
<td>2.87</td>
<td>1.00</td>
</tr>
<tr>
<td>English isn’t really my thing.</td>
<td>2,480</td>
<td>2.90</td>
<td>0.97</td>
</tr>
</tbody>
</table>

*Note.* TIMSS = Third International Mathematics and Science Study; TOEFL = Test of English as a Foreign Language.

(Appendices continue)
Appendix B

Descriptive Statistics for Items Used to Assess Students’ Value Beliefs

<table>
<thead>
<tr>
<th>Item (and task value subcomponent)</th>
<th>Mathematics</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>English</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>I’m really keen to learn a lot in mathematics/English. (attainment)</td>
<td>2,011</td>
<td>2.52</td>
<td>0.91</td>
<td></td>
<td></td>
<td></td>
<td>2,050</td>
<td>2.81</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>Mathematics/English is important to me personally. (attainment)</td>
<td>1,983</td>
<td>1.97</td>
<td>0.90</td>
<td></td>
<td></td>
<td></td>
<td>2,038</td>
<td>2.41</td>
<td>0.89</td>
<td></td>
</tr>
<tr>
<td>It is important to me personally to be a good mathematician/good at English. (attainment)</td>
<td>1,976</td>
<td>2.12</td>
<td>0.92</td>
<td></td>
<td></td>
<td></td>
<td>1,997</td>
<td>2.82</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td>I enjoy puzzling over mathematics/English problems. (intrinsic)</td>
<td>2,002</td>
<td>2.36</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td>2,041</td>
<td>2.72</td>
<td>0.92</td>
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</tr>
<tr>
<td>When I’m working on a mathematics/English problem, I sometimes don’t notice time passing. (intrinsic)</td>
<td>1,984</td>
<td>2.03</td>
<td>0.90</td>
<td>2,035</td>
<td>2.32</td>
<td>0.93</td>
<td></td>
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<tr>
<td>I would like to have more mathematics/English lessons. (intrinsic)</td>
<td>1,998</td>
<td>2.33</td>
<td>1.02</td>
<td>2,000</td>
<td>2.17</td>
<td>0.83</td>
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<tr>
<td>I always look forward to mathematics/English lessons. (intrinsic)</td>
<td>1,987</td>
<td>2.11</td>
<td>0.88</td>
<td>2,021</td>
<td>2.11</td>
<td>0.86</td>
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<tr>
<td>If I can learn something new in mathematics/English, I’m prepared to use my free time to do so. (intrinsic)</td>
<td>1,980</td>
<td>2.11</td>
<td>0.86</td>
<td>1,994</td>
<td>2.34</td>
<td>0.82</td>
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<tr>
<td>I’ll need good mathematics/English skills for my later life (training, studies, work). (utility)</td>
<td>2,000</td>
<td>2.59</td>
<td>0.92</td>
<td>2,028</td>
<td>3.16</td>
<td>0.79</td>
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<tr>
<td>Good grades in mathematics/English can be of great value to me later. (utility)</td>
<td>1,991</td>
<td>2.74</td>
<td>0.90</td>
<td>1,991</td>
<td>3.10</td>
<td>0.75</td>
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</tr>
<tr>
<td>I’d have to sacrifice a lot of free time to be good at mathematics/English. (cost)</td>
<td>1,994</td>
<td>2.31</td>
<td>0.95</td>
<td>2,006</td>
<td>2.62</td>
<td>0.87</td>
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</tr>
<tr>
<td>I’d have to invest a lot of time to get good grades in mathematics/English. (cost)</td>
<td>1,991</td>
<td>2.24</td>
<td>0.96</td>
<td>1,999</td>
<td>2.68</td>
<td>0.94</td>
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</tr>
</tbody>
</table>

Appendix C

Annotated Syntax for Mplus

! Title can be freely chosen
TITLE: Expectancy-Value Interaction;
! Read in the data provided in an ASCII-file.
DATA: File is data00.dat;
! Label the variables in the datafile
Variable: NAMES are
  idsch schltype sex math_g10 kft
  exp1 exp2 exp3 exp4
  val1 val2
  maths;

! Missing values are identified by -9
Missing are all (-9);
! Observations are clustered within schools
Cluster is idsch;

! Analysis takes nesting of students into
! schools into account (TYPE = complex).
! TYPE = RANDOM is necessary for the latent
! interaction effects modeled with LMS;
! TYPE = MISSING indicates that FIML is
! to be used to handle missing values.
! (This is the Mplus default and does not
! have to be separately specified.)
Type = complex missing random;

! The model is estimated by numerical
! integration, statement is required for the
! LMS-analysis of latent interactions.
Algorithm = integration;
MODEL:
! Definition of the measurement models for
! Expectancy and Value.
exp by exp1 exp2 exp3 exp4;
val by val1 val2;
! Definition of the latent product variable
! using the XWITH-statement.
expXval XWITH val;

! Outcome is regressed on control variables.
maths on schltype sex math_g10 kft;
! Outcome is regressed on latent predictors
! and their latent interaction.
maths on exp val expXval;
! Control variables are free to correlate
! with latent predictors and with each other.
expl with val schltype sex math_g10 kft;
val with schltype sex math_g10 kft;
schltype with sex math_g10 kft;
schltype with sex math_g10 kft;
sex with math_g10 kft;

Output: sampstat;

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