Why Elusive Expectancy × Value Interactions May Be Critical for Theory and Intervention: A Simulated Power Analysis

Michael W. Asher[1], Cameron A. Hecht[2], Judith M. Harackiewicz[3], John J. Curtin[3], Cora Parrisius[4,5], and Benjamin Nagengast[4,6]

[1] Human Computer Interaction Institute, Carnegie Mellon University

[2] Department of Psychology, University of Rochester

[3] Department of Psychology, University of Wisconsin-Madison

[4] Hector Research Institute of Education Sciences and Psychology, University of Tübingen, Germany

[5] University of Education Karlsruhe, Germany

[6] Department of Education and the Brain & Motivation Research Institute (bMRI), Korea University, Seoul, Republic of Korea

This research was supported by the National Institutes of Health (Grant R35GM141556 to JMH at the University of Wisconsin). Correspondence concerning this article should be addressed to Michael W. Asher, Human Computer Interaction Institute, Carnegie Mellon University, Newell-Simon Hall, 5000 Forbes Avenue, Pittsburgh, PA 15213, United States. Email: masher@andrew.cmu.edu. All data and code for study are openly available in OSF at https://osf.io/tzq2s.

Abstract

According to expectancy-value theories of motivation, individuals choose to pursue tasks that they expect to succeed at and find personally valuable. Historically, researchers have often suggested that these two factors interact to motivate behavior. However, expectancy × value interactions are rarely observed in empirical research and, when detected, they are often small in magnitude. Does this mean they can safely be ignored in models of motivation? In this paper we conduct two power analyses with simulated data to argue that expectancy × value interactions are likely far more important than a straightforward interpretation of effect sizes would suggest, and that downplaying them risks oversimplifying theory and recommendations for intervention. Specifically, Study 1 demonstrates that a realistic combination of three constraints (measurement error, skew, and correlation) can negatively bias expectancy × value interaction estimates by more than 50%. Study 2 shows that these interactions can create meaningful variability in motivation interventions and may contribute to a better understanding of treatment heterogeneity.

Keywords: expectancy value theory, motivation, statistical analysis, intervention science

Students face a variety of motivational challenges. Some doubt their ability to succeed. Others question the value of learning. Eccles' expectancy-value theory (Eccles & Wigfield, 2020) identifies these two factors—expectancy for success and perceived task value—as the two most proximal predictors of academic motivation. What insights, then, can it offer about motivating students with these differing concerns?

The answer hinges on what initially seems to be a secondary aspect of the theory: whether (and the degree to which) these two motivational variables interact. Additive expectancy-value models assume no interaction—suggesting that a boost to expectancy or value should equally benefit all students. A student doubting herself would be just as motivated by a teacher emphasizing the importance of the material as addressing her doubts. Likewise, a student who sees no value in the material would be just as motivated by a confidence boost as a demonstration of relevance. In contrast, interactive expectancy-value models (e.g., Feather, 1982; Tolman, 1938; Vroom, 1964) predict that an increase in expectancy or value cannot compensate for a lack of the other.

Evidence to date suggests expectancy and value do interact, but the magnitude of the interaction is quite small. The best-powered test of this interaction, conducted in a representative international sample of 400,000 students, found expectancy × value interactions that were statistically significant but with small coefficients of b = .05-.07, as compared to main effects of up to b = .53 for value and b = .25 for expectancy (Nagengast et al., 2011; see also Guo, Marsh, et al., 2015; Guo, Parker, et al., 2015; J. Lee et al., 2013; Y. Lee et al., 2022; Meyer et al., 2019; Trautwein et al., 2012 for tests of the interaction with thousands of students). A straightforward interpretation of these relative effect sizes is that the relationship between expectancy and value is essentially additive, with the interactive effect explaining only a small portion of the variance.

Indeed, Eccles and Wigfield, the key contributors to the development and refinement of modern expectancy-value theory, recently concluded that expectancy × value interactions "add small but reliable increments in predictive validity" to models of student achievement (Eccles & Wigfield, 2020).

Here, we argue—and demonstrate with simulated data—that this evidence is insufficient to dismiss expectancy × value interactions. In Study 1, we show that small interactions are largely attributable to common empirical constraints. In Study 2, we demonstrate that even when expectancy × value interactions are difficult to detect, they may play a critical role in determining the most effective intervention strategies for specific groups of students. We conclude that expectancy × value interactions are likely far more important than the straightforward interpretation of effect sizes suggests, and that downplaying them risks oversimplifying theory and providing misguided recommendations for intervention.

Study 1: Empirical Constraints and Biased Estimates

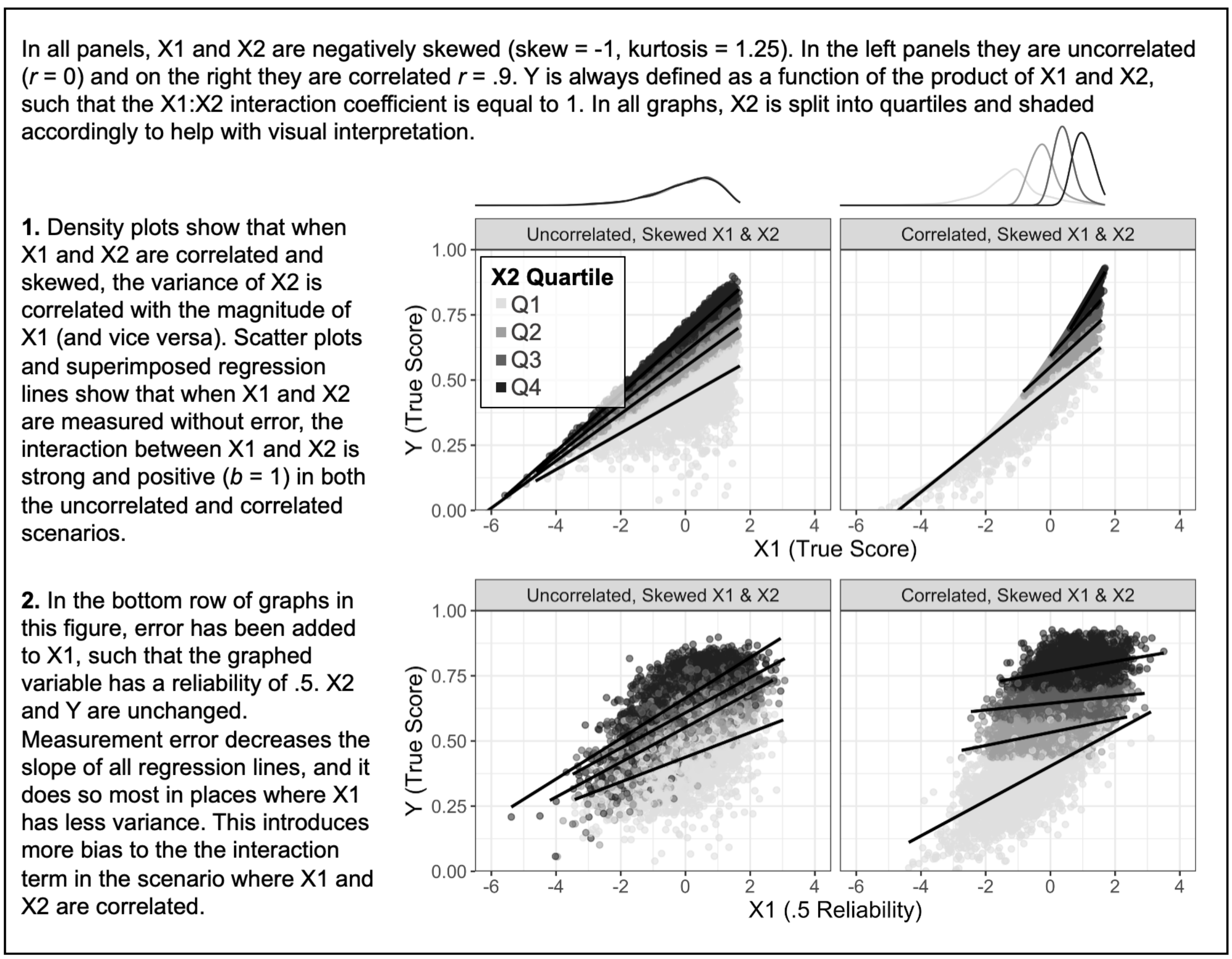
In Study 1 we estimated the extent that measurement error, correlation, and skew might combine to obscure the magnitude of expectancy × value interactions.

Bohrnstedt & Marwell (1978) demonstrated that when measured variables are normally distributed and uncorrelated, the reliability of their interaction term approximates the product of their individual reliabilities. Thus, if expectancy and value measures have a reliability of .80 (as is reported by Nagengast et al., 2011), the estimated interaction term will be biased downward to 64% of its true magnitude. At a reliability of .70 (the typical threshold for "adequate reliability"), the estimate drops to just 49% of its actual size.

In addition, expectancy and value tend to be positively correlated and negatively skewed. Representative samples show that confident students also value tasks more (e.g., r = .54), and that there are usually more students on the high end than the low end of these two variables (e.g., skew = -0.4; OECD, 2007). Skew can be even larger in college samples, where students with lower expectancies and values are underrepresented (e.g., skew = -0.64 in Harackiewicz et al., 2023). In the presence of measurement error, correlation and skew can further bias interaction estimates by the process illustrated in Figure 1. To make this bias visually apparent, we present an extreme case (*r* = .9, skew = -1). However, we predict that these two factors can meaningfully bias regression coefficients at levels common in expectancy-value research.

Figure 1

Skew, Measurement Error, and Correlation Can Interact to Bias Interaction Coefficients



Method

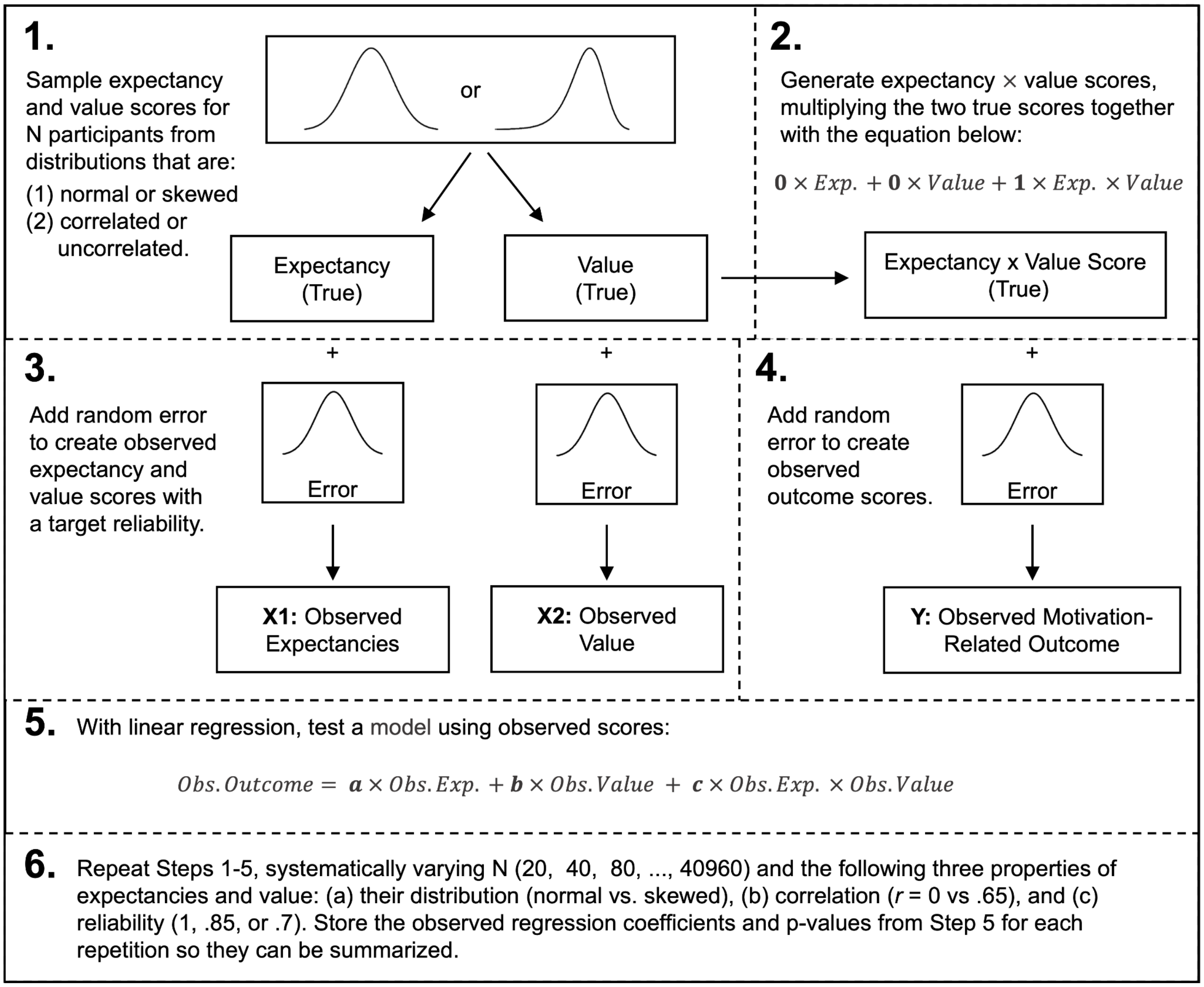
We conducted a simulated power analysis to estimate the extent to which error, correlation, and skew might lead researchers to underestimate the magnitude of an expectancy × value interaction. We began by assuming that expectancy and value influence achievement-related outcomes solely through their interaction—consistent with early expectancy-value theories (e.g., Vroom, 1964). Although expectancy and value may also have independent, asymmetric, or reciprocal effects in reality (e.g., Jacobs et al., 2002), we used this simplified model to isolate how empirical constraints could obscure a fundamentally important interaction.

Simulation Design

We employed a 2 × 2 × 3 design, manipulating (a) the distribution of expectancy and value (normal vs. skewed), (b) the correlation between these two variables ($r = 0.65$ vs. $r = 0$), and their measurement reliability (1.0 vs. 0.85 vs. 0.7). We chose values of $r = .65$ and skew = -0.5 to approximate data from representative, international samples (OECD, 2007). Motivation-related outcomes were generated by multiplying expectancy and value scores and adding random error. We then ran regression analyses to estimate the magnitude and significance of expectancy, value, and their interaction. This process, detailed in Figure 2 and the Supplementary Materials, was repeated 1,000 times per condition. Data and code are available at https://osf.io/tzq2s.

Figure 2

Method for Study 1



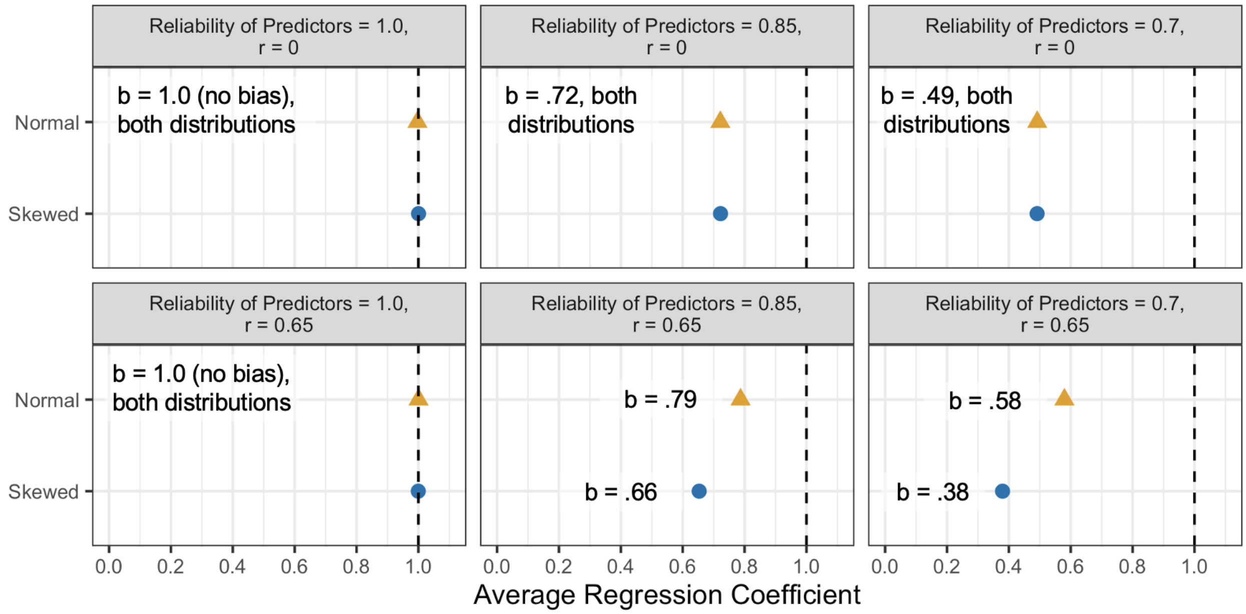
Results and Discussion

Measurement Error Introduced Bias, Especially with Skewed and Correlated Variables

Figure 3 illustrates the bias introduced by measurement error, skew, and correlation. With perfect reliability, the estimated interaction effect remained unbiased at 1.0 across all conditions. However, as measurement error increased, estimates dropped sharply. When predictors were uncorrelated, effect sizes matched the product of predictor reliabilities (Bohrnstedt & Marwell, 1978). For instance, with 0.7 reliability, the average interaction effect was 0.49—less than half of its true value. Critically, bias was particularly severe when predictors were correlated and skewed, with estimates dropping to b = 0.38 at 0.7 reliability.

Figure 3

The Magnitude of Regression Coefficients

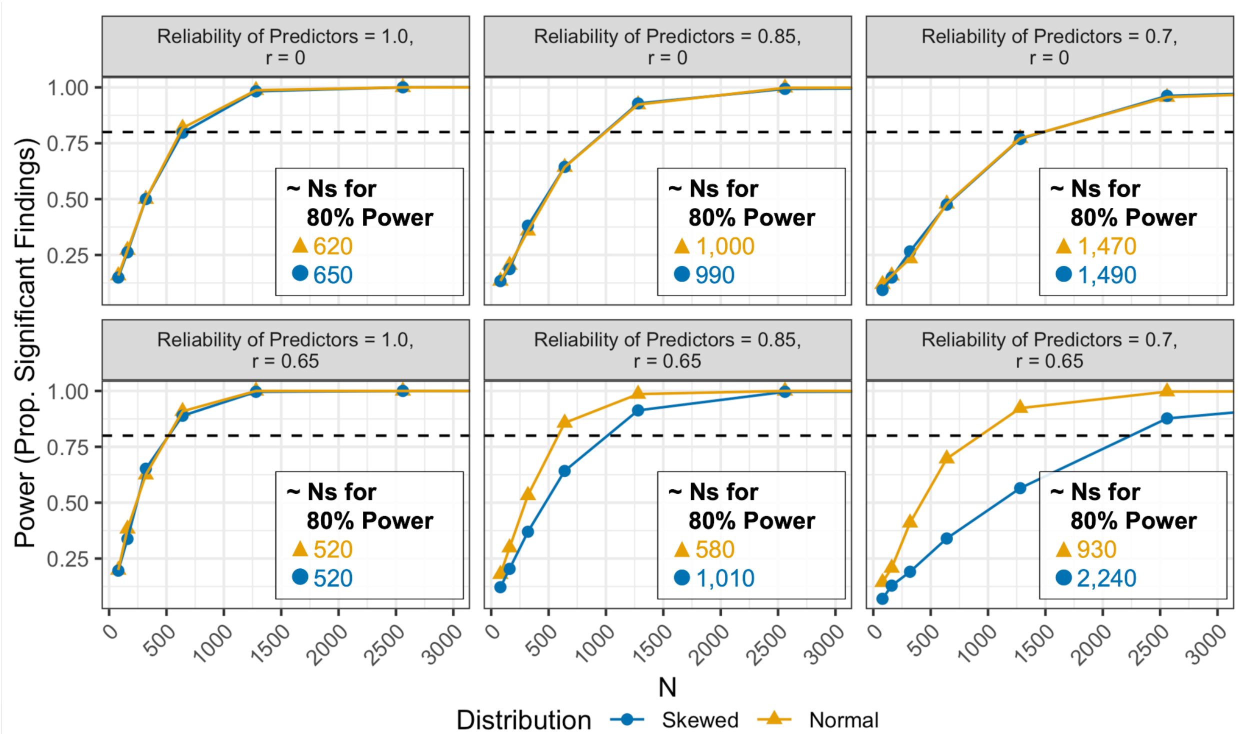


Large Samples Were Needed to Detect Interactions

Figure 4 shows the results of our power analyses, which highlight the difficulty of detecting interactions even when they fully account for the data. Across all conditions, at least 500 participants were needed to achieve 80% power for detecting an expectancy × value interaction. As measurement error increased, so did the required sample size, particularly when expectancy and value were skewed and correlated (as many as 2,240 participants were needed). In contrast, main effects were much less prone to bias (see Supplementary Materials); even under the most challenging conditions, only 100 participants were needed to reliably detect them.

Figure 4

Power Analysis for the Expectancy × Value Interaction



Although expectancy × value interactions are elusive and often small when detected, these findings suggest their true effect sizes could easily be underestimated by 50% or more due to empirical constraints. However, an important question remains: can an interaction so difficult to detect have meaningful practical implications? In Study 2, we examined how empirically elusive expectancy × value interactions might influence intervention research.

Study 2: Implications for Intervention

Many interventions aim to enhance students' expectancy- or value-related beliefs. For example, utility-value interventions (UVIs) encourage students to reflect on course material's relevance to boost interest and improve performance (Hulleman & Harackiewicz, 2009). Personalized learning interventions integrate students' interests (e.g., sports, music) into tasks to increase value (Bernacki & Walkington, 2018; Walkington, 2013). Attributional reframing interventions strengthen expectancies by framing academic struggles as normal and controllable (Perry et al., 2014).

Yet, these interventions have yielded mixed results. For example, while early research found that UVIs improved course grades (Harackiewicz et al., 2016; Hulleman et al., 2010), other studies failed to replicate these effects (Edwards et al., 2023; Price et al., 2024). Could expectancy × value interactions explain these inconsistencies? For instance, UVIs may have been more effective at flagship universities (Harackiewicz et al., 2016, 2023) than at two-year colleges (Canning et al., 2019) because students in the first context had greater confidence. Understanding these interactions could improve our understanding of treatment heterogeneity, a key challenge in behavioral sciences (Bryan et al., 2021; Tipton et al., 2022).

Furthermore, if expectancy × value interactions influence for whom interventions work, can researchers reliably detect these effects within their samples? It is common to examine interactions between UVIs and students' baseline confidence or prior performance (e.g., Asher et al., 2023; Canning et al., 2018; Gaspard et al., 2021; Harackiewicz et al., 2016; Hecht et al., 2019; Hulleman & Harackiewicz, 2009; Price et al., 2024; Priniski et al., 2019; Rosenzweig et al., 2019). However, given the challenges of detecting expectancy × value interactions, researchers testing treatment × expectancy interactions may be severely underpowered.

Method

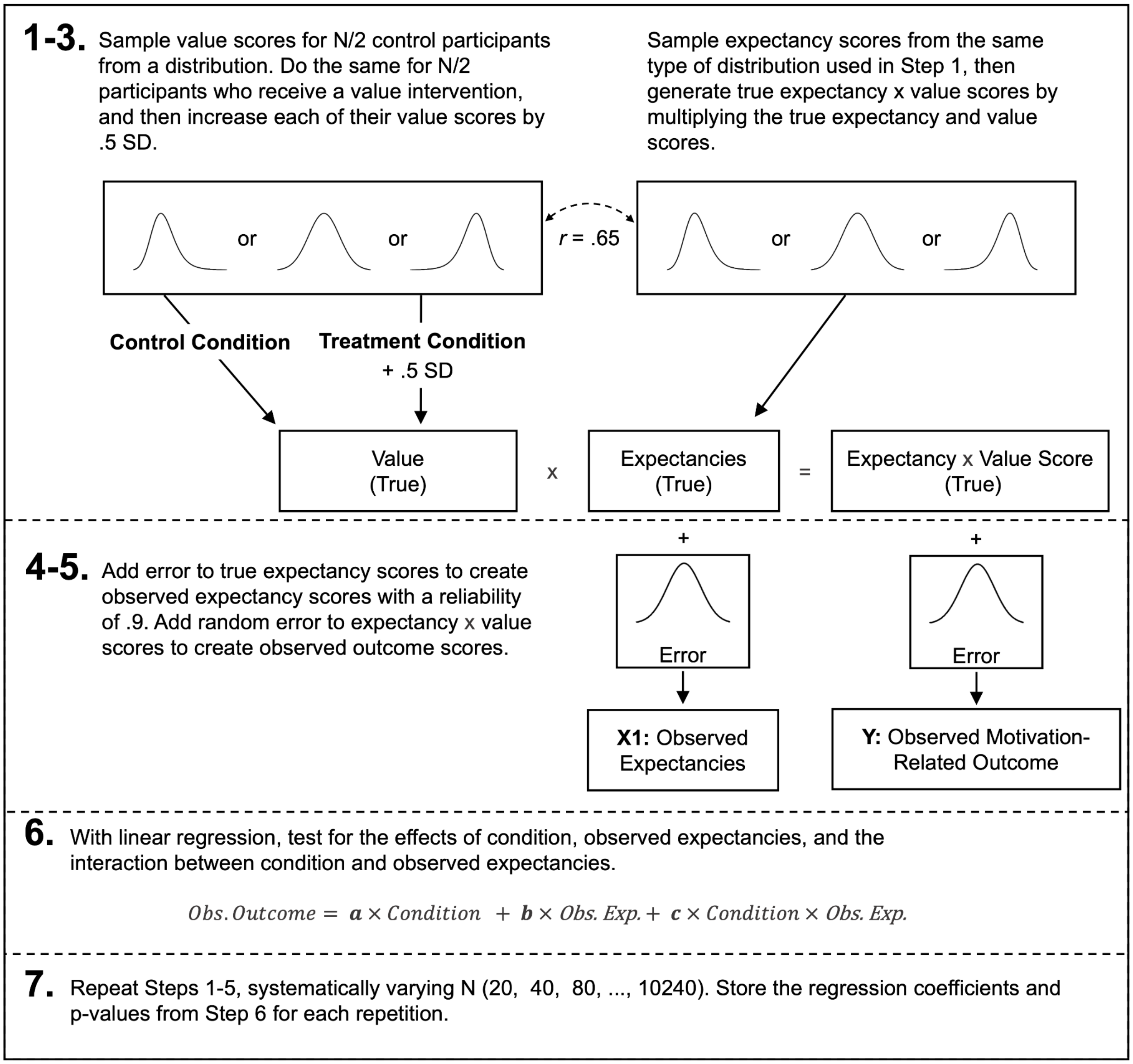
To test these questions, we simulated an intervention designed to increase students' perceptions of an academic field's value (similar to a UVI) and affect a motivation-related outcome like academic performance.

Simulation Design

Figure 5 summarizes the method for Study 2.

Figure 5

Procedure, Study 2



We simulated 1,000 interventions in three distinct samples: (1) a sample where many students were initially unmotivated (with low expectancies and value perceptions), (2) a sample where students' expectancies and value perceptions were more moderate on average, or (3) a sample where many students had high expectancies and value. We assumed that the intervention had a .5 SD effect on students' value perceptions, which in turn interacted with their expectancies to influence an achievement-related outcome.

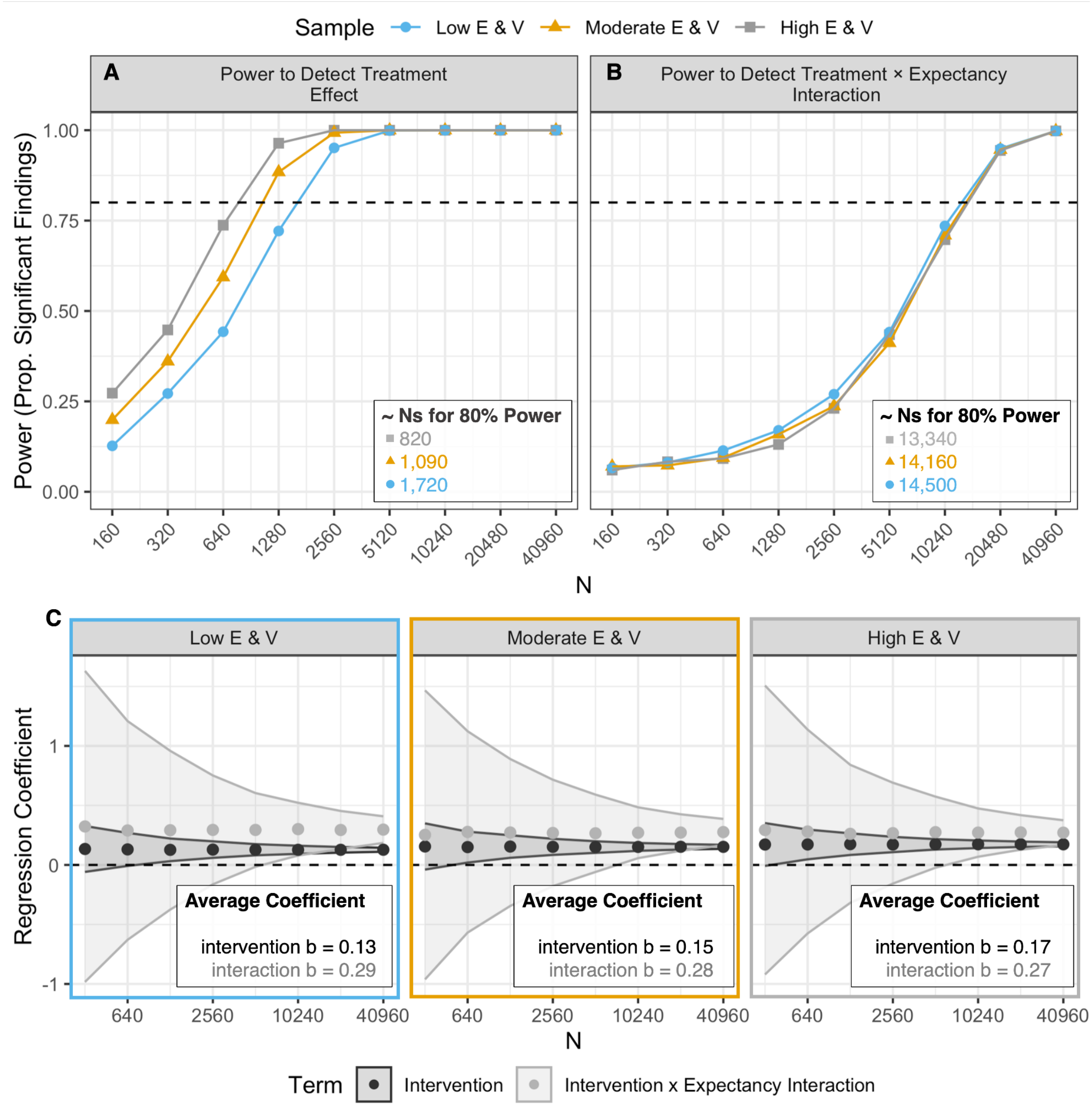
Results and Discussion

Twice as Many Participants Were Needed in Low-Expectancy Samples

Figure 6 illustrates the relationship between sample size and statistical power for detecting treatment effects (6A) and treatment × expectancy interactions (6B) across the three samples. Panel 6C shows average effect sizes.

Figure 6

Results, Study 2



Note. Error envelopes in Panel 6C show 95% confidence intervals.

Simulations revealed substantial heterogeneity in intervention effects due to expectancy × value interactions. In high-expectancy samples, intervention effects on value perceptions led to larger changes in motivation-related outcomes (0.17 SD), requiring ~800 participants for 80% power. In low-expectancy samples, average effects were smaller (0.13 SD), requiring more than twice as many participants (~1,700) to achieve the same level of power.

These findings suggest that if motivation-related outcomes—such as performance, effort, and persistence—result from an expectancy × value interaction, interventions targeting either factor will have dramatically different levels of power depending on students' baseline beliefs.

Tests of Treatment × Expectancy Effects Required Thousands of Participants

Researchers often attempt to explain heterogeneous intervention effects by testing for interactions with treatment. However, our simulations indicate that detecting treatment × expectancy interactions is far more challenging than identifying main effects (Figure 6B). Across all conditions, detecting an interaction with 80% power required over 13,000 participants—seven times the sample size needed to detect a main effect.

This lack of power may help explain the mixed findings in past research. Expectancy × value interactions have been negative in some studies (Hulleman et al., 2010; Hulleman & Harackiewicz, 2009), positive in others (Canning et al., 2018; Hecht et al., 2019), and inconclusive elsewhere (Priniski et al., 2019; Rosenzweig et al., 2019). Our simulations suggest that even in large-scale studies (e.g., 2,500 students; Asher et al., 2023), statistical power may still be insufficient, leading to possible Type II errors. In addition, negative expectancy × value interactions may occur because students with lower expectancies possess other traits that make value interventions more effective for them. Prior research shows that interventions tend to benefit at-risk students more (Hecht et al., 2021), meaning that students with low expectancies may experience greater improvements, which could create a counteracting effect that obscures expectancy × value interactions.

General Discussion

We conducted two simulation studies to examine the potential importance of expectancy × value interactions. Study 1 demonstrates that these interactions could realistically be twice as strong as empirical estimates suggest. Study 2 shows that these interactions can create meaningful variability in motivation interventions, even though treatment × expectancy (or value) interactions may require 10,000 or more students to consistently detect. These findings have broad implications for studying expectancy × value interactions, designing effective interventions, and understanding interactions in psychological theories more generally.

Studying Expectancy × Value Interactions

To improve statistical power when examining expectancy × value interactions, Study 1 highlights the importance of reducing measurement error, which can be achieved by carefully assessing subcomponents of expectancies and values, such as self-efficacy, intrinsic value, and perceived costs. Additionally, researchers should aim to collect data in samples that minimize skewed predictor distributions, which will weaken power because expectancy and value are correlated. When large, representative samples are not feasible, controlled laboratory manipulations may provide more precise tests of theory. By manipulating expectancy and value to extremes, researchers can maximize the variance of these variables' joint distribution and increase power (McClelland & Judd, 1993) and decrease their correlation so that skew will no longer be a methodological problem.

Designing Interventions

Study 2 highlights the importance of considering expectancy × value interactions when designing interventions, suggesting that when students lack both expectancies for success and perceived value, addressing only one factor might be ineffective. If researchers do not take expectancy × value interactions into account when considering where to intervene, we may accumulate a confusing body of intervention literature, containing both successful replications (e.g., Rosenzweig et al., 2020, 2022) and non-replications of the same interventions (e.g., Hulleman et al., 2017; Price et al., 2024), with little evidence for the causes of treatment heterogeneity. By conducting multi-site interventions in a diverse range of settings, researchers could explicitly examine how contextual differences moderate intervention effects (see Walton et al., 2023; Yeager et al., 2019 for examples of this approach applied to other psychological interventions).

Broader Implications for Interactions in Psychological Theories

Although this paper focuses on expectancy × value interactions, the findings apply to any theory involving the interaction of two measured, continuous variables. Many psychological theories rely on such interactions. Person × environment interactions, for example, help explain phenomena ranging from cognitive dissonance to stereotype threat to the onset of mental illness (Ingram & Luxton, 2005; Ross & Nisbett, 1991). Yet, as with expectancy-value theory, empirical evidence for these interactions is often inconsistent (e.g., Ajzen, 1991).

Given the complexity of forces that determine human beliefs and behavior, it is essential to study and theorize about interactions. Questions about “the effect of X on Y” are overly simplistic, and questions about the causes of variance in an effect are more appropriate (Bryan et al., 2021; Tipton et al., 2022; Walton & Yeager, 2020). However, as demonstrated in this investigation, empirical constraints—including the distributions of variables, correlations, and measurement error—make detecting and accurately estimating interactions exceptionally difficult. Standard research practices can lead to underestimated and overlooked interactions. As we have illustrated in the context of expectancy-value theory, even small, hard-to-detect interactions can be essential for psychological theories and interventions.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Asher, M. W. (2025, March 11). Code for "Why Elusive Expectancy × Value Interactions May Be Critical for Theory and Intervention." https://doi.org/10.17605/OSF.IO/TZQ2S

Asher, M. W., Harackiewicz, J. M., Beymer, P. N., Hecht, C. A., Lamont, L. B., Else-Quest, N. M., Priniski, S. J., Thoman, D. B., Hyde, J. S., & Smith, J. L. (2023). Utility-value intervention promotes persistence and diversity in STEM. *Proceedings of the National Academy of Sciences*, *120*(19), e2300463120. https://doi.org/10.1073/pnas.2300463120

Bernacki, M. L., & Walkington, C. (2018). The role of situational interest in personalized learning. *Journal of Educational Psychology*, *110*(6), 864–881. https://doi.org/10.1037/edu0000250

Bohrnstedt, G. W., & Marwell, G. (1978). The reliability of products of two random variables. *Sociological Methodology*, *9*, 254. https://doi.org/10.2307/270812

Bryan, C. J., Tipton, E., & Yeager, D. S. (2021). Behavioural science is unlikely to change the world without a heterogeneity revolution. *Nature Human Behaviour*, *5*(8), 980–989. https://doi.org/10.1038/s41562-021-01143-3

Canning, E. A., Harackiewicz, J. M., Priniski, S. J., Hecht, C. A., Tibbetts, Y., & Hyde, J. S. (2018). Improving performance and retention in introductory biology with a utility-value intervention. *Journal of Educational Psychology*, *110*(6), 834–849. https://doi.org/10.1037/edu0000244

Canning, E. A., Priniski, S. J., & Harackiewicz, J. M. (2019). Unintended consequences of framing a utility-value intervention in two-year colleges. *Learning and Instruction*, *62*, 37–48. https://doi.org/10.1016/j.learninstruc.2019.05.001

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, *61*(101859). https://doi.org/10.1016/j.cedpsych.2020.101859

Edwards, O. V., White, K. R., Rainwater, C., & Simmons, E. (2023). Utility value intervention fails to boost student motivation and performance in psychology courses. *Scholarship of Teaching and Learning in Psychology*, *9*(1), 108–114. https://doi.org/10.1037/stl0000207

Feather, N. T. (Ed.). (1982). *Expectations and actions: Expectancy-value models in psychology*. Lawrence Erlbaum Associates.

Gaspard, H., Parrisius, C., Piesch, H., Kleinhansl, M., Wille, E., Nagengast, B., Trautwein, U., & Hulleman, C. S. (2021). The potential of relevance interventions for scaling up: A cluster-randomized trial testing the effectiveness of a relevance intervention in math classrooms. *Journal of Educational Psychology*, *113*(8), 1507–1528. https://doi.org/10.1037/edu0000663

Guo, J., Marsh, H. W., Parker, P. D., Morin, A. J. S., & Yeung, A. S. (2015). Expectancy-value in mathematics, gender and socioeconomic background as predictors of achievement and aspirations: A multi-cohort study. *Learning and Individual Differences*, *37*, 161–168. https://doi.org/10.1016/j.lindif.2015.01.008

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. S. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology*, *51*(8), 1163–1176. https://doi.org/10.1037/a0039440

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2016). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. *Journal of Personality and Social Psychology*, *111*(5), 745–765. https://doi.org/10.1037/pspp0000075

Harackiewicz, J. M., Hecht, C. A., Asher, M. W., Beymer, P. N., Lamont, L. B., Wheeler, N. S., Else-Quest, N. M., Priniski, S. J., Smith, J. L., Hyde, J. S., & Thoman, D. B. (2023). A prosocial value intervention in gateway STEM courses. *Journal of Personality and Social Psychology*, *125*(6), 1265–1307. https://doi.org/10.1037/pspa0000356

Hecht, C. A., Harackiewicz, J. M., Priniski, S. J., Canning, E. A., Tibbetts, Y., & Hyde, J. S. (2019). Promoting persistence in the biological and medical sciences: An expectancy-value approach to intervention. *Journal of Educational Psychology*, *111*(8), 1462–1477. https://doi.org/10.1037/edu0000356

Hecht, C. A., Yeager, D. S., Dweck, C. S., & Murphy, M. C. (2021). Beliefs, affordances, and adolescent development: Lessons from a decade of growth mindset interventions. In *Advances in Child Development and Behavior* (Vol. 61, pp. 169–197). Elsevier. https://doi.org/10.1016/bs.acdb.2021.04.004

Hulleman, C. S., Godes, O., Hendricks, B. L., & Harackiewicz, J. M. (2010). Enhancing interest and performance with a utility value intervention. *Journal of Educational Psychology*, *102*(4), 880–895. https://doi.org/10.1037/a0019506

Hulleman, C. S., & Harackiewicz, J. M. (2009). Promoting interest and performance in high school science classes. *Science*, *326*, 1410–1412. https://doi.org/10.1126/science.1177067

Hulleman, C. S., Kosovich, J. J., Barron, K. E., & Daniel, D. B. (2017). Making connections:

Replicating and extending the utility value intervention in the classroom. *Journal of Educational Psychology*, *109*(3), 387–404. https://doi.org/10.1037/edu0000146

Ingram, R. E., & Luxton, D. D. (2005). Vulnerability-stress models. In B. Hankin & J. Abela, *Development of Psychopathology: A Vulnerability-Stress Perspective* (pp. 32–46). SAGE Publications, Inc. https://doi.org/10.4135/9781452231655.n2

Jacobs, J. E., Lanza, S., Osgood, D. W., Eccles, J. S., & Wigfield, A. (2002). Changes in children's self-competence and Values: Gender and domain differences across grades one through twelve. *Child Development*, *73*(2), 509–527. https://doi.org/10.1111/1467-8624.00421

Lee, J., Lee, M., & Bong, M. (2013). High value with low perceived competence as an amplifier of self-worth threat. In D. M. McInerney, H. W. Marsh, R. G. Craven, & F. Guay (Eds.), *Theory driving research: New wave perspectives on self-processes and human development* (pp. 205–231). IAP Information Age Publishing.

Lee, Y., Freer, E., Robinson, K. A., Perez, T., Lira, A. K., Briedis, D., Walton, S. P., & Linnenbrink-Garcia, L. (2022). The multiplicative function of expectancy and value in predicting engineering students' choice, persistence, and performance. *Journal of Engineering Education*, *111*(3), 531–553. https://doi.org/10.1002/jee.20456

McClelland, G. H., & Judd, C. M. (1993). Statistical difficulties of detecting interactions and moderator effects. *Psychological Bulletin*, *114*(2), 376–390. https://doi.org/10.1037/0033-2909.114.2.376

Meyer, J., Fleckenstein, J., & Köller, O. (2019). Expectancy value interactions and academic achievement: Differential relationships with achievement measures. *Contemporary Educational Psychology*, *58*, 58–74. https://doi.org/10.1016/j.cedpsych.2019.01.006

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K. T., & Trautwein, U. (2011). Who took the “×” out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science*, *22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

OECD. (2007). *PISA 2006: Science Competencies for Tomorrow’s World: Volume 1: Analysis*. OECD. https://doi.org/10.1787/9789264040014-en

Perry, R. P., Chipperfield, J. G., Hladkyj, S., Pekrun, R., & Hamm, J. M. (2014). Attribution-based treatment interventions in some achievement settings. In S. A. Karabenick & T. C. Urdan (Eds.), *Motivational interventions (Advances in motivation and achievement, Volume 18)* (pp. 1–35). Emerald Group Publishing Limited.

Price, P. C., Crisosto, K., Carvalho, A., Jones, C. J., McCready, M., Shaver, A., & Wiemann, A. N. (2024). Testing the effects of a utility value intervention in an online research methods course: A conceptual replication of Hulleman et al. (2017, study 2). *Teaching of Psychology*, *51*(3), 260–268. https://doi.org/10.1177/00986283221101850

Priniski, S. J., Rosenzweig, E. Q., Canning, E. A., Hecht, C. A., Tibbetts, Y., Hyde, J. S., & Harackiewicz, J. M. (2019). The benefits of combining value for the self and others in utility-value interventions. *Journal of Educational Psychology*, *111*(8), 1478–1497. https://doi.org/10.1037/edu0000343

Rosenzweig, E. Q., Harackiewicz, J. M., Priniski, S. J., Hecht, C. A., Canning, E. A., Tibbetts, Y., & Hyde, J. S. (2019). Choose your own intervention: Using choice to enhance the effectiveness of a utility-value intervention. *Motivation Science*, *5*(3), 269–276. https://doi.org/10.1037/mot0000113

Rosenzweig, E. Q., Song, Y., & Clark, S. (2022). Mixed effects of a randomized trial replication study testing a cost-focused motivational intervention. *Learning and Instruction*, *82*, 101660. https://doi.org/10.1016/j.learninstruc.2022.101660

Rosenzweig, E. Q., Wigfield, A., & Hulleman, C. S. (2020). More useful or not so bad? Examining the effects of utility value and cost reduction interventions in college physics. *Journal of Educational Psychology*, *112*(1), 166–182. https://doi.org/10.1037/edu0000370

Ross, L., & Nisbett, R. E. (1991). *The person and the situation: Perspectives of social psychology*. Mcgraw-Hill Book Company.

Tipton, E., Bryan, C., Murray, J. S., McDaniel, M., Schneider, B. L., & Yeager, D. S. (2022). *Why meta-analyses of growth mindset and other interventions should follow best practices for examining heterogeneity*. https://doi.org/10.13140/RG.2.2.34070.01605

Tolman, E. C. (1938). The determiners of behavior at a choice point. *Psychological Review*, *45*(1), 1–41. https://doi.org/10.1037/h0062733

Trautwein, U., Marsh, H. W., Nagengast, B., Lüdtke, O., Nagy, G., & Jonkmann, K. (2012). Probing for the multiplicative term in modern expectancy–value theory: A latent interaction modeling study. *Journal of Educational Psychology*, *104*(3), 763–777. https://doi.org/10.1037/a0027470

Vroom, V. H. (1964). *Work and Motivation*. Weiley.

Walkington, C. A. (2013). Using adaptive learning technologies to personalize instruction to student interests: The impact of relevant contexts on performance and learning outcomes. *Journal of Educational Psychology*, *105*(4), 932–945. https://doi.org/10.1037/a0031882

Walton, G. M., Murphy, M. C., Logel, C., Yeager, D. S., Goyer, J. P., Brady, S. T., Emerson, K. T. U., Paunesku, D., Fotuhi, O., Blodorn, A., Boucher, K. L., Carter, E. R., Gopalan, M., Henderson, A., Kroeper, K. M., Murdock-Perriera, L. A., Reeves, S. L., Ablorh, T. T., Ansari, S., … Krol, N. (2023). Where and with whom does a brief social-belonging intervention promote progress in college? *Science*, *380*(6644), 499–505. https://doi.org/10.1126/science.ade4420

Walton, G. M., & Yeager, D. S. (2020). Seed and soil: Psychological affordances in contexts help to explain where wise interventions succeed or fail. *Current Directions in Psychological Science*, *29*(3), 219–226. https://doi.org/10.1177/0963721420904453

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., Paunesku, D., Romero, C., Flint, K., Roberts, A., Trott, J., Iachan, R., Buontempo, J., Yang, S. M., Carvalho, C. M., … Dweck, C. S. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature*, *573*, 364–369. https://doi.org/10.1038/s41586-019-1466-y

Supplementary Materials for

Why Elusive Expectancy × Value Interactions May Be Critical for Theory and Intervention: A Simulated Power Analysis

Michael W. Asher, Cameron A. Hecht, Judith M. Harackiewicz, John J. Curtin, Cora Parrisius, and Benjamin Nagengast

Corresponding author: Michael W. Asher
Email: masher@andrew.cmu.edu

Table of Contents

Additional supporting information can be found at: https://osf.io/tzq2s

Studies that Report Significant Expectancy × Value Interactions

Table S1 summarizes examples of studies that report significant expectancy × value interactions.

Table S1

Summary of Studies that Report Significant Expectancy × Value Interactions

Author(s)	Year	Sample	Modeling Technique	Value Constructs	*β* Range†	Outcome(s)	N
Guo, Parker, et al.	2015	Australian 15-year-olds, a representative, longitudinal PISA sample	LIM	Intrinsic	.07 to .08	Achievement; course taking*	10,370
Guo, Marsh, et al. ††	2015	A representative sample of 8th graders in Hong Kong schools	LIM	Utility	-.07 to -.05	Achievement; aspirations*	13,621
Guo et al.	2016	German 9th graders, academic track	LIM	Combined	.05 to .15	Achievement; effort*; engagement*	1,868
Hensley	2014	Undergraduates, midwestern U.S. university	Multiple Regression	Combined	.14 to .17	Meeting deadlines*; procrastination	320
Lauermann et al.	2017	Students at public schools in Michigan, surveyed from elementary school to adulthood.	LIM	Utility, Interest	.13 to .19	Career choice	980
J. Lee et al.	2013	Korean 8th-9th grade students	Multiple Regression	Attainment, Intrinsic, Utility	.03 to .09	Self-handicapping*; test anxiety *	6,783
J. Lee et al.	2014	Korean 11th grade students	Multiple Regression	Intrinsic	.08 to .11	Cheating*; procrastination*	574
Y. Lee et al.	2022	Engineering students at a U.S. public university	LIM	Utility, Interest	.14 to .30	Career intentions*; engineering retention	2,420
Meyer et al.	2019	13th grade German students from 44 schools; all tracks	LIM	Attainment, Intrinsic, Utility, Cost	.04 to .16	Achievement	3,367

Nagengast et al.	2011	15-year-olds, 57 countries, representative PISA sample.	LIM	Enjoyment	.06 to .07	Aspirations*; extracurricular participation*	398,750
Nagengast et al.	2013	German 8th-9th grade students, 9 schools, academic track	Multi-level LIM	Combined	.06	Homework engagement*	511
Perez et al.	2019	Undergraduates, mid-Atlantic U.S.	Path Modeling	Effort Cost	-.02 (unst.)	Course Grades	234
Trautwein et al.	2012	German secondary students, 156 schools, academic track	LIM	Attainment, Intrinsic, Utility, Cost	.09 to .12	Achievement	2,508

Note. LIM = latent interaction modeling. † The *β Range* column shows the range (smallest to largest) of the significant, standardized interaction coefficients. Coefficients associated with negative outcomes (e.g., procrastination, anxiety) have been reversed, so all synergistic expectancy × value interactions are positive. * An asterisk indicates that the corresponding outcome was measured via self-report. †† This study by Guo and colleagues (2015) detected a compensatory expectancy × value interaction, with expectancies predicting the outcomes more strongly at low levels of perceived value. All other studies detected synergistic interactions, consistent with most expectancy-value theories.

Study 1

Methods, Details

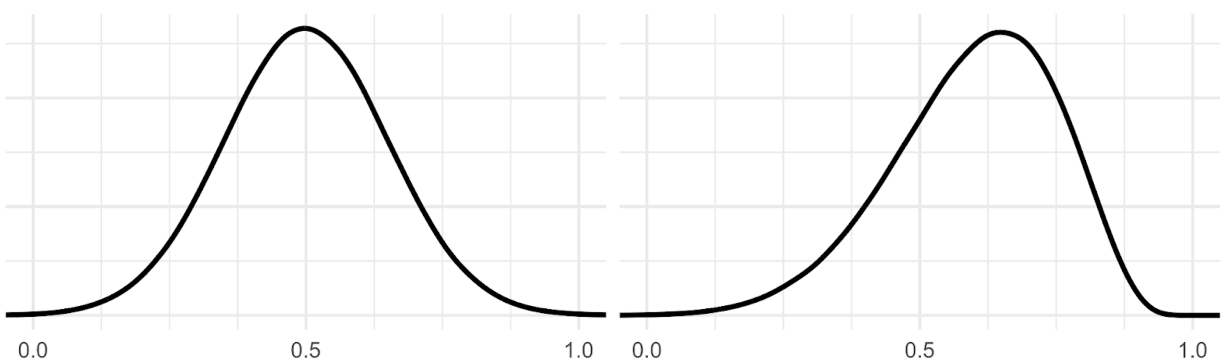
In a 2 x 2 x 3 design, we tested how the distribution (normal vs. skewed), correlation (.65 vs. 0), and measurement reliability (1 vs. .85 vs. .7) of students' expectancies and value perceptions can limit researchers' ability to detect the size and significance of expectancy × value interactions.

Specifically, for some number of simulated students (*N*) we took the following steps:

First, we randomly sampled students' expectancy and value scores from a distribution that was normal (mean = .5, skew = 0, kurtosis = 0), or negatively skewed (mean = .6, skew = -.5, kurtosis = 0). Following Eccles and colleagues' expectancy-value theory, we conceptualize expectancy as a subjective probability of success, and we conceptualize subjective task value as the overall strength of a students' belief that a task is valuable. Although value beliefs can be disaggregated into different sources of value (e.g., usefulness, identity-related importance, costs), they can also be considered or modeled in aggregate form (see Eccles et al., 1998; Wang, 2012). We set the standard deviation of both variables to .15 so > 99.9% of simulated observations would fall between 0 and 1, putting each construct on a ratio scale in which "zero" represents a complete absence of each construct and "one" represents each construct's theoretical maximum. The normal and skewed distributions that we used in Study 1 are illustrated in Figure S1. Third, we manipulated whether expectancies and value were correlated ($r = .65$) or uncorrelated ($r = 0$). For our fourth and final manipulation, we added varying amounts of measurement error to the predictor variables to create versions with observed reliabilities of 1, .85, or .7.

Figure S1

Distributions of Expectancies and Value Used in Study 1



Note. Figure S1 shows normal (left) and skewed (right) distributions from which we sampled participants' expectancy and value scores for Study 1.

After completing the manipulations, we multiplied each participant's true (error-free) expectancy and value scores to generate an expectancy × value score. We then transformed this product score into a simulated, motivation-related outcome score (e.g., a test score or the number of courses that a student chose to take) by adding random error, which represents non-motivational influences on the outcome (e.g., circumstances that affect test performance or academic choices like life stressors or the quality of a student's education, see McClelland et al., 1953; Weiner, 1986). We gave this normally distributed error a mean of zero and a standard deviation of .2, such that it explained approximately 50% of the outcome variance in a model in which expectancies and values were uniformly distributed and measured without error. Given that measures of psychological constructs rarely explain more than 9% of the variance in any behavior-related outcome (Ross & Nisbett, 1991) we believe that this is a conservative assumption and that non-motivational influences likely have an even larger effect in many cases.

Finally, we regressed this observed outcome score on students' observed expectancies, their observed value perceptions, and an expectancy × value interaction. We predicted that the interaction would be much more difficult to detect than the main effects, even though an interaction generated the data. This process was repeated 1000 times for different sample sizes with each set of constraints, using the *rIG* function in R (Foldnes & Olsson, 2016). We tracked how often the p-value for the interaction was less than .05 to determine the impact on statistical power, and we also monitored effect sizes and the detection of main effects under each condition.

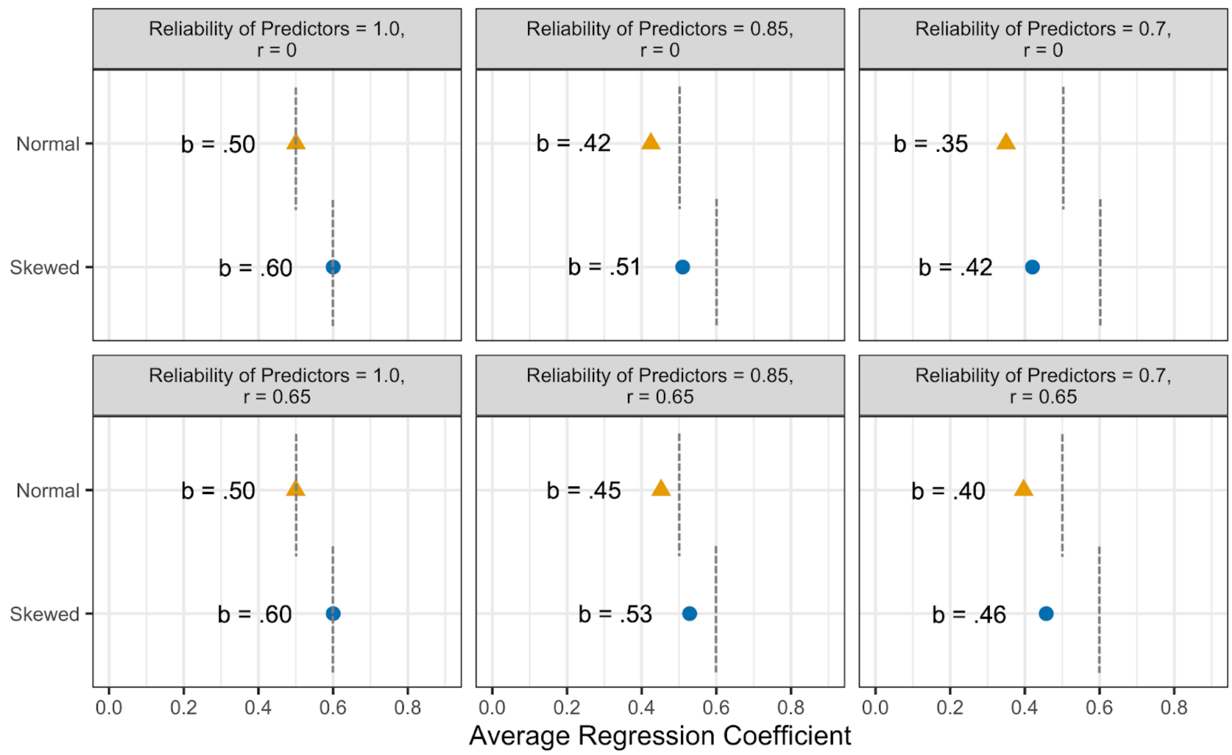
Results, Details

Main Effects of Expectancies and Value Perceptions are Easier to Detect

Because in our simulated analysis we centered predictor variables before running regressions, the simple effects of students' expectancies and value perceptions represent the average effect of each predictor on the outcome when the other predictor is held constant at its mean (Jaccard & Turrisi, 2003), and can be interpreted as main effects. In normally distributed scenarios (which are simulated to have a mean of .5), we expect main effects of $b = .5$, and in skewed scenarios (which are simulated to have a mean of .6), we expect main effects of $b = .6$.

Figure S2

Average Coefficients for the Main Effects of Expectancies and Value Perceptions.

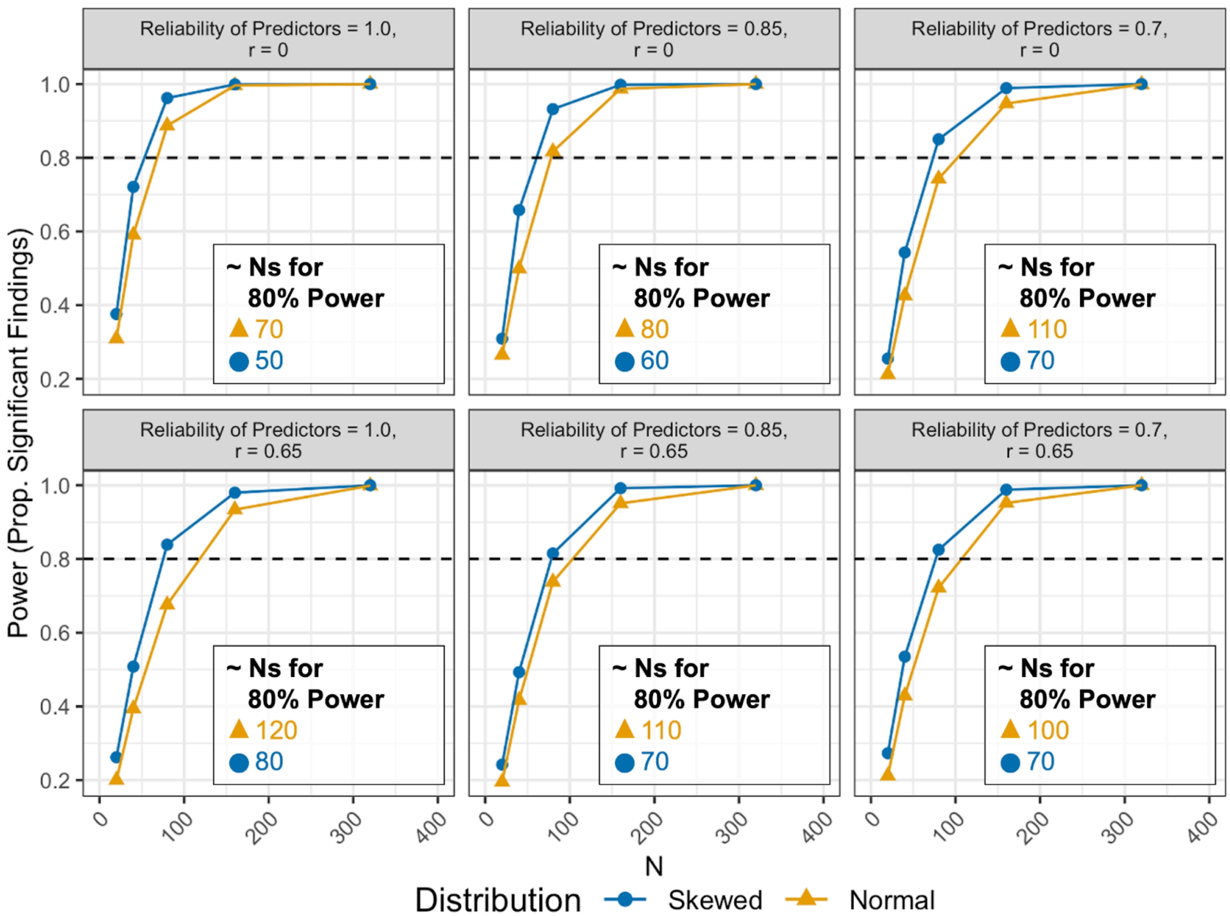


Note. Dashed vertical lines show the magnitude of the true average effect for each scenario.

Figure S2 shows how changes in the variance, skew, correlation, and reliability of the two simulated predictors affect the bias and variance of their regression coefficients. Figure S3 shows the corresponding power analysis for the main effect of either predictor.

Figure S3

Power to Detect the Main Effect of Either Predictor



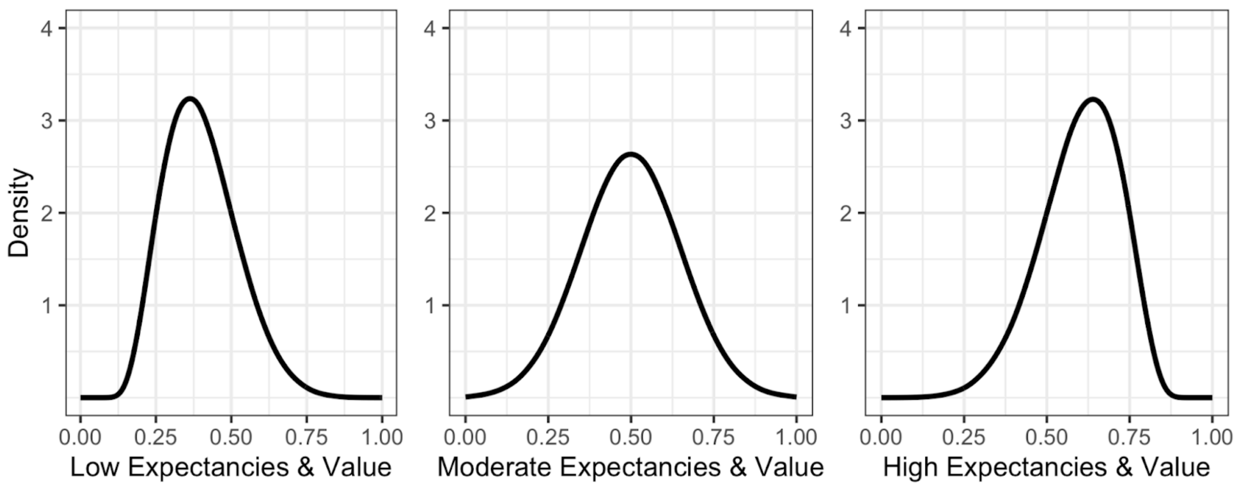
Study 2

Methods, Details

Figure S4 shows the distributions of expectancies and value perceptions in the three simulated samples of Study 2.

Figure S4

Distributions of Expectancies and Value Perceptions Used in Study 2



Note. The center distribution is normal (*M* = .5, *SD* = .15, skew = 0, kurtosis = 0). The left and right distributions are skewed (*M* = .4 or .6, *SD* = .15, skew = -.5 or .5, kurtosis = 0).

To conduct Study 2, we took the steps that are summarized in Figure 5 of the main text. Specifically, for varying numbers of participants (N) we did the following: First, we sampled participants' expectancies and value perceptions from one of the three distributions depicted above, assuming a correlation of r = .5 between the two variables. Next, we randomly assigned half of the participants to a value intervention and increased their value scores by .5 standard deviations. Third, we multiplied participants' expectancies and their value perceptions together to generate their true expectancy × value scores. Fourth, we added error to participants' true expectancy scores to create observed scores with a reliability of .9. Fifth, we generated motivation-related outcome scores by adding error to the expectancy × value scores to represent the influence of omitted, non-motivation-related variables (as we did in Study 1).

Once these scores were generated, we ran a linear regression, testing for the effects of treatment (intervention = .5, control = -.5), observed expectancies (centered), and the treatment × expectancy interaction on the motivation-related outcome (standardized). Finally, as we did in Study 1, we then repeated this process 1,000 times for different sample sizes with each of the three distributions, tracking the proportion of simulations that resulted in significant intervention effects. We also tracked the proportion of simulations that resulted in significant treatment × expectancy effects (to determine how often individual researchers would be able to detect that an expectancy × value interaction is causing heterogeneity within their intervention).

Supplementary References

Eccles, J. S., Wigfield, A., & Schiefele, U. (1998). Motivation to succeed. In W. Damon & N. Eisenberg (Ed.), *Handbook of child psychology: Social, emotional, and personality development* (5th ed., pp. 1017–1095). John Wiley & Sons, Inc.

Foldnes, N., & Olsson, U. H. (2016). A simple simulation technique for nonnormal data with prespecified skewness, kurtosis, and covariance matrix. *Multivariate Behavioral Research*, *51*(2–3), 207–219. https://doi.org/10.1080/00273171.2015.1133274

Guo, J., Marsh, H. W., Parker, P. D., Morin, A. J. S., & Yeung, A. S. (2015). Expectancy-value in mathematics, gender and socioeconomic background as predictors of achievement and aspirations: A multi-cohort study. *Learning and Individual Differences, 37*, 161–168. https://doi.org/10.1016/j.lindif.2015.01.008

Guo, J., Nagengast, B., Marsh, H. W., Kelava, A., Gaspard, H., Brandt, H., Cambria, J., Flunger, B., Dicke, A.-L., Häfner, I., Brisson, B. M., & Trautwein, U. (2016). Probing the unique contributions of self-concept, task values, and their interactions using multiple value facets and multiple academic outcomes. *AERA Open*, *2*(1), 1–20. https://doi.org/10.1177/2332858415626884

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. S. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology, 51*(8), 1163–1176. https://doi.org/10.1037/a0039440

Hensley, L. C. (2014). Reconsidering active procrastination: Relations to motivation and achievement in college anatomy. *Learning and Individual Differences*, *36*, 157–164. https://doi.org/10.1016/j.lindif.2014.10.012

Jaccard, J., & Turrisi, R. (2003). *Interaction Effects in Multiple Regression*. SAGE Publications, Inc. https://doi.org/10.4135/9781412984522

Lauermann, F., Tsai, Y.-M., & Eccles, J. S. (2017). Math-related career aspirations and choices within Eccles et al.'s expectancy–value theory of achievement-related behaviors. *Developmental Psychology*, *53*(8), 1540–1559. https://doi.org/10.1037/dev0000367

Lee, J., Bong, M., & Kim, S. (2014). Interaction between task values and self-efficacy on maladaptive achievement strategy use. *Educational Psychology*, *34*(5), 538–560. https://doi.org/10.1080/01443410.2014.895296

Lee, J., Lee, M., & Bong, M. (2013). High value with low perceived competence as an amplifier of self-worth threat. In D. M. McInerney, H. W. Marsh, R. G. Craven, & F. Guay (Eds.), *Theory driving research: New wave perspectives on self-processes and human development* (pp. 205–231). IAP Information Age Publishing.

Lee, Y., Freer, E., Robinson, K. A., Perez, T., Lira, A. K., Briedis, D., Walton, S. P., & Linnenbrink-Garcia, L. (2022). The multiplicative function of expectancy and value in predicting engineering students' choice, persistence, and performance. *Journal of Engineering Education*, *111*(3), 531–553. https://doi.org/10.1002/jee.20456

McClelland, D. C., Atkinson, J. W., Clark, R. A., & Lowell, E. L. (1953). *The achievement motive.* Appleton-Century-Crofts. https://doi.org/10.1037/11144-000

Meyer, J., Fleckenstein, J., & Köller, O. (2019). Expectancy value interactions and academic achievement: Differential relationships with achievement measures. *Contemporary Educational Psychology*, *58*, 58–74. https://doi.org/10.1016/j.cedpsych.2019.01.006

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K. T., & Trautwein, U. (2011). Who took the "×" out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science*, *22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

Nagengast, B., Trautwein, U., Kelava, A., & Lüdtke, O. (2013). Synergistic effects of expectancy and value on homework engagement: The case for a within-person perspective. *Multivariate Behavioral Research*, *48*(3), 428–460. https://doi.org/10.1080/00273171.2013.775060

Perez, T., Dai, T., Kaplan, A., Cromley, J. G., Brooks, W. D., White, A. C., Mara, K. R., & Balsai, M. J. (2019). Interrelations among expectancies, task values, and perceived costs in undergraduate biology achievement. *Learning and Individual Differences, 72*, 26–38. https://doi.org/10.1016/j.lindif.2019.04.001

Ross, L., & Nisbett, R. E. (1991). *The person and the situation: Perspectives of social psychology*. Mcgraw-Hill Book Company.

Trautwein, U., Marsh, H. W., Nagengast, B., Lüdtke, O., Nagy, G., & Jonkmann, K. (2012). Probing for the multiplicative term in modern expectancy–value theory: A latent interaction modeling study. *Journal of Educational Psychology*, *104*(3), 763–777. https://doi.org/10.1037/a0027470

Wang, M.T. (2012). Educational and career interests in math: A longitudinal examination of the links between classroom environment, motivational beliefs, and interests. *Developmental Psychology, 48*(6), 1643–1657. https://doi.org/10.1037/a0027247

Weiner, B. (1986). *Human Motivation.* Springer.