# Measuring Discrepancies Using Latent Variable Modeling

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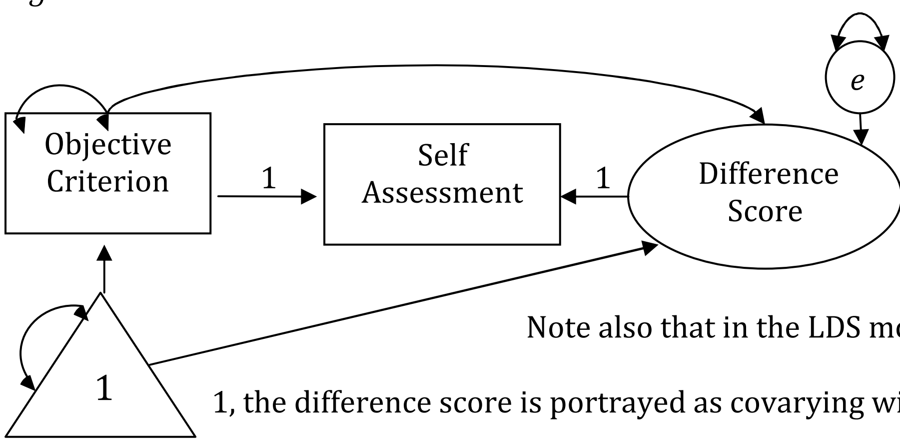
## Abstract

This paper aims to describe an innovative use of a new approach to latent variable modeling that involves latent difference scores (LDS: McArdle, 2009), reflecting the degree of difference between subjective self-views and more objective assessments of the self. We created latent difference scores reflecting the degree of accuracy across the domains of intelligence, general health, body mass, and attractiveness, using data from the third wave of the National Longitudinal Study of Adolescent Health (Add Health). We tested structural models examining the consequences of self-perception accuracy on a variety of socioeconomic and mental health outcomes assessed roughly six years later. What is innovative about our use of the LDS framework is that we use it to model intra-individual discrepancies at the same point of time. This approach avoids the weaknesses of prior methods because measurement error is removed from the latent difference score.

The goal of this paper is to describe an innovative use of a new approach to latent variable modeling that sheds light on the adaptive value of accurate self-perceptions among young adults. The methodological innovation involves the application of latent variable modeling to create latent difference scores (LDS: McArdle, 2009), reflecting the degree of difference between subjective self-views and more objective assessments of the self. Self-perceptions that are closer to more objective assessments are regarded as more accurate. In this paper, we first attempt to create a single latent difference score reflecting the degree of accuracy in self-perception across the domains of intelligence, general health, body mass, and attractiveness, using data from the third wave of the National Longitudinal Study of Adolescent Health (Add Health). Then we create and test structural models examining the consequences of self-perception accuracy on a variety of health and socioeconomic outcomes assessed roughly six years later, during the fourth wave of Add Health.

Our analyses rely on the use of the LDS framework, in which one observed variable (here, a self-assessment) is conceptualized as a linear function of another observed variable (here, a more objective criterion) and a difference score (See Figure 1). Typically the LDS framework is used for data points at multiple points in time within the individual. For example, it can be used to model intra-individual change on a single variable, that is, how a score on a variable at Time 2 is a function of a score on the same variable at Time 1 and some change ($\Delta$). What is innovative about our use of the LDS framework is that we use it to model intra-individual discrepancies on two domain-related variables at the same point of time. As shown in Figure 1, this approach is useful because it avoids the weaknesses of prior methods of representing difference scores, usually involving one score being subtracted from another. The problem with the simple subtraction method is that the resulting difference score contains the combined measurement errors of the two scores (e.g., Cronbach & Furby, 1970). In contrast, with the LDS framework, that measurement error is removed from the latent difference score.

*Figure 1*. Latent Difference Score Models with Self-Assessments as a Linear Function of Objective Criteria and a Difference Score




Note also that in the LDS models, as shown in Figure 1, the difference score is portrayed as covarying with the objective criterion. This link is particularly relevant to the psychological literature regarding self-perceptions. For example, the size of the discrepancy between self-viewed and objective assessments of ability have been shown to be affected by the objective measures of ability (Kruger & Dunning, 1999; Dunning, Johnson, Ehrlinger, & Kruger, 2003; Ehrlinger, Johnson, Banner, Dunning, & Kruger, 2008). Specifically, many studies have demonstrated that the discrepancy between the self-perception and objective criterion is greater for people of lower ability than people of average or high ability (Dunning, 2005).

In addition to making this methodological contribution, this paper makes a contribution to psychological theory in that it focuses on an area that has generated a great deal of controversy over the last 30 years. Two competing theoretical perspectives have emerged regarding the value of accurate knowledge about the self: the “traditional” model of mental health, in which accurate self-perceptions are considered a marker of psychological health (Jahoda, 1958) and Taylor and Brown’s (1988) Social Psychological

Model of mental health in which positive illusions about the self are portrayed as promoting adaptation and psychological well-being. Each perspective on the value of accurate self-knowledge is supported by a body of literature (Chang, Chang, Sanna, & Kade, 2008).

Accurate self-knowledge may be especially important for adolescents and young adults. During this time in the life course, individuals make choices that establish or limit future conditions and options, including those for future socioeconomic status and health (Mirowsky & Ross, 2003; Elder, 1985; 1994). In this paper, we examine the consequences of accurate self-knowledge. Competing psychological theories generate competing expectations. On one hand, overestimation of the self in terms of intelligence, for example, may promote motivation, encouraging young adults to push themselves to persist in academics, leading ultimately to greater educational attainment. On the other hand, inaccurate self-views may hinder young adults' abilities to be aware of their own limitations and to take actions that protect themselves, such as applying to "safety schools."

**The Current Study**

Despite the robust literature on each of the three competing perspectives on the value of accurate knowledge about the self, most psychological research in this area has been conducted in college laboratories with members of college communities as research participants (Chang *et al*., 2008). In this investigation, we assess the consequences of accurate self-knowledge, using data from the National Longitudinal Study of Adolescent Health (Add Health), a longitudinal data source that allows us to assess the qualities of young adults across four domains of the self, both objective and perceived, and link degrees of differences between the objective and perceived within these domains to socioeconomic and health outcomes measured six years later.

Our two main research questions are:

(1) Do discrepancies in self-knowledge across four domains load onto a single, generalized difference score, reflecting the degree of an individual's accurate self-knowledge?

(2) How well does the latent factor reflecting accurate self-knowledge predict future socioeconomic and health outcomes?

# Method

## Data Source

Our study is based on analyses of data from a longitudinal data source known as the National Longitudinal Study of Adolescent Health (Add Health: Harris, Halpern, Whitsel, Hussey, Tabor, Entzel, & Udry, 2009). The selection of participants into the sample was initially based on the schools they attended during the 1994-95 school year. Schools were selected from a complete list of American high schools (Quality Education Database) based on their region, school type, racial composition, urbanicity, and size. A subgroup of these high school participants was selected to participate in in-home interviews, on which we base the majority of our analyses. These participants were followed across three subsequent waves in 1996 (Wave II), 2001-2002 (Wave III), and 2007-2008 (Wave IV). At Wave IV, the staff of Add Health found 92.5% of the participants who had participated in the first Wave I in-home interview and successfully completed interviews of 80.3% of the eligible sample members. Data from parents of in-home youth participants were also collected at Wave I, with effort made by Add Health staff for this Parental Questionnaire to be completed by the resident mother.

***Sample Selection***. We applied three filters to the Add Health data prior to data analysis. First, we limited our sample to those participants who belonged to a participating Add Health school at Wave I, which eliminated persons added to the Add Health data because of their association with the main respondent, for example, as a sibling or cousin attending a non-participating school. This filter allows us to examine the impact of school contexts on difference scores; however, these analyses are not described in this paper. This filter reduced the sample from $N$ = 20,774 to $N$ = 15,425. Second, we limited our sample to those with valid Wave IV weights, which allows us to apply sampling weights to our models and thus ensure representativeness to the population of U.S. young adults. This filter reduced our sample to $N$ = 9,419. Third, we limited our sample to those participants over 19 years of age at the third wave, which would allow us to classify participants into BMI categories according to standards set by the Centers for Disease Control and Prevention (2011), and to focus our analyses on emerging adulthood. This last filter brought our sample to its final size, $N$ = 8,283.

***Variables***. We utilized measures from Wave I, Wave III, and Wave IV of the Add Health data. Background variables and markers of self-knowledge were drawn from the Wave III data, control variables were drawn from the Wave I data, and consequence variables were drawn from the Wave IV data.

Background Variables, Wave III. In order to describe our sample, we created variables to assess the ethnicity, race, and gender of the sample members. We based race/ethnicity on a series of Wave III variables in which Add Health participants reported whether they were of Latino/Hispanic origin, and their race, for which respondents could indicate as many racial groupings as they felt applied to them. Based on these variables, we categorized participants into the following groups: non-Hispanic White only, non-Hispanic Black only, Asian only, Native American only, Latino/Hispanic in combination with any racial group, and Multiethnic. We based biological sex on the interviewer's report of the respondent's biological sex at Wave III, which was coded with a 0 (male) or 1 (female).

Markers of Self-Knowledge, Wave III. We created markers of self-knowledge for four domains of the self (intelligence, general health, body mass, and attractiveness) using two variables for each domain: one, more objective and one, self-rated. In order to promote consistency of interpretation, all markers of self-knowledge were placed on a four-point scale prior to modeling. A full list of the more objective and self-rated measures, and along with a brief description of the calculations performed on these scores to place them on 4-point scales, is presented in Table 1. These variables were used to create the first-order factors that loaded onto the higher-order Self-Inaccuracy factor (see Figure 2).

Outcome Variables, Wave IV**.** For purposes of this paper, we selected a few, key Wave IV variables to illustrate the consequences of self-inaccuracy. These items focused on socioeconomic and mental health outcomes. We used these variables as dependent variables in our longitudinal models, theorizing that scores on these variables would be affected either positively or negatively by scores on the latent Self-Inaccuracy factor. A full list of the outcome variables, along with the items manipulated to yield them, is available in Table 2.

Control Variables, Wave I. We utilized control variables drawn from the Wave I data in order to determine the effect of self-inaccuracy measured at Wave III, net of these earlier

(Wave I) life effects, on Wave IV outcomes. The control variables were selected to match the outcome variable. When the Wave IV outcome of interest was educational attainment, we used as a control variable, their parents' educational attainment, measured at Wave I. When the outcomes were personal earnings, household income, and job satisfaction, we used as a control variable one constructed from first wave data to represent the family-income-to-needs ratio (Huston, McLoyd, & Garcia Coll, 1994). When the outcome was mental health, specifically, mean depression scores at the fourth wave, the control variable was mean depression scores at the first wave. A full list of the control variables used, and transformative calculations performed on them, is available in Table 3.

**Analysis Plan**

**Estimation.** After coding and cleaning the variables in SAS Version 9.1, we began analyses in Mplus Version 5.2 We applied Wave IV grand sample weights to our data to ensure representativeness to the population of U.S. young adults by accounting for the unequal probability of selection into the Add Health sample (Chantala & Tabor, 1999). Because Mplus does not permit the use of sampling weights with maximum likelihood (ML) estimation, we chose to estimate our model using maximum likelihood estimation with robust standard errors (MLR), which does allow for sampling weights (Muthén & Muthén, 2010). We utilized subpopulation weights in models estimated separately by gender. This was done using Mplus' SUBPOPULATION command, in which the nonselected groups are given sampling weights of zero. Mplus treats missing data with full information maximum likelihood methods when raw data are provided.

**Research Questions.** To address our first research question concerning whether discrepancies in self-knowledge load onto a generalized "self-inaccuracy" factor, we assessed the loading of each of the four discrepancy score models (one for each domain) onto a higher-order latent "Self-Inaccuracy" factor (see Figure 2). Factor loadings of each latent difference score onto the generalized factor were examined for direction and strength, in order to indicate whether discrepancies in various domains of the self were indicators of the single latent factor.

Next, to address our second research question concerning the effect of discrepancies in self-knowledge on the socioeconomic and mental health outcomes, we linked scores on the generalized Self-Inaccuracy factor (based on Wave III indicators) to Wave I control variables and Wave IV outcome variables (see Figure 3). Controlling for specific Wave I variables allowed us to determine the effect of Self-Inaccuracy on socioeconomic and mental health outcomes, above and beyond specific control variables at the first wave. Note that outcomes measured with ordinal categories (job satisfaction, household earnings, and depression) were specified as categorical in Mplus in model estimation.

# Results

## Description of the Sample

Our sample of 8,283 young adults consisted of 3,814 young men and 4,469 young women between the ages of 20 and 27 ($M$ = 21.99, $SD$ = 1.37). The sample was 54.09% non-Hispanic White, 19.68% non-Hispanic Black/African American, 0.73% Native American, 6.01% Asian/Pacific Islander, 15.34% Hispanic/Latino, and 4.16% Multiethnic.

## Descriptive Statistics for Each Domain

Table 4 shows means and standard deviations for scores on the more objective and self-rated scores in each domain, for the whole sample and by gender. Means across gender were weighted with Wave IV grand sample weights. Means by gender were weighted using subpopulation weighting in Mplus. We see from the means in Table 4 that the difference scores between the self-rated and objective scores are approximately equal for the two genders, except for the domain of body mass.

**Preliminary Fitting of LDS Models in Each Domain**

A preliminary step in the creation of our Self-Inaccuracy latent factor was to run a series of four models to create the first-order factors, one for each domain of the self (see Figure 2). Models for all four domains converged successfully in Mplus, and also revealed a common theme: those with higher objective scores for intelligence, general health, body mass, and attractiveness tended to exhibit smaller discrepancies in these domains. This was seen in the statistically significant, negative correlations in each lower-order model between more objective score in the domain and the latent difference score: $r = -.69$, $p < .001$ for intelligence; $r = -.26$, $p < .001$ for health; $r = -.62$, $p < .001$ for body mass; $r = -.69$, $p < .001$ for attractiveness. The models also converged successfully for each gender, and the correlations between objective scores and latent difference score in each domain were very similar for men and women.

These results indicate that young men and women who score better on more objective measures of intelligence, general health, and attractiveness tend to have more accurate self-knowledge. Note, however, a somewhat different pattern is suggested for body mass: young adults who had higher BMI scores tended to have more accurate self-knowledge.

**Loading of LDS Models, by Domain, onto the Generalized Factor**

Next, to address our first research question concerning whether discrepancies in self-knowledge load onto a generalized "self-inaccuracy" factor, we assessed the loading of each of the four first-order factors onto a higher-order Self-Inaccuracy factor (see Figure 2). Then we ran the model exploring the loadings of the first-order factors onto the higher-order factor separately by gender using Mplus' subpopulation command.

**Fit and Loadings Across All Participants.** Because of the sensitivity of the $\chi^2$ statistic to large sample sizes (Keith, 2006), we based our assessment of fit on the RMSEA, CFI, and TLI indices. Across both genders, this higher-order model had good fit to the data, $\chi^2(10, 8283) = 92.567$, $p < .0001$, RMSEA = 0.032, CFI = 0.963, TLI = 0.918. The RMSEA and CFI indices suggested good fit to the data, with an RMSEA statistic less than the recommended upper limit for good fit of .05, and a CFI statistics greater than the recommended lower limit for good fit of .95. The TLI suggested reasonable fit to the data, with a statistic greater than the recommended lower limit for reasonable fit of .90.

In order to determine how well each of the four domains loaded onto the single latent factor, we examined the standardized loadings of each latent difference score on the generalized Self-Inaccuracy factor. We used .30 as a rule of thumb for sizable loading and found that only two of the latent difference scores yielded a standardized loading that reached or exceeded $\lambda = .30$: the attractiveness latent difference score, which loaded at $\lambda = .41$, and the general health latent difference score, which loaded at $\lambda = .33$. The intelligence difference score loaded at $\lambda = .20$, while the body mass difference score loaded at $\lambda = -.18$. The negative loading of the latent difference score for body mass is consistent with our finding that body mass was the only domain for which a higher objective score denotes a less favorable (i.e., obese) outcome.

**Fit and Loadings by Gender.** The model had good fit to the data among young men, $\chi^2(10, 3814) = 29.680$, $p = .0010$, RMSEA = 0.023, CFI = 0.980, TLI = 0.955. The model also had good fit to the data among women according to the RMSEA and CFI, and reasonable fit according to the TLI, $\chi^2(10, 4469) = 61.861$, $p = .0010$, RMSEA = 0.034, CFI = 0.961, TLI = 0.914.

We found that the standardized loadings among men were similar to those found when we ran the model across all participants: $\lambda = .39$ for attractiveness, $\lambda = .35$ for health, $\lambda = .23$ for intelligence, and $\lambda = -.15$ for body mass. Loadings were slightly different for women, with a noticeably higher loading seen for attractiveness at $\lambda = .57$, lower loadings for health and intelligence at $\lambda =.23$ and $\lambda =.15$ respectively, and a similarly sized-loading of $\lambda = -.16$ for body mass.

**Summary.** Even though the data provided a good fit to the model representing the single Self-Inaccuracy latent variable, the finding that not all latent difference scores loaded at .30 or higher onto the higher-order factor suggests that a single higher order latent factor representing all four domains was not appropriate. Thus, we decided to treat each latent difference score as a separate, yet correlated predictor of five Wave IV outcomes of interest: personal earnings, household income, job satisfaction, educational attainment, and depression.

## Impact of Discrepancy Factors on Outcomes

Next, to address our second research question about the effects of latent discrepancy scores on socioeconomic and mental health outcomes, we considered the results of longitudinal models in which the five Wave IV outcomes of interest (personal earnings, household income, job satisfaction, educational attainment, and depression) were regressed on each of the Wave III latent discrepancy scores, controlling for relevant Wave I variables. Results are shown in Table 5.

Models for all five outcomes showed good to reasonable fit to the data according to the RMSEA index, with the RMSEA fit statistic less than .08 for all models. Fit according to the CFI and TLI differed by model; this is an important consideration for future work involving these models. Across all models, latent discrepancy scores in various domains of the self were highly intercorrelated, all *p*s $< .001$. The one exception was the correlation between latent discrepancies for intelligence and body mass, *r*s ranging from -.01 to -.02, all *ns*.

Considering results for all outcomes, the strongest and most consistent effects of discrepancy scores on outcomes were seen in the health domain. For each of the five outcomes of interest, having a view of one's health that is more positive than reflected by more objective physical assessments lead to better socioeconomic and mental health outcomes: $b^* = .05$, $p < .01$ for personal earnings; $b^* = .10$, $p < .001$ for household income; $b^* = .09$, $p < .001$ for job satisfaction; $b^* = .08$, $p < .001$ for educational attainment; $b^* = -.10$, $p < .001$ for depression. Note that the sign of the beta is negative for the outcome of depression, which is intuitive because lower scores reflect a healthier outcome. Though the size of the standardized betas reflect small effects, the effects are robust, or consistent across the models. Note that these effects hold even after controlling for Wave I family income-to-needs-ratio.

Effects of discrepancies in other domains of the self were generally less consistent for the five outcomes, and less intuitive. For example, greater discrepancies in the intelligence domain led to significantly *worse* outcomes for household income, job satisfaction, and depression, all *p*s < .001; intelligence discrepancies had only marginally significant effects on personal earnings and educational attainment. Future attention should be given to why positive discrepancies in the health domain appear to be consistently helpful, while positive discrepancies in the intelligence domain generally appear to be harmful.

## Discussion

In this paper, we have presented an innovative use of the LDS framework (McArdle, 2009), which is typically used for modeling intra-individual change across time points. Our methodology is innovative in that we use this framework instead to model latent differences as intra-individual differences for two related variables at a single point in time. This use of the LDS framework overcomes problems with other ways to measures discrepancies in self-knowledge, such as the use of difference scores, which are often viewed as having poor reliability (e.g., Cronbach & Furby, 1970). We successfully used this approach to construct latent difference score models for four different domains of the self (intelligence, general health, body mass, and attractiveness).

We then utilized the resulting latent difference scores as first-order latent factors to be loaded onto a higher-order latent Self-Inaccuracy factor to be used in predicting future socioeconomic and mental health outcomes. Since not all of the first-order factors loaded highly onto the latent factor, we instead utilized the first-order factors as separate, yet correlated, predictors of the outcomes. Results from these longitudinal models revealed a small but consistent effect of positive discrepancies in the health domain on all five outcomes of interest. Specifically, even controlling for relevant Wave I variables, participants who assessed their own health to be better than indicated by objective physical health criteria earned more money, had greater household income, were more satisfied with their job, achieved more years of education, and reported fewer depressive symptoms at Wave IV. This finding suggests that positive subjective judgments of one's own health, above and beyond objective assessments of health, promote socioeconomic success, contentment in the workplace, and good mental health. In future analyses, we would like to assess whether this function should be best thought of as linear or curvilinear.

Models of discrepancies in other domains were less consistent and perhaps counterintuitive. For example, intelligence discrepancies produced *negative* rather than positive effects on depression. It is possible that our finding, that young adults with less objective intelligence have greater discrepancies, contributes to differentials in these outcomes. That is, less able people were found to be less accurate in their self-knowledge, and they also reported more depression symptoms, net of depressive symptoms they reported at the first wave of assessment. More theoretical attention needs to be given as to why large discrepancies in the health domain appear to be *helpful* across many outcomes, while large discrepancies in the intelligence domain appear to be *harmful* in certain domains, especially mental health.

Overall, this project makes several contributions, both methodological and theoretical. First, our innovative use of LDS framework overcomes prior methodological limitations of difference scores. We hope that other researchers will utilize and improve upon this creative application of a methodological framework to a measurement problem that is well-known in the psychology literature. Second, we present evidence that discrepancies in self-knowledge should not be thought to reflect a generalized latent factor, but should be treated separately by domain. This finding runs counter to theory arguing for a generalized self-enhancement factor (Colvin & Griffo, 2008). Finally, we demonstrate that large discrepancies appear to be helpful for some domains of the self (health) but not others (intelligence).

This project also leaves open several avenues for future work in this area. First, future work should attempt to construct models that have good fit as assessed by several fit indices. Second, future work should address whether the effects of discrepancies on outcomes are linear or nonlinear. Third, future work should investigate how models do or do not differ by gender and other social characteristics.

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Table 1

*Description of Items used in Measures of Objective and Self-rated Intelligence, Health, Body Mass, and Attractiveness*

| Domain | Description | Original Coding | Recoding / Calculations |
|---|---|---|---|
| Intelligence | | | |
| Objective | Based on scores on the Add Health Picture Vocabulary Test (AHPVT), an assessment of comprehension of spoken English vocabulary. The test was an abridged version of the revised Peabody Picture Vocabulary Test (PPVT; Dunn, 1981), for which scores have been found to correlate moderately well with scores on other tests of intelligence, such as the Stanford-Binet Intelligence Scale. | Utilized Add Health's percentile score version of this variable. | Divided the percentile scores into four quartiles to create a 4-point scale. |
| Intelligence | | | |
| Self-rated | Based on a Wave III item asking the participant, "Compared to other people your age, how intelligent are you?" | Original response options were: 1 = moderately below average, 2 = slightly below average, 3 = about average, 4 = slightly above average, 5 = moderately above average, and 6 = extremely above average. | Folded the bottom and top categories (.99% and 6.66% of the cases respectively) into their adjacent categories, which contained more cases (3.36% and 29.29% respectively). This resulted in a 4-point scale. |
| Health | | | |
| Objective | Based this measure on five physical health items drawn from Wave III that marked the degree to which participants were limited by poor health in performing the following physical activities: vigorous activities such as such as running, lifting heavy objects, or participating in strenuous sports; lifting or carrying a bag of groceries; climbing several flights of stairs; bending, kneeling, or stooping; and walking more than one mile. | Original response options were: 0 = not limited at all, 1 = limited a little, or 2 = limited a lot. | Conducted an exploratory factor analysis in Mplus to determine whether these items loaded onto a single factor. The Scree plot and fit statistics suggested a one factor solution: CFI = .989, TLI = .989, RMSEA = .041. All five items loaded onto the single factor at.77 or higher. We reverse-scored then totaled scores on the items (with Mplus treating missing data under missing data theory), divided by the total possible score of 10, and divided these percentages into four quarters. This resulted in a 4-point scale. |

Table 1 (Continued)

*Description of Items used in Measures of Objective and Self-rated Intelligence, Health, Body Mass, and Attractiveness*

| Domain | Description | Original Coding | Recoding / Calculations |
|---|---|---|---|
| Health | | | |
| Self-rated | Based this measure on a Wave III item asking the participant, "In general, how is your health?" | Original response options ranged from 1 (excellent) to 5 (poor). | After reverse-scoring responses, we folded the bottom category ("poor," 0.37% of cases) into the next-higher category (4.30% of cases). This resulted in a 4-point scale. |
| Body Mass | | | |
| Objective | Based on biospecimen measurements taken by Add Health staff at Wave III, in pounds and inches. | Weights in the original Add Health data ranged from 78 to 330 pounds. 71 additional participants weighed over 330 pounds, and thus did not have valid measurements for this item. Heights ranged from 4 to 7 feet. | Calculated BMI scores and categorized into four groups as defined by the CDC (2011) for persons over 19 years old: < 18.5 as underweight, 18.5 to 24.9 as normal, 25.0 to 29.9 as overweight, and 30.0 and above as obese. This resulted in a 4-point scale. |
| Body Mass<br>Self-rated | Based on a Wave III item asking the participant, "How do you think of yourself in terms of weight?" | Original response options were: 1= very underweight, 2 = slightly underweight, 3 = about the right weight, 4 = slightly overweight, 5 = very overweight. | Folded the bottom category (1.16% of cases) into the next higher category (11.09% of cases). This resulted in a 4-point scale |
| Attractiveness<br>Objective | Based on a Wave III item in which the interviewer responded to the question, "How physically attractive is the respondent?" | Original response options were: 1 = very unattractive, 2 = unattractive, 3 = about average, 4 = attractive, 5 = very attractive. | Folded the bottom category (2.06% of the cases) into the next higher category, which contained more cases (4.88%). This resulted in a 4-point scale. |

| | | | |
|---|---|---|---|
| Attractiveness | | | |
| Self-rated | Based on a Wave III item asking the participant, "How attractive are you?" | Original response options were: 1 = very attractive, 2 = moderately attractive, 3 = slightly attractive, 4 = not at all attractive. | Reverse-scored responses. This scale already contained four points. |

Table 2

Wave IV Variables Used as Outcome Variables in Longitudinal Models

| Outcomes | Description | Original Coding | Recoding/Transformations |
|---|---|---|---|
| Educational Attainment by Young Adulthood | Based on item in which the respondent reported the credentials/partial credentials he/she had earned. | Original response options ranged from 1 (8th grade or less) to 13 (completed post-baccalaureate professional education). | None. |
| Personal Earnings in Young Adulthood | Based on item asking the participant: "Now think about your personal earnings. In {2006/2007/2008}, how much income did you receive from personal earnings before taxes—that is, wages or salaries, including tips, bonuses, and overtime pay, and income from self-employment?" | Original response options ranged from $0 to $999,995, measured in whole dollar amounts. | No recoding, but scores were transformed using a natural log transformation. |
| Household Earnings in Young Adulthood | Based on item asking the participant: "Thinking about your income and the income of everyone who lives in your household and contributes to the household budget, what was the total household income before taxes and deductions in {2006/2007/2008}? Include all sources of income, including non-legal sources." | Original response options were:<br>1 = < $5,000;<br>2 = $5,000 - $9,999;<br>3 = $10,000 - $14,999;<br>4 = $15,000 - $19,999;<br>5 = $20,000 - $24,999;<br>6 = $25,000 - $29,999;<br>7 = $30,000 - $39,999;<br>8 = $40,000 - $49,999;<br>9 = $50,000 - $74,999;<br>10 = $75,000 - $99,999; 11 = $100,000 - $149,999; 12 = $150,000 or more. | None. |
| Job Satisfaction in Young Adulthood | Based on item asking the participant: "How satisfied (are/were) you with this job, as a whole?" | Original response options ranged from 1 (extremely satisfied) to 5 (extremely dissatisfied). | Reverse-scored the responses. |
| Depressive Symptoms in Young Adulthood | Based on items drawn from the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977) which asked participants to indicate frequency of feeling a certain way in the past seven days. | Original response options were: 0 = never or rarely, 1 = sometimes, 2 = a lot of the time, or 3 = most of the time of all of the time. | Calculated mean score across all the items. |

Table 3

*Wave I Variables used as Control Variables in Longitudinal Models*

| Control (Outcome) Variables | Description | Original Coding | Recoding / Calculations |
|---|---|---|---|
| Parental Education (Educational Attainment of Young Adult) | Based on the parental respondent's self-reported level of educational attainment, in credentials or partial credentials. | Original response ranged from 1 (eighth grade or less) to 10 (never went to school). | Recoded the response options to reflect a logical order, ranging from 0 (never went to school) to 9 (training beyond a 4-year college or university). |
| Family-Income-to-Needs Ratio (Personal Earnings, Household Income, Job Satisfaction) | Based on two variables: the parental respondent's self-reported household income in 1994, and the adolescent's report of the number of persons living in the household. This combined variable reflects depth of amount (or depth) of poverty or affluence in childhood (Huston et al., 1994). | Add Health's parental income variable ranged from $0 to $999 (in thousands). Number of persons living in the household ranged from 0 to 20. | Divided the household income by the 1994 poverty line for a family of the size indicated by the adolescent. Poverty lines were drawn from guidelines published by the U.S. Department of Health & Human Services (U.S. Department of Health & Human Services, 2011). |
| Depressive Symptoms (Depressive symptoms) | Based on items drawn from the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977) which asked participants to indicate frequency of feeling a certain way in the past seven days. | Original response options were: 0 = never or rarely, 1 = sometimes, 2 = a lot of the time, or 3 = most of the time of all of the time. | Calculated mean score across all the items. |

*Note.* Control variables were determined by the nature of the outcome variable. Parental education was the control variable when the outcome variable was the educational attainment of the young adult. The Family-Income-to-Needs ratio, based on Wave I data, was the control variable when the outcome variables were the personal earnings, household income, or job satisfaction of the young adult. Mean depressive symptoms of the adolescent was the control variable when the mean depressive symptoms at Wave IV was the outcome variable.

Table 4

*Weighted Means and Standard Deviations for Objective and Self-rated Scores in Four Domains : Whole Sample and By Gender*

| | Whole Sample (*N* = 8,283) | | Young Men (*N* = 3,814) | | Young Women (N = 4,469) | |
|---|---|---|---|---|---|---|
| Domain | Objective *M (SD)* | Self-rated *M (SD)* | Objective *M (SD)* | Self-rated *M (SD)* | Objective *M (SD)* | Self-rated *M (SD)* |
| Intelligence | 2.52 (1.12) | 2.89 (0.94) | 2.56 (1.11) | 2.96 (0.94) | 2.47 (1.14) | 2.82 (0.93) |
| Health | 3.89 (0.40) | 2.99 (0.86) | 3.91 (0.37) | 3.07 (0.84) | 3.86 (0.43) | 2.91 (0.87) |
| Body Mass | 2.60 (0.93) | 2.33 (0.78) | 2.61 (0.88) | 2.15 (0.74) | 2.58 (0.97) | 2.53 (0.77) |
| Attractiveness | 2.49 (0.77) | 3.03 (0.73) | 2.41 (0.73) | 3.07 (0.74) | 2.57 (0.81) | 3.00 (0.72) |

*Note*. Means and standard deviations were determined in Mplus, with grand sampling weights applied. Subpopulation weighting was employed in determining weighted means by gender. Both objective and self-rated indices were recoded and/or adjusted to fit onto a 4-point scale, with a 1 indicating low and 4 indicating high scores.

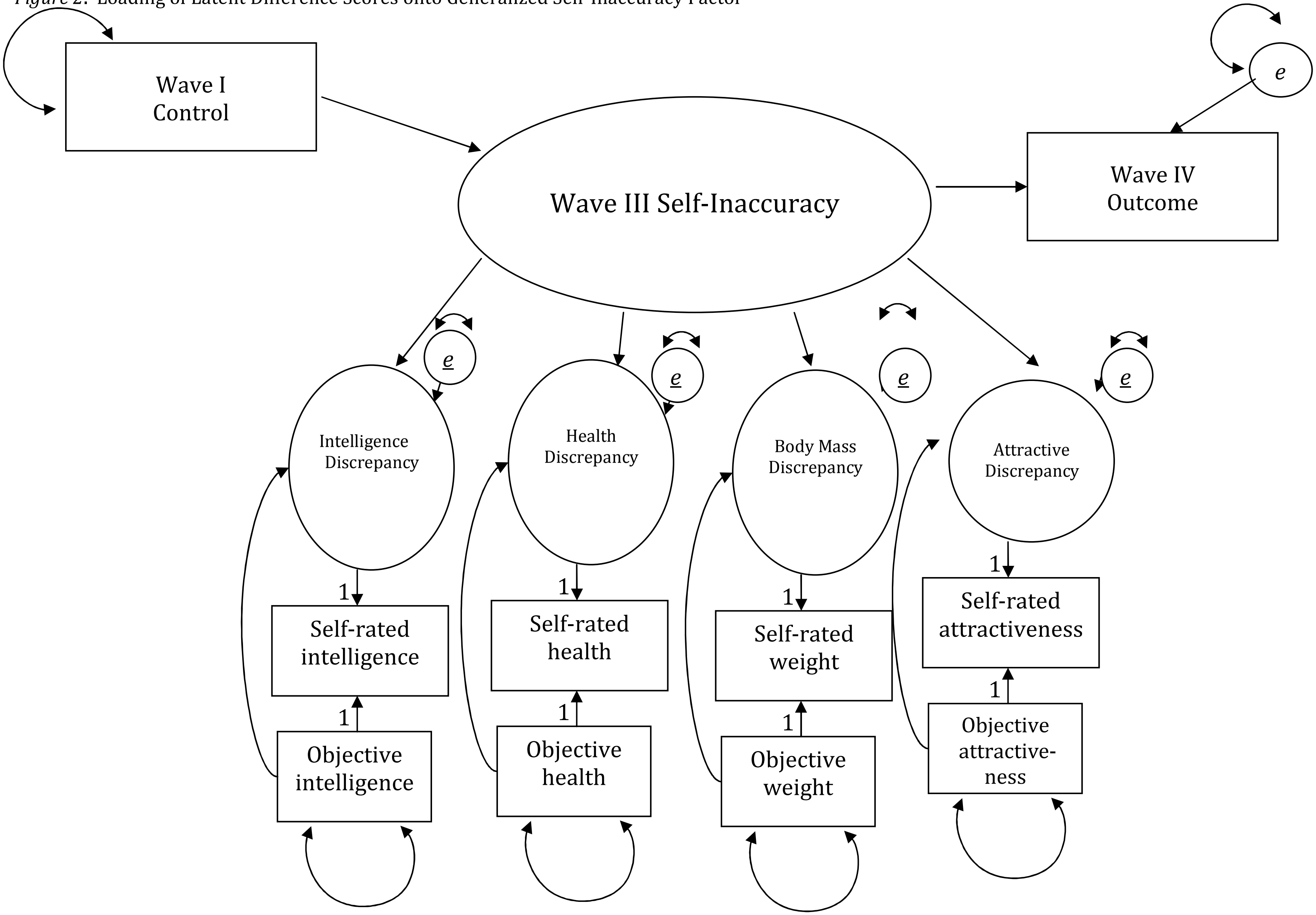
Table 5

*Standardized Results of the Longitudinal Models Predicting Wave IV Outcomes from Self-Discrepancy Scores, With Wave I Controls*

| | Outcomes | | | | |
|---|---|---|---|---|---|
| | Personal Earnings | Household Income | Job Satisfaction | Educational Attainment | Depression |
| | *b** | *b** | *b** | *b** | *b** |
| Effects of Wave I Controls on Discrepancy and Outcome | | | | | |
| Wave I Control on Intelligence Discrepancy | .06*** | -.09*** | .06*** | .12*** | -.06*** |
| Wave I Control on Health Discrepancy | .07*** | .10*** | .07*** | .07*** | -.18*** |
| Wave I Control on Body Mass Discrepancy | -.01 | .00 | -.01 | -.03* | .06*** |
| Wave I Control on Attractiveness Discrepancy | .00 | -.10*** | .00 | .01 | -.06*** |
| Wave I Control on Wave IV Outcome | .08** | .13** | .03* | .39*** | .28*** |
| Effects of Discrepancy on Outcome | | | | | |
| Intelligence Discrepancy on Wave IV Outcome | -.03† | .06*** | .03† | -.08*** | .05*** |
| Health Discrepancy on Wave IV Outcome | .05** | .07*** | .09*** | .08*** | -.10*** |
| Body Mass Discrepancy on Wave IV Outcome | -.05** | -.01 | -.01 | .04*** | .01 |
| Attractiveness Discrepancy on Wave IV Outcome | -.01 | .00 | -.03* | -.11*** | .03* |
| Correlations between Discrepancy Scores | | | | | |
| Intelligence w/ Health | .10*** | .10*** | .10*** | .10*** | .10*** |
| Intelligence w/ Body Mass | -.02 | -.02 | -.02 | -.01 | -.01 |
| Intelligence w/ Attractiveness | .16*** | .16*** | .16*** | .16*** | .16*** |
| Health w/ Body Mass | -.11*** | -.11*** | -.11*** | -.11*** | -.10*** |
| Health w/ Attractiveness | .16*** | .16*** | .16*** | .16*** | .15*** |
| Body Mass w/ Attractiveness | -.13*** | -.13*** | -.13*** | -.13*** | -.12*** |
| Model Fit | | | | | |
| *df* | 16 | 16 | 16 | 16 | 16 |
| $\chi^2$ | 330.353**** | 467.675**** | 195.768**** | 715.152**** | 250.575**** |
| CFI | .870 | .813 | 0.926 | .813 | .920 |
| TLI | .715 | .592 | 0.838 | .591 | .824 |
| RMSEA | .049 | .058 | 0.037 | .073 | .042 |

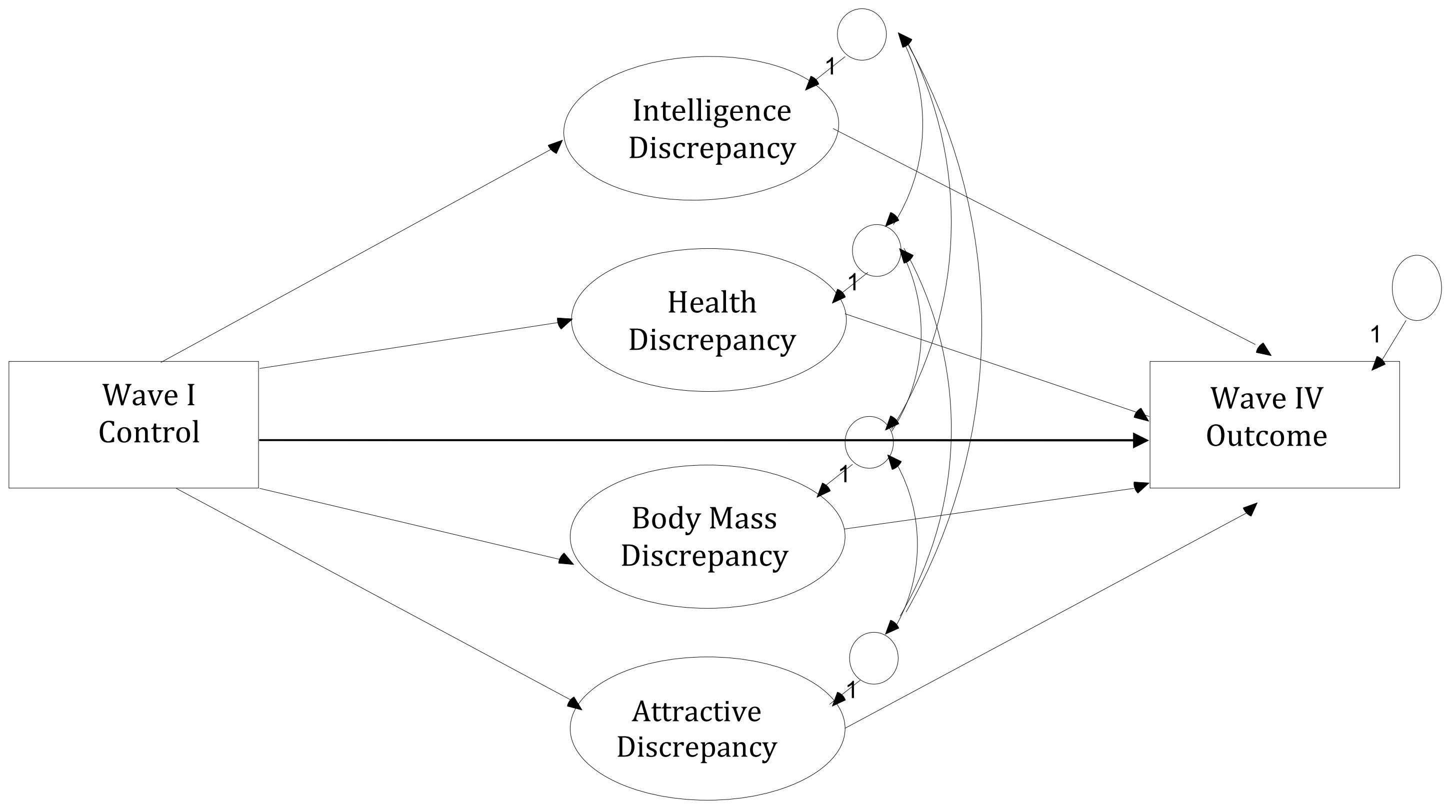
*Note*. $N$ = 8,283. Personal Earnings were transformed using a natural log transformation. The control variable for predicting Wave IV Personal Earnings, Household Income, and Job Satisfaction was Family Income to Needs Ratio. The control variable for predicting Wave IV Educational Attainment was Mother's Education. The control variable for predicting Wave IV Depression was Wave I Depression.
†$p$<.10. *$p$ < .05. **$p$ < .01. ***$p$ < .001. ****$p$ < .0001.

*Figure 2*. Loading of Latent Difference Scores onto Generalized Self-Inaccuracy Factor




*Note*. Means are estimated but not depicted for the sake of simplicity.

*Figure 3*. Prediction of Wave IV Outcome From Self-Inaccuracy Factor, Controlling for Relevant Wave I Variable




*Note*. Latent difference scores reflect latent difference between self-rated and objective measures in each domain. Means are estimated but not depicted for the sake of simplicity.