Motivation Science

ISSN: 2333-8113

2025, Vol. 11, No. 4, 502–510
https://doi.org/10.1037/mot0000394

CONCEPTUAL BRIEF REPORT

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

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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 article, 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

Supplemental materials: https://doi.org/10.1037/mot0000394.supp

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).

This article was published Online First April 10, 2025.
Rex A. Wright served as action editor.
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This research was supported by the National Institutes of Health (Grant R35GM141556 to Judith M. Harackiewicz at the University of Wisconsin). All data and code for the study are openly available in the Open Science Framework and can be found as the additional online materials (https://osf.io/tzq2s).
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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.

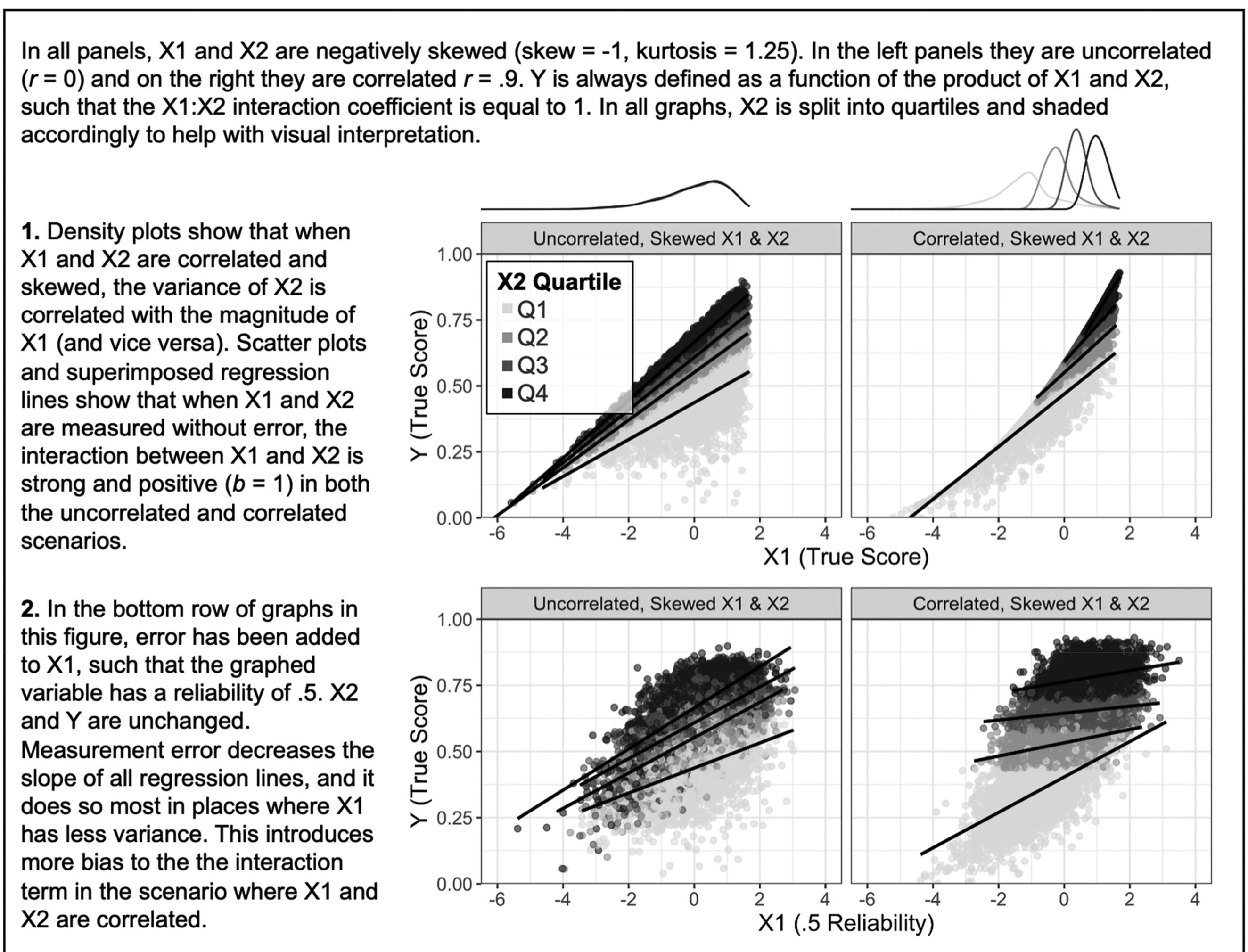
Study 1: Empirical Constraints and Biased Estimates

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

Bohrnstedt and 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 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,

Figure 1
Skew, Measurement Error, and Correlation Can Interact to Bias Interaction Coefficients



Note. Q1 = Quartile 1; Q2 = Quartile 2; Q3 = Quartile 3; Q4 = Quartile 4.

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.

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 ($r = .65$ vs. $r = 0$), and (c) their measurement reliability (1.0 vs. .85 vs. .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 online supplemental materials, was repeated 1,000 times per condition. Data and code are available and can be found as the additional online materials (https://osf.io/tzq2s; Asher, 2025).

Results and Discussion

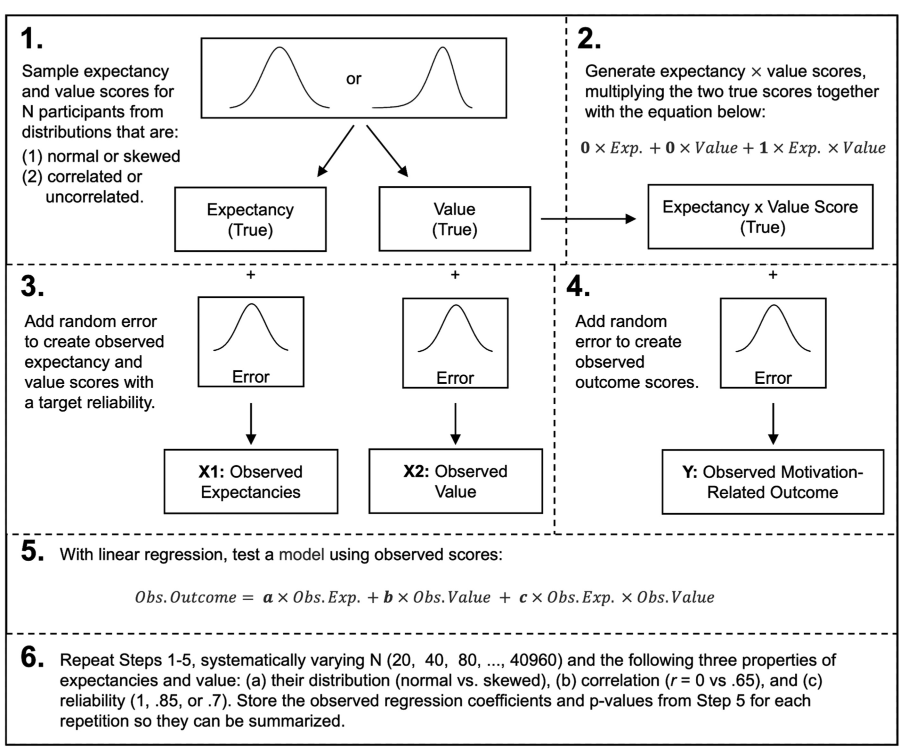
Measurement Error Introduced Bias, Especially With Skewed and Correlated Variables

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 .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 .7 reliability.

Large Samples Were Needed to Detect Interactions

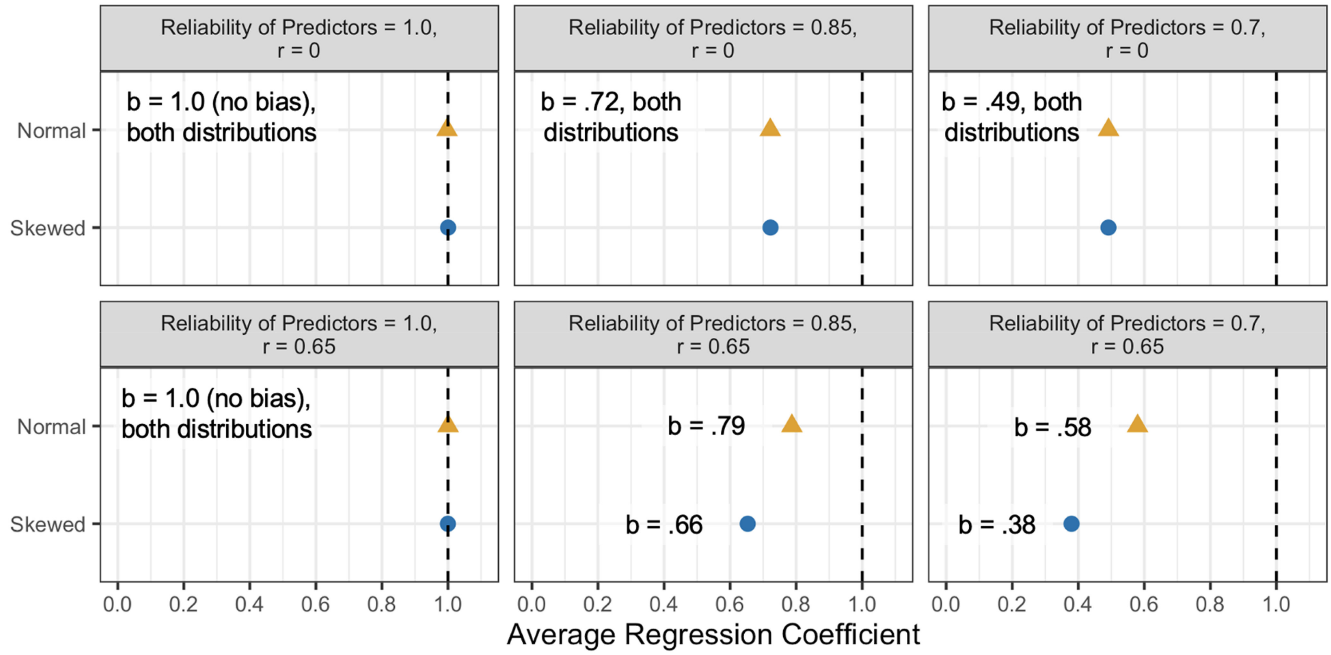
Figure 4 shows the results of our power analyses, which highlight the difficulty of detecting interactions even when they fully account for the data. Across all conditions, at least 500 participants were needed to achieve 80% power for detecting an Expectancy × Value interaction. As measurement error 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, the main effects were much less prone to

Figure 2
Method for Study 1



Note. Obs. = observed; Exp. = expectancy.

Figure 3
The Magnitude of Regression Coefficients



Note. See the online article for the color version of this figure.

bias (see the online supplemental materials); even under the most challenging conditions, only 100 participants were needed to reliably detect them.

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 because of 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 the 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 2-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.

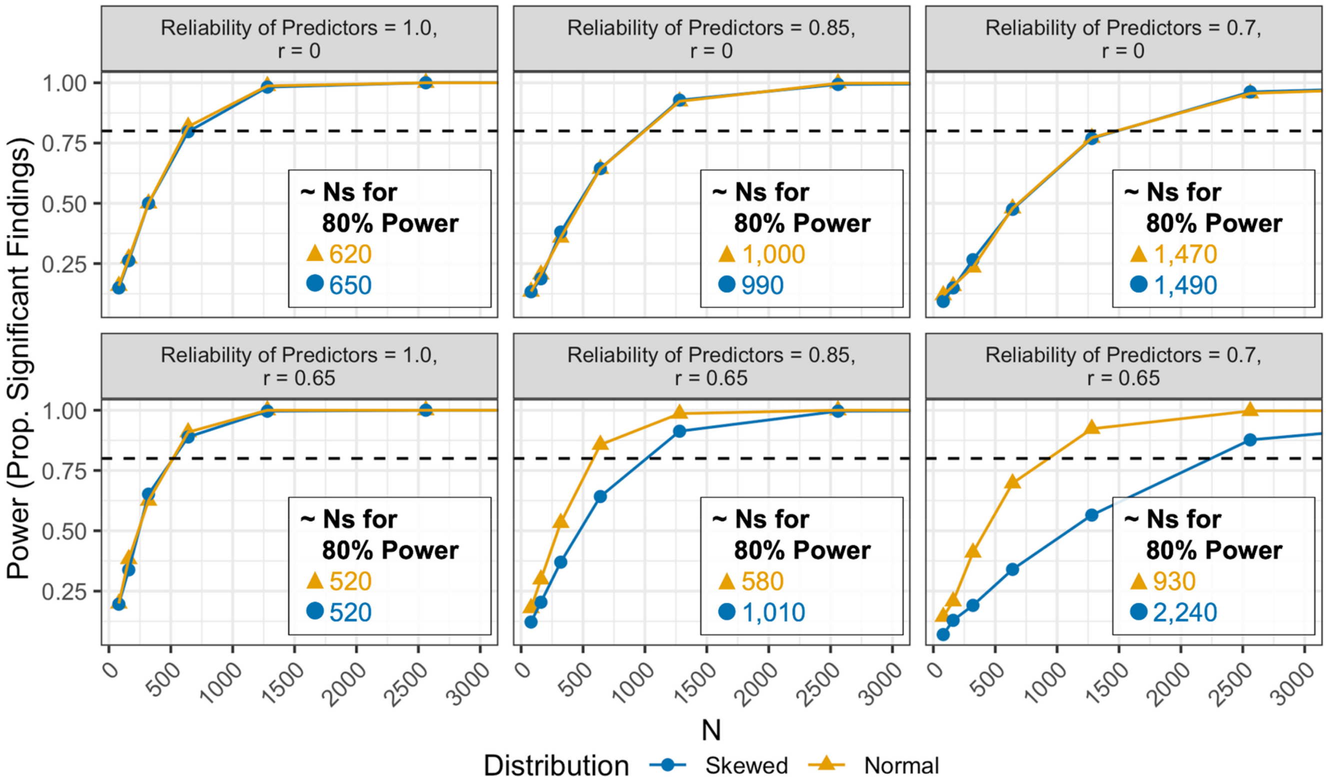
Method

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. We simulated 1,000 interventions in three distinct samples: (a) a sample where many students were initially unmotivated (with low expectancies and value perceptions), (b) a sample where students' expectancies and value perceptions were more moderate on average, or (c) a sample where many students had high expectancies and value. We assumed that the intervention had a 0.5 *SD* effect on students' value perceptions, which in turn interacted with their expectancies to influence an achievement-related outcome.

Figure 4
Power Analysis for the Expectancy × Value Interaction



Note. Prop. = proportion; Ns = number of participants. See the online article for the color version of this figure.

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 (Figure 6A) and Treatment × Expectancy interactions (Figure 6B) across the three samples. Figure 6C shows average effect sizes.

Simulations revealed substantial heterogeneity in intervention effects because of 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

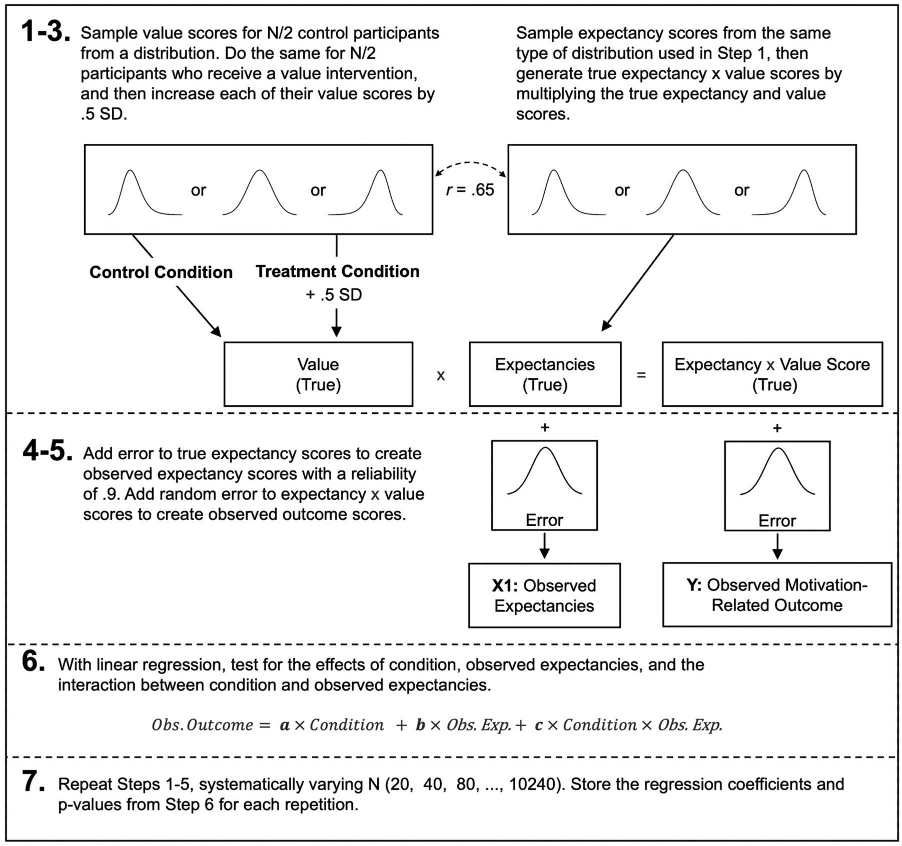
Researchers often attempt to explain heterogeneous intervention effects by testing for interactions with treatment. However, our simulations indicate that detecting Treatment × Expectancy interactions is far more challenging than identifying their main effects (Figure 6B). Across all conditions, detecting an interaction with 80% power required over 13,000 participants—7 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 & Harackiewicz, 2009; Hulleman et al., 2010), 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 suggests that these interactions can create meaningful variability in motivation interventions, even though Treatment × Expectancy (or value) interactions may require

Figure 5
Procedure for Study 2



Note. Obs. = observed; Exp. = expectancy.

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 the 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.

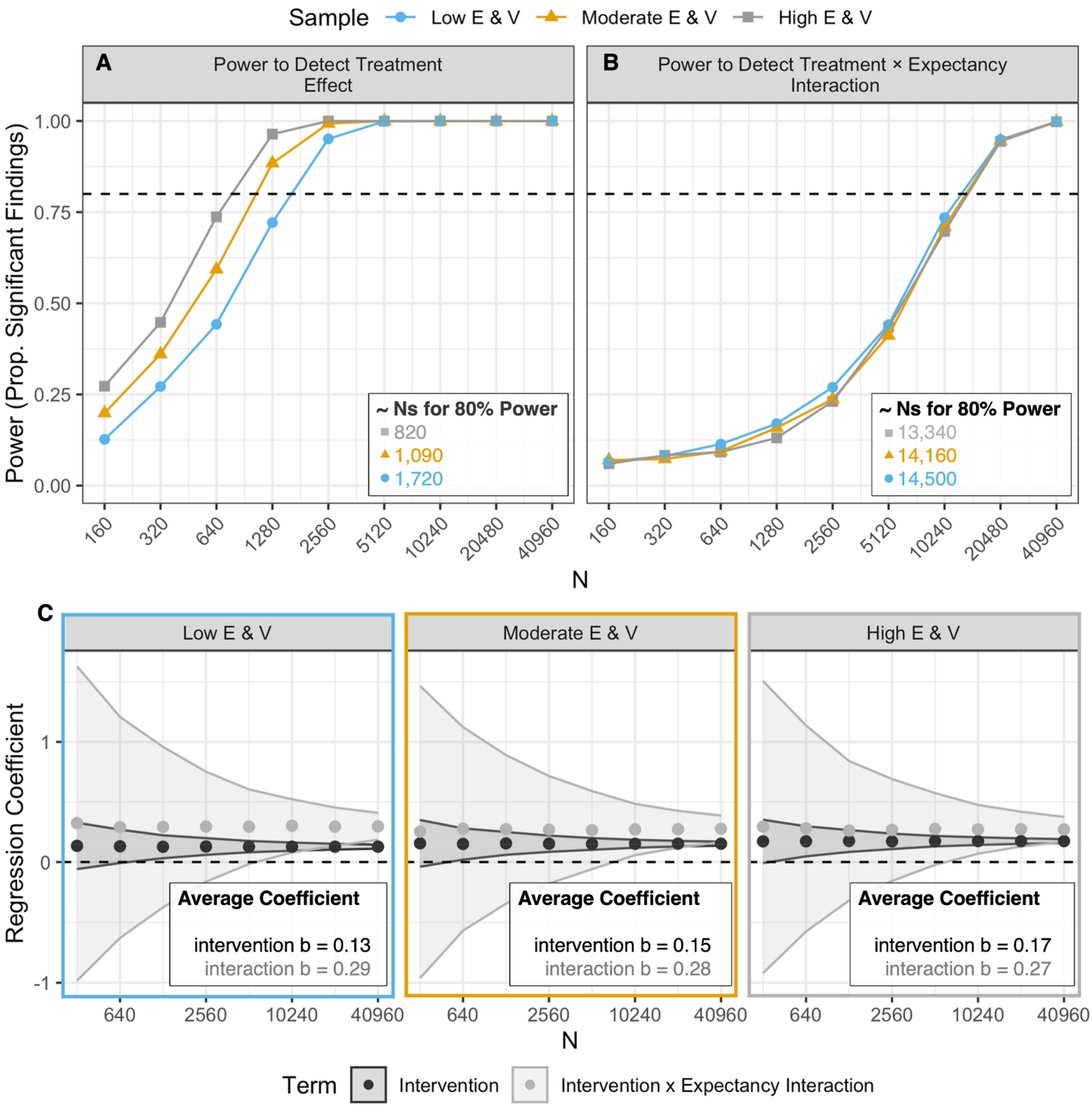
Designing Interventions

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 nonreplications 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 multisite 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 article 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).

Figure 6
Results for Study 2



Note. (A) Power to detect treatment effect; (B) power to detect Treatment × Expectancy interaction; and (C) effect sizes in low E and V, moderate E and V, and high E and V samples. Error envelopes in Panel C show 95% confidence intervals. E = expectancy; V = value; Prop. = proportion; Ns = number of participnts. See the online article for the color version of this figure.

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.

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Received October 11, 2024
Revision received March 7, 2025
Accepted March 9, 2025 ■