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“For the first time, I feel, scientific knowledge and mastery of physical nature can be matched by scientific knowledge and mastery of our moral nature. Natural science has changed the world; value science, too, once it is known, developed and applied, is bound to change the world.”

—Robert S. Hartman

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TABLE OF CONTENTS

About this Issue of the Journal

Articles

THE ICEBERG METAPHOR OF HUMAN COGNITION

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Abstract

This paper sought to verify or disprove the metaphor known as the "iceberg model" of human cognition. It is a report of an empirical study in which research participants ($N = 215$) were asked to complete two assessments related to human cognition, the Hartman Value Profile (HVP) and the Metacognitive Awareness Inventory (MAI) as a step towards determining if, indeed, people's conscious awareness of their thinking was derived from, and/or is similar to, their deep-seated, often unconsciously held thought patterns. This study revealed very little correlation between these two assessments and little or no ability of the HVP to predict a person's responses to the MAI. The author concluded, therefore, that these two instruments do, in fact, measure substantially different aspects of human cognition.

Introduction

I've been an avid student of Hartman's work since 2002. That's more than twenty years. Still, I find it difficult to explain to someone who is new to the theory of formal axiology what exactly it is that the Hartman Value Profile (HVP) measures. Hartman himself states that he HVP does not measure a person's values; rather, it measures the *structure* of those values (Hartman, 1967). When I phrase it that way, people are even more bewildered and ask, "What does that mean?" I've often been at a loss for words. I have better success when I borrow the phrase that I learned from Leon Pomeroy. I reply that the HVP measures a person's deep-seated, often unconsciously held, evaluative thought patterns (Pomeroy, 2005). That's still a mouthful, but it does convey quite a bit.

Lately, I've taken to using what I call the "iceberg metaphor" for describing human cognition and to illustrate what part of cognition the HVP measures. When you see an iceberg floating in the ocean, you only see the top 5% of it—the part that floats above the waterline. Fully 95% of the iceberg is under the water and unseen. Using this metaphor, I maintain that it's the same with human cognition. My contention is that we humans are only consciously aware of about 5% of our cognitive predispositions. The remainder are unconsciously held. Lakoff (1999, p. 18) uses exactly this same metaphor to make the same point. Freud once made the same analogy. Wilson (2002), in recalling Freud's use of this metaphor, insists that Freud was too generous to conscious awareness. Wilson writes: "When he said… that consciousness is the tip of the mental iceberg, he was sort off the mark by quite a bit—it may be more the size of a snowball on top of that iceberg" (p. 6). While most survey-based assessments capture only that small part of our cognition that is above the waterline, the HVP measures that which is below the waterline.

In a paper published five years ago, (Hurst, 2019), I elaborated on the concepts of cognition, metacognition, and metacognitive awareness. I used the iceberg metaphor in that paper. It was a paper in an academic journal, which meant that it went through what is known as a "blind" peer review process. That is, the manuscript—before it would be accepted for publication—was reviewed by two academics whose identity would not be known to me. Hence, their reviews were blind to me. One of the reviewers challenged my use of the iceberg metaphor. This reviewer asked, "Is this existence of a large part of human cognition being unconsciously held something you can validate, or is it merely a claim?" I had to admit that it was simply a claim. The reviewer commented that my argument would be stronger if I could validate it.

That reviewer's comment has been on my mind ever since. Might it be possible to validate that the HVP does, indeed, measure a different aspect of cognition than other, mostly survey-based, assessment measures? In pursuit of an answer, I've been collecting data to establish the validity of—or to point out the error in my thinking about—unconscious evaluative thought patterns. This paper presents preliminary findings and conclusions from this research.

Assessments Used

I used a computerized version of the HVP based on Hartman's version in the *Manual of Interpretation, 2nd Ed.* (2006). Both the word choices used in the assessment and the scoring methods were the same as those developed by Hartman. This allowed me to go to the source when comparing my results with the theory and its validations explained by Hartman in the Manual and Pomeroy (2005).

Following Hartman's original scoring methodology, it is essential to note that many subscales indicating stronger or more fully developed evaluative thought patterns are revealed as lower numbers than less well-developed ones. This is a crucial point to keep in mind for any reader who may be more familiar with the several published versions of the HVP that invert those raw scores and re-state them in terms of a 1to10 or 1 to 100 scale. That kind of inversion of scales makes the results easier to comprehend for people who are new to this instrument. Consequently, it makes comparisons with the *Manual of Interpretation* (2006) more difficult.

In this study, lower HVP scores are often stronger than higher scores on most—but not all—of the HVP subscales. For instance, dimensions of the intrinsic, extrinsic, systemic, differentiation, dimension, integration, and distortion scales are stronger when scores are lower, and weaker when the scores are high. This is because, in Hartman's original methodology, lower scores indicate less deviation from the theoretical norm of formal axiology.

The main exceptions to this rule are Spearman's Rank Order Correlation Coefficients, also known as Rho scores. Rho scores on each part of the HVP can range from -1.0 to 1.0. Scores approaching +1.0 are most closely aligned with the theoretical norm of formal axiology. According to Hartman, most respondents who are not facing undue stress or tension in their lives tend to score in a range greater than 0.7 (Hartman, 2006). Mean Rho scores in the current data set tend to vary more widely than they do for other sets of data I have seen (Hurst and Rama, 2015). This is likely because the current sample is drawn primarily from young adult college students.

It is also important to remember that the HVP assessment does not have a single summary score. At the highest level are two Rho scores, one each for Part 1 and Part 2 of the instrument, which best describe a respondent's results.

When studying for that previously mentioned paper (Hurst, 2019), I first learned of a survey-based instrument measuring metacognitive awareness that is widely used, validated, and reliable (Schraw & Dennison, 1994). It is known as the Metacognitive Awareness Inventory (MAI). I refer to it as a survey-based instrument because the respondent answers questions about metacognitive awareness consciously. Schraw and Dennison validated their instrument using a response scale from 1 to 100. Some versions of the MAI use a Likert scale; I chose a version that uses a yes/no response to each of the 52 items in this assessment. For instance, one of the 52 statements asks the respondent to answer Yes or No to the statement: "I think of several ways to solve a problem and choose the best one." Scores on this version of the MAI can, therefore, range from 0 to 52, with scores at the upper range reflecting more fully developed self-reported metacognitive awareness.

Scores are clustered into seven subscales, each of which rolls up into one of two categories: *Knowledge about Cognition* and *Regulation of Cognition*. Subscales known as *Declarative Knowledge, Procedural Knowledge*, and *Conditional Knowledge* comprise the category of *Knowledge about Cognition*. Sub-subscales of *Planning*, *Information Management Strategies*, *Comprehension Monitoring, Debugging*, and *Evaluation* comprise the category of Regulation *of Cognition*. Together, scores of the *Knowledge about Cognition* and *Regulation of Cognition* subscales comprise the overall MAI score.

You can experience the MAI by simply searching for Metacognitive Awareness Inventory. You will find several hand-scored versions of this assessment that you can download and respond to, as used by Lafayette College, Rowan College, and the University of Iowa.

Research Hypothesis

If my iceberg metaphor is correct—meaning that a person's above-the-waterline, consciously held thought patterns have very little in common with that person's below-the-waterline unconsciously held evaluative thought patterns—then a comparison study would show very little or no correlation between HVP and MAI indices and little or no ability for HVP scores to predict MAI scores within a population. If that is the case, I could conclude that the HVP and the MAI (and, by proxy, other survey-based measures of metacognition) measure different aspects of human cognition. One cannot be substituted for the other.

Suppose correlation and linear regression analysis show that correlation and prediction are mainly absent. In that case, one can conclude that a person's scores on the HVP have very little ability to predict that person's MAI scores. I could then further conclude that what people consciously say they know about their metacognitive awareness does not tell a complete story. The unconscious mind has a vital role in the study of cognition and, to my knowledge, the HVP is the first and only assessment instrument that identifies a person's below-the-waterline cognitive habits.

Review of Empirical Studies using the HVP

In describing his purpose in writing *The New Science of Axiological Psychology*, Pomeroy (2005) lamented the lack of empirical support for Hartman's theory of formal axiology. He writes that the culture of psychological research "demands empirical evidence to support all theoretical activity." (p. xv). He summarizes both the purpose and the limitations of his contributions to the field of formal axiology in the following manner:

> My research supporting Hartman's work needs replication by independent investigators to achieve a critical mass of credibility and leap into popular culture and politics. The conservative aspect of science demands evidence, proof, facts, and ruthless empirical support all along the way. My work is a successful pilot study, demonstrating flexibility and practicality. I challenge others to replicate these empirical findings that support axiological psychology (p. 26).

Since the publication of Pomeroy's book, axiologists, who have been writing in this journal and elsewhere, have begun to expand the empirical support of formal axiology that Pomeroy initiated.

Such studies have accelerated within the past five years, growing from a trickle to a steady stream. No single article conclusively validated the HVP's validity and reliability. Still, recent studies are beginning to demonstrate the effectiveness of using the HVP to understand human judgment, cognition, emotions, and behavior. These recently published studies generally take one of three approaches.

First Approach

Some studies used the HVP to measure similarities and differences among different groups using the same instrument—the HVP. Such were Pomeroy's (2005) samples of inter-cultural differences measured by the HVP and his pilot study of psychiatric outpatients and the doctors who treated them.

Acquaviva (2015) asked, "Can axiological testing distinguish between unprincipled individuals and others who are guided by morality?" Echoing Pomeroy, cited earlier, he continued, "Only empirical scientific research can answer this beyond speculation" (p. 119). His 2015 article in this Journal summarized his empirical findings, which he elaborated upon in greater detail in his book *Values, Violence, and Our Future (2000)*.

Hurst (2019) continued with this method of using one instrument to analyze similarities and differences among two or more groups when he compared and contrasted HVP scores of early-stage entrepreneurs and senior managers.

Second Approach

A second approach used the HVP and at least one other measure with the same sample of respondents to see to what extent one or other of these measures predict significant outcomes. This is the approach taken by Pomeroy (2008) in the inaugural publication of this Journal, wherein he reported on a pilot study of medical students through which he undertook to determine whether, and to what degree, a medical school student's HVP scores predicted that person's performance on various measures used to accept students into medical school. Such other measures included interviews, the MCAT exam, and grade-point averages. His sample was small at 55, requiring him to use a split-halves testing model. His preliminary findings were that a person's HVP scores, particularly their Rho_2 scores, predicted a person's interviewing skills. He concluded, "This is not surprising given the fact that Rho_2 is a marker of self-esteem, personal efficacy, and the apprehension of purpose and meaning" (p. 148).

Axiologist and Professor Malcolm North has led the way, often with co-authors, in conducting empirical studies that invoke the HVP with other measures of various leadership characteristics. In 2019, North, Nelson, and Hurst published in the *Journal of Scholarly Engagement* their report of findings using the HVP, the Authenticity Scale, and the Authentic Leadership Inventory (ALI). The Authenticity Scale is a self-report scale based on the work of Carl Rogers. The ALI is a 360-degree survey that measures employees' perceptions of their leaders. They concluded, "This study provided evidence that value judgment significantly interacts with personal congruence, authenticity, and authentic leadership and is a predictor of overall congruence and intrinsic judgment in leadership" (p. 84).

In 2021, Clowney Johnson and North published the results of their study of ethical leadership and its opposite, toxic leadership. They used the HVP, the Moral Foundations Questionnaire, and the Dark Triad Dirty Dozen assessment with a sample of 374 diverse adults across the United States in health, education, business, and politics. They concluded that "the potential of value judgment to predict the value structure of ethical and toxic leaders was demonstrated and should aid organizations in various leader development, hiring, and recruiting functions." (p. 59).

A similar theme was pursued by Dunbar and North (2023) using a different assessment known as the Leader's Ethical Orientation scale and the HVP to determine if a person's HVP scores can significantly predict a leader's ethical type. They concluded, "This study…showcased the power of value judgment, using the HVP, and its potential to identify strengths and weaknesses in elected officials' value structure and predict when those become self-serving"(p. 70).

In 2023, Weinkauf published a report on her dissertation research involving transformational leadership in this Journal. She used the Multifactor Leadership Questionnaire coupled with the HabitFinder™ version of the HVP to explore the nature of transformational leadership (Weinkauf, 2023). As a field of inquiry, transformative leadership focuses on the effect on employees' job satisfaction, mental health and well-being, driven by their leaders' characteristics and behaviors. Weinkauf explained, "The significance of this study was to understand what is beneath the surface of a leader's thought process and begin understanding what drives their behavior" (p 23).

Third Approach

A third approach to empirical studies using the HVP is to conduct longitudinal studies—that is, studies of changes in people over time as measured by the HVP in some pre- and post-engagement contexts. In this instance, the engagement usually involves some form of leadership coaching, training, or development program between the pre-test and post-test. Longitudinal studies are rarer than other kinds simply because data collection takes a long time. Nonetheless, two longitudinal studies have recently been published in this Journal.

Jaimes-Bautista and Zenion (2021) reported on their longitudinal study of teachers' role in influencing students' ethical and moral foundations. They used the Acutest™ version of the HVP for their research to analyze changes in educators' value judgments over four years. Their results are particularly intriguing, as the period of time in which they took their sample (2017 to 2021) included the year of educational remote learning due to COVID-19. Their study showed an improvement in teachers' overall ability to value the outside world during Covid (p. 45). This improvement, the authors deduce, stemmed partly from teachers' already highly developed evaluative capacities. This gave them the energy, creativity, and resilience to adjust to the demands of teaching remotely during Covid. In the authors' words: "It is also possible that with the pandemic, the risk of dying, losing a loved one, getting sick, losing a job or material goods and living under uncertainty, have become factors that have changed the way we value people, the world and ourselves. Perhaps it has allowed us to see more clearly, what is essential: life and the people who live it" (p. 47).

Rodiles-Hernandez (2023) reported in this Journal of a pre- and post-test using the HVP in a clinical setting with a small number of participants. She emphasized the importance—and the difficulty—of getting all participants to complete both the pre- and the post-tests. She concludes, "the findings of this study are compatible with other studies that have evaluated in pre–post designs the impact of interventions, finding both positive changes and some setbacks in certain areas" (p. 87).

In the 2019 Journal, Nicoletti reported on an empirical, axiological, longitudinal study of their use of the HVP at the Yale New Haven Health System's Institute for Excellence. Acknowledging the influence of Byrum's work in this area, Nicoletti wrote, "the HVP seems to hold a key, especially regarding its sophistication for 'opening up' the whole person to conversation that can foster insight and self-awareness critical for development. This is made possible by the assessment's breadth and depth…." (p. 51). The comprehensiveness and complexity of insights gained from studying the HVP are the very things that give it its power to aid in human development. Yet, this same complexity is a bane to empirical researchers who want quantitative answers to theoretical questions. In an effort to bring order to complexity, Nicoletti here made creative use of alluvial diagrams to illustrate changes over time in people's tendencies to lead with I, E, or S dimensions of thought in both the external and internal world. He also discussed the importance of looking at CQ1 and CQ2 scores in both pre-and post-test responses in future longitudinal studies.

My goal in the current article is to continue this growing body of empirical studies. None of them establishes the reliability or validity of the HVP alone, but together, they form a growing body of evidence of its usefulness—and limitations—as an empirical tool.

Methodology

Adapting to Norms of Quantitative Research

The way in which quantitative research hypotheses are normally constructed presented me with a quandary. My assumption was that the two instruments I have chosen (the HVP and the MAI) measure something different, and if that is true, there will be very little correlation between them. Also, if there is very little correlation, there cannot be much causation, either. What quantitative researchers call a null hypothesis would validate my assumption. However, this way of approaching a research project is contradictory to the way that quantitative research is customarily undertaken. Researchers customarily craft a research hypothesis stating that a correlation and, possibly, causation will exist between one measuring tool and another. They use the null hypothesis as a sort of foil against which to demonstrate if the research statement is valid or not.

To stay consistent with standard research protocols, I will restate my research hypothesis as though my goal was to establish that respondents' scores on the HVP do predict their scores on the MAI in a meaningful way.

Spoiler alert: My finding is that the HVP is not very predictive of MAI scores.

How did I get there? It begins with stating a null hypothesis. In this study, I will describe two types of variables. One type is known as the independent variable or variables, sometimes called predictor variables. The HVP and its many subscales will be my independent predictor variables. The other is known as the dependent variable, or sometimes as the response variable. I will consider the MAI to be the dependent response variable. This means that when I formulate my research hypothesis, I expect, to some greater or lesser extent, that a person's MAI scores will respond to or be dependent upon that person's HVP scores. My expectation is that stronger (often meaning lower) HVP scores will predict stronger, that is, higher MAI scores. The strength of the prediction to be meaningful is debatable. Therefore, I take several approaches with multiple iterations to come up with a solid answer. In a spirit of full transparency, I'll describe throughout this paper the methods I used to investigate this hypothesis, the rationale behind the selection of scales I used, how I came up with the relations I found, and what conclusions I derived from those findings. By describing my thought process as well as my findings, I hope to aid the reader to understand better some of the opportunities and the potential pitfalls of using the HVP in quantitative studies.

It is customary for researchers to state a null hypothesis as referring to the population under study and for the research hypothesis to refer to the sample obtained. The population that I refer to here incudes literate adults who speak and write English well. The assessments were administered by an online response, which required both access to an internet-connected computer and the ability to read and respond to written instructions. Both assessments I used were written in English, hence I cannot pretend to measure the cognitive patterns of people who speak languages other than English. Given the expectations of Institutional Review Boards, I am not permitted to include assessment responses from anyone under the age of 18. So, all of my respondents are adults. Because my respondents were largely solicited among university students, the average and median age of my sample is skewed to younger adults.

Consequently, the revised null hypothesis in this case is that there is no significant or meaningful relationship between people's unconsciously held evaluative thought patterns, as measured by the HVP, and their metacognitive awareness, as measured by the MAI. In addition, the null hypothesis infers that any correlation or relationship that does appear may be due largely to chance.

My research hypothesis is that stronger (often lower) HVP scores in this sample can be used to predict a person's MAI scores because unconsciously held evaluative thought patterns impact one's metacognitive awareness. Specifically, stronger HVP scores are predicted to lead to stronger (higher) MAI scores.

Data Analysis Plan

I followed the guidelines for statistical analysis advocated by Salkind (2011) and Frost (2019) in exploring this research hypothesis. This means I started with descriptive statistics, paired with various graphic depictions of my data, followed by correlation analysis, then regression analysis, using each of these tools in an iterative way while looking at various scales and subscales of each of these two instruments. All data analysis shown here was performed within Excel, using the optional Data Analysis Toolpak available within Excel. I will explain next how I conducted data analysis and what I found at each step along the way.

Results

Rho_1 and Rho_2 HVP Scores Compared with MAI Scores

I chose to start by exploring the highest-level overall scores first. There is no single overall score for the HVP. Two measures do provide high-level overall scores for each of Part 1 and Part 2 of the HVP (Pomeroy, 2005, pp. 40 and 53). These are the rank-order correlation coefficients, represented by Spearman's Rho. I refer to them as Rho_1 and Rho_2. Rho scores of the HVP show how closely in accord with the theoretically correct ranking of the 18 words or phrases from each of the two parts of the index a respondent's answers are. Part 1 focuses on the person's view of the outside world, often referred to as the world view of the HVP. Part 2 focuses on the person's view of him/herself, often referred to as the self-view of the HVP.

Visually Representing Descriptive Data

Salkind and Frost exhort researchers to display their data visually before analyzing it numerically. I followed their advice. The following two histograms showed that both Rho_1 and Rho_2 scores were highly skewed (See Figures 1 and 2). That is, they did not form a normal, bell-shaped curve. This may indicate that the data was not structured appropriately for parametric statistical tools to compare them with the MAI, which was monitored throughout the analysis. Additional summary data for the two histograms is provided in Table 1.

Figure 1

Histograms of Rho_1 and Rho_2, N = 215

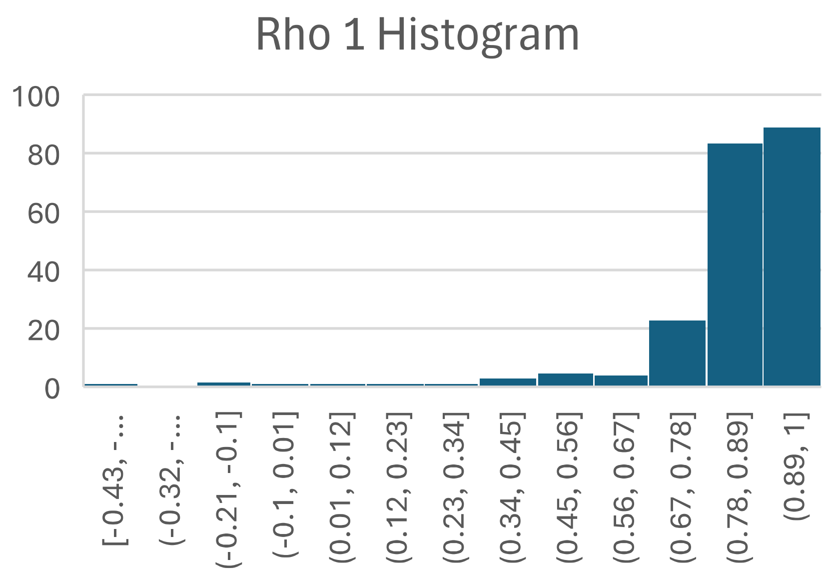


Figure 2

Histograms of Rho_2, N = 215

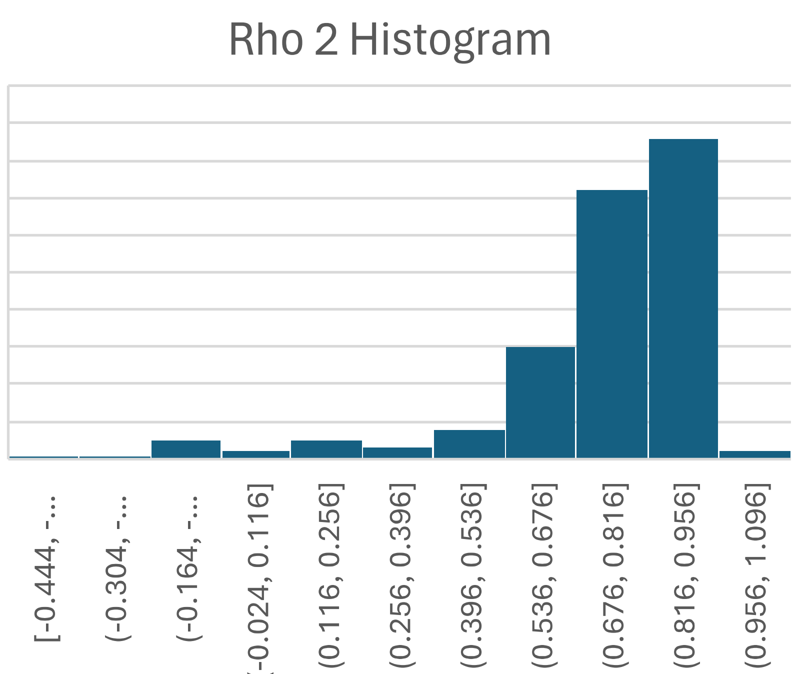


Table 1

Summary Data for Rho_1 and Rho_2 Scores

	Rho_1		Rho_2
Mean	0.82	Mean	0.72
Median	0.88	Median	0.79
Mode	0.92	Mode	0.8
Minimum	-0.43	Minimum	-0.44
Maximum	0.97	Maximum	0.97

N = 215

MAI scores, on the other hand, were more normally distributed. Figure 3 and Table 2 show a histogram and summary data for the MAI scores in this data set.

Figure 3

Histogram for MAI Scores

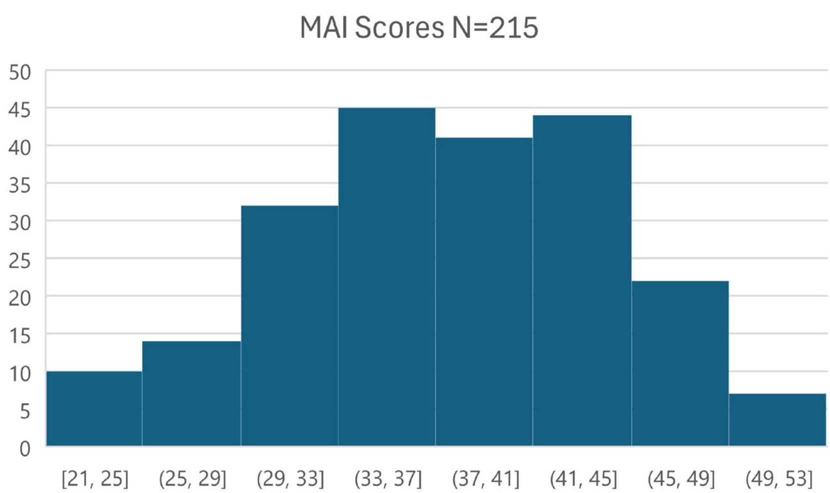


Table 2

Summary Data for MAI Scores

	MAI
Mean	37.98
Median	38.00
Mode	39.00
Minimum	21.00
Maximum	52.00

N = 215

Correlations

After visually reviewing the data and studying these summary statistics, the next step is to evaluate the correlations between variables. Frost (2019) states, "A correlation between variables indicates that as one variable changes in value, the other variable tends to change in a specific direction. Understanding that relationship is useful because we can use the value of one variable to predict the value of the other variable" (p. 5). This is known as the correlation index or correlation coefficient. Like Rho scores, correlation values can range from -1.0 to 1.0. Since larger Rho scores are stronger, I predicted that higher Rho scores correlate positively with higher MAI scores.

There is no single best answer to the question, "How large of a correlation is enough to establish that they tend to move with each other?" A typical rule of thumb for interpreting correlation coefficients is explained in Table 3, taken from Salkind (2011, p. 88):

Table 3

General Interpretation Guide for Correlation Analysis

Size of the Correlation	Interpretation
0.8–1.0	Very strong relationship
0.6–0.8	Strong relationship
0.4–0.6	Moderate relationship
0.2–0.4	Weak relationship
0.0–0.2	Weak or no relationship

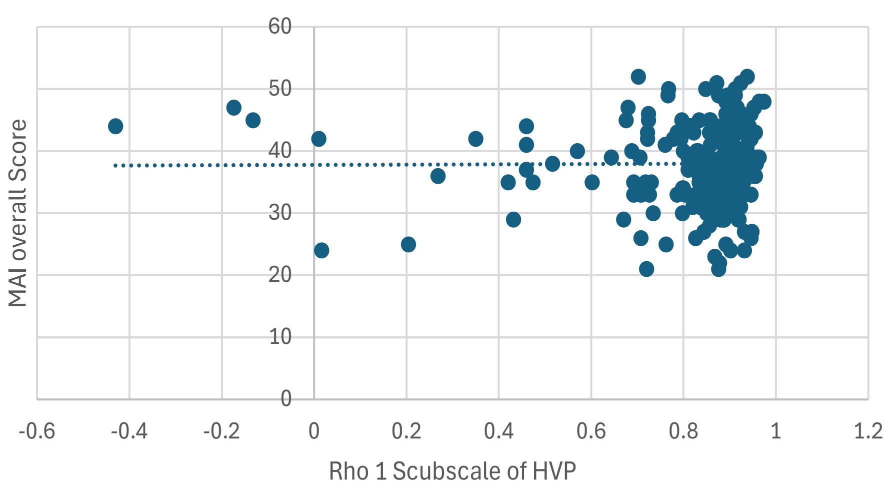
I discovered that the correlation between Rho_1 and MAI scores was only 0.01. This implies only a 1% correlation between Rho_1 and MAI scores in the sample.

Scatterplots

When interpreting correlations, viewing them graphically as scatterplots is often helpful. Figure 4 shows a scatterplot of Rho_1 scores compared to MAI scores for this sample.

Figure 4

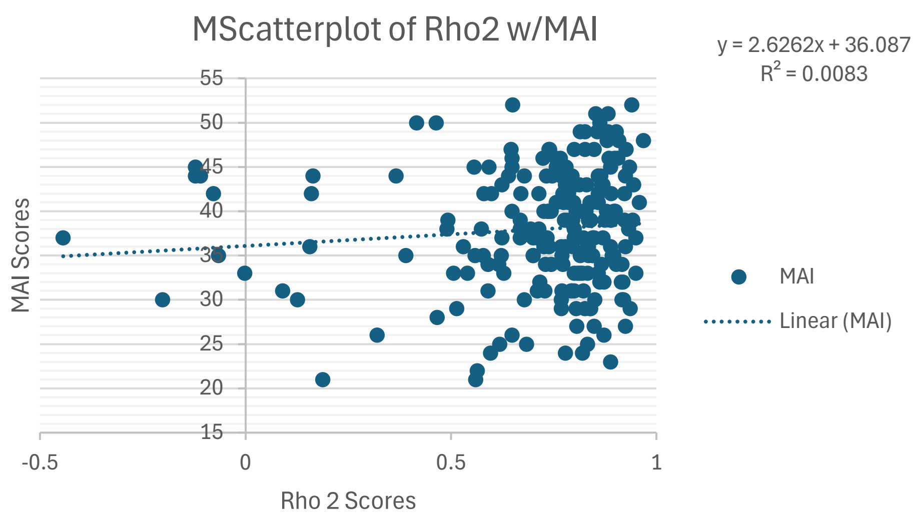
Scatterplot of Rho_1 v MAI Scores



The correlation coefficient between Rho_2 and MAI is 0.09. It is a positive correlation, as expected, and although it is stronger than the Rho_1 correlation, it is still weak. A scatterplot of Rho_2 with MAI scores is shown in Figure 5.

Figure 5

Scatterplot of Rho_2 with MAI Scores



The next typical step in analyzing data of this sort is to perform a regression analysis. Notice that data for the Rho_1 and Rho_2 scores were clustered towards these graphs' right (upper) end. This indicated that the data are highly skewed. Running a regression analysis with skewed data can lead to inaccurate or misleading results. Therefore, it is common statistical practice to "standardize" or "normalize" such data by converting them to *z*-scores scores before performing regression analysis. Skewness is typically resolved after converting to standardized scores, since standardized scores are measured in terms of how far they are from the mean score and expressed in standard deviations. *Z*-scores are derived by subtracting the mean score from the individual score and dividing by the standard deviation. This can be done within Excel, using the formula "=(standardize….)." A challenge with using standardized scores is that they can be difficult to understand.

I standardized the Rho_1, Rho_2, and MAI in this sample before running a multiple linear regression using Rho_1 and Rho_2 as the independent or predictor variables and MAI as the dependent or outcome variable. I repeated the same process without standardizing the scores. I concluded that the results were similar both ways. However, it is clearer to understand without standardizing them. Therefore, I am presenting the non-standardized multiple linear regression analysis results below. The following results, shown in Table 4, are produced in Excel, rounded to 2 decimals. I have also omitted related but largely extraneous output produced by Excel.

Table 4

Regression Analysis of Standardized Rho_1 and Rho_2 Scores with MAI Scores

Regression Statistics		
R-squared	0.01	
Observations	215	

	Coefficients	*p*-value
Intercept	36.74	0.00
Rho_1	-1.10	0.67
Rho_2	2.97	0.16

For the data set, the R-squared is one percent. According to Frost (2019), "R-squared is a primary measure of how well a regression model fits the data. This statistic represents the percentage of variation in one variable that other variables explain." (p. 16). In this sample, respondents' Rho_1 and Rho_2 scores together predicted only one percent of the changes in MAI scores.

Furthermore, it allowed interpretation of the effect of the two independent variables on the dependent variable, which I express in the following way: for every one-unit increase in Rho_2, a respondent's MAI score is predicted to rise by 2.97, holding Rho_1 constant. Additionally, for every one-unit change in Rho_1 a respondent's MAI is expected to decrease by -1.10, holding Rho_2 constant.

Next, the *p*-values are considered. A *p*-value indicates the likelihood that the relationship between variables could occur by chance. A low *p*-value helps reduce the possibility the observed difference happened by chance. In social sciences, it is typical to describe "low" as being $p < .05$. This means that across 100 samples of the population, fewer than 5% of them would reflect differences other than what I have found here. A *p*-value of less than 5% would give a relatively high level of confidence that the sample is, in fact, reflective of the population.

The *p*-values of 0.67 and 0.16, respectively, indicated a high probability that any change in the independent variables influencing the dependent variable was due to chance. The regression analysis supports a tentative conclusion from studying the summary data and correlations and from viewing the graphic displays of the data that there is not much likelihood that respondents' Rho_1 or Rho_2 scores predict their MAI scores to a meaningful extent. Of these two independent variables, Rho_2 scores predicted an individual's MAI scores more. However, the predictive value of Rho_2 scores was slight.

The residual plots produced by Excel may help discern whether the relationship between each of the independent variables and the dependent variable was, in fact, linear. The residual plots indicated that Rho_1 and Rho_2 scores were linearly related to MAI scores, which reinforced the decision to use linear regression techniques rather than non-linear regression techniques in this project. The residual plots are shown in Figures 6 and 7. Perhaps other key variables of the HVP could better predict MAI scores.

Figure 6

Residual Plot of MLR with Rho_1 with MAI Scores

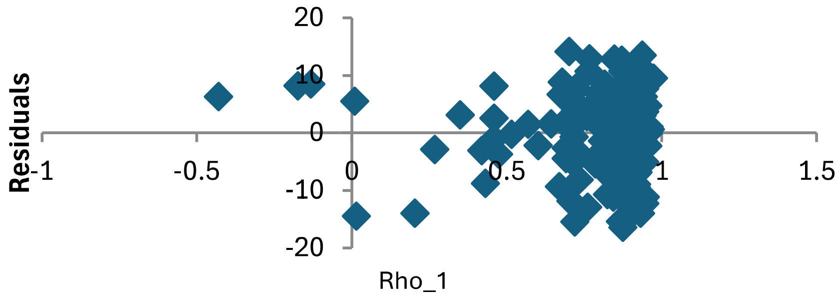
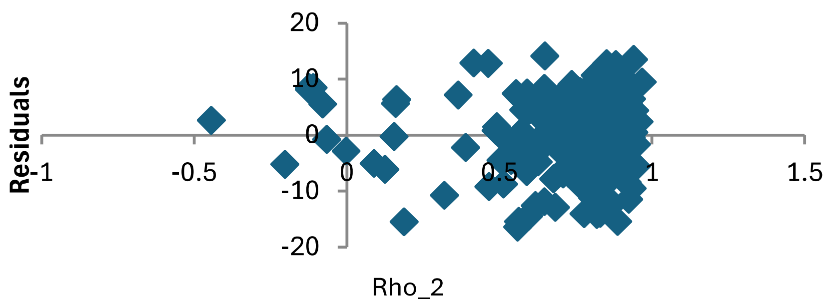


Figure 7

Residual Plot of MLR with Rho_2 with MAI Scores



Other Variables

So, neither the Rho_1 nor Rho_2 nor both together did much to predict MAI scores. However, there are about 50 other variables of the HVP to consider. Statisticians warn against trying to "overfit" the data, which would be like trying to make a mountain out of a molehill. Nevertheless, it may be wise to experiment a bit more.

The Big Four

Hartman (2006) called the differentiation (Dif), the dimension (Dim), the integration (Int), and the distortion (Dis) scores the "Big Four" indices of the HVP. I followed the same process as described above for analyzing these big four, starting with Part 1 and proceeding to Part 2 of the HVP. I created histograms, developed summary scores, drew scatterplots, derived correlations between them and the MAI, converted them to standardized z-scores, and then performed simple and multilinear regression analyses with and without standardized scores. Summary statistics for these Big 4 (x2) are shown below in Table 5.

Table 5

Summary Statistics for Big Four HVP Subscales, Parts 1 and 2

	Dif_1	Int_1	Dim_1	Dis_1	Dif_2	Int_2	Dim_2	Dis_2
Mean	41	17	12	2	52	26	15	3
Median	36	12	11	2	48	21	13	2
Mode	32	8	9	2	46	15	12	0
Minimum	16	0	0	0	18	1	1	0
Maximum	140	105	40	10	142	107	60	14

$N = 215$

Without belaboring the entire process, Table 6 describes what multiple regression analyses of these indices revealed.

Table 6

Multiple Regression of Dif_1, Int_1, Dim_1, and Dis_1 Scores with MAI Scores

Regression Statistics		
R-squared	0.03	
Observations	215	

	Coefficients	*p*-value
Intercept	35.49	0.00
Dif_1	0.05	0.75
Dim_1	0.21	0.01
Int_1	-0.13	0.47
Dis_1	0.06	0.87

The R-squared shows that only about 3% of the change in MAI scores is explained by differences in these four indices from Part 1 of the HVP. However, only one variable has a *p*-value of less than 0.5, which means that only the dim_1 score predicts MAI confidently, with a low probability that this relationship occurred by chance. While holding Dif_1, Int_1, and Dis_1 scores constant, a one-unit change in Dim_1 scores will predict a 0.21-point change in MAI scores.

Remember, MAI scores can range from 0 to 52, with the sample's mean MAI score of 38. Hartman (2006) states that the "Dim_1 score varies in practice between 0 and 40 and in theory between 0 and 60," with 0–3 being excellent and 20–23 very poor (p. 52). The sample's mean score for Dim 1 is 12, which Hartman labeled "Very Good." Respondents' scores in the sample ranged from 0 to 40.

The same analysis for Part 2 Dif, Dim, Int, and Dis scores showed a slightly stronger but still very slight influence on MAI scores, as shown in Table 7.

Table 7

Multiple regression of Dif_2, Int_2, Dim_2, and Dis_2 scores with MAI scores

Regression Statistics		
R-squared	0.05	
Observations	215	

	Coefficients	*p*-value
Intercept	43.21	0.00
Dif_2	-0.22	0.14
Dim_2	0.00	0.98
Int_2	-0.32	0.08
Dis_2	-0.76	0.01

Here, the R-squared shows that about 5% of the change in MAI scores is explained by differences in these four indices of the HVP. However, only the Dis_2 had a *p*-value of $< .05$. The observed impact of the other three indices was too likely to be happening by chance to put much faith in them. For each one-unit increase in the Dis_2 score, a 0.76-unit decrease in the MAI is predicted. A negative correlation is expected, as lower Dis_2 scores are stronger scores.

Hartman states, "The Dissimilarity Score measures the subject's Propensity to Value Distortion, that is, towards confusion of valuation and disvaluation" (p. 54). Dis scores can range from 0 to 8+ (See Table 8). Dis_2 scores ranged from 0 to 14 in the sample, with a mean of 3.

Table 8

Descriptions of Dis Scores in HVP

Dis score	Descriptor
0	Excellent
2	Good
4	Average
6	Bad
8+	Very Bad

Fundamental scores of Dim_i, Dim_e, and Dim_s

Since each of the "big four" of the Dif, Dim, Int, and Dis are, in themselves, factors derived from other HVP scores, perhaps the more basic indices of the HVP related to each of the Intrinsic, Extrinsic, and Systemic dimensions measured by the HVP in both Parts 1 and 2. I'll abbreviate those as Dim_i, Dim_e, and Dim_s, and will designate whether I am talking about Part 1 or Part 2 by appending a number to the end of each abbreviation, as in Dim_i_1 or Dim_s_2. A summary of the descriptive statistics for these subscales of the HVP is shown in Table 9 below.

Table 9

Summary Statistics for Dim I, E, and S, Parts 1 and 2 of HVP

	Dim_i_1	Dim_e_1	Dim_s_1	Dim_i_2	Dim_e_2	Dim_s_2
Mean	13	13	16	15	19	18
Median	10	11	14	13	17	16
Mode	9	10	15	11	17	15
Minimum	2	2	4	2	2	3
Maximum	57	48	52	54	55	50

N = 215

Hartman (2006) described how Dim I, E, or S scores can range from 0 to 43+, with lower scores being stronger. Table 10 shows Hartman's descriptions for the various score ranges. Respondents in the sample averaged generally Good and Very Good Part 1 scores and typically Good Part 2 scores.

Table 10

Score Description of Dim I, E, and S Scores in HVP

Score	Description
0–7	Excellent
8–14	Very Good
15–21	Good
22–28	Average
29–35	Poor
36–42	Very Poor
43+	Extremely Poor

Histograms show these scales were skewed but less so than the Rho scores. Hence, I chose not to standardize these scores once again. Table 11 shows a regression analysis of the six measures with the MAI as the dependent variable.

Table 11

Regression Analysis of Dim I, E, S, Parts 1 and 2 with MAI Scores

Regression Statistics	
R-squared	0.04
Observations	215

	Coefficients	*p*-value
Intercept	39.57	0.00
Dim_i_1	0.03	0.72
Dim_e_1	0.02	0.88
Dim_s_1	-0.04	0.71
Dim_i_2	-0.16	0.03
Dim_e_2	0.09	0.19
Dim_s_2	-0.05	0.51

The R-squared showed that only about 4% of the change in MAI scores can be predicted by changes in these six subscales of the HVP. The likelihood of the observed influence of one upon the other being due to chance exceeds the threshold of 0.05 for each of the sub-dimensions of the HVP except the Dim_I_2, whose *p*-value is 0.03. The coefficient for Dim_I_2 indicated that for every one unit change in the Dim_I_2 score, holding all other variables constant, a -0.16 unit decrease in the MAI can be predicted. This negative correlation was expected, as lower Dim I_2 scores are stronger than higher scores. From this regression analysis, the Dim_I_2 variable was the only one with any meaningful and significant impact on MAI scores. Although, its effect was slight.

Expanded Analysis Using 46 Subscales of the HVP

I performed a correlation analysis using 46 commonly identified HVP and MAI subscales. Analysis revealed that only one HVP subscale correlated above .02: the Ai%_2 subscale. Its correlation coefficient with the MAI was -0.21, barely creeping above a weak correlation. Not willing to rely solely on this cutoff, I investigated which HVP subscales correlated with the MAI at> .15. Table 12 shows the four subscales that did.

Table 12

Correlation of 4 subscales of HVP with MAI scores

Subscale of the HVP	Its correlation with MAI scores
Dim%_1	0.18
Dim_i_2	-0.16
Dis_2	-0.18
Ai%_2	-0.20575

The Ai%_2 and Dis_2 were most highly correlated with MAI scores. However, covariance may have been an issue. If any scales among independent variables are highly correlated, then the variables should be removed in a regression analysis related to the dependent variable. One of these four subscales comes from Part 1 of the HVP, so it was unlikely to co-vary with the three subscales from Part 2. On the other hand, the other three correlated very strongly with each other, as depicted in Table 13.

Table 13

Correlations of the four Subscales of HVP with MAI

	Dim%_1	Dim_i_2	Dis_2	Ai%_2
Dim%_1	1	-0.08	-0.08	-0.87
Dim_i_2		1	0.72	0.68
Dis_2			1	0.94
Ai%_2				1

Only slight correlations existed between the Dim%_1 score and the other three subscales from Part 2 of the HVP. This was expected, as Parts 1 and 2 are scored entirely differently. However, the strong correlations among the three Part 2 scores were problematic and could lead to incorrect conclusions if all variables were used in a regression analysis. Therefore, I calculated another regression analysis using only the Dim%_1 and the Ai%_2 scores to see how much change in MAI scores they may, together and separately, predict. Below are summary statistics for the sample's Dim%_1 and Ai%_2 subscales of the HVP.

Table 14

Descriptive Statistics for Dim%_1 and Ai%_2 Subscales of HVP

	Dim%_1	Ai%_2
Mean	31	62
Median	30	60
Mode	50	50
Maximum	0	50
Minimum	90	99

N = 215

Hartman (2006) described the range of possible Dim%_1 scores in the following manner: "The relative Dimension Score (Dim%) measures the person's sense of meaning, both of himself and of the world. The score varies in practice between 0 and 128" (p. 52). The mean score in the sample reflected an "Average" sense of meaning of him/herself.

A scatterplot revealed an interesting aspect of Ai%_2 scores that is not readily evident from Histogram or summary data alone but is made clear with a scatterplot, shown in Figure 8. As the scatterplot indicated, 70 out of 215 scores in the sample were at the strongest possible score of 50 (or 50%). This could have indicated heteroscedasticity within the data and could be problematic when conducting linear regression. Therefore, caution must be exercised when interpreting regression results with Ai%_2 scores. Table 14 shows the results of multiple linear regression with these two subscales of the HVP and the MAI.

Figure 8

Scatterplot of Ai%_2 and MAI Scores

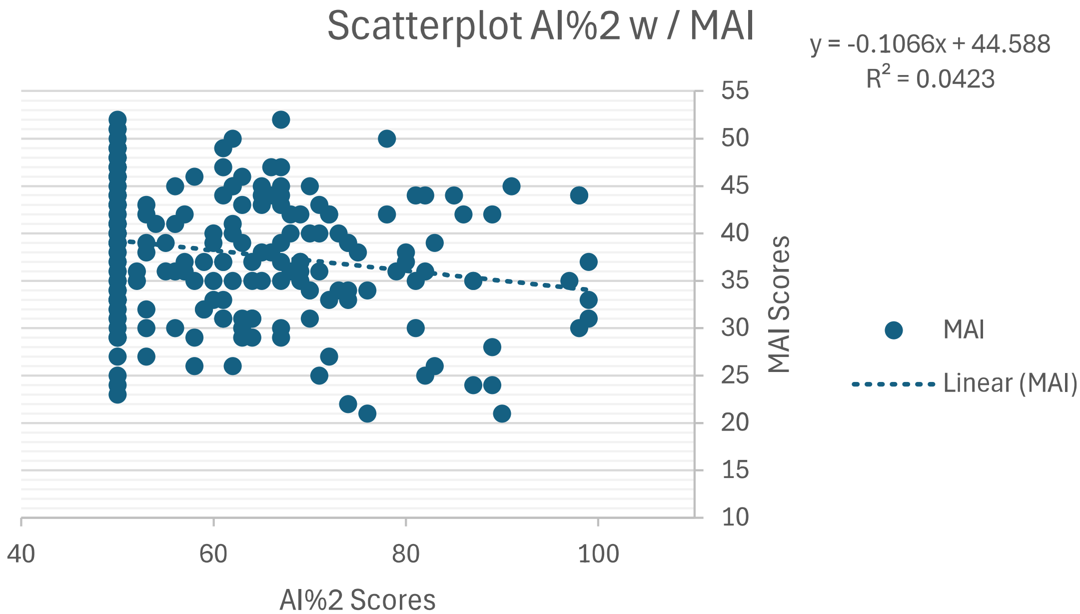


Table 14

Regression Analysis of Dim%_1, Ai%_2, and MAI Scores

Regression Statistics		
R-squared	0.07	
Observations	215	
	Coefficients	*p*-value
Intercept	39.57	0.00
Dim%_1	0.07	0.02
Ai%_2	-0.10	0.00

These two HVP subscales accounted for about 7% of the variation in MAI scores. Both independent variables have a *p*-value below the .05 threshold, so the predictions were unlikely to occur by chance. For every one-unit change in Dim%_1 scores predicted a 0.07 unit change in MAI scores, holding Ai%_2 scores constant. A one-unit change of Ai%_2 scores resulted in a 0.10-point decrease in MAI scores. However, heteroscedasticity in the Ai%_2 scores could have affected the results. Nonetheless, these two HVP subscales have more effect on MAI scores than any combination analyzed so far, but the impact remains reasonably small at 7%. So far in this search, there was little evidence that HVP scores—alone or in small combinations—have much meaningful and significant influence on predicting MAI scores. But other measures still need examination.

While remaining wary of trying to over-fit the data in this analysis, it may be informative to look at some of the HVP subscales that axiologists tend to skim over when debriefing clients on

HVP scores. I refer to a handful of subscales comprising various combinations of Part 1 and Part 2 scores, called the VQ, SQ, BQr, BQa, and CQ subscales. With these scales, Hartman (2006) makes a confusing change in meaning. For these scales, Hartman no longer refers to Part 1 as the worldview and Part 2 as the self-view. For these subscales, Part 1 refers to quantitative evaluative thought patterns, and Part 2 as qualitative thought patterns. Each of these subscales is derived from other subscales in Part 1 and Part 2 of the HVP. Thus, each contains portions of a person's worldview and self-view. If this sounds confusing, it is. See the Manual of Interpretation (2nd Ed., 2006) for a detailed explanation of Hartman's reasoning. For twenty years, I tended to ignore these subscales until a conversation with North (personal communication, 2022) led me to recognize their importance.

Once again, I begin with descriptive statistics. Each of the scales is reviewed in Table 15.

Table 15

Descriptive Statistics for 10 More Subscales of the HVP

	VQ1	VQ2	SQ1	SQ2	BQr1	BQr2	BQa1	BQa2	CQ1	CQ2
Mean	72	31	96	44	2	2	84	37	145	79
Median	60	24	84	36	1	1	74	31	110	56
Mode	58	19	98	23	1	1	65	23	142	70
Minimum	21	5	28	7	0	0	25	8	32	14
Maximum	286	146	283	141	7	9	254	130	1188	691

N = 215

Hartman (2006) provided descriptions and ranges of scores for each in the Manual of Interpretation. Next, I continued with a correlation analysis to test for multi-collinearity. The results are shown in Table 16 below. In many instances, there were stronger correlations between HVP subscales than between each of those subscales and the MAI. Additionally, the results of a multi-linear regression are shown in Table 17 utilizing the VQ1, VQ2, SQ1, SQ2, BQR1, BQR2, BQA1, BQA2, CQ1, and CQ2 subscales of the HVP and the MAI.

Table 16

Correlation Analysis of 10 Subscales of the HVP and MAI Scores

	VQ1	VQ2	SQ1	SQ2	BQr1	BQr2	BQa1	BQa2	CQ1	CQ2	MAI
VQ1	1	0.99	0.37	0.34	-0.38	-0.39	0.80	0.78	0.20	0.13	-0.01
VQ2		1	0.36	0.33	-0.39	-0.41	0.78	0.77	0.19	0.11	0.01
SQ1			1	0.98	0.61	0.49	0.86	0.86	0.85	0.83	-0.11
SQ2				1	0.62	0.53	0.83	0.85	0.84	0.84	-0.10
BQr1					1	0.92	0.19	0.20	0.77	0.80	-0.08
BQr2						1	0.11	0.12	0.64	0.74	-0.04
BQa1							1	0.99	0.67	0.61	-0.08
BQa2								1	0.67	0.62	-0.06
CQ1									1	0.97	-0.09
CQ2										1	-0.06
MAI											1

Table 17

Multiple Linear Regression Results Using VQ, SQ, BQR, BQA, and CQ Subscales (both Parts 1 and 2) of the HVP and MAI Scores

Regression Statistics		
R-squared	0.07	
Observations	215	
	Coefficients	*p*-value
Intercept	44.12	0.00
VQ1	-0.23	0.03
VQ2	0.41	0.02
SQ1	0.08	0.26
SQ2	-0.17	0.17
BQr1	-3.06	0.45
BQr2	0.84	0.63
BQa1	0.00	#NUM!
BQa2	0.00	#NUM!
CQ1	-0.04	#NUM!
CQ2	0.08	0.08

Together, these ten subscales account for 7% of the change in MAI scores. The SQ and BQR were ignored due to their high *p*-values. The BQA and CQ subscales did not meaningfully contribute to changes in MAI scores, but the VQ1 and VQ2 scores showed promise. The error message "#NUM!" was shown in Excel as representing a number too small to calculate. I can consider it zero.

Hartman (2006) described these two subscales and their ranges in the Manual of Interpretation in this way: "The Value Score (V.Q.) "measures the objective valuation capacity of the person, that is, his capacity of valuing outside situations. The first figure (VQ1) measures his total capacity, and the second (VQ2) qualifies it according to his inner harmony or discord" (p. 52). Hartman continued, "The scale of the second part of the V.Q. follows the Sub-Dimension scale" (Hartman, 2006, p. 52). Ratings of VQ1 scores are shown in Table 18, and VQ2 is shown in Table 19.

Table 18

Rating of VQ1 Subscale of the HVP

Error	Scores
0–55	Excellent
56–70	Very Good
71–85	Good
86–100	Poor
116–130	Very Poor
131+	Bad

Table 19

Rating of VQ2 Subscale of the HVP

Score	Rating
0–7	Excellent
8–14	Very Good
15–21	Good
22–28	Average
29–35	Poor
35–42	Very Poor
43+	Bad

The sample respondents' mean VQ1 score is 72, which is Good, and their mean VQ2 score is 31, which is poor. This was surprising because the VQ1 and VQ2 scores were highly correlated, at 0.99.

The analysis to this point has found several significant relationships. The Rho_2 score had a modest but more meaningful impact on MAI scores than the Rho_1 score. Within the Big Four subscales, the Dim_1 and Dis_2 were significant predictors. The Dim_I_2, Dim_%_1, and AI%_2 scales seemed to have a meaningful impact on MAI, as do the VQ1 and VQ2. Therefore, a combined analysis of the significant predictors was prudent. Let me refer to these significant eight measures as the "Big Eight."

The Big Eight

A multiple linear regression using these eight scales was performed to see how much they can predict MAI scores. However, these scores overlap or are used to calculate measures in the analysis. This increases the risk of multicollinearity. Given that so many HVP subscales are derived from others, multicollinearity is always a consideration when performing quantitative analyses such as this. I can view the potential for multicollinearity by looking at a correlation analysis, shown in Figure 20.

Table 20

Correlation Analysis of Big Eight HVP Subscales

	Rho_2	Dim_1	Dis_2	Dim_i_2	Dim%_1	AI%_2	VQ1	VQ2	MAI
Rho_2	1	-0.21	-0.86	-0.86	0.10	-0.80	-0.38	-0.37	0.09
Dim_1		1	0.19	0.14	0.65	0.15	0.66	0.75	0.13
Dis_2			1	0.72	-0.08	0.94	0.33	0.32	-0.18
Dim_i_1				1	-0.08	0.68	0.27	0.26	-0.16
Dim%_1					1	-0.09	-0.06	0.07	0.18
AI%_2						1	0.30	0.29	-0.21
VQ1							1	0.99	-0.01
VQ2								1	0.01
MAI									1

Table 21 shows the results from a multiple linear regression using all eight of the Big Eight measures of the HVP as independent variables and the MAI as the dependent variable.

Table 21

Multiple Linear Regression Between Big Eight of the Subscales of the HVP and MAI Scores

Regression Statistics		
R-squared	0.12	
Observations	215	

	Coefficients	*p*-value
Intercept	58.62	0.00
Rho_2	-15.59	0.00
Dim_1	0.18	0.42
Dis_2	-0.30	0.55
Dim_i_2	-0.26	0.01
Dim%_1	0.05	0.51
AI%_2	-0.14	0.16
VQ1	0.09	0.59
VQ2	-0.20	0.53

An initial glance suggests these measures accounted for 12% of the change in MAI scores, the highest prediction found yet. However, due to multicollinearity, the findings were likely to be unreliable. A correlation analysis showed strong associations between the measures. Additionally, several measures had large *p*-values: Dim_1, Dis_2, Dim%_1, VQ_1, and VQ_2. These subscales are so closely related that they interfere with interpreting the results. Therefore, a multicollinearity test is appropriate.

A correlation analysis is one method for testing multicollinearity. A second method regresses each variable against the others to determine the amount of variance the independent variable explains (Bandhari, 2024). The closer the R-squared approaches 1.00, the more likelihood of multicollinearity. This method is known as the Variance Inflation Factor (VIF), and a VIF analysis is shown in Table 22.

Table 22

Variance Inflation Factor Analysis Using the Big Eight

HVP Sub-scale treated as the dependent variable by the remaining seven subscales	R^2
Rho_2	0.86
Dim_1	0.92
Dis_2	0.91
Dim_i_2	0.75
Dim%_1	0.88
AI%_2	0.88
VQ_1	0.99
VQ_2	0.99

Even though Rho_2 and Dim_i_2 still varied quite a lot with the other independent variables, they were the least collinear of the eight subscales. Thus, another regression analysis was performed using the Rho_2 and Dim_i_2 to determine the amount of variance explained in MAI scores. The results are shown in Table 23.

Table 23

Regression Analysis Between Rho_2 and Dim_i_2 Subscales of HVP and MAI

Regression Statistics		
R-squared	0.03	
Observations	215	

	Coefficients	*p*-value
Intercept	45.36	0.00
Rho_2	-5.06	0.19
Dim_i_2	-0.24	0.02

The analysis indicated that the two measures explained only 3% of the variance in MAI scores. However, these results should be considered with caution. The two measures co-varied a lot. Their correlation was 0.86, which is a strong correlation.

Emotional Balance of HVP Scores

So far, the analysis has explored measures of the HVP that were derived from the portion of the assessment that measures a person's strength of judgment. The analysis showed no or little correlation or predictive ability of these HVP scores to predict MAI scores. However, another set of measures report on what is known as the emotional balance that the respondent has in each of the three dimensions of intrinsic, extrinsic, and systemic in Parts 1 and Parts 2. In addition to measuring how well developed that person's deeply held evaluative thought patterns are in each of these dimensions, the assessment reports on the degree to which the respondent has an emotionally balanced view of those dimensions or a negative (pessimistic) view of what he or she knows, or a positive (optimistic) view of what he or she knows. For this reason, I felt it essential to evaluate whether respondents' balance indicator (Bi) scores in each dimension might predict their MAI scores.

I created visualizations, scatterplots, correlation analyses, and regression analyses for each of the six indicators of emotional balance. The following table shows the mean and median scores of participants in the sample for the Balance Indicators. Note that for this sample, Balance indicators were negative for five subscales and only positive for how people perceive the Systemic dimension in Part 2. This is shown in Table 24 below.

Table 24

Mean and Median Scores of Balance Indicators in HVP

Balance Indicators	Mean Score	Median Score
Bi_i_1	-4.49	-2
Bi_e_1	-3.35	-2
Bi_s_1	-1.92	-1
Bi_i_2	-11.04	-9
Bi_e_2	-6.20	-5
Bi_s_2	0.3	3

I conjecture that the noticeably negative Bi_2 and Be_2 scores in this sample reflect the fact that most of this sample are college students. Traditionally, college students are at a stage in life where they are starting to figure out "Who am I?" and "What am I supposed to do with myself as an adult?" Hence, this sample may not represent the adult population at large.

I performed a correlation analysis of all six of the HVP's subscales with the MAI. As the last row in Table 25 reveals, no strong, moderate, or even weak correlations (> 0.20) exist for any of these pairs.

Table 25

Correlation Analysis of Balance Indicators of HVP with MAI Scores

	Bi_i_1	Bi_e_1	Bi_s_1	Bi_i_2	Bi_e_2	Bi_s_2	MAI
Bi_i_1	1	0.34	0.44	0.25	0.22	0.25	0.04
Bi_e_1		1	0.27	0.14	0.25	0.17	-0.08
Bi_s_1			1	0.10	0.11	0.16	0.04
Bi_i_2				1	0.47	0.41	0.05
Bi_e_2					1	0.40	0.14
Bi_s_2						1	0.15
MAI							1

The strongest correlations were between Bi_e_2 and bi_s_2 and the overall MAI score, with correlations of 0.14 and 0.15, respectively. Hence, I only created scatterplots for only those two measures. The plots are shown in Figures 9 and 10 below.

Figure 9

Scatterplots of Bi_e_2 Scores of HVP with MAI

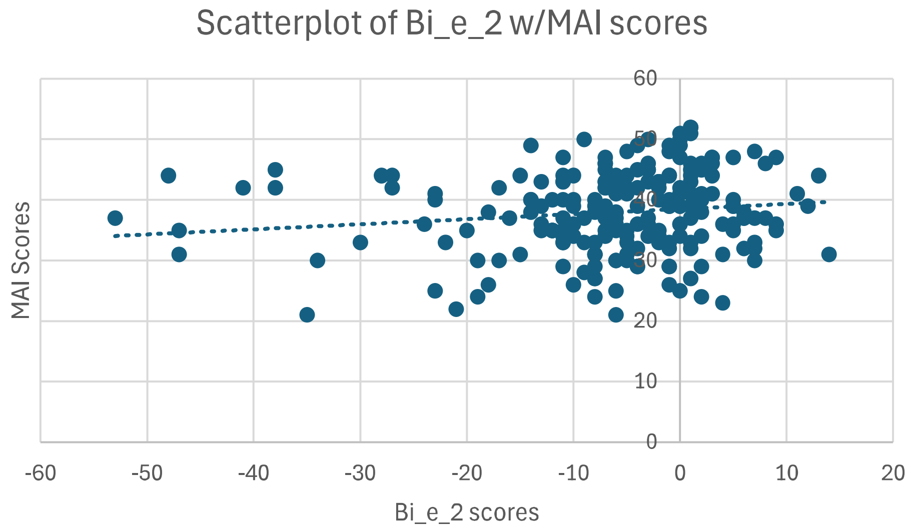
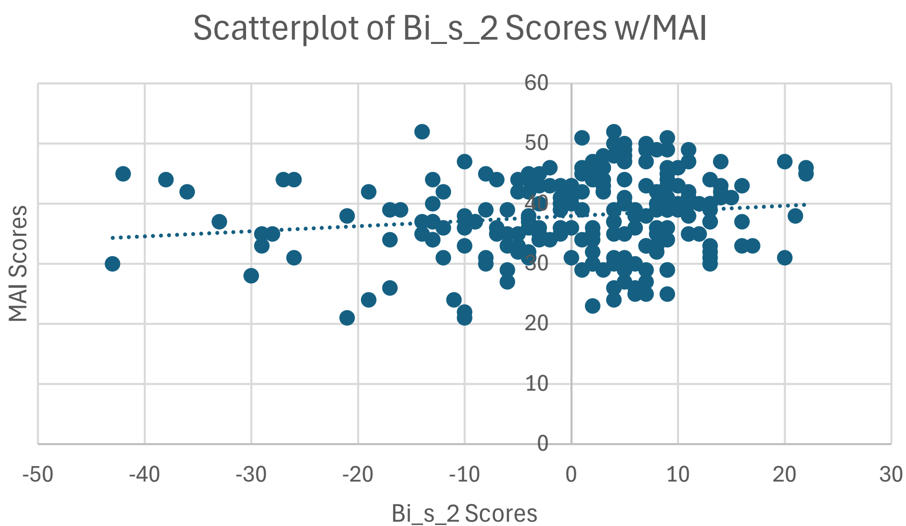


Figure 10

Scatterplots of Bi_s_2 Scores of HVP with MAI



A linear regression analysis of these two balance indicator subscales of the HVP with overall MAI scores revealed the following, as shown in Table 26. The R-squared accounted for about 3% of the overall variance in MAI scores. Also, each measure had a high *p*-value, exceeding the .05 threshold. Therefore, the emotional balance indicators of the HVP did not have any significant ability to predict people's MAI scores.

Table 26

Regression Analysis of Bi_e_2 and Bi_s_2 Scales of the HVP with MAI.

Regression Statistics		
R-squared	0.03	
Observations	215	

	Coefficients	*p*-value
Intercept	38.31	0.00
Bi_e_2	0.06	0.22
Bi_S_2	0.06	0.13

Throughout this study, multiple analyses were performed using combinations of subscales of the HVP to see if, and to what degree, they predict a person's responses to the Metacognitive Awareness Index. The results indicate only slight predictiveness in each iteration. There may be stronger relationships that I have been unable to find due to limitations inherent in this study.

Limitations

This study has several limitations. First, the sample size of 215 is adequate for the data analysis but too small to perform multiple linear regression analyses using all HVP subscales and the overall MAI score. A much larger data set is necessary. Over the next few years, I strive to more than double the size of the data sample. A larger sample size may also afford reductions in *p*-values in instances where high *p*-values were encountered.

Second, I have only examined the overall MAI scores as the dependent variable in this study. However, the overall MAI score comprises two subscales and ten sub-subscales. With a larger data set, I could explore whether specific subscales of the HVP are more capable of predicting the subscales of the MAI.

Third, it is necessary to point out that the sample's demographics are peculiar to the setting in which this research has been undertaken. I am a college professor, and my research interests center on the cognitive development of college-age students, especially transformative learning. Therefore, younger adults are overrepresented in this sample compared to the general adult population.

Fourth, there are other ways of measuring metacognition. I have chosen to examine the MAI. Some versions of the MAI use a Likert scale so that respondents can respond to each statement with a range of 1 to 7. I used a version that requires a simple Yes or No response to each statement. I did this for two reasons. First, it is easier and quicker for participants to complete, which helps improve completion rates. Second, I agree with Hartman (2002, p. 312), who warns against accepting the "fictitious scalability" imposed upon phenomena by researchers in the social sciences. I wrote about this in more detail in my article entitled *Hartman v. Rokeach* in this Journal (Hurst, 2009).

Conclusion

In this study, I have explored several approaches to validating the research hypothesis that a person's unconsciously held evaluative thought patterns, as measured by the HVP, can be used to predict that person's consciously held metacognitive awareness, as measured by the MAI. I have sought to explain my reasoning for each step so that readers can follow what I have done and interpret their meanings from the data I have analyzed. Quantitative findings are always subject to interpretation. After taking several different approaches to seeking predictiveness, I have found a combination of subscales of the HVP, which, at a maximum, seem to account for 3% to 7% of the change with a respondent's MAI scores. And those findings leave some elements in doubt as to their reliability.

With each approach, even the strongest associations were weak and often not significant. Hence, I conclude that the null hypothesis—that there is not a meaningful or statistically significant relationship between what these two assessments—is the one we must accept.

In short, as espoused by Lakoff (1999) Wilson (2002), Hurst (2019) and others, people in this study are prone to be not very consciously aware of their unconscious thought patterns. Subsequently, their unconscious thought patterns have little impact upon their metacognitive awareness as measured by the Metacognitive Awareness Inventory. I can further conclude from this investigation that, indeed, the Iceberg Metaphor serves as an apt description of human cognition.

This is not to say that either of these two assessments is right or wrong. They are different. They apparently measure two different aspects of human cognition. We need more than one lens with which to understand human cognition.

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