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The shape of self-evaluation: Implicit theories of intelligence and judgments of intellectual ability

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Abstract

Self-report distributions of self-evaluations are proposed to convey information beyond unidimensional (e.g., Likert-type) measures. Two studies tested the hypothesis that the shape of a distribution-type measure of self-evaluation of intellectual ability, as well as the central tendency and variability, is a meaningful indicator of individual differences. Specifically, one correlational study showed that measures of central tendency, variability, and skew were uniquely associated with self-ratings of ability level, self-certainty, and implicit theories of intelligence, respectively. An experiment explored the finding that incremental theorists (Dweck, 1999) reported more negatively skewed distributions than entity theorists. Only incremental theorists who wrote essays about recent intellectual growth created negatively skewed distributions; entity theorists did not. Evidence supports the hypotheses that self-report distributions are multiply informative and idiographic measures of self-evaluation, that negative skew on intellectual ability distributions can represent perceptions of growth, and that incremental theorists typically take this perspective when evaluating their own intellectual ability.

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1. Introduction

Typically, when social and personality psychologists measure a person's self-evaluation, they use a scale comprised of Likert-type items (for a review, see Blascovich & Tomaka, 1991; Pelham & Swann, 1989; Rosenberg, 1965). The Rosenberg Self-Esteem Scale (Rosenberg, 1965) is one of the most popular of such measures (Blascovich & Tomaka, 1991) and is typical of those designed to measure self-worth. Participants respond to a series of Likert-type scale items, which are summed or averaged to provide a single score. The value of such measures is indisputable. However, recent research reveals that measures assessing only the level (i.e., the central tendency) of some dimension tap only one feature of self-evaluation. Such measures neglect valuable information about variability in self-evaluation.

2. Variability in self-evaluation

Research on self-evaluation variability is based on the assumption that important information can be gleaned by considering how individuals' self-evaluations change over time or the range of self-evaluations individuals endorse. Although in principle such research could be conducted on any self-evaluative dimension (e.g., athletic ability, social competence, intellectual ability), nearly all of the work has focused on one global dimension, self-esteem, reflecting the predominance of self-esteem as a topic of psychological research. One approach (Greenier, Kernis, & Waschull, 1995; Kernis, 1993) takes multiple measurements of participants' self-esteem over several days and uses the standard deviation of these self-esteem scores as an index of self-esteem stability. Individuals with small deviations are considered stable; those with larger standard deviations, unstable. Another approach focuses on inter-item variability within self-report inventories (Baumeister, 1991; Baumeister & Tice, 1988; Britt, 1993). Baumeister and Tice (1988) argue that this variability indicates the degree to which an individual is "traited" on a given individual difference. According to their "metatrait" hypothesis, as inter-item variability decreases, individuals' traitedness increases, which makes the individual difference index a better predictor of behavior. A third approach measures individuals' perceptions of variability on evaluative dimensions. For example, Baumgardner (1990) developed the Latitude of Self-Description Questionnaire (LSDQ), where participants report their percentile rank on a variety of positive and negative personality traits and also the range of percentile ranks that apply to them. In this way, participants are able to indicate a single point (i.e., central tendency) on a dimension and also their perceptions of variability on that dimension.

Research has demonstrated that the variability measured by these three approaches is associated with meaningful psychological states (Baumeister & Tice, 1988; Baumgardner, 1990; Kernis, Grannemann, & Barclay, 1989). In addition, variability in specific self-evaluations has meaningful psychological implications as well. For example, Baumgardner's (1990) research revealed that perceived variability associated with specific self-judgments predicts positive affect about the self. This research in particular indicates that individuals are at least to some degree aware of variability in their specific self-evaluations and that considering variability is profitable in understanding the affective consequences associated with those dimensions.

3. A distribution measure of self-evaluation

The self-esteem stability, "traitedness," and self-certainty programs converge to indicate that measures of self-evaluation variability are associated with important psychological states. The aim of the current research is to investigate perceptions of self-evaluation variability using a measure that allows self-evaluation to be expressed in a multi-dimensional way. This approach, like Baumgardner's (1990) scale, allows participants to identify a range of scores around their "point estimate" in which they may be better or worse on a trait. In addition, however, participants have the opportunity to allocate a set number of "points" to each score on the underlying scale to indicate the likelihood that a given scale interval represents their self-evaluation. This procedure thus creates a self-evaluation distribution.

For example, a person that assesses her self-esteem on a Likert-type measure where scores range from 1 to 10 can select a single number from this scale (e.g., 8). On the Latitude of Self-Description Questionnaire (Baumgardner, 1990), she would also indicate a range of scores around that number (e.g., 5–9). On the distribution measure, our participant would go one step further and weight each scale interval in that range. She may believe that 8 is most representative of her self-evaluation and thus allocate the majority of points to the score 8. She may then allocate some points to "7" and "9" to indicate that those categories also apply to a lesser degree. Finally, she might also allocate very few points to the scores 5 and 6 to suggest that while she also holds a much lower self-evaluation, she holds this level of self-evaluation to a lesser extent. This distribution could not only be described in terms of its central tendency and variability, but also in terms of its shape. In this example, shape may be particularly informative, indicating that the person's self-evaluation is negatively skewed.[1] In addition, the kurtosis of the

[1] kew indicates the extent to which the distribution is asymmetrical. Symmetric distributions, if divided in half at the mean, create two mirror-image halves. By contrast, asymmetric (or skewed) distributions are those where the length of one of the distribution's tails (from the mean to the end of the distribution) is much longer than the other tail. Distributions can be either *positively skewed*, where a thin tail extends to the right of the distribution, or *negatively skewed*, where a thin tail extends to the left of the distribution center.

distributions could be indexed; some participants might construct distributions that are relatively flat or rather peaked.[2]

The benefits of such a measure are threefold. First, a distribution measure allows a way of simultaneously measuring the central tendency and variability of an individual's self-evaluation. Second, it provides specific idiographic information about the degree to which participants endorse each score on the self-evaluation scale. Third, it allows for the assessment of the shape of self-evaluation. Researchers have already used distribution measures profitably to study the central tendency and variability of other psychological variables: subjective perceptions of others' general attitudes (Nisbett & Kunda, 1985), others' abilities (Campbell, 1986), and the characteristics of ingroups and outgroups (Linville, Fischer, & Salovey, 1989). In addition, some models of basic cognitive processes (Fried & Holyoak, 1984; Hintzman, 1986; Kahneman & Miller, 1986; Kraus, Ryan, Judd, & Hastie, 1993; Rehder & Hastie, 1996) propose that people use distribution information when making judgments. For example, Kahneman and Miller (1986) argue that people use implicit distributions about stimulus attribute values to help them interpret and evaluate events. It is likely that individuals also have mental representations of how their self-evaluations on particular dimensions vary and can communicate both the magnitude of the variability (Baumgardner, 1990) and shape of this variability on a distribution-type measure. To our knowledge, however, no research has exported these idiographic measures to the study of self-evaluation. In addition, none of the research cited above has examined whether the shape of participants' responses on such measures is a meaningful indicator of individual differences.

4. A distribution measure of self-evaluation of intellectual ability

To explore whether a distribution measure could be used to assess self-evaluations, we developed a measure on which individuals construct a distribution of their intellectual ability. More conventional Likert-type self-evaluation measures

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[2] Kurtosis is often referred to as the "peakedness" of the distribution, and simultaneously, to the thinness of the distribution tails. A more specific definition of kurtosis refers to the movement of a distribution's mass that does not affect the distribution's variance; this definition of kurtosis focuses on the shift of the distribution's mass from the tails and center of the distribution, to the distribution's shoulders (DeCarlo, 1997). The distribution center refers to the normal distribution's peak, and the tails refer to the ends of the distribution. The shoulders, however, refer to the section of the distribution that falls in between the center and the tails. Distributions with negative kurtosis are called *platykurtic* distributions, which are often described as "flat" distributions. Here, the distribution mass shifts from the tails and center to the shoulders which results in "light tails and flatness" (DeCarlo, 1997, p. 294). Distributions with positive kurtosis are called *leptokurtic* distributions, and are often described as "peaked" distributions. Here, the distribution mass shifts from the shoulders to the tails and center which results in "an excess [of mass] in either the tails, the center, or both..." (DeCarlo, 1997, p. 294).

were also included in the study to predict the relevant distribution indices. The domain of intellectual ability was employed because intellect is a part of everyday parlance and is relatively important to our participant population (university undergraduates). More importantly, however, this dimension was selected because it afforded some interesting hypotheses about distribution shape. Specifically, the skew of a distribution of intellectual ability could indicate perceptions of intellectual growth.

4.1. Hypotheses

Dweck and colleagues (Dweck, 1999; Dweck & Leggett, 1988) have found that individuals differ in the degree to which they believe intelligence is malleable or stable. Individuals with *entity theories* of intelligence believe that intellectual ability is fixed; they tend to focus on achieving favorable judgments of competence. By contrast, individuals with *incremental theories* of intelligence believe intellectual ability can improve over time; they tend to focus on increasing their competence. This tendency for incremental theorists to focus on intellectual growth may be reflected in the skew of their ratings of intellectual ability on a distribution measure. On one hand, because of their forward-thinking focus with regard to improvement, incremental theorists may tend to report more positively skewed distributions. Such a focus on growth may lead one to report a distribution that has a relatively small number of points that are allocated to the upper level of the scale as a way of saying, "I may not be up there yet, but I could be if I keep working at it." On the other hand, incremental theorists may be more likely to report negatively skewed distributions. Their orientation toward improvement and mastery may lead them to construct distributions that are focused on growth that has already taken place. They may allocate a few points to the lower end of the scale as a way of conveying that "I used to be down there, but I have grown so much since then." By contrast, if distribution skew is an index of intellectual growth, the distributions of entity theorists would not be skewed at all. That is, they should be normally distributed because entity theorists believe intelligence is stable. The following studies were designed to test whether the skew of the self-evaluation of intellectual ability is related to implicit theories of intelligence.

In addition, if a distribution measure of this type is a valuable tool, then specific types of self-evaluations should be uniquely related to different indices derivable from the measure. First, individuals' overall self-evaluation of intellectual ability should be positively correlated with a distribution's central tendency. If the measure captures overall self-evaluation, the central tendency of these distributions should approximate their self-evaluation on a traditional single-item Likert scale. Likewise, the certainty with which people hold these evaluations should be negatively correlated with distribution variability. As demonstrated in Baumgardner's (1990) work, lower certainty in one's self-evaluation is associated with a wider range of values endorsed, thus increasing the variability in a distribution measure.

5. Study 1: A simulation

Before testing these hypotheses, a data simulation was conducted for two reasons. First, the simulation provided a basis for testing the inherent mathematical associations among the measures of central tendency, variability, and shape derived from the distributions. Second, such a simulation should generate descriptive information about the measures of central tendency, variability and shape, such as the possible range of scores available on such a measure.

5.1. Method and results

To meet these goals, hypothetical data on the distribution measure was generated for 100,000 participants. To generate the data, a program (created in Microsoft Visual Basic 5.0 programming language) produced the data using a similar method that real participants were believed to use when asked to complete distributions of their intellectual ability. Actual participants are given a range of scores from 1 to 10, told to assign points to scores in that range (where point allocations associated with a score represented the likelihood that the score represented the participant's level of intellectual ability), and instructed to assign a total of 100 points. To generate data using a procedure similar to the one that the participants were believed to use, the program was written to randomly select one of the 10 scores on the distribution measure and then randomly assigned a number from 1 to 100 to that score. Then, it randomly selected another score (that had not been previously selected) and randomly assigned another number that ranged from 1 to 100 (-prior allocations). This procedure continued until a total of 100 points had been assigned for each of 100,000 randomly generated participants.

Measures of central tendency, variability, and shape were calculated using standard equations (see Appendix A for details).[3] The mean and median were used for measures of central tendency. Range and standard deviation were used for measures of variability. Finally, skew and kurtosis were used for measures of shape (kurtosis was included for exploratory purposes). Descriptive statistics and bivariate correlations among the distribution measures can be found in Table 1. Analysis revealed that, as expected, the mean and median were highly correlated with each other, as were the measures of variability (but to a lesser degree). Analysis also indicated that the measures of central tendency are negatively correlated with the skew of the distribution. This most likely reflects the tendency for distributions with high and low central tendencies to be more skewed by virtue of the fact that they are bumping up against the "ceiling" and "floor" of the distribution measure. Finally, there were negative associations between the measures of

[3] SPSS syntax is available by email from the authors to calculate these descriptive statistics.

Table 1
Means, standard deviations, score range, and bivariate correlations among the measures of central tendency, variability, and shape of the distribution measure: Study 1 (Simulation)

Distribution	*M*	*SD*	*Range*	1	2	3	4	5	6
1. Mean	5.49	1.92	1.00–10.00	1.00					
2. Median	5.49	2.62	1.00–10.00	.92*	1.00				
3. Range	8.05	1.98	1–10	.00	.00	1.00			
4. Standard deviation	1.95	.86	0.00–4.50	.00	−.00	.65*	1.00		
5. Skew	.01	2.25	−9.85 to 9.85	−.67*	−.62*	−.00	−.00	1.00	
6. Kurtosis	4.76	13.52	−2.00 to 95.01	.00	.00	−.27*	−.53*	.00	1.00

Note. $N = 100{,}000$.
$^{*}p < .05$.

variability and distribution kurtosis. As measures of variability increase (i.e., distributions become wider or more disperse), distributions become less peaked and flatter.[4]

5.2. Discussion

This data simulation offers two types of information: first, it demonstrates the range of scores that are possible for each of the distribution indices for this distribution (see Table 1), and second, it demonstrates the mathematical associations that exist between measures of central tendency and skew and between variability and kurtosis due to the inherent structure of the measure. While these associations are of some academic interest, they can also aid in the interpretation of relationships discovered in data collection with the measure.[5]

[4] One qualification to this effect, however, is that the standard deviation statistic was more negatively correlated with distribution kurtosis than the range statistic. This discrepancy between range and standard deviation is perhaps best explained by the fact that some distributions can be wide without being disperse, and it is these types of distributions that tend to be peaked. Reference to two of the sample distributions generated by real participants in Study 2 (see participants 84 and 111, Fig. 2) demonstrates this distinction between the range and standard deviation measures as they relate to kurtosis. For participant 84, the distribution range is quite wide (range = 5); however, because the distribution is peaked (kurtosis = 2.00), the distribution has relatively low standard deviation (.77). For participant 111, the distribution is also quite wide (range = 6); contrary to participant 84's distribution, however, this distribution is relatively flat (kurtosis = −.47) and consequently has a higher standard deviation (1.29). Thus, it is not surprising that the standard deviation statistic is more negatively related to kurtosis than the range statistic.

[5] It was expected that participants would not make as wide a variety of distributions that were created with the simulation. For example, we expected the central tendency of most distributions to fall above the midpoint of the scale range (5.5). However, what the simulation provides is descriptive information about the distribution indices, particularly the possible range of scores and the mathematical associations that inherently result from equations used to calculate measures of central tendency, variability, and shape. To effectively do so, the simulation program was allowed to create any kind of distribution possible within the confines of the procedure described in Method.

6. Study 2: A correlational study

The following study was designed to explore the validity of a self-evaluation distribution measure of intellectual ability. Self-rated level of intellectual ability and certainty of the evaluation were predicted to be uniquely related to the central tendency and variability, respectively, of the distribution measure. A measure of participants' implicit theories of intelligence was also included and expected to predict the skew of participants' distributions: entity theorists were predicted, on average, to report distributions without skew, whereas the distributions of incremental theorists were predicted to be skewed (in an unspecified direction). While no a priori hypotheses existed about kurtosis, this measure of distribution shape was also calculated and analyzed in order to explore the value of multiple indices of distribution shape.

6.1. Method

6.1.1. Participants

In all, 112 participants (76 women and 36 men)[6] from the Ohio State University received course credit for their participation. One person incorrectly completed the material, and this person's data were dropped. In addition, one participant assigned 100 points to one box of the distribution, thereby constructing a distribution with zero variability and no shape. This distribution was believed to be a meaningful response and not simply a matter of error; thus, these data were not dropped. As a consequence, the sample size was larger for analyses of central tendency and variability ($N = 111$) than it was for analyses of shape ($N = 110$).

6.1.2. Procedure

The study consisted of three parts. First, all participants were pre-tested on the implicit theories of intelligence scale (Hong, Chiu, & Dweck, 1995) five to eight weeks prior to the session. Second, at the time of the study, participants completed a set of single-item evaluations of their intellectual ability, and finally, they completed a distribution measure of their intellectual ability. Participants were then debriefed.

6.1.3. Implicit theories of intelligence scale

This three-item questionnaire (Hong et al., 1995) is designed to measure the extent to which individuals adopt incremental or entity theories associated with their intelligence (e.g., "You have a certain amount of intelligence and you really can't do much to change it"). Participants responded to these items on a six-point Likert-type scale (1, *Strongly Disagree* to 6, *Strongly Agree*). Internal consistency was strong ($\alpha = .92$). Thus, ratings were summed yielding a potential range of scores from 3 to 18; lower scores indicate tendency towards adopting an incremental theory of

[6] Analysis of the data revealed no consistent effects of gender on central tendency, variability, or shape of the distribution measure in any of the studies.

intelligence and higher scores indicate a tendency towards adopting an entity theory of intelligence.

6.1.4. Self-ratings of intellectual ability

Participants completed a set of ratings regarding intellectual ability adapted from Pelham and Swann's (1989) Self-Attributes Questionnaire. First, participants assessed their level of intellectual/academic ability relative to other college students (1, *Much Lower than Average*; 10, *Much Higher than Average*). Participants then assessed the certainty of this evaluation (1, *Not at All Certain*; 10, *Extremely Certain*) and the importance of this attribute to the individual (1, *Not at All Important to Me*; 10, *Extremely Important to Me*). The importance rating was included for exploratory purposes.

6.1.5. Intellectual ability distribution

Participants then completed a distribution measure of their intellectual/academic ability, which was introduced with the following directions:

> Even though you now have a total score (say 6 or 4), there is probably some range above and below this total score you think could accurately describe your overall rating on intellectual ability. The one single number may not describe the range of ratings you might feel best describes you.
>
> To indicate this range of ratings that could accurately describe a person's standing on intellectual ability, he or she could distribute 100 points along the scale. You might want to think of these 100 points as percentages, or probability points, with each point representing 1/100 of the likelihood that the score is an accurate description of your self-evaluation.

To give participants a better idea of how they could complete the distribution measure, a second page presented four examples of how the distribution measure could be completed. The examples differed in central tendency, variability, and shape to illustrate a variety of ways that the participants could complete the measure, but were on an unrelated topic, leadership ability.

The final page directed participants to complete the distribution measure. (The measure is presented in Fig. 1.) Before completing the measure, participants transcribed the value of their single-item rating of their intellectual ability made on the previous page; it was intended that participants would then be more likely use this score as an anchor and construct a distribution around it. Participants were then in-

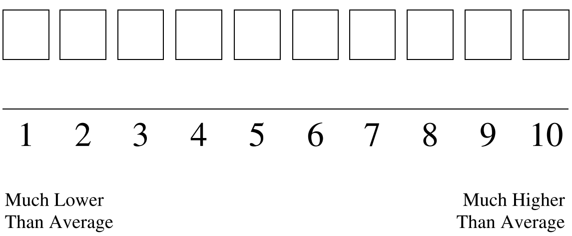

Fig. 1. The distribution measure used for the self-evaluation of intellectual ability.

structed to allocate 100 points among the 10 boxes presented in this measure, where each box represents a different level of self-evaluation of intellectual ability (values ranging from 1 to 10), the same range as the single score evaluation of their intellectual ability that they had reported earlier. Finally, participants were asked to verify that they had allocated exactly 100 points.[7]

6.2. Results

For purposes of analysis, implicit theories of intelligence and the single-item self-evaluation measures of intellectual ability were treated as predictors and the distribution indices were treated as criterion variables. The distribution indices could also have served as predictors; however, the approach we used keeps the focus on the distribution measure as the target of study and a useful dependent measure (as will be the case in Study 3).

In order to assess the relationship between the predictor variables prior to analyses and to document associations not addressed in the prior literature, the correlations between the predictors were examined (see Table 2). Analysis revealed that implicit theories of intelligence was marginally correlated with participants' ratings of their level of intellectual ability such that incremental theorists reported a higher level of intellectual ability than entity theorists. This effect is consistent with the idea that entity theorists, when faced with failure, consider failure to be diagnostic of their self-conceptions of intelligence (Dweck, 1999; Zhao & Dweck, 1994).

Also of interest, analyses revealed that implicit theories of intelligence are associated with the importance people ascribe to intellectual ability, such that incremental theorists find intellectual ability to be more important than entity theorists do. In addition, the perceived discrepancy between actual and ideal levels of intellectual ability was also related to implicit theories of intelligence; incremental theorists tend to report less discrepancy between their current level of intellectual ability and their ideal level of intellectual ability than do entity theorists. To our knowledge, the literature on implicit theories of intelligence has not previously examined the association between importance and self-discrepancy measures, but these results appear generally consistent with the portrayals of incremental and entity theorists. Incremental theorists, who believe that their intellectual abilities improve over time and see persistence as a central framework of their intellectual growth, may be less likely to perceive a discrepancy between actual and ideal selves. On the other hand, entity theorists, who believe that their abilities are fixed and static, may see themselves as discrepant from where they want to be (perhaps this is more likely after a performance failure). In addition, entity theorists may be more likely to derogate the importance of intellectual ability to their self-concept as a way to reduce the impact of performance failure on their self-worth and self-conceptions of intellectual abili-

[7] The directions for the distribution measure were quite lengthy in an effort to help students understand what it was they needed to do. It is possible that individuals who were less educated than our sample might face a greater challenge understanding instructions. Future research will examine whether the directions can be simplified so that any individual, regardless of education, can complete the measure.

Table 2
Means, standard deviations, score range, and bivariate correlations among the predictor variables: Study 2

Predictor variables	*M*	*SD*	Actual range	1	2	3	4	5
1. Implicit theories of intelligence	7.61	4.11	3–18	1.00				
2. Intellectual ability rating	6.92	1.37	2–10	−.18***	1.00			
3. Certainty	7.18	1.69	2–10	−.10	.58**	1.00		
4. Importance	8.85	1.51	1–10	−.25**	.26**	.08	1.00	
5. Perceived self-discrepancy score	8.21	2.00	2–10	−.31**	.31**	.26**	.25**	1.00

Note. On the implicit theories of intelligence scale, lower numbers indicate incremental theories and higher numbers indicate entity theories. On the perceived self-discrepancy measure, lower numbers indicate greater self-discrepancy.

** $p < .01$.

*** $p < .10$.

ties (Major & Schmader, 1998; Pelham & Swann, 1989; Schmader & Major, 1999). Finally, implicit theories of intelligence were not correlated with certainty of intellectual ability, supporting evidence reported by Hong et al. (1995).

6.2.1. Central tendency, variability, and shape of self-evaluation

Casual examination of participants' responses indicated that they generated unique distributions of their intellectual ability that differed not only in central tendency, but also in variability and shape. (A few examples are included in Fig. 2.) Some distributions spanned relatively wide areas (e.g., participant 111), whereas others were more constricted (e.g., participants 14 and 108). In addition, some distributions were fairly normal (e.g., participant 64), while others appeared to be quite skewed (e.g., participants 14 and 24), peaked (e.g., participant 84), or flat (e.g., participants 108 and 111).

Clearly, individual differences are apparent in how these distributions were constructed. In order to summarize responses on the distribution measure, quantitative measures indexing central tendency, variability, and shape were calculated (See Appendix A for equations). The descriptive statistics and correlations among these variables are reported in Table 3. Analysis revealed that, as expected, the two central tendency measures (i.e., mean and median) and the two variability measures (i.e., standard deviation and range) were highly correlated because these pairs of measures, by definition, represent similar features of the distribution. Also, the skew of the distributions was negatively correlated with the mean and median, reflecting a ceiling effect: as measures of central tendency reach the ceiling of the measure (i.e., 10), distribution variance must be negatively skewed. Consequently, as demonstrated in the simulation study, the negative correlations between the measures of central tendency and skew represent the mathematical association that exists between these two measures.[8] To control for this mathematical association, analyses that examined skew were completed using the median as a covariate.[9] Likewise, when central tendency was submitted to analysis, skew was entered as a covariate. However, these analyses resulted in the same effects as the analyses without the skew covariate; to simplify presentation, then, these additional analyses are not presented.

In addition, analysis revealed that standard deviation was negatively correlated with kurtosis, replicating the effect found in the simulation. The more disperse distributions were, the flatter (and less peaked) they were. Consistent with the data simulation, range scores were less associated with kurtosis than were standard deviation scores (for an explanation, see Footnote 4).

6.2.2. Association between predictors and central tendency, variability, and shape

The central tendency, variability, and shape of the distribution were submitted to a simultaneous regression analysis with implicit theories of intelligence scores, the intellectual/academic ability rating, and the certainty, importance and perceived self-discrepancy ratings as predictors. The partial correlations for the predictors with each of the distribution measures are presented in Table 4.

Central tendency. The simultaneous regression analysis revealed that only the intellectual/academic ability and importance ratings uniquely predicted the mean and median. The ability rating was highly positively correlated with both central tendency measures; as the perceived level of intellectual ability increased, the central tendency on the distribution increased. The positive association between level of intellectual ability and the measures of central tendency suggests that participants used their scores as anchors and construct distributions around them, although the lack of a one-to-one correspondence indicates that some participants did not feel totally restricted to center their distributions around these scores. In addition, the importance

[8] The observations in this study were primarily restricted to the upper portion of the underlying distribution scale, as is evident by the fact that measures of central tendency are higher among real responses (Table 3) than among randomly generated responses (Table 1). Thus, the correlation between the measures of central tendency and skew is likely primarily a function of a ceiling effect. In addition, the negative correlation between skew and kurtosis and the positive correlation between central tendency and kurtosis could also be a function of distributions located near the top of the scale. If these correlations are a function of a ceiling effect, which was also believed to be the cause of the correlation between central tendency and skew, then controlling for the shared variance between central tendency and skew should reduce the other two correlations (i.e., between central tendency and kurtosis and between skew and kurtosis) to nonsignificance. Kurtosis scores were submitted to a simultaneous regression analysis with median and skew scores as predictors. This analysis removes the shared variance between central tendency and skew from the regression equation, and thus, the associations with kurtosis should not be significant. However, analysis revealed that the association between the median and kurtosis remained marginally significant ($\beta = .16,\ p = .10$) and the association between skew and kurtosis remained significant ($\beta = -.22,\ p = .03$). Thus, it appears that the correlations among central tendency, skew, and kurtosis are not a function of the same source.

[9] The median was chosen as the covariate over the mean because the median has a significant correlation with skew and the mean did not, and thus provided a more stringent test of the implicit theories of intelligence hypothesis on skew. Additional analyses also were completed using the mean as covariate and produced essentially the same effects.

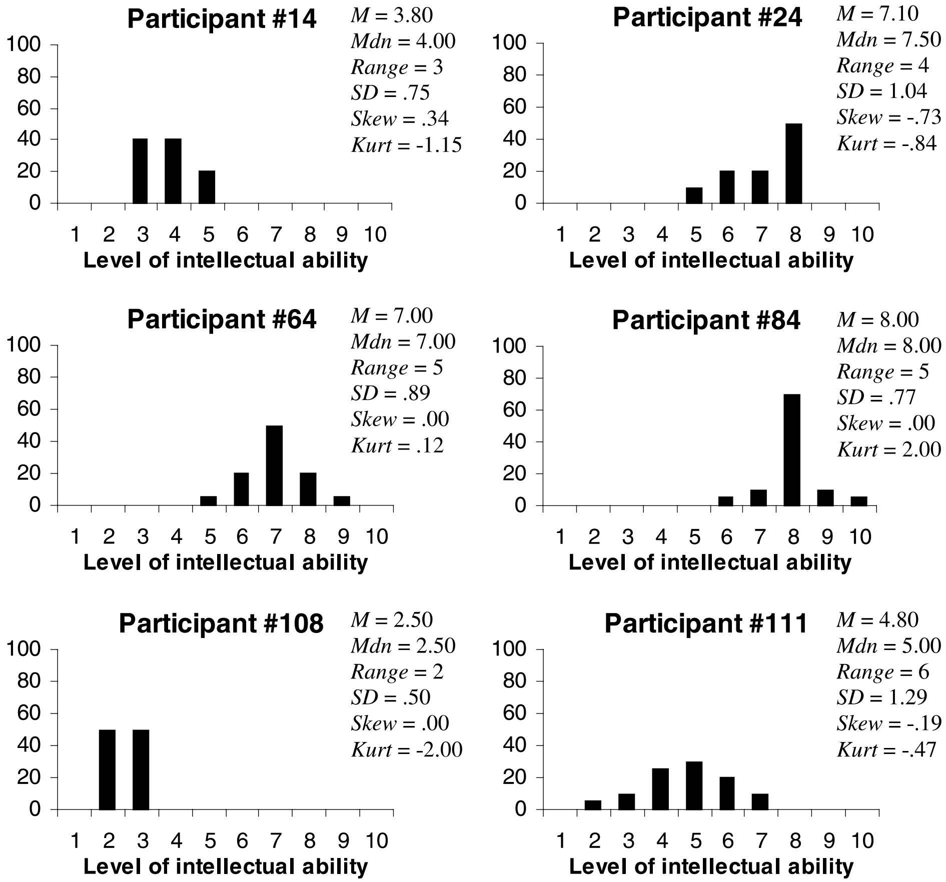

Fig. 2. Some participants' self-generated distributions of their intellectual ability: Study 2.

Table 3
Means, standard deviations, score range, and bivariate correlations among the measures of central tendency, variability, and shape of the distribution measure: Study 2

Intellectual ability distribution	*M*	*SD*	Actual range	1	2	3	4	5	6
1. Mean	6.83	1.30	2.50–9.80	1.00					
2. Median	6.90	1.34	2.00–10.00	.98**	1.00				
3. Range	4.19	1.20	1–9	−.04	.01	1.00			
4. Standard deviation	.90	.32	0.00–2.26	−.10	−.04	.87**	1.00		
5. Skew	−.22	.67	−2.67 to 2.67	−.15	−.24*	−.09	−.04	1.00	
6. Kurtosis	.061	1.66	−2.00 to 7.00	.21*	.21*	−.06	−.38**	−.26**	1.00

* $p < .05$.
** $p < .01$.

Table 4
Partial correlations between predictor variables and central tendency, variability, and shape of the distribution measure: Study 2

Predictor variables	Intellectual ability distribution					
	Mean	Median	Range	Standard deviation	Skew	Kurtosis
Implicit theories of intelligence	−.02	−.07	.06	.04	**.26****	−.01
Intellectual ability rating	**.76****	**.79****	.10	.02	**−.17*****	.12
Certainty	.05	.04	**−.24***	**−.18*****	−.09	.05
Importance	**−.22***	**−.25***	−.02	−.02	.06	.01
Perceived self-discrepancy score	.03	−.02	−.01	−.08	.08	.09

Note. On the implicit theories of intelligence scale, lower numbers indicate incremental theories and higher numbers indicate entity theories. On perceived self-discrepancy, lower numbers mean greater self-discrepancy.
* $p < .05$.
** $p < .01$.
*** $p < .10$.

measure was inversely related to both measures of central tendency. As importance of intellectual ability increased, the mean and median of the distribution decreased.

Variability. Analysis yielded a negative relation between certainty of the intellectual ability evaluation and both measures of variability. As certainty increased, the range and standard deviation of the distribution decreased. No other effects were significant.[10]

Shape. Analysis yielded a positive relation between implicit theories and distribution skew. To facilitate interpretation, predicted means (Aiken & West, 1991) of distribution skew were calculated at implicit theories of intelligence scores one standard deviation below and above the mean (to represent incremental and entity theorists, respectively). Incremental theorists reported more negatively skewed distributions ($M = -.40$) than entity theorists ($M = -.05$). In addition, single sample t tests for pre-

[10] Linville et al. (1989) examined a descriptive index for their research, called *differentiation*, which was intended to measure the likelihood that two randomly chosen points in a distribution will differ. As explained by Linville et al., this measure, although similar to measures of dispersion (e.g., standard deviation), should be treated as conceptually distinct from these measures. Differentiation is maximized under conditions where the distribution is uniform (i.e., flat; each score in the distribution has a likelihood assigned to it equal to the likelihood assigned to other scores). By contrast, measures of variability are maximized in a bimodal distribution where half of the points are allocated to the lowest possible score and the other half of the points are allocated to the highest possible score. Exploratory analysis revealed that differentiation was highly correlated with range, $r(109) = .61$, $p < .001$, and standard deviation, $r(109) = .79$, $p < .001$. As differentiation increases, variability increases and the distribution becomes flatter. In addition, analysis also revealed that is was highly negatively correlated with kurtosis, $r(108) = -.79$, $p < .001$; as differentiation increases, distribution kurtosis became flatter. However, when differentiation was submitted to the simultaneous regression analysis with the intellectual ability predictors, analysis revealed no significant personality predictors. Consequently, it is unclear what exactly differentiation indicates in distribution measures of self-evaluation of intellectual ability.

dicted means (using an extension of the Aiken & West, 1991 procedure for calculating predicted means; see Leonardelli & Hermann, 2001), indicated that the predicted mean for incremental theorists significantly differed from zero, $t(104) = -4.49,\ p < .001$, but the mean for entity theorists did not, $t(104) = -.51,\ p = .61$.

This correlation could be due to the mathematical association between central tendency and skew; perhaps incremental theorists reported more negatively skewed distributions because their distributions were closer to the ceiling (as the correlation between the median and skew implies). Such an effect implies that the distributions of incremental theorists have higher central tendencies than those by entity theorists; however, Table 4 reveals that implicit theories of intelligence does not uniquely predict the mean or median of the distribution measure. In addition, the relation between implicit theories of intelligence and distribution skew remained significant even after controlling for the correlation between the median and skew, $pr(103) = .26,\ p = .008$. This effect thus appears to reflect a meaningful relation between implicit theories of intelligence and skew of the intellectual ability distribution.

Participants' ability ratings also predicted the skew of their distributions, but this effect was marginally significant (see Table 4). This effect was apparently due to the correlation between central tendency and skew; when the median was entered as a covariate, the relation between the ability ratings xand skew became nonsignificant, $pr(103) = .11,\ p = .28$, suggesting that the relationship is accounted for by the central tendency of the distribution.

Simultaneous regression analysis revealed no significant effects on distribution kurtosis.[11]

6.3. Discussion

The results from this study are encouraging and suggest that distributions are idiographic and multi-faceted, and the multiple facets of the measure are meaningful in unique ways. Analyses supported the idea that the central tendency and variability of an intellectual ability distribution each index different aspects of self-evaluation (i.e., level and certainty). However, what is particularly novel is that the distribution shape is uniquely related to characteristics of the individuals who constructed them. Specifically, incremental theorists were more likely than entity theorists to report negatively skewed intellectual ability distributions.

An additional study was conducted to replicate the findings and establish divergent validity for the skew effect (Leonardelli, Hermann, & Arkin, 2002). Specifically, it was believed that implicit theories of intelligence would again be positively correlated with skew of an intellectual ability distribution, but not with skew of an unrelated ability distribution. The evidence supported this hypothesis: implicit theories of intelligence were positively correlated with skew of the intellectual ability

[11] None of the research revealed consistent systematic effects on distribution kurtosis. Thus, it will not be discussed further.

distribution, but not the skew of an athletic ability distribution.[12] Thus, some evidence suggests that this correlation is a genuine effect, and not simply a statistical artifact.

6.3.1. The meaning of negative skew

However, the meaning of the negative skew reported by incremental theorists is unclear. On the face of it, as suggested earlier, it appears that incremental theorists consider their intellectual growth and acknowledge that their level of ability was lower in the past. Although this study is consistent with Dweck and her colleagues' (Dweck, 1999; Dweck & Leggett, 1988) characterization of incremental theorists as having a mastery orientation and focusing on improving their abilities, it provides no direct evidence that this negative skew reflects perceptions of intellectual growth.

To test this interpretation, we performed an experiment designed to examine whether incremental and entity theorists who think about their intellectual growth would be likely to construct distributions that are negatively skewed. If negative skew on the distribution measure reflects judgments of intellectual growth, then incremental theorists who think about such growth should continue to report negatively skewed distributions. However, when incremental theorists focus on the performance concerns rather than growth, the outcome is unclear. On one hand, they may still create negatively skewed distributions because growth-oriented thoughts about their intellect predominate. On the other hand, an evaluative focus could prompt incremental theorists to abandon thoughts about their growth and create more normally shaped distributions.

In contrast, entity theorists harbor theories that do not allow for perceptions of growth in their intelligence. Entity theorists who focus on the concerns of performance should therefore report normally shaped distributions because it is not a departure from their typical thinking. Inducing entity theorists to consider recent intellectual growth, in contrast to incremental theorists, may have little impact on the skew of their distribution. Even if entity theorists do perceive themselves to have learned a great deal in the recent past, any perceived change in performance should translate into very little change in perceived "growth" or change in their perception of their basic level of intelligence.

7. Study 3: An experiment

This study was designed to test these hypotheses and consisted of a prime condition (growth, validation) $\times$ implicit theories of intelligence (continuous) between-participants design. It was predicted that incremental theorists who were primed with growth would be most likely to report negatively skewed distributions, more

[12] The negative correlations between importance and measures of central tendency that were found in Study 2 were not observed in this study. Consequently, this replication also raises the question whether perceived importance reliably predicts central tendency of an intellectual ability distribution.

than incremental theorists who were primed with evaluations of their intellectual ability, or entity theorists primed with growth or self-evaluations of their intellectual ability.

7.1. Method

In all, 95 students (52 women and 43 men) from the Ohio State University received course credit for participation. One participant reported an intellectual ability distribution with zero variability and, consequently, no shape; because the purpose of this study was to examine the meaning of distribution skew, this participant's data were excluded from analysis ($N = 94$).

At the beginning of the experimental session, participants completed an eight-item version of the implicit theories of intelligence scale (Dweck, 1999) presumably as part of a paper-and-pencil survey for another researcher. This eight-item scale was used instead of the three-item scale to take advantage of its presumed greater reliability. The rest of the study, which participants were told focused on "life scenarios," was completed on computer using MediaLab (Jarvis, 2000). The experimental induction took place at this time. Participants who were randomly assigned to the growth condition wrote essays about their intellectual growth. Specifically, they were asked to:

> Take three minutes to write about your intellectual/academic ability. Consider your growth. Imagine where you were four years ago as a budding high school freshman. Consider the many ways that your academic abilities have improved since then.

Those assigned to the validation condition wrote an essay about a recent performance:

> Take three minutes to write about your intellectual/academic ability. Consider your level of ability. Write about recent instances in which your intellectual/academic ability was important because you needed to show how well you could do something (for instance, explain a problem, tell a story, write an article).

Participants then completed a single-item assessment of their intellectual ability and a distribution describing their intellectual ability.

7.2. Results

Hierarchical regression analyses were conducted to determine whether implicit theories of intelligence moderated the impact of prime condition (i.e., a growth essay or a validation essay) on the central tendency, variability, and shape. Following standard procedures (Cohen & Cohen, 1983), implicit theories of intelligence scores and prime condition were entered first (to test for main effects), and the product of the two was entered next (to test for interaction effects). To simplify interpretability of the regression analysis (Aiken & West, 1991), implicit theories of intelligence scores were centered (i.e., the sample mean was set equal to zero). Prime condition was dummy coded (Aiken & West, 1991): zero for growth condition and one for validation condition.[13] The interactions were plotted using the predicted means for each prime condition at levels of implicit theories of intelligence one standard deviation below and above the mean of the implicit theories of intelligence scale (for incremental and entity theorists, respectively). All analyses were conducted and all graphs constructed in this manner, unless specified otherwise.

7.2.1. Distribution central tendency and variability

Analysis yielded no significant effects on the mean or median of the distribution (ps $> .21$). Analysis also yielded no significant effects on the range or standard deviation of the distribution (ps $> .38$).

7.2.2. Distribution skew

Analysis revealed a significant interaction of prime condition and implicit theories ($\beta = -.30,\ p = .04$; see Fig. 3 for predicted means). Simple effect analysis (Aiken & West, 1991) indicated that the prime condition produced a marginally significant effect on skew for incremental theorists ($\beta = .27,\ p = .07$). For incremental theorists, writing an essay on the growth of their intellectual ability led to more negatively skewed distributions than writing an essay on the validation of their intellectual ability. Single sample t tests (Leonardelli & Hermann, 2001) indicated that the predicted mean for incremental theorists in the growth condition was marginally different from zero, $t(90) = -1.80,\ p = .08$, but that the mean for incremental theorists in the validation condition was not significantly different from zero, $t(90) = .66,\ p = .51$. For entity theorists, there was a slight trend for individuals in the validation condition to report more negatively skewed distributions than individuals in the growth condition, but this effect was not significant ($\beta = -.17,\ p = .28$). The means for the two entity theorist conditions did not differ from zero, ts $< |1.14|$, ps $> .52$.

This interaction may in part be due to the pre-existing correlation between skew and the median; that is, the negative skew reported by incremental theorists may be due to their tendency to report higher median scores. In order to investigate this alternative explanation, the simple effect analyses were completed again, this time with the median as a covariate. For incremental theorists, the simple effect for prime condition became statistically significant ($\beta = .27,\ p = .05$). For entity theorists, controlling for the median decreased the variance accounted for by the prime condition ($\beta = -.06,\ p = .68$). Thus, the nonsignificant trend for entity theorists to report more negatively skewed distributions after writing an essay of intellectual ability validation is attributed to differences in their median scores.

7.2.3. Content analysis: Growth

The interaction between implicit theories of intelligence and prime condition on skew demonstrated that the manipulation influenced responses of incremental theo-

[13] Dummy coding was opted over effect coding because, in the words of Aiken and West (1991), "When the interactions involve a categorical variable and a continuous variable, dummy variable coding produces immediately interpretable contrasts with the comparison group, whereas effect coding does not" (p. 129).

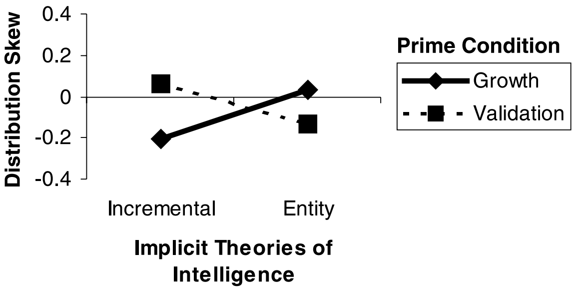

Fig. 3. Intellectual ability skew as a function of prime condition and implicit theories of intelligence: Study 3.

rists, but not of entity theorists. This interaction raises two possibilities. First, entity theorists may not be able to write about their intellectual growth; thus, essays in the growth condition may be the same as essays in the validation condition. Second, entity theorists may be able to write about their intellectual growth, but do not internalize it into their self-evaluation.

In order to explore these possibilities, two judges (who were blind to hypotheses and participants' conditions) rated the essays on "how much growth the students reported in their essay" using a five-point scale (1, *Did not Discuss Growth* to 5, *A Great Deal of Growth Discussed*). The judges' ratings were highly correlated, $r(89) = .93$, $p < .001$; thus, the ratings were averaged together to produce a single score ranging from 1 to 5, where higher numbers indicate greater growth.[14] If the interaction on skew is due to a failure of the entity theorists to follow directions, analysis of the growth ratings should reveal an interaction between implicit theories of intelligence and prime condition (i.e., the essays of incremental theorists in the growth condition should have higher ratings of growth than any other condition). However, if entity theorists simply failed to internalize growth into their self-evaluation, then there should be a main effect of the prime condition, where individuals in the growth condition reported greater growth than individuals in the validation condition, regardless of participants' implicit theories. The judges' ratings were submitted to regression analysis, which revealed a main effect of prime condition ($\beta = -.62$, $p < .001$). Growth ratings were higher for essays in the growth condition ($M = 2.65$, $SD = 1.24$) than for essays in the validation condition ($M = 1.10$, $SD = .28$). The interaction was not significant ($\beta = -.14$, $p = .21$). Thus, these data are consistent with the idea that entity theorists can write about their intellectual growth, but do not internalize it.

7.2.4. Content analysis: Effort

The growth ratings revealed that the manipulation was effective. The question remains, however, as to what prompted incremental theorists to incorporate growth

[14] The sample for content analyses ($N = 91$) is lower than the full sample, because three essays were lost due to computer failure.

into their self-evaluation more than the entity theorists. One explanation may be differences in perceptions of ability and effort (Dweck, 1999). Whereas entity theorists believe that effort is negatively correlated with ability, endorsing statements like "Things come easily to people who are true geniuses," incremental theorists believe that effort and ability go hand in hand, endorsing statements like "Even geniuses have to work hard for their discoveries" (Leggett & Dweck, 1986; Mueller & Dweck, 1997). Furthermore, evidence reveals that incremental theorists are more likely to respond with increased effort than entity theorists when faced with setbacks (Dweck & Leggett, 1988). Although there is scant direct evidence in the literature indicating so, it seems likely that incremental theorists also believe that it is through effort that one not only achieves, but also grows intellectually. Because their theories link effort to intellectual growth, we expected incremental theorists who had written about their growth to be particularly likely to mention effort in their essays.

Analysis of effort. The essays were rated by two judges on "how much effort students mentioned exerting in pursuit of academic achievement" using a five-point scale (1, *No Effort Exerted* to 5, *A Great Deal of Effort Exerted*). Analysis of the judges' ratings revealed that they were highly correlated, $r(89) = .88$, $p < .001$; thus, the ratings were averaged together to produce a single score ranging from 1 to 5, where higher numbers indicate more effort exerted. These scores were submitted to analysis, which indicated a significant interaction between implicit theories of intelligence and prime condition ($\beta = .34$, $p = .02$). Predicted means are presented in Fig. 4. For incremental theorists, prime condition had a significant effect on effort ratings ($\beta = -.29$, $p = .05$); incremental theorists in the growth condition reported exerting effort more than incremental theorists in the validation condition. By contrast, entity theorists reported more effort in the validation condition than in the growth condition, although this difference was not significant ($\beta = .20$, $p = .20$). Perhaps entity theorists find it more valuable to exert effort to defend their current level of self-evaluation than to grow intellectually.

The following analyses were conducted to determine whether judgments of growth were related to judgments of effort for incremental and entity theorists. First,

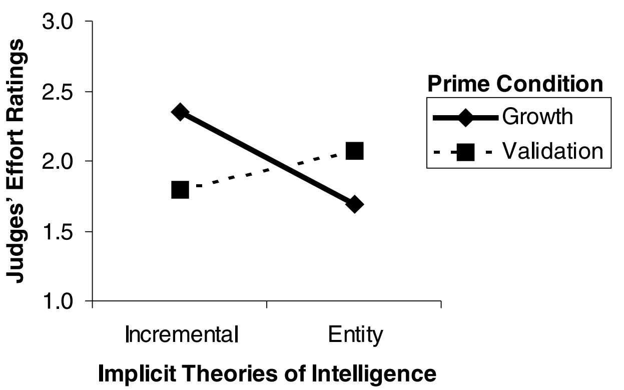

Fig. 4. Judges' effort ratings as a function of prime condition and implicit theories of intelligence: Study 3.

a median split on implicit theories of intelligence scores was used to classify people as incremental or entity theorists (low or high scores, respectively). For each subgroup, correlations between judgments of growth and effort were calculated. Analysis indicated that for incremental theorists, judgments of growth and effort were positively correlated, $r(45) = .46$, $p < .001$, but for entity theorists, ratings of growth and effort were not correlated, $r(42) = -.14$, $p = .38$. Fisher's z test (used to calculate the significance of differences between two independent correlations) revealed that the difference between the correlations was significant, $z = 2.94$, $p < .01$. Thus, incremental theorists were particularly likely to tie growth to effort and did so more than entity theorists.

Skew and effort. Incremental theorists in the growth condition created distributions with the most negative skew and mentioned more effort in their essays. Thus, it seems likely, given that effort and growth are positively associated, that perceptions of effort are also linked to distribution skew. Incremental theorists may be more likely to have a negatively skewed distribution when they report exerting effort. By contrast, entity theorists would not link effort to their perceptions of intellectual growth nor would it be likely to affect their self-evaluation. If so, the implicit theories by prime condition interaction on distribution skew may be moderated by the judges' effort ratings. Specifically, a three-way interaction was expected: only under conditions of high effort, incremental theorists in the growth condition should report the greatest negative skew on the intellectual ability distribution.

To test this hypothesis, distribution skew was submitted to a hierarchical regression analysis with implicit theories scores, judges' ratings of effort, and prime condition as predictors. Standard procedures (Cohen & Cohen, 1983) were followed to test for two-way and three-way interactions; in addition, the distribution median was entered as a covariate in the first step of the analysis to control for the relationship between skew and central tendency. To simplify interpretability, implicit theories of intelligence scores, distribution median scores, and judges' ratings of effort were centered. Analysis revealed the two-way interaction between implicit theories scores and prime condition ($\beta = -.24$, $p = .09$), but this was moderated by a marginally significant three-way interaction between implicit theories scores, prime condition, and effort ratings ($\beta = -.23$, $p = .10$). The three-way interaction was plotted using the predicted means for each prime condition at levels of implicit theories of intelligence one standard deviation below and above the mean of the implicit theories of intelligence scale (for incremental and entity theorists, respectively) and at levels of rated effort one standard deviation below and above the mean of the effort scores (for low and high effort, respectively).

Simple interaction analysis (Aiken & West, 1991) revealed that implicit theories scores did not interact with prime condition when rated effort was relatively low ($\beta = -.01$, $p = .97$), but they did interact when effort was high ($\beta = -.48$, $p = .03$). Further probing of this interaction revealed that prime condition significantly affected distribution skew for incremental theorists ($\beta = .40$, $p = .04$), but not for entity theorists ($\beta = -.29$, $p = .16$). As is evident in Fig. 5, incremental theorists in the growth condition who reported a relatively high level of effort were likely to report negatively skewed distributions of intellectual ability. Single sample t tests

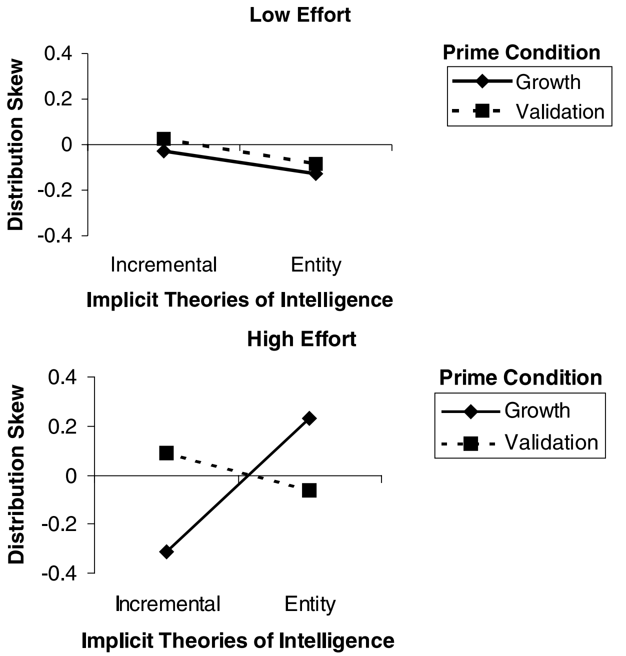

Fig. 5. Intellectual ability skew as a function of prime condition, implicit theories of intelligence, and judges' ratings of effort: Study 3.

for predicted means (Leonardelli & Hermann, 2001) confirmed that the negative skew in only one condition was significantly different from zero, $t(82) = -2.53$, $p = .01$: only incremental theorists in the growth condition who reported expending a relatively high amount of effort showed skew. All the other predicted means were not significantly different from zero, ts $< |1.52|$, ps $> .15$.

This same analysis was also completed on measures of central tendency and variability (without the median covariate). However, analysis yielded no significant main effects or interactions on any of the measures (ps $> .28$). Consequently, this three-way interaction between implicit theories, prime condition, and effort is localized to differences in distribution skew.

7.3. Discussion

The analyses revealed that only incremental theorists who thought about their intellectual growth reported negatively skewed distributions, but those who thought about a recent performance did not. This interaction provides support for the idea that the negative skew of the intellectual ability distribution, when reported by incremental theorists, reflects the growth associated with their intellectual ability. Furthermore, the content analyses contribute to our understanding of the interaction in two ways. First, they demonstrate that entity theorists are as able to write about growth as incremental theorists, but entity theorists seem unable or unwilling to internalize this growth into their self-evaluation. Second, they demonstrate that incremental theorists are most likely to report negatively skewed distributions of intellectual ability when they focus on their growth and report relatively high effort.

8. General discussion

Prior research on self-evaluation variability has focused on temporal variability (Greenier et al., 1995; Kernis, 1993), inter-item variability (Baumeister & Tice, 1988), or subjective perceptions of variability (Baumgardner, 1990), but has not explored the importance of the shape of self-evaluation. The present studies converge to demonstrate that distribution measures can be used profitably to measure self-evaluation and that such measures are rich with information. Central tendency and variability of the distribution measure were uniquely associated with the level of participant's self-evaluation and certainty of that evaluation, respectively (Study 2). More importantly, however, both correlational and experimental evidence demonstrate that the skew of the distribution measure is related in a logical manner to implicit theories of intelligence. Furthermore, Study 3 demonstrated that negative skew indicates perceptions of past growth and that distribution skew could be altered in a predictable and theoretically meaningful fashion. In sum, a distribution-type measure of self-evaluation of intelligence seems to gauge efficiently an individual's overall evaluation of their intelligence, the certainty of that evaluation, and the degree to which they believe they have grown intellectually.

8.1. The meaning of shape

It is important to note that although we have provided evidence that skew indicates perceptions of growth when evaluating intellectual abilities, it may be associated with other constructs when the distribution measure is used to assess other dimensions. Furthermore, assessing the skew of self-evaluation variability may also be meaningful when using other methods of measurement. For example, it seems likely that skew (or a skew-like index) might be used profitably in research on temporal variability in self-evaluation (Greenier et al., 1995; Kernis, 1993). For example, in addition to calculating the standard deviation of participants' self-esteem scores over repeated measures, one could calculate the skew of the distribution of scores and take into account whether the variability is normally distributed around the mean. In the context of temporal variability in self-esteem, skew may indicate a variety of things. Low mean self-esteem scores and a positive skew might reflect a desire for self-improvement (Taylor, Neter, & Wayment, 1995). Regardless, it is important to consider the context of the self-evaluation variability in order to appreciate the meaning of skew.

Distribution shape can be meaningful not only in self-evaluation, but also with regard to attitude measurement more broadly. For example, the shape of an attitude distribution on capital punishment might distinguish between different kinds of weak attitudes, such as an ambivalent attitude (where an individual reports a wide bimodal distribution) or an uncertain attitude (where the distribution is flat and wide). In addition, the skew of an attitude distribution may reveal a better understanding of an individual's susceptibility to persuasion attempts. For instance, an attitude with a negative skew may indicate that the person's attitude will only change in a negative direction; conversely, an attitude with a positive skew may indicate that the person's attitude is inclined toward change in a positive direction.

The research presented here demonstrated that distribution skew can be a meaningful indicator of individual differences, but has not provided a basis for interpreting kurtosis. Perhaps this index may better serve to determine whether the underlying construct (e.g., self-esteem, an attitude toward abortion or George Bush) should be measured using a Likert-type scale or a distribution measure. A Likert-type scale may measure attitudes that are peaked as efficiently as by the distribution measure. By contrast, as distributions become less peaked, that is, as kurtosis approaches zero and becomes negative in value, a distribution measure may be a better measure than a Likert-type scale. The kurtosis of participants' distributions of their intellectual ability in Studies 2 and 3 was near or below zero in all three studies ($M = -.38$, averaged across both studies), suggesting that a distribution measure may be used profitably.

8.2. Implications for implicit theories of intelligence

Our findings also indicate that incremental and entity theorists differ in the way that they evaluate their own intelligence. Prior investigations (Dweck, 1999; Zhao & Dweck, 1994) found that, after receiving negative feedback in a performance setting, entity theorists have lower self-rated intelligence than incremental theorists. These findings reflect differences in the central tendency of self-evaluation.[15] However, the present studies also reveal that participants' implicit theories of intelligence can be consistently related to the shape of these self-evaluations. Incremental theorists are more likely to exhibit negatively skewed distributions than entity theorists, and it appears that this skew reflects their perceptions that they have grown intellectually. Furthermore, our content analyses suggest that the intellectual growth represented in these distributions is growth of a particular kind: growth based on one's effort. In contrast to intellectual growth experienced as a result of others' help or natural development, incremental theorists seem to place particular personal importance on growth only when they perceive such growth to be caused by their own actions (Bandura, 1997).

[15] In Study 2, incremental theorists report higher central tendency and level of ability than entity theorists, but the correlations, on average, did not achieve significance (in Study 2, average $r = -.16$, average $p = .12$). In addition, in Study 3, these correlations were close to zero (average $r = .03$, average $p = .75$). This is not surprising, given that in these studies, participants were not given failure feedback. It is in performance settings after failure feedback when these correlations should be most evident.

8.3. Conclusion

The current research has empirically established that the distribution measure provides a multi-dimensional approach to self-evaluation: central tendency, variability and shape of self-evaluation can be used as meaningful indices of different facets of self-evaluation. In addition, this research lends some insight into the perspective of incremental theorists: they maintain a growth orientation in self-evaluation that persists in and out of performance contexts, but also, they seem able to turn off this orientation when the context requires it. Ultimately, these studies provide a good starting point for future research on the utility of self-evaluation distribution measures, the self-evaluative tendencies of incremental and entity theorists, and the significance of the shape of self-evaluation.

Acknowledgments

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Appendix A. Calculation of distribution indices

A.1. Measurement of central tendency

The mean and median were calculated as indices of distribution central tendency. The mean was calculated using the following equation: $(\sum_{x=1}^{10} X * n_x)/100$. The symbol X represents the value of a given box on the distribution measure (which could range from 1 to 10) and n_X represents the number of points allocated to value X (which could range from 0 to 100). Each value X is multiplied by the allocation n_X, and these multiples are summed together and divided by the total number of the allocation, 100.

The median is defined as the score at the 50th percentile of the distribution. The median was calculated using the following equation: $(X_{50} + X_{51})/2$. The value X_{50} represents a value between 1 and 10 where the cumulative frequency of points reaches 50%. The value X_{51} represents a value between 1 and 10 where the cumulative frequency of points reaches 51%. Averaging these two values together produces the median.

A.2. Measurement of variability

The range and standard deviation were calculated as indices of the distribution variability. The range refers to the width of the distribution, specifically, the number of boxes that fall between the upper and lower limits of each distribution. The following equation was used to calculate range:$X_{\max} - X_{\min} + 1$. The symbol $X_{\max}$ represents the highest possible value that participants believed could represent their level of intellectual ability; $X_{\min}$ represents the lowest possible value that participants believed could represent their level of intellectual ability. Adding 1 corrects the equation so that it represents the number of values contained in the range; scores here could thus range from 1 to 10 with higher numbers indicating wider distributions.

The standard deviation represents the dispersion of the distribution, where higher numbers indicate more disperse distributions. The following equation was used for calculating the standard deviation:

$$\sqrt{\frac{\sum_{x=1}^{10}((X-\bar{X})^2 \ * n_x)}{100}}.$$

The symbol $\bar{X}$ represents the mean of the sample calculated using the equation above.

A.3. Measurement of distribution shape

Skew indicates the extent to which the distribution is asymmetrical. Skew can be measured quantitatively, using the following equation (equation adapted from Beyer, 1988):

$$\frac{\frac{1}{100}\sum_{x=1}^{10}((X-\bar{X})^3 \ * \ n_x)}{\left(\frac{1}{100}\sum_{x=1}^{10}((X-\bar{X})^2 \ * \ n_x)\right)^{3/2}}.$$

This measure represents the extent to which a distribution is skewed, and the direction of that skew. Numbers close to zero indicate that the distribution is approximately symmetrical; positive numbers indicate a positive skew and negative numbers indicate a negative skew. For examples of representative skew scores on the distribution measure see Fig. 2.

A second characteristic of distribution shape is kurtosis. Kurtosis can be measured quantitatively, using the following equation (equation adapted from DeCarlo, 1997):

$$\frac{\frac{1}{100}\sum_{x=1}^{10}((X-\bar{X})^4 \ * \ n_x)}{\left(\frac{1}{100}\sum_{x=1}^{10}((X-\bar{X})^2 \ * \ n_x)\right)^{2}}.$$

Values produced by this equation are interpreted as follows: numbers close to zero indicate that the distribution is approximately normal; positive numbers indicate a more peaked, thinly tailed (i.e., leptokurtic) distribution, whereas negative numbers indicate a flatter, thicker tailed (i.e., platykurtic) distribution. For examples of representative kurtosis scores on the distribution measure, see Fig. 2.

References

Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Newbury Park, CA: Sage Publications.

Bandura, A. (1997). *Self efficacy: The exercise of control*. New York: W.H. Freeman.

Baumeister, R. F. (1991). On the stability of variability: Retest reliability of metatraits. *Personality and Social Psychology Bulletin, 17*(6), 633–639.

Baumeister, R. F., & Tice, D. M. (1988). Metatraits. *Journal of Personality, 56*(3), 571–598.

Baumgardner, A. H. (1990). To know oneself is to like oneself: Self-certainty and self-affect. *Journal of Personality and Social Psychology, 58*(6), 1062–1072.

Beyer, W. H. (1988). *CRC handbook of tables for probability and statistics*. Boca Raton, FL: CRC Press.

Blascovich, J., & Tomaka, J. (1991). Measures of self-esteem. In J. P. Robinson & P. R. Shaver et al. (Eds.), *Measures of personality and social psychological attitudes* (Vol. 1, pp. 115–160). San Diego, CA: Academic Press.

Britt, T. W. (1993). Metatraits: Evidence relevant to the validity of the construct and its implications. *Journal of Personality and Social Psychology, 65*(3), 554–562.

Campbell, J. D. (1986). Similarity and uniqueness: The effects of attribute type, relevance, and individual differences in self-esteem and depression. *Journal of Personality and Social Psychology, 50*(2), 281–294.

Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation: Analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

DeCarlo, L. T. (1997). On the meaning and use of kurtosis. *Psychological Methods, 2*(3), 292–307.

Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development*. Philadelphia, PA: Psychology Press.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256–273.

Fried, L. S., & Holyoak, K. J. (1984). Induction of category distributions: A framework for classification learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 10*(2), 234–257.

Greenier, K. D., Kernis, M. H., & Waschull, S. B. (1995). Not all high (or low) self-esteem people are the same: Theory and research on stability of self-esteem. In M. H. Kernis (Ed.), *Efficacy, agency, and self-esteem* (pp. 51–71). New York: Plenum Press.

Hintzman, D. L. (1986). "Schema abstraction" in a multiple-trace memory model. *Psychological Review, 93*(4), 411–428.

Hong, Y.-y., Chiu, C.-y., & Dweck, C. S. (1995). Implicit theories of intelligence: Reconsidering the role of confidence in achievement motivation. In M. H. Kernis (Ed.), *Efficacy, agency, and self-esteem* (pp. 197–216). New York: Plenum Press.

Jarvis, W. B. G. (2000). MediaLab 2000 Research Software. Empirisoft Software. Available from: www.empirisoft.com.

Kahneman, D., & Miller, D. T. (1986). Norm theory: Comparing reality to its alternatives. *Psychological Review, 93*(2), 136–153.

Kernis, M. H. (1993). The roles of stability and level of self-esteem in psychological functioning. In R. F. Baumeister (Ed.), *Self-esteem: The puzzle of low self-regard* (pp. 167–182). New York: Plenum Press.

Kernis, M. H., Grannemann, B. D., & Barclay, L. C. (1989). Stability and level of self-esteem as predictors of anger arousal and hostility. *Journal of Personality and Social Psychology, 56*(6), 1013–1022.

Kraus, S., Ryan, C. S., Judd, C. M., & Hastie, R., et al. (1993). Use of mental frequency distributions to represent variability among members of social categories. *Social Cognition, 11*(1), 22–43.

Leggett, E. L., & Dweck, C. S. (1986). *Individual differences in goals and inference rules: Sources of causal judgements*. Manuscript, Urbana-Champaign: University of Illinois.

Leonardelli, G. J., & Hermann, A. D. (2001). *Single sample t tests of predicted means: An extension of Aiken and West's [1991] simple slope tests*. Manuscript in preparation, Kellogg School of Management, Northwestern University, Chicago, IL.

Leonardelli, G. J., Hermann, A. D., & Arkin, R. M. (2002). *Implicit theories of intelligence and distribution skew of an intellectual ability distribution: Divergent validity*. Unpublished manuscript, Columbus: The Ohio State University.

Linville, P. W., Fischer, G. W., & Salovey, P. (1989). Perceived distributions of the characteristics of in-group and out-group members: Empirical evidence and a computer simulation. *Journal of Personality and Social Psychology, 57*(2), 165–188.

Major, B., & Schmader, T. (1998). Coping with stigma through psychological disengagement. In J. K. Swim & C. Stangor (Eds.), *Prejudice: The target's perspective* (pp. 219–241). San Diego, CA: Academic Press.

Mueller, C. M., & Dweck, C. S. (1997). *Implicit theories of intelligence: Malleability beliefs, definitions, and judgments of intelligence*. Data, New York: Columbia University.

Nisbett, R. E., & Kunda, Z. (1985). Perception of social distributions. *Journal of Personality and Social Psychology, 48*(2), 297–311.

Pelham, B. W., & Swann, W. B. (1989). From self-conceptions to self-worth: On the sources and structure of global self-esteem. *Journal of Personality and Social Psychology, 57*(4), 672–680.

Rehder, B., & Hastie, R. (1996). The moderating influence of variability on belief revision. *Psychonomic Bulletin and Review, 3*(4), 499–503.

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton, NJ: Princeton University Press.

Schmader, T., & Major, B. (1999). The impact of ingroup vs outgroup performance on personal values. *Journal of Experimental Social Psychology, 35*(1), 47–67.

Taylor, S. E., Neter, E., & Wayment, H. A. (1995). Self-evaluation processes. *Personality and Social Psychology Bulletin, 21*(12), 1278–1287.

Zhao, W., & Dweck, C. S. (1994). *Implicit theories and vulnerability to depression-like responses*. Manuscript, New York: Columbia University.