# **Motivation as a Complex System: Semester-Long Recursive Dynamics of Expectancy-Value Constructs in Undergraduate Biology**

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**Abstract**

The predominant aggregate-statistical analyses in motivational research manifest assumptions that stand in tension with understandings of motivational phenomena as dynamic, contextual, and variable among individuals. Using constructs from expectancy-value theory, we collected 13 weekly waves of data from 145 undergraduate students during one semester of an introductory biology course. We analyzed the data using dynamic autoregressive mixed-effects modeling, which captures the individual-level recursive processes among constructs, and then examined patterns across individuals' motivational trajectories to discern general principles by which the expectancy-value system operates. The findings contribute to robust theoretical understandings of expectancy-value processes, and demonstrate the application of an analytical approach to motivational research that is compatible with the nature of motivational phenomena.

## Motivation as a Complex System: Semester-Long Recursive Dynamics of Expectancy-Value Constructs in Undergraduate Biology

Whereas motivational research has contributed tremendously to conceptual understandings of motivational processes, recent critiques have challenged the predominant methodological approach in the field. Motivational processes are continuous, dynamic, complex, contextualized, and involve multiple interdependent constructs that vary across individuals (Kaplan, Katz, & Flum, 2012; Yeager & Walton, 2011). In contrast, in prevalent motivation research, constructs are assessed only once or a few times across long spans of time and contexts; are treated as independent rather than as interdependent with each other and with outcomes; and are analyzed at the *aggregate* level, with coefficients interpreted as reflecting "true" values for all *individuals* in the population, masking individual variability (Glass, Willson, & Gottman, 2008; Speelman & McGann, 2013).

In the current study, we demonstrate an alternative approach to the analysis of motivational data that addresses some of these limitations (Gregson & Guastello, 2011; Funatogawa & Funatogawa, in-press). Using 13 weekly waves of data from 145 undergraduate students during one semester in one course, we analyzed constructs from expectancy-value theory using dynamic autoregressive modeling, which captures individual-level recursive processes. We then examined patterns across individuals' motivational trajectories to discern principles by which the motivational system operates. The dual purpose of this study was to gain robust theoretical understandings of expectancy-value processes and to demonstrate the application of an analytical approach that is more compatible with the nature of motivational phenomena.

### Expectancy-Value Theory

Expectancy-value theory contends that students' investment in schoolwork and future decisions are the product of their perceived expectancies to do well and their valuing of the domain (Wigfield & Eccles, 2000). Task value comprises four elements: intrinsic value—the pleasure the person expects to derive from the task; attainment value—the importance of the task to the person's sense of identity; utility value—the usefulness of the task to the person's goals; and cost—prices and risks that the person associates with engagement in the task, such as the investment of effort, loss of opportunities, and risks to relationships and self-worth (Eccles, 2009).

Extensive research in expectancy-value theory has established the positive relations between task-value—commonly operationalized as the combination of the intrinsic, attainment, and utility value components—and students' choice, interest, and persistence in the task, and the positive relations between expectancies for success and students' achievement (Wigfield, Tonks, & Klauda, 2016). Research also found that expectancies for success and task value are commonly positively related to each other, suggesting that people tend to perceive tasks in which they expect to succeed as more valuable, and vice versa (Wigfield et al., 2016). In addition, however, some research also supports the theoretical assumption that expectancies for success and task value interact in predicting outcomes (Nagengast, Marsh, Scalas, Xu, Hau, & Trautwein, 2011).

The extensive research on expectancies and task values in students' engagement and success over the last few decades contributed to a sizable body of knowledge about the operation of these motivational constructs. Yet, the majority of research in expectancy-value theory has relied on aggregate, variable-centered, regression-based analyses. Such research derived coefficients that express the magnitude and direction (positive or negative) of relations among expectancies, values, and outcomes across an entire group of participants. Recently, scholars have critiqued this dominant analytical approach as harboring assumptions that are incompatible with the individual-level, dynamic, and contextualized nature of motivational phenomena (Kaplan et al., 2012).

## Dynamic Modeling of Recursive Processes

In the current study, we present an alternative approach for analyzing dynamic and complex phenomena—autoregressive mixed effects modeling (Guastello & Gregson, 2011;

Guastello, Koopmans, & Pincus, 2009). The approach reflects the assumption that each individual has its own continuously emerging motivational system of interdependent constructs, but that different individual systems manifest general principles that can be discerned from patterns across individuals. The approach is based on the recursive principle, which analyzes a longitudinal process as a series of states of the phenomenon in which prior states serve as the basis of future states. This principle is modeled with "recursive equations" ($y_{t+1}=f[y_t]$), in which each iteration of the system serves as an output of its previous iteration and an input for its next iteration (van Geert & Steenbeek, 2005). In addition, the interdependence among the variables that constitute the motivational system is modeled through inclusion of all the variables in the system as predictors of the recursive equations of all other variables.

**The current study**

The current study took place within a larger federally-funded intervention project in undergraduate introductory biology course that aimed to improve students' motivation, learning, and achievement. The course followed a traditional design of lectures, labs, and weekly discussion groups, with weekly quizzes, four within-semester exams, and a final exam. Participants were randomly assigned to a no-treatment control group or one of four different experimental conditions delivered through an online course-management system. Conditions included: (1) videos of worked examples (WE) delivered weekly, (2) four open prompts for brief relevance-writing (RW) delivered one week before each exam, (3) a combination of the WE with the RW, and (4) a combination of the WE with four *structured* RW. Intervention assignments were ungraded and delivered as "add-ons" to the regular course instruction in exchange for extra course credit.

**Research Questions**

(1) What were the longitudinal relations among expectancy-value constructs among students?

(2) How do expectancy-value processes differ among students in the different experimental conditions?

## Methods

In Fall 2016, participants consented and completed untimed pre-intervention measures in the first two weeks of the semester, were given online access and reminded to access the intervention materials throughout the semester, completed brief weekly surveys on Qualtrics, and completed post-intervention measures at the end of the semester. Weekly surveys were administered from week two (beginning of study) to week 15 (final week of the course), except during Thanksgiving break. The current study uses only the data from these weekly surveys.

## Data Sources

### Participants

Data in the current study were collected from 145 consenting students ($M_{age}$ = 19.6, *SD* = 2.1; 61% female; 40.6% freshmen, 29.2% sophomores, 20.8% juniors; 34.4% White, 40.6% Asian, 7.3% Black; 43.7% first-generation college students).

### Measures

Weekly surveys were administered on Friday afternoon following the last lecture of the week, and included 24 items asking students about their motivation and experiences in the course during that week. Each survey opened by noting the content covered in the course for that week, followed by items with Likert-response scales ranging from "0-not at all" to "10-very much." In this study, we focus on four items assessing constructs from the expectancy-value framework: reported level of investment in the course, expectancy, value, and cost. We also included an item assessing frustration—an emotion that is conceptually distinct from the expectancy-value constructs relative to other emotions (e.g., enjoyment, interest, hopeless). Table 1 presents the items used in the study. The course instructor provided students' grades on the exams.

### Analytic Approach

We used MATLAB to specify five recursive equations for each participant, one for each of the five variables in the expectancy-value motivational system: Investment, Expectancy, Value, Cost, and Frustration. In each equation, the recursive change in each of the variables is a linear, interdependent, function of all other variables at the prior measurement. Two contextual variables that were expected to influence students' weekly motivation and hence the dynamics of the motivational system's trajectory were also included in the equations—the anticipation of a looming exam on Monday in the following week, and the student's score on the exam. Each variable's equation took the following form:

$$X_i^{t+1} = a_{1i}X_1^t + a_{2i}X_2^t + a_{3i}X_3^t + a_{4i}X_4^t + a_{5i}X_5^t + a_{6i}X_6^{t+1} + a_{7i}X_7^{t+1}$$

With $X_{1\ to\ 5}^t$ representing the variables of Investment, Expectancy, Value, Cost, and Frustration at time "t", respectively; $X_{6\ to\ 7}^{t+1}$ representing the variables of anticipating an exam and the exam scores at time "t+1", respectively; $X_i^{t+1}$ representing the outcome variable—with "i" standing for each of the five variables at time "t+1"; and $a_{i1\ to\ 7}$ representing the respective relations of the seven variables in the equation with the outcome variable, with "i" standing for the respective number of the outcome variable.

The analysis produces a matrix of 35 coefficients for each participant. We examined patterns in the coefficient matrices through range and distributions to search for general characteristics of this motivational system across participants. We also used feature analyses (e.g., PCA) to identify patterns that may differentiate among participants in the different experimental conditions.

## Results

Figure 1 presents the individual longitudinal lines of all participants on the Investment variable as an example of the data, in which the individual variability in trajectories is very clear. Figures of the other four variables were similar in depicting substantial variability between individuals' lines. The autoregressive mixed effects analysis generated recursive equations that represent the shape of the longitudinal lines of a particular participant as a function of the trajectories of the five variables of the motivational system and the two contextual variables.

Table 2 presents sets of recursive equations from two example participants. Comparison between the two participants demonstrates the marked differences in direction and magnitude of various parameters. For example, whereas the coefficients reflecting the role of prior reported investment in future reported investment were positive for both participants, one (1.73) was markedly higher than the other (.60). More significantly, whereas the role of value in future reported investment was negligible for one participant (.04) it was strong and negative for the other (-1.64). The great variability in coefficients' direction and magnitude suggests a very substantial idiosyncratic facet of the expectancy-value motivational system.

However, it is possible that despite this diversity, the expectancy-value motivational system operates according to certain general principles and within certain boundaries, particularly in specific contexts such as the current course. In order to discern such possible general characteristics across individuals in this sample, we examined patterns in the coefficients. First, we looked at the distributions of particular coefficients across individuals' equations. Table 3 presents descriptive statistics of the 35 coefficients. Reflecting diversity, all coefficients ranged from negative to positive with no variable holding a consistent direction of effect across all individuals. However, certain patterns emerged. For example, some coefficients had very low variability while others had very high variability across individuals' motivational systems. Figure 2 presents the range of coefficients' size across participants, indicating, for example, that the coefficients predicting Cost and Frustration had ranges from very low (.43) to moderate (1.94), whereas the coefficients predicting Investment, Value, and Expectancy had ranges from moderate (1.81) to high (3.49). Interestingly, the modes of all coefficients were negative (see Figure 3). The modes provide an aggregate picture, and this finding could suggest an overall collective recursive decline in the motivational systems in the current course. However, first, coefficients varied in the magnitude of the mode, reflecting low collective decline in the recursive dynamics of Frustration and Cost, moderate collective decline in Investment, and high collective decline in Expectancy and Value. Second, the modes mask the complex combinations of positive and negative coefficients within individuals' motivational systems. Therefore, in order to investigate possible patterns in these combinations, we examined the coefficient correlation matrix.

To demonstrate robust patterns, Table 4 lists correlations among coefficients that are larger than the high threshold of .60. There were very high negative correlations (-.91, -.68, -.61) between the coefficients of Expectancy and Value in predicting the recursive processes of Cost, Frustration, and Investment respectively. These indicated a robust pattern across individuals' motivational systems in which the more positive the role of expectancy in the recursive emergence of these three variables, the more negative was the role of value. In turn, a high positive correlation (.62) between the coefficient of Value in predicting the recursive processes of Expectancy and of Value indicated the role of value in the interdependence of the dynamic longitudinal interdependence of expectancy and value—the higher the role of value in one, the higher it is in the other. Notably, the corresponding correlation of the Expectancy coefficients in predicting the recursive processes of Expectancy and Value was also positive and relatively high (.49). The other very high positive correlations (.68-.75) were between coefficients of Anticipation of exam and of Exam scores in predicting the recursive processes of all five motivational variables, indicating the (unsurprising) very high interdependence of the experience of anticipating an exam with the exam scores in the emergence of the students' motivational systems. In the presentation, we will elaborate on the implications of these and other patterns to understanding principles of the expectancy-value motivational system. Initial analyses to distinguish patterns of coefficients between participants in different experimental conditions did not generate clear findings. We are now pursuing additional analyses.

## Scholarly Significance

The current paper demonstrates a dynamic analytical approach for the investigation of motivation that addresses the epistemological incompatibilities of the currently prevalent aggregate statistical methods with the complex and recursive conceptions of motivational phenomena. Findings from such research promise to generate more accurate theoretical insights about the characteristics of the motivational system while upholding the variability of motivational processes between individuals.

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Table 1

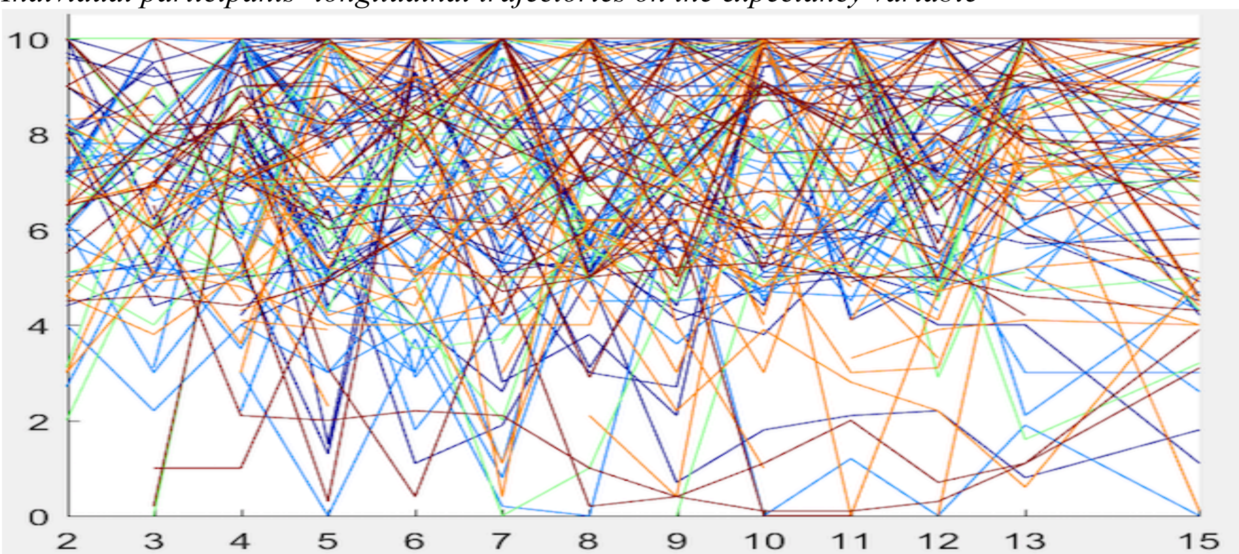
*Variables and items used in the current analysis*

| Variable | Item |
|---|---|
| Investment | "How invested were you in the course this week?" |
| | *"How much did you experience the following during this week's course?"* |
| Expectancy | "That I can do well on the course assignments" |
| Value | "That this week's material is important for me to learn" |
| Cost | "That this week, I'm overwhelmed by the work" |
| Frustration | "Frustrated" |

*Note*: all response scales were Likert-type ranging from 0-"not at all" to 10-"very much"

Figure 1

*Individual participants' longitudinal trajectories on the expectancy variable*




*Note*: different colors indicate different experimental conditions.

Table 2

*Sets of recursive equations for participants #001 and #027*

| | Predicted Variable | Equation |
|---|---|---|
| *Participant #001* | Investment$^{t+1}$ | $= .60X_1^t + .23X_2^t + .04X_3^t - .10X_4^t + .28X_5^t - .13X_6^{t+1} - .08X_7^{t+1}$ |
| | Expectancy$^{t+1}$ | $= -.32X_1^t + .96X_2^t + .15X_3^t + .09X_4^t + .36X_5^t - .11X_6^{t+1} - .12X_7^{t+1}$ |
| | Value$^{t+1}$ | $= .57X_1^t - .42X_2^t + .68X_3^t + .04X_4^t + .18X_5^t - .18X_6^{t+1} - .10X_7^{t+1}$ |
| | Cost$^{t+1}$ | $= 1.37X_1^t - .47X_2^t - .41X_3^t + .61X_4^t - .46X_5^t + .09X_6^{t+1} + .01X_7^{t+1}$ |
| | Frustration$^{t+1}$ | $= .82X_1^t - .21X_2^t - .39X_3^t + .30X_4^t - .62X_5^t + .02X_6^{t+1} + .10X_7^{t+1}$ |
| *Participant #027* | Investment$^{t+1}$ | $= 1.73X_1^t + .65X_2^t - 1.64X_3^t + .57X_4^t + .14X_5^t + .00X_6^{t+1} - .13X_7^{t+1}$ |
| | Expectancy$^{t+1}$ | $= 1.42X_1^t - .54X_2^t + .20X_3^t - .06X_4^t - .50X_5^t + .02X_6^{t+1} - .47X_7^{t+1}$ |
| | Value$^{t+1}$ | $= 2.29X_1^t - .23X_2^t - 1.03X_3^t - .01X_4^t - .20X_5^t + .04X_6^{t+1} - .15X_7^{t+1}$ |
| | Cost$^{t+1}$ | $= 1.42X_1^t - .48X_2^t - .08X_3^t - 1.02X_4^t + .42X_5^t + .12X_6^{t+1} + .37X_7^{t+1}$ |
| | Frustration$^{t+1}$ | $= .46X_1^t - 2.45X_2^t + 3.54X_3^t - 3.86X_4^t + 1.20X_5^t + .12X_6^{t+1} + .59X_7^{t+1}$ |

*Note*: Investment= $X_1$; Expectancy = $X_2$; Value = $X_3$; Cost = $X_4$; Frustration = $X_5$; Anticipation of exam= $X_6$; Exam score= $X_7$

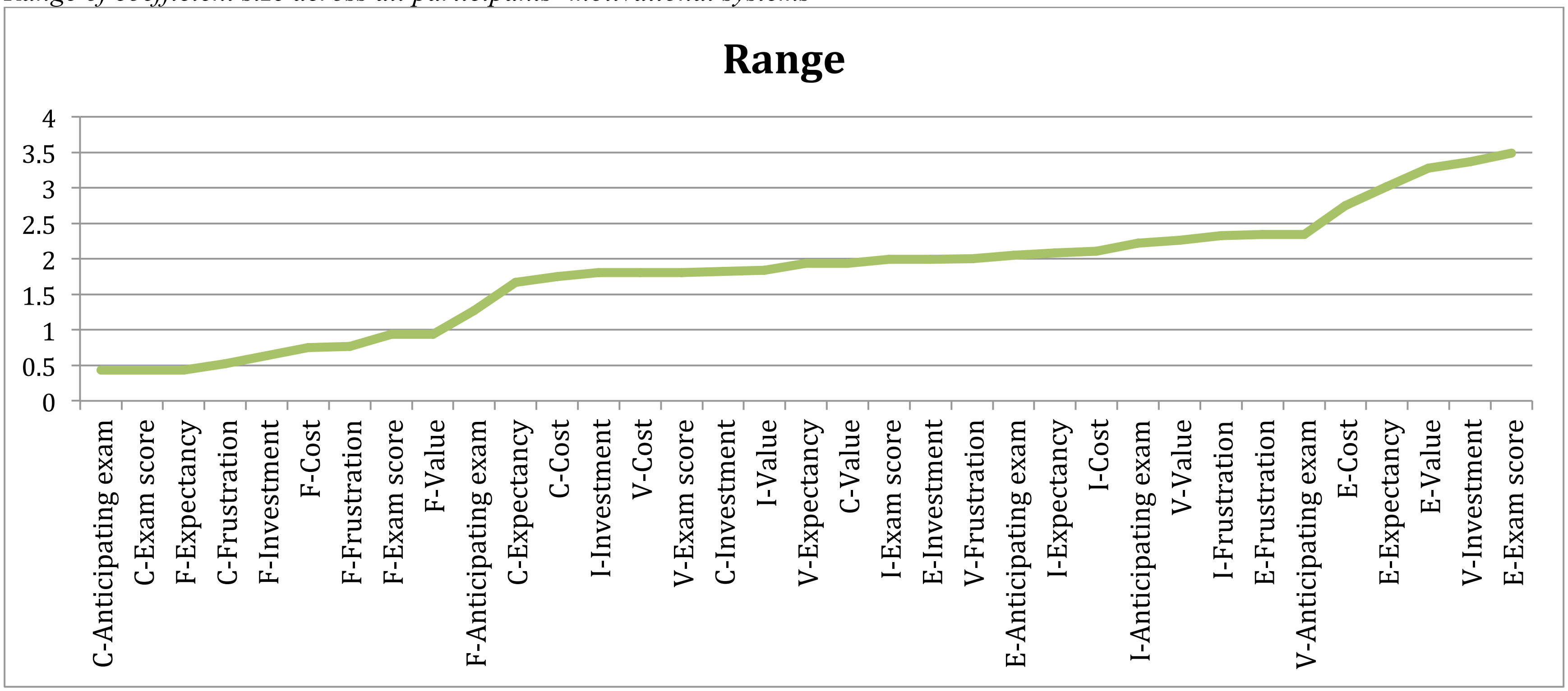
Table 3

*Statistical characteristics of the coefficients in all participants' motivational systems*

| Variable predicted | Coefficient | Minimum | Maximum | Range | Mode | Mean | Standard Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| Investment | Investment | -0.53 | 1.28 | 1.81 | -0.53 | 0.34 | 0.40 | -0.11 | 2.47 |
| | Expectancy | -0.66 | 1.42 | 2.08 | -0.66 | 0.16 | 0.42 | 0.62 | 3.23 |
| | Value | -0.78 | 1.06 | 1.84 | -0.78 | 0.13 | 0.38 | 0.23 | 3.01 |
| | Cost | -1.02 | 1.09 | 2.11 | -1.02 | -0.05 | 0.47 | 0.13 | 2.68 |
| | Frustration | -1.24 | 1.09 | 2.33 | -1.24 | -0.01 | 0.47 | -0.06 | 2.57 |
| | Anticipating exam | -0.96 | 1.26 | 2.22 | -0.96 | 0.11 | 0.42 | 0.15 | 3.59 |
| | Exam score | -0.61 | 1.38 | 1.99 | -0.61 | 0.41 | 0.46 | -0.06 | 2.40 |
| Expectancy | Investment | -0.67 | 1.32 | 1.99 | -0.67 | 0.17 | 0.40 | 0.51 | 3.53 |
| | Expectancy | -1.35 | 1.67 | 3.02 | -1.35 | 0.12 | 0.62 | 0.35 | 2.79 |
| | Value | -1.55 | 1.73 | 3.28 | -1.55 | 0.14 | 0.66 | -0.11 | 3.13 |
| | Cost | -0.97 | 1.78 | 2.75 | -0.97 | 0.19 | 0.54 | 0.43 | 3.35 |
| | Frustration | -0.89 | 1.45 | 2.34 | -0.89 | 0.26 | 0.48 | 0.06 | 2.98 |
| | Anticipating exam | -0.86 | 1.19 | 2.05 | -0.86 | 0.44 | 0.46 | -0.79 | 3.01 |
| | Exam score | -1.46 | 2.03 | 3.49 | -1.46 | 0.28 | 0.73 | 0.17 | 2.90 |
| Value | Investment | -1.68 | 1.69 | 3.37 | -1.68 | 0.12 | 0.65 | -0.15 | 3.18 |
| | Expectancy | -1.01 | 0.93 | 1.94 | -1.01 | 0.06 | 0.39 | -0.21 | 3.02 |
| | Value | -1.07 | 1.19 | 2.26 | -1.07 | 0.01 | 0.39 | 0.31 | 4.00 |
| | Cost | -0.74 | 1.07 | 1.81 | -0.74 | 0.06 | 0.34 | 0.51 | 3.31 |
| | Frustration | -0.77 | 1.23 | 2.00 | -0.77 | 0.16 | 0.50 | 0.09 | 2.30 |
| | Anticipating exam | -1.15 | 1.19 | 2.34 | -1.15 | 0.13 | 0.50 | 0.03 | 2.70 |
| | Exam score | -0.83 | 0.98 | 1.81 | -0.83 | 0.03 | 0.37 | 0.13 | 2.91 |
| Cost | Investment | -0.87 | 0.95 | 1.82 | -0.87 | 0.03 | 0.39 | -0.10 | 2.93 |
| | Expectancy | -0.67 | 1.00 | 1.67 | -0.67 | 0.09 | 0.30 | 0.11 | 3.25 |
| | Value | -1.01 | 0.93 | 1.94 | -1.01 | 0.15 | 0.42 | -0.33 | 2.62 |
| | Cost | -0.64 | 1.11 | 1.75 | -0.64 | 0.26 | 0.45 | -0.05 | 2.17 |
| | Frustration | -0.22 | 0.30 | 0.52 | -0.22 | 0.01 | 0.10 | 0.30 | 3.20 |
| | Anticipating exam | -0.22 | 0.21 | 0.43 | -0.22 | 0.00 | 0.09 | -0.14 | 2.94 |
| | Exam score | -0.24 | 0.19 | 0.43 | -0.24 | -0.01 | 0.09 | -0.31 | 3.34 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Frustration | Investment | -0.26 | 0.38 | 0.64 | -0.26 | 0.05 | 0.13 | -0.05 | 2.71 |
| | Expectancy | -0.20 | 0.23 | 0.43 | -0.2 | 0.02 | 0.10 | 0.24 | 2.36 |
| | Value | -0.58 | 0.36 | 0.94 | -0.58 | -0.02 | 0.18 | -0.59 | 3.76 |
| | Cost | -0.47 | 0.28 | 0.75 | -0.47 | -0.03 | 0.16 | -0.70 | 3.67 |
| | Frustration | -0.45 | 0.32 | 0.77 | -0.45 | -0.03 | 0.14 | -0.54 | 3.63 |
| | Anticipating exam | -0.61 | 0.66 | 1.27 | -0.61 | 0.08 | 0.25 | 0.12 | 2.98 |
| | Exam score | -0.41 | 0.53 | 0.94 | -0.41 | 0.04 | 0.21 | 0.19 | 2.84 |

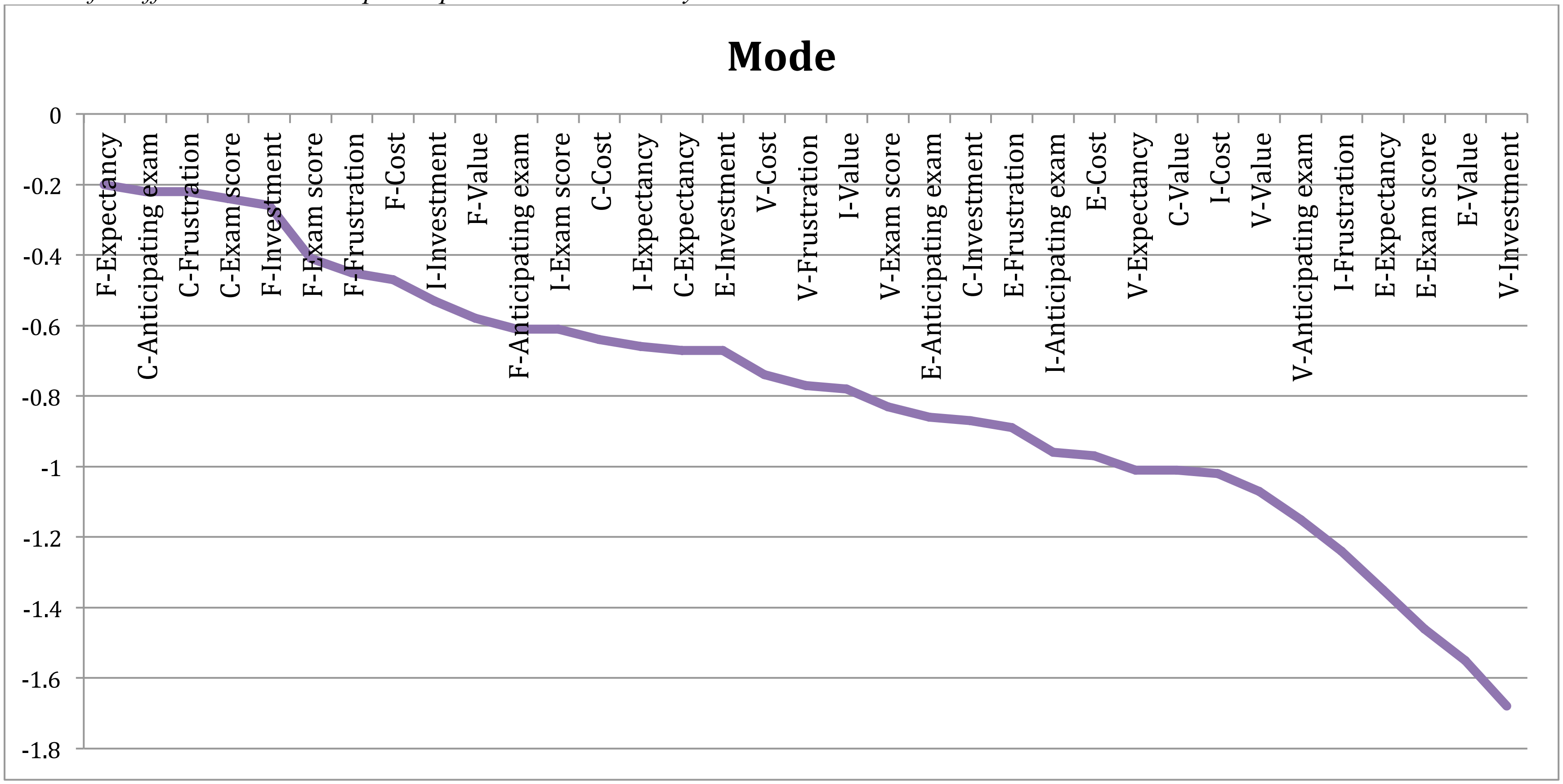
Figure 2
*Range of coefficient size across all participants' motivational systems*




*Note:* Coefficient labels are made of the first letter of the outcome variable and the predictor variable name. C=Cost, F=Frustration, I=Investment, V=Value, E=Expectancy.

Figure 3

*Mode of coefficients across all participants' motivational systems*




*Note:* Coefficient labels are made of the first letter of the outcome variable and the predictor variable name. C=Cost, F=Frustration, I=Investment, V=Value, E=Expectancy.

Table 4
*Coefficient correlations above .60*

| Coefficient 1 | Coefficient 2 | Correlation |
|---|---|---|
| C-Expectancy | C-Value | -.91 |
| F-Expectancy | F-Value | -.68 |
| I-Expectancy | I-Value | -.61 |
| E-Value | V-Value | .62 |
| C-Anticipation of exam | C-Exam score | .67 |
| I-Anticipation of exam | I-Exam score | .68 |
| E-Anticipation of exam | E-Exam score | .68 |
| V-Anticipation of exam | V-Exam score | .72 |
| F-Anticipation of exam | F-Exam score | .75 |

*Note: N*=145; Coefficient labels are made of the first letter of the outcome variable and the predictor variable name. C=Cost, F=Frustration, I=Investment, V=Value, E=Expectancy.